

Effective Posture Classification using Statistically Significant Data from Flexible Pressure Sensors

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Abstract—Advancements in flexible and printable sensor technologies to overcome the limitations of conventional rigid counterparts offer an excellent opportunity to design various healthcare applications for humans, and their potential flexibility can be used in real-time health monitoring and personalized physical conditions with minimal or no inconvenience. However, managing a large volume of obtained sensor datasets and ensuring accurate predictions can take time and effort. While statistical analysis and the Pearson correlation coefficient can reduce data volume, whether this would lead to losing important information and affect downstream application performance is still being determined. In this paper, we use posture classification as an exemplar of timely services in digital healthcare, especially for bedsores or decubitus ulcers. Our sensors, placed under hospital beds, have a thickness of just 0.4mm and collect pressure data from 28 sensors (7 by 4) at an 8 Hz cycle, categorizing postures into 4 types from 5 patients. We then collected sensor data to explore the possibility of using a small number of pressure sensors for patient posture classification. Next, we apply a statistical analysis to the datasets obtained to select the featured sensor data cells and evaluate the performance of posture classification models on various groups of sensors. Our evaluation involves the analysis of reduced datasets through statistical methods and the Pearson correlation coefficient. The classification performance using datasets comprising 5 featured and 28 sensors are 0.93 and 0.99, respectively. These results suggest comparable performance and the viability of useful classifiers for both cases. Consequently, comparable posture classification performance can be achieved using only 17.9% of the entire dataset.

Index Terms—Flexible and Printable Sensor, Posture Monitoring, IoT Monitoring, Pressure Sensor, Classification

I. INTRODUCTION

Sensors translate the physical world into data and serve a foundational role in the era of digital transformation [2]. With the advancements of sensors, which are highly integrated and miniaturized, modern sensors serve adequately as the

components of smart electronics/machines. Still, their small and rigid form factors restrict their usage in many applications, such as healthcare domains. In digital healthcare, effectively exploiting actionable knowledge obtained from a steady input stream of sensor data can offer helpful information for timely services. For example, in the case of patients with dementia or critically ill patients who have difficulty moving on their own, there is a high possibility of severe health disease, bedsores, or decubitus ulcers caused by remaining in a long time in the same posture. Pressure ulcers or bedsores due to a lack of caregivers or less changing posture could result in a partial or complete blood flow obstruction in soft tissue, leading to damage in the skin or underlying tissue [3]. Preventing these health diseases requires a periodic change in the patient's posture by the nursing staff or others. The predictive alarm using adequately captured patient posture data can enable more efficient proactive steps. However, the growing demand for recording pressure signals to improve the effectiveness of preventing serious health diseases such as bedsores or safe driving is contributing large amounts of sensor datasets, which is cost prohibitive.

This study demonstrates the feasibility of using a few flexible pressure sensors or even small extracted features for patient posture monitoring, suggesting research directions for designing a better, cost-effective application. Flexible sensors have received extensive research interest due to their potential applications in personalized healthcare and human motion detection [4]. Thus, flexible sensors are gradually becoming integral to wearable devices or equipment for understanding various aspects of daily human life. Unlike rigid sensors, flexible sensors are attached to flexible substrates [5] to bend and stretch easily, which have the advantages of softness, miniaturization, being lightweight, and biocompatibility [5]. These meaningful characteristics lead to a significant combination of human activity and treatment strategies by attaching medical devices. Therefore, with data analytics in place, flexible pressure sensors are ideal choices for measuring postural information, as they cause minimal or no inconvenience to the patient.

In this paper, we first collected experimental data to explore the possibility of using a small number of pressure sensors for patient posture classification. Experimental data contains measurement errors and class imbalance issues. Consequently, preprocessing and resampling procedures are conducted to mitigate these errors and improve the overall data quality. The insight of this paper is to evaluate the impact of using a

Manuscript received February 29, 2024; revised May 7, 2024.

An earlier version of this paper was presented at the IEEE International Conference on Flexible and Printable Sensors and Systems (FLEPS) 202 [1] and was published in its Proceedings [DOI: <https://10.1109/FLEPS57599.2023.10220219>].

This work is supported by the Korea Innovation Foundation (INNOPOLIS) grant funded by the Korean government (MSIT) (2020-DD-UP-0278). This material is also partly based upon work supported by the National Science Foundation under Grant No. 1751143. The Titan X Pascal used for this research was donated by the NVIDIA Corporation.

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significantly reduced amount of data on a posture classification model. In our experiment, we reduce from 28 sensor data to the selected five sensors by statistical analysis and Pearson correlation coefficient to obtain an 82.1% data reduction. We then apply four different supervised machine-learning techniques to detect the postures of each patient and evaluate their prediction performance. Our experimental results show that the optimized RF (random forest) classifier outperforms the other classifiers with an average classification accuracy of 0.93 and 0.91 in the case of data reduction by statistical and Pearson correlation and the statistically selected sensors, respectively.

