Continuous Monitoring for Diagnosis: A Wearable for Covid-19 Detection in Symptomatic Patients

Sumaiya Afroz Mila, Md Rafiul Kabir, and Sandip Ray
Department of ECE, University of Florida, Gainesville, FL 32611. USA.
mila.s@ufl.edu, kabirm@ufl.edu, sandip@ece.ufl.edu

2023 IEEE International Conference on Consumer Electronics (ICCE) | 978-1-6654-9130-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCE56470.2023.10043456

***Abstract*—We develop an approach for systematically designing continuous monitoring solutions for early symptom diagnosis. Effective early diagnosis requires collecting and correlating symptoms derived from a number of vitals. For designing a continuous monitoring solution, it is crucial to determine the vitals to be monitored for targeted detection, the errors that can be tolerated, various parameters that need to be tuned, etc. Furthermore, this determination must be made before the design of the monitoring solution itself. Our approach shows how to use a variety of machine learning techniques to systematically derive, tune, and optimize the vitals to be monitored before accessing the continuous monitoring data. We show the effectiveness of our approach in the design of a wearable for early detection of COVID-19 infections in symptomatic patients.**

I. Introduction

In recent years, the consistent rise in global infectious diseases, combined with population growth and rising life expectancy, has prompted a search for new ways to make the best use of limited resources. Typical infectious disease detection technology involves invasive tests or samples taken within hospital facilities. On the other side, the increasing incorporation of Internet-of-Things (IoT) and AI is revolutionizing the medical system. Given the critical need for early diagnosis of infections, it is worthwhile to explore ways for the proliferation of AI and IoT in this domain.

In this paper, we develop a methodology for the disciplined design of wearable solutions for continuous monitoring solutions to target infection detection. We showcase the viability of the framework in designing a wearable for identifying Covid-19 positivity in symptomatic patients.

A key challenge with the design of a continuous monitoring solution is to determine *a priori* which combination of vitals needs to be targeted for monitoring. Each vital that a doctor uses for diagnosis may not be amenable to continuous monitoring. Even for features that we can monitor, it may not be convenient to do so through a wearable. Consequently, we must identify which vital must be monitored directly and with what accuracy, which vital we can derive indirectly from some other parameter with acceptable accuracy, etc. An obvious way to achieve this objective is to develop a solution, test its viability through a sequence of human trials, and iteratively refine the approach until the desired accuracy is achieved. However, that is costly and time-consuming. A key contribution of this paper is to address the above problem through the systematic use of ML solutions. Our observation is that even in the absence of a continuous monitoring solution, there are datasets available from hospitals on the various vitals monitored for patients. This monitoring is generally *not* continuous, but performed at regular intervals. However, by "tweaking" the monitoring frequency of the data it is possible to estimate the relative importance of various parameters in the diagnosis and use them as targets for a monitoring wearable. We demonstrate an instance of our approach in our Covid-19 case study.

Covid-19 is one of the most complicated healthcare concerns of the twenty-first century and it is far from over, at least in a large number of countries. Consequently, a low-cost continuous monitoring solution for effective detection of Covid-19 remains of critical interest. However, the goal of the paper is to develop a customized solution specifically targeted for detecting Covid-19 which of course can now be detected fairly accurately with rapid antigen tests that can be conveniently taken at home. Rather, we focus on a systematic methodology for developing continuous monitoring wearable solutions for infection detection; Covid-19 is used as an illustrative target because significant patient data has been made available over the past two years which makes it possible to demonstrate the viability of ML-based solutions for continuous monitoring. Nevertheless, the wearable developed is of interest as a means of Covid-19 diagnosis, particularly in parts of the world where testing remains expensive and not conveniently accessible. It can be useful as a non-disruptive and convenient early indicator of infection that can be used as part of a person's attire without additional effort and can prevent misdiagnosis and motivate us to take necessary precautions early in the disease onset.

II. Related work

Recent years have seen considerable interest in continuous monitoring solutions. Hassanuzzaman *et al.* [1] developed a wearable solution for capturing ECG signals with cloud-based analysis for diagnosing heart disease. Fouad [2] has designed an architecture for a Wireless Body Area Network that allows sensors positioned or implanted under the skin in different areas of the body to be connected and acquire data continuously. Arvind [3] has proposed a glucose monitoring device consisting of multiple tissue piercing elements for continuous glucose monitoring.

