RESEARCH ARTICLE

Piezoresistive-Based Gait Monitoring Technique for the Recognition of Knee Osteoarthritis Patients

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ABSTRACT Knee osteoarthritis (Knee OA) is a degenerative disease that often perplexes the elderly and the whole society, and its timely recognition receives interest worldwide. However, traditional imaging examinations cannot reflect dynamic function nor implement long-term monitoring. To address this issue, this article suggests a piezoresistive-based gait monitoring method to recognize patients with Knee OA by assessing the plantar pressure signals during the subjects' walking, which is mobile, wearable, low-cost, and convenient. Eighteen subjects diagnosed with Knee OA and twenty-two control subjects participated in the experiment. Considering the asymmetric pressure distribution in feet and the landing habits of Knee OA patients, the plantar surface was split into eight areas, calculating the contact time and maximum force of each area in a gait cycle. Using these characteristics to train, the support vector machine (SVM) reached an accuracy of 93.15%, a precision of 92.39%, and a recall of 92.79%. Furthermore, a prediction model was proposed for the application that aggregates all the results in one test and gives a more accurate result, and the classification accuracy for individuals in the ensemble model is 90.90%. Our technique fills the vacancy of the recognition of patients with Knee OA based on wearable instruments. It provides ideas for intelligent healthcare, which benefits potential Knee OA patients' early diagnosis and treatment.
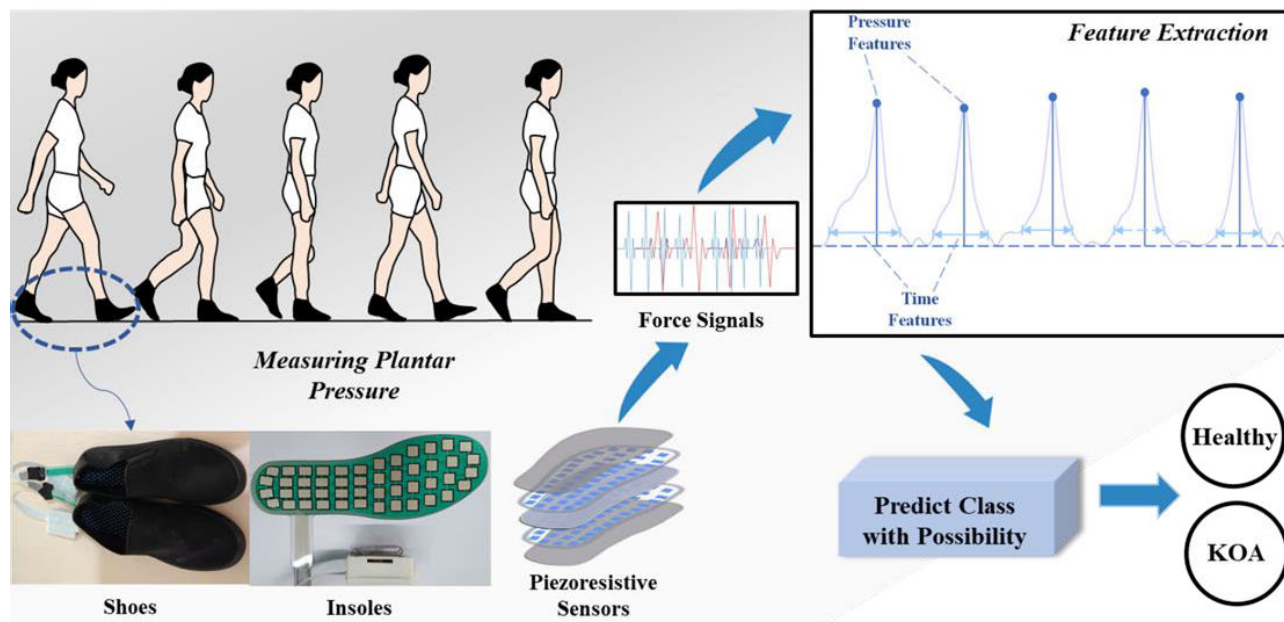
INDEX TERMS Intelligent sensors, machine learning, piezoresistive devices, pressure sensors, support vector machines.

I. INTRODUCTION

Knee osteoarthritis (Knee OA) is a degenerative disease common in the elderly [1]. As people age, the possibility of getting a Knee OA increases. People with Knee OA suffer from pain and dysfunction. Some even need to undergo total knee replacement surgery, which increases the physical and economic burden of patients. Knee OA causes a great burden to the public health care system, especially in aging societies [2], [3]. The accurate recognition of Knee OA can help conduct treatments early and evaluate the rehabilitation of Knee OA patients. Traditional diagnostic techniques for Knee OA include X-ray and Magnetic Resonance Imaging (MRI). However, the imaging examinations are usually static, which cannot show the patients' dynamic function, nor can they be applied in long-term health monitoring. Previous studies have shown no strong correlation between pain severity and imaging findings [4], [5]. Several researchers support that the dynamic assessment of knee function is necessary [6], [7]. Meanwhile, the fast development of electrical computer engines allows people to use intelligent algorithms as auxiliary tools to process and assess the data generated from

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FIGURE 1. The user walks on the flat with the insoles while data are obtained and transformed into a computer in time, and the model will predict whether he or she is a patient with Knee OA or not after the data has been processed.

the dynamic examinations. Machine learning algorithms have been used to predict diseases, and researchers have proposed methods to recognize patients with Knee OA based on different physiological signals, including surface electromyography (sEMG) [8], [9], [10], knee joint vibration signal (VAG signal) [11], [12], [13], [14], gait data obtained from a camera [15], and plantar pressure signals [16], [17], [18].

Among the signals above, plantar pressure measurement has shown application prospects in the diagnosis and treatment of Knee OA. It has been proved that the differences between patients with Knee OA and normal people can be shown by their plantar pressure. In [6], Saito et al. found that the partial foot pressures as a percentage of body weight are lower in patients with Knee OA than in healthy people. In [7], Zhang et al. found that females with Knee OA had higher peak pressure in midfoot and first to second metatarsal head during walking compared with healthy females. In [19], Anzai et al. demonstrated that the Knee OA group had a smaller single support phase, greater stance phase time, smaller great toe peak pressure and greater medical midfoot peak pressure than controls. Also in [20], Munoz-Organero found the weight dynamic reallocation at the midfoot and the major asymmetries between pressure patterns in both feet of Knee OA patients. In [21], Liikavainio et al. found that even in asymptomatic patients with early-stage Knee OA, alterations in plantar loading could be observed during walking. Some poor posture may contribute to disease progression, which can be shown early in plantar pressure measurement [22].

Thus, plantar pressure analysis is of great application value, especially in the early diagnosis and intervention of Knee OA. The first step is the recognition of patients with Knee OA based on plantar pressure signals. Previous researchers have worked on predicting Knee OA by measuring plantar pressure by the force plate. In [16], Mezghani et al. used 3-D ground reaction force (GRF) measurements integrated by force platforms to obtain the gait data of patients with Knee OA and apply discrete wavelet transform on the GRF signals, attaining the classification accuracy of 91.00%. In [17], Kirkwood et al. used a camera and force plate to record the gait data of older women with Knee OA and implemented principal component analysis to assess the gait data, reaching an accuracy of 71.8% for classification. In [18], Kotti et al. used a force plate embedded with piezoelectric 3-component force sensors to measure the plantar pressure and calculated parameters of GRF, achieving detection accuracy for Knee OA of 72.61%.