II. RELATED WORK

Since flexible sensors have good deformability, enabling the elimination of expensive and bulky detection instruments, the potential flexibility ability can be used in real-time health monitoring. From a data analytics view, the massive volumes of datasets generated by flexible sensors and applications of significant importance can extract actionable knowledge discoveries to reach better and faster decisions for timely services.

Matar et al. [3] estimated the posture using body pressure distribution images of 4 postures (supine, left, right, and prone). In [6], they used two pressure mats made by XSENSOR technology corporation with a resolution of 42 by 44. They showed that the random forest (RF) outperformed others like support vector machine (SVM) and multilayer perceptron (MLP) [7]. The automatic classification of position and the duration of the position for the lying patient on the bed is essential. Thus, several studies proposed a monitoring system for recognizing and correcting the importance of sitting posture using these pressure sensors [8], [9]. Lee et al. [10] presented a method for identifying sleep postures using an intelligent fabric pad with 14 pressure sensors placed on top of a mattress that can detect the pressure distribution of a person's body during sleep. However, the accuracy of the proposed fabric pad depends on the pressure distribution patterns and the person's body shape and height. While the robustness of the algorithm proposed in this paper could also be affected by similar factors, the approach proposed in [10] could suffer more due to a relatively simpler algorithm based on the total ratio of the pressure measurements in each row.

Davoodnia et al. [11] conducted posture estimation and classification during sleep using the Vista Medical FSA SoftFlex 2048 sensors. This sensor comprises 2,048 sensors spread over a 32 by 64 grid, utilizing pressure map data. They employed a convolutional neural network (CNN) architecture to distinguish between users and their sleeping postures. They successfully classified a total of 17 sleeping postures. Rivera et al. [12] used a 32 by 64 pressure sensor grid to collect measurements of the main postures of patients on a bed. For posture estimation, they extracted features using the gray level co-occurrence matrix (GLCM) for texture analysis and classified four postures in bed using the SVM algorithm. Another related work [11], [12] used 32x64 pressure sensors for posture estimation and classification. However, using a vast number

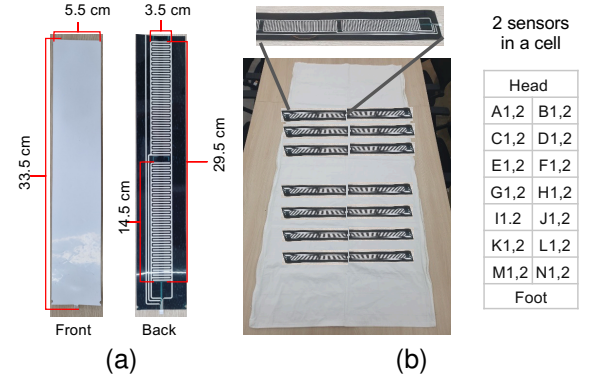


Fig. 1. (a) Specification of an individual cell comprising two pressure sensors. (b) The layout of pressure sensors deployed on the test bed.

of sensors (2,048) can lead to high computational complexity, potentially slowing the processing speed and causing latency.

In the application research utilizing flexible pressure sensors, Bourahmoune et al. [13] proposed an IoT cushion called LifeChair. It utilizes nine e-textile pressure sensors covering users' shoulder and lumbar regions. For posture estimation, machine learning classifiers such as RF, Decision Trees-Classification and Regression Trees (DT-CART), and Naive Bayes (NB) were applied and compared, detecting 15 sitting postures and six seated stretching activities.

III. MATERIALS AND METHODS

A. Data Acquisition

Fig. 1a shows the specification of sensory cells (from A to N) containing two flexible pressure sensors in each cell: 33.5 cm in length, 5.5 cm in width, 0.4 mm in thickness, and 10 μ s of response time. This thin thickness causes minimal inconvenience and discomfort to patients or users. We use a prototype stretchable pressure sensor manufactured by MiDAS H&T [14], a simple structure file type sensor using stretchable electrode wire. The details of the sensor specifications other than thickness are as follows. The resistance and sensing weight ranges are $\infty - 500 \Omega$ and 5 gf–2 Kgf, respectively. The durability metric for stroke is over 40 times for 8 hours with 4 kg and 16 hours idle. The durability metric for heavy-weight is over 500,000 strokes (force of 100 gf). We attach 14 cells (7 rows and 4 columns as depicted in Fig. 1b) to a mat and collect data in 00-FF hexadecimal (or 0-255 in decimal) format at 8 Hz (or 8 cycles/second). Fig. 2 shows the data format for the collected data for a 1-second duration from Cell A, which contains 40 data points. Columns marked as Sen 1 and Sen 2 in Fig. 2 are the average values collected at 8 Hz, and we use them as representative values of Cell A. We follow the same method to extract data for the remaining cells (from Cells B to N).