With the onset of the Covid-19 pandemic, there has been an explosion of ML-based techniques for detecting infection. A few research works to automatically detect COVID-19 based

978-1-6654-9130-3/23/$31.00 ©2023 IEEE

on machine learning or deep learning methods have been done in recent years. Kassani *et al.* [4] have proposed automatic COVID-19 detection approaches based on feature extractor-based deep learning and machine learning classification using X-ray and CT images. Das *et al.* have developed an automated deep transfer learning-based method using the Xception model to detect COVID-19 infection in chest X-rays [5]. Nigam *et al.* [6] have used deep learning methods to correctly classify patients with COVID-19 positive or negative states, patients with pneumonia, influenza, and other illnesses that affect the chest region, and patients with an unaffected chest area. There has also been work on a variety of ML models for predicting infection from a variety of symptoms such as cough and breathing data [7], [8]. n another work, Das *et al.* have proposed an ensembled learning model based on conventional deep convolutional neural networks to detect COVID infection in patients [9]. However, none of these works focuses on continuously monitored data using a wearable for detection.

Many companies are developing wearables and configuring them with cloud-based infrastructure to address various health assessments including Covid-19. However, these devices can only measure or track one or two COVID-19 symptoms. Stojanović *et al.* [10] introduced a headset-like wearable device (*i.e.*, a mask) to track key COVID symptoms using general-purpose electronic components. They monitor the vital signs using devices like smartphones, sensors, and Arduino boards and network the system to the cloud. Jiang *et al.* [11] described various wearable telehealth solutions for tracking a number of physiological indicators that are crucial for COVID.

III. Methodology

Our methodology for infection detection entails the use of hospital data to identify "monitorable" features, and tune ML models for predicting infections. Fig. 1 shows the three stages of experiments performed for our developed method as explained below. Sections IV through VI illustrate the approach for Covid-19.

a) Data Pre-processing:: All the real-world datasets have some common critical issues (*e.g.*, missing values, unstructured data, unlabelled/mislabeled data, etc.) that must be addressed before proceeding with any analysis. In the data preprocessing step, we address and resolve these key issues to make the filtered dataset appropriate for our analysis.

b) ML Model and Data Frequency Selection:: Developing a disease classifier requires tuning and determining appropriate hyper-parameters for ML models. Our methodology entails dividing the dataset into two parts: (1) with the monitorable features; and (2) with all the relevant features. The initial monitorable feature set is identified based on the feasibility of continuous monitoring. We train ML models using both datasets with different data frequencies and hyper-parameters to determine the optimal model for predicting the targeted infection.

Table I: Brief Description of the Filtered Data

COVID positive patients	2788
COVID negative patients	2663
Total patients	5451
Total Number of Features	117
Total Number of Monitor-able Features	5

c) Wearable Design:: We assess the sensors used for monitoring the vital features to determine the constraints of a wearable device. We develop an iterative approach to fine-tune our model with features and use the model to determine the priority and desired accuracy of a specific monitorable feature. This entails alternate ways of measuring the critical features, tweaking the dataset according to that alternate approach, and adding necessary noise to determine the uncertainty tolerance of the models. Finally, we design the wearable device with the finally selected monitorable features.

IV. Covid-19 Data Preprocessing

The dataset used for our Covid-19 study was generated by the UF Integrated Data Repository, the UF Clinical and Translational Science Institute, and UF Health IT Services. It includes all patients treated at any UF Health facility who underwent testing for COVID-19 as well as patients with symptoms related to COVID-19 (such as respiratory disease, cough, fever, etc.). Note that missing or inconsistent values are a typical issue in most real-world datasets. Such data points can skew the outcomes of a machine learning model, resulting in poor model performance. Following are some of the critical challenges.

a) Multiple Visit:: The dataset includes information on all the visits of the patients, some occurring over a large span of time. In. particular, this includes visits where no Covid-19 testing is performed. Clearly, data from these visits were not correlated with Covid-19 diagnosis and consequently irrelevant to training or evaluating ML models. To avoid bias, we discard all data points that do not correspond to a test value label.

b) Data points with Irrelevant and Missing Features:: The dataset contains various patient-specific feature information. For example, '$2745 - 8$' is a feature that measures the pH of capillary blood. The data reading of this feature was taken on less than 10 patients. Such features represent specific patient conditions and are not germane to their Covid-19 diagnosis. Note that after filtering out these features we still are left with 117 features. Obviously, not all of these 117 features are monitorable. Given the available monitoring technology available, we choose 5 features (Temperature, Table I shows a brief description of the filtered dataset. Some of the patients do not have enough data reading for the five monitorable features. Some patients in the dataset only have their COVID results. After dropping these patients, we have a total of 5451 patients in our filtered dataset. Among these patients, 2788 patients (51%) were tested positive and 2663 patients (49%) were tested negative for COVID-19. Table I shows a brief description of the filtered dataset.

