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Design of Wearable Patient Lying Position Tracking and Warning System to Prevent Pressure Injury

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Abstract
Within the scope of this study, a wearable lying position tracking system equipped with inertial measurement unit sensors has been developed to prevent the formation of pressure injuries in bedridden patients. Three inertial measurement unit sensors were placed on the patient's chest, one on the right upper leg and the other on the left upper leg, and the angular orientation expressions of the limbs were calculated. Datasets were created for three different lying positions, and machine learning models were used to classify the patient's lying position. The success of the classifiers was compared by calculating the accuracy, sensitivity, specificity, precision and F1 score values. The average accuracy values in the lying position classification were obtained as 99.506%, 99.977%, 99.972%, 99.838%, and 99.967% respectively, using linear discriminant analysis, k-nearest neighbor, decision tree, support vector machine and random forest classification methods. The highest accuracy rate was obtained as a result of the k-nearest neighbor method with high variation. The time that the person remained fixed in the determined lying position was also calculated, and if it remained longer than the specified time, an audible warning signal was generated to change the position. Thus, it has been tried to prevent the person to apply pressure by lying on a single muscle group and tissue for a long time and to prevent the formation of pressure injuries over time.

1. Introduction

Prolongation of people's life expectancy, unhealthy diet, diabetes, etc. Pressure injuries from prolonged sitting and laying have become more common as a result of diseases and sedentary lifestyles, particularly in the elderly and the disabled [1]. Pressure injuries, also known as bedsores and pressure sores, are more common in people who use wheelchairs and those who are paralyzed and must lie down for long periods of time as Figure 1

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Figure 1. Bed- and wheelchair-bound patient with high risk of pressure injuries

The main factors contributing to pressure injuries;

- the skin without changing the position frequently bed, chair, etc. is placed on it.
- skin contact of the patient with urine or feces,
- diabetes,
- injuries,
- unhealthy diet
- several medical conditions that affect circulation system of the blood

Localized lesions known as pressure sores are caused by a reduction in blood supply to immobile bodily parts that are subjected to persistent pressure [2]. Over the bony prominence, these lesions typically develop in the skin and subcutaneous tissues [3].

In the European Pressure Injuries Advisory Panel (EPUAP), pressure injuries are divided into four main stages according to tissue type and wound width and depth [4]. From Stage 1 to Stage 4, there is an increase in the depth of tissue injury and the degree of damage at the wound site [5]. These stage of pressure injuries are shown in Figure 2.

Figure 2. Stages of pressure injury [5]

Stage 1 involves undamaged skin in the pressure injury area and red skin on the surface. The skin is still red even when the pressure is released, primarily because this is muscular tissue. Because of its aerobic metabolism, muscle tissue has a greater need for oxygen than the skin surface. Deep muscle levels experience lesions due to inadequate blood flow. Stage 1 pressure injuries may cause the area they are applied to to become uncomfortable, warm, or softer than the nearby tissues. Stage 2 involves damage and opening to the top layer of skin in the pressure sore location. Skin tissue damage and pink or red coloration appear where the skin layer is lacking. Where the pressure injury occurred, stage 3 damage extends to the adipose tissue and may include dead tissue. The deepest ulcer from a pressure injury occurs in stage 4, and the damage may even affect the bones and/or muscular tissue. Pressure injuries in stage 4 may contain dead tissue. The quality of life is impacted by pressure injuries since they are so painful.

Despite the fact that most inpatients get pressure injuries, if they are detected early enough, they can be averted [6]. Integrative medicine and a multidisciplinary team approach are necessary for the prevention and treatment of pressure ulcers [7]. Depending on the nature and extent of the pressure damage, a different course of treatment may be necessary. To prevent infection when the wound is still healing, it needs to be gently cleaned and properly dressed. If poor circulation and other risk factors such malnutrition, diabetes, vascular disease and inactivity are constantly present together with a pressure injury that is in Stage 3 or Stage 4, healing could take many months.