An alternate way to obtain plantar pressure signals is using wearable instruments [23], [24]. Compared with force plates, the wearable instrument is convenient enough to obtain more data, can avoid nervousness and alteration in the walking habits of patients in a specific laboratory and is more appropriate for remote monitoring [25]. In [20], Munoz-Organero et al. used commercial insoles with eight force sensors to obtain data from patients with Knee OA and healthy subjects and compared the classification efficiency of characteristics extracted, achieving an accuracy of 92.86% using a Decision Tree. In [26], Yamada and Nagamune. developed a foot pressure measurement system using force and inertial sensors for Knee OA patients. Still, the system was tested only on healthy subjects, and no diagnoses were made by it. However, the small number of sensing points and interspaces between the
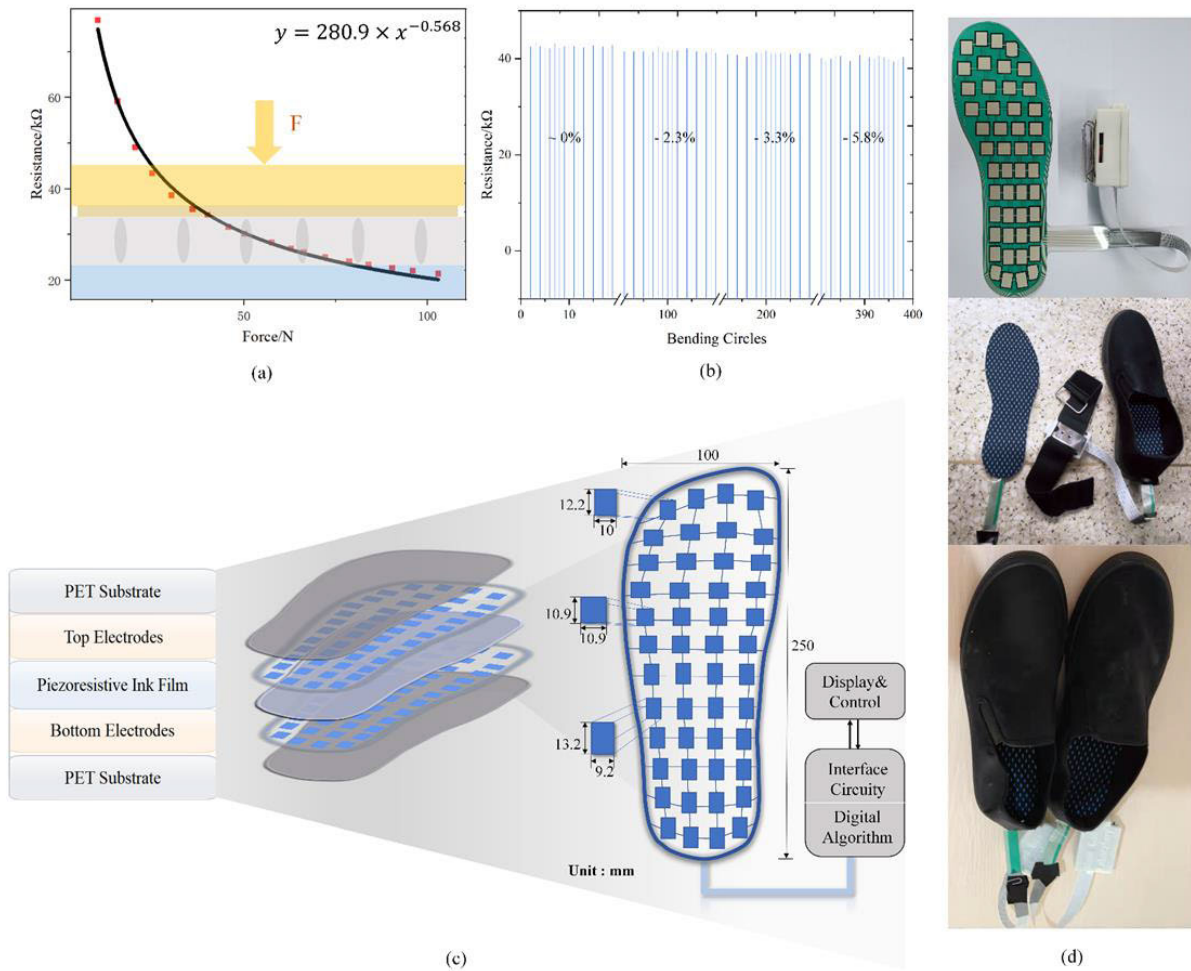
FIGURE 2. (a) The calibration process of one channel of the piezoresistive array. (b) The result of bending-releasing repeatedly several times. (c) Structure and electrodes' distribution of one insole. (d) The photos of the insoles.

insoles and the sole of the foot limited the data quality and further applications.

Generally, the application of plantar pressure measurement in sports medicine is still minimal. A possible explanation is that the complicated experimental equipment in previous studies made it challenging to be popularized. How to balance the number of sensors, circuit complexity, and the overall cost is a disturbing problem. Additionally, there is a lack of algorithms to organize and assess the large amount of data generated from plantar pressure measurement, which benefits from simplicity [27].

To overcome these weaknesses, a device with more sensors was applied, and a robust algorithm was implemented to process the signal. In this study, a pair of insoles embedded with a 48-channel piezoresistive array was developed, and a method was presented to recognize patients with Knee OA based on the plantar pressure signal obtained by our instrument. The features extracted from the processed data are contact time and maximum force of the gait circle. After applying Random Forest, AdaBoost, and support vector machine (SVM) to classify Knee OA patients and control subjects without Knee

OA, we suggest choosing SVM as the base prediction model, which attains the highest accuracy of 93.15%.

For the actual application, the user walks for some time with the insoles placed inside the shoes in the flat. Meanwhile, data are obtained from the circuit, and transferred to the computer. Data of steps are extracted to fit the SVM model pre-trained, and the prediction class will be given with the possibility (Figure 1). This model can help to assess the situation of patients as an auxiliary diagnostic tool.

II. MATERIALS
A. PRESSURE SENSING ARRAY FABRICATION
Piezoresistive sensors were applied to obtain the plantar pressure signals. Piezoresistive materials' advantage of being printable makes the sensors convenient for batch production. And its flexibility allows the insoles to fit the sole of feet well. Moreover, compared with capacitive- and piezoelectric-based procedure, the piezoresistive-based procedures experience less environmental interference for insole gait analysis, providing a more accurate result [28], [29], [30].
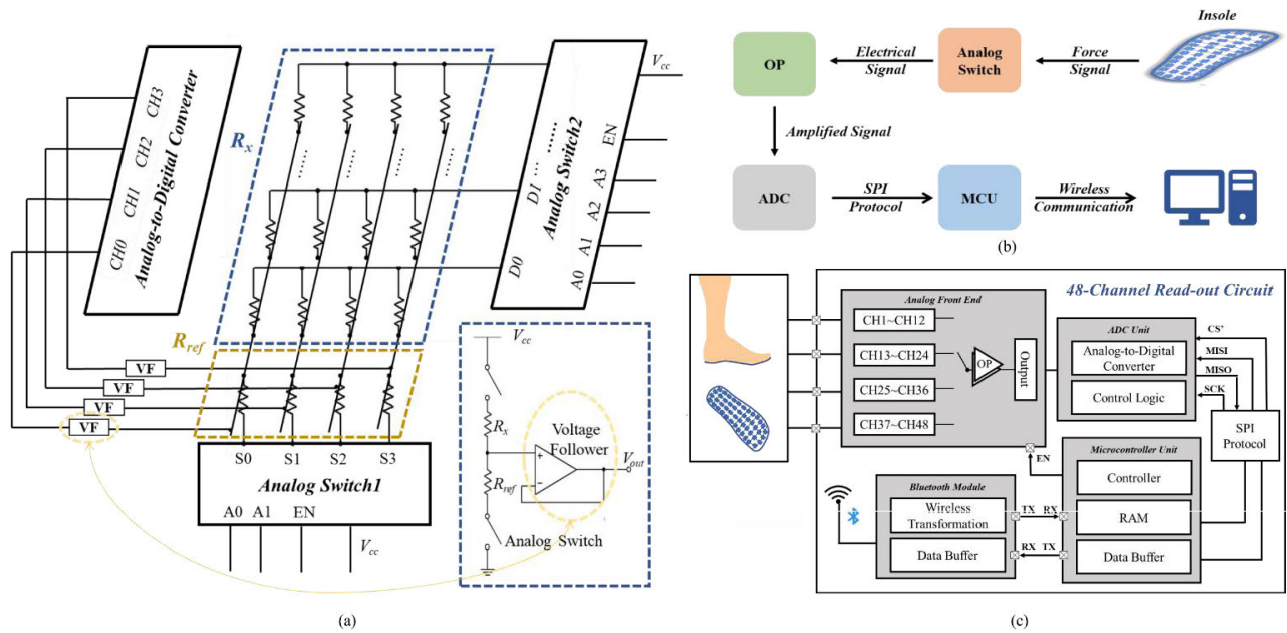
FIGURE 3. (a) Circuit structure used to scan the pressure distribution of the piezoresistive array. (b) The process of how the signal obtained by the insole is transformed into the host computer. (c) Schematic of the read-out circuit to obtain plantar pressure data.