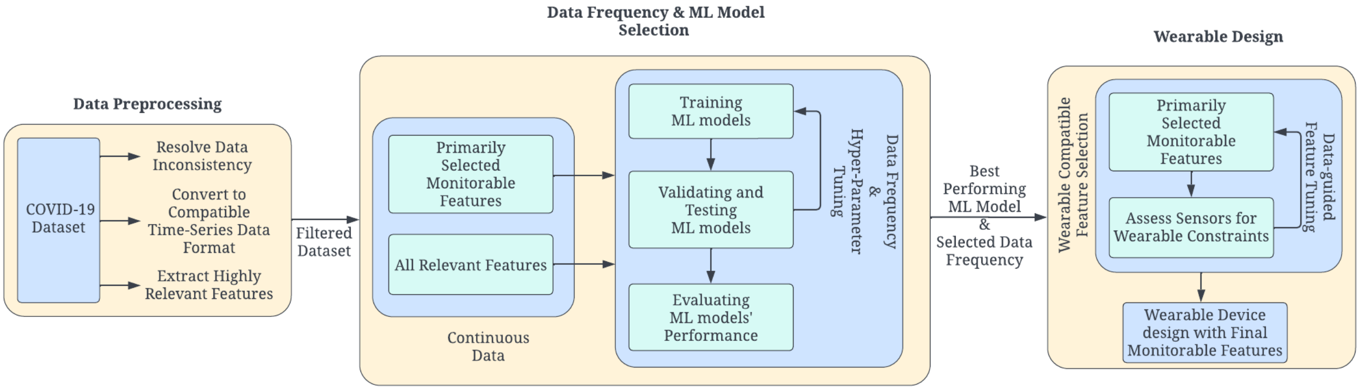


Figure 1: Workflow for Infection Detection Approach through Continuous Monitoring

c) Incompatible Data for TimeSeries Analysis:: Time series analysis requires the data length for each variable in the dataset to be equal and recorded at a constant time interval. However, in our dataset, patients have measurement readings recorded at different intervals, and the data length of different variables is not uniform either. To address this, we perform interpolation to "fill in" missing data. Note that this introduces synthetic data in the interpolated points. However, the approach is common in time series data preprocessing and has been shown to be effective in various domains [12].

V. Model training and analysis

On our time series dataset, we compared the performances of several deep learning and machine learning methods. The classifier models below were specifically taken into account: (1) Long Short Term Memory (LSTM); (2) Convolutional Neural Network (CNN); (3) Time-Series ForestClassifier (TSF); and Supervised TimeSeries Forest [13] (STSF).

Remark 1: Conventional feed-forward neural networks consider the test cases to be independent. These networks do not deal with the feature values from earlier days while fitting the model for a particular day. LSTM model can selectively "remember" patterns for a long duration. The LSTM model in our experiment was executed in a loop to find the optimal hyper-parameters via grid search. We have chosen 256 memory units (smart neurons) for the first layer. Since our experiment is a binary classification problem, we chose a dense output layer with a single neuron, binary cross-entropy as the loss function, and sigmoid as the activation function to make binary predictions for the two classes(COVID positive and negative). The optimal values for other hyperparameters (epochs, learning rate, and batch size) were set to 100, .001, and 128, respectively. We include TSF and STSF since these are ensemble models consisting of multiple decision trees.

The performance comparison of the selected models at different data frequencies is shown in Fig. 3. We have experimented with all the models with two types of feature setups. In setup one, we have kept all the selected features (a total of 117). In setup two, we kept only the five monitorable features. We have used accuracy, precision, recall/sensitivity, and f-score as evaluation metrics for comparing the performance.

