Project implementation & Results

Team 4: COVID-19 Health Informatics

Cheng Ding, David Lin,
Jayden Myers, Zewei Lei

Contributions

Cheng Ding
- LSTM model
- Data preprocessing

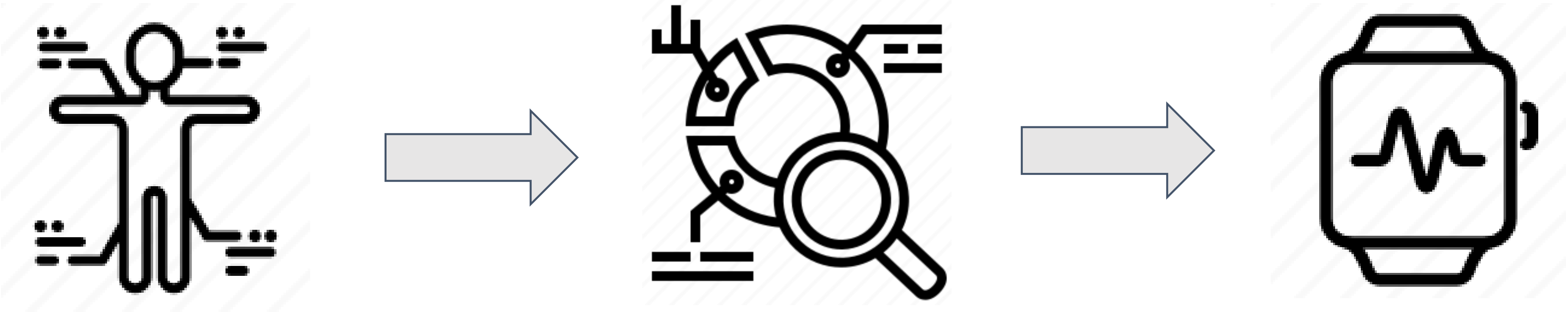
David Lin
- LSTM model
- Pattern Classifier

Zewei Lei
- Data preprocessing
- Mock-up GUI
- Presentation

Jayden Myers
- LSTM model
- Pattern Classifier

Problem Statement - Part I

Utilizing heart rate, steps, and sleep data to discover patterns suggestive of COVID-19 and develop an interpretable model for COVID-19 detection on a smartwatch



Current Challenges - Part I

Downsides of current diagnostic methods:

1. PCR test:
- Accurate, but results may take hours to days

2. Rapid antigen test:
- Limited accuracy, may produce false negatives

3. Antibody Tests:
- Not useful for early detection or active infection

The need for a new solution:

- Harnessing physiological data for accessible, trustable diagnosis

- Addressing limitations of existing testing methods (i.e., limited accuracy, high time consumption…)

- Developing a cost-effective and widely available model

Literature Critique (1) - Part I

Survey of COVID-19 Management + Detection [3, 4, 7]:

- The use of BioMets - System utilizing sensor data (Fitbit) to detect viral disease
- Current implementations include non-DL models
  - KNN, Decision Trees, Random Forest
  - Future focus on Neural Networks

The needs (**interpretable model**):

- Explains previous model choices
- Trust + Reliability are key factors to model success
- The largest pitfall is poor data quality

Literature Critique (2) - Part I

BioMet/Algorithm Implementations[1, 5, 6, 9, 10, 11]:

- Utilize features including RHR, Respiration, RMSSD (HR Var), and Symptom data
  - Day of Detection, utilizing a CNN: 0.77 AUC
  - 12% of the dataset was asymptomatic
  - These features show visible shifts around day of diagnosis
- Utilizing smartphone capabilities - Temperature, Breathing
- Inclusion of IMU data
  - Random Forest, 79% Accuracy at H1N1 detection
- Similar data used in Influenza Like Illness (ILI) detection
  - Increased RHR and abnormal Sleep found to be the most contributing factors

Literature Critique (3) - Part

Literature Review - Long Short Term Memory (LSTM) [8, 12, 13, 14]:

- Has been used to predict case and death numbers from real time data (r > 0.98)
  - Pattern Matching to determine risk states
- Anomaly Detection
  - Trained on baseline (control) cases, RHR data
  - Able to detect >50% prior to diagnosis time, Acc = .91
  - Later improved to 80% by utilizing a variational auto-encoder
  - Individualized Model
  - Linear and Sequential model layouts found to perform best
- Global Model
  - Contrastive Convolutional Auto-encoder
  - Converts 2 Weeks of time series data into an image
  - Able to achieve roughly 0.9 AUC with 100% Sensitivity on RHR data

Method Summary - Part II

Random Forest:

- Global model rather than individualized
- Lowest performance

Convolutional Neural Network:

- *Better performance*
- *Tuned hyperparameters/layers, worse performance*

Long Short Term Memory (LSTM):

- Higher interpretability, previously used for COVID detection
- High computational complexity, overfit
- Very strong performance in anomaly detection

Contrastive Auto-Encoder (CAE):

- Best classification performance
- Limited replication, less representative
- Data used may not be representative of our data

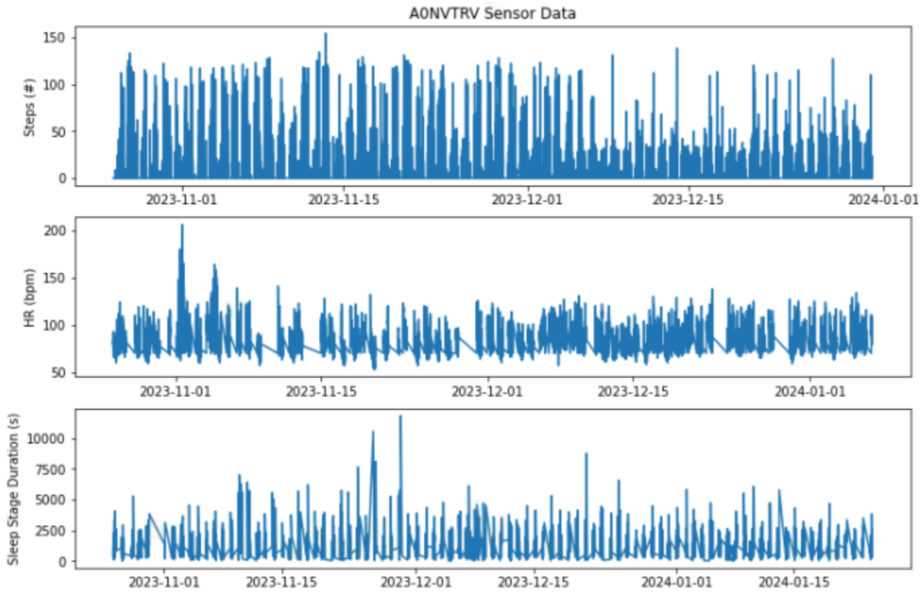
Data Methodology - Part II - **Data source: Mishra et al., 2020**

Patient Level Information

	Number of Patients	Average Timeseries Duration [days]
Covid patients	32	82
Healthy patients	74	81

