IoT-based smart triage of Covid-19 suspicious cases in the Emergency Department

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***Abstract*—According to scientific reports, the main and most common Covid-19 symptoms are fever and shortness of breath. Therefore, monitoring of vitals such as temperature, breathing and heart rate and blood oxygen saturation is of essence. Our team has designed and developed a wrist-worn wearable device that continuously monitors relevant vital signs with the aim to prioritize and triage Covid-19 patients in the Emergency Department.**

***Keywords*—photoplethysmography, Covid-19, respiratory evaluation, wrist wearable, triage, emergency department, tinyML**

I. Introduction

Despite the fact that we are in the middle of a significant transformation regarding the way products and services are produced and distributed, known as Industry 4.0, Health 4.0 is still in its infancy [1]. However, new IoT technologies and techniques are making the difference aiming to change the way healthcare is delivered. The recent Covid-19 outbreak highlighted the weaknesses of healthcare systems across the world and revealed the clinical need for new innovative IoT solutions.

In order to limit the spread of Covid-19, certain measures are needed to alleviate the burden from public health organisations, including reference hospitals. One of the most significant is to reduce Emergency Department (ED) overcrowding, minimising waiting time of suspicious incidents and increase in-hospital safety. Fever and shortness of breath are considered as two of the main symptoms of patients infected by Covid-19 [2],[3]. Both symptoms can be objectively tracked by measuring vital signs, such as body temperature, breathing rate and/or oxygen saturation levels. Continuous monitoring of those vitals is not currently considered as an option offered by EDs, unless a patient is admitted to the ICU. Instead sporadic checks may occur depending on the availability of human resources (usually limited and under huge pressure). In addition, the commercially available medical devices are not always portable, while more than one device is needed to provide the full spectrum of required vital signs. In this work, we present the ongoing development of a wrist-wearable device we have designed and developed, which uses advanced digital signal processing algorithms on PPG (Photoplethysmogram) to continuously extract heart rate, blood oxygen saturation levels, body temperature estimation and respiratory classification.

The wearable device has been already integrated with a cloud-based infrastructure. The wrist-wearable device supports common communication protocols, thus being able to transfer processed data to other third-party systems and apps through an API. A mobile application for the ED personnel that we also developed is used for real-time detection of health deterioration and enables highlighting the most critical Covid-19 cases, thus reducing clinical decision-making and patient waiting time and allowing for more efficient triage. Finally, recorded vital signs might act as a complementary source of information to the results of the clinical examination to make a final diagnosis of patients.

The proposed solution has been set up and piloted in the Emergency Department of AHEPA hospital in Thessaloniki, Greece, where suspicious Covid-19 cases are referred to from the Region of Central Macedonia. To our knowledge, a similar application of Covid-19 continuous monitoring in the ED has not been applied in clinical settings yet. This paper demonstrates the development of such a smart device and its feasibility to collect vital signs in the clinical operational environment.

II. Related Work

The use of wearable medical sensors is limited due to several practical factors, such as lack of comfortable wearable sensors and absence of low-power affordable hardware [4]. These restrictions have resulted in a very limited number of commercial wearable devices already in use inside hospitals. Despite these restrictions, with the advent of the Covid-19 outbreak, there has been an increased interest in the implementation of telemedicine techniques, including robotics and wearable electronics [5]. The employment of the latter, as of the writing of this paper, has been restricted to either the development of new applications utilizing novel materials for the detection of specific pathophysiological symptoms related to the disease, or to the use of already existing devices and technologies to either predict the early onset of the disease [6], or to monitor patients already in quarantine [7][8]. One such example is a study by Natarajan et al (2020) [9], that utilizes Fitbit device measurements of confirmed, (via PCR test) Covid-19 patients, in various stages and outcomes of the infection, the purpose of which was the creation of a commercial system aimed at predicting the need for hospitalization.

There has been, however, to the best of our knowledge, a lack of suitable IoT infrastructure to provide critical clinical information of patients' bio signals during triage and the initial stages of treatment.

