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Cuffless Non-invasive Blood Pressure Measurement Using CNN-LSTM Model: A Correlation Study

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***Abstract* - Cardiovascular disease is a major concern for people all around the world and still remains as the main cause of death worldwide. Blood pressure has been identified as the most important risk factor. Having the ability to acquire continuous monitoring on this biological parameter plays a significant role in reducing the risk of getting cardiac disease. Many studies conducted utilize two biosignals and features manually extracted from signals as input to the model. However, these methods increase the computational complexity in the pre-processing stage as it involves signal synchronization, and the model performance is highly dependent on the selection of features. The main objective of this study is to build a hybrid convolutional neural network combined with Long-Short Term Memory (CNN-LSTM) model to estimate blood pressure from PPG signals, which eliminates the need for manual feature extraction. Correlation study is performed to evaluate the performance of the model, and it gives a direct visualization of the model's performance in percentage. This research compared the correlation performance between MIMIC-II dataset, UKM dataset, and PPG-BP dataset using the CNN-LSTM model to estimate blood pressure from PPG signals. The results show that the UKM dataset performs the best, having the highest overall correlation at 0.53 for systolic blood pressure, and 0.29 for diastolic blood pressure. The model trained with this dataset is suitable to estimate systolic blood pressure ranging from 141 to 150mmHg, and diastolic blood pressure ranging 81 to 90 mmHg. In conclusion, among the three datasets, UKM dataset is the most suitable dataset to be used as the input of the CNN-LSTM model to perform cuffless blood pressure measurement with PPG signals.**

Keywords—* *Blood Pressure, Artificial Intelligence, Photoplethysmography, Correlation.

I. Introduction

Cardiovascular diseases are diseases that are related to the heart or blood vessels. According to the statistics provided by the World Health Organization (WHO) [1], there are around 17.9 million deaths per year due to cardiovascular diseases. Around 85% of these deaths are due to heart attacks and strokes. In Malaysia, ischemic heart disease, a type of cardiovascular disease is the principal cause of death in year 2020 [2]. Cardiovascular disease is found to be related to high blood pressure [3-4] This is because high blood pressure destroys the inner layer of artery, causing them to be vulnerable to formation of plaque, which leads to the narrowing of artery that provides blood to the heart and brain [5]. Hence, blood pressure has been identified as the most important biomarkers and indicators for cardiovascular diseases. The ability to acquire a

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continuous monitoring on this biological parameter would play a key role in preventing cardiac diseases [1].

Many studies have been conducted, and techniques have been introduced to obtain monitoring of blood pressure. Based on previous studies, blood pressure monitoring technique can be divided into two parts, which are the invasive and non-invasive method. A catheter must be inserted into the body of the subject to perform invasive blood pressure monitoring. Although it enables a continuous monitoring on blood pressure, this method needs to be performed by skilled operator, and potentially exposes the subject to major complications, such as embolism if done wrongly [6]. Hence, non-invasive methods are given attention.

There are two types of non-invasive methods introduced. Firstly, we will be discussing non-invasive blood pressure monitoring with cuffs. The instrument used is a sphygmomanometer. This method works by having a rubber cuff cuffed around the arm of the subject and depending on the inflation of the cuff and the Korotkoff sound, the blood pressure can be determined [7]. However, the disadvantages of using a sphygmomanometer are, it does not allow a continuous monitoring on blood pressure [8], and the subject may experience inconvenience when being cuffed, especially people who have obesity [9-10].

Hence, the cuffless non-invasive blood pressure measurement techniques are introduced. This is further divided into two parts. Pulse Transit Time (PTT), and Pulse Arrival Time (PAT) are among of the works that been done to monitor blood pressure continuously. Parry Fung et al. [11] has proved that the PTT changes inversely with blood pressure. A photoplethysmography (PPG) signal, and an electrocardiogram (ECG) signal are required to obtain the PTT and PAT [12]. Although it provides continuous blood pressure assessment, the downside is it would require calibration in accordance with the subject's physiological characteristics [13]. Since this method requires two signals, it might also cause the subject to feel uncomfortable as more than two sensors need to be located on the subject's body. In addition to that, this would impose challenge on the hardware as it requires a synchronization between two signals [14].