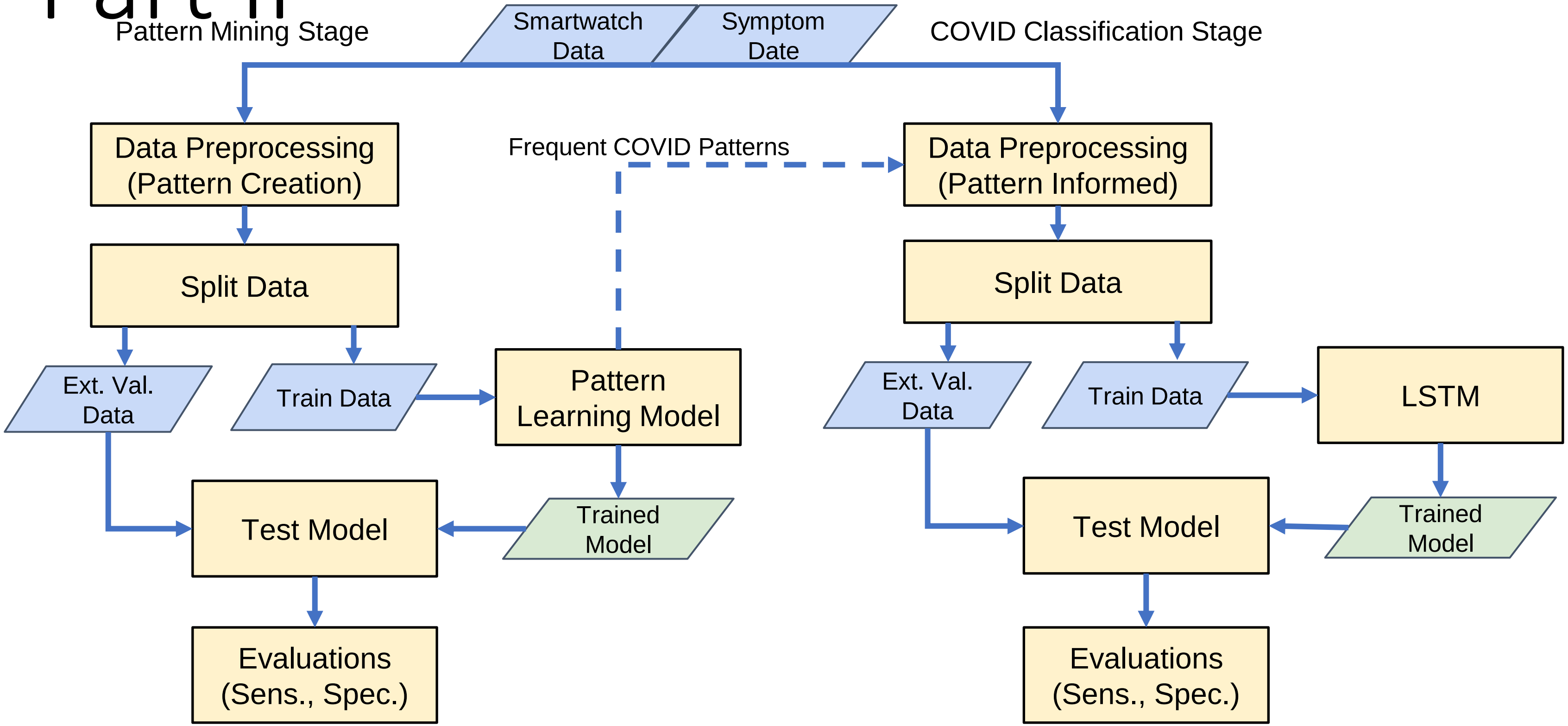
Sensor Data Information

	Sampling Rate [s]	Available Data [%]
Steps Data	60	100
HR Data	5	100
Sleep Data	N/A	**27**

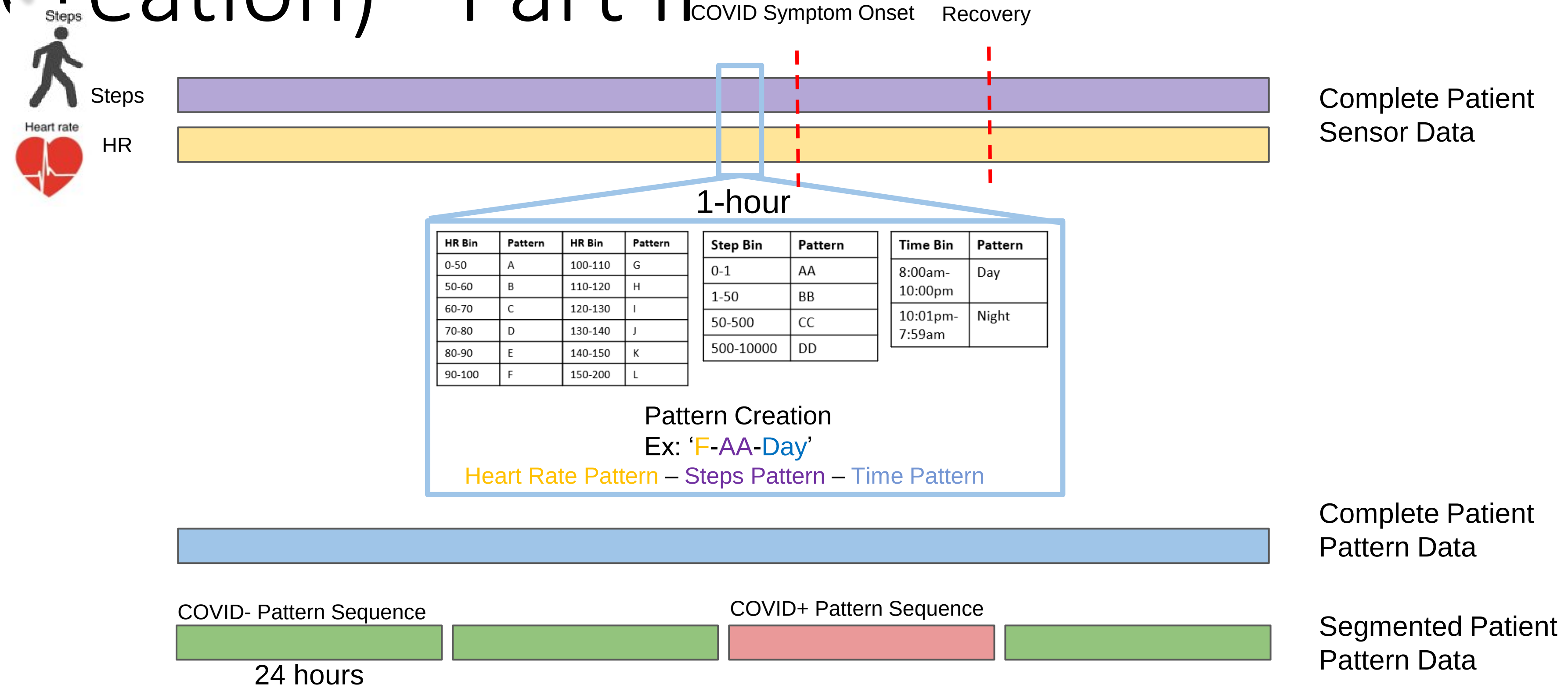


Example Timeseries for 1 Subject

Informatics System Workflow - Part II



Data Preprocessing (Pattern Creation) - Part II

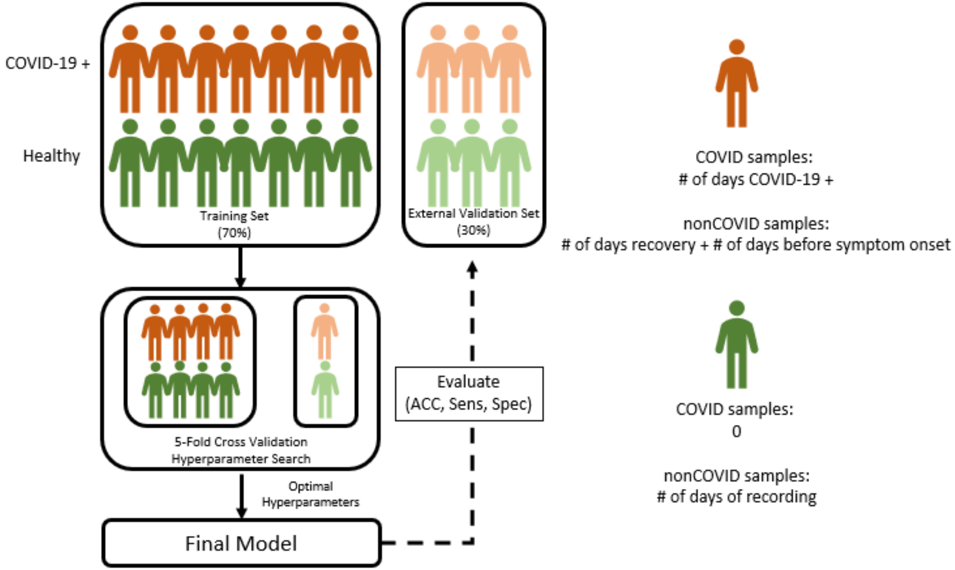


HR Bin	Pattern	HR Bin	Pattern
0-50	A	100-110	G
50-60	B	110-120	H
60-70	C	120-130	I
70-80	D	130-140	J
80-90	E	140-150	K
90-100	F	150-200	L