B. Data Preprocessing

We collect patient posture data and categorize it into one of four predefined postures (supine, left lateral, right lateral, and head elevation) at 2-hour intervals to develop a real-time

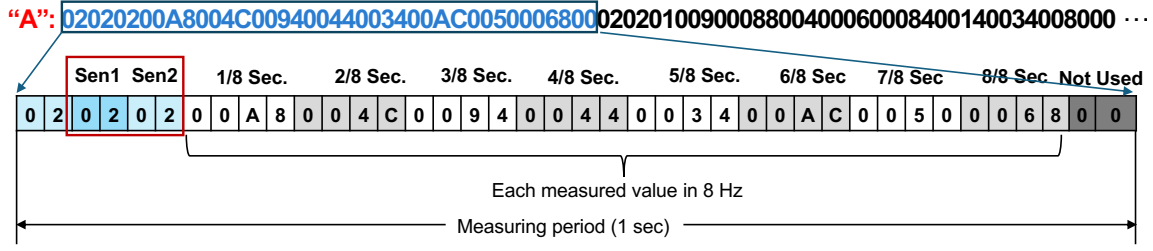


Fig. 2. The data format collected at each pressure sensor data for a 1 second measuring period with 8 Hz sampling frequency.

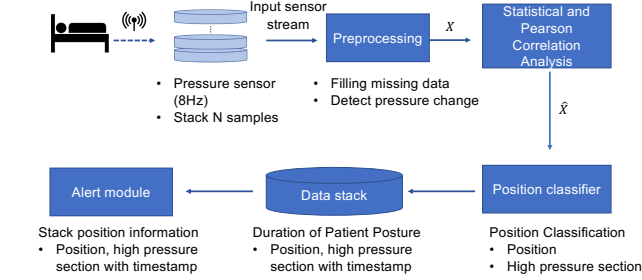


Fig. 3. Overview of the proposed posture classification system.

posture classifier. The patient's demographic information is as follows. The age ranges between 41 and 69, with two females and three males. Their weights and BMI ranges are 40.1–78.6 kilograms and 17.3–33.2, respectively. The patients were diagnosed with various symptoms, including *Staphylococcus aureus* bacteremia Abscess, psoas, etc., and the patient's data were collected while they were hospitalized during November/December 2020. The human observers, caregivers in our case, labeled the postures. For instance, the caregivers record patients' postures every 2 hours, and then the final posture information labeled uses this information. We also impute sensor data since measurement error is inevitable due to potential malfunctioning in communication/network, hardware/sensor, or power/battery [15]. Imputation is, in general, filling missing values with estimated values. Our imputation method is performed every three seconds and uses sensor data values around the missing value. We use the average value if the middle cell is missing; otherwise, we use the closest sensor value during the imputation process.

Even though we collect pressure sensor data 8 times per second from our in-bed sensors, the observed patient's posture information is rare and not synchronized due to the 2-hour intervals of posture. Therefore, to construct classification models using the observed data collected at two-hour intervals, we assume that there is no change in posture within 10 minutes from the time of posture recording. Through this process, we construct 64,800 posture data and use them as input sensor streams to our posture learning and classification system, as shown in Fig. 3. Fig. 4 shows the distribution of pressure sensor values for different postures. The data presents the cumulative pressure values recorded by each sensor, depicting the pressure applied to each sensor throughout the experimental periods. It is evident that the data exhibits concentration on specific sensors corresponding to their locations.

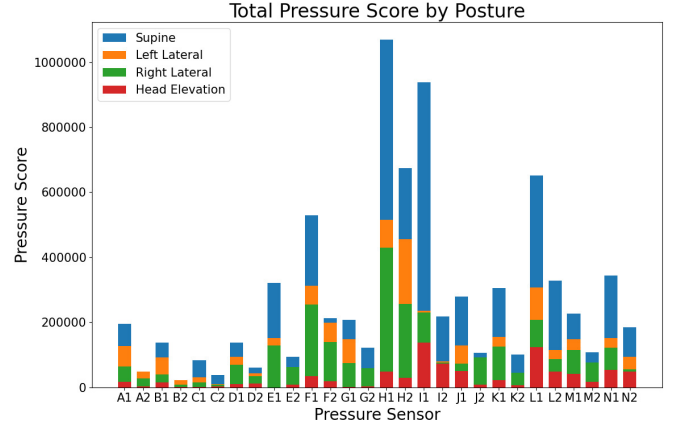


Fig. 4. Distribution of pressure sensor values by posture.