Fig. 3 shows that every model gives a better result at one-hour data frequency with both feature setups. One notable observation from this graph is that accuracy and f-score are quite close in both setups for all the models. ***We can conclude from this observation that model accuracy does not significantly decrease if five monitorable features are considered only and the most ideal frequency for our analysis is hourly data.***

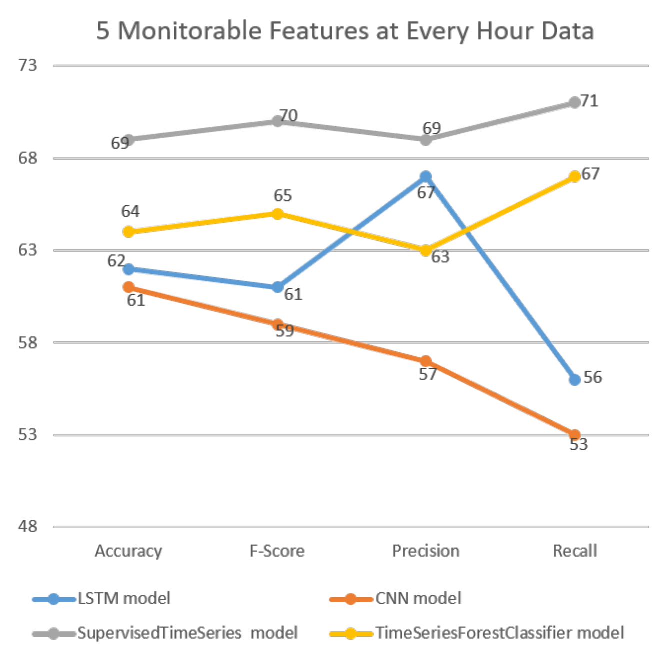


Figure 2: Comparing Different ML Models on One-hour Data

In order to determine which model is the most appropriate for our wearable device, we have compared various models' performance at an hourly data frequency with the selected 5 monitorable features. Fig. 2 shows that the STSF model outperforms all other models at our desired data frequency. The STSF classifier model gives the optimum accuracy and

Table II: Performance comparison of various models without SPO2

		5 Monitorable Features (%)	Without SPO2 (%)	Drop (%)
LSTM	Accuracy	64	59	**7.8**
	F-score	65	58	**10.8**
CNN	Accuracy	64	62	**3**
	F-score	62	59	**4.8**
STSF	Accuracy	70	60	**14.28**
	F-score	71	58	**18.3**
TSF	Accuracy	65	60	**7.7**
	F-score	66	60	**9**

Table III: Performance Comparison of STSF Classifier with derived Respiratory Rate and BPT

	Performance with original data	Performance with RR derived from HR	Performance with noise integrated BP	Performance with derived RR & noise integrated BP
Accuracy	70	68	68.5	68
F-score	71	69	70	70
Precision	71	68	69.8	69
Recall	72	71	70.5	70

recall value (predicting COVID-positive patients as positive) with the monitorable features at every hour data frequency. Additionally, the STSF model has a lower computation time than other models, which makes the model more suitable for our experiment. ***From these observations, we can conclude that the STSF model is the most appropriate choice for the wearable.***

VI. Wearable design

Our proposed wearable solution is based on data analysis with machine learning algorithms. It aims to function as a continuous health monitoring device used at home that can measure several indicators constantly at once, enabling users to keep tabs on their well-being and health as they go about their daily lives.

Our methodology to come up with the wearable is to balance the convenience of wearing and the criticality of monitoring certain features. This balance is determined by performing a variety of hypothesis testing experiments using the dataset. For instance, in order to keep the wearable strictly wrist-based, we considered discarding spo2 from monitorable features since spo2 measurement techniques require direct contact with the fingertip of the patient. To consider the viability of such a solution, we removed spo2 from the set of monitorable features and evaluated the ML models with other monitorable features. The result is shown in Table II. It clearly shows that discarding the spo2 measurement significantly affects the performance of all the models. Based on this experiment we conclude that spo2 monitoring cannot be avoided, and consequently, we must consider a wearable design that enables finger-based spo2 monitoring.