III. WEARABLE DEVICE

The key objective of the device is to perform digital signal processing techniques on raw PPG signal in order to extract heart rate, blood oxygen saturation and body temperature estimation and transmit this information to the cloud platform real-time. Moreover, a neural network is currently under development based on TinyML in order to be deployed locally on the processor, compressed as a header file, aiming to evaluate respiration.

A. *EMBEDDED SYSTEM*

The embedded system consists of three main electronic circuits blocks: a) the processor, b) the sensors and c) the power management circuit. The embedded system is based on Espressif's ESP8266EX System on Chip (SoC) that integrates a powerful 32-bit Tensilica L106 32-bit RISC processor and the WiFi stack protocol. More specifically, we are using the WROOM-02 module, which integrates a high speed 2MB SPI flash memory and a printed antenna.

The wearable device is equipped with MAX30102 from Maxim Integrated™, which includes internal LEDs an infrared with wavelength 880nm and the other red with wavelength 660nm, photodetectors, optical elements, and low-noise electronics with ambient light rejection, able to sense high accuracy Photoplethysmogram. A 9 axis IMU (Inertial Measurement Unit) ICM-20948 from TDK-InvenSense is added for motion tracking and gesture recognition aiming to future algorithm optimization and extended applications. The wearable device is powered by a Polymer Lithium Ion battery at 3.7V with 400mAh capacity capable of continuously extracting and transmitting vital signs for more than 9 hours. Inductive charging is used for fast charging based on XKT-510 integrated circuit and a receiving coil terminal with 21mm outer and 10mm inside diameter and 0.5mm thickness. The inductive charging circuit is controlled by an NPN-transistor in order to handle charging events.

Figure 1 Device enclosure.

B. *FIRMWARE*

In order to establish communication between the processor and the sensor, a high speed I^2C (Inter-Integrated Circuit) interface bus is routed at 400kHz. Given the fact that the wearable device is meant to be placed on the wrist, specific sensor configuration is applied.

TABLE 1 REGISTER CONFIGURATION

REGISTER CONFIGURATION		
Setting	***Value***	***Register***
FIFO Configuration	0x01010000	0x08
Mode Configuration	0x00000011	0x09
SpO_2 Configuration	0x00100111	0x0A
IR LED amplitude	0x00110010	0x0C
Red LED amplitude	0x00111111	0x0D

The values presented in Table 1 are set to corresponding sensor's register through the I^2C bus from the processor. The internal First In First Out (FIFO) memory can store up to 32 samples and the above FIFO configuration corresponds to a) 4 samples averaged per sample, b) FIFO address rolls over to zero and continues to fill with new data and c) Interrupt the processor when 3 samples are remaining in FIFO. The mode configuration wakes up the sensor and set its mode to Multi-LED mode enabling IR and red LED slots. The SpO_2 configuration sets the ADC (Analog to Digital Converter) range control to 4096nA, sample rate at 100 samples per second and pulse width to 410.75μs with 18 bits ADC resolution. Finally, the IR and red LEDs current level are set to 6.2mA and 12.6mA respectively. The processor reads two sensor's registers; read pointer (0x03) and write pointer (0x04). A mismatch between them indicates that a new sample is available. Following this procedure raw data are captured, as shown at fig. 2.

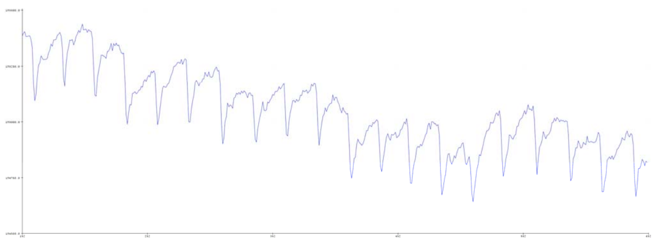

Figure 2 Raw IR PPG data.

IV. DIGITAL SIGNAL PROCESSING

A. *Noise removal*

It is obvious that the DC component of the raw signal has to be removed in order to avoid any related noise from ambient light and DC offset drifting aiming to keep only the AC component. For each FIFO sample the following two equations are applied.

$$x(t) = y(t) + a * x(t-1) \quad (1)$$

$$w(t) = x(t) - x(t-1) \quad (2)$$

where x(t) is the intermediate value, y(t) is the current value, w(t) is the output value and α is filter's response constant. After a while the signal stops oscillating and drifting and results to a smoother output.

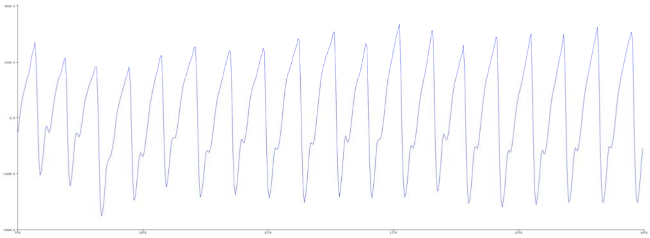

Figure 3 AC component of PPG signal.

Next a mean median filter with 15 samples size is applied to further clean up the signal. Storing the timestamps of two consecutive peaks, the hearth rate can be calculated with the following formula

$$Heartrate/min = \frac{60.000sec}{currentpeak - previouspeak} \tag{3}$$

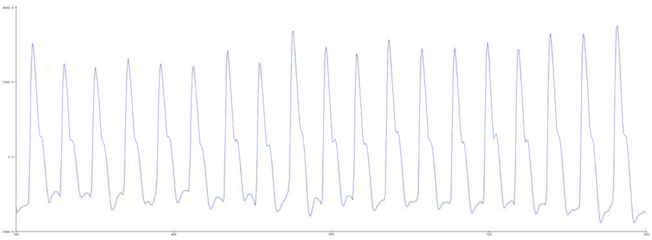

Figure 4 Mean median filter output.

B. *Algorithms for SpO2 and body temperature calculation*

Pulse oximeters apply the Beer-Lambert law to estimate blood oxygen saturation (SpO_2) [10]. The law describes that light intensity diminishes exponentially when traveling in an absorbing medium and the absorption is dependent to the wavelength [11]. Oxygenated haemoglobin preferentially absorbs infrared light and transmits red light while deoxygenated haemoglobin behaves in the opposite manner [12] [13]. Therefore, blood oxygen saturation is defined by equation (4)

$$SpO_2 = \frac{HbO_2}{HbO_2 + Hb} \tag{4}$$

where Hb is deoxygenated haemoglobin and HbO_2 oxygenated haemoglobin and can be expressed as the ratio R between absorbed light from infrared LED and red LED. According to Beer-Lambert Law and a standard model for computing SpO_2 [10], we use the following mathematical formula to calculate blood oxygen saturation.

$$SpO_2 = 110 - 25 * R \tag{5}$$

The ratio R is calculated from the equation

$$R = \frac{\frac{AC_{RMSRED}}{DC_{RED}}}{\frac{AC_{RMSIR}}{DC_{IR}}} \tag{6}$$

which can be expressed like:

$$R = \frac{log(I_{AC}) * \lambda_1}{log(I_{AC}) * \lambda_2} \tag{7}$$

where, λ_1 is the wavelength of red radiation (660nm) and λ_2 is the wavelength of the infrared radiation (880nm). Fig. 6 shows relevant recordings of both wavelengths.

The MAX30102 has an accurate on-board temperature sensor to measure temperature based on Stefan-Boltzmann law [14]. It is obvious that sensor's field of view is limited to a specific part of the wrist, therefore it is safe to assume that the sensor measures skin temperature of this part. Given the fact that several environmental conditions are met (e.g. room temperature between 20-25 Celsius degrees, device temperature should be stabilized about 10 minutes after power on) skin temperature can lead to a body temperature estimation. The wearable device cannot identify the exact body temperature but it is capable of classifying increased temperature events.

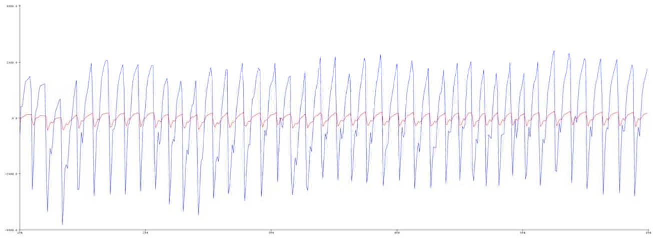

Figure 5 For each signal peak calculation of the RMS of both wavelengths is performed.

C. *RESPIRATION PATERNS*

There are several techniques and algorithms aiming to measure respiration rate continuously in real time [15],[16],[17]. A completely different approach is proposed for respiratory evaluation by identifying three major features regarding respiration and deploy them on the wearable device in order to identify respiration patterns locally and offline through neural networks highlighting the advantages of edge computing.

The three respiration patterns, our neural network identifies are: a) Normal breathing (12-18 breaths/minute), b) Heavy breathing (>18 breaths/minute) and c) Bradypnea (< 10 breaths/minute). Classical signal processing will fail to do successful stratification as it is extremely difficult to recognize any feature or distinguish any pattern as presented in fig. 6.

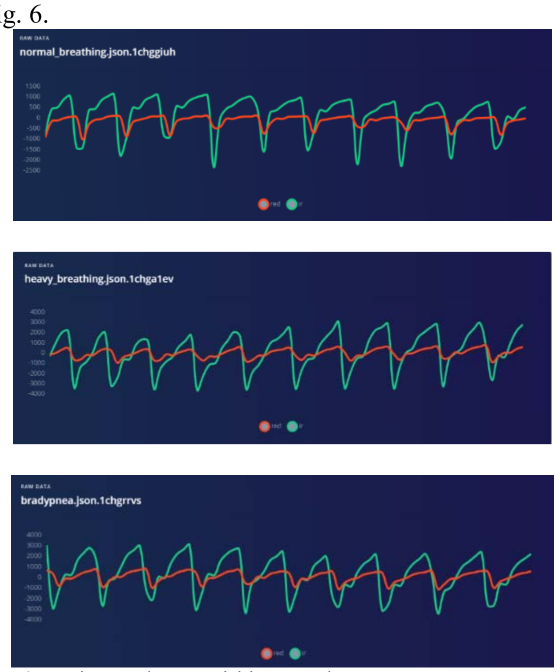

Figure 6 Respiratory data acquisition samples.

After the data acquisition procedure, pre-processing techniques are applied aiming to distinguish the most important features from the collected data in order for the final machine learning model to be smaller, which is better given the fact that it will be stored and executed on a memory limited embedded device. The main processing block is spectral analysis in order to identify the frequency and power characteristics of the signals. For each one batch an 8th order low pass filter with 3Hz cutoff frequency and Fast Fourier

Transform (FFT) with 128 FFT points is applied. Going over the collected dataset of 11min and 38s slicing up in 2000ms window with 80ms window increase, creates 5,284 training windows.

Edge Impulse (EI), is a San Francisco start-up that provides a user-friendly web application in order to execute the whole toolchain of a neural network, from raw data acquisition and extracting features to training models and deploy them on embedded devices. Exploiting the TCP/IP protocol stack, which is integrated to ESP8266EX SoC, we used EI's ingestion service which allows data acquisition wirelessly. Specifically, the wearable device collects locally raw PPG data, creates a json file containing batches of them given a predefined format and then sends the file to a Hypertext Transfer Protocol Secure (HTTPS) end point. As mentioned on section B raw PPG data are noisy, therefore dc removal is performed before data acquisition. Running EI's feature extraction tool we were able to successfully classify the collected data, as presented in fig. 7.

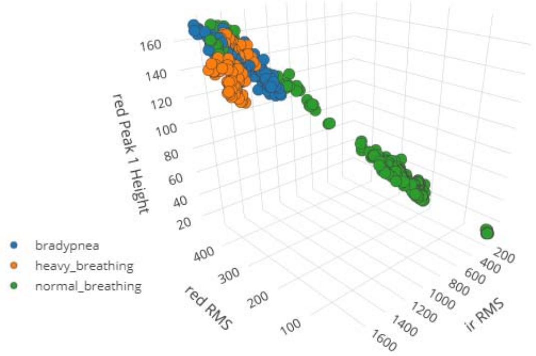

Figure 7 Feature extraction.

The next step was to design the Neural Network (NN) architecture and the training parameters. The selected NN architecture consists of consecutive regular densely-connected layers in pyramid format. Fig. 8 presents the architecture in details.

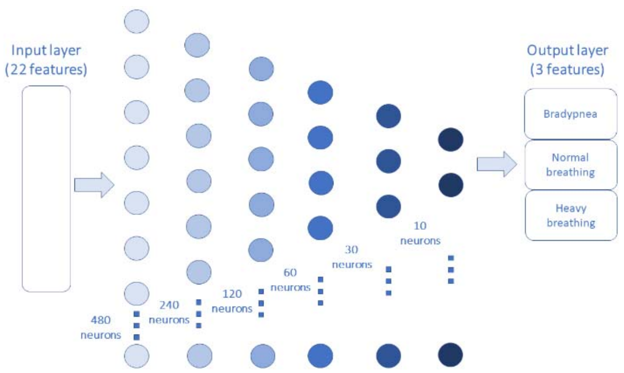

Figure 8 Neural Network Architecture.

Using empirical models for achieving higher accuracy, the training procedure was repeated for 250 training cycles with 0.0001 learning rate and minimum confidence rating of 0.70.

The confusion matrices reveal confident results (77.1% accuracy) for an optimized deployment considering processor's computing capabilities, but the neural network accuracy rises impressively (up to 95.1%) by trading off on-device performance, as clearly presented on fig. 9 and fig. 10 respectively. It is worth mentioning that the on-device performance is estimated for ARM Cortex-M4F 64Mhz, which is less powerful than the actual wearable's processor.

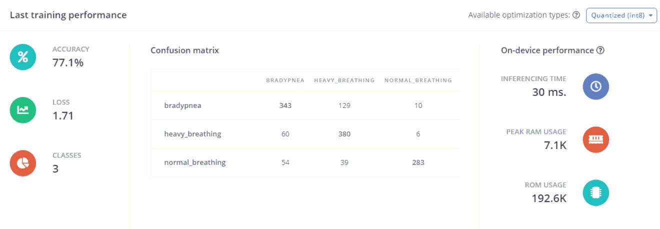

Figure 9 Confusion matrix and on-device performance for optimized deployment considering embedded systems.

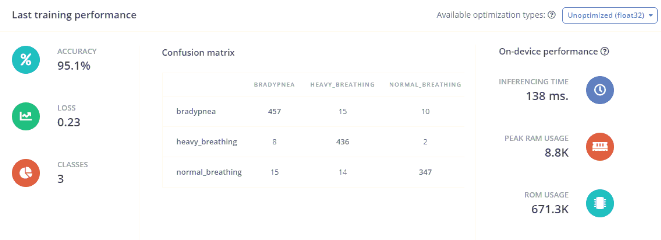

Figure 10 Confusion matrix and on-device performance for unoptimized deployment considering embedded systems.

V. APPLICATION LAYER

The main objective of the application layer is to visualize vital signs, collect patient's short medical history and Covid-19 related symptoms and timely notify physicians for health events.

A. Physician's applications

The main functionalities include: a) insertion of a new patient with Covid-19 symptoms and assignment of a wearable device, b) continuous monitoring of vital signs and receipt of real-time notifications in case of patient adverse events (i.e. abnormal values or trends of one or more vital signs for a specific time window) and c) real-time tracking of patients within the ER area using a real-time location system (RTLS) based on Wi-Fi fingerprinting. Furthermore, we have designed and built a web application in order to offer a better understanding of collected data and increase user experience. Fig. 10 presents the main monitoring view.

Figure 11 Vital signs monitoring through the web application.

B. Backend infrastructure

Multiple HTTPS endpoints are exposed in order to receive data from the wearable device and to establish bilateral communication between backend services and the physician's mobile application. Moreover, a data schema of two databases is used to optimize storage and management of real time series data, as shown in fig. 12.

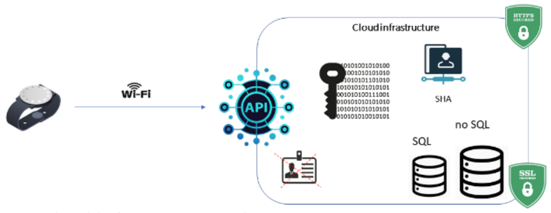

Figure 12 Cloud infrastructure and components.

VI. MEDICAL SCENARIO & ONGOING PILOTS

The trial of the wearable device on Covid patients was realized through the use of three mobile phone devices, providing network coverage over areas of importance during patient's visit at the hospital, with the main consideration being to maximize coverage during treatment. As seen in fig. 13, the localization of hotspot regions was informed by a heuristic approach to area partitioning, by initially covering the ER area where patients would spend most of their time, marked as area (1) – (triage and examination rooms), and followed by nearby regions that could become necessary during treatment, such as the negative pressure and radiology (computed tomography scanner and X-ray) units, marked as areas (2) and (3) respectively.

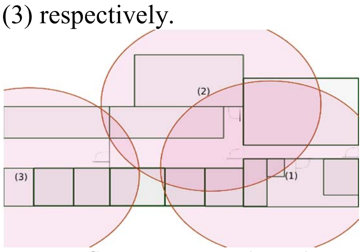

Figure 13 Mobile Hotspot Coverage Map on AHEPA Hospital Covid-19 ED.

Fig. 14, 15, 16 presents Covid-19 patients collected vital signs, from trials on 29th of July, 14th and 31th of August.

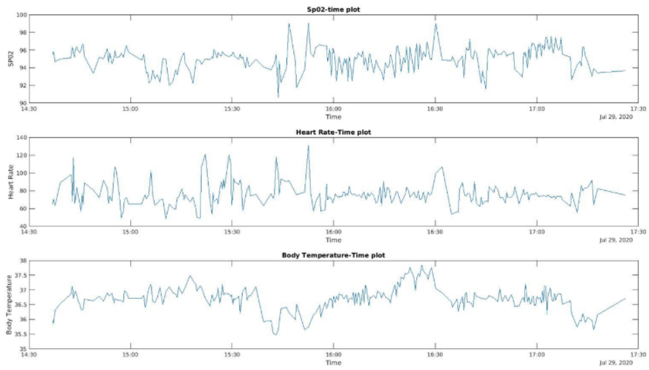

Figure 14 Collected data for July 29th trial run.

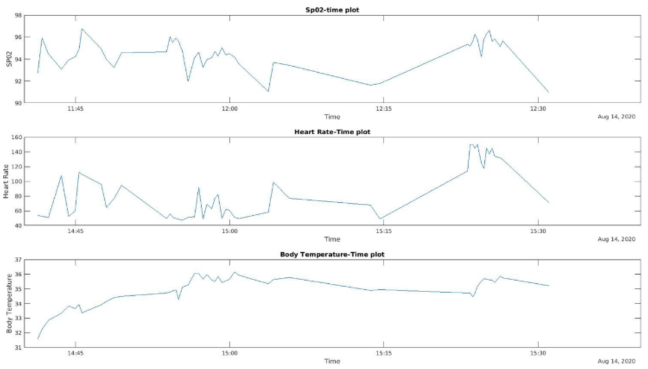

Figure 15 Collected data from August 14th trial run.

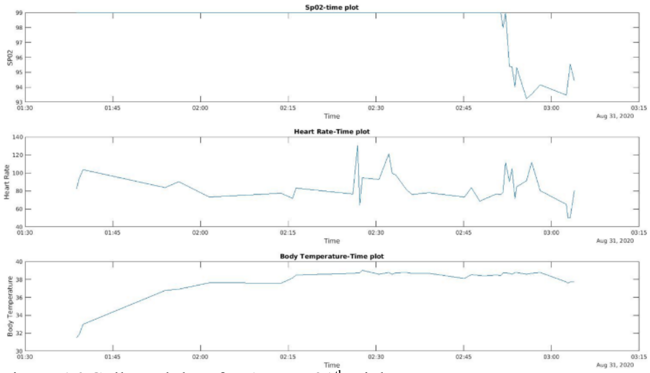

Figure 16 Collected data for August 31th trial run.

As mentioned on section IV. B, the device temperature stabilizes about 10 minutes after power on and it is clearly indicated by body temperature plots.

VII. TRIAGE & DECISION-MAKING PROCESS

All patients arriving at the Emergency Department [ED] of AHEPA University Hospital undergo a pre-triage procedure for identification of suspected or confirmed COVID-19 cases according to the National Organisation of Public Health criteria. Those who meet the criteria are shown to the COVID-19 ED area, where triage based on the Emergency Severity Index (ESI) protocol is performed by specialized physicians. Patients >18 years old classified as ESI level 3 or 4 are enrolled in this study. A special questionnaire form developed by the researchers is then applied to all subjects. Questions concern demographics, vital signs, past medical history, main presenting symptoms, arrival time, total examination time and time of doctor's diagnosis and patient outcome. Simultaneously, ESI 3 subjects undergo real-time recording of vital signs (SpO_2, body temperature and heart rate) by the wearable device, which enables the detection of potential patient deterioration that demands immediate medical attention and/or care. Final decision making is based upon the collection of questionnaire information, electronically extracted data as well as the assessment of laboratory tests, chest X-ray and computed tomography scanning (CT-scan) results.

VIII. DISCUSSION

Respiration evaluation is a valuable indicator for Covid-19 patients and for this reason it is our first priority to improve machine learning model's accuracy. As presented in fig. 7, there is an area where bradypnea data intersect with normal breathing, since the collected dataset is too small. Despite the encouraging results, the model will perform poorly on operational environment if it will be deployed based on the collected dataset, therefore several optimizations are foreseen to be applied. Our first goal is to retrain the model with new data collected from Covid-19 patients visiting AHEPA emergency department. Then an anomaly detection feature will be added in order to train the model to respond more accurately when unknown data are captured. Additionally, another on-device performance upgrade could be achieved by deploying the neural network with EON™ Compiler [18] in order to reduce inferencing time, Read Only Memory (ROM) and Random Access Memory (RAM) usage maintaining the high accuracy for unoptimized deployment. Regarding the physician's mobile application for future work, the formal Covid-19 symptoms questionnaire and ESI triage procedures will be integrated.

The proposed technique, regarding the respiration evaluation and by extension the wearable device, is aligned with the revolutionary approach of the semiconductor industry aiming to invest on Artificial Intelligence (AI) Integrated Circuits (IC) [19]. Additionally, this approach is supported from market research studies foreseeing that the estimated Compound Annual Growth Rate (CAGR) for AI ICs it is expected to be 5 times higher than traditional IC industry by 2025[20]. One of the main reasons that led to this trend is the fact that for higher bandwidth sensors, such as PPG, it is more efficient to continuously run AI locally than transmit data over a radio channel to expensive, power hungry and vulnerable cloud infrastructures. Our novel technique integrates this approach and smartly avoids the aforementioned disadvantages.

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