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A Non-Contact Paraparesis Detection Technique Based on 1D-CNN

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ABSTRACT In clinical practice, doctors are using bedside tests to assist in the diagnosis of paraparesis. The disadvantage is that it depends on the doctor's clinical experience and the supervisor's judgment. Therefore, there is an urgent need for an objective and efficient diagnostic equipment. With the rapid development of wireless technology, ubiquitous RF signals become a promising sensing technology. In this study, we propose a non-contact wireless sensing method based on RF signals to detect paraparesis. Our system can reduce the burden on doctors and improve work efficiency. Outlier filters and wavelet hard threshold decomposition are used to filter the wireless signal. A 1D-CNN model is designed to automatically extract valid features and classifications. The results analyze in two bedside tests, our system perform efficiently and accurately patient screening with suspected paraparesis. This provide more effective guidance and assistance for further treatment. The proposed method has an average accuracy of 99.4% and 98.5% in the Barre test and Mingazzini test respectively.

INDEX TERMS Barre, CNN, lower limb paraparesis, Mingazzini, wireless sensing.

I. INTRODUCTION

Paraparesis may be caused by a variety of neuromuscular diseases. For example, cerebral palsy, stroke, Charcot-Marie-Tooth disease and so on. Paraparesis can lead to the weakening or disappearance of the patient's voluntary movements, causing serious psychological harm to the patient, bring a great burden to families and society, and affecting the quality of life of the patient. Generally speaking, doctors can do paraparesis tests to diagnose mild paraparesis when they are not sure about the general method used. However, such clinical examinations often have disadvantages such as subjectivity and low sensitivity. An accurate diagnosis is a prerequisite for providing a reasonable treatment or rehabilitation plan for the patient [1]. With the rapid development of wireless technology, a non-contact diagnostic paraparesis scheme based on wireless channel information (WCI) is proposed in this paper. This method is efficient and fast, and can provide reference for the diagnosis of lower limb paraparesis. In addition, it is also encouraging because patients do not be required professional skills to install and can use the system at home and in the community.

In the clinical practice, the lower limb drop test is used t in diagnosis of paraparesis. The Barre test and the Mingazzini test are also often used. In 2015, Hirose [2] reviewed a large number of literatures and expounded the importance of Barre test and Mingazzini test in clinical practice of paraparesis. It is concluded that the diagnosis of paraparesis is based on the observation of premature leg droop in the leg test. Teitelbaum *et al.* [3] performed a Barre test, a Mingazzini test, a finger tap, a forearm tumbling, a segmental force, and an anterior cyclone drift in 180 patients with no lesions in the area of exercise. They found that the Barre test, finger tapping and Mingazzini test were the most reliable and time-effective tests for detecting subtle motor injuries. This exercise detection has high sensitivity and detection efficiency and can be used as a powerful tool for emergency doctors when assessing patients with possible minor sports injuries. Landon-Cardinal *et al.* [4] found that combining some functional tests and endurance tests (Barre/Mingazzini) is a reliable, time-saving method for assessing patients with active myositis in everyday clinical practice. Early prognosis and functional recovery of lower

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limb functional disorders has been an important issue in clinical practice. Smania *et al.* [5] collected data on active ankle flexion and Mingazzini movements in 53 patients with stroke. These simple bedside tests are based on previous studies of lower extremity paraparesis, and the Barre test and the Mingazzini test are considered to be the basis for assessing paraparesis of the lower extremities.

As described in [2], in order to find a slight limb paraparesis, the so-called Barre test and Mingazzini test have been routinely applied in the clinic. The Barre test or Mingazzini test is positive if it shows symptoms of paralysis or paraparesis, and if they are absent, it is negative. Feil *et al.* [6] found that these two bedside test combinations are the most sensitive and time-saving methods for detecting minor lesions in the lower extremities. This simple, non-invasive test is a valuable diagnostic tool for clinical diagnosis. Bed side tests are described as follows:

Mingazzini test: The Mingazzini experiment performed in this paper is referred to [3]. The experiment required the participants to lie on their backs. The hips are bent at an angle of 75 to 80° and the knees are held at an angle of 100° to level the calf and bed. The ankle is dorsiflexed 90°. A healthy person can maintain this posture for a long time. However, after a few seconds, the person whose limbs could not be supported and drooped showed an early paraparesis.

Barre test: Participants try to keep their muscles relaxed. The subjects are instructed to lie prone with their legs flexed at right angles. After a few seconds, the affected leg will gradually drop. The test is positive and indicate early paraparesis.