Between 10% and 18% of pressure injuries occur in intensive care units, and 0%-29% in home care units. Even with all the safeguards adopted as part of preventive care, pressure injuries still happen [8]. Pressure sores are an important health problem worldwide due to high care costs and also one of the most important indicators of the quality of care in hospitals [9-12]. Therefore, it is extremely important to prevent pressure injuries before they occur. This can only be possible with the follow-up of inpatients and intermittent position changes. However, considering the patient density in hospitals, it is not possible for each patient to be followed up continuously by nurses or caregivers. For this reason, there is a need for wearable technologies that will warn the patient or their relatives and remind them that the patient needs to change position.

In the field of identification of movements by means of inertial measurement unit (IMU) sensors, researchers focused on basic daily movements such as going up and down stairs, getting up and walking, and sitting [13-18]. The degrees of freedom (DoF), number of sensors and information, signal processing and motion detection techniques and sensor configuration used in studies in this field differ from study to study [13,19,20]. There is no generally accepted protocol on this subject [15]. Barshan conducted a laboratory study on the classification of 19 daily body and sports activities by means of MIMU sensors produced by X-sens company, and the results they presented are the most detailed study in this field [21-24]. Altun and Barshan tried to classify the movements of walking, running, climbing stairs, sitting on a chair and getting up. Volunteers wore a 9 degree of freedom IMU sensor (gyroscope, accelerometer and magnetometer) on their right or left ankles and motion data were collected. These data were evaluated in the motion detection algorithm they developed and the motion type of the person was determined. Xia et al. [25] proposed a deep learning method for accurate and robust motion type classification with only a single inertial measurement unit (IMU) sensor and achieved a maximum success of 87.16% and a minimum of 73.80%. The most specific movement recognition studies are carried out in the field of sports. For example, table tennis [26], baseball [27], basketball [28], volleyball [29], and swimming [30] have studies on the recognition of sports movements. Vleugels [31]; developed a CNN algorithm to classify six movements in ice hockey and classified them with an average success rate of 76%.

Within the scope of this study, aimed to develop a wearable technology that will prevent the formation of pressure sores in the bed care processes of the elderly, special care patients, and short-term patients. Machine learning algorithms have been developed to determine the lying positions of people. If the person stays in the same lying position for a long time, an audible warning will be given and an incentive to change position will be made. The organization of the study, on the other hand, contains details of the methods used for the collection, feature extraction, and classification of lying position data in Section 2: Material Method. In addition, this section contains information about the metrics used to test the success of classification methods. In Section 3, under the heading Experimental Results and Discussion, the performance comparison table and confusion matrices of the five classification methods used in the study are included.

2. Material and Method

The methodological approach of this study is given in Figure 3. Within the scope of the study, first of all, IMU sensor data were collected. One of the three IMU sensors was placed on the patient's chest, one on the right upper leg and the other on the left upper leg.

