Imperial College London

Linking Photoplethysmography to Dengue Patients' Physiological Parameters

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Background & Motivation

Annually, there are approximately 400 million Dengue infections recorded, with a quarter of those people falling sick and around 22 thousand of them dying from severe infection e.g. dangerously low blood pressures leading to shock [1]. Up to date, no targeted treatment is available but fortunately, an early clinical evaluation and detection of severe Dengue can cause the rate of fatalities to drop significantly [1].

Photoplethysmography (PPG) uses optical sensors, e.g. photo diodes, and pulses of light emitted from a light source, e.g. a light-emitting diode (LED), to monitor vital sign parameters such as heart rate and blood pressure [2]. PPG detects blood volume alterations, measuring and recording changes in the absorption of light through tissue on measuring sites i.e. fingertip, as seen on Figure 1. PPG can be used on wearable devices to monitor vital parameters continuously, inexpensively and non-invasively.

Motivation Highlights

- Establishing a relationship between PPG and Dengue patient's physiological parameters can allow for an inexpensive and effective clinical decision support for low-income countries;
- Timely severe Dengue diagnosis through PPG analysis can boost patient recovery rates;
- Through automated diagnosis and severe Dengue prediction we can allow for better organization and resource allocation in healthcare facilities, improving working and care conditions;
- This project is the first of its kind and therefore conducting it can lead to interesting and valuable findings.

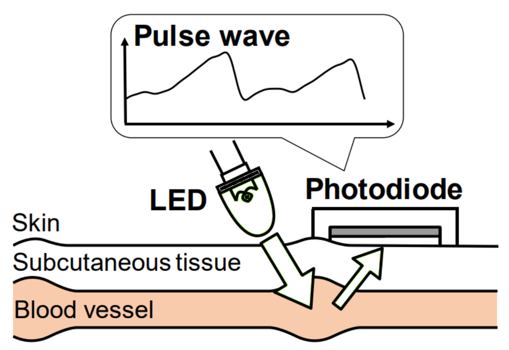

Figure 1: PPG Recording Procedure and Sample Waveform (Image Sourced From[3]).

Key Objectives

- Explore, process and structure the raw PPG/Clinical dataset;
- Employ signal processing and data analysis techniques to improve, characterise and visualise recorded PPG signals;
- Extract features from PPG signals for deeper representations;
- Design exploratory experiments, apply ML modelling for their investigation and use standard metrics for their evaluation;
- Analyse results and draw sensible conclusions on the link between PPG and Dengue's physiological parameters;
- Present findings that are useful for future research.

Design & Implementation

The study was based on raw clinical data consisting of multiple hours of Dengue patient data from study "01nva", recorded in 2020 in Vietnam's Hospital of Tropical Diseases by Oxford University's Clinical Research Unit. The data was supplied by Imperial College London. For our project, raw PPG data from11 Adult patients, each of different length, were made available as separate records, but only 9 of those were used in the final study. The dataset included continuous PPG records for each patient, along with a raw record of clinical events i.e. shock.