A second constraint on wearable design is to consider a form factor that enables comfortable usage. Integrating conventional methods for wrist-based blood pressure monitoring and respiratory rate computation will make the wearable large in size and unfeasible for users. We considered blood pressure trending (BPT) as an alternate for the actual blood pressure and evaluated the performance of the STSF model with one-hour data frequency, incorporating the standard error for BPT into our dataset. For the respiratory rate, we have used the rule of thumb derivation of respiratory rate from the heart rate of the patient. Table III shows the change in performance of the STSF model with the derived values for these two features, individually and all together, is very insignificant. The working functionality of the wearable is based on three layers:

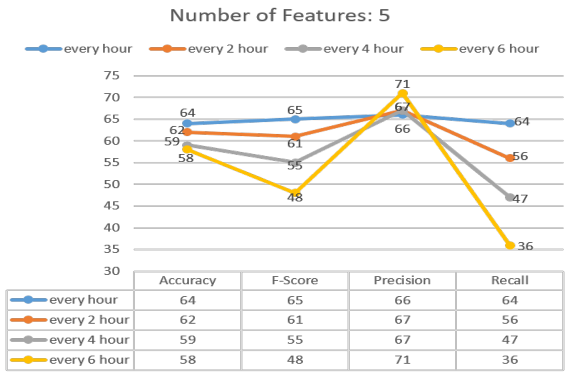
- *First Layer*: The sensors are located on the first layer. They are placed closest to the body. All five features discussed, are monitored by the sensors.
- *Second Layer*: The connectivity and control layer is the second layer. Integrated Wi-Fi is a very suitable mode of wireless communication in this regard, with a microcontroller module as the control node.
- *Third Layer*: The wearable supplies and reads data from the cloud in this layer.

A. Wearable components

Wearable sensors are usually affixed to the body and used to monitor vital functions. A trend in health monitoring systems is the use of these affordable, wearable sensors with precise readings [14]. Two major sensors are used for measuring all five features as our primary health indicators. The MAX30205 temperature sensor measures the human body temperature with an accuracy of ±0.1°C [15]. This sensor uses a high-resolution, sigma-delta, analog-to-digital converter to transform temperature readings into digital form. Our second component is – pulse express breakout board which has sensor MAX30102 and MAX32664D biometric sensor hub integrated into it. MAX30102 is an integrated pulse oximetry and heart-rate monitor device that is responsible for providing us with the majority of the features. The sensor functionality and usability are fairly standard [16]. We expect a continuous reception of data covering the heart rate, pulse oximeter, photoplethysmography (PPG), and respiratory rate. MAX32664D sensor hub has a built-in algorithm for generating output from the data received from the Optical sensor.

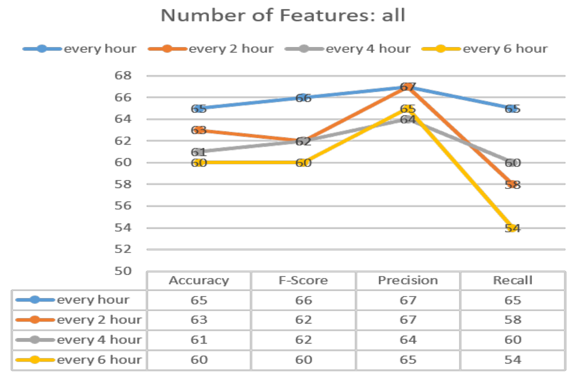
B. Design and interface

The wearable device we design is a wrist-based wearable similar to a smartwatch with an extension to the finger base/tip of the user. The block diagram of the system is shown in Fig. 4 (a). The temperature sensor and the microcontroller are situated on the wrist, with the other sensor fixed on the index finger. With this setup, a conceptual visualization of the wearable on a person is depicted in Fig. 4 (b). On the action, the sensory data is collected and stored by the MCU from both sensors and subsequently sent to the cloud or server. The result notification is sent to the user via SMS or email. The wearable will also have the option to notify via LED and display, supported by the built-in functions of the MCU.



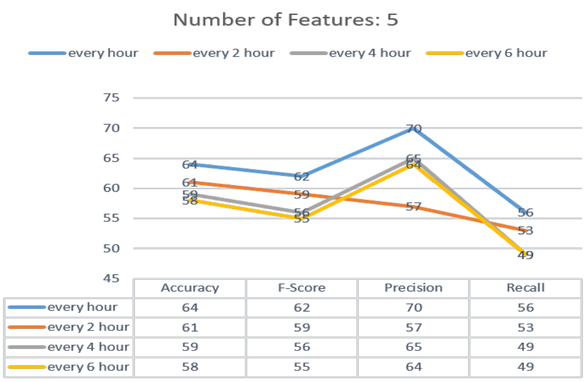
	Accuracy	F-Score	Precision	Recall
every hour	64	65	66	64
every 2 hour	62	61	67	56
every 4 hour	59	55	67	47
every 6 hour	58	48	71	36