C. Data Resampling Processing

Since our patient's posture classification has four categorized classes, we can use supervised machine learning-based predictive models. One critical precondition for effectively training a supervised machine learning model is obtaining large-scale datasets with proper labels [16]. In other words, the learning datasets need a balanced ratio between classification classes. Therefore, we synthetically resample to alleviate the class imbalance issue as demonstrated in Table I. The number of data points for Supine (majority class) is approximately 33,200, about 8 times more than that of Head Elevation (minority class). As depicted in Fig. 5a, the scatterplot using the original data (i.e., before handling class imbalance issues) shows a much smaller number of red dots (Head Elevation), as compared with the green dots (Supine). This data imbalance can affect classification and potentially lead to overfitting the model to Supine, decreasing the accuracy for the Head Elevation class. This imbalanced condition leads to biased outcomes by the majority class. In other words, most machine learning-based algorithms can be overwhelmed by the majority of data unless they adequately address the imbalance problem.

TABLE I
NUMBER OF DATA POINTS PER CATEGORIZED POSTURE CLASS.

Class	Supine	Left Lateral	Right Lateral	Head Elevation
Count	33,200	14,000	13,200	4,400

Data resampling techniques, including undersampling and oversampling, offer solutions to mitigate data imbalances. Undersampling can reduce the dataset size and shorten the

training time. However, it risks losing important information by removing important samples from the majority class. On the other hand, oversampling techniques can solve the data imbalance problem without information loss by increasing the number of samples in the minority class while maintaining the samples of the majority class. However, this method has the disadvantage of increasing the computational cost [17]. This study endeavors to employ oversampling and undersampling techniques to improve the data balance, compare and analyze the classification performance with the original data, and select the most suitable algorithm for the given data.

Undersampling is a technique that balances imbalanced datasets by randomly eliminating samples from the majority class using the Random Under-Sampling (RUS) algorithm. It achieves this by randomly removing samples from the majority class until the number of samples matches that of the minority class. The dataset is first divided into majority and minority classes, and then the number or proportion of samples to be removed from the majority class is determined based on the number of samples in the minority class [18]. Finally, samples are randomly selected from the majority class and removed until the two classes have equal samples.

Furthermore, we utilize the Synthetic Minority Oversampling Technique (SMOTE) method [19], which enhances the advantages and mitigates the drawbacks of traditional oversampling techniques, to address the class imbalance issue in our posture classification training data. The following equation describes SMOTE:

$$\mathbf{x}_{\text{new}} = \mathbf{x}_i + r \cdot (\mathbf{x}_{zi} - \mathbf{x}_i), \quad (1)$$

where $\mathbf{x}_{\text{new}}$ is a generated sample, $\mathbf{x}_i$ is an arbitrary sample point, and $\mathbf{x}_{zi}$ is a randomly selected sample based on $\mathbf{x}_i$ using the nearest neighbor method. SMOTE works by randomly selecting a data point from the minority class and then using the k-nearest neighbors algorithm to find the k-nearest neighbors of that data point. All of the k nearest neighbors will be from the minority class. SMOTE then generates a new data point along the line connecting the selected data point and its nearest neighbor. This process is repeated to generate new data points and increase the number of data points in the minority class.

Fig 5 illustrates the outcomes of the initial dataset following resampling using SMOTE. In particular, as depicted in Fig 5b, the outcome demonstrates the generation of new data points by connecting neighboring data points, aligning with the previously described SMOTE methodology.

D. Statistical-based Feature Selection

As shown in Table II, datasets through oversampling (using SMOTE) achieved the highest accuracy. The data sampled using SMOTE was increased by about 2 times compared to the original dataset (64,800), oversampling it to 132,800. Since 28 feature sensors are used for classification, the computational cost also increases. Therefore, to mitigate this overhead, the top five features were selected from the SMOTE-based oversampled data, as shown in Fig. 6, to classify each posture class and compare it to the case where all features were used.

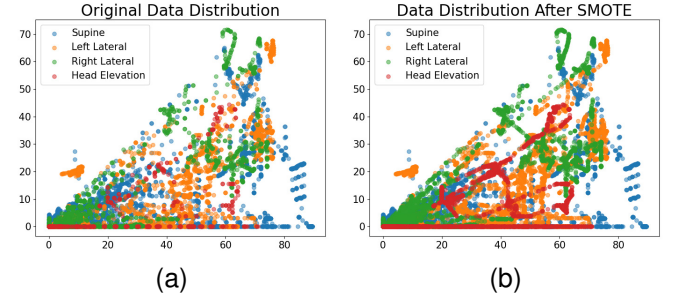


Fig. 5. Comparison of data distribution (a) before and (b) after applying SMOTE oversampling, the latter of which visually increased the red dots (Head Elevation, which is only 1/8 of the green dots, which represent Supine) while preserving the patterns of the original data distribution.