In this paper, Mingazzini test and Barre test are used to aid in the detection of paraparesis. We design a set of OFDM transceivers. Transmitters and receivers are placed on both sides of the participants. The center frequency of the transmitted signal is 5.32 GHz. During the above bedside test, we use wireless sensing technology to continuously monitor the movement of participants. The movement of lower limbs affects the transmission of wireless signals. We obtain the frequency response of the wireless channel caused by lower limb motion through channel estimation in the receiver. The wireless channel information (WCI) records all motion information during the participant's bedside test. It is expressed as the phase information and amplitude information of each subcarrier. Then, wavelet filtering technology and artificial intelligence algorithm are used for data preprocessing and recognition.

Wavelet decomposition has obvious advantages such as low entropy, multi-resolution and de-correlation in de-noising. Its results have been widely used in image processing, speech synthesis, and seismic exploration. In practical engineering applications, most signals are non-stationary and contain many spikes and mutations. Signal de-noising by wavelet can well preserve the abrupt part of the useful signal. In this paper, the appropriate wavelet and wavelet decomposition level are selected to filter the wireless signal.

Traditional machine learning and neural network can solve many problems successfully in some fields. But the main problem of traditional machine learning is insufficient generalization ability. That is, the model has been trained to recognize samples that have not been seen. This disadvantage is not obvious when dealing with low-dimensional problems. Once dealing with high-dimensional data, the difficulty of solving generalization problem increases exponentially. Deep learning can solve this problem. Convolutional neural networks play an important role in deep learning. Enlightened by the biological visual nervous system, CNN has designed sparsely connected neural networks in the field of image processing, and medical image processing in the field of speech recognition has achieved great success. CNN combines several convolution layers and sampling layers to process the input signal, and then establishes the mapping between the full connection layer and the target. The input signal is extracted by convolution filter, and the input signal is subsampled in pooling layer, so that useful information can be retained while reducing the amount of data. Our system continuously monitors the channel changes affected by the paraparesis detection performed by volunteers. In fact, the data we collected are time series signals of one dimension. Therefore, we use 1D-CNN to "feature learning" for Wireless Channel Information (WCI).

The main contribution of this article:

1) To the best of our knowledge, this is the first work to detect paraparesis using non-contact wireless sensing technology. We used the wireless channel information from the physical layer to monitor volunteers' lower limb activities during the implementation of the clinical test.
2) We propose a 1-D CNN deep neural network to diagnose whether participants are positive in the sputum test. And compared to other models, the model is proved to have higher performance.
3) The experimental results show that the average accuracy of our system in the Barre test and Mingazzini test is 99.4% and 98.5% respectively. Our system can be used as a screening tool for people suspected of having paraparesis of the lower extremities. Therefore, non-contact detection technology will play an important role in the early detection and treatment of diseases.

The rest of this article is organized as follows. Section 2, introduces previous work on wireless sensing. Section 3, proposed system is presented, Section 4, experimental setup is discussed. Section 5 methods applied for diagnosis of Paraparesis. Section 6, Results and evaluate the performance of the proposed system. Section 7. Finally, the conclusions are summarized.

II. PREVIOUS WORK ON WIRELESS SENSING

In recent years, with the rapid development of wireless technology. The ubiquitous RF signal has become a novel sensing technology and has attracted the attention of many researchers. During wireless signal propagation, moving objects can cause wireless signal reflection, multipath effects, or frequency selective fading. Combined with signal processing technology and machine learning, researchers can use RF signals to implement gesture recognition [7], [8], intrusion detection [8], [9], and respiratory detection [11], [12]. Most current wireless sensing solutions are based on channel detection technology or frequency modulated continuous wave radar. Adib *et al.* [13] proposed a Vital-radio system based on low-power FM continuous wave. The system can remotely monitor the vital signs of up to 3 people, including breathing and heartbeat, in a non-contact manner. Khan *et al.* [14] built a USRP-based OFDM transmitter and receiver that can acquire wireless channel information. The platform can be used for human activity monitoring, security, medical monitoring and so on. Wang *et al.* [15] designed a universal deep learning framework for IoT RF sensing. They used the proposed framework for indoor positioning, activity identification, health care, etc., and received exciting results.

III. PROPOSED SYSTEM

In this research, non-contact Paraparesis clinical diagnosis system based on three main stages. In first stage data is collected through wireless sensing technology. When we obtained enough WCI data through a lot of bedside testing. In the next stage data preprocessing through Hampel and wavelet decomposition are used to process signal waveform, and data calibration is used to rapidly increase sample data. In final stage, the processed data are input into CNN classifier to detect paralysis as shown in Fig. 1.

