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Deposited on 17 January 2022

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UWB Radar Sensing for Respiratory Monitoring Exploiting Time-Frequency Spectrograms

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Abstract—Regarding health-related application domains, including COVID-19 sign revealing, diagnosis, and screening, wireless or non-intrusive technology for sensing abnormalities in an obscure and distanced setting is critical. Wireless strategies are particularly important during the COVID-19 pandemic since they entail the minimum level of interaction between infected persons and medical workers. COVID-19 contaminated persons with the novel COVID-19-Delta divergent had a heightened breathing rate to be the cause of widespread disease in the lungs, based on the most recent medical research studies on coronavirus. This devastating circumstance necessitates instantaneous monitoring of breathing patterns that could assist in preventing potentially vicious situations. A “XeThru X4M200” Ultra-Wideband radar sensor is used in this research to extract critical breathing patterns. This radar appears to work in the 6.0-8.5 GHz and 7.25-10.0 GHz bands, correspondingly, in the high and low-frequency range. By performing eupnea (regular) and tachypnea (irregular) breathing exercises, the data were acquired in the form of spectrograms. A cutting-edge deep learning method known as Residual Neural Network (ResNet) is being used to train, analyse, and evaluate the acquired spectrogram. The confusion matrix, accuracy, retrieval, F1-score, and accuracy rate are often exploited to examine the skilled ResNet model’s performance. Moreover, the deep learning ResNet technique anomalous bypass relation method minimises two complications, one is underfitting and the other is over-fitting, providing an accuracy rate of up to 97.5%.

Index Terms—XeThru X4M200, UWB radar sensor, ResNet, Wireless healthcare, Deep learning.

I. INTRODUCTION

Coronavirus or COVID-19 is an epidemic first thought to be discovered in late 2019 in Wuhan, China. This virus outspread rapidly from one person to another causing breathing (or respiratory) illness. Moreover, it can be fatal in some cases [1]. When an infected person coughs, sneezes, talks, or breathes anywhere around you, the virus is transmitted in respiratory droplets (within six feet). This is considered the primary reason when the disease is transmitted. People may start to exhibit COVID-19 symptoms 2 to 14 days after being exposed to the virus. The COVID-19 affected breathing rate can be determined by pulmonary activity evaluation [2], [3].

One of the key symptoms of COVID-19 is an abnormal breathing rate. The total number of breaths taken in one minute is based on the movement of the human chest. [4] Most common diseases like fever, fatigue, asthma, and some other underlying medical conditions can also elevate the breathing rate. [5] The breathing rate is severe for evaluating the patients’ pulmonary activity in COVID-19 cases since the irregular values could signify the patient’s weakening [6]. The health nurses evaluate the breathing rate, so it is generally performed in medical centers. Conversely, the breathing rate and pulmonary function analysis of the diagnosed patients raises the risk of infectiousness due to the clinical necessity inflicted by COVID-19. [7] Initially, most of the patients do not indicate COVID-19 symptoms, healthcare staff determines to send them to their homes on the assumption that they can self-monitor. Quarantined patients whose pulmonary activity and breathing rates are normal do not need treatment must be pursued via e-health technology. [8], [9]

The Food and Drug Administration (FDA) has granted the approval to utilize appliances that can distantly examine a patient’s critical symptoms. [10] Nevertheless, there are some existing sorts of gadgets that can be exploited for instantaneous screening in one’s own space. [11], [12]. Invasive technologies like smartwatches and digital cameras are being utilized for real-time evaluation. [13] The wireless electronic devices are initially projected to ease the hassle initiated by determining portable widgets to evaluate symptoms. [14], [15] Fingertip oximeter is one of the examples as it was replaced by smartphones that can monitor oxygen saturation. [16] The major advantage of wireless sensing is constant observation without any contact with the body. Patients do not need to be conscious of these wireless devices. [17] Some of the most known wireless (contactless, non-contact, or non-invasive) sensors are pressure sensors, heart-monitoring sensors, vibration sensors, and Radio-Frequency (RF) sensors. [18], [19]

Amongst the prevalent innovative technologies is RF that uses inductive motion which is derived from radar mechanics. [20] Even so, there is no on-hand radar-supported system designed for abnormal respiratory pattern screening to provide an extensive framework for patients instantaneous screening and transmitting reports to clinical nurses/health workers for immediate exploitation. [21] In this paper, we scrutinize the vision of using wireless mechanics to examine COVID-
We introduced a system that can monitor COVID-19 patients by exploiting a widely viable Ultra-Wideband (UWB) radar sensor (XeThru X4M200) created by NOVELDA. For screening the symptoms of many infections by detecting irregular breathing rates, essentially dyspnea (breath shortness), tachypnea (rapid or elevated breathing), bradypnea (slow respiratory), hyperventilation, hyperpnea (caused by anemia, asthma, and metabolic acidosis), and platypnea are projected exploiting microwave radar detectors. Our main focus in this work is to recognize the tachypnea breathing rate because of the irregularity pattern that is normally seen in COVID-19 infected individuals.

In this manuscript, we have focused on two types of breathing patterns: eupnea/normal and tachypnea/abnormal. Eupnea consents to survival and is considered as a regular and relaxed breathing rate. Usually, the breathing rate is 12-20 inhales/min. Neural output to breathing rate regularly flows with wonted patterns. Other than this, tachypnea refers to inhaling more air than usual into the lungs. Generally, the breathing rate is more rapid since higher oxygen requirement. Tachypnea can also be influenced by a natural reaction to one’s behavior or habitat, or it can be induced by a respiratory illness. Therefore, particularly during COVID-19, prompt screening and diagnosis of irregular breathing rates in patients are of utmost importance.

II. RELATED WORK

Earlier to the effects of the COVID-19 epidemic, Acute Respiratory Distress Syndrome (ARDS) was considered for 10-15 percent of Intensive Care Unit registrations and 5 percent of medical centers. ARDS is defined as when a breathing fall induced by a pervasive infectious disease in the respiratory tract grows abruptly. Symptoms entail Cyanosis (bluish skin develops suddenly with Dyspnea) and Tachypnea (increased/elevated breathing rate). While emerging stages of the COVID-19 epidemic, facts on the physio-pathology (physiology combines with pathology) of the infections emerged from asymptomatic (showing no symptoms), severely ill, and yet expired individuals. Based on the present affirmation, lung impairment is associated with a distinctive pulmonary vascular disease in the emerging phases of illnesses.

For data organization, the research teams then used Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Google-Net techniques. This part also presents knowledge on cutting-edge research in the field of human activity identification, in which radar sensor-based technologies were successfully integrated with intelligent machine learning and deep learning methodologies. Those certain algorithms’ accuracy seemed to be 78.25 percent, especially for SVM, precisely for KNN it is 77.15 percent and 74.70 percent for Google-Net. The researchers used radar Spectral waterfalls (Spectrograms) of many actions such as walking, falling, leaning down, and sitting. The spectrogram was exploited for data validation, data imputation and grayscale were developed from pictures. The two main algorithms utilized for data mining (business data-preprocessing) and their achieved precision results are SVM with 78 percent and Deep Neural Network (DNN) with 87 percent.

The SVM approach was then utilized to classify the images and the spectrograms were derived using the radar system. The writers conceived a sequential forward selection technique for feature selection. The precision results obtained seem to be up to 95 percent, regardless of the number of cases applied. Convolutional Neural Network (CNN) with Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) are some deep learning approaches using radar sensor Doppler images to determine six different human activities. These activities entail waving, running, boxing and clapping. The RNN algorithm with LSTM reached up to 92 percent precisely, while the CNN gained accuracy up to 82 percent, based on the findings of this article.

Significantly for classification spectrograms of diverse human behavior and range maps were combined. Five distinct human behaviors, bending, falling, walking, sitting, and kneeling was examined in this study. Mainly the two techniques, Principle Component Analysis (PCA), KNN were utilized to produce simulation results with an accuracy score of up to 82 percent. These two techniques applied to the fusion method, the researchers improved the scores precisely, from 82 to 91 percent for different human behavior. Impulse Radio Ultra-Wideband (IRUWB) radar sensors, were utilized by writers to
record twelve distinct types of human gestures in [38]. Besides this, utilizing KNN, the attributes in the spectrograms were identified during the data mining phase. The CNN was then used to retrieve and define the power spectrum and Doppler shifts. Human body action detection was achieved with up to 98 percent precisely. To trace everyday activities and fall over CNN along with IRUWB radar sensor were utilized by the proposed system model in [39]. The CNN technique achieved a score of up to 96 percent precisely. Binary classification algorithms were used in this study to differentiate between both the fall and any other type of activity in the home.

The research precisely achieved a total of 80 percent with the random forest technique. The data was collected whereas other individuals remained present within the facility. Many reside in an adjacent home unit conducted to imitate a real-life residential care environment. UWB radar was used by researchers to generate data records escorted by ten participants aged from 22 to 39 years and engaging in fifteen different activities. Similarly, the researchers observed it on seven individuals undertaking four, unlike activities. These activities were walking, sitting, standing, and falling. By the 10-Fold Cross-Validation approach, the collected data was processed with a precise score of up to 94 percent and revealed that KNN outperformed. The writers utilized UWB radar to gather information for binary classification of falling and non-falling tragedies. To obtain information from ten participants in three different fields of such proposed residence and the researchers deliberately put their research results to the test and realized that the proposed system model could achieve a precise score of up to 90 percent just by employing deep learning architecture CNN-LSTM.

III. PROPOSED METHODOLOGY

A. UWB Radar Chip

This research is primarily based on a XeThru UWB radar sensor that is being used to design a system capable of continuous monitoring of abnormal breathing in COVID-19 and ARDS-infected individuals. This radar sensor is a highly configurable one-chip solution and has an implicit transceiver to contact a subject without being physically connected. The UWB radar sensor has X4 SoC (System on Chip) with an inflated structure that enables the sensor to provide accurate human presence sensing. It is considered a groundbreaking innovation that can also track multiple objects at the same time. When an individual remains passive, such a device can capture the breathing rate up to five meters. Fig 2 illustrates the UWB radar sensor while Fig 3 indicates the entire flowchart.

B. Radar sensor Signal Processing

All firmware algorithms for motion sensors and breathing rate measurements are conducted by the UWB radar chip. [40] The radar chip data frames are stored in a buffer. Two Range-Doppler (RD) matrices are functioning concurrently. In the fast and slow RD matrices, data collected from different timings of radar frames are utilized. Depending on the profile the lengths of the fast and slow phases differ. To determine whether a reflection at some range and frequency surpasses a threshold in both, RD matrices can be utilized by individual noise maps. Therefore, you’ll get numerous threshold values at different frequencies and distances when you set a noise map. Except if the noise map adaption mode is shut off, the noise maps would adapt to environmental transformation. Noise map adaption is an ongoing procedure that leads to reducing the sensing of reflectors with very little mobility at a given distance. If a stationary person is observed with a breathing rate mirroring the predefined RPM level, then the noise map would never be revised.

When the ideal person remains still, the slow RD matrix’s slow-motion sensor and breathing sensor capture their appearance and evaluate the individual breathing rate and distance towards the respiration target. The breathing sensor and slow-motion sensor possess three parameters: motion, stationary, and breathing. The slow M/N connector employs these states to derive the Local-State-Slow. An M/N connector specifies that for the outcome to vary, M of N observations should have a fixed value. Similarly, the fast RD matrix’s rapid motion sensor instantaneously captures an individual’s position when it reaches the detection zone. The rapid motion sensor comes up with two states, motion or stationary. To establish the Local-State-Fast, the rapid M/N connector utilizes those two states. An M/N connector specifies that for the output to alter, M of N detections should have a particular value. Considering every detection technique is conducted, each sec, which implies every output including state, RPM, and distance are revised each sec.

C. Radar Sensor Micro-Doppler Signatures

Micro-Doppler (MD) is generated by the periodic motion of any structural component of an object, and it produces sidebands around the bulk Doppler frequency, leading to micromotion. [42] Necessarily, the phasing of such entity’s radar sensor reflected wave varies, as in some human activities, running, walking, or chest movements. In this way, if the radar is consistent, fluctuations in the value of the assets of
successive beeps in Frequency-Modulated Continuous-Wave (FMCW) radar would instantly correspond to Doppler variations. Referring to the records, a velocity-time spectrogram or the RD waveform might be produced to analyze the MD characteristics. To acquire Doppler data from FMCW radar chip data, the two-dimensional Fast Fourier Transform (FFT) is being used. Initially, each signal is exposed to FFT, which determines the profile range. Also, for a particular bin range, the next FFT is performed on a definite number of consecutive chirps. The Short-Time Fourier Transform (STFT) is being used to draw such graphs because, conversely to Fourier Transform (FT), it offers both temporal and frequency data in [43]. This is performed by fragmenting the data and then performing the FT towards each fragment in order. Due to alteration in window length, the temporal and frequency levels are affected; for example, one rises while the other falls and vice versa. The level of Doppler information in radar data is given by monitoring the proficiency of the device. The maximal unambiguous frequency of Doppler in FMCW radar is \( f_{d, \text{max}} = 1/2t_s \), in which \( t_s \) is the chirping time.

In this paper, we appraise a situation to monitor human breathing rate in which object point (chest), is positioned at a distance \( D(t) \) from the monitor. \( U(t) \) denotes the object point movement in front of the radar sensor, and \( P(t) \) is the transferred signal.

\[
P(t) = B \cos(2t)
\]  

The obtained signals are represented by \( O(t) \),

\[
O(t) = B' \cos \left( 2\pi f \left( t - \frac{2D(t)}{c} \right) \right)
\]  

\( B' \) represents the reflection coefficient while \( c \) represents the speed of light. At angle directed to radar sensor, if the wave is mirrored off the desired point, then the mirrored signals are as follow,

\[
O(t) = B' \cos \left( 2\pi f \left( 1 + \frac{2U(t)}{c} \right) t - \frac{4\pi D(\theta)}{c} \right)
\]  

The corresponding Doppler shift can be represented as,

\[
f_d = \frac{2U(t)}{c}
\]  

As a result, any Doppler shift would be the outcome of a complex connection of numerous Doppler shifts induced by different body components moving at different paces. The properties of such Doppler traces are absolutely critical in detecting and diagnosing human breathing in an accurate manner.

D. Deep Learning based ResNet for Respiratory Classification

Machine learning-based techniques have been effectively applied in the past for various applications [44]–[49]. In this research, by applying the deep learning approach ResNet, we have been using the captured spectrograms to identify the normal and affected human respiratory system. To train such a system, a skip connection approach is employed. The input and output feed layer elevates the stack. The key objective of the ResNet learning approach is to see if it would simulate the target function \( f(x) \). When the input, as well as the outcome of the network, are related, for as through forming a skip connection, the network tends to depict \( h(x) = f(x) \) instead of \( f(x) (x) \). The title for this is “Residual Learning”. Initially, when a standard DNN is launched, the network only gives scores near zero because the weights are nearly zero. If a skip network is employed in the emerging network, it generates a replica of its input. It also represents the identity function when putting that differently. The proposed technique can be significantly improved if the objective function is intimate to the identity function which is typically the case. However,
TABLE I: Healthy participant details employed to acquire breathing data [41].

<table>
<thead>
<tr>
<th>Gender</th>
<th>Age</th>
<th>Weight (Kg)</th>
<th>Height (cm)</th>
<th>Physique Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>26</td>
<td>59</td>
<td>168</td>
<td>Ectomorph</td>
</tr>
</tbody>
</table>

Fig. 5: Acquired spectrograms sample (a) normal/eupnea breathing (b) abnormal/tachypnea breathing [41].

IV. SIMULATION RESULTS AND DISCUSSION

A. Data Collection

The dataset for this experimental study was obtained from [41]. Section III contains detailed information on the radar chip. Six volunteers were requested to sit in front of the UWB Detector at a distance of typically one meter; although, the XeThru UWB radar chip can potentially catch crucial signs up to a distance of five meters. Fig 4 illustrates the UWB radar detector in a static position on top of the notebook screen. The research was carried out in a safe setting. When the radar detector senses the movement, during respiration, in particular, chest movement, the RF wave gets emitted and captured inside the area. The captured signal from the UWB radar sensor can be applied to create unique spectrograms. Every breathing pattern was replicated by the volunteers repeatedly in terms of creating sets of data for this research. The recorded spectrograms for regular and irregular breathing were 230, comprising 120 used for learning, 20 for affirmation, and 90 for evaluation. Likewise, Table I provides data about individuals who took part in the research study. Figure 5 illustrates the individuals practicing each breathing cycle for 15 seconds, with Doppler [Hz] on the y-axis and time[s] just on the x-axis. In the condition of regular breathing, the participant was to perform a normal respiratory rate for 15 seconds continuously. This is shown in Figure 5(a), the breathing rate ranges from 8 to -8 in terms of Doppler [Hz]. In the condition of irregular breathing function, the participant was instructed to conduct a regular respiratory rate for perhaps the first five seconds (roughly) and abnormal reparation for the next ten sec. To simulate an actual event, this is performed. Faster (or elevated) respiration was accomplished by rapidly inhaling and expelling air via the nose. Figure 5(b) illustrates that the rapid breathing rate has a significant reaction on the captured spectrograms as Doppler [Hz] swings from 10 to -10. Each body movement produces a distinct signal on the spectrogram, which can be utilised to identify many kinds of individual body movements.

B. Results and Discussion

In this research, to recognize various human breathing systems, the employed ResNet technique was developed in Python language using the TensorFlow and NumPy modules. Furthermore, in this study, the confusion matrix, precision, recall, F1-score, and classification accuracy metrics have been utilised to assess the efficiency of a trained model (see equations 6, 7, 8, 9). Classification accuracy is defined as the proportion of accurately identified human breathing patterns to the total number of breathing patterns. Besides this, the F1-score, sometimes referred to as the F-measure, is the harmonic mean of precision and recall. For inaccurately recognized datasets, F1-score is a crucial statistic as it provides a more accurate measurement than that of the classification evaluation metric.

\[
\text{Precision} = \frac{\text{True Positives}}{\text{Predicted Positives}} \tag{6}
\]
Recall = \frac{\text{True Positives}}{\text{Actual Positives}} \quad (7)

F1 - \text{score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (8)

Accuracy = \frac{\text{Number of respiratories recognised}}{\text{Total number of respiratories}} \quad (9)

The grid search method has been used to obtain the best parameters for developing the ResNet system. Considering the amount of the obtained data-set, the iteration number used to develop the system was fixed to fifty. The model’s accuracy was assessed after being developed utilising several techniques. As demonstrated in Fig 6, as the number of iterations increases, the ResNet learner proved the ability with an accuracy rate of more than 0.9, whereas a model loss was somewhat less of about 0.4. Besides this, Fig. 7 illustrates a confusion matrix of a developed deep ResNet method classification of healthy and unhealthy individual breathing.

Among regular (eupnea) and irregular (tachypnea) breathing, only a small percentage of breathing anomalies results. Ultimately Table II presents the comprehensive classified information (ordered data) of the ResNet model in relative terms. The regular breathing group revealed high accuracy results of 100%. On the other hand, the irregular breathing class gives an accuracy of 95%. For regular respiratory the recall rate is 95% and for irregular, it is 100%. Similarly, the F1-score for the regular breathing is 97% while for irregular it is 98%. The deep learning-ResNet approach achieved an accuracy rate of 97.5% as shown in Table II.

V. CONCLUSION AND FUTURE WORKS

COVID-19 is currently causing a pandemic, and in this unwelcome circumstance, the contribution of modern innovation in assisting throughout the phase is essential. While irregular breathing problems are among the most obvious signs of the COVID-19 epidemic, mainly in the later years in aged people, the emerging COVID-19-Delta version is triggering more irregular breathing problems in young adults. As a result, a lightweight analytical system is required for real-time monitoring of individual breathing patterns. This study proposes a wireless or non-invasive technique established on a widely viable UWB Detector and inventive deep neural network ResNet. The proposed method is intended to identify and track irregular breathing patterns such as tachypnea (rapid breathing), which seem to be common during coronavirus disease. The ResNet model was trained, tested, and validated by using spectrograms of various individuals breathing patterns recorded by the Ultra-Wideband radar. Since being developed, the ResNet algorithms (with an accuracy up to 97.5%) were appraised to differentiate between regular and irregular individual breathing rates.

There are also a few implications in this case study that we plan to address in future case studies. This recommended approach, in particular, could be utilized for a specific individual in a stationary and fixed environment. However, apart from that, the experiment was not undertaken on real COVID-19 affected persons because of some other factors. Subsequently, for future studies, we would recommend performing the experiment with various participants breathing rates in an uncontrollable setting with varying muscle moves. Furthermore, employing the pliability (or flexibility) of UWB radar sensor-based technologies and using self-learning advanced machine learning techniques. Besides that, various breathing rates such
as Kussmaul, biot, apnea, sighing, and Cheyne strokes could be evaluated in enhancing the scheme’s reliability.

REFERENCES