Due to technological advancement, recent studies have diverted their focus to integrate artificial intelligence in solving this problem, which will be the focus of this research. This is because a cuffless non-invasive continuous blood pressure measurement is achievable by only utilizing one sensor to obtain the PPG signals [15]. The trained model can be further adapted and optimized into device for continuous blood pressure measurement. Table 1 shows eight studies which uses machine learning and deep learning modes to predict blood pressure using different types of inputs and databases from year 2001 to 2021.

TABLE 1. Investigation on the performance of different machine learning and deep learning models.

Reference	Model and Input	Type of Database Used	Performance		Limitations/Suggestions
			SBP	DBP	
Chan et al. [16]	Linear Regression Algorithm (PTT Features)	Self-built Database	ME: 7.49 STD: 8.82	ME: 4.08 STD: 5.62	Dependent on the calibration for each subject due to the difference in physiological parameter
Kachuee et al. [17]	AdaBoost (Features from PPG and ECG signals based on Pulse Arrival Time)	MIMIC-II Database	MAE: 8.21 STD: 5.45	MAE: 4.31 STD: 3.52	Include other biosignals and subject's demographic information to increase the accuracy of the model
Y. Zhang & Feng [18]	Support Vector Machine (Time domain PPG signal features)	University of Queensland Database	ME: 11.64 STD: 8.20	ME: 7.62 STD: 6.78	Increase data size to increase the accuracy of the model
Shobitha et al. [19]	Relevance Vector Machine (7 features from PPG signals)	Self-built Database	Kappa: 0.99	Kappa: 0.99	Use larger database that contains subject with cardiovascular disease
Kurylyak et al. [20]	Artificial Neural Network (21 features from PPG signals)	MIMIC Database	ME: 3.80 STD: 3.46	ME: 2.21 STD: 2.09	Optimize the model into smartphones
Slapničar et al.[21]	ResNet, combined between CNN+GRU (Original, first derivative, and second derivative of PPG signals)	MIMIC-III Database	MAE: 9.43	MAE: 6.88	Noise in derivatives of PPG signals affects the model's performance during training phase
Su et al. [22]	Recurrent Neural Network (Features from PPG and ECG signals)	Self-built Database	RMSE: 3.90	RMSE: 2.66	Using Bi-LSTM would further increase the performance of the deep learning model in measuring blood pressure
Yang et al. [23]	CNN+LSTM hybrid model (Features from PPG and ECG signals with demographic information)	Self-built Database	ME: 4.43 STD: 6.09	ME: 3.23 STD: 4.75	Tuning hyperparameters based on the data of each individual to increase prediction accuracy. Use larger dataset to test the model

Evdochim et al. [24]	Fiducial Points from PPG signals	MIMIC-III Database	Pekali korelasi: 0.47	Lack of an algorithm to ensure and check signals quality

Based on Table 1, we can observe that the overall performance of deep learning model is better than using machine learning algorithms to predict blood pressure. Besides that, there are various databases used to conduct the studies, such as the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) database, and self-built database. However, the correlation coefficient is not specified. Correlation coefficient does not only quantify the linear relationship between the targeted and inference value, but it also gives us a direct visualization on the model performance in percentage. Furthermore, we can observe that some studies used two signals as input to the model, but this would increase the computational complexity as it requires synchronization between signals. Moreover, most of the studies performed manual feature extraction, and the extracted features are fed into the model as inputs. Performing feature engineering manually would increase the workload in the pre-processing stage.

To solve these problems, this paper aimed to build a pre-processing algorithm to clean up the PPG signals. Besides that, this paper proposed a deep learning model that can automate the process of feature extraction using a hybrid model consisting of convolutional neural network (CNN) and Long-Short Term Memory (LSTM). A correlation study based on three different datasets using the proposed model is performed to identify the most suitable dataset to be used as an input to the proposed model. Lastly, the performance of the model trained with the selected dataset is then further analyzed.