(a) LSTM model with 5 features



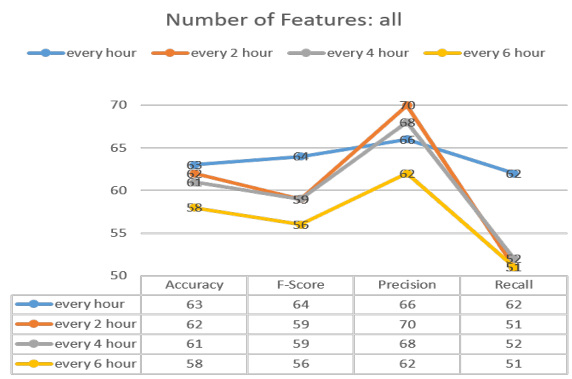
	Accuracy	F-Score	Precision	Recall
every hour	65	66	67	65
every 2 hour	63	62	67	58
every 4 hour	61	62	64	60
every 6 hour	60	60	65	54

(b) LSTM model with all features



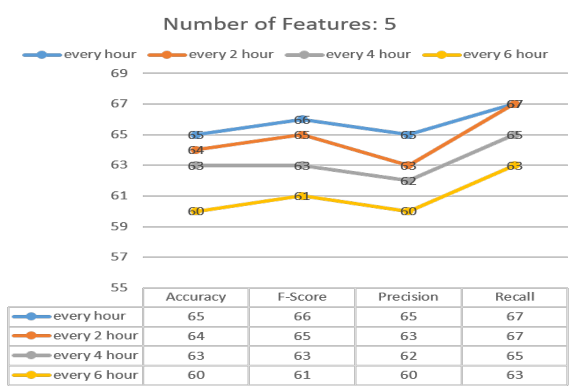
	Accuracy	F-Score	Precision	Recall
every hour	64	62	70	56
every 2 hour	61	59	57	53
every 4 hour	59	56	65	49
every 6 hour	58	55	64	49

(c) CNN model with 5 features



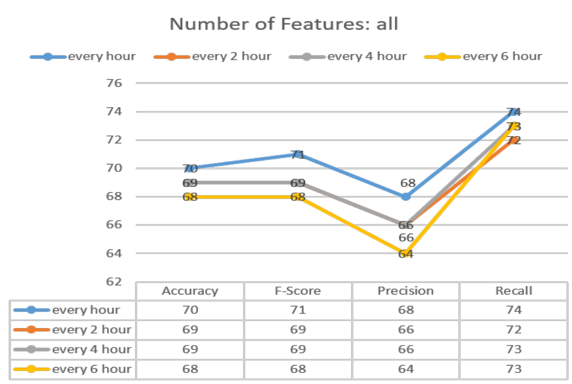
	Accuracy	F-Score	Precision	Recall
every hour	63	64	66	62
every 2 hour	62	59	70	51
every 4 hour	61	59	68	52
every 6 hour	58	56	62	51

(d) CNN model with all features



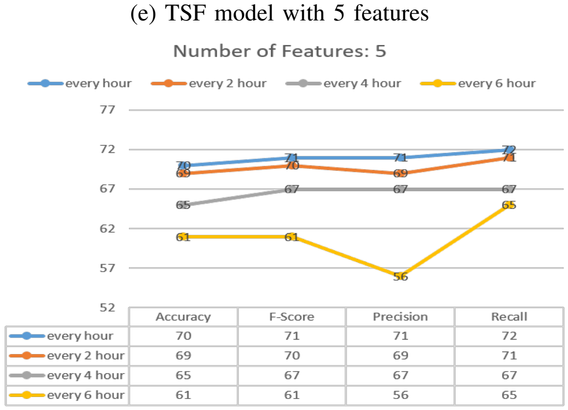
	Accuracy	F-Score	Precision	Recall
every hour	65	66	65	67
every 2 hour	64	65	63	67
every 4 hour	63	63	62	65
every 6 hour	60	61	60	63

(e) TSF model with 5 features



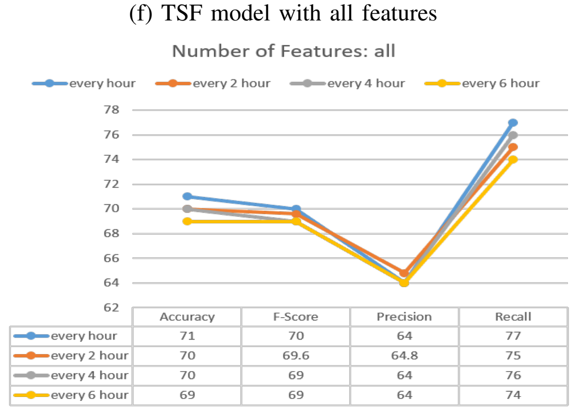
	Accuracy	F-Score	Precision	Recall
every hour	70	71	68	74
every 2 hour	69	69	66	72
every 4 hour	69	69	66	73
every 6 hour	68	68	64	73

(f) TSF model with all features



	Accuracy	F-Score	Precision	Recall
every hour	70	71	71	72
every 2 hour	69	70	69	71
every 4 hour	65	67	67	67
every 6 hour	61	61	56	65

(g) STSF model with 5 features



	Accuracy	F-Score	Precision	Recall
every hour	71	70	64	77
every 2 hour	70	69.6	64.8	75
every 4 hour	70	69	64	76
every 6 hour	69	69	64	74

(h) STSF model with all features

Figure 3: Model Performance at Different Data Frequency

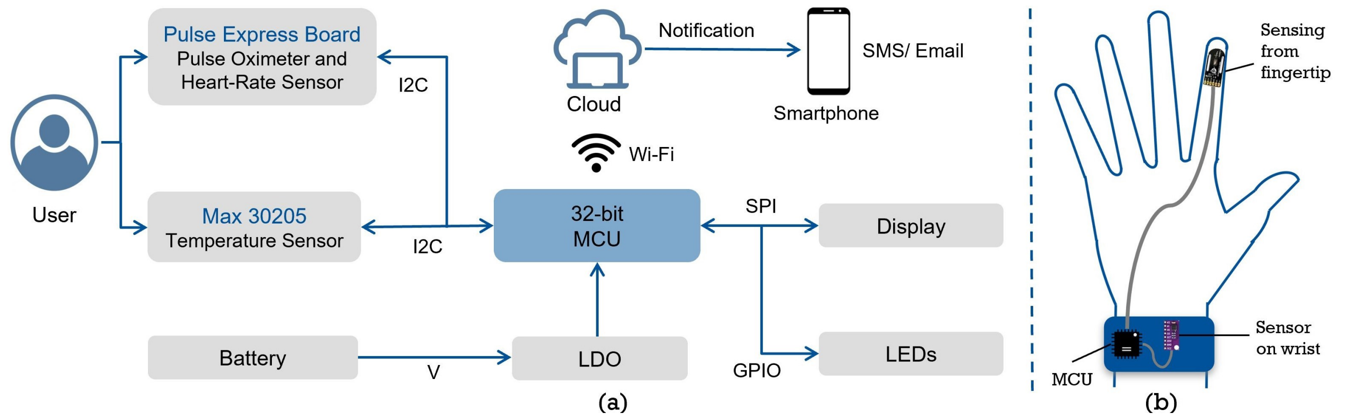


Figure 4: Wearable Design; **(a)** the block diagram of system architecture and **(b)** visualization of the wearable on a person

VII. Conclusion

We have considered the problem of continuous monitoring solutions to detect infections. A key challenge with developing such solutions is to be able to identify features to be monitored. This must be determined *before* the wearable is built and therefore before the monitoring solution is available for efficacy determination. The current approach, — using field testing on preliminary designs followed by iterative improvement based on field conclusion, — is insufficient because of the number of alternatives and tweaks that need to be considered for optimizing the wearable. We showed how to achieve this effect from available (non-continuous) medical data available through hospitals by making use of interpolation and various fine-tuning tweaks to identify trends, determine the efficacy of different ML models, and fine-tune ML parameters. We used this strategy to develop a wearable solution for predicting Covid-19 in symptomatic patients. Although monitoring vital signals of patients has been available for a while, most of these approaches are one-off, based on human insight for a specific disease. Our approach enables systematic analysis based on data to determine optimal monitoring requirements for the wearables. Our Covid-19 detection wearable can be used as a convenient, non-intrusive approach to monitor the infection, particularly in parts of the world where tests are not readily available or for patients who find swabs inconvenient.

In future work, we plan to extend by incorporating more infectious diseases as potential use cases to establish a more advanced monitoring solution.

Acknowledgements: We thank UF Clinical and Translational Science Institute, UF Health IT Services for providing access to the Covid-19 dataset from UF Integrated Data Repository which formed the basis of the work in this paper. We also thank Srivalli Boddupalli for several valuable insights.

References

[1] M. Hassanuzzaman, P. Biswas, and T. Rahman, "End to end solution for continuous monitoring and real-time analysis of vital signs from ecg signal," in *2019 IEEE R10 Humanitarian Technology Conference (R10-HTC)(47129)*, 2019, pp. 55–60.

[2] H. Fouad, "Continuous health-monitoring for early detection of patient by web telemedicine system," in *International Conference on Circuits, Systems and Signal Processing, Saint Petersburg State Politechnical University, Russia*, 2014, pp. 23–25.

[3] J. N. ARVIND, "Devices, systems, methods and tools for continuous glucose monitoring," U.S. Patent WO-2006105146-A3, 2005.

[4] S. H. Kassania, P. H. Kassanib, M. J. Wesolowskic, K. A. Schneidera, and R. Detersa, "Automatic Detection of Coronavirus Disease (COVID-19) in X-ray and CT Images: A Machine Learning Based Approach," *Biocybern Biomed Eng*, vol. 41, no. 3, pp. 867–879, 2021.

[5] N. Narayan Das, N. Kumar, M. Kaur, V. Kumar, and D. Singh, "Automated Deep Transfer Learning-Based Approach for Detection of COVID-19 Infection in Chest X-rays," *Ing Rech Biomed*, vol. 43, no. 2, pp. 114–119, Apr 2022.

[6] B. Nigam, A. Nigam, R. Jain, S. Dodia, N. Arora, and B. Annappa, "COVID-19: Automatic detection from X-ray images by utilizing deep learning methods," *Expert Syst Appl*, vol. 176, p. 114883, Aug 2021.

[7] C. Brown, J. Chauhan, A. Grammenos, J. Han, A. Hasthanasombat, D. Spathis, T. Xia, P. Cicuta, and C. Mascolo, "Exploring automatic diagnosis of covid-19 from crowdsourced respiratory sound data," in *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, ser. KDD '20. New York, NY, USA: Association for Computing Machinery, 2020, p. 3474–3484. [Online]. Available: https://doi.org/10.1145/3394486.3412865

[8] M. Pahar, M. Klopper, R. Warren, and T. Niesler, "Covid-19 cough classification using machine learning and global smartphone recordings," *Comput. Biol. Med.*, vol. 135, no. C, aug 2021. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2021.104572

[9] A. K. Das, S. Ghosh, S. Thunder, R. Dutta, S. Agarwal, and A. Chakrabarti, "Automatic covid-19 detection from x-ray images using ensemble learning with convolutional neural network," *Pattern Anal. Appl.*, vol. 24, no. 3, p. 1111–1124, aug 2021. [Online]. Available: https://doi.org/10.1007/s10044-021-00970-4

[10] R. Stojanović, A. Škraba, and B. Lutovac, "A headset like wearable device to track covid-19 symptoms," in *2020 9th Mediterranean Conference on Embedded Computing (MECO)*. IEEE, 2020, pp. 1–4.

[11] W. Jiang, S. Majumder, S. Kumar, S. Subramaniam, X. Li, R. Khedri, T. Mondal, M. Abolghasemian, I. Satia, and M. J. Deen, "A wearable tele-health system towards monitoring covid-19 and chronic diseases," *IEEE Reviews in Biomedical Engineering*, vol. 15, pp. 61–84, 2021.

[12] C. Ratanamahatana and E. J. Keogh, "Three myths about dynamic time warping data mining," in *SDM*, 2005.

[13] N. Cabello, E. Naghizade, J. Qi, and L. Kulik, "Fast and accurate time series classification through supervised interval search," in *2020 IEEE International Conference on Data Mining (ICDM)*, 2020, pp. 948–953.

[14] V. V. Garbhapu and S. Gopalan, "Iot based low cost single sensor node remote health monitoring system," *Procedia computer science*, vol. 113, pp. 408–415, 2017.

[15] S. Sudha, P. Shruthi, and M. Sharanya, "Iot based measurement of body temperature using max30205," *Int. Res. J. Eng. Technol*, vol. 5, pp. 3913–3915, 2018.

[16] U. A. Contardi, M. Morikawa, B. Brunelli, and D. V. Thomaz, "Max30102 photometric biosensor coupled to esp32-webserver capabilities for continuous point of care oxygen saturation and heartrate monitoring," *Engineering Proceedings*, vol. 16, no. 1, p. 9, 2021.