The instrument, the insole, can measure the plantar pressure during walking by embedding a flexible piezoresistive array. The piezoresistive array contains two layers of polyethylene terephthalate substrate outsides, top, and bottom electrodes with a piezoresistive ink film in the middle. Each insole with a piezoresistive array has 48 electrodes, and the obtained data 96 channels.

Considering the sole's irregular shape, the electrodes' size includes three kinds (10-mm × 12.2-mm, 10.9-mm × 10.9-mm, and 13.2-mm × 9.2-mm) so that the insole can cover more area as possible. Roughly, the insole is 100-mm in width and 250-mm in length, which fits most soles of people.

The sensors have been calibrated before the measurement, and the increase in the force applied obviously decreases the sensor resistance (Figure 2(a)). A force of 26 N was also applied to finish the bending-releasing processes, and one example is shown in Figure 2(b). The change in resistance is −5.8% after 400 bending cycles. Our previous researches have also demonstrated that this technology has relatively high sensitivity and accuracy in gait signal detection and has been applied to accurate locomotion mode recognition in healthy subjects [28], [29], [30], [31], [32]. Therefore, our instrument meets the requirements of medical application. Figure 2(c) shows the structure and electrodes' distribution of the insole. Figure 2(d) shows the illustration of the insoles.

B. STRUCTURE OF CIRCUIT

The same row (column) of electrodes of the top (bottom) layer are connected, and 12 × 4 wires are led out. As indicated in Figure 3(a), sensors range from D0~D11 in a row, while

TABLE 1. The read-out circuit parameters.

Symbol	Quantity
Input Dynamic Range	0~5 V
ADC Resolution	12 bit
Wireless Transmission Rate	230,400 bps
Scanning Rate	50 Hz
Battery Capability	800 mAh
Working Current	50 mA
Working Hour	>16 hours

those in a column range from S0~S3. Therefore, a certain set of 'D' and 'S' wires can uniquely indicate one certain sensor.

The read-out circuit can be divided into conversion, reading, and transmission parts. As shown in Figure 3(b), The force signal obtained will be transformed into the electrical form by the analog switch, and an Operational Amplifier (OP) amplifies the signal from Analog to Digital Converter (ADC) circuit, Micro Control Unit (MCU), and wireless forwarding circuit, the signal will be sent to the host computer for further processing. The schematic of the read-out circuit (Figure 3(c)) includes Analog Front End (AFE), ADC circuit, MCU, and Bluetooth Module. For MCU, the controller decides whether the AFE obtains data or not, and the collected data are cached into its RAM. And the Bluetooth Module transmits the data to the host computer wireless at a baud rate of 230, 400. The read-out circuit parameters are indicated in Table 1.

TABLE 2. Information of all subjects enrolled.

Characteristics	Patients with knee OA (n=18)	Control subjects (n=22)	P[1]
Age (year)	61.1±7.3	54.4±8.8	0.014[2]
Gender (male/female)	8/10	12/10	0.751
Body mass index (kg/m^2)	28.1±5.9	25.8±3.1	0.138
Visual analogue score (%)	51.1±11.5		
Duration of symptoms (months)	52.7±66.2		
Grade of radiographic knee OA (n)			
2	5		
3	11		
4	2		

Abbreviation: knee OA, knee osteoarthritis.
[1] Continuous variables were compared using independent sample t-tests, while classified variables were compared using Fisher's exact tests.
[2] Statistically significant at p<0.05.

C. PARTICIPANTS AND EXPERIMENTAL APPROACH

After the instruments are well prepared, patients with symptomatic Knee OA scheduled for surgery between June and July 2021 at our institution were recruited. The inclusion criteria were age >40 years, unilateral symptoms, unsuccessful conservative treatment, and radiological findings consistent with clinical symptoms. The exclusion criteria were the inability to finish the gait test, the recent use of oral or intravenous analgesics, and other neurological and metabolic diseases that affected gaits, such as cerebral infarction, lumbar stenosis, and arteriosclerosis obliterans. Control subjects were recruited from our institution. The inclusion criteria were age >40 years, no history of back or lower limb disorders, and no functional limitations.

Therefore, 18 subjects diagnosed with Knee OA and 22 control subjects took the walking tests on the indoor ground. The control group included nine patients with cervical spondylotic radiculopathy, one patient with a benign neoplasm in the upper limb, and 12 healthy staff members at our institution. The control group members were considered healthy subjects in this experiment on Knee OA. The demographic and clinical data, including age, gender, body mass index (BMI), visual analog score, symptom duration, and Kellgren-Lawrence grade of radiographic knee OA [33], of all subjects enrolled are indicated in Table 2. Patients with knee OA are significantly older than healthy controls. However, research has revealed that age has little influence on the plantar pressure distribution for people over 40 years old [34]. There was no difference in gender and BMI between subjects with and without Knee OA.

The plantar pressure signals were obtained: Preoperatively, participants were asked to walk at their self-selected speed on a 20-m trail in a hallway marked in the hospital, wearing a pair of shoes embedded with the abovementioned insoles. Then, they were asked to stop for a few seconds, turn around, and walk back along the trail. The research conducted was performed according to Helsinki's Declaration. Approval for the study was obtained from the institutional ethics committee.

Informed consent was collected from all subjects involved in the study.

III. METHODS

A. DENOISING AND BASELINE CORRECTION

The data obtained by the above methods require preprocessing. High-frequency disturbances accompanied the collected pressure signal, and it was first smoothed using a Savitzky-Golay filter. The pressure signals have obvious offset, even at the minimum. Therefore, the pressure measured is higher than the actual value. The baseline drift of the pressure signals from various channels was corrected separately using the method of adaptive iteratively reweighted penalized least squares (airPLS) [35]. The target of airPLS is to reduce the cost function:

$$Q = F + \lambda R = (x - b)' W (x - b) + \lambda \|Db\|^2 \qquad (1)$$

where x denotes the pressure signal, b denotes the baseline drift, Db represents the second-order difference sequence of b, and W is a diagonal matrix with weight w_i on its diagonal.

During the iteration process, w_i can be obtained adaptively by the following expression:

$$w_i^t = \begin{cases} 0, & x_i \geq b_i^{t-1} \\ exp(\dfrac{t\left(x_i - b_i^{t-1}\right)}{|d^t|}), & x_i < b_i^{t-1} \end{cases} \qquad (2)$$

where t denotes the iterative step and d^t represents the sum of the negative elements of the difference values between x_i and b_i^{t-1} in the t iteration. Figure 4(a) shows an example of our data processed using airPLS. And Figure 4(b) shows the actual gait data of different parts of the feet after data preprocessing.

B. FEATURE EXTRACTION

The preprocessed data can be used for feature extraction. The sensor array can be simplified to a 4 × 12 matrix, and the distribution is indicated in Figure 5(a). Take the right foot
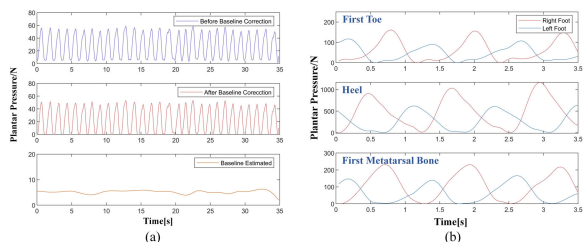
FIGURE 4. (a) Comparison of the signal from the 13th channel of the right foot before the baseline correction (purple line) and after that (red line). The Savitzky-Golay filter processes the signal. (b) The actual gait data of different parts of the feet after data preprocessing.

as an example; the pressure matrix shows typical situations during walking, which also proves that our insoles measure the plantar pressure distribution effectively (Figure 5(b)).

Each time-pressure sequence is segmented into steps before the feature extraction. The plantar surface was split into eight areas of interest (Figure 6(a)): medial toes, lateral toes, first to second metatarsal head, third to fifth metatarsal head, medial arch, lateral arch, medial heel, and lateral heel. Each area reaches its maximum at a different time (Figure 6(b)). Time characteristics include contact time (CT, the period when the pressure is higher than 10% of the maximum force) of each area per step (vectors of 2×8). Considering the velocity difference among subjects, all the time features were scaled to the percentage of a gait circle. Pressure characteristics include the maximum force (MF) of each area per step (vectors of 2×8), which are normalized to body weight. The definition of the characteristics is shown in Figure 6(c). The features extracted have 32 dimensions in summary, and the initial and terminal steps were eliminated from the data. Therefore, the number of valid steps varies from one to another.

C. SPLIT THE TRAIN/TEST DATA
After completing the feature extraction using the described technique, the data were further split into the train and test datasets. Considering that the gait data from the same subjects are intrinsically similar, the data of one subject is included only in the train dataset or test dataset. 12 Knee OA and 17 control subjects were chosen randomly to train the model (29/40), while six Knee OA and five control subjects were included in the test dataset (11/40). The ratio of the train/test dataset is roughly 7:3. And the ratios of Knee OA/control in the train and test datasets are roughly at 1:2. The gait test ultimately produced 3285 valid steps. After the data were split, 2300 and 985 steps were included in the train and test datasets, respectively.

D. TRAIN AND FIT THE MODEL
1) RANDOM FOREST
Random Forest is an effective ensemble learning technique for classification, especially for imbalanced datasets. Random Forest uses Bootstrap to sample the dataset. The Decision Tree is the base estimator for Random Forest, and all base estimators vote for the classification.

TABLE 3. The results of different ML models and features selected.

Features Selected	Accuracy (%)		
	Random Forest	AdaBoost	SVM
Time Features	80.30	83.15	83.55
Pressure Features	88.82	91.84	92.15
Both Features	90.94	92.95	93.15

TABLE 4. The performances of five models on the test dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	AUC
AdaBoost[1]	91.84	94.04	89.25	0.97
SVM[2]	92.15	92.92	91.23	0.97
Random Forest[3]	90.84	93.60	86.24	0.97
AdaBoost[4]	92.95	95.03	89.08	0.98
SVM[5]	93.15	92.39	92.79	0.98

[1] Features: Pressure Features, number of weak learners: 400, Maximal number of decision splits: 10, weak learner: DT.
[2] Features: Pressure Features, Kernel: Gaussian, C=6, gamma=4.
[3] Features: Both Features, number of weak learners: 200, Maximal number of decision splits: 25, weak learner: DT.
[4] Features: Both Features, number of weak learners: 100, Maximal number of decision splits: 18, weak learner: DT.
[5] Features: Both Features, Kernel: Gaussian, C=8, gamma=6.

TABLE 5. The performances of five models on the test dataset.

Method	Measurement Instrument	Algorithm	Accuracy
[10]	sEMG Sensors	Deep Neural Network, K-Nearest Neighbor	91.3%
[11]	Miniature Accelerometer	Maximum Posterior Probability Criterion	91.76%
[17]	Eight Cameras, Two Force Plates	Principal Component Analysis	71.8%
[20]	Commercial Insoles with 8 Force Sensors	Decision Tree	92.86%
[20]	3-D Ground Reaction Force Measurements	Nearest Neighbor	91.00%

2) ADABOOST
AdaBoost is also an ensemble learning algorithm based on the Decision Tree. The weights of base estimators were learned, and the model gives the results by weighted majority voting. AdaBoost performs outstandingly in dealing with the over-fitting problem. Random Forest samples from the dataset without weighing while AdaBoost does.

3) SVM
SVM is an effective algorithm for classification in high-dimensional spaces. The SVM maps data to points in space and tries to find a hyperplane to classify various types of
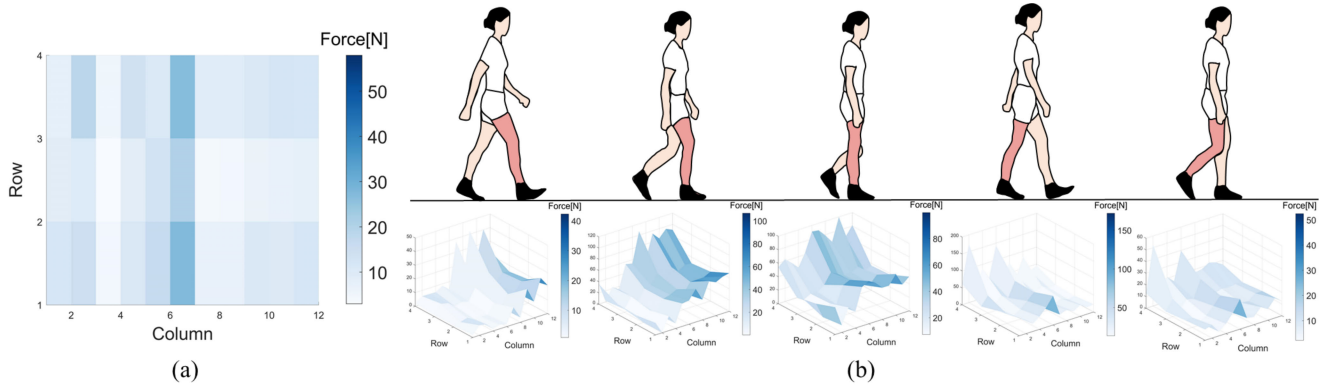
FIGURE 5. (a) The simplified pressure matrix of sensors' distribution. (b) Three-dimensional (3D) pressure matrix of the right foot during walking.
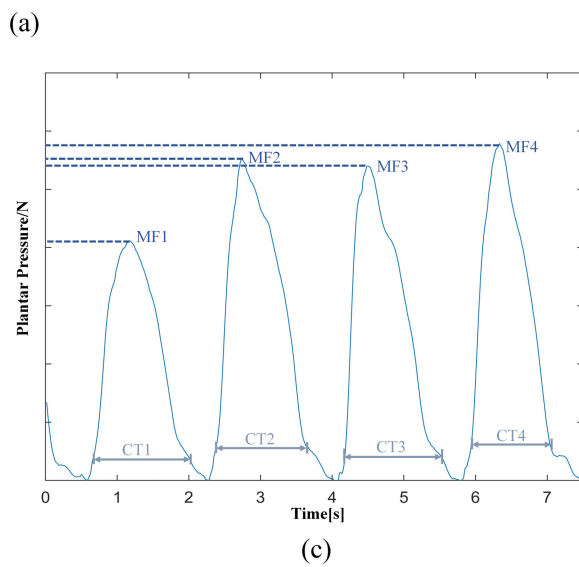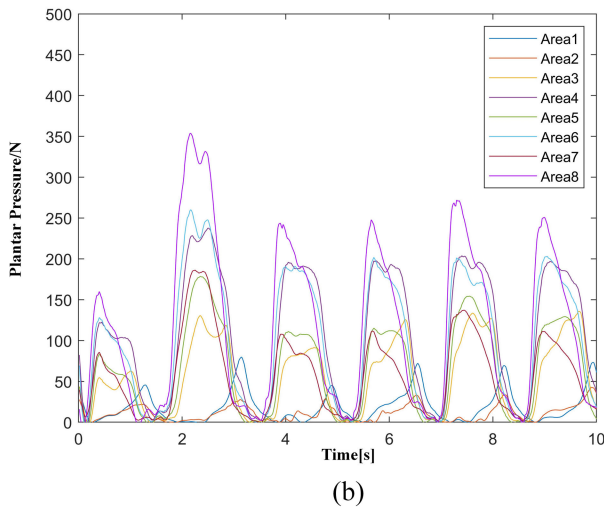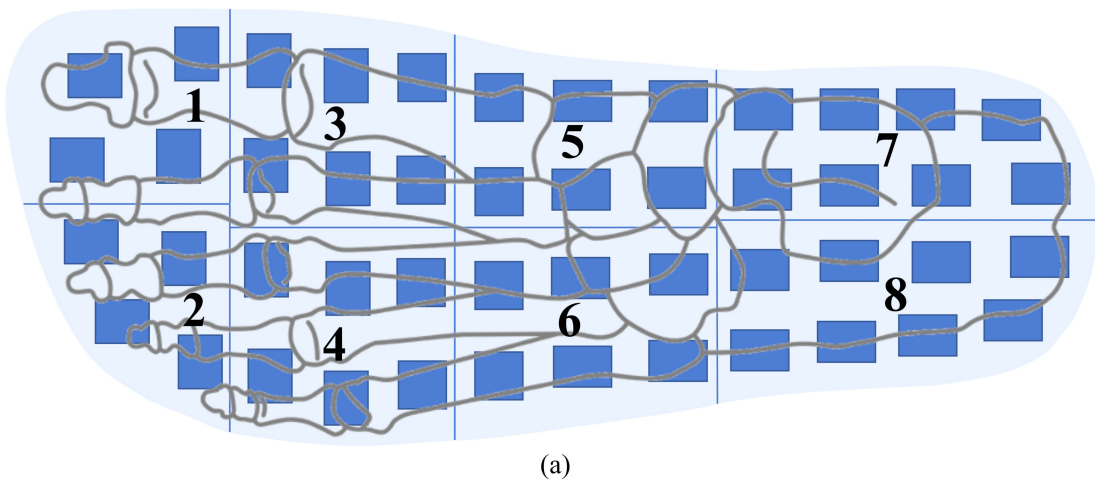

FIGURE 6. (a) The area split of the plantar surface: 1- hallux, 2- lateral toes, 3- first to second metatarsal head, 4- third to fifth metatarsal head, 5- medial arch, 6- lateral arch, 7- medial heel, 8- lateral heel. (b) The time-pressure sequence of each area. (c) Definition of the features extracted.

points. Kernel functions include the polynomial, the Gaussian, and the sigmoid kernels.

IV. RESULTS

A. COMPARISON OF ALGORITHMS AND FEATURES

To analyze the classification efficiency of the extracted characteristics, we made three selections on the parameters: only

time feature, only pressure feature, and time and pressure feature. Parameters are selected to train the Random Forest, AdaBoost, and SVM models separately. The accuracy results of various models are shown in Table 3 in detail. The Receiver Operating Characteristic Curve (ROC) with Area Under Curve (AUC) is an effective indicator to assess
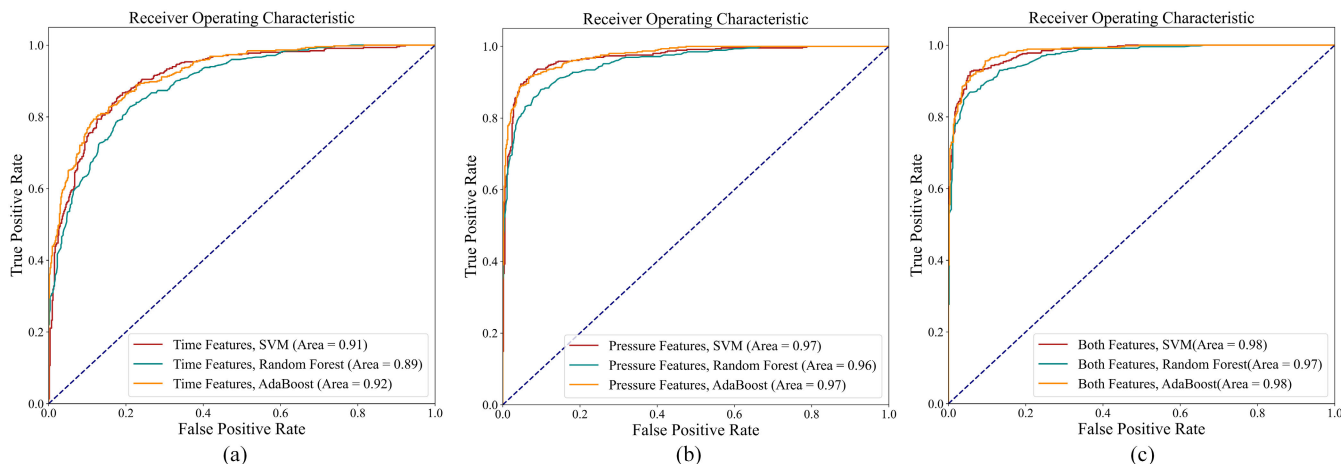
FIGURE 7. (a) The ROC of Random Forest (green line, AUC=0.89), AdaBoost (orange line, AUC=0.92) and SVM (red line, AUC=0.91) based on time features. (b) The ROC of Random Forest (AUC=0.96), AdaBoost (AUC=0.97) and SVM (AUC=0.97) based on pressure features. (c) The ROC of Random Forest (AUC=0.97), AdaBoost (AUC=0.98) and SVM (AUC=0.98) based on both features.
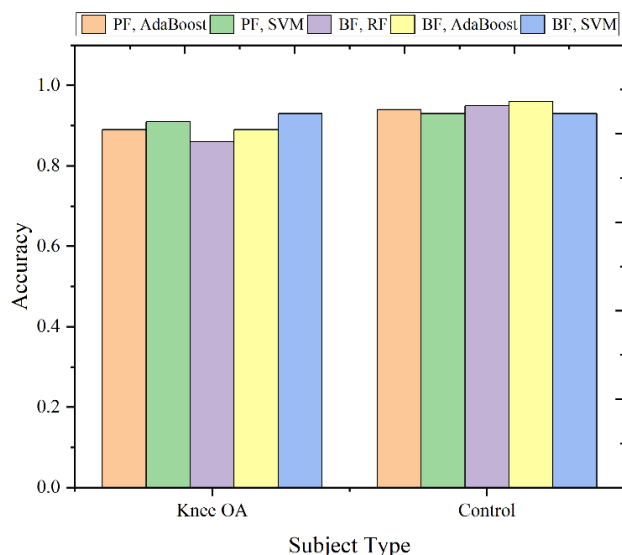
FIGURE 8. A comparison of the classification accuracy among the five models is shown (PF: Pressure Features, BF: Both Features, RF: Random Forest).

the classification model. Figure 7 compares Random Forest, AdaBoost, and SVM based on various parameters.

Five of the nine models above perform better, with accuracy higher than 90% and AUC higher than 0.97. Further comparison of classification accuracy is shown in Figure 8; and detailed results is shown in Table 4.

Reaching the best accuracy, the SVM model also performs well in the balance of the classification. Although the AdaBoost classifier achieves the highest precision, we hope for a higher recall rate regarding disease recognition. Therefore, we choose the SVM model with the Gaussian kernel as

the base classifier, reaching an accuracy of 93.15%, a precision of 92.39%, and a recall of 92.79%.

B. PREDICTION MODEL

For this application, a prediction model is proposed. When a patient walks on the floor with our insoles, the signals can be obtained and transferred into the computer for further processing. The data experience the same process as the train and test datasets do, then the features are inputted into the SVM classifier loaded previously. The predictions for every step are integrated to give the final output, which includes the predicted class and its possibility. The class that is predicted the more will be considered the final class, and the potential can be expressed:

$$possibility = 1 - \frac{W}{S} \tag{3}$$

where S represents the number of steps in one test and W denotes the number of predicted results that vary from the final class. This possibility can be considered the degree of confidence in the result. The prediction model can fully use the information obtained to give an accurate estimation. The whole process for the actual application is shown in Figure 9.

V. DISCUSSION

In summary, this study introduced an accurate and reliable method that can be easily applied in the home or clinical settings in the diagnosis of Knee OA. A pair of insoles embedded with a 48-channel piezoresistive array for each can obtain the time-pressure sequences as the subject walks. The SVM model exhibits an accuracy of 93.15%, a precision of 92.39%, and a recall of 92.79% based on the data obtained from one step. Automatic diagnosis has essential implications in the medical field. Although imaging examination is still the gold standard for diagnosis, the insole gait analysis exhibits the advantages of mobility and convenience, making it more
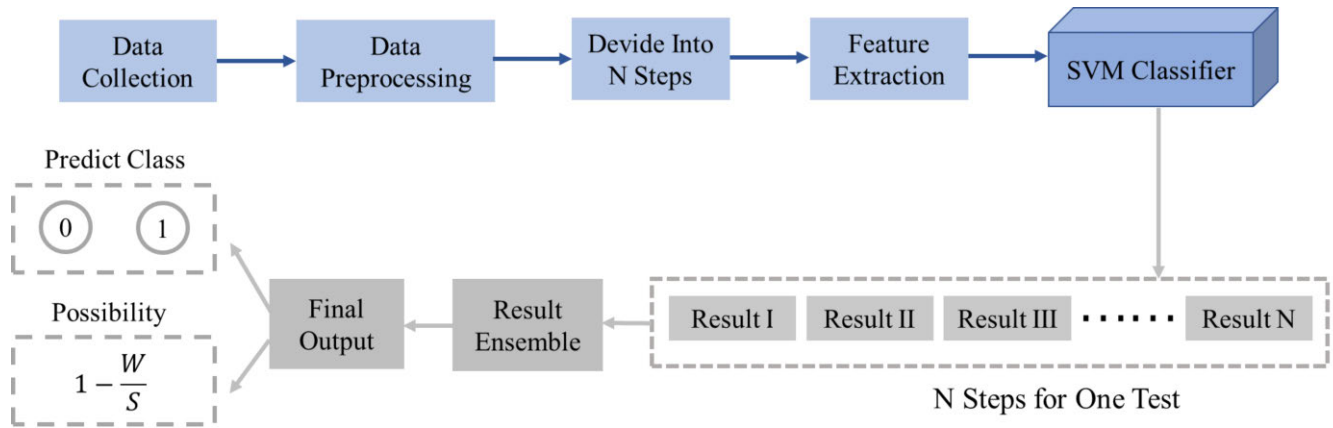
FIGURE 9. The process of the prediction model for the application.

feasible in screening and long-term monitoring of Knee OA. With deep research, an insole gait analysis will play an essential role in assessment, classification, and clinical outcome prediction.

Our work was compared with the previous research on Knee OA detection based on the dynamic gait analysis, shown in Table 5. Our work was based on a piezoresistive measurement instrument we developed ourselves, which has the advantages of being accurate, low-cost, wearable, and portable. Our insoles can cover more area of the foot and easily obtain the number of step data in a single walking test. And parameters for the recognition model are based on foot biomechanics, with contact time and maximum force extracted from the processed data. We got a promotion for the classification and efficiency compared to previous work. Taking all steps into account, our ensemble model can decrease accidental errors during the measuring process. The prediction result with the possibility also gives auxiliary diagnostic information for doctors to estimate the subject's situation.

For subjects in the test dataset, the error rate for individuals (the rate of predicted results different from the final class) is 4.81% on average, which means that around one-twentieth steps in all subject steps in a single test are classified in the wrong class. After the results integrating, only one control subject (1/11) was wrongly classified as a patient with Knee OA, so the classification accuracy for individuals was 90.90%. It has been reported that over one-third of people over 50 years are diagnosed with radiographic knee OA, many of which were asymptomatic [36]. In this study, all control subjects were over 40 years old. The altered gait owing to the early stage of Knee OA might be found in control subjects. Further radiological examination is required to validate the hypothesis that this control subject is actually a patient with Knee OA.

Regarding gender, female subjects have a higher error rate of 7.39%, compared with that of male subjects of 5.54%. The reason can be explained using the same size of the insoles,

which might be oversized for female subjects so that some sensors were not fully pressed. For our future work, we will change our sensor distribution and the size of the sensors to overcome such weaknesses.

In addition to gender, there are still many other possible factors affecting the accuracy of the gait analysis. First, the symptoms of Knee OA fluctuate. The pain may worsen with increased activity or alterations in the weather [37]. Therefore, a single randomized test may be insufficient for diagnosis. In this study, our countermeasure was that all subjects were tested in a defined time (2:00–3:00 p.m.), which made the activity situation and the testing environment similar for each subject. Second, shoe type and ground conditions may also affect the analysis results [38]. Although these conditions are uniform in this study, more data are needed for further practical application. Third, to the best of our knowledge, since gait analysis technology has not been applied on a large scale, there are insufficient data to show that age, body height, and comorbidities significantly affect gait features in middle-aged and elderly people. However, these confounders remain of interest [27]. Fourth, some particular cases, such as an accidental unbalance stride, may cause unusual signals during the gait test [32]. We attempted to exclude the abnormal data by setting thresholds and manually selecting them. However, this cannot wholly prevent misinformation. The relatively small sample size in this study limits further examination on the above-mentioned factors. The factors were controlled as consistently as possible between subjects with and without Knee OA to ensure the credibility of the results. We plan to conduct further designed studies to validate and improve this technique's generalizability.

Despite the limitations, we believe that this gait monitoring method is of great application value. It exhibits satisfactory accuracy in diagnosing Knee OA. It is an important addition to clinical diagnosis and teaching as a dynamic auxiliary test. Through further data analysis, differences between subjects with and without Knee OA can be found, which is meaningful for understanding disease progression and

biomechanical mechanisms. Previous studies have discovered that even in the early KOA stages, patients show some abnormal gait characteristics, which may be a risk factor for disease progression [21], [39]. Therefore, abnormal gait can be diagnosed and corrected early by gait monitoring, decreasing the cost of treating Knee OA. Furthermore, plantar pressure measurement can be added to developing multi-sensor information fusion method. Visual, audio, and EMG signals have been combined effectively recently [27], [40], [41]. We also tried applying plantar pressure measurement together with EMG signals [32]. With further research, long-term health monitoring and home rehabilitation based on these methods will be well developed in the future.

VI. CONCLUSION

In this article, a piezoresistive-based gait monitoring method for the recognition of Knee OA was presented. A pair of insoles embedded with a 48-channel piezoresistive array for each was developed and was applied to conduct walking experiments for patients with Knee OA and control subjects. The time-pressure sequences obtained by the insoles are transformed from the electrical signal, and features are extracted to train the models. On the test dataset, the SVM model attains an accuracy of 93.15%, a precision of 92.39%, and a recall of 92.79% on the steps. We also proposed a prediction model for the application that aggregates all the results in one test and provides a more accurate result, with 90.90% accuracy for individuals in the test dataset. This recognition technique is mobile, wearable, low-cost, and convenient, which can help find possible patients with Knee OA and benefit their early diagnosis and treatment. Our work fills the vacancy of wearable instruments for the recognition of patients with Knee OA and provides ideas for intelligent healthcare. In our future work, we will try finding more characteristics to classify and try new piezoresistive materials to obtain better accuracy while applying our instrument and prediction model in the actual scene.

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REFERENCES

[1] N. Arden and M. C. Nevitt, "Osteoarthritis: Epidemiology," *Best Pract. Res. Clin. Rheumatol.*, vol. 20, no. 1, pp. 3–25, 2006, doi: 10.1016/j.berh.2005.09.007.

[2] A. Tiulpin, S. Klein, S. M. A. Bierma-Zeinstra, J. Thevenot, E. Rahtu, J. V. Meurs, E. H. G. Oei, and S. Saarakkala, "Multimodal machine learning-based knee osteoarthritis progression prediction from plain radiographs and clinical data," *Sci. Rep.*, vol. 9, no. 1, p. 20038, Dec. 2019, doi: 10.1038/s41598-019-56527-3.

[3] A. D. Woolf, "Global burden of osteoarthritis and musculoskeletal diseases," *BMC Musculoskelet Disord*, vol. 16, no. Suppl 1, 2015, Art. no. S3, doi: 10.1186/1471-2474-16-S1-S3.

[4] L. Arendt-Nielsen, H. Nie, M. B. Laursen, B. S. Laursen, P. Madeleine, O. H. Simonsen, and T. Graven-Nielsen, "Sensitization in patients with painful knee osteoarthritis," *Pain*, vol. 149, no. 3, pp. 573–581, Jun. 2010, doi: 10.1016/j.pain.2010.04.003.

[5] C. M. Phan, T. M. Link, G. Blumenkrantz, T. C. Dunn, M. D. Ries, L. S. Steinbach, and S. Majumdar, "MR imaging findings in the followup of patients with different stages of knee osteoarthritis and the correlation with clinical symptoms," *Eur. Radiol.*, vol. 16, no. 3, pp. 608–618, Feb. 2006.

[6] I. Saito, K. Okada, T. Nishi, M. Wakasa, A. Saito, K. Sugawara, Y. Takahashi, and K. Kinoshita, "Foot pressure pattern and its correlation with knee range of motion limitations for individuals with medial knee osteoarthritis," *Arch. Phys. Med. Rehabil.*, vol. 94, no. 12, pp. 2502–2508, Dec. 2013, doi: 10.1016/j.apmr.2013.07.017.

[7] Z. Zhang, L. Wang, K. Hu, and Y. Liu, "Characteristics of plantar loads during walking in patients with knee osteoarthritis," *Med. Sci. Monitor*, vol. 23, pp. 5714–5719, Dec. 2017, doi: 10.12659/msm.905136.

[8] A. Vijayvargiya, P. L. Singh, S. M. Verma, R. Kumar, and S. Bansal, "Chapter 12—Performance comparison analysis of different classifier for early detection of knee osteoarthritis," in *Sensors for Health Monitoring*, vol. 5, N. Dey, J. Chaki, and R. Kumar Eds. Cambridge, MA, USA: Academic Press, 2019, pp. 243–257.

[9] L. Parisi and N. RaviChandran, "Evolutionary denoising-based machine learning for detecting knee disorders," *Neural Process. Lett.*, vol. 52, no. 3, pp. 2565–2581, Dec. 2020, doi: 10.1007/s11063-020-10361-1.

[10] J. D. D. Uwisengeyimana and T. Ibrikci, "Diagnosing knee osteoarthritis using artificial neural networks and deep learning," *Biomed. Statist. Informat.*, vol. 2, no. 3, p. 95, 2017.

[11] Y. Zheng, Y. Wang, J. Liu, H. Jiang, and Q. Yue, "Knee joint vibration signal classification algorithm based on machine learning," *Neural Comput. Appl.*, vol. 33, no. 3, pp. 985–995, Feb. 2021, doi: 10.1007/s00521-020-05370-z.

[12] R. Gong, K. Hase, H. Goto, K. Yoshioka, and S. Ota, "Knee osteoarthritis detection based on the combination of empirical mode decomposition and wavelet analysis," *J. Biomech. Sci. Eng.*, vol. 15, no. 3, 2020, Art. no. 2000017, doi: 10.1299/jbse.20-00017.

[13] K. Kręcisz and D. Bączkowicz, "Analysis and multiclass classification of pathological knee joints using vibroarthrographic signals," *Comput. Methods Programs Biomed.* vol. 154, pp. 37–44, Feb. 2018, doi: https://doi.org/10.1016/j.cmpb.2017.10.027.

[14] N. Befrui, J. Elsner, A. Flesser, J. Huvanandana, O. Jarrousse, T. N. Le, M. Müller, W. H. W. Schulze, S. Taing, and S. Weidert, "Vibroarthrography for early detection of knee osteoarthritis using normalized frequency features," *Med. Biol. Eng. Comput.*, vol. 56, no. 8, pp. 1499–1514, Aug. 2018, doi: 10.1007/s11517-018-1785-4.

[15] S. B. Kwon, H.-S. Han, M. C. Lee, H. C. Kim, Y. Ku, and D. H. Ro, "Machine learning-based automatic classification of knee osteoarthritis severity using gait data and radiographic images," *IEEE Access*, vol. 8, pp. 120597–120603, 2020, doi: 10.1109/access.2020.3006335.

[16] N. Mezghani, S. Husse, K. Boivin, K. Turcot, R. Aissaoui, N. Hagemeister, and J. A. De Guise, "Automatic classification of asymptomatic and osteoarthritis knee gait patterns using kinematic data features and the nearest neighbor classifier," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 3, pp. 1230–1232, Mar. 2008, doi: 10.1109/TBME.2007.905388.

[17] R. N. Kirkwood, R. A. Resende, C. Magalhães, H. A. Gomes, S. A. Mingoti, and R. F. Sampaio, "Application of principal component analysis on gait kinematics in elderly women with knee osteoarthritis," *Brazilian J. Phys. Therapy*, vol. 15, pp. 52–58, Feb. 2011.

[18] M. Kotti, L. D. Duffell, A. A. Faisal, and A. H. McGregor, "Detecting knee osteoarthritis and its discriminating parameters using random forests," *Med. Eng. Phys.*, vol. 43, pp. 19–29, May 2017, doi: 10.1016/j.medengphy.2017.02.004.

[19] E. Anzai, K. Yamashita, Y. Matsunaga, M. Sato, H. B. Menz, and Y. Ohta, "Foot posture and dynamic foot function in people with and without knee osteoarthritis," *Osteoarthritis Cartilage*, vol. 25, pp. 131–132, Apr. 2017, doi: 10.1016/j.joca.2017.02.211.

[20] M. Munoz-Organero, C. Littlewood, J. Parker, L. Powell, C. Grindell, and S. Mawson, "Identification of walking strategies of people with osteoarthritis of the knee using insole pressure sensors," *IEEE Sensors J.*, vol. 17, no. 12, pp. 3909–3920, Jun. 2017, doi: 10.1109/jsen.2017.2696303.

[21] T. Liikavainio, J. Isolehto, H. J. Helminen, J. Perttunen, V. Lepola, I. Kiviranta, J. P. Arokoski, and P. V. Komi, "Loading and gait symmetry during level and stair walking in asymptomatic subjects with knee osteoarthritis: Importance of quadriceps femoris in reducing impact force during heel strike?" *Knee*, vol. 14, no. 3, pp. 8–231, Jun. 2007, doi: 10.1016/j.knee.2007.03.001.

[22] K. M. Leitch, T. B. Birmingham, I. C. Jones, J. R. Giffin, and T. R. Jenkyn, "In-shoe plantar pressure measurements for patients with knee osteoarthritis: Reliability and effects of lateral heel wedges," *Gait Posture*, vol. 34, no. 3, pp. 391–396, Jul. 2011, doi: 10.1016/j.gaitpost.2011.06.008.

[23] S. Gao, "Insole systems for disease diagnosis and rehabilitation," *TechRxiv*, Feb. 2022, doi: 10.36227/techrxiv.19200425.v1.

[24] S. Gao, J. Chen, Y. Dai, and B. Hu, "Gait detection technologies," in *Wearable Systems Based Gait Monitoring and Analysis*. Cham, Switzerland: Springer, 2022, pp. 27–100.

[25] X. Zeng, L. Ma, Z. Lin, W. Huang, Z. Huang, Y. Zhang, and C. Mao, "Relationship between Kellgren-Lawrence score and 3D kinematic gait analysis of patients with medial knee osteoarthritis using a new gait system," *Sci. Rep.*, vol. 7, no. 1, p. 4080, Jun. 2017, doi: 10.1038/s41598-017-04390-5.

[26] M. Yamada and K. Nagamune, "A development of measurement system for foot pressure by using optical force sensors," in *Proc. World Autom. Congr. (WAC)*, Jun. 2018, pp. 1–5.

[27] S. Qiu, H. Zhao, N. Jiang, Z. Wang, L. Liu, Y. An, H. Zhao, X. Miao, R. Liu, and G. Fortino, "Multi-sensor information fusion based on machine learning for real applications in human activity recognition: State-of-the-art and research challenges," (in English), *Inform Fusion*, vol. 80, pp. 241–265, Apr. 2022, doi: 10.1016/j.inffus.2021.11.006.

[28] J. Chen, M. Zhang, Y. Dai, Y. Xie, W. Tian, L. Xu, and S. Gao, "A force-voltage responsivity stabilization method for piezoelectric-based insole gait analysis for high detection accuracy in health monitoring," *Int. J. Distrib. Sensor Netw.*, vol. 16, no. 3, 2020, Art. no. 1550147720905441, doi: 10.1177/1550147720905441.

[29] Y. Dai, Y. Xie, J. Chen, S. Kang, L. Xu, and S. Gao, "A lamination-based piezoelectric insole gait analysis system for massive production for internet-of-health things," *Int. J. Distrib. Sensor Netw.*, vol. 16, no. 3, 2020, Art. no. 1550147720905431, doi: 10.1177/1550147720905431.

[30] J. Chen, Y. Dai, S. Kang, L. Xu, and S. Gao, "A concurrent plantar stress sensing and energy harvesting technique by piezoelectric insole device and rectifying circuitry," *IEEE Sensors J.*, vol. 21, no. 23, pp. 26364–26372, Dec. 2021, doi: 10.1109/JSEN.2021.3064235.

[31] S. Gao, J.-L. Chen, Y.-N. Dai, R. Wang, S.-B. Kang, and L.-J. Xu, "Piezoelectric-based insole force sensing for gait analysis in the Internet of health things," *IEEE Consum. Electron. Mag.*, vol. 10, no. 1, pp. 39–44, Jan. 2021, doi: 10.1109/MCE.2020.2986828.

[32] Y. Zhao, J. Wang, Y. Zhang, H. Liu, Z. Chen, Y. Lu, Y. Dai, L. Xu, and S. Gao, "Flexible and wearable EMG and PSD sensors enabled locomotion mode recognition for IoHT-based in-home rehabilitation," *IEEE Sensors J.*, vol. 21, no. 23, pp. 26311–26319, Dec. 2021, doi: 10.1109/Jsen.2021.3058429.

[33] I. F. Petersson, T. Boegard, T. Saxne, A. J. Silman, and B. Svensson, "Radiographic osteoarthritis of the knee classified by the Ahlback and Kellgren & Lawrence systems for the tibiofemoral joint in people aged 35–54 years with chronic knee pain," *Ann Rheum Dis*, vol. 56, no. 8, pp. 6–493, Aug. 1997, doi: 10.1136/ard.56.8.493.

[34] E. Sutkowska, K. Sutkowski, M. Sokolowski, E. Franek, and S. Dragan, "Distribution of the highest plantar pressure regions in patients with diabetes and its association with peripheral neuropathy, gender, age, and BMI: One centre study," *J. Diabetes Res.*, vol. 2019, pp. 1–11, Jul. 2019.

[35] Z. M. Zhang, S. Chen, and Y. Z. Liang, "Baseline correction using adaptive iteratively reweighted penalized least squares," *Analyst*, vol. 135, no. 5, pp. 46–1138, May 2010, doi: 10.1039/b922045c.

[36] E. Laxafoss, S. Jacobsen, K. K. Gosvig, and S. Sonne-Holm, "Case definitions of knee osteoarthritis in 4,151 unselected subjects: Relevance for epidemiological studies," *Skeletal Radiol.*, vol. 39, no. 9, pp. 859–866, Sep. 2010.

[37] Y. Xue, Y. Chen, D. Jiang, L. Wang, X. Wang, M. Li, Y. Wu, M. Zhang, J. Pang, H. Zhan, Y. Zheng, D. Ding, and Y. Cao, "Self-reported weather sensitivity is associated with clinical symptoms and structural abnormalities in patients with knee osteoarthritis: A cross-sectional study," *Rheumatology Therapy*, vol. 8, no. 3, pp. 1405–1417, Sep. 2021, doi: 10.1007/s40744-021-00340-w.

[38] M. Teymouri, F. Halabchi, M. Mirshahi, M. A. Mansournia, A. M. Ahranjani, and A. Sadeghi, "Comparison of plantar pressure distribution between three different shoes and three common movements in futsal," *PLoS ONE*, vol. 12, no. 10, Oct. 2017, Art. no. e0187359, doi: 10.1371/journal.pone.0187359.

[39] L. Sharma, J. Song, D. T. Felson, S. Cahue, E. Shamiyeh, and D. D. Dunlop, "The role of knee alignment in disease progression and functional decline in knee osteoarthritis," (in English), *Jama*, vol. 286, no. 2, pp. 188–195, Jul. 2001, doi: 10.1001/jama.286.2.188.

[40] G. Marta, F. Simona, C. Andrea, B. Dario, S. Stefano, V. Federico, B. Marco, B. Francesco, M. Stefano, and P. Alessandra, "Wearable biofeedback suit to promote and monitor aquatic exercises: A feasibility study," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 4, pp. 1219–1231, Apr. 2020, doi: 10.1109/Tim.2019.2911756.

[41] Y. Celik, S. Stuart, W. Woo, E. Sejdic, and A. Godfrey, "Multi-modal gait: A wearable, algorithm and data fusion approach for clinical and free-living assessment," *Inf. Fusion*, vol. 78, pp. 57–70, Feb. 2022, doi: 10.1016/j.inffus.2021.09.016.

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