II. METHODOLOGY

A. Data Acquisition

There are three databases that are used in this project. The first database is the MIMIC-II Database. This database is taken from the University of California, Irvine (UCI) Machine Learning Repository [17]. This database is adapted from the original database which is in the publicly available database at Physionet [25]. This database contains records of several physiological signals, such as PPG, artery blood pressure (ABP), and electrocardiogram (ECG). All records are sampled at 125Hz. The ABP has been taken as the to calculate the systolic blood pressure (SBP), and diastolic blood pressure (DBP) of corresponding subject [26] as ground truth. The database from the UCI repository has 12000 records stored in 4 MAT files, with each cell containing the record of each individual. In this project, the PPG signals of the first 692 subjects from this database are taken to form the MIMIC-II dataset. Figure 1 shows the data distribution of SBP and DBP for this dataset.

Next, the second database that is used in this project is the UKM Database. This database contains continuous PPG signal records for subjects without diabetes, which are classified as healthy subjects, and diabetic patients. A total of 50 subjects are used to form the UKM Dataset. Each record that is chosen from this database is taken from the subject's left hand at arms bed level. Each record has a duration of 1.5 minutes, sampled at 275Hz. Figure 2 shows the data distribution of SBP and DBP for the UKM Dataset.

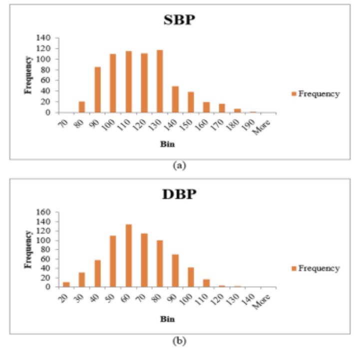


FIGURE 1. Data distribution in MIMIC-II Dataset for (a) SBP and (b) DBP.

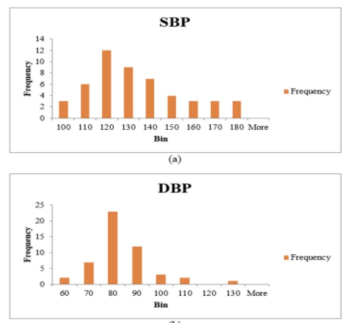


FIGURE 2. Data distribution in UKM Dataset for (a) SBP and (b) DBP.

Lastly, the third database selected for this project is the PPG-BP Database. The PPG-BP Database is a database that is established through research conducted by [27]. In this database, there are 657 PPG signals taken from 219 subjects. The database covers individuals aged from 21 to 86 years old, and it contains healthy individuals as well as high blood pressure patients. All PPG signals in this database are sampled at 1000 Hz. For each subject, three PPG signal segments are recorded with each record having a duration of 2.1 seconds. All records in this database have been taken to form the PPG-BP Dataset.

Figure 3 shows the data distribution of SBP and DBP for the PPG-BP Dataset. Hence, there are three datasets that engage in this project, which are the MIMIC-II Dataset, UKM Dataset, and PPG-BP Dataset. All the records in these datasets then underwent the signal pre-processing stage.

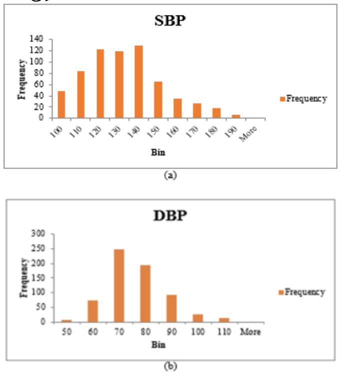


FIGURE 3. Data distribution in PPG-BP Dataset for (a) SBP and (b) DBP.

B. Signal Pre-processing

The PPG signals from each dataset will undergo pre-processing stage before they are used to train the deep learning model. This process involved signal filtering, signal normalization, signal segmentation, and down-sampling. Firstly, all the signals underwent signal filtering. This is because PPG signals contain direct current (DC) components, and alternating current (AC) components [28]. The DC components represent the absorption of light by body tissues, and it is affected by the respiration rate [29]. On the other hand, the AC components represent the volume of blood which is affected by the heartbeat [30]. Hence, filtering is crucial to ensure clean and suitable PPG signals are obtained to train the model.

Thus, for UKM Dataset, a Butterworth Bandpass Filter ranging from 0.6Hz to 15.0Hz is used. 0.6Hz has been selected as the lowest cut-off frequency because according to Chowdhury et al. [31], the respiration rate is around 0.15Hz to 0.5Hz. As for the high cut-off frequency, 15.0Hz is selected as it can retain the signal features as much as possible while filtering out the high frequency noise. For PPG-BP Dataset, a Butterworth Lowpass Filter at 25.0Hz is selected to filter the PPG signals in the dataset as suggested by Chowdhury et al. [31]. However, for the MIMIC-II dataset, the signals from the UCI repository have been pre-processed previously [17], and hence, the signals do not undergo filtering process.