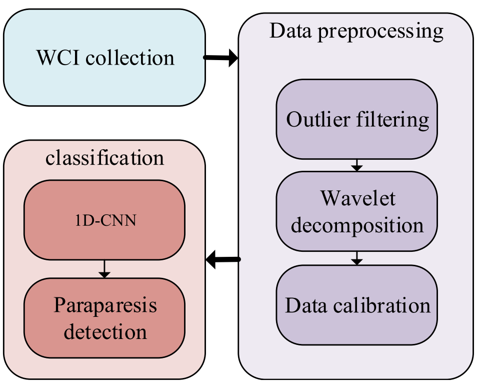

FIGURE 1. Workflow of the proposed system.

IV. EXPERIMENTS

The Barre test and Mingazzini test for the detection of lower extremity paraparesis were performed in our laboratory (7m × 4m) as shown in Fig. 2. Our system is a single input multiple output (SIMO) system. The wireless signal transmitter consists of an industrial control system and an omnidirectional antenna. The receiver consists of an industrial control system and three omnidirectional antennas. The distance between transmitter and receiver is 2m. The transmitter transmits at a rate of 100 packets per second. The transmitter transmits the wireless signal with the center frequency

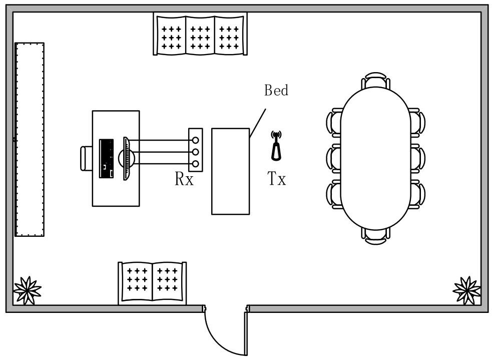

FIGURE 2. Experimental setup.

of 5.32GHz at the transmitting power of 15dBm. We monitor each bedside test for 20s. We place the antenna close to the lower limb in order to effectively capture the wireless signal disturbance caused by the leg movement. In this study, our focus is on the feasibility of detecting paraparesis; therefore, simulated patients were considered. Before the experiment, we fully informed the participants of all relevant matters and contents of the clinical experiment. All participants received rigorous training by watching videos of bedside tests and reading related literature [2]–[6]. 10 people (9 males and 1 female) participate in the experiment. During the experiment, 5 volunteers simulate patient behavior and perform the experiment in strict accordance with the patient's behavior as described in [3]. Each volunteer performed 20 times Barre and Mingazzini test, respectively. The other 5 volunteers perform the bedside test normally.

V. METHODLOGY

Following methods and approaches are applied to Barre test and Mingazzini test for the detection of lower extremity paraparesis.

A. DATA COLLECTION

In wireless communication systems, the received signals fluctuate over time due to the shadow effect caused by obstacle blocking between the receiver and the transmitter. The wireless channel information is used to evaluate the quality of the transmitted signal and the reliability of the transmission. Specifically, the wireless channel information includes information such as multipath fading, scattering, reflection, and other information during propagation of the signal between the transmitter and the receiver.

$$Y = H \times X + N \tag{1}$$

where H is used to characterize the channel matrix of the channel frequency response (CFR) of the communication link. The channel matrix H contains amplitude information and phase information of a carrier acquired by the receiver through the measurement channel. The signal is modulated using orthogonal frequency division in the IEEE 802.11n/a/c standard. Specifically, high-speed serial data (20 MHz) converts 56 parallel low-speed data streams, each data corresponding to one sub-carrier, and each sub-carrier is orthogonal to each other. A pair of transceiver antenna pairs in our wireless sensing system can acquire 30 subcarriers. Therefore, the channel frequency response of each pair of transceiver antennas is:

$$\mathrm{H} = [\mathrm{h}_1, \mathrm{h}_2, \mathrm{h}_3 \ldots h_n] \tag{2}$$

where h_n is the CFR of the $\mathrm{n_{th}}$ subcarrier, and each h_n is a complex number containing the amplitude and phase information of the sub-carrier. The amplitude value is obtained by calculating the absolute value of h_n, and the inverse tangent of h_n is calculated to obtain the phase. The Fig.3 shows the amplitude and phase of the subcarriers measured in the absence of any moving objects:

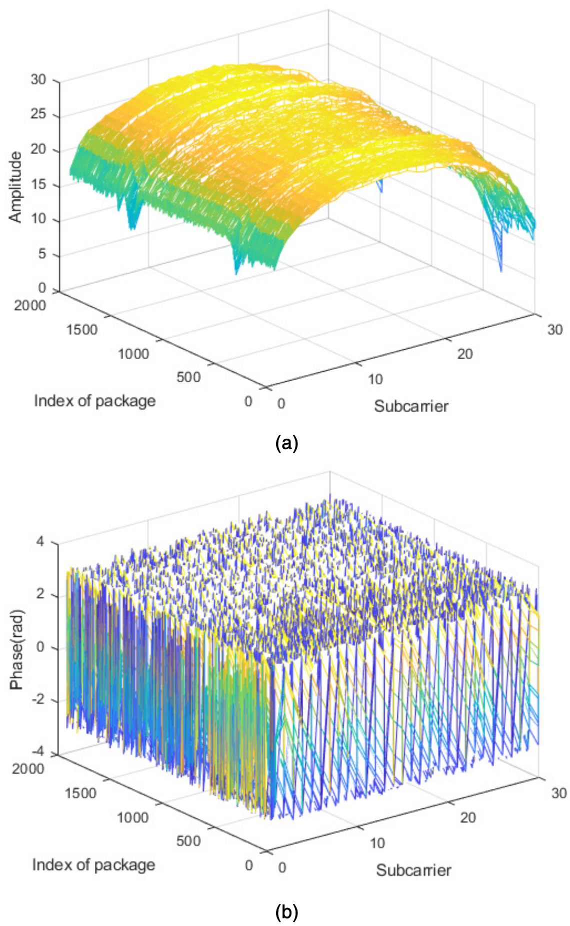

FIGURE 3. (a) Row amplitude information of WCI. (b) The row phase information of WCI.

From Fig. 3(b), we find a lot of noise in phase data. The reason is that carrier frequency offset (CFO), sampling frequency offset (SFO), packet detection delay (PDD) [8] and so on are caused by the asynchronization of receiver and transmitter and the imperfection of hardware. These reasons lead to phase information distortion cannot be used directly. In this paper, we only use the robust amplitude information of WCI which is used to diagnose lower limb paraparesis.

B. DATA PREPROCESSING

During continuous channel monitoring, there will be outliers which are not caused by participants' actions. In the non-linear time series, Hampel filter uses appropriate local values to replace the detected abnormal values. In this paper, the variance of three sigma statistical rules with strong robustness to outliers is used. As shown in the Fig. 4. the abnormal point marked by the white square is not caused by the volunteer's knee flexion.

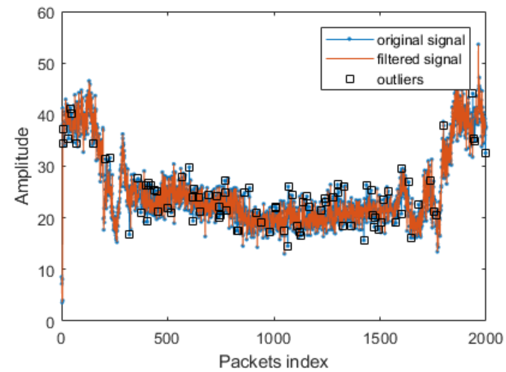

FIGURE 4. Outlier removal on amplitude.

After the outlier detection, the amplitude data still has noise. These noises tend is of high frequency signals, however, we focus on the low frequency information of non-stationary time series. Compared with the traditional filtering method, the wavelet filtering method has unique advantages such as time-frequency localization and multi-resolution. In addition, wavelet decomposition preserves the signal mutation while de-noising. In this paper, the wavelet decomposition is selected to de-noise the amplitude data after the outlier processing. We use sym6 wavelets with better symmetry and regularity. In general, after wavelet decomposition, the coefficient of the signal is greater than the coefficient of noise. The appropriate number λ is used as the threshold. A decomposition coefficient greater than the critical threshold λ is caused by the signal and is retained [16]. Then reconstruct with wavelet coefficients. The threshold function is expressed as follows:

$$w_{new} = \begin{cases} w & |w| \geq \lambda \\ 0 & |w| < \lambda \end{cases} \tag{3}$$

where w_{new} and w are wavelet transform coefficients before and after wavelet denoising, respectively. The threshold λ is set to $\sigma^2 \log(M)$, where $\sigma = \frac{|media(|w_{j,k}|)|}{0.6745}$ is an estimate of the noise level and M is the length of the signal. When the absolute value of wavelet coefficient is less than the given threshold value, it is set to 0; when it is greater than the threshold value, it remains unchanged. Finally, reconstruction of the signal can achieve the purpose of signal denoising. We use wavelet hard threshold filtering to filter the signal processing by the outliers. The results of the three-level wavelet decomposition filtering of 5 Mingazzini data are shown in the Fig.5. We find that the filtered signal become clean.