Five sensors were selected based on the ascending order of their statistical analysis results presented in Fig. 7. These results show the characteristics of pressure sensor data, such as mean, standard deviation, variance and 75% value. The 75% value refers to the third quartile when the data is divided into quartiles, representing the upper 25% of the data distribution. Some pressure sensors exhibit temporarily high values when pressure is applied. This characteristic can be utilized to classify various postures. Therefore, comparing and analyzing the third quartiles for each posture can help identify how the sensors corresponding to the upper values differ for each posture. These characteristics delineate the specific values collected based on the positioning of pressure sensors.

However, due to the proximity and shared characteristics among sensors with the same alphabet in Fig. 1, only one sensor per alphabet group was selected for the top five. The selection process utilizes the Pearson correlation coefficient, calculated as:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}, \quad (2)$$

where r is the Pearson correlation coefficient, x_i, y_i are the individual observations of the two variables, respectively. $\bar{x}, \bar{y}$ are the mean values of the two variables, respectively. This coefficient, ranging from -1 to +1, quantifies the linear correlation between two continuous variables (x and y). Values closer to +1 indicate a positive linear relationship, meaning when one variable increases, the other also increases proportionally. Conversely, values closer to -1 suggest a negative linear relationship, where an increase in one variable leads to a proportional decrease in the other [20].

Therefore, in this study, a Pearson correlation coefficient closer to +1 indicated similar characteristics between the two sensors. Consequently, the sensor with a higher statistical analysis value was selected, while the one with a lower value was excluded. Finally, the next highest sensor from the remaining sorted sensor was selected, resulting in a final set of five sensors used for classification.

While a reasonable observer could identify the optimal sensor location without statistical methods like the one proposed in this paper, stretchable sensors' characteristics might alter or decay over time, necessitating continuous human involvement,

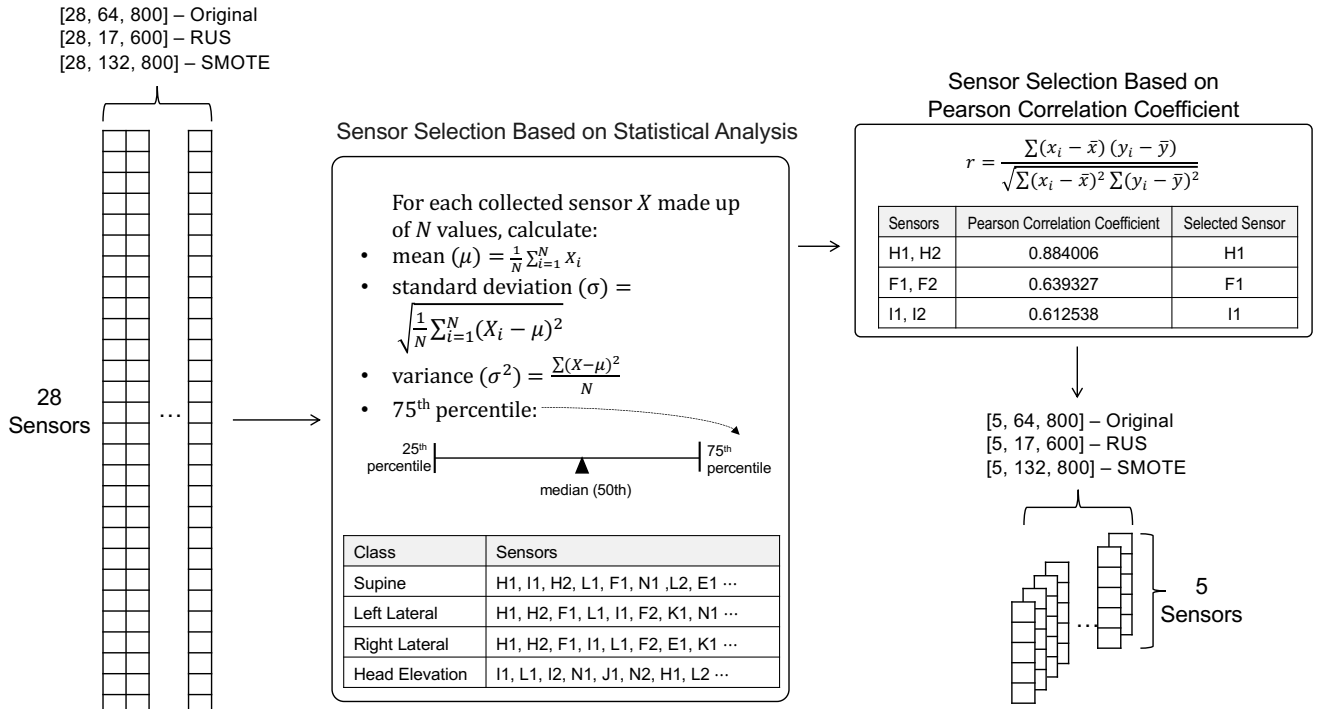


Fig. 6. Our proposed statistic-based feature selection architecture.