To further reduce the computational complexity, signal normalization has been done to all datasets. Min-max normalization has been chosen in our project. Normalization is done to ensure that the deep learning model can treat all features equally. Besides that, this could also restrict the effect of outlier as all features are scaled from 0 to 1. In addition to that, normalization could reduce the computational complexity and speed up the processing time. This is because the process of summing up and subtracting small numbers can be performed easily by the computer [13]. The equation below shows the equation of min-max normalization used in this project.

$$X_{norm} = \frac{x - min\,(x)}{max(x) - min\,(x)} \tag{1}$$

After normalization has been done, signal segmentation is performed. The main objective of this project is to increase the size of the dataset, which also indirectly creates variation in the available data to increase the generalization of the model [32]. In this project, the sliding window technique is used. A window which has a duration of 8 seconds is slid across the PPG signals with 75% overlapping, which is sufficient to capture useful information in the signal [33-34]. Table 1 shows the total number of signals for each dataset after this process.

All the signals are then down sampled to 250 samples while preserving the essential information in the signals [35]. The signals are down-sampled to further reduce the computational complexity, dan it allows the optimization of model into resource-constrained platform such as smartphones. Then, all the data are rearranged randomly for each dataset. Lastly, for each dataset, 80% of the signals are classified as training dataset, while the remaining 20% of the signals in the dataset are classified as testing dataset.

TABLE 2. Total number of signals for each dataset.

Type of Dataset	Number of Signals
MIMIC-II	2076
UKM	2050
PPG-BP	657

C. Deep Learning Model Training and Evaluation

In this project, the deep learning model chosen is the hybrid model consisting of CNN and LSTM (CNN-LSTM). This model consists of only one input, which is the PPG signal, and the model can produce two outputs, which are the SBP, and DBP values. This model begins with two layers of one-dimensional CNN (1DCNN), which aims to automate the process of feature extraction from PPG signals that is received. Each layer of 1DCNN is also intercepted with ReLU activation layer, max-pooling layer, and dropout layer to prevent overfitting situation. After the 1DCNN layers, the extracted features from 1DCNN layers are passed on to two layers of LSTM to predict the value of SBP and DBP. The CNN-LSTM model is built using Python language using Spyder integrated development environment. The model is built on Pytorch 1.10.2 framework with CUDA 11.3. The hardware used in the training is the AMD Ryzen 5 3550H with Radeon Vega Mobile GFX CPU, and NVIDIA GeForce GTX 1050 GPU. Figure 4 shows the architecture of the CNN-LSTM model used in this project.

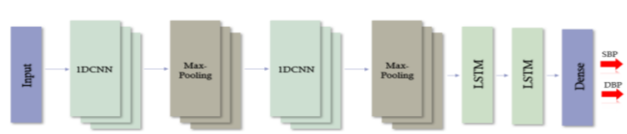


FIGURE 4. Architecture of CNN-LSTM model.

To evaluate the performance of the model, a standard evaluation metric for machine learning and deep learning model is used. Correlation coefficient and mean squared error (MSE) are the most common metric that are used to evaluate the deep learning model performance, especially model which is used to solve regression problem [36-37]. Besides showing the strength of linear relationship between two values, correlation coefficient can evaluate how good the predicted value is matched with the targeted value. At the same time, the MSE is used to calculate the loss of each CNN-LSTM model. This evaluation has been conducted so that we are able to have a better understanding of the generalization of the model. Generalization of a model indicates the ability of the model to adapt to predict a value that has not been trained from dataset.

Each dataset is used to train the CNN-LSTM model, and three models are produced, respectively. Based on the correlation performance, the most suitable dataset to be used as an input to the CNN-LSTM model to predict blood pressure from PPG signal is determined. Then, the performance of the model trained with the selected dataset is further analyzed.