The Project's Implementation Pipeline

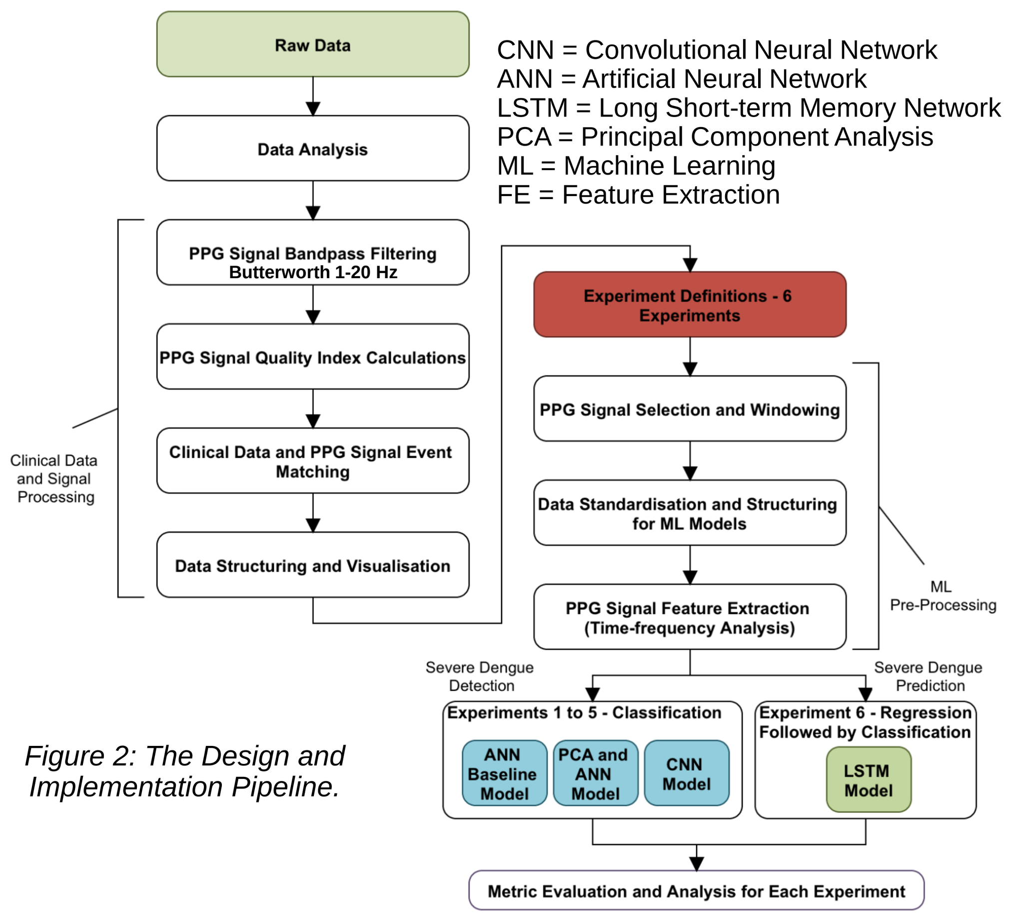

Figure 2: The Design and Implementation Pipeline.

For the Implementation, Python was used as the primary tool, whereas the Pandas, SciPy and TensorFlow libraries were mainly used for data and signal processing, and ML model implementation and testing. In Figure 3 you can see an example of Pleth and Infrared PPG signals, along with matched clinical events, resulting from the first stage of clinical data and signal processing.

Experiment Definitions

- Exp. 1: Binary Classification (BC) - Admission with shock vs. admission without shock;
- Exp. 2: BC – Pre-shock vs. post-shock PPG signal windows;
- Exp. 3: BC – Pre-shock and post-shock PPG signal windows for a patient admitted with shock;
- Exp. 4: Multi-class Classification (MC) – Using classes from Exp. 1 and 2 combined;
- Exp. 5: MC – Using classes from Exp. 1, 2 and 3 combined;
- Exp. 6: BC on a time-series regression output to evaluate PPG's capacity on predicting Dengue shock.

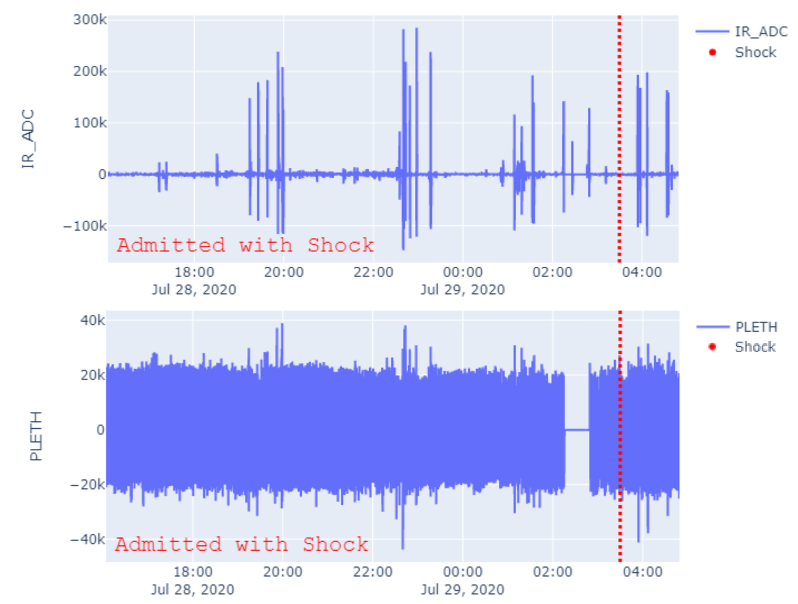

Figure 3: Example Plots of Filtered Infrared and Pleth PPG signals along with Event Annotations Fetched from Clinical Data – For Patient 003-2009.

ML Pre-Processing

- Patient record segments were selected for each experiment based on calculated signal SQIs i.e. skewness, entropy etc.
- Selected signals were windowed in 1 or 1.2 minute windows
- Data was split into training and test sets (Stratified K-Fold)
- Standardized data using z-score
- STFT was employed to perform time-frequency analysis on windowed data, calculating a matrix of power spectral densities corresponding to a time instance and frequency value. Example shown on Figure 4.

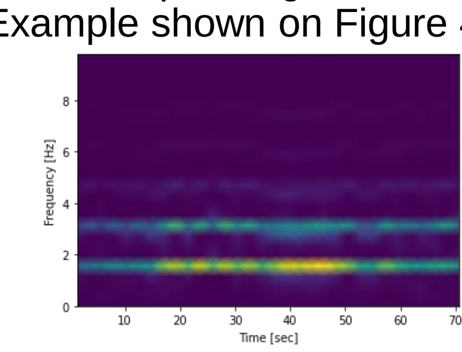

Figure 4: Spectrogram Example. Empirically, 1-10 Hz was Chosen as the Frequency Range.

To perform each of the experiments defined, multiple ML models were designed and implemented. Both experiment results and model architectures were used to evaluate our study's problem statement. In Table 1, a summary of the ML model types employed is presented. Model types 1-3 were implemented for experiments 1-5, whereas model type 4 was implemented for experiment 6. Model types 1-3 were directly compared between them for each experiment, raising valuable observations.

ML Model Type No.	Model Pipeline Description
1	FE using STFT and classification using an ANN.
2	FE using STFT followed by PCA for dimensionality reduction and classification using an ANN.
3	FE using STFT followed by further FE using a CNN and classification using CNN's MLP.
4	FE using STFT followed by either, no further processing **or** PCA for dimensionality reduction (both scenarios will be tested). Regression utilising an LSTM network will follow. Then, the regression's output will be classified using a pre-trained ANN binary classifier.

Table 1: Defined ML Model Types Employed in the Study.

Test Accuracy, Precision and Recall were used as our evaluation metrics, with classes being always equally represented in train and test sets. All models were executed using K-Fold cross-validation and results were averaged. Grid-search methodology was used for optimization, followed by manual fine-tuning. In summary, ANNs were implemented as the baseline model, PCA was then implemented on top of ANNs to reduce dimensionality and CNNs were implemented for their powerful FE properties. LSTM networks are powerful in handling time-series data, where the output is based on prior inputs.

Figure 5 shows an example CNN architecture, implemented for Experiment 1, and similarly in other experiments

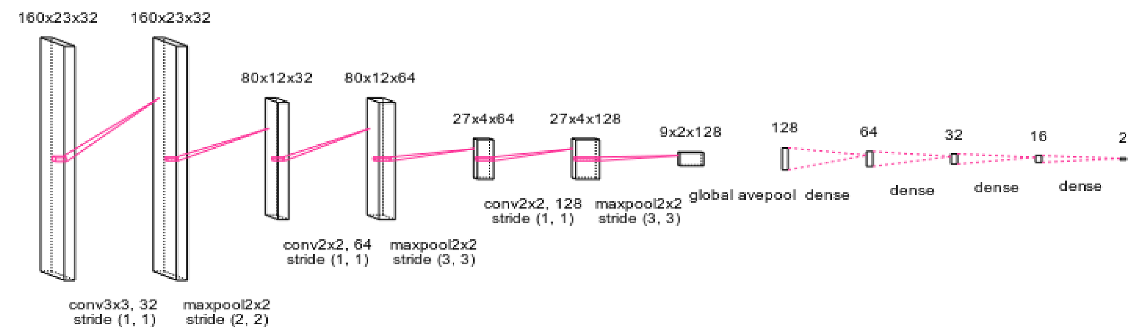

Figure 5: Visualising Experiment 1's CNN Architecture as an Example.

Results

Best Performing Model Results for Each Experiment	Experiment 1 CNN using IR ADC	Experiment 2 CNN using IR ADC	Experiment 3 CNN using IR ADC	Experiment 4 Baseline using Pleth	Experiment 5 CNN using IR ADC	Experiment 6 LSTM Model Using Pleth PCA Features
5 Fold Cross Validation Test Accuracies	0.975	0.900	0.806	0.837	0.785	0.830
	0.950	0.900	0.839	0.925	0.731	0.870
	0.900	0.900	0.839	0.825	0.739	0.860
	0.860	0.925	0.968	0.900	0.794	0.890
	0.860	0.950	0.733	0.913	0.794	0.870
Min Test Accuracy	0.860	0.900	0.733	0.825	0.731	0.830
Max Test Accuracy	0.975	0.950	0.968	0.925	0.794	0.890
Test Accuracy Avg	0.909	0.915	0.837	0.880	0.768	0.864
Test Accuracy St. Dev.	0.047	0.020	0.076	0.041	0.028	0.020
Recall Avg	0.909	0.915	0.837	0.880	0.769	Macro - 0.550
Precision Avg	0.912	0.921	0.847	0.895	0.781	Macro - 0.520
F1 Score Avg	0.910	0.918	0.842	0.887	0.775	Macro - 0.535

Table 2: Overview of Model Results. Along with the Model Type, the Type of Input Signal is Also Stated. Highlighted in Orange are the Most Important Metrics.

Key Observations

- Overall performance in all models indicates a strong correlation between PPG and severe Dengue physiological parameters. High test accuracies, precision and recall scores are observed, particularly in Experiments 1,2 and 4. Experiments 3, 5 and 6 have a poorer performance but correlation between PPG and severe Dengue is still present.
- CNN models, with Infrared PPG signal Spectrograms as inputs outperformed other model configurations. Infrared signals appear to be more information rich.
- Time-frequency analysis was an appropriate choice for FE and resulted in efficient ML convergence.
- Pleth Signals performed relatively better on simpler ML algorithms whereas Infrared signals required more complex architectures. This can suggest that the latter is more noisy.
- It's hard to establish a relationship in Experiment 6, when looking at the macro-averaged recall and precision scores. However, that was highly influenced by the lack of data for the second class (post-shock of patient 003-2009). Even though further research is required, performance on the first class is reflected on the test accuracy score and can be promising.
- Model type 1 and 2 performance was still good enough given the reduced complexity of the models and the data. This may suggest that more lightweight models can be effective.
- Model generalisation was adequate but needs validation.
- Given the results, PPG are highly suitable for Dengue clinical decision support – for detection and prediction.

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