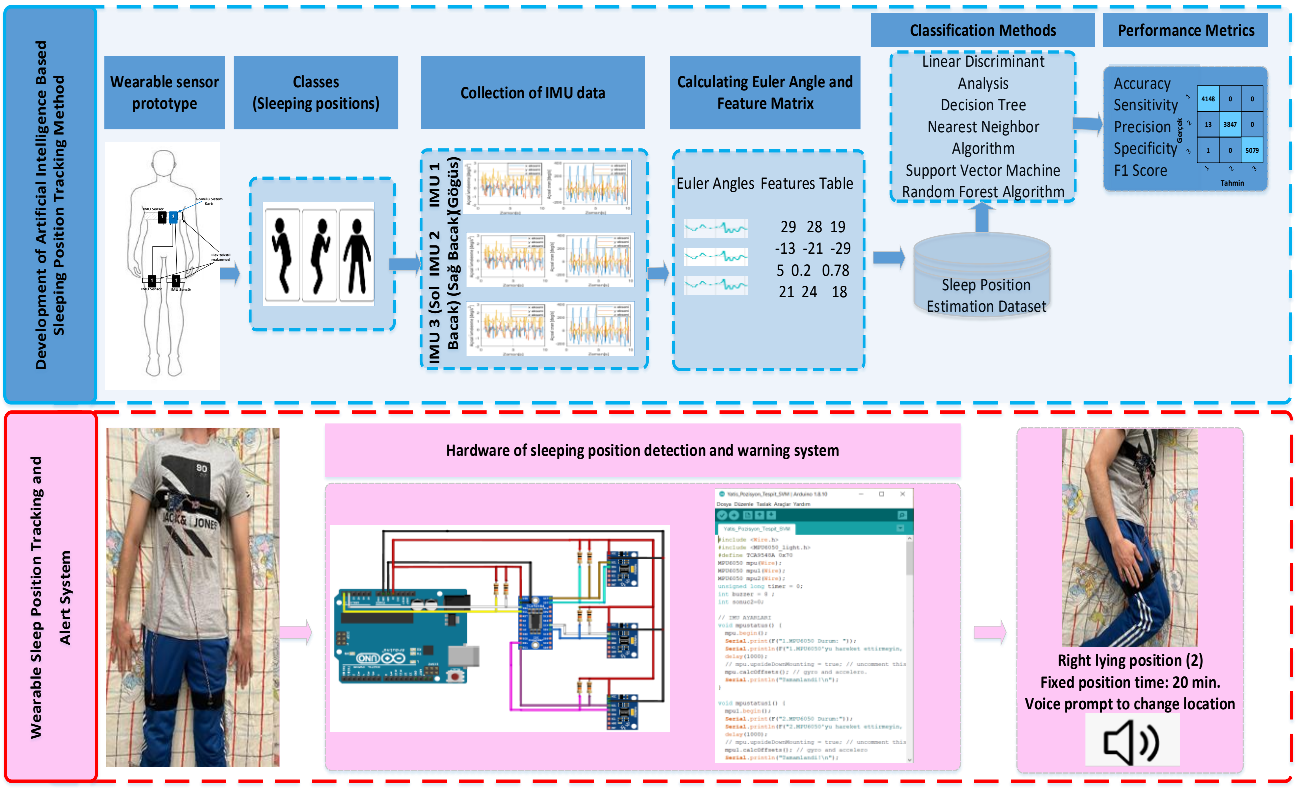
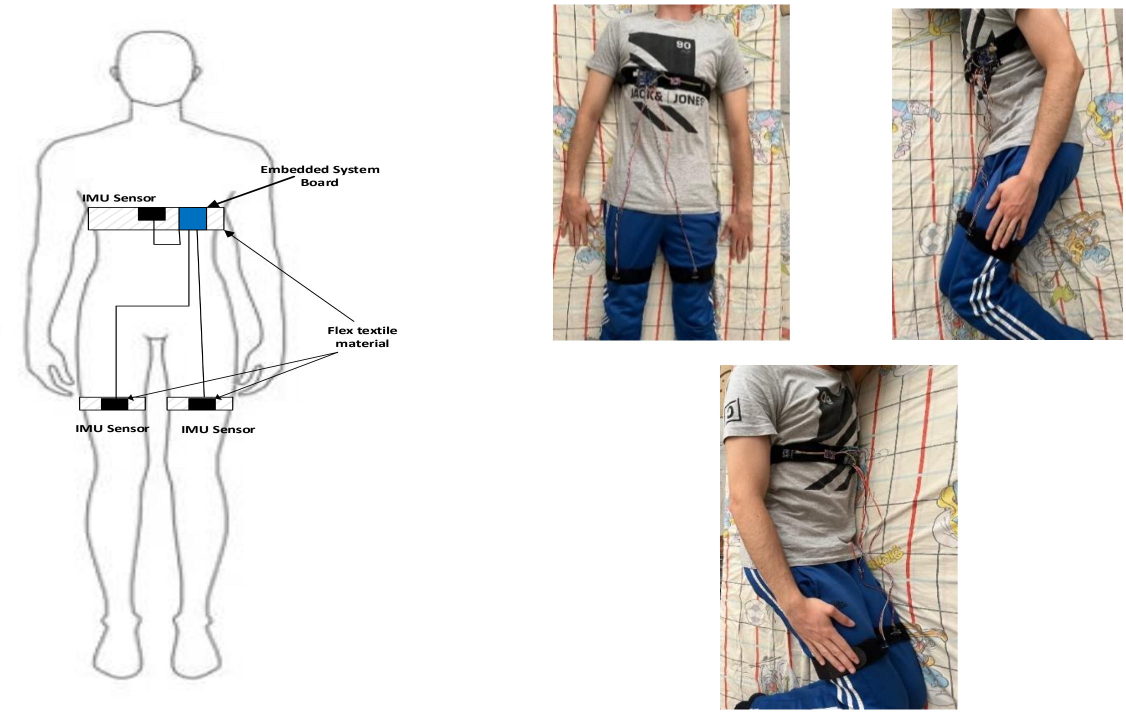