III. Results And Discussions

A. Correlation Performance and Model Loss

The optimizer used is Adam optimizer, and the scheduler for learning rate used is exponential with gamma = 0.99. The hyperparameters for the model of each dataset are optimized, and the results obtained are the best result for each model. Figure 5 shows the graph and correlation coefficient of SBP of each model trained with the three datasets, respectively.

Based on Figure 5, the output of the model trained with UKM dataset has the highest correlation coefficient when predicting SBP, which is at 0.534826, followed by model trained with MIMIC-II dataset at 0.452832, and with PPG-BP dataset at 0.293501. Based on the result, we observed that the model trained with the MIMIC-II dataset can only predict SBP values more than 130 mmHg, which leads to a poor correlation between the targeted and predicted value. Besides that, for PPG-BP dataset, the predictions made by the model can exceed 130mmHg, however, the predictions made by the model are all scattered around, indicating many predictions made by the model do not match with the targeted value. Hence, while predicting SBP value, UKM dataset has the best correlation performance as compared to another dataset.

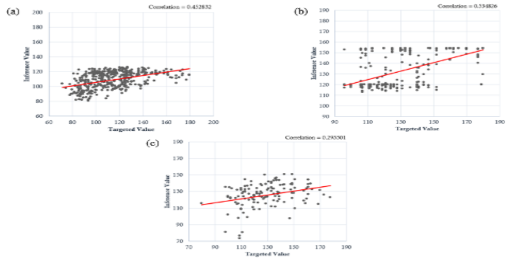


FIGURE 5. Correlation graph of SBP for (a) MIMIC-II, (b) UKM, and (c) PPG-BP Dataset.

Next, Figure 6 shows the graph and correlation coefficient of DBP of each model trained with the three datasets, respectively. Based on Figure 6, it is observable that both model outputs trained with MIMIC-II dataset and UKM have similar correlation performance while predicting DBP, which are at 0.296664 and 0.290799 respectively, while PPG-BP dataset is only at 0.091125. The poor correlation performance of the PPG-BP dataset might be due to the insufficient data in the dataset, which caused the model to fail to extract the relevant features to predict the data.

Figure 7 shows the loss graph of each model trained with respective dataset. Based on Figure 8, the loss in MSE for each model decreases and converges as the number of epochs increases. The model trained with UKM dataset has the highest model loss during training and testing phase, whereas the model trained with the MIMIC-II dataset has the lowest model loss during both phases.

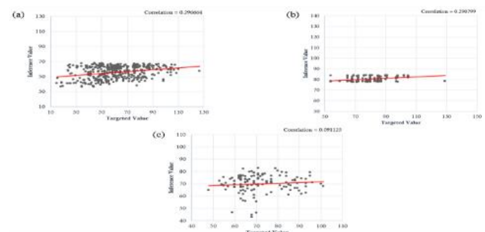
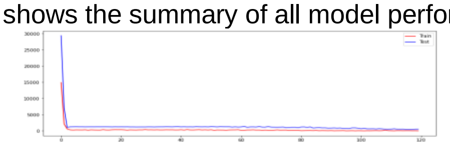
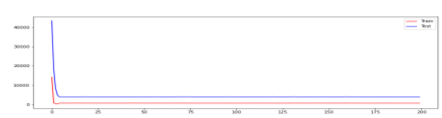


FIGURE 6. Correlation graph of DBP for (a) MIMIC-II, (b) UKM, and (c) PPG-BP Dataset.

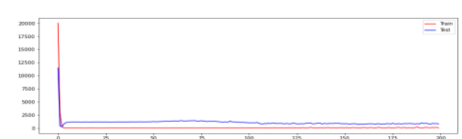
However, there is a significant difference between the model loss during the training phase and testing phase for all three models, which indicates that these models are experiencing overfitting problem. This situation can also be observed in Figure 7 where there is a significant gap between the training and testing loss graph for all three models. Overfitting situation represents the trained model might not be able to predict the blood pressure correctly if other PPG signal were used as an input. Table 3 shows the summary of all model performance.



(a)



(b)



(c)

FIGURE 7. Model Loss in MSE for (a) MIMIC-II, (b) UKM, and (c) PPG-BP Dataset.

Based on the results in Table 3, the results show that the CNN-LSTM model has a better prediction for SBP values as compared to the DBP values for all three datasets. However, based on the correlation performance, the UKM dataset has the highest overall performance, with correlation coefficient of 0.534826 for SBP values, and 0.290799 for DBP values. Hence, UKM dataset is determined to be the most suitable dataset to be used as input to the CNN-LSTM model to predict blood pressure from PPG signals.