such as changing sensor positions, for an optimal posture classification. Given the characteristics of stretchable sensors and the potential expansion of diverse patient groups, the classification algorithm can be more adaptable and robust with the extracted statistical information in conjunction with the deployed sensors. Therefore, the selected five sensors would work best with the current patient's data (such as weight). However, the proposed approach can be seamlessly applied to future patients by combining uniformly placed sensor arrays with statistical analysis for adaptability.

E. Design of the Classification Model

After the preprocessing and selecting featured sensor cells through statistical analysis and Pearson correlation, which also involves balancing the class distribution of given data by resampling processing, normalization, and missing value analysis, selecting an appropriate classification model is essential since determining a general yet superior algorithm is not feasible. Therefore, we evaluate four representative classification methods, DT (decision tree), RF (random forest), AB (adaptive boosting), and MLP (multi-layer perceptron), which have demonstrated their superior performances in various real-world applications [21].

DT is a popular non-parametric supervised learning method that operates by repeatedly dividing a feature space of a given dataset by using the Gini index and Entropy (E) until the specific terminal condition is satisfied.

$$\text{Gini} = 1 - \sum_{i=1}^k p_i^2, E = - \sum_{i=1}^k p_i \log_2(p_i), \quad (3)$$

$$E = - \sum_{i=1}^k p_i \log_2(p_i), \quad (4)$$

where p_i indicates the proportion of the number of elements in i -th class to the number of elements in the given data.

RF is an ensemble model correlated with DTs, whose subtree is learned using different bootstrap samples from the training data. Then, by aggregating the results of the subtrees using averaging, plurality voting, or weighted voting, RF solves classification or regression problems using:

$$H(x) = \arg \max_i \sum_{t=1}^T I(h_t(x) = i), \quad (5)$$

where $h_t(x)$ indicates the t -th output of base classifier.

AdaBoost is another improved version of a DT-based algorithm with relatively weak classifiers. Its underlying assumption is that grouping multiple classifiers can be robust even if each classifier performs poorly. However, unlike RF, which trains its subtrees in parallel, AdaBoost progressively trains its base classifiers using copies of the original dataset for training, which have different weights for incorrectly classified samples. After that, the classification results are aggregated.

Lastly, MLP has a connected set of ANN consisting of an input layer, one or more hidden layers, and an output layer. The learning process involves adjusting the weights to improve the performance of the result by minimizing the observed errors using backpropagation and gradient descent methods [22]. It works well even with insufficient knowledge of the target system, which has nonlinear and complicated relationships, does not impose any restrictions on the input variables, and is

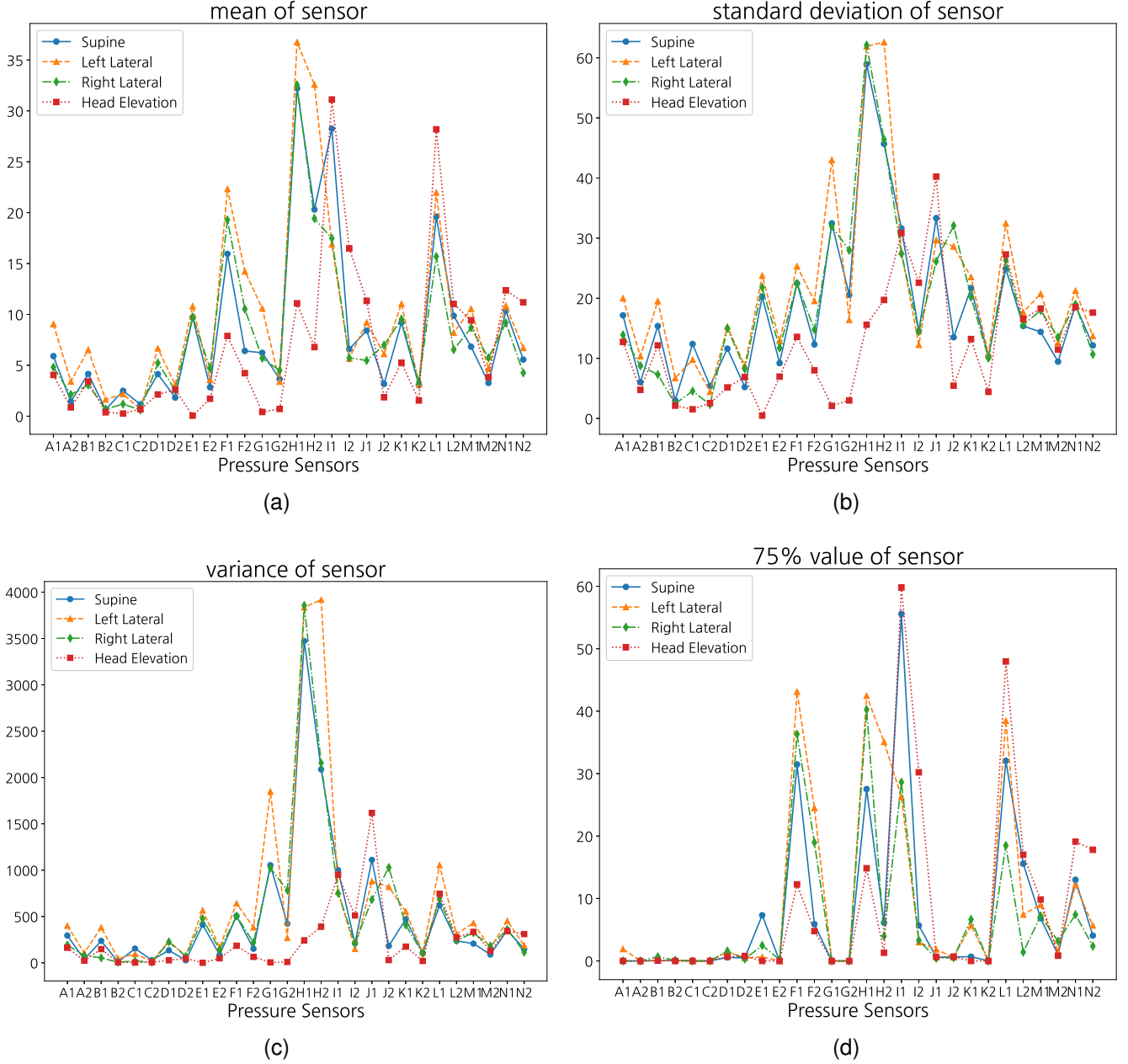


Fig. 7. Statistical characteristics of the collected pressure sensor data measured in (a) mean, (b) standard deviation, (c) variance, and (d) 75% value.

robust to noise. On the other hand, it tends to overfit, and the derived model is not easily understandable.

IV. EVALUATIONS

A. Datasets

In our evaluation, we define three data groups derived from the pressure sensor datasets obtained from patients.

- **Group 1:** The datasets using all 28 sensors (Fig. 1).
- **Group 2:** The five sensors (F1, H1, H2, I1, L1) were selected through statistical analysis illustrated in Fig. 7.
- **Group 3:** The five sensors (F1, H1, I1, N1, L1) were selected based on statistical analysis and Pearson correlation coefficient.

B. Performance Metrics

The following metrics are measured, which are primary indicators of how well the proposed scheme performs in classification performance.

- We measure the prediction performance using Accuracy, Precision, Recall, and F1 score.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}.$$

$$\text{Precision} = \frac{TP}{TP+FP}.$$

$$\text{Recall} = \frac{TP}{TP+FN}.$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}.$$

TP, TN, FP, and FN indicate true positive, true negative, false positive, and false negative, respectively.

TABLE II
COMPARISON OF CLASSIFICATION PERFORMANCE FOR GROUP 1.

Data	Original Datasets				Undersampling Datasets				Oversampling Datasets			
	DT	RF	MLP	AB	DT	RF	MLP	AB	DT	RF	MLP	AB
accuracy	0.59	0.99	0.93	0.56	0.56	0.98	0.91	0.54	0.56	0.99	0.94	0.55
recall	0.59	0.99	0.93	0.55	0.56	0.98	0.91	0.54	0.56	0.99	0.94	0.55
precision	0.59	0.99	0.93	0.53	0.56	0.98	0.91	0.79	0.60	0.99	0.95	0.55
F1-score	0.53	0.99	0.93	0.51	0.53	0.98	0.91	0.54	0.55	0.99	0.95	0.55

TABLE III
COMPARISON OF CLASSIFICATION PERFORMANCE FOR GROUP 2.

Data	Original Datasets				Undersampling Datasets				Oversampling Datasets			
	DT	RF	MLP	AB	DT	RF	MLP	AB	DT	RF	MLP	AB
accuracy	0.56	0.91	0.63	0.50	0.49	0.83	0.54	0.41	0.48	0.91	0.61	0.39
recall	0.56	0.91	0.63	0.50	0.49	0.83	0.54	0.41	0.48	0.91	0.61	0.39
precision	0.58	0.91	0.63	0.46	0.49	0.84	0.53	0.41	0.48	0.92	0.62	0.38
F1-score	0.50	0.91	0.61	0.46	0.49	0.83	0.53	0.41	0.46	0.91	0.60	0.38

TABLE IV
COMPARISON OF CLASSIFICATION PERFORMANCE FOR GROUP 3.

Data	Original Datasets				Undersampling Datasets				Oversampling Datasets			
	DT	RF	MLP	AB	DT	RF	MLP	AB	DT	RF	MLP	AB
accuracy	0.58	0.91	0.62	0.50	0.49	0.86	0.57	0.43	0.50	0.93	0.62	0.43
recall	0.58	0.91	0.62	0.50	0.49	0.86	0.57	0.43	0.50	0.93	0.62	0.43
precision	0.62	0.91	0.62	0.45	0.49	0.86	0.57	0.42	0.50	0.93	0.62	0.43
F1-score	0.50	0.91	0.59	0.45	0.48	0.86	0.57	0.42	0.48	0.93	0.61	0.42

C. Results

As shown in Table I (Supine is 33,200 compared to Head Elevation of around 4,400), we observed a class imbalance problem in the dataset. To address this issue, we applied the undersampling technique using RUS and the oversampling technique using the SMOTE. We evaluated the classification performance using various machine learning libraries to compare and analyze the performance of the original data and the resampled data. Table II, III, and IV show the experimental results for four classification algorithms on the entire dataset (Group 1), the dataset based on statistical analysis (Group 2), and the dataset based on statistical analysis and Pearson correlation coefficient (Group 3). Experiments were conducted on three datasets within each group: original, undersampled, and oversampled.

The classification performance of pressure sensor datasets was assessed using the machine learning library available in scikit-learn [21]. Specifically, we train and evaluate four machine learning algorithms: DT, RF, AB, and MLP. The primary hyperparameters for these classification methods are as follows: DT uses the Gini index to tree split, AB uses $n_estimators=50$, MLP uses RELU and Adam for activation and weight optimization. We adopted an MLP model with a single hidden layer of a range of 8–30 neurons, and RF employs parameters of $max_features=3$ and $n_estimators=70$. We allocate 70% of the data for training and the remaining 30% for testing.

The results presented in Table II, III, and IV demonstrate that the RF model outperforms other models in classification. While different application domains suit different algorithms, and there could be sensitivity even with the same application domain for different populations of patients, the RF model, in general, is superior in classification as it is less prone to overfitting (than such as a decision tree) and robust (and more with hyper-parameter tuning). The undersampled dataset shows the lowest performance among the three datasets, losing important information. On the other hand, the oversampled

dataset not only solves the data imbalance problem without losing important information but also achieves better performance. However, as mentioned in Section III-B, this method has the disadvantage of increased computational cost. We selected the top 5 (out of 28 sensors) to improve this and evaluated the classification performance. Table III, and IV show that the top 5 sensors were selected differently, as in Section III-D, and the data selection method of Group 3 shows better performance than Group 2. When comparing Table II and IV, the performance is about 0.6 lower than when using all 28 sensors. However, it can still maintain a high prediction performance of about 0.93 using 5 featured sensors, which means classifying human posture using only 17.9% datasets.

V. CONCLUSION AND FUTURE WORK

This paper proposed a posture monitoring system for bedridden patients, especially critically ill, to prevent bedsores using a flexible printing pressure sensor. We used a pressure sensor manufactured using a flexible printing process technique to measure the pressure loaded on the body. We collected pressure data at an 8 Hz cycle from a pressure mat composed of 28 (7 rows and 4 columns) pressure sensors and categorized postures into four types: supine, left/right lateral postures, and upper body raised posture (or head elevation). To understand the influence of posture classification when the number and posture of the sensors deployed in the test bed get reduced, we evaluated three data groups: entire sensors (Group 1), the statistically selected sensor groups (Group 2), and the five featured sensors by statistical analysis and Pearson correlation coefficient (Group 3). We validated their effectiveness with four classification algorithms. Our results showed that Group 3 achieved a prediction performance of approximately 0.93 using RF. The oversampled dataset, which applied the SMOTE algorithm to address the class imbalance issue in the original data, showed the best prediction performance. This was similar to the performance of the original data, suggesting that the SMOTE algorithm can resolve the class imbalance issue without losing information. Furthermore, although Group 3 demonstrated lower performance compared to Group 1 (which utilizes all sensors), it illustrated that high prediction accuracy is achievable even with only 5 sensors. Hence, successful classification can be achieved with condensed sensor information.

In our future work, we plan to reduce the number of sensors to enable a model to operate in edge nodes with limited computation and storage capabilities. We also intend to provide the alarm message for proactive healthcare steps to prevent bedsores. The alarm function will activate when a patient maintains the same posture for a predetermined duration, customized based on the patient's symptoms as identified by our posture classifier.

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VI. BIOGRAPHY SECTION

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