Figure 3. Methodical approach

Angular acceleration and gyroscope data were combined and the angular orientation (Euler) angles of the limb were calculated. Then, machine learning algorithms were developed for the classification of the patient's lying position by using the collected data set for three different lying positions. The time the person remained fixed in the determined position was calculated and if the person remained fixed in the determined position for a long time, an audible warning signal was generated to change the position. Thus, it has been tried to prevent the person to apply pressure by lying on a single muscle group and tissue for a long time and to prevent the formation of pressure sores over time.

2.1. Design of Wearable Sensor Structure and Collection of Lying Position Dataset

The MPU6050 IMU sensors placed on the chest and legs are mounted on a soft-bottomed flex tape textile material that will not deform the skin. The total weight of the entire system is around 200 g. The Arduino Uno embedded system board is positioned between the chest/waist as seen in Figure 4. Angular acceleration and gyroscope information from all sensors are collected on a single embedded system board with the serial communication protocol. The TCA9548A I2C multiplexer module is used to transmit data from three IMU modules to a single embedded system board.



a) b)

Figure 4. a) preliminary wearable sensor suit design and b) prototype images

Permission was obtained from the non-interventional ethics committee of Fırat University to collect data from volunteers. In this study, three participants are joining the study, two of them are male and one female in the 18-40 age range. They are healthy individuals. They have no any neurological, orthopedic, or systemic diseases and have active hearing and speaking abilities. Since it is important for the volunteers to have both legs and both arms to perform the movement correctly, it was sought as a criterion in the selection of volunteers.
During the data collection phase, people were asked to lie still for 5 minutes in each of the lying positions shown in Figure 4. In the meantime, motion data were collected from the designed wearable IMU sensors. The person was verbally instructed to move from one position to another. Total data recording time for each person is 15 minutes. The serial bound rate of the embedded system board is 115200 bits per second. The sample rate is 0.01 s.

2.2. Calculating Euler Angles and Features Extraction

IMU is an electronic unit that collects the angular velocity and linear acceleration data sent to the main processor in a single module. The components of the system are an accelerometer, a gyroscope and sometimes a magnetic field meter (magnetometer). accelerometer; Measures angular acceleration in three axes. Due to the propulsion system and physical limits, the most important thing in these sensors that measure acceleration is that they are affected by gravity. The sensor is constantly under the influence of gravity. The gyroscope can also be referred to as a turn meter. Gyroscopes and accelerometers alone cannot provide secure and stable data. For this reason, information from gyroscopes and accelerometers is usually synthesized and used in the most appropriate way. Synthesis algorithms conceptually consist of two separate blocks;

- Orientation value calculated from gyroscopes

- Orientation value calculated from accelerometers

This combines the results of the two independent predictions and the orientation angles (Euler angles) are calculated. Euler angles are used to describe the rotational motion of objects in 3D space and are the common name given to the three angles (pitch, yaw, and roll).
In this study, three IMU sensors are placed on the patient's chest and right and left upper legs. Accelerometer and gyroscope data measured from the sensor for three axes were collected on the embedded system board and Euler angles were calculated. The maximum value of the rolling angle was used as the feature set to detect the lying position. Figure 5 shows

the variation of the rolling angles calculated based on the information collected from the three sensors

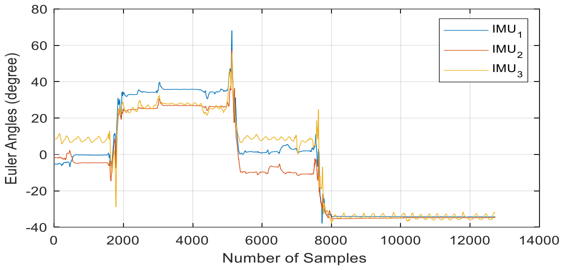


Figure 5. Rolling angle variation graph calculated for three different lying positions

2.3. Development of Motion Classification Algorithms and Lying Position Detection

Five basic machine learning algorithms were used to determine the lying position and the results were compared. Detailed information about the used algorithms is briefly summarized.

Support vector machines are learning machines that use the inductive principle of Structural Risk Minimization to achieve a high level of generalization over a small number of learning models. SVM is an effective learning method for identifying patterns in complex datasets that are difficult to evaluate. The Support Vector Machine algorithm looks for a hyperplane in N-dimensional space (N — number of features) that clearly classifies the data points. There are many possible hyperplanes that can be used to separate classes of data points. The aim is to find the planes with the largest margin, which is the largest distance between data points in each class [32].

A supervised machine learning technique called a decision tree continuously separates data based on a particular parameter. Two entities can be used to describe the tree: decision nodes and leaves. Decision trees are one of the most widely used methods in classification models. Since it is a simpler technique to configure and grasp, it gives transparency to the model and has a visual presentation [33].

The k-nearest neighbor method is a non-parametric classification algorithm. The KNN model is easy as it is based on basic mathematical expressions and is widely used in many industries. The basic principle is based on the assumption that the class of an unknown variable will be the same as that of its nearest neighbors. The average of the current states of the k nearest elements in the training dataset is used to calculate the prediction result. The number of neighbors is indicated by the letter "k" in the method name. The k number is very important when it comes to determining the optimum classification or estimation. It can use trial and error or cross-validation approaches to choose the correct k number [33]. The data class is determined by averaging the k data points calculated as the closest distance to the training set. The threshold value is calculated before the found value is interpreted.

The random forest model is a method of creating a decision ensemble (forest) consisting of multiple decision trees. The RF model is a combination of hundreds of decision trees, and the decision results from all trees are evaluated by majority voting method to produce the final result of the decision tree to get a comprehensive result.

The purpose of the linear discriminant analysis technique is to project the original data matrix into a lower-dimensional space. To achieve this goal, three steps need to be accomplished. The first step is to calculate the separability (i.e. the distance between the means of different classes) between different classes, called the between-class variance or the between-class matrix. The second step is to calculate the distance between the mean and samples of each class, called the within-class variance or the within-class matrix. The third step is to create a sub-dimensional space that maximizes the variance between classes and minimizes the variance within the class [34].

The hyper parameters used in the design of the classification methods developed for the detect of the lying position type within the scope of this study are presented in Table 1.

Table 1. Hyper parameters of used classification algorithm

Decision Tree	K-Nearest Neighbor	Support Vector Machine
Present: Fine Split Criterion: Gini index Maximum number of splits: 100	Present: Fine Distance metric: Euclidean Distance weight: Equal Number of Neighbors: 3 Standardize data: True	Present: Linear SVM Kernel scale: Automatic Kernel function: Linear Box constant level : 3 Multi-class method: One vs one Standardize data: True
Linear Discriminant Analysis	**Random Forest**	
Present: Linear Dicriminat Covariance Structure: Full	Present: Bagged trees Maximum number of splits: 12727 Number of learners: 30	

2.4. Performance Evaluation Method (PEM)

We used five standard evaluation methodologies to compare the performance of machine learning classification algorithms for detect lying position. These are accuracy, sensitivity, specificity, precision, f1 score The performance evaluation criteria used are given in Table 2 [32]. An estimate is made for performance measures for true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Table 2. Performance evaluation metrics used in the study