TABLE 3. Summary on model performance based on types of datasets.

Type of Dataset	Correlation Coefficient		Model Loss	
	SBP	DBP	Training Phase	Testing Phase
MIMIC-II	0.447402	0.296664	5.81125	517.2136
UKM	0.534826	0.290799	88.46954	4034.4727
PPG-BP	0.293501	0.091125	52.49256	834.15497

B. Analysis on Selected Model

Since the CNN-LSTM model trained with UKM dataset has the highest overall correlation performance, this session further analyzed the model performance in predicting SBP and DBP of a subject. Table 4 shows the model performance in predicting SBP values according to bins.

Table 4 shows that the selected model has the highest prediction for SBP values ranging between 131 and 140 mmHg. This is because the correlation coefficient for this range is the highest, which is 0.698117. On the other hand, due to the SBP values ranging between 141 and 150mmHg having the lowest correlation coefficient at -0.62234, this model has the lowest prediction for the SBP values falling within the range. This situation indicates that the model performs the best in predicting the blood pressure of a subject whose SBP is falling within 131 to 140mmHg from PPG signals.

TABLE 4. SBP correlation coefficient based on bins.

Bin (mmHg)	Correlation Coefficient
100	-0.36518
110	0.486483
120	0.114053
130	0.465304
140	-0.62234
150	0.698117
160	0.501342
170	-0.20663
180	-0.09088

Table 5 shows the model performance in predicting DBP values according to bins. From Table 5, the correlation coefficient for DBP values ranging from 81 to 90 mmHg is the highest, at 0.255321. This indicates that the trained model has the highest prediction for DBP values falling in this range. However, this model has the lowest prediction for DBP values that ranges from 101 to 110mmHg. This is shown by the lowest correlation coefficient indicated at -0.60813. Therefore, the model performs the best when it is predicting the DBP values from 81 to 90mmHg. In short, the trained CNN-LSTM model is suitable to predict SBP values ranging from 131 to 140mmHg, and DBP values with range between 81 to 90mmHg.

TABLE 5. DBP correlation coefficient based on bins.

Bin (mmHg)	Correlation Coefficient
60	-0.33005
70	0.215726
80	0.234839
90	0.255321
100	-0.54296
110	-0.60813
120	-
130	0.137269

IV. CONCLUSION

In this project, a pre-processing algorithm to clean up the PPG signals is built to ensure the data are suitable to be used as an input to the CNN-LSTM model for training and testing purposes. Besides that, a hybrid CNN-LSTM model that consists of two layers of CNN followed by two layers of LSTM is built to perform cuffless non-invasive blood pressure measurement based on PPG signals only. Moreover, the UKM dataset has been identified as the most suitable dataset as input to the CNN-LSTM model to predict blood pressure due to the model trained with this dataset having the highest correlation performance as compared to other datasets. By using the model trained with the selected dataset, it has the highest prediction for SBP values ranging from 141 to 150 mmHg, and DBP values ranging from 81 to 90mmHg.

The issue faced in this project is that the MIMIC-II dataset that is obtained from the UCI repository contains signals that has been preprocessed by other researchers previously. This is because we are unable to have access to the original database that is on the Physionet website. Hence, we are unable to control the quality of the signal obtained, which is believed to be the reason the correlation coefficient of this dataset is low. Besides that, all the models trained are experiencing overfitting problems.

In the future, we would suggest studies to obtain the signals from the original database instead of a preprocessed database. This is to ensure that the quality of the signal used to train the deep learning model is controlled and in good condition. Besides that, demographic information of the subject can be used as an input to the deep learning model. Furthermore, increasing the complexity of the deep learning model is suggested so that the model can learn more about the relationship between the extracted features with the targeted values to increase prediction accuracy. Lastly, to ensure the quality of the signal used as input to the model, one algorithm can be established to check the signal quality to reduce the time needed in the pre-processing stage and increase the efficiency of studies in the future.

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AUTHOR CONTRIBUTIONS

Vanessa Leong Jie Shan: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;

Gan Kok Beng: Project Administration, Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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