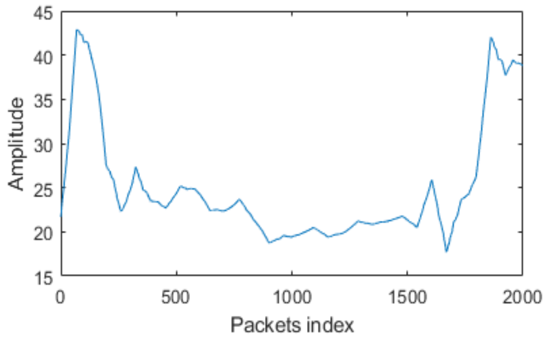

FIGURE 5. Waveform after wavelet decomposition.

As mentioned above in data collection, we collect 30 subcarriers per pair of transmit and receive antennas. However, we found that the received 30 subcarrier amplitude data are not consistent. The main reason is that there are different DC components. In this paper, the amplitude data is calibrated by subtracting its DC component from each subcarrier. The result is shown in the Fig.6 (b) we find that the amplitude data of all carriers after calibration is consistent.

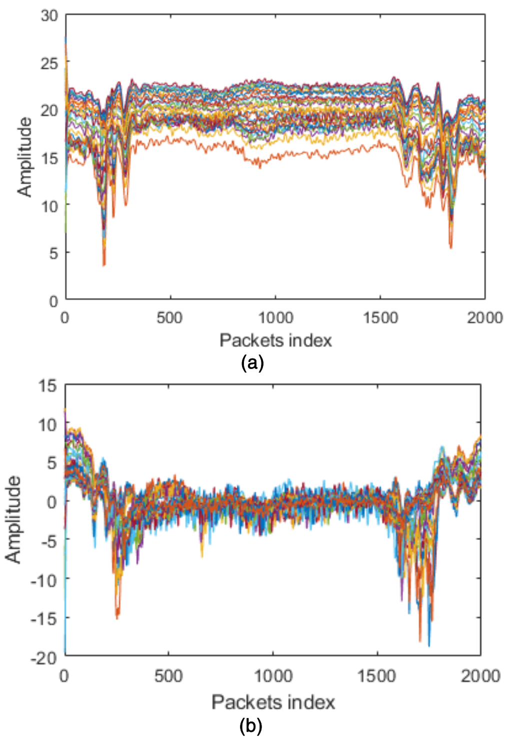

FIGURE 6. (a) Un-calibrated amplitude information. (b) Calibrated amplitude information.

It is encouraging that all the waveforms of the pre-processed carriers are similar. Therefore, we treat each subcarrier as a sample in our SIMO (1×3) system. In one experiment we could get $3*30 = 90$ samples, where 3 represents the number of receive antennas and 30 represents the number of subcarriers. In addition, five simulated paraparesis volunteers and five healthy volunteers were tested in each experiment, and each volunteer was tested 20 times in each paraparesis test. Therefore, we can get $5*90*20 = 9000$ samples in each test. We can quickly increase our data through this strategy. All sample data are shown in the Table 1. In each clinical test sample, we chose 70% of the data for training and the remaining 30% for testing.

TABLE 1. Distribution of data for each bedside test.

	Number of abnormal samples	Number of normal samples
Barre test	9000	9000
Mingazzini test	9000	9000
Total	18000	18000

C. CLASSIFICATION

The convolutional layer is the most important part of CNN and completes most of the calculations. It is also the key to making convolutional neural networks successful in the fields of image recognition and speech recognition. The conv layer is generated by convoluting the previous layer with W kernels of receptive filed R and depth c which is equal to the number of channels in the previous layer. The convolution layer Y=$\{y_{lm}$: $1 \leq l \leq W, 1 \leq m \leq W\}$ can be obtained by convolving X= $\{x_{i,j} : 1 \leq i \leq c, 1 \leq j \leq z\}$, where c is the number of channels in the layer and z is the number of neurons in each channel, with W kernels w^l, $l = 1, 2, \ldots, W$ each of receptive field R and depth c,

$$y_{lm} = \sum\nolimits_{d=1}^{c} \sum\nolimits_{e=1}^{R} w_{d,e}^{l} