MITIGATION OF PRESSURE INJURIES UTILIZING MACHINE LEARNING AND AN INERTIAL WEARABLE

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ABSTRACT

Pressure ulcers, or pressure injuries, are localized areas of skin and/or underlying tissue necrosis that typically occur over bony prominences due to a prolonged pressure or friction. They can lead to serious morbidity and mortality, emphasizing the need for prevention. This project utilizes a database of demographic and clinical features of a large patient data set and applies machine learning to determine the higher risk patients, coupled with a complimentary device to assist in the prevention of pressure injuries. A complementary monitoring system is built based on an inertial wearable utilizing an inexpensive microcontroller and a gyroscope. The combined approach is evaluated, fine-tuned, and assessed based on different performance metrics.

KEYWORDS

Pressure ulcers, Machine Learning, Inertial Wearable

1. INTRODUCTION

Pressure ulcers, also known as bed sores or pressure injuries (PIs) have a significant negative impact on patients and the health care system through an increase in pain experienced by the patient, longer stays in the hospital, a higher probability of nosocomial infections, and ultimately, increased morbidity and mortality which contribute significantly to the financial impact of public hospital system management [1].

PI care is complex, and improved PI prevention would give a better quality of life to the patients and reduce healthcare costs. These soft tissue injuries form due to a prolonged period of pressure applied to an area of the skin but are influenced by many factors, including skin moisture and skin condition, and occur when pressure reduces or cuts off blood flow to the skin. Certain predispositions, such as poor circulation or malnutrition, can lead to faster progression and/or increased severity of the ulcers. Experts estimate that 2.5 million Americans develop PIs every year, with essentially anyone being susceptible to them. They are most often found over bony prominences, such as the tailbone or lower spine area, heels, or shoulder blades. A meta-analysis of PI observational studies concluded that the most affected area was the sacrum with a frequency of 44% and the buttocks with a frequency of 15% [2]. A lack of blood flow can cause a pressure wound injury to develop in as little as two hours. This is when skin cells on the epidermis (human skin's outer layer) begin to die. As the dead cells break down, a PI forms, and the injury can

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extend to deeper tissues. There are multiple stages of bed sores, ranging from a simple red or pink spot on the skin to the most severe cases of exposed muscle, tissue, or bone [3].

The development of PIs can lead to several complications, from sepsis to pain, cellulitis, depression, and even death. The mortality rate has been reported to be as high as 60% within one year of hospital discharge for older patients who developed a PI during their stay [4].A study in 1990 reported 22% mortality over a 6-year follow-up of 23 patients with pressure ulcers [5]. In 2005, there was a report of 68.8% mortality amongst elderly patients with stage 3 and 4 PIs, because of secondary systemic complications [5].

One of the objectives of this project was to identify the features within health records that can be captured within the first 24-48 hours of a patient's admission and use them to model and estimate the likelihood of PIs forming during their hospital stay. We identified the MIMIC-III data set as a source of data,as it is one of the largest patient data sets from the ICU setting and contains features from all lab tests run on a patient, from oxygen levels to blood pressure, combined with other information in the patient's electronic health record [6]. When a patient arrives to the hospital, the patient's data would then be entered into this model and if they are identified to be at a higher risk, they would be equipped with a microcontroller-based inertial wearable that would track and time the patient's movement and provide the hospital personnel with alerts to manually turn the patient to a different position.

2. RELATED WORK

Prolonged bed rest without repositioning or movement can lead to PIs. Although PIs are influenced by mobility, activity, and sensory factors, the most widely used approach to estimate the risk and prevent PIs is the Braden scale. The Braden scale, however, is a subjective scaling criterion that has "insufficient predictive validity and poor accuracy in discriminating intensive care patients at risk of pressure ulcers developing" [7]. Additionally, none of the risk assessment scales were developed especially for use in an intensive care unit (ICU) where patients are more likely to experience the need for repositioning [8].Some of the variables that heighten a patient's risk for PIs include decreased mobility (such as from a spinal cord injury), low nutritional status (resulting in low albumin levels), orimpaired skin healing (due to low O_2 levels).Cramer et al. [9]published a machine learning technique that tried to identify associations between the data values and suggest which patients should receive care, for they are most susceptible to PI development. Their resulting model had a very low precision of 9% and recall of 71% for future PI development, and its performance did not improve with the incorporation of the Braden score.
Medical and household devices have been developed with the intent to solve the problem of the prevention and treatment of PIs. Specialized devices such as beds, overlays, or mattresses have been designed to mitigate the health risks of these bed sores and PIs. These types of mattresses work on pumping up or making different points of the bed higher/lower, shifting the weight of the patient instead of having to manually turn the patient to a different position. There are uncertainties regarding the relative effectiveness of other support surfaces for preventing and treating PIs and their efficacy ranking, but most of these approaches are too expensive or cumbersome to be provided to every ICU patient[10].In a separate study, wearable pressure sensors were placed on the patient's pressure points, in hopes that the pressure sensor would correctly identify when the subject would need to be turned to prevent pressure ulcers. These sensors would be placed at different high-pressure and susceptible points on the body such as the elbows, shoulder blades, tailbone, and heels, connected to a computer using wires. This approach is very invasive on the patient as requires a large number of wires connected to the surface under the patient, potentially causing other PIs and giving less comfort to the patient. Another limitation is that forces are more difficult to measure on mattresses of different firmness, resulting in too much variability in pressure sensor readings [11].

3. METHODOLOGY

We first discuss the data set, machine learning model, and the wearable system that we built to be worn by the patients that are at the highest risk of PI development as determined by our model.

3.1. Data Set and pre-Processing

MIMIC-III (V.1.4) is a publicly available, credentialed, and comprehensive critical care relational database containing de-identified electronic health records (EHR) for 38,597 distinct adult patients and their 58,976 admissions to the ICU between 2001 and 2012 at the Beth Israel Deaconess Medical Center [12]. The data is over 3TB in size and includes demographics, vital sign measurements, lab results, procedures, medications, and clinical notes in more than 26 relational database tables.The retrospective cohort of patient IDs and their admission IDs was selected from the MIMIC-III critical care subset published by Goodwin [13, 14], who based the selection solely on clinical notes recorded within the first 24–48hour window from admission. Goodwin et al. did not utilize any of the structured features of the MIMIC-III data set beyond the clinical notes. It was our goal to utilize only the variables that can be obtained within the first 24-48 hours from patient's admission, as this timeframe provides the opportunity for timely interventions, but not rely on clinical notes. Only the patients whose hospital stay lasted at least 48 hours, and who reported PIs in their demographic bucket (including patient's age, sex, and race) were included and matched with their negative PI patient cohorts. This procedure left a total of 25,733 patient-admission pairs used to identify and extract structured features from the original MIMIC-III tables, for a total of 23 extracted structured features. 1,483 (5.8%) of these patients acquired a PI during their hospital stay, and 24,250 (94.2%) of patients did not. Data from multiple files was joined by the hospital admission ID and stored in a comma-delimited format.

A total of four features were removed from the data set before machine learning was applied: "date of birth" and "chart year" (the values across patients may not be comparable, for example, year 2150 recorded for one patient may not be the same calendar year for another patient), subject ID, and hospital ID. Ulcer label was added as the predicted variable, with 1 representing a positive or present ulcer diagnosis, and 0 representing a negative ulcer diagnosis. Machine learning algorithms require that the data has no missing values, giving us the option of removing records that are missing values, or imputing/interpolating their values from the remaining records. Instead of removing the records, I first removed the five features that had more than 50% missing records for the variable: Albumin, Arterial 0_2 pressure, Arterial CO_2 pressure, Bilirubin, and Troponin. The remaining features that contained missing values had approximately 25% of the records missing. Since no significant differences were found between the PI positive and negative populations, the missing values for each remaining feature were imputed with the feature's median value. Replacement of values with the median is a better approach for this data set that has large standard deviations for several variables. Categorical labels cannot be used by most machine learning algorithms, and it is not recommended that their values be replaced with integer representations, simply because they may not have an ordinal relationship (male gender cannot be ordered 0 or 1 when compared to female gender, for example). Categorical labels were thus replaced with the one-hot-label approach, which creates new features (columns) based on the categories of the existing variable, dropping the previous version of the variable. This gave us an additional 8 features for our data set, resulting in a total of 24 features plus the predicted category (ulcer).Since different features have a varied range of maximum and minimum values, the variables were normalized to a zero mean and variance to prevent individual feature from being over or underweighted and to generate interpretable, reliable predictions.

3.2. KNN, Logistic Regression and Decision Tree Models

Python, SciKit-learn, Pandas, and associated libraries were employed for modeling and analysis, conducted in Jupyter Notebook on a Mac computer. We identified the K-Nearest Neighbors (KNN), logistic regression, and decision tree classifiers as the three most widely utilized machine learning approachesfor a variety of data.The KNN algorithm is a non-parametric, supervised learning classifier which uses proximity to make classifications or predictions. Logistic regression uses a logistic function to model the dependent variable into one or two classes. Decision tree is also a non-parametric supervised learning method used for classification and regression. To evaluate and compare the classification models, weperform cross-validation using the model being iterated, the scaled training data features without the PI label, and the pressure ulcer labels as targets. The accuracy of the model, F1 score, precision, recall, and support are used to evaluate the results.

The data imbalance can be anissue for the classification task, since only 1,483 (5.8%) of the records are positive for pressure ulcer, and 24,250 (94.2%) are not. Imbalance is addressed by reducing the set of negative records, using the cluster centroid approach to replace the original samples by the centroids of the clusters from the original data set. The new data training set now has 1,152 positive pressure ulcer records and 1,152 negative PI records. The test set contains 331 positive and an equal number of negative records.

3.3. Inertial Wearable

The inertial wearable device is based on a microcontroller (ESP8266), gyroscope/accelerometer (MPU6050), voltage regulator, and battery components that are soldered and connected using a prototyping board. The microcontroller is connected to the MPU6050 gyroscope/accelerometer that captures the data of inertial movements of the patient. The MPU6050 Gyroscope/Accelerometer contains a 3-axis gyroscope, a 3-axis accelerometer, and a Digital Motion Processor (DMP).A custom-designed Printed Circuit Board (PCB) is created for the final system after the prototype was designed and tested, and the PCB and system are attached to a wearable harness (Figure 1).

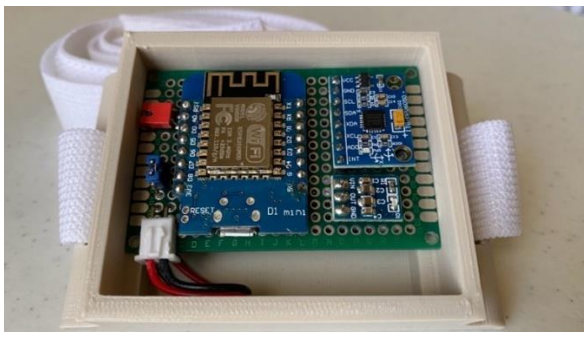

Figure 1. Inertial wearable device

The microcontroller collects the gyroscope and accelerometer values (accelX, accelY, accelZ, gyroX, gyroY, gyroZ). It sends them, using WiFi, to a PHP script executed on the Web server which is hosted on a Raspberry Pi Zero W minicomputer. The accelerometer indicates the patient's orientation while the gyroscope indicates the patient's rotational motion – the patient's motion in the X/Y/Z direction. The PHP script receives the data and inserts it into the database (see MySQL Database Storage) for additional processing.

The data map of the full system is shown in Figure 2. The Mac Address, Gyroscope, and Accelerometer data are provided by the ESP8266 microcontroller. This data is passed to the storeData.php script on the Raspberry Pi server. The wearable device is placed at the sternum area with the Velcro strap wrapped around the patient's torso. The patient is positioned and orientation (accelX/Y/Z) as well as movement (gyroX/Y/Z) values are recorded for six different bed positions (supine flat bed, right side-lying flat bed, left side-lying flat bed, supine torso at 30-degree elevation, right side-lying torso at 30-degree elevation, left side-lying at 30-degree elevation). These values are broadcast from the ESP8266 microcontroller to the Web Server hosted on the Raspberry Pi Zero W and stored in the database.The microcontroller on the wearable device is put into deep sleep mode between subsequent runs and consumes at that time approximately 8-20µA, extending the battery life.

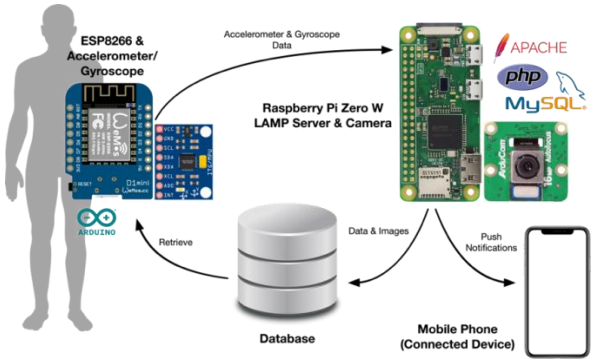

Figure 2. Data map of the full system

4. RESULTS AND DISCUSSION

Summary statistics for demographic and clinical features were calculated and are shown in Table 1.Several features have a large percentage of missing values.For example, troponin is missing in 80% of the records, albumin and total bilirubin are missing for more than 60% of the records.All continuous variables were compared using a two-sample t-test, and although some features have a different mean, none are statistically significantly different.

Table 1. Demographic and clinical features for the two populations

	No Ulcer (n=24,250)	**Ulcer (n=1,483)**	**% missing**
Demographics			
Age	82.75 (61.35)	80.92 (57.89)	0
Gender (% male)	57.5	59.1	0
Weight (kg, mean, SD)	82.07 (23.2)	84.23 (29)	35
Insurance (%)			0
Public	72.4	76.5	
Private	27.4	23.1	
Uninsured	0.1	0.3	
Ethnicity (%)			0
Asian	0.5	1.6	
Black/African American	5.8	9.0	
Hispanic	0.6	2.3	
Other or unknown	5.3	13.2	
White	87.9	74.0	
Admission (mean, SD)			
Glasgow Coma Scale (GCS)	3.04 (1.3)	2.93 (1.3)	23
Arterial pO_2 (mmHg)	220.41 (135)	211.73 (141)	68
Arterial pCO_2 (mmHg)	41.55 (10.8)	43.19 (12.5)	68
Hemoglobin (g/dL)	10.89 (2.05)	10.23 (1.95)	25
Hematocrit (%)	32.33 (6.07)	30.8 (5.6)	24
White blood cell count	12.08 (10.95)	13.76 (8.7)	24
Platelet count	215.8 (107.7)	243.4 (141.2)	24
Blood glucose (mg/dL)	143.42 (68.67)	153.6 (86.3)	24
Sodium (mmol/L)	138.54 (4.95)	138.6 (5.98)	24
Potassium	4.2 (3.17)	4.2 (0.77)	24
Creatinine (mg/dL)	1.35 (3.19)	1.70 (1.6)	24
BUN (mg/dL)	25.2 (20.5)	35.18 (26.7)	24
Albumin (g/dL)	3.06 (0.65)	2.65 (0.62)	67
Total bilirubin (mg/dL)	1.47 (3.2)	1.53 (3.3)	65
Troponin (ng/mL)	1.18 (4.65)	1.13 (4.05)	80
International Normalized Ratio (INR)	14.26 (8.06)	15.48 (9.97)	32

The output in Figure 3 shows the range of cross-validation accuracy scores for the three chosen models on the *training* data using a 6-fold split for each model where 1/6 of the data (16.67%) was left for testing and the remaining records were used for training in each of the folds. We can see each model's median cross-validation accuracy (the number of correct predictions made by the model divided by the total number of predictions) represented by the orange line in each box. Logistic regression achieved the best median score (95.5% accuracy), with the KNN model trailing close behind (93.5% accuracy) but with a larger spread, and the decision tree achieving the lowest median score (92%).

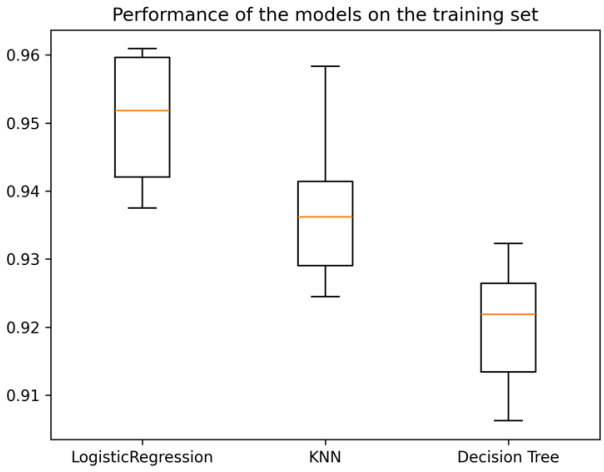

Figure 3. Accuracy of the logistic regression, KNN, and decision tree classifiers on the training data set using 6-fold cross-validation

When we evaluated the accuracy scores on each of the fold's *test* data sets, logistic regression achieved an accuracy of 93.8%, KNN an accuracy of 91.4%, and decision tree classification an accuracy of 87.9%. KNN classifier depends a lot on the number of nearest neighbors that it captures, and if the K value is too low, it captures too much noise (overfit), and if it is too large, it will over-generalize. KNN classifier gave us the best results with the K value set to 6. Figure 4 is a plot of the accuracy across varying K values, with the optimal K value, the one with the highest accuracy, at K=6.

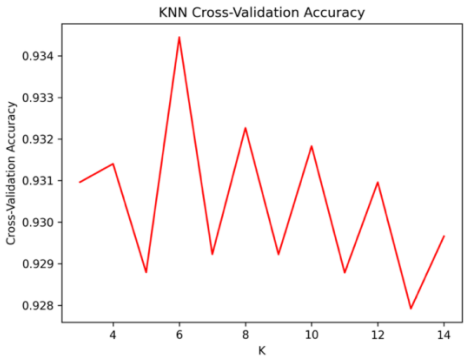

Figure 4. KNN cross-validation accuracy for different values of K, the number of neighbours

The confusion matrix (Figure 5) on the test data set achieves the true negative score of 85% and true positive score of 98%, which gives us the information to calculate the precision, recall, F1, and accuracy scores for the evaluation of the model's performance (Figure 6). While the average F1 score was 92%, both classes have a similar F1 score with a one percentage point difference. Better average precision was achieved on the records without ulcer as labeled with 1 (98%), which would lead us to conclude that on average it would give us fewer false negative results (2%) than false positive results (15%). Recall (sensitivity) is a measure of the model's ability to find all of the true positive samples, and it is at 98% for positive PI records.

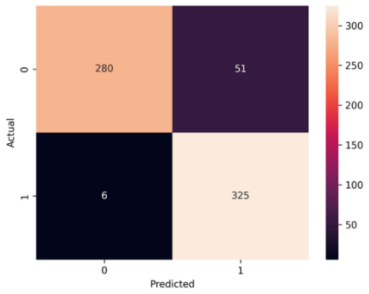

Figure 5. Heatmap of the confusion matrix for the KNN classifier on the test data set with predicted (columns) and actual (rows) classes

	precision	recall	F1-score	support
No Ulcer	0.98	0.85	0.91	331
Ulcer	0.86	0.98	0.92	331
accuracy			0.91	662
macro avg	0.92	0.91	0.91	662
weighted avg	0.92	0.91	0.91	662

Figure 6. KNN classifier's performance on the test data set

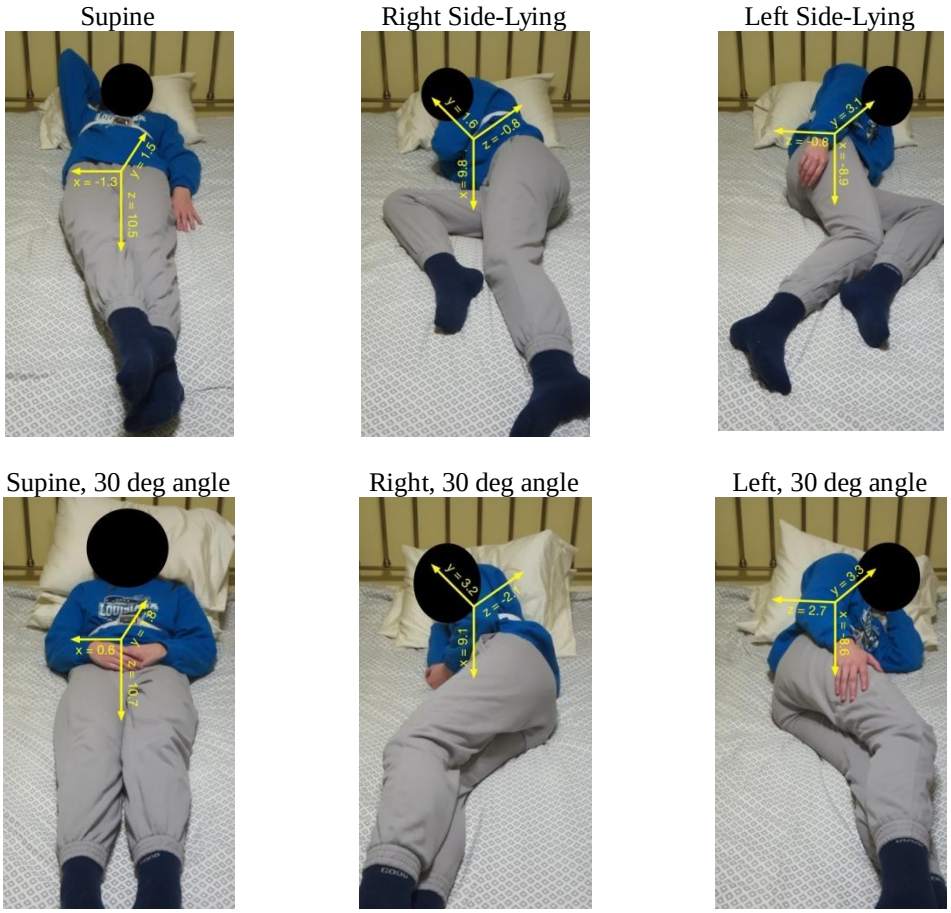

Figure 7. Examples of positions of patients with vectors

The data is sent into the database by the microcontroller from the gyroscope/accelerometer: the *MAC address*, accel*X/Y/Z* values, and the *gyroX/Y/Z* values. The wearable device provides us with information on the length of time the patient has been in a certain position. Figure 7 shows the direction the accelerometer vectors are pointing to. For example, when the patient is in the supine position, or lying on their back, the *z* accelerometer value will be the greatest. On the other hand, when the patient is lying on either their left or right side, the absolute *x* accelerometer values will be the largest. The gyroscope values show the angular velocity radians per second around the given axis the patient is moving while the data is being captured. Therefore, if a patient moves at the exact time the data is captured, the gyroscope values will indicate that. The data can infer the patient's position on the bed based on the accelerometer and gyroscope data. Looking at the last *n* entries in the database, we can determine the duration that the patient has been in one position and use this information to alert healthcare workers of the need for the patient to be rotated.

5. CONCLUSIONS

In conclusion, this research presents a machine learning modelbased on the MIMIC-III public healthcare dataset to identify the ICU patientsthat at the highest risk for the formation of pressure ulcers. Using features available within 24-48 hours of their ICU arrival, we can now identify the patients that are at the highest risk for developing PIs.

Once high-risk patients are identified, increased attention is directed towards them and the intervals between rotations (by the nurses) are shortened. Alternatively, these patients can be equipped with an inertial wearable in order to provide healthcare providers with audible alerts and notifications when these patients must be turned to prevent the formation of PIs. In creating a wearable inertial device that includes a gyroscope and accelerometer, the patient's position and time in the position is identified and tracked.

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