Step Bin	Pattern
0-1	AA
1-50	BB
50-500	CC
500-10000	DD

Time Bin	Pattern
8:00am-10:00pm	Day
10:01pm-7:59am	Night

Split Data - Part II



Classification/Modelling (Apriori)- Part II

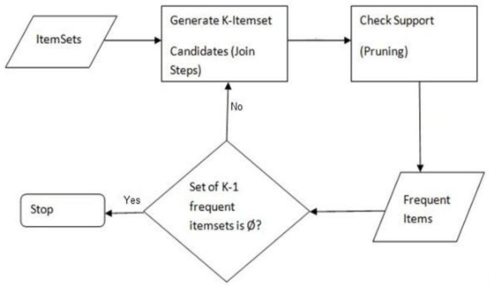
Frequent Itemset Mining (Apriori)

- Returns the frequent individual items found within a database, in this case pattern sequences

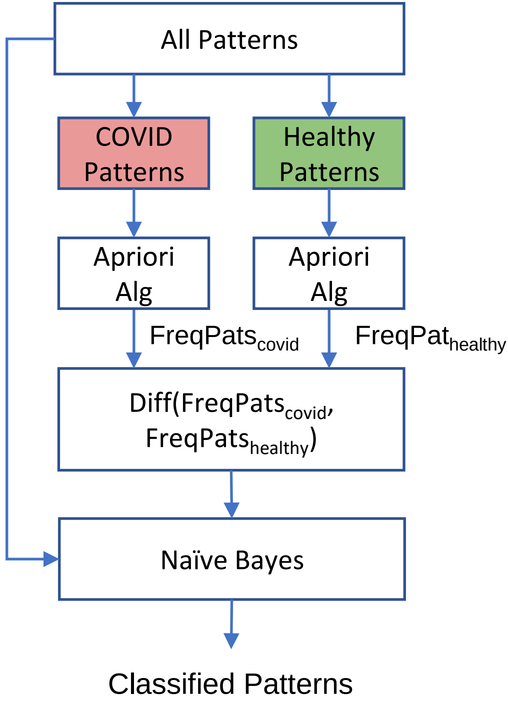
- Hyperparameters:
  Min_support: % of patterns that have to exist in the group (range: 30%-50%)
  Pattern Length: how much to chunk the preprocessing step (range: 8hours – 2 days)

- Frequent COVID only specific patterns were found by taking the difference in frequent covid patterns and frequent healthy patterns

- Naïve bayes was used to classify patterns by how often they occur in the frequent covid only specific pattern set



Apriori Algorithm



Robust Model Parameter (Pattern Learning)

- Pattern length did not change any of the files

- As minimum support increases: the length and number of pattern sequences decreases

- Frequent COVID Only Patterns

  At max support (50): [['C-AA-day']] is the only pattern

  At min support (30): [['D-AA-day', 'F-BB-day'], ['D-BB-day', 'E-BB-day'], ['D-AA-day', 'E-AA-day'], ['E-AA-day', 'C-AA-night'], ['D-AA-day', 'D-AA-night', 'C-AA-night'], ['D-BB-day', 'D-AA-night'], ['D-AA-night', 'F-BB-day'], ['C-AA-night', 'F-BB-day'], ['E-BB-day', 'D-AA-day'], ['D-BB-day', 'C-AA-night'], ['D-AA-day', 'D-AA-night', 'E-AA-day'], ['E-BB-day', 'C-AA-night'], ['E-BB-night'], ['D-BB-day', 'D-AA-day'], ['D-AA-day', 'C-AA-day'], ['D-AA-night', 'C-AA-night'], ['D-AA-day', 'C-AA-night', 'C-AA-day'], ['E-BB-day', 'D-AA-night', 'C-AA-night'], ['D-BB-day', 'D-AA-day', 'D-AA-night'], ['E-BB-day', 'C-AA-night', 'D-AA-day'], ['E-BB-day', 'E-AA-day'], ['E-BB-day', 'D-AA-night', 'D-AA-day'], ['D-BB-day', 'D-AA-night', 'C-AA-night'], ['E-BB-day', 'F-BB-day'], ['D-BB-day', 'E-BB-day', 'C-AA-night'], ['D-BB-day', 'C-AA-night', 'C-AA-day'], ['D-BB-day', 'D-AA-day', 'C-AA-night']] is the list of different patterns found more frequently in covid patients

Most frequent patterns have a larger first letter, and lower second:

This indicates high heart rate and low steps → High Resting Heart Rate

'Heart Rate Pattern – Steps Pattern – Time Pattern'

Pattern Key

Performance Metrics - Part II

$$\textbf{Sensitivity} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}}$$

$$\textbf{Specificity} = \frac{\textbf{True Negatives}}{\textbf{True Negatives} + \textbf{False Positives}}$$

True Positive: Correctly classifying a COVID+ section

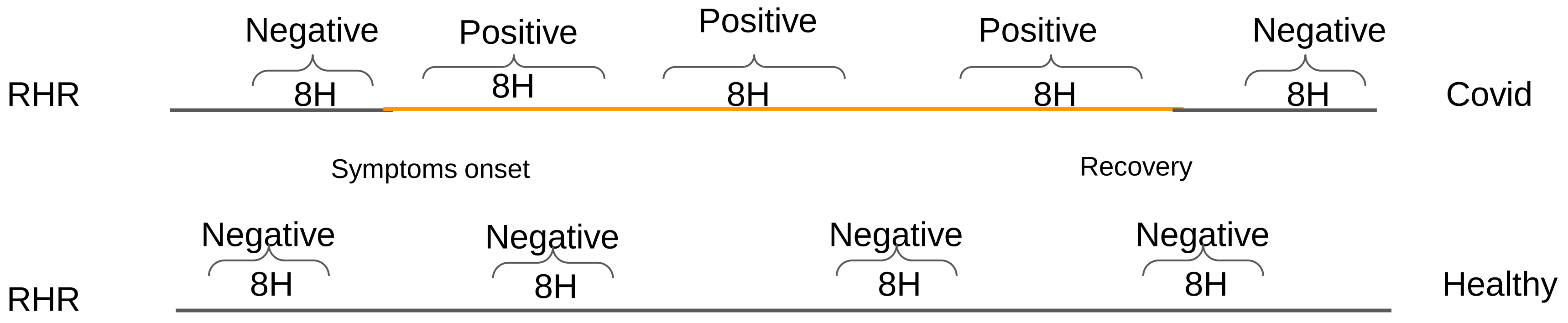
Model Results - Part III

Minimum Support	Sensitivity	Specificity	Average [Sens, Spec]
30	0.653,0.365, 0.620, 0.776, 0.276	0.458,0.388,0.387, 0.389,0.421	[0.6, 0.467]
35	0.184, 0.428, 0.25,.443,0.411	0.702,0.650,0.645, 0.651,0.648	[0.366,0.704]
40	0.316,0.602,0.653, 0.569,0.606	0.466,0.473,0.514, 0.424, 0.635	[0.556,0.511]
45	0.21,0.338,	0.707,0.65,0.68	[0.338,0.724]

Data preprocessing

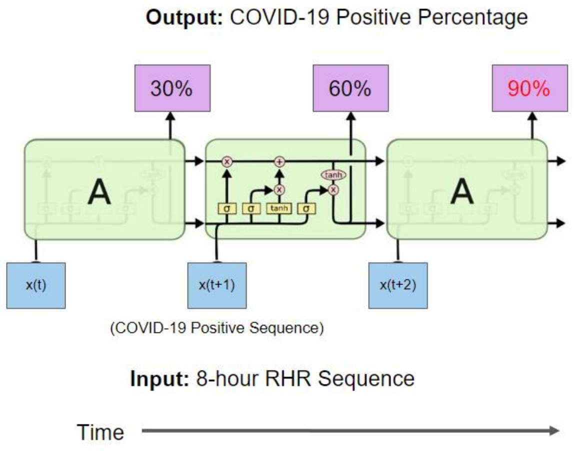
Resting **H**eart **R**ate

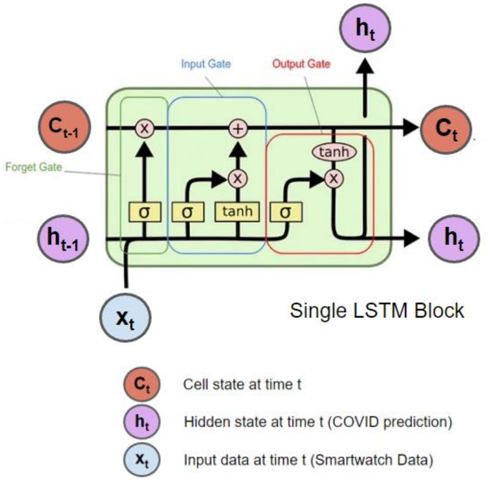
define RHR as the HR measurements recorded when there were zero steps taken during a rolling time window of the preceding 12 minutes (including the current minute).



Long Short-Term Memory networks (LSTM) - Part II

- LSTMs learn temporal dependencies in timeseries data *very* well over long and short periods of time
- Used in prior works for COVID-19 anomaly detection with strong results (*Bogu et. al, Abir et. al*)
- LSTM is made up of cells that selectively retain and reject information that represents the whole sequence being fed in.
- Hyperparameters:
  - LSTM hidden state units: 16-128
  - Number of layers: 3-8
  - Batch Size: 16-128
  - Learning rate: 1e-4 - 0.05





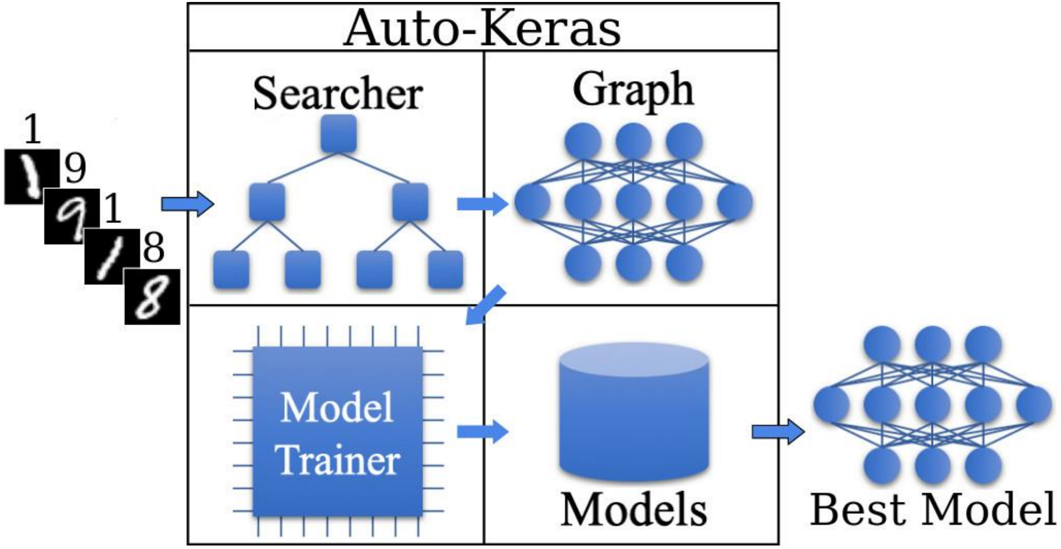
Data preprocessing

Data augmentation

- Scaling
- Rotation
- Permutation
- Magnitude_warp
- Time_warp
- window_slice
- window_warp

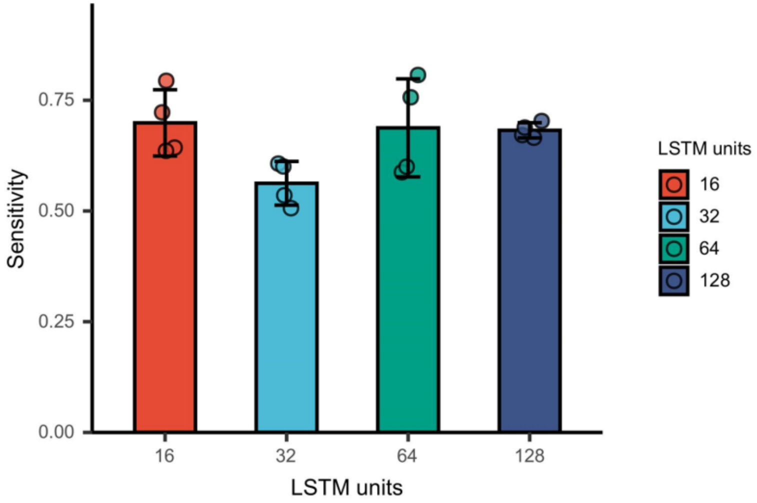
	#patients	#strips
Covid patients	32	5716/45728(after DA)
Healthy patients	74	54571

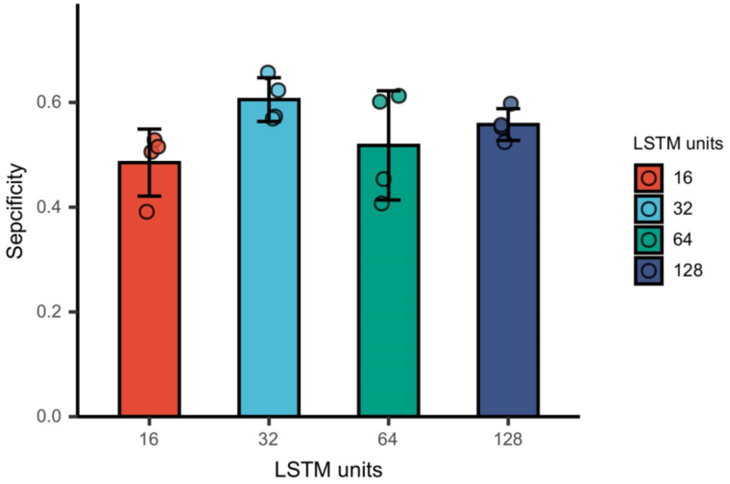
AutoML does not work



Autokeras is difficult to deal with imbalance dataset. We have to tune the parameters manually.

Robust Model Parameter Selection - Part II





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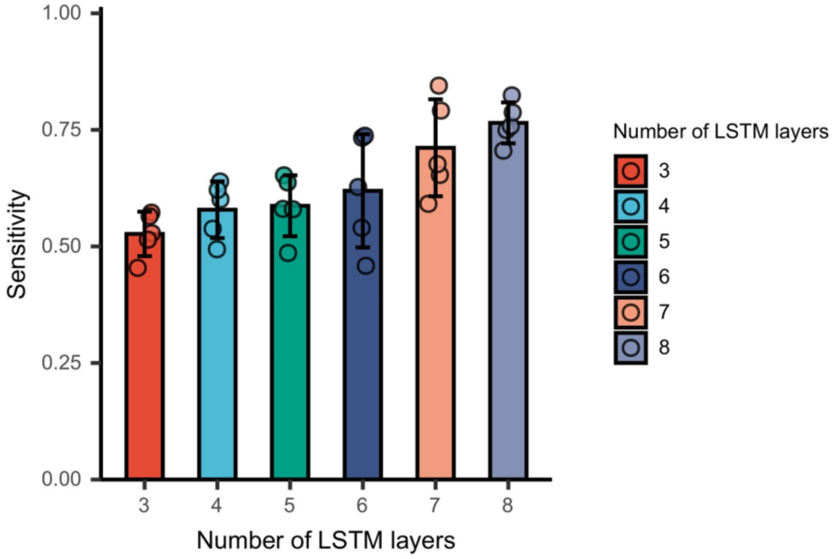
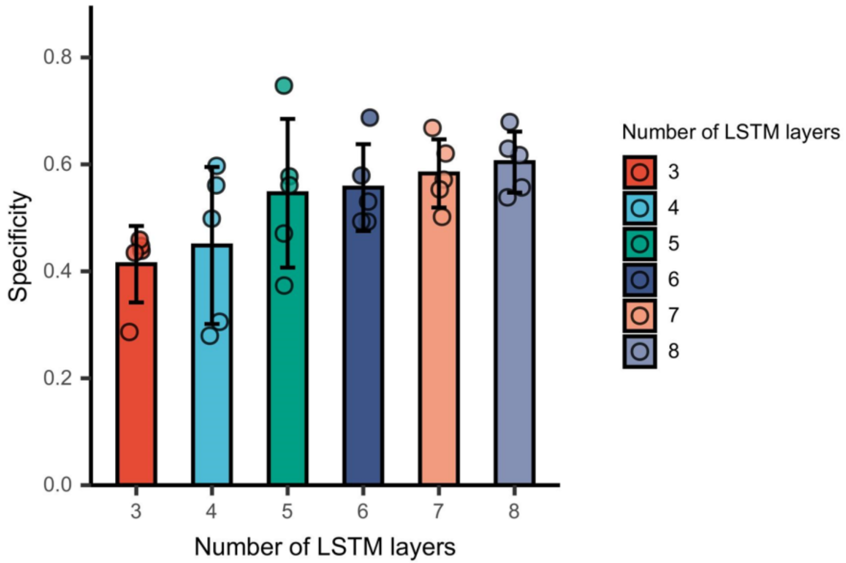
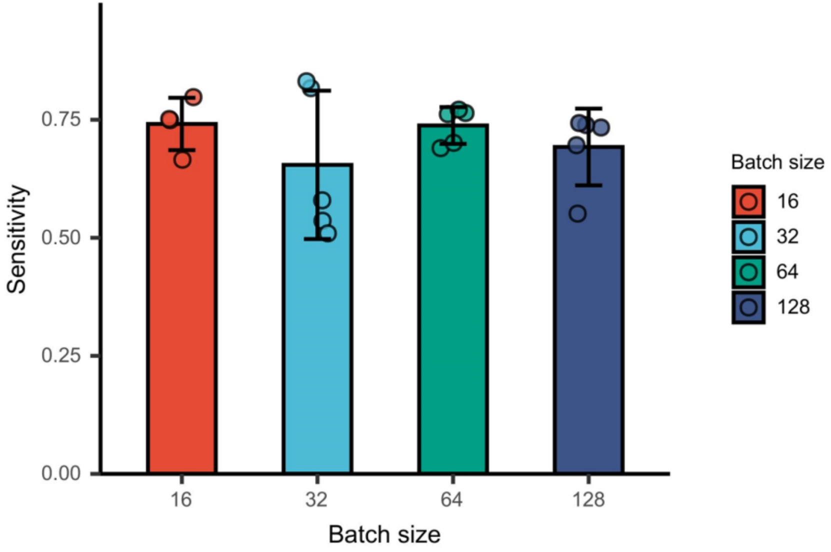
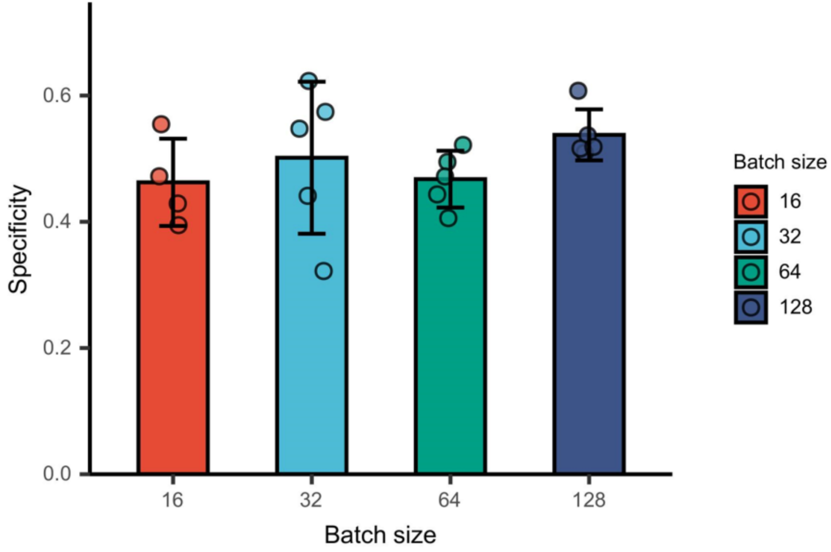


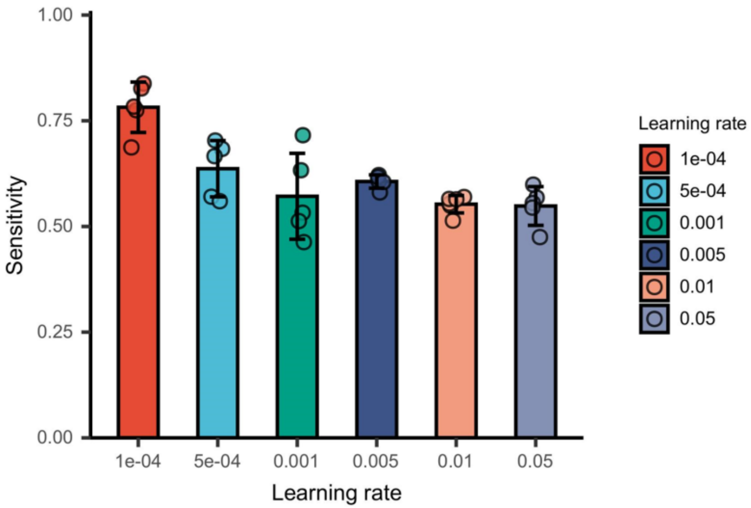


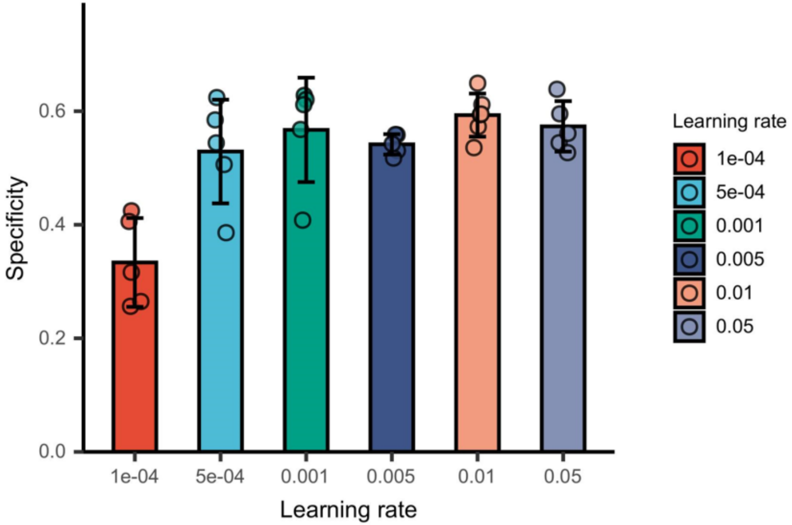
Robust Model Parameter Selection - Part II





Robust Model Parameter Selection - Part II





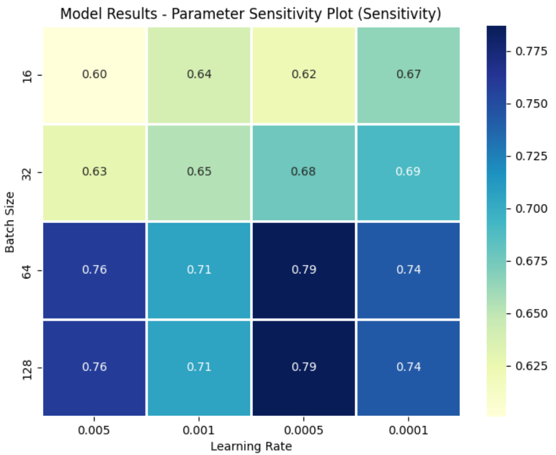
Final model

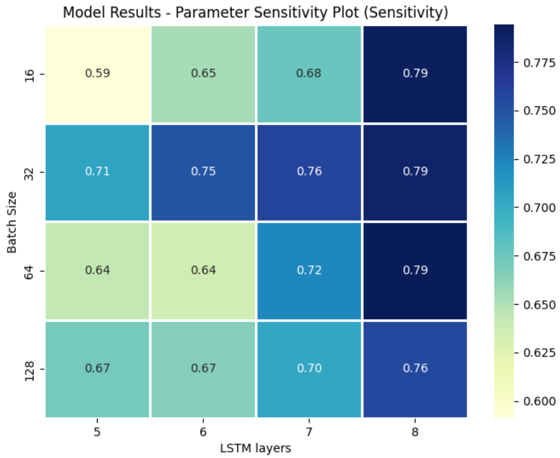
```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_40 (LSTM)              (None, 8, 64)             16896

 lstm_41 (LSTM)              (None, 8, 32)             12416

 lstm_42 (LSTM)              (None, 8, 32)             8320

 lstm_43 (LSTM)              (None, 8, 32)             8320

 lstm_44 (LSTM)              (None, 8, 32)             8320

 lstm_45 (LSTM)              (None, 8, 32)             8320

 lstm_46 (LSTM)              (None, 8, 32)             8320

 lstm_47 (LSTM)              (None, 16)                3136

 dropout_12 (Dropout)        (None, 16)                0

 dense_12 (Dense)            (None, 1)                 17

=================================================================
Total params: 74,065
Trainable params: 74,065
Non-trainable params: 0
```

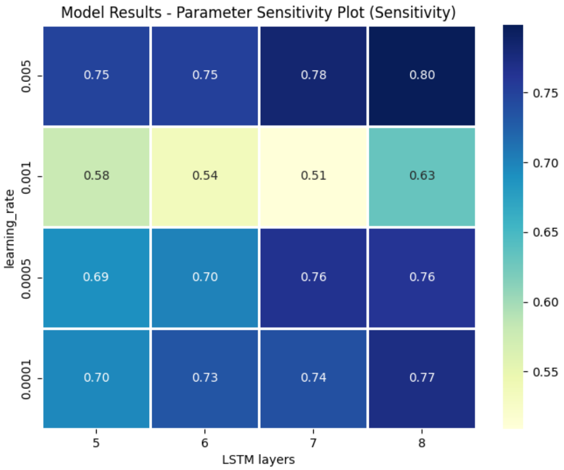
```
EPOCHS = 20
BATCH_SIZE = 128
LEARNING_RATE = 5e-4
model.compile(optimizer='adam',
loss='binary_crossentropy')
```

Best epoch is selected based on least loss on validation set

Parameter Sensitivity Plot





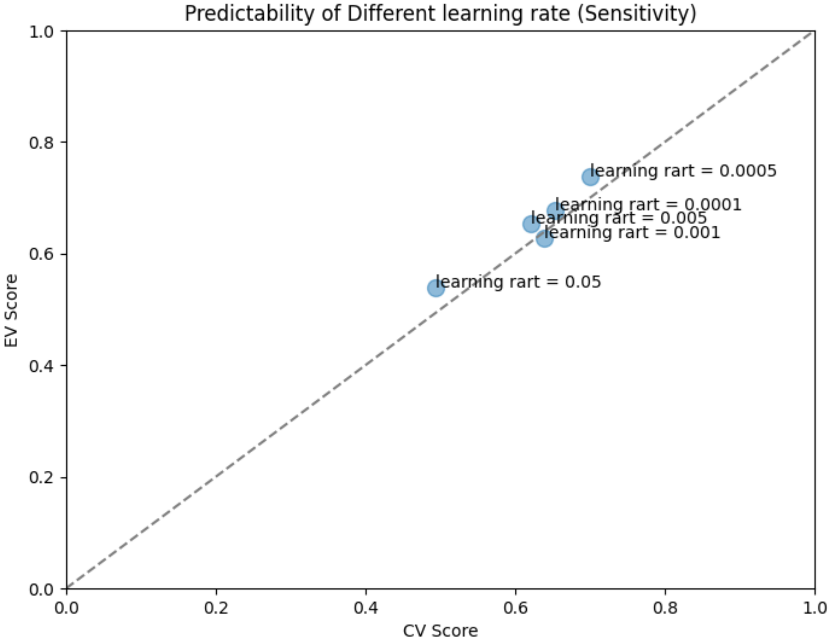


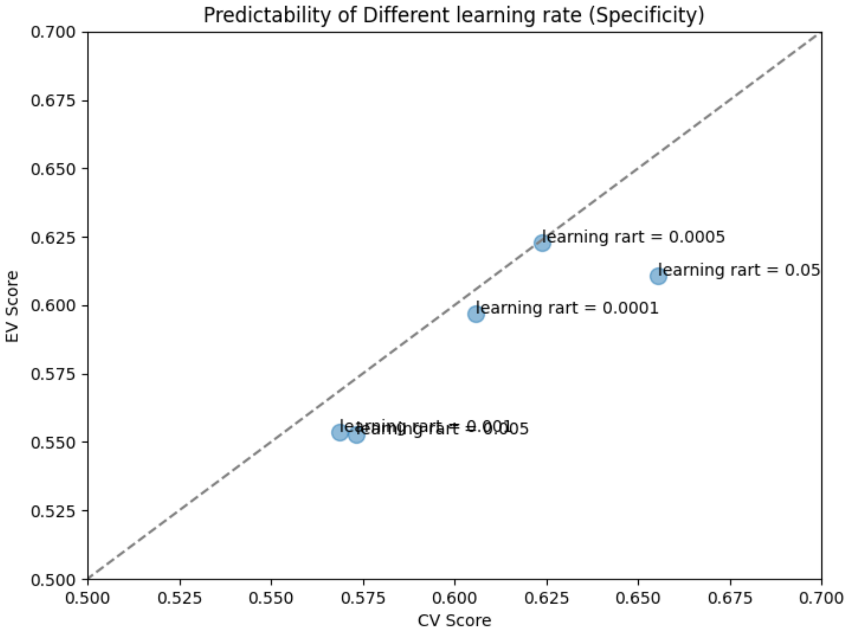
Quantitative Data Analysis - Part III

Strip level

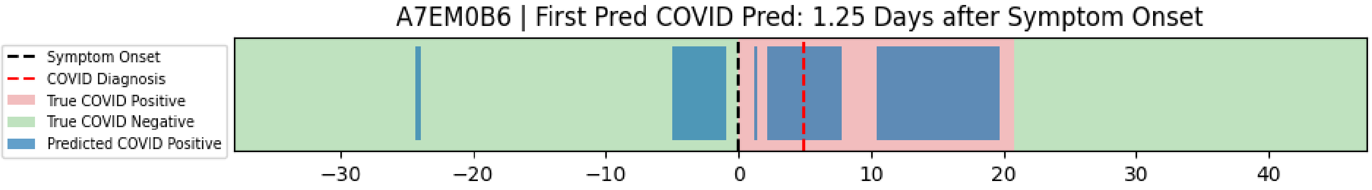
	Sensitivity	Specificity
Fold 1	0.600804	0.568869
Fold 2	0.535325	0.623907
Fold 3	0.807007	0.405905
Fold 4	0.587593	0.602265
Fold 5	0.599655	0.611008
Mean	0.626077	0.562391
STD	0.10463	0.089816

Predictability of Mod



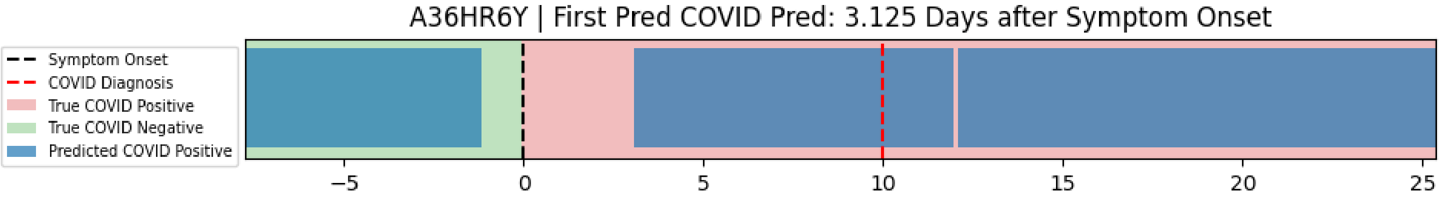


Result Discussion/Interpretation – Covid patients



Average RHR in first day: 65.5

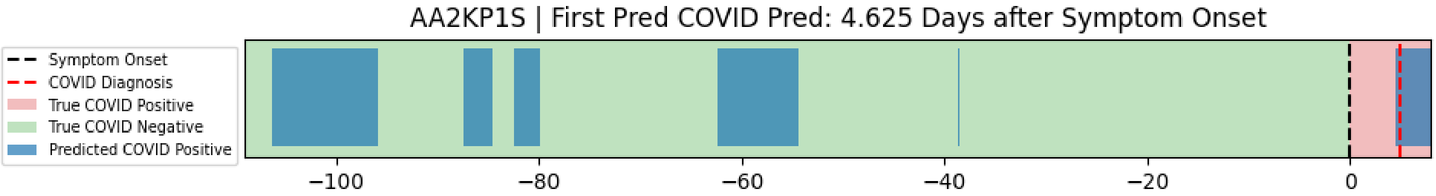
Symptom date	Diagnosis date	Recovery date
2023-12-26	2023-12-31	2024-01-08



Average RHR in first day: 81.3

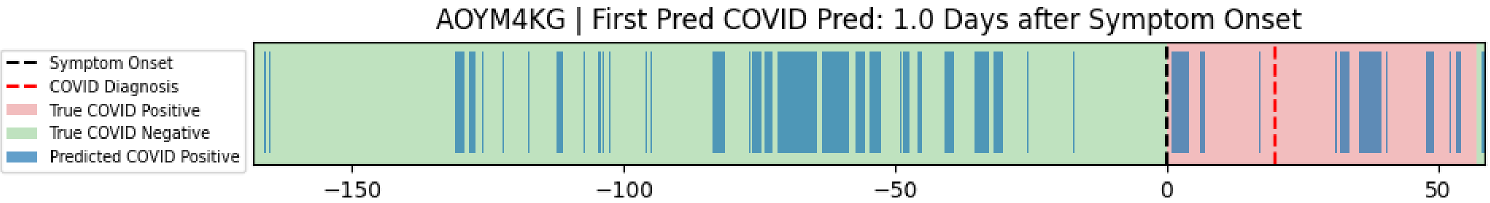
Symptom date	Diagnosis date	Recovery date
2023-04-06	2023-04-16	2023-06-10

Result Discussion/Interpretation – Covid patients



Average RHR in first day: 76.8

Symptom date	Diagnosis date	Recovery date
2025-01-06	2025-01-11	2025-01-25 (+14 days) **Not reported**

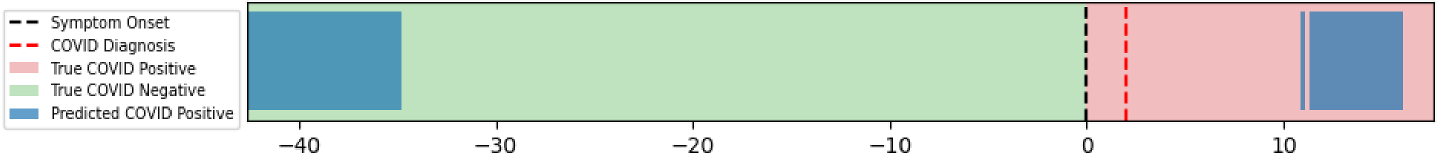


Average RHR in first day: 67.1

Symptom date	Diagnosis date	Recovery date
2023-08-29 2022-11-14 2023-07-04 2023-10-24	2023-09-18	2023-09-19

Result Discussion/Interpretation – Covid patients

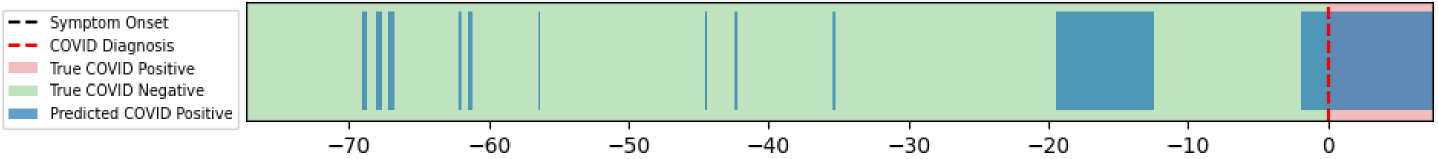
AQC0L71 | First Pred COVID Pred: 10.875 Days after Symptom Onset



Average RHR in first day: 73.2

Symptom date	Diagnosis date	Recovery date
2028-06-17	2028-06-19	**2028-07-03(+14 days)** 2028-05-16 (reported) 2028-05-15 (reported)

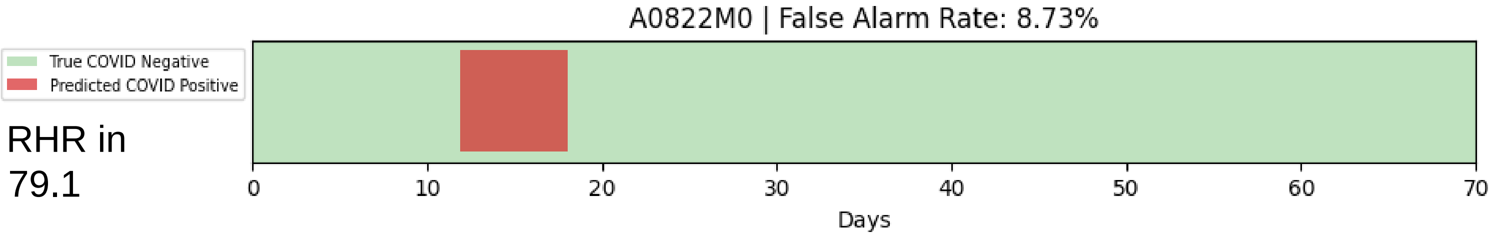
AUY8KYW | First Pred COVID Pred: 0.0 Days after Symptom Onset



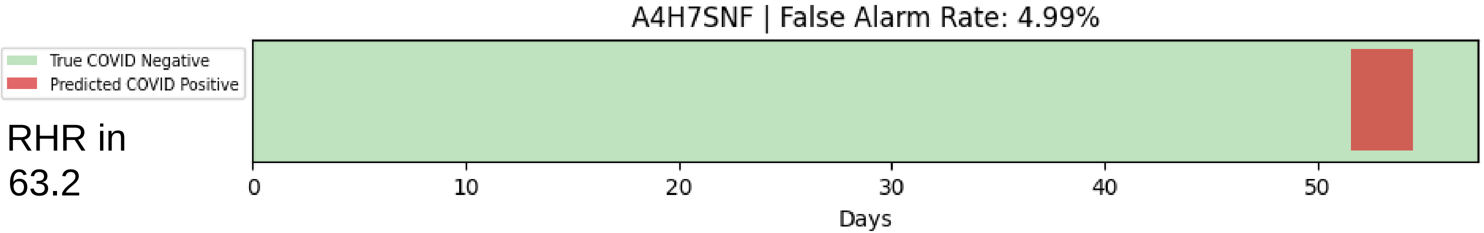
Average RHR in first day: 60.2

Symptom date	Diagnosis date	Recovery date
2024-03-11(-7 days) Real date not reported	**2024-03-18**	**2024-04-02(+14 days)** Real date not reported

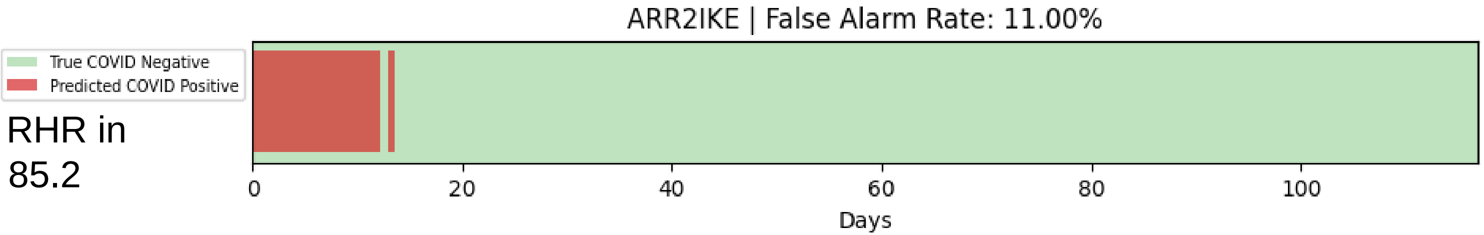
Result Discussion/Interpretation – Healthy patients



Average RHR in first day: 79.1



Average RHR in first day: 63.2



Average RHR in first day: 85.2

Result Discussion/Interpretation – Part III

Pattern Classifier

- We found that most of the Covid specific patterns included a high resting heart rate
- As support increases, pattern length and quantity decreases
- With more patterns, sensitivity increases
- With fewer patterns specificity increases

LSTM Strip Classification

- Able to achieve sensitivity greater than pattern classifier
- Captured the 5 day period of physiological change prior to symptom onset in some patients
- The model would greatly benefit from additional data
- Lower learning rate and an increased number of LSTM layers lead to higher sensitivity
- Batch size and hidden layers had much less of an impact on performance

Comparison vs. Previous works

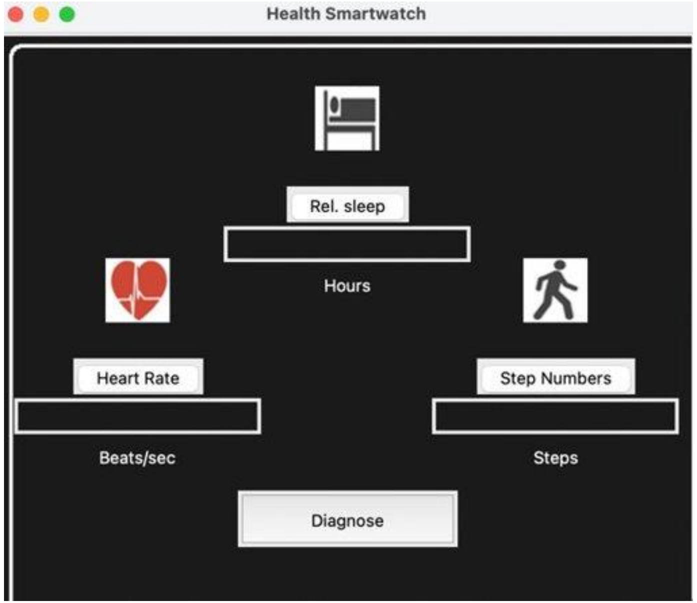
Bogu, Snyder
- Using RHR data with LSTM for anomaly detection (trained on healthy patients)
- Sensitivity = 0.36, Precision = 0.91
- Our model is much less precise, but more often predicts covid patients as positive

Abir, et.al
- Utilizes Variational-AutoEncoder with LSTM, RHR data for anomaly detection
- Sensitivity = 0.534, Precision = 0.993
- Trained on a much larger dataset
- Able to achieve almost 50% pre-symptomatic detection
- Much more precise than our model, with similar sensitivity

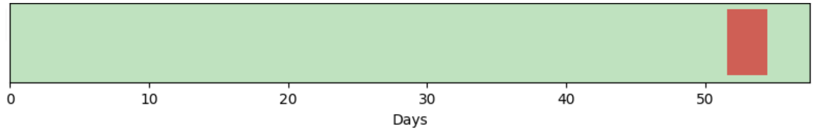
Mishra, et.al - Dataset source
- Anomaly detection using HROS
- 63% pre-symptomatic detection

Our model works to classify strips of time rather than perform anomaly detection, so the results are difficult to compare directly.
However, our model is much more prone to false positives

Mock-up System Implementation - Part III



User (Smartwatch)



Prediction Window

Conclusion

- Through discretizing patient data into patterns, we were able to find out that covid patient's patterns are more likely to be high heart rate with low step count, indicative of high resting heart rate
- Utilizing LSTM for strip classification, we were able to achieve recall = 0.63, specificity = 0.56, which means the model is very likely to make a false positive, but has covid positive results that are comparable to other literature

Limitations

- More data is absolutely needed to improve the quality of the model
- Currently, heavy dataset augmentation was necessary to achieve adequate results
- Discretizing data into pattern bins leads to a large data loss, but made the model more explainable
- A high false positive rate compared to literature is not suitable for a real-world implementation

Summary

- Covid testing can be very costly in terms of resources and time
- Many people wear devices like Fitbits that capture physiological data that can be suggestive of Covid

- We transformed the data into sequences of patterns, such that we could find key elements that differentiated between healthy and sick
- Resting Heart Rate is a key indicator for Covid used by many previous works and was found as a key factor in our findings as well

- We were able to match classification of Covid patients, however with many more false positives than that of previous works
- Limitations in data is the biggest issue to tackle, as not enough or poor-quality data will drastically decrease performance

Reference

1. Goergen, Craig J., et al. "Detection and monitoring of viral infections via wearable devices and biometric data." Annual review of biomedical engineering vol. 24. pp. 1-27. 2022.
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3. Natarajan, Aravind, et al. "Assessment of physiological signs associated with COVID-19 measured using wearable devices." NPJ digital medicine 3.1 pp. 156. 2020.
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