Performance Metric	Abbreviation	Equation
Positive Predictive Value	PPV, Precision	$\frac{TP}{TP+FP}$
Negative Predictive Value	NPV	$\frac{TN}{TN+FN}$
True Positive Ratio	TPR, Sensitivitiy	$\frac{TP}{TP+FN}$
True Negative Rate	TNR , Specificity	$\frac{TN}{TN+FP}$
Multi-Class Accuracy	ACC	$\frac{TP+TN}{TP+TN+FP+FN}$
F1-Score	F1	$\frac{TP+TN}{TP+TN+FP+FN}$

3. Experimental Results and Discussion

In this study, a computer with 3.60 GHz Intel i7-7700 CPU, Windows 10 and 16 GB RAM was used. The Matlab 2020 program was used to implement the proposed methodological approach. The cross-validation rate was selected k=10 for this data set, and each classification algorithm was run 100 times to calculate the best, minimum, mean and standard deviation values for accuracy, sensitivity, specificity and precision and are presented in Table 3.

In the lying position detection problem, an average accuracy of 99.506%, 99.972%, 99.838%, and 99.967% was achieved with linear discriminant analysis, k-nearest neighbor, decision tree, support vector machine, and random forest classification methods, respectively. sensitivity, specificity, precision, F1 values obtained for all methods are 99% and above. The highest success was obtained with the random forest method.

Table 3. Performance of classification methods

Classifier	Metric	Accuracy	Sensitivity	Specificity	Precision	F1
Linear Discriminant Analysis	**Maximum**	99.520	99.516	99.451	99.449	99.484
	Minimum	99.505	99.501	99.435	99.433	99.468
	Average	99.506	99.515	99.450	99.448	99.483
	Standard deviation	0.0032	0.0037	0.0038	0.0038	0.0037
K-Nearest Neighbor	**Maximum**	100	100	100	100	100
	Minimum	99.960	99.985	99.985	99.985	99.985
	Average	99.977	99.998	99.998	99.998	99.998
	Standard deviation	0.0065	0.0041	0.0041	0.0041	0.0041
Decision Tree	**Maximum**	99.992	99.991	99.990	99.990	99.991
	Minimum	99.929	99.953	99.956	99.956	99.954
	Average	99.972	99.990	99.988	99.988	99.989
	Standard deviation	0.0114	0.0062	0.0053	0.0053	0.0057
Support Vector Machine	**Maximum**	99.866	99.857	99.849	99.849	99.853
	Minimum	99.803	99.831	99.822	99.822	99.827
	Average	99.838	99.856	99.849	99.849	99.853
	Standard deviation	0.0144	0.0035	0.0038	0.0038	0.0037
Random Forest	**Maximum**	99.984	99.982	99.982	99.982	99.982
	Minimum	99.937	99.966	99.966	99.966	99.966
	Average	99.967	99.981	99.981	99.981	99.981
	Standard deviation	0.0109	0.0029	0.0027	0.0027	0.0028

In addition, confusion matrices were obtained for each classifier showing the number of correct and incorrect predictions of our classification model and are given in Figure 6.

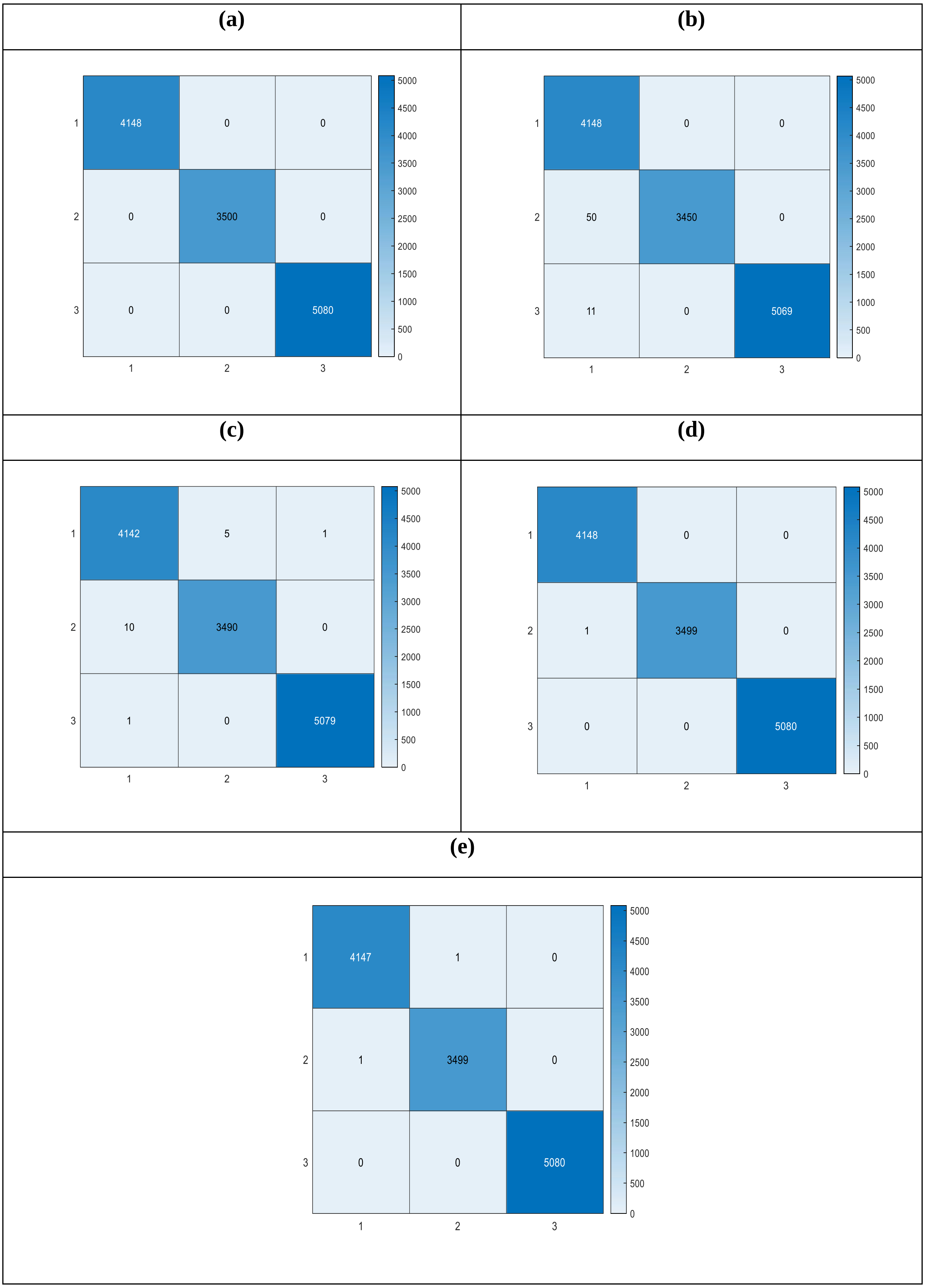


Figure 6. Confusion matrix of (a) K-nearest neighbor, (b) Linear discriminant analysis, (c) Support vector machine, (d) Decision tree, (e) Random forest.

4. Conclusion

Although pressure sores can be seen in most inpatients, it is known to be preventable if diagnosed early. With this proposed wearable sensor technology, the application success of the patient position tracking system on the real-time embedded system board is 99% on average. This success shows that the system is reliable enough to be used for monitoring the lying position of the patients under expert control. This application has the potential to create a solution to an important problem in the field of health.

In future studies, it is aimed to increase the lying position dataset collected from volunteers, especially in the clinical setting, to carry out method validation studies in which patients are included under the supervision of specialist physicians.

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The data set collected and used in this study can be obtained by contacting the responsible author of the article to be used for academic purposes.

Contributions of the Authors

The contributions of each author to the article should be indicated.

Conflict of Interest Statement

There is no conflict of interest between the authors.

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