

Feature Engineering with High-Frequency Physiologic Data

Akash Bhandari



Introduction:

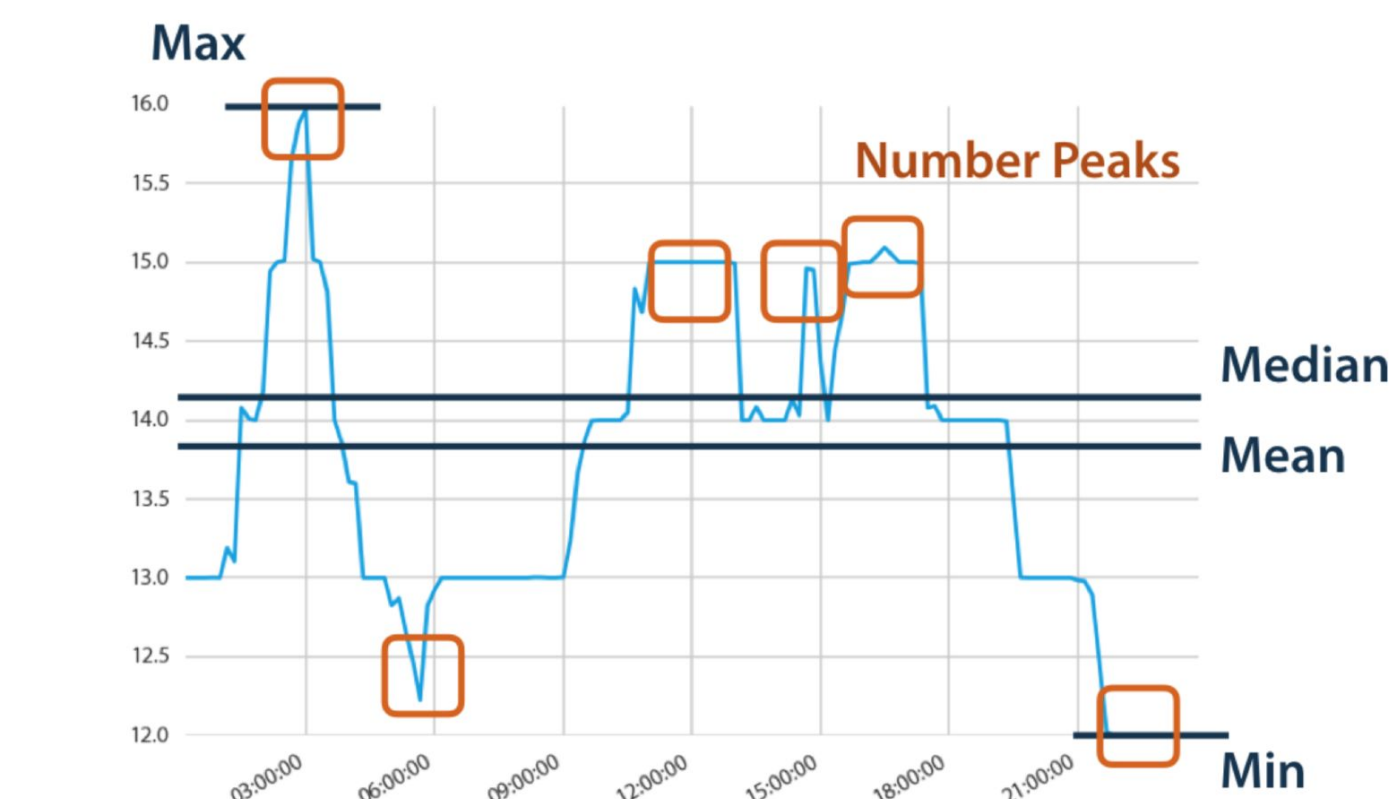
Fever is defined as a state of having body temperature $\geq 38^{\circ}\text{C}$. Diagnosis of fever is a major challenging task to the physicians which often remains undiagnosed and delays the treatment. Therefore, monitoring of fever provides valuable information for diagnosis and prognosis of the disease. Previously, Convolutional Neural Networks and different machine learning models have been used to predict dengue fever where surrounding atmospheric data (humidity, temperature, precipitation etc.) was included. In the study, features are extracted and a model is built to predict the onset of fever on ICU patients using the high frequency physiologic waveform data.

ID	Date	MDC_PRESS_CUFF_SYS	MDC_PRESS_CUFF_MEAN	MDC_PRESS_CUFF_DIA	MDC_PULS_OXIM_SAT_O2	MDC_PULS_OXIM_PULS_RATE	MDC_EC
0	2330393 2016-01-29 08:16:03	85.0	73.0	61.0	NaN	NaN	
1	2330393 2016-01-29 12:26:31	NaN	NaN	NaN	99.0	128.0	
2	2330393 2016-01-29 12:27:31	NaN	NaN	NaN	100.0	130.0	
3	2330393 2016-01-29 12:28:31	NaN	NaN	NaN	99.0	126.0	
4	2330393 2016-01-29 12:29:31	NaN	NaN	NaN	99.0	123.0	
5	2330393 2016-01-29	NaN	NaN	NaN	98.0	126.0	

3

Out[5]:	MDC_PRESS_CUFF_SYS	100.000000
	MDC_PRESS_CUFF_MEAN	100.000000
	MDC_PRESS_CUFF_DIA	100.000000
	MDC_PULS_OXIM_SAT_O2	99.861496
	MDC_PULS_OXIM_PULS_RATE	99.861496
	MDC_ECG_CARD_BEAT_RATE	99.168975
	MDC_TTHOR_RESP_RATE	97.922438
	MDC_PRESS_BLD_ART_SYS	25.900277
	MDC_PRESS_BLD_ART_DIA	25.900277
	MDC_PRESS_BLD_ART_MEAN	25.900277
	MDC_ECG_V_P_C_RATE	25.484765
	MDC_TEMP	18.005540
	MDC_ECG_AMPL_ST_II	16.897507
	MDC_PRESS_BLD_VEN_CENT_MEAN	6.371191
	MDC_ECG_AMPL_ST_I	5.401662
	MDC_ECG_AMPL_ST_III	4.432133
	MDC_PRESS_INTRA_CRAN_MEAN	2.908587
	MDC_PRESS_BLD_MEAN	2.770083
	MDC_PRESS_BLD_SYS	2.770083

2



1

35 Variables

'MDC_CO2_RESP_RATE', 'MDC_CONC_AWAY_CO2_ET',
'MDC_CONC_AWAY_CO2_INSP', 'MDC_ECG_AMPL_ST_AVF',
'MDC_ECG_AMPL_ST_AVL',
'MDC_ECG_AMPL_ST_AVR', 'MDC_ECG_AMPL_ST_I', 'MDC_ECG_AMPL_ST_II',
'MDC_ECG_AMPL_ST_III', 'MDC_ECG_AMPL_ST_V',
'MDC_ECG_CARD_BEAT_RATE',
'MDC_ECG_PACED_BEAT_RATE', 'MDC_ECG_V_P_C_RATE',
'MDC_PRESS_BLD_ART_DIA', 'MDC_PRESS_BLD_ART_MEAN',
'MDC_PRESS_BLD_ART_PULM_DIA', 'MDC_PRESS_BLD_ART_PULM_MEAN',
'MDC_PRESS_BLD_ART_PULM_SYS', 'MDC_PRESS_BLD_ART_SYS',
'MDC_PRESS_BLD_ATR_LEFT_MEAN', 'MDC_PRESS_BLD_DIA',
'MDC_PRESS_BLD_MEAN', 'MDC_PRESS_BLD_SYS',
'MDC_PRESS_BLD_VEN_CENT_MEAN', 'MDC_PRESS_CEREB_PERF',
'MDC_PRESS_CUFF_DIA', 'MDC_PRESS_CUFF_MEAN', 'MDC_PRESS_CUFF_SYS',
'MDC_PRESS_INTRA_CRAN_MEAN', 'MDC_PULS_OXIM_PULS_RATE',
'MDC_PULS_OXIM_SAT_O2', 'MDC_TEMP', 'MDC_TTHOR_RESP_RATE'

6

7 Variables

MDC_PRESS_CUFF_SYS
MDC_PRESS_CUFF_MEAN
MDC_PRESS_CUFF_DIA
MDC_PULS_OXIM_SAT_O2
MDC_PULS_OXIM_PULS_RATE
MDC_ECG_CARD_BEAT_RATE
MDC_TTHOR_RESP_RATE

7

Results:

After signal processing (fig.1) using tsfresh, a total of 6,352 features (fig. 8 & 9) are selected. The next step would be to fit different machine learning models to predict the onset of fever. The accuracy of the model could be found by calculating various scores such as F1, specivity, sensitivity, area under the curve etc.

```
In [31]: extracted_features = extract_features(dfsub0_t4, column_id = "sample_id", column_sort = "delta_Reduced")
extracted_features.to_csv("Fever_extracted_features_t4.csv")

Feature Extraction: 100% | 90/90 [04:38<00:00, 3.10s/i
t]

In [32]: extracted_features = extract_features(dfsub0_t5, column_id = "sample_id", column_sort = "delta_Reduced")
extracted_features.to_csv("Fever_extracted_features_t5.csv")

Feature Extraction: 100% | 84/84 [04:26<00:00, 3.17s/i
t]
```

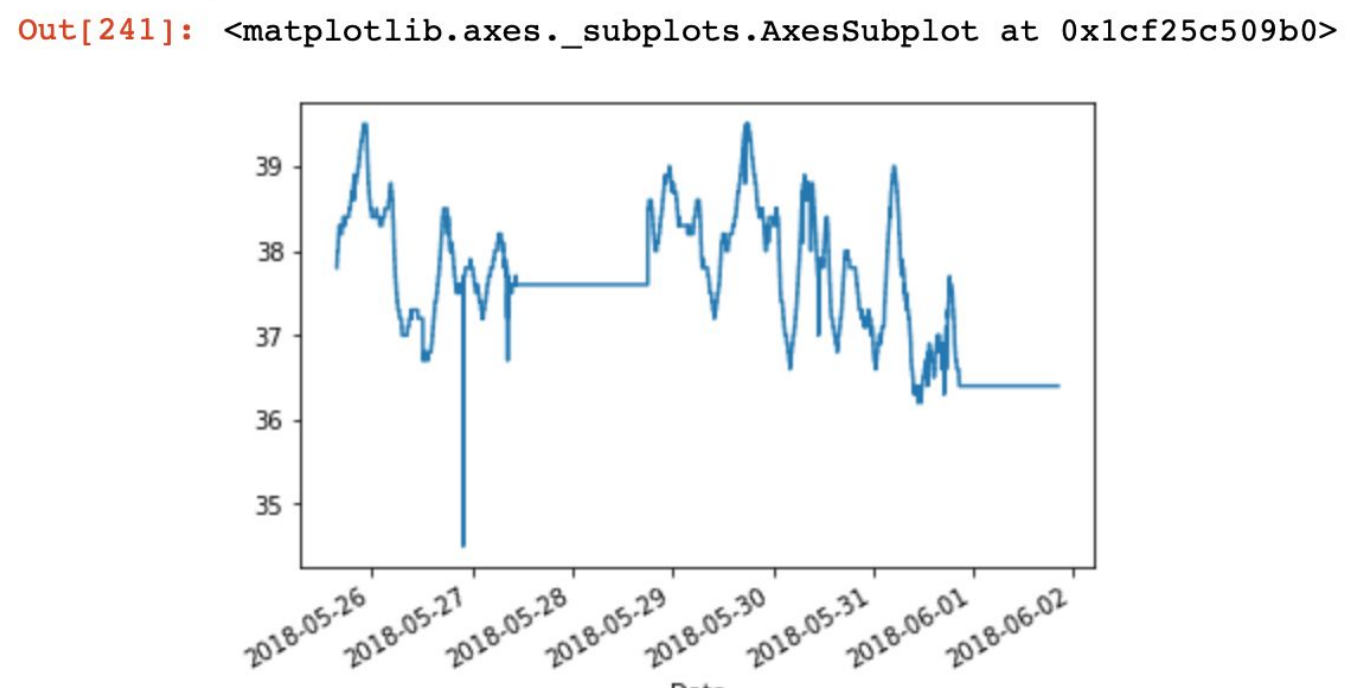
8

variable	MDC_ECG_CARD_BEAT_RATE_abs_energy	MDC_ECG_CARD_BEAT_RATE_absolute_sum_of_changes	MDC_ECG_CARD_BEAT_RATE_agg_autocorrelation_f
id			
2330315_1517381194.0	7916613.0	11382.0	
2330315_1517381254.0	8649.0	0.0	
2330315_1517381314.0	9216.0	0.0	
2330315_1517381374.0	18050.0	0.0	
2330315_1517381434.0	8836.0	0.0	
2330315_1517381494.0	8836.0	0.0	
2330315_1517381554.0	8649.0	0.0	
2330315_1517381614.0	8649.0	0.0	
2330315_1517381674.0	8649.0	0.0	

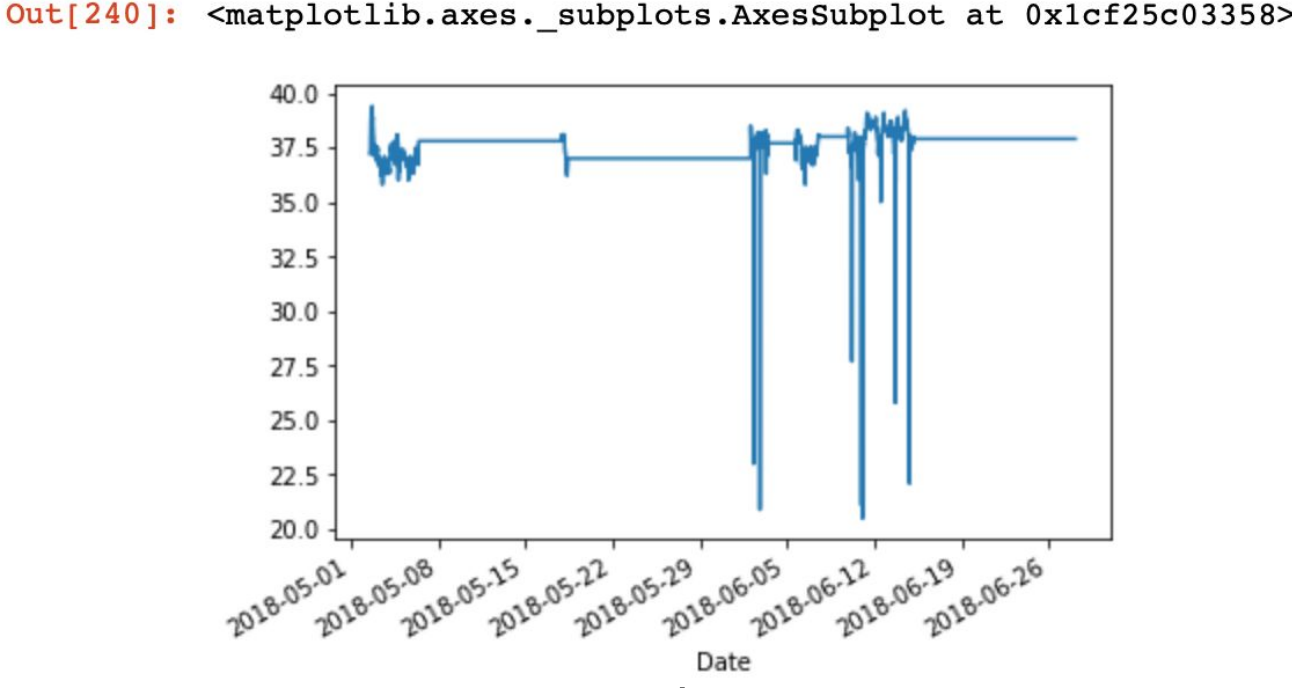
9

Data:

The data (fig. 3) is a high frequency physiologic ICU sensor data with 722 patients and more than 5 million observations. The total number of physiologic variables were 35 (fig. 6) out of which only 7 (fig. 7) were selected after downsampling.



5



4

Methods:

The initial step is to select relevant data ($\geq 90\%$ non-NaN values). The data is then filtered out in such a way that only data before the events of fever is taken. The data had two instances (cases: 16,093 and controls: 112). For cases, the data is extracted up to 6 hours back from fever event, and delta time (feverTime - recordedDateTime) is calculated respectively. Different signal processing features are extracted from 6 hour window time and the calculated delta time is used. If patients have multiple fever episodes during their stay, each episode is treated independently– provided there was 24 hour gap between them. For controls, patients who never have temperature (fig. 4) over 38°C are identified. Likewise, a random fever time is generated to calculate the respective delta time. A 6 hour window time is selected to extract significant features within that window time.

Conclusion:

The bulk of the project is data pre processing along with feature engineering of more than 5 millions data points. Different machine learning and regression models are to be applied to the extracted signal-processed features.

Acknowledgement:

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References:

<https://towardsdatascience.com/dengue-fever-and-how-to-predict-it-a32eab1db>