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E-Textile: Affordable Textile Fabric Sensor For Remote Health Surveillance Of Solitary Patients

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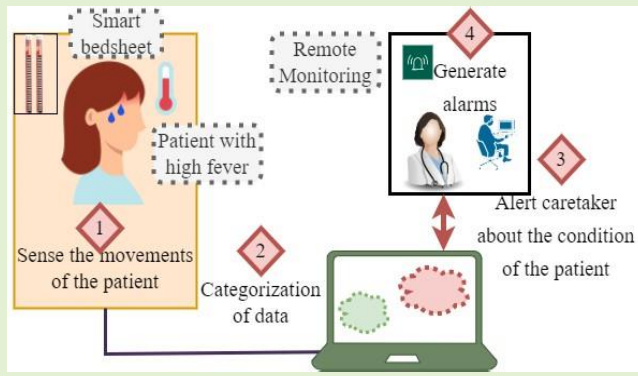
Abstract—In this manuscript, we present a cutting-edge textile innovation called E-Textile for remote medical diagnosis of COVID-19 and OLD patients. Timely health surveillance is critical for COVID-19 and OLD patients to prevent health deterioration. Traditional medical care monitoring systems necessitate manual input from patients to commence monitoring, posing challenges during nocturnal periods. As an illustration, monitoring oxygen saturation levels during sleep is arduous. Additionally, there is a pressing need for a system to monitor their health condition as various vital signs may be affected, and complications may arise even after recovery. E-Textile capitalizes on these challenges to offer health monitoring for COVID-19 and OLD patients based on the pressure applied to the fabric. The operational mechanism unfolds in three phases:



1) Detecting the patient pressure applied on E-Textile, 2) Classifying data into segments(normal and abnormal) based on variations, and 3) The individual record is conveyed to their caretaker. Experimental findings underscore the effectiveness of e-textiles in patient health monitoring. E-Textile adeptly categorizes a patient's condition with a precision of 99.3% and consumes 17.5W of power. Furthermore, the monitoring delay with E-textile is minimal at 2s, making it suitable for clinical deployment

Index Terms— Intelligent textile, distant observation, COVID-19, Detectors, Machine Learning

I. Introduction

In December 2019, a novel coronavirus, named SARS Cov-2, emerged in Wuhan, China, which caused the COVID-19 disease when infecting humans. COVID-19 is a serious illness that can lead to the death of the infected host [1]. The threat posed by COVID-19 led the World Health Organization (WHO) to declare the COVID-19 pandemic by March 2020 [2]. Coronaviruses are a group of highly diverse, enveloped, positive-sense, single-stranded RNA viruses that are widely spread in birds and mammals. Sometimes these viruses infect humans, causing mild to moderate respiratory diseases [3]. Before SARS-CoV-2, two coronaviruses were known to cause severe human disease: SARS-CoV, which causes Severe Acute Respiratory Syndrome (SARS); and MERS-CoV, which causes Middle East Respiratory Syndrome (MERS) [4, 5].

However, in contrast to SARS and MERS, the symptom onset for COVID-19 is significantly larger, or it may appear in a mild form, allowing infection to spread by asymptomatic patients, which in turn has led to the current pandemic [6]. Although the WHO has emphasized the need for massive testing and contact tracing to better tackle the pandemic, not all countries have the required laboratory infrastructure and reagents to effectively address this task. Additionally, getting results from some of these tests may take a couple of days, leading to non-confirmed COVID-19 patients with mild or no symptoms to further spread the disease while waiting for the test results. With the rise of deep learning techniques, medical imagery has increasingly claimed attention for the computed assisted analysis of pulmonary conditions. Automated analysis of Computed Tomography (CT) scans, has enabled the identification of malignant nodules [7].

In this paper, we propose E-Textile, a novel technology that tracks people's movements to assess their health both during and after COVID-19. People's applied pressure is detected by E-Textile, which then uses that information to calculate how comfortable they are. The intelligent textile communicates patient-related data for remote health surveillance, as depicted in Fig. 1. To separate the data into groups of stable and unstable patients, we use a machine learning (ML) technique. Carers or healthcare professionals can monitor a patient's health remotely and receive notifications thanks to this data.

Consider the following hypothetical situation: Suppose that a patient with COVID-19 is prone to health fluctuations, especially at night. An intelligent bedsheet collects data on the pressure the patient applies to monitor their condition, as seen in Figure 1. The technology uses pressure variations to classify the patient's status and instantly sends out a notification to the medical professional or carer for remote surveillance.

The bias for E-Textile

The E-Textile adopts a simplified strategy in comparison to other sophisticated fabric sheets that exist on the market that use an assortment of sensors and intricate machine learning (ML) techniques to assess posture. It avoids using computationally demanding machine-learning techniques an relying only on three flex force detectors to detect patient movement. Rather, it makes use of data volatility and uses K-means clustering to classify. This low-tech method drastically lowers expenses and computing demands. Flex force sensors were used for the E-Textile because of their subtle design and capacity to identify minute surface deflections without inflicting discomfort. These sensors are also reasonably priced, which adds to the E-Textile solution's affordability. With an emphasis on affordability and ease of use, E-Textile provides a useful substitute for distant medical surveillance without compromising precision or comfort.

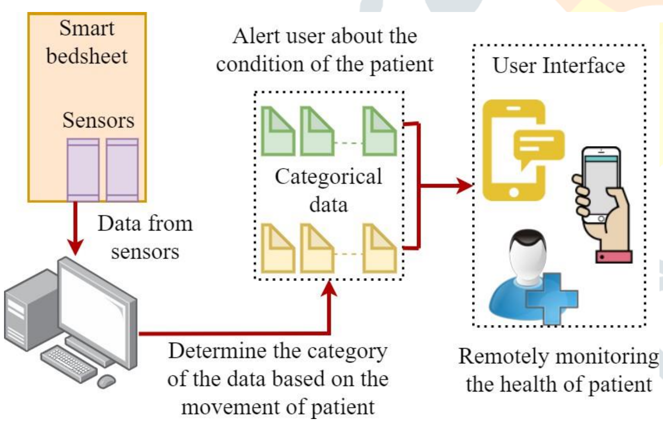


FIG.-1: Overview of E-Textile for health surveillance

A. *Tendency for K-Means*

The incoming spherical values in the data from the E-Textile span a large range and fluctuate at different speeds. Categorization is crucial in interpreting this data and determining patients' comfort levels. This is accomplished by machine learning (ML) models, of which K-means is used as a proof of concept. It's crucial to remember that E-Textile is still unaffected by any particular ML model. The selection of K-means is based on its versatility, computational efficiency, convergence guarantee, and compatibility with spherical data. It is the perfect option for classifying the variety of data that E-Textile captures because of these features. We also investigate the effectiveness of E-Textile in conjunction with other machine learning methods, including fuzzy C means, affinity propagation, and density-based spatial clustering (DBSCAN).

B. *Motivation*

Amidst the COVID-19 epidemic, it is imperative to sustain ongoing patient monitoring to avert any decline in health. Nevertheless, patient human input is necessary for wearables and traditional monitoring systems that are currently on the market, which makes monitoring at night impossible. Effective patient health monitoring is hampered by the impossibility of continuous human input. Furthermore, COVID-19 can impact multiple vital signs, and even in the post-recovery phase, patients may experience hazards such as hypertension, heart failure, and lung failure. We suggest an intelligent bedsheet that is made to stop health from declining to reduce these hazards and guarantee that patients are continuously monitored before, during, and after COVID-19.

C. *Contribution*

We propose a smart textile solution for the continuous remote monitoring of patient health. Our work offers the following specific contributions:

1. *Smart Textile Platform:* We present the E-Textile, a smart textile platform that continuously measures the patient's pressure. This helps medical professionals or carers to keep an eye on a patient's health from a distance and prevent possible decline.
2. *Automated Monitoring:* Without requiring any input from the patient, E-Textile runs independently and continuously senses the pressure of the patient. Based on this information, it categorizes patient conditions as either stable or unstable.
3. Round The Clock Monitoring: E-Textile ensures 24/7 health monitoring, providing constant vigilance regardless of the time of day.
4. Post-recovery Health Surveillance: Our solution provides a comprehensive monitoring tool beneficial not only during COVID-19 but also post-recovery. E-Textile monitors patients' health after COVID-19, which is crucial given the potential for various vital failures such as lung, heart, and kidney issues.
5. Universal Applicability: E-Textile proves valuable in monitoring the health of patients with diverse medical conditions, extending beyond COVID-19. It detects patient conditions based on the pressure exerted on the textile, offering a versatile solution.
6. Evaluation: Through rigorous experimentation and deployment, we demonstrate the feasibility and efficiency of E-Textile in remote patient health monitoring.

It is vital to emphasize that we are only concerned with health-related problems for data-centric patient condition classification. Other influences on sensor data, such as deliberate movements or nightmares, are not taken into account. The remaining portions of the article are arranged as follows: An overview of recent studies on COVID-19 monitoring and smart textile platforms is given in Section II. Our system model and suggested remedy are described in Section-III.

Our experimental design, findings, and comparison with alternative methods are presented in Section-IV. Section-V, which covers future directions, wraps up our findings.

Paper	Real-time Monitoring	Comfortable	Automatic	Complexity	Price
Schollas[7]	✓	×	×	High	High
Filho et al.[8]	✓	✓	×	High	High
Ahmed et al[3]	✓	✓	✓	High	High
Jyotilakshmi[4]	✓	✓	✓	High	High
Thiyagarajan[12]	✓	✓	×	High	High
Rehman [13]	✓	✓	×	High	High
E-Textile Proposed	✓	✓	✓	Low	Low

TABLE I: DIFFERENCE OF E-TEXTILE WITH EXISTING SOME HEALTH MONITORING SYSTEM

II. LITERATURE REVIEW

Various techniques have been proposed in the literature regarding remote health surveillance. Many of these techniques provide a variety of observations at affordable cost while some provide complex observations.

COVID-19 has to be detected properly without any negligence else it can lead to a severe impact on the country's economy and country citizen health [5]. The person who is suspicious of COVID-19 is suggested to undergo a chest CT Scan.

Analysis of CT Scans by humans can lead to various human errors, which can lead to a huge impact on patients and society. So, a computer-aided system can help the doctors for proper analysis of chests of the COVID-19 affected human. Throughout underdeveloped and developing nations, where the number of patients is high and medical care cannot be adequately delivered, these programs may be a tremendous benefit [6, 7]. The authors have worked on CT Scan imaging techniques for the detection of bone fractures. They have applied edge detection and segmentation techniques to ease the process of the diagnosis system. These methods will reduce the processing time and other physical evaluation procedures [8]. So, while working with CT Scan images, we need to consider the noises that have to be reduced. The random noises occurring during the process of image acquisition degrade the image quality leading to an incorrect diagnosis. Researchers suggest the application of the temporal recursive filter. Also, they propose an improved self-adaptive filter. This was a combination of FPGA with image processing techniques [9]. The authors have recommended region localization which offers a close level of precision. A few other image preprocessing techniques are adaptive histogram-based equalization, adaptive contrast enhancement, and histogram equalization. There is the presence of multiple noises during the capturing of the images because of device mobility and motion artifact [10]. But in CT Scan images mostly Gaussian, salt and pepper noises are present. To reduce the noise, a digital median filtering technique is used as per the research. Chest CT Scans aid in the diagnosis of pneumonia. Researchers seek the help of CNN in classifying normal and abnormal CT Scans [11]. The feature extracted from the chest CT Scan improves the functionality of the classifier. This method is useful where a large dataset is received. In another similar work, deep learning techniques are applied for the analysis of chest CT Scans. Pulmonary infections are easily identified using these radiography images. This is extended in the detection of coronavirus disease [12]. The authors have brought hope in applying artificial intelligence in the early detection of the disease. Supervised learning techniques have been applied in the classification of a normal/abnormal pneumonia dataset. A labeled dataset aids this process in reducing the error [13].

III. EXISTING SYSTEM

The OCC (Optical Camera communication) operates with visible light communication. The entire system is designed in an such a way that the patient's condition is always monitored by

CCTV so that whoever is connected with it can access easily also automatically update the server. ECG monitoring is also done in this project along with live video.

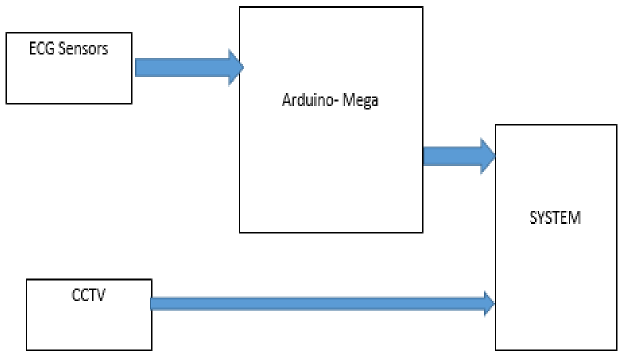


FIG-2: EXISTING SYSTEM BASED ON OPTICAL CAMERA COMMUNICATION

On the contrary, health care and surveillance of patients need simultaneous and noninvasive monitoring of biomarkers and assessing health status. The heart rate(HR) and pulse oxygen saturation level(SpO_2) is one of the most important statuses for health monitoring.

IV. PROPOSED SYSTEM

For health monitoring to begin, traditional healthcare monitoring systems usually require manual patient input. Ongoing patient health monitoring is crucial, even after recuperation from disease, particularly in light of financial limitations. Our proposal is a one-stop shop that aims to fulfill the requirement for an all-inclusive and economical way to monitor different health concerns. To maintain optimal health and quality of sleep, humans need to have proper sleeping posture. To offer ongoing, affordable health monitoring, our system makes use of the natural activity that occurs during sleep. We can provide an all-encompassing, cost-effective method of health monitoring by integrating monitoring features into sleep-related activities, like sleeping positions.

The information gathered by E-Textile includes a broad spectrum of spherical values, all of which fluctuate at different rates. To classify this data efficiently, we utilize K-means clustering. K-means is selected since it is an appropriate option for our needs because of its versatility and computational efficiency. Additionally, we assess E-Textile's performance with alternative clustering algorithms, including affinity propagation and density-based spatial clustering of applications with noise (DBSCAN). This enables us to evaluate E-Textile's efficacy across various clustering strategies and guarantee its resilience when classifying patient conditions using the gathered data.

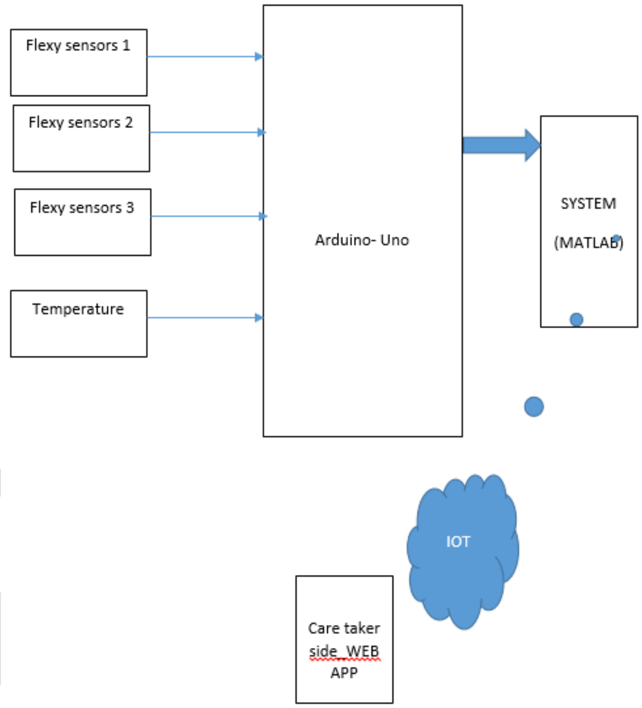


FIG-3: BLOCK DIAGRAM OF AN PROPOSED SYSTEM MODEL

In this proposed model, FIG-3 shows how flexi force sensors detects patient's conditions and transmits data. And then sensed data is going to be monitored by a caretaker.

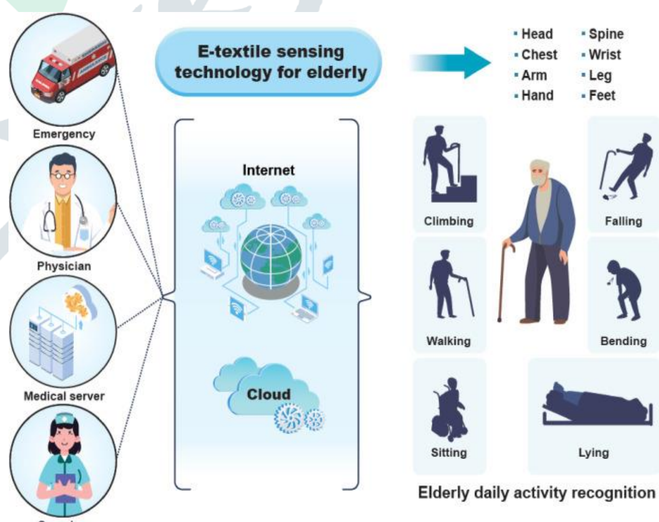


FIG-4: OVERVIEW OF E-TEXTILE FOR HEALTH SURVEILLANCE

V. METHODOLOGY

The methodology of the proposed model in E-Textile involves several key steps to enable effective remote health monitoring. In Fig-4 it is a smart bedsheet or fabric textile which is used to sense the movements of the patients. And then the data is transmitted which is further categorized into two segments i.e.; Normal and abnormal. If the person is abnormal then based on the data it generates a message and then it alerts the caretaker by the generation of alarm. So, it will become easy for caretakers to monitor a person even from remote places with the help of E-Textile Health Surveillance. We create a sensor that tracks how much the surface bends or deflects as the patient moves, as shown in fig-4. Equation (1) shows that the variation in the resistance of the sensor is directly proportional to the bending of itself. The link between this and the resistance of the sensor is caused by the bending-induced changes in voltage and current [20]. The resistance of the bending sensor surface rises in direct proportion to the bend angle. This resistance variance keeps pace with the patient's movements, which are frequently prompted by discomfort. Making use of this idea, we keep an eye on the patient's status all day long. There are surface deflections and erratic changes in sensor data as a result of more frequent motions brought on by discomfort. Carers can determine how comfortable the patient is by keeping an eye on these changes and making the appropriate adjustments.

$$R \propto B \qquad (1)$$

ALGORITHM 1: Algorithm for monitoring the health condition of patients.

INPUT: Data Sensed By E-Textile
OUTPUT: Condition of patients
Procedure
while E-Textile senses data do
  Initialize i=1;
  Initialize an array A[size=5]
  // Retains the last five sensor readings to illustrate variations
  Analyzes the data;
  Compare the data d_i with the data stored in array A.
  Calculate the average difference of d_i with the data in A.
  Apply K-means on the difference to categorize the data.
  while $i \leq 4$ **do**
    $a[i] = a[i+1]$;
    $i = i + 1$;
  end
  $a[i] = d_i$;
  // Historical data is updated when fresh data is received.
end

A. Model Of Power Usage

As certain the flex force sensors' power usage is included in the bedsheet. This includes calculating each sensor's power consumption in both active and standby modes. Ascertain the communication interface's power usage (e.g., Bluetooth, Wi-Fi) when sending sensor data to a remote monitoring platform. When transmitting and receiving data, measure the power consumed. Conduct controlled experiments in a setting to validate the power consumption model. Determine the real power consumption of the E-textile components under various operation scenarios and contrast it with the predictions of the model.

The system's power consumption, which is as follows, is determined by the voltage and current requirements of the monitoring devices and the sensor.

$$P = I_s \times V_s + I_m \times V_m \qquad (2)$$

where Im is the current required by the monitoring device, Vm is the voltage required by the monitoring device and Is is the current requirement of the sensor. Furthermore, the value of Is is determined by the sensor's active sequence i, it's average current (Ii), and the active sequence's time duration (ti) during T. It is expressed as follows:

$$I_s = \left(\sum_{i=1}^{m} \left(\frac{t_i}{T} \times I_i \right) \right). \qquad (3)$$

Additionally, the following represents the total power used to monitor the patient's health:

$$P = \left(\sum_{i=1}^{m} \left(\frac{t_i}{T} \times I_i \right) \right) \times V_s + I_m \times V_m. \qquad (4)$$

B. Complete Data Transmission

When a patient moves over the fabric-sheets, E-Textile records the movement-related data and further classifies it to identify if the patient is pleasant or unpleasant. E-Textile creates alerts on the device to notify the carer based on the patient's state and sends a message packet to the registered number.

C. Health surveillance by E-Textile

We use the sensed data to evaluate the patient's status, keeping an eye on their health with the E-Textile system. The primary factor used to classify the patient's health status is the variation seen in the data. For instance, as shown in Algorithm 1, if fluctuations stay within a specific range, the patient's status is considered normal; if not, it is reported as abnormal. To further assess fluctuations, we compare the values of the current data with those of the past data. We use the K-means clustering technique as a proof of concept to classify the data and subsequently ascertain the patient's status. The monitoring system notifies carers and medical specialists of changes based on this assessment. Remarkably, the suggested algorithm's complexity for a single iteration is O(n^2), where n is the size of the input data.

VI. Evaluation of efficacy

A. Investigation Setup

We assess the suggested E-Textile's ability to track the patient's health in this area. The data detected by the E-Textile(sampling rate: 1 kHz) is collected and further categorized into groups based on the variations in the E-Textile values to test the effectiveness of the device. Additionally, our model creates a client-server scenario wherein the server notifies the carer when an anomalous circumstance is detected.

Gather sensor data from the E-Textile prototype using data acquisition hardware and software. The pressure that is continuously applied to the bedsheet surface should be recorded by this system. Adjust the flex force sensors integrated into the E-Textile prototype to guarantee precise pressure variation measurement. Getting accurate data for analysis requires doing this step.

For the duration of the experiment, keep the ambient noise level, humidity levels, and room temperature constant. By standardizing these variables, external variables that can affect the outcome are reduced.

Over a predetermined period, continuously gather sensor data to record fluctuations in the pressure applied to the bedsheet surface. To evaluate daily fluctuations in the patient's state, make sure that data collection encompasses both day and nighttime hours. Utilizing the proper statistical and machine learning methods, analyze the sensor data that has been gathered. Analyze the data for trends, patterns, and anomalies to determine how well E-Textile detects changes in patient condition.

A microcontroller unit (MCU) that can process and analyze sensor data in real time should be interfaced with the data acquisition system. To process data effectively, choose an MCU with enough memory and computing power. Provide a platform that allows medical professionals and carers to remotely monitor a patient's health in real-time. Incorporate alert systems, historical data analysis, and user-friendly interfaces for data visualization. To assess the efficacy of E-Textile, define performance criteria such as accuracy, sensitivity, specificity, false alarm rate, response time, and user input.

Compile a validation report by analyzing gathered data and cross-referencing the findings with expert opinions or ground truth observations.

In addition, we test the effectiveness of E-Textile at different times of day and at different temperatures. To achieve this, we adjust the room's temperature to a range of temperatures, including 10 ◦C, 20 ◦C, 30 ◦C, and 40 ◦C. In addition, we repeat our tests to document the observations at various times throughout the day, including 4 A.M., 8 A.M., 12 P.M., 4 P.M., 8 P.M., and 12 A.M. Additionally, we test i-Sheet's efficacy by expanding its sensing area. To verify the effectiveness of E-Textile, we run our experiments on a 1-hour data set (3.6 M data values) as a proof of concept.

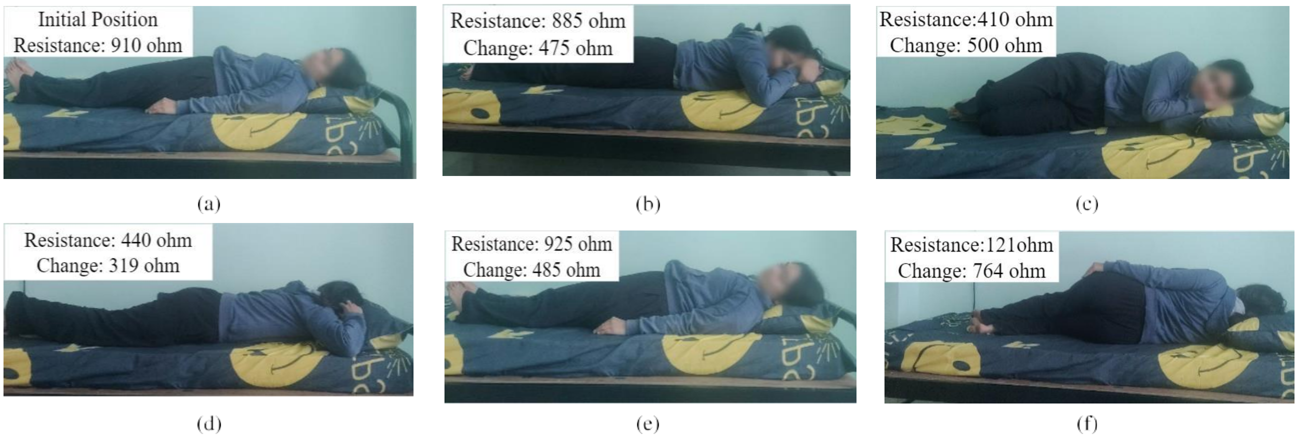


FIG-5: The position patient in abnormal condition. (a) 12 A.M., (b) 12:10 A.M., (c) 12:20 A.M., (d) 12:30 A.M., (e) 12:40 A.M., and (f) 12:50 A.M.

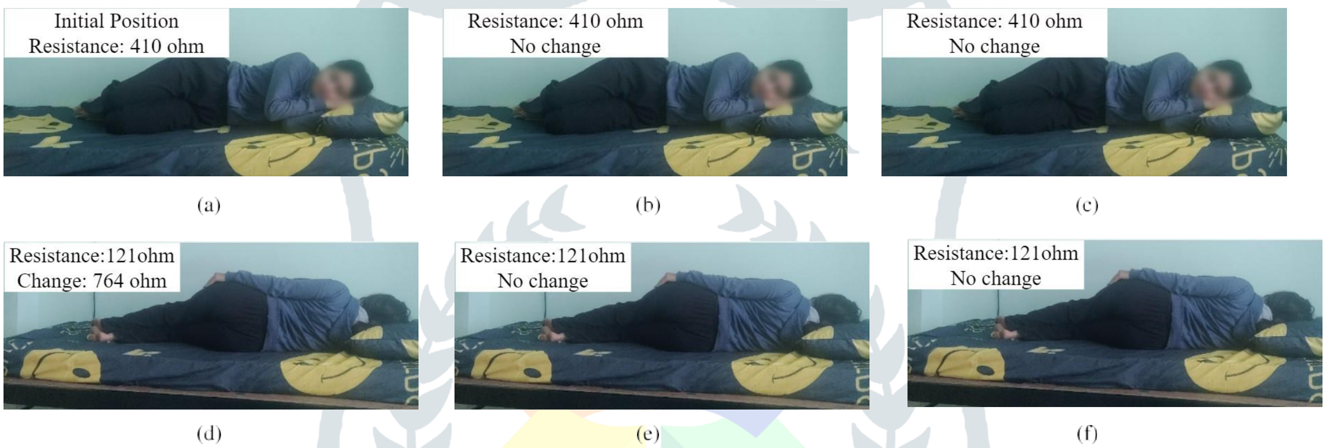
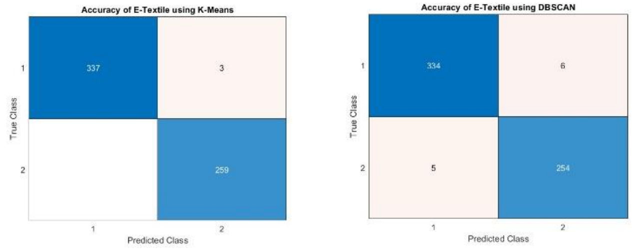


FIG-6: The position of patient in normal condition. (a) 2 A.M., (b) 2:10 A.M., (c) 2:20 A.M., (d) 2:30 A.M., (e) 2:40 A.M., and (f) 2:50 A.M.

B. Results

Human Posture Analysis: As a proof of concept, we record a person's movements as they sleep by taking a random COVID-19 virus-infected individual. After spending an hour watching the subject while he slept, we saw that, as illustrated in Fig. 5, when a person is uncomfortable, he moves more than when he is sleeping soundly. In addition, Fig. 6 illustrates that in a comfortable sleeping environment, the individual alters his gestures just twice as often as in an uncomfortable one. E-Textile tracks the person's motions by measuring the changes in pressure applied by 1) Human Posture Analysis: As a proof of concept, we record the movements of an individual as they sleep by imagining a random COVID-19 virus-infected person. We watch the subject for one hour while he sleeps, and as Fig. 5 illustrates, when an individual is uncomfortable, they move more than when they are sleeping well. Moreover, Fig. 6 illustrates that in contrast to the circumstances in which he experiences discomfort, the individual only modifies his gestures twice during a comfortable sleep. E-Textile tracks the patient's movements by identifying changes in pressure as they occur. We note that the suggested E-Textile effectively identifies the patient's pain during sleep.

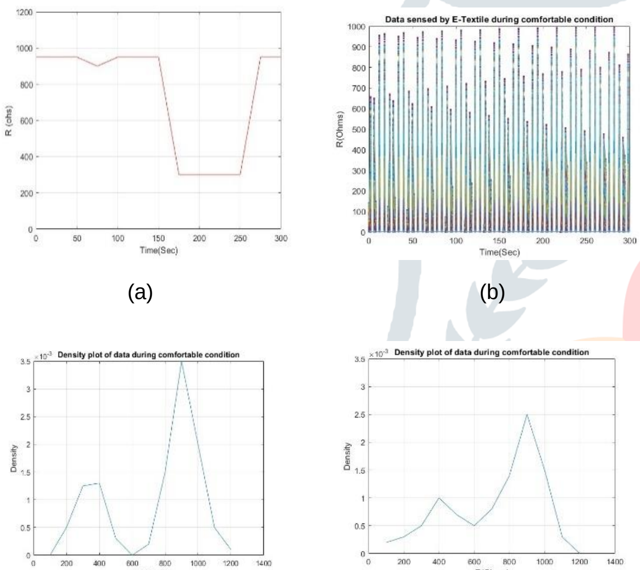
Reliability of E-Textile: Based on the information detected by E-Textile, we classify the patient's condition. We can see in Fig. 6 that when we employ the K-means, only 0.9375% of the E-Textile is unable to appropriately monitor the discomfort. This makes intuitive sense given the sudden shift in the patient's pressure under typical circumstances. On the other hand, E-Textile tracks the patient's actual state 99.0625% of the time. There are only three situations, as seen in Figs. 7(a) where the patient is in a comfortable state; however, E-Textile recognizes it as discomfort. We note a significant identification of the patient's suffering. This is so that E-Textile can identify all of the sudden variations in the stress that the patient applies, and as a result, the patient's state is classified. Additionally, as Figs. 7(b) demonstrate, that using DBSCAN(Density-Based Spatial Clustering Of Applications With Noise) respectively, results in 96.56% and 92.18% accuracy in identifying pain. Based on our analysis, the K-means. The suggested smart fabric sheet is best suited for the K-means clustering method approach introduces an external computation burden.



(a)

(b)

FIG-7: Accuracy of E-Textile using clustering algorithms. (a) *K* -means. (b) DBSCAN

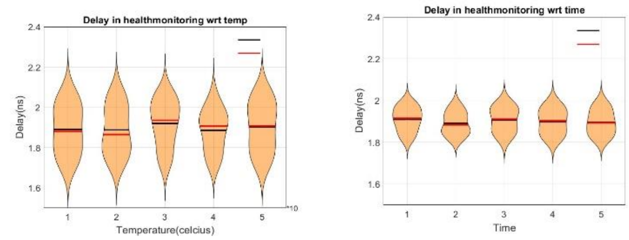


(a) (b)

(c) (d)

FIG-8: Data Analysis of E-Textile (a) and (b)Data Sensed by E-Textile during comfortable condition, (c) and (d) Density Plot during comfortable condition on different days.

1) Data Analysis of E-Textile for Comfortable Patient: We monitor the resistance of data and values collected by E-Textile for a duration of one hour. The resistance of the E-Textile does not change much during a period of 170 s, as seen in Fig. 7(a). The resistance value remains rather constant for the first 170 s, falling between 910 and 925Ω. This is because the patient does not move, causing the pressure on the bedsheet to remain constant. The resistance does not change either. Furthermore, there is a difference in the resistance and pressure as a result of the patient's movement at the 170th second. Between 170 and 260 s, the resistance value falls between 310 and 330Ω and then reaches 910 }. This is because when an individual is in a comfortable posture, their position varies less and the values of most data points fall within the same range. Moreover, the density of the data points only falls between 910 and 925Ω and 310 and 330Ω, as Fig. 7(b) illustrates. We deduce that the E-Textile is effective in identifying the patient's state and can pick up on even the smallest movements made by the patient.



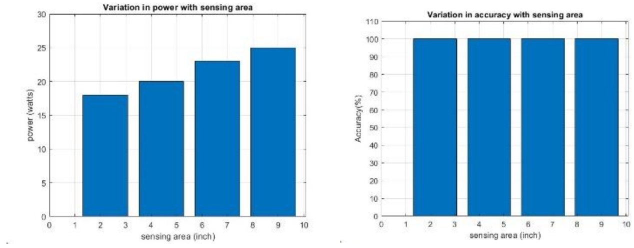
(a) (b)

FIG-9: Change in delay with a) Temperature b) Time

2)Data Extraction from the Uncomfortable Patient on E-Textile: When a patient experiences respiratory distress, we conduct tests to identify the type of E-Textile. We note that there is no discernible trend in the data that E-Textile senses; instead, it varies suddenly. The resistance values detected by E-textile, as depicted in Fig. 8(c), range from 40 to 1000Ω. Nevertheless, E-Textile does not identify any specific resistance change or value once the patient's condition deteriorates. Moreover, the density of the data points is nonuniformly distributed across the range of 0–1300Ω, as illustrated in Fig. 8(d). It makes intuitive sense that these fluctuations in the E-Textile's value relate to the patient's movements brought on by their discomfort and the stress from the same source.

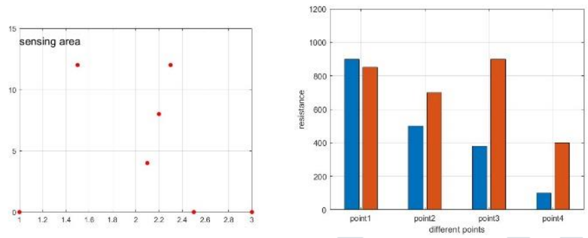
3)Delay in Health Monitoring: Delay in Health Monitoring: Large amounts of data must be categorized to track a patient's condition. Figure 9 illustrates the time lags associated with checking the patient's status at various times of the day. We note that the latency associated with data sensing and alert generating is minimal. To monitor health, data must be categorized as comfortable or uncomfortable, which causes a significant delay. Moreover, the delay is nearly constant at 2 s regardless of the time of day or the external environment conditions, including temperature. Since the E-Textile is insensitive to temperature, the sampling rate and data range are constant, which causes a continuous lag in the health monitoring process. While Fig. 9 does not show the temperature association between delay and temperature, it does demonstrate the temperature insensitivity of the E-Textile. We note that there has been a very slight and tolerable overall delay in monitoring the patient's condition. This slight delay makes it easier to keep an eye on the patient's status and take timely preventive action. This further aids in keeping the patient's condition from getting worse.

4)Energy Usage in Health Monitoring: We track the energy usage of E-Textile to keep an eye on the patient's condition. Our goal is to observe our readings after 50 iterations. Our observations show that as the sensing area grows, so does the power usage. With a 2.2-inch sensing area, E-Textile uses 17.5 W of electricity; for 75% increase in the sensing area, that power consumption rises to 30%, as illustrated in Fig. 10(a). From this, we can deduce that as the sensing area grows, so does consumption.



(a) (b)

FIG-10: Change in (a) power and (b) accuracy.



(a) (b)

FIG-11: Resistance on various points(a) Different sensing points on E-Textile. (b) Resistance across various points.

5)Sensing Area Accuracy: As the sensing area grows, we see a rise in the accuracy of patient condition monitoring. We document our observations through 40 iterations. As we can see from Fig. 10(b), the accuracy remains constant as the sensing area increases. This makes intuitive sense since a tiny sensor area can identify the COVID-19 patient's motions and classify their level of comfort or discomfort.

6) *Resistance throughout E-Textile:* We note resistance throughout E-Textile. To capture our observations at four distinct points, we run thirty iterations, as Fig. 11(a) illustrates. We find that resistance reduces as we move away from the sensing area when the patient is in a comfortable position. That being said, no clear pattern emerges in an uncomfortable circumstance. This can be attributed to the instability of the pressure applied during the uncomfortable situation. In comfortable and uncomfortable conditions, the resistance value at point 1 is 910 and 880Ω, respectively, as Fig. 11(b) illustrates. In an uncomfortable condition, we deduce that the pressure applied is not stable.

C. Validation

We employ two test scenarios to evaluate the efficacy of E-Textile:

a. Uncomfortable Sleeping: E-Textile tracks the motions people make as a result of their uncomfortable sleeping experiences. We see only real advantages.
b. Health Tracking: E-Textile uses motion sensors on its surface to detect people's movements and remotely check on their health. We used E-Textile to track the health (when the person is ill) for thirty test runs, and we saw 100% true positives.

D. Analysis and Restrictions

Our suggestion is a smart fabric sheet that can be used to remotely monitor each person's health. Fabric sheets can recognize how people move across their surface and classify their comfort level accordingly. Additionally, we investigate the effectiveness of E-Textile in various environmental circumstances and find that it is not affected by changes in operating settings. We find that, with a 2-second latency and 99.06% accuracy, E-Textile is effective in determining a patient's condition.
One drawback of the suggested bedsheet is that it does not classify motions that people make intentionally or out of pain. When movements are deliberate and not the result of discomfort, E-Textile provides a lot of false negatives.

VII. Conclusion

In this study, we introduced a smart textile solution called E-Textile for remote health surveillance of COVID-19 and Old Patients. E-Textile effectively monitors a patient’s health regardless of the time or external environmental conditions, remaining independent of these factors and relying solely on the patient’s pressure on the fabric sheet or bedsheet. The operation of the E-Textile consisted of three phases: 1) Detecting the patient’s pressure applied on the E-Textile, 2) Classifying data into segments(normal and abnormal) based on variations, and 3) The individual record is conveyed to their caretaker. In the initial stage, E-Textile utilized its surface to identify the motions of patients. In the second stage, we classified the data by using E-Textile's detected oscillations in data values. We classified the conditions of the patients using the sensed data as a proof of concept by applying the K-means clustering technique. We finally informed carers of the patient's health state throughout the final phase. To illustrate the effectiveness of E-Textile in patient health monitoring, we shared the results of our experiments.
Because of other factors, including intentional movements or troubling nightmares, we did not classify the movements of the patients in this study. Instead, when it came to data categorization, we only considered healthcare challenges that patients faced. Our goal is to classify patients' deliberate actions in subsequent studies. Additionally, we want to create a system that recognizes where patients are on the fabric so that alerts can be set off to prevent falls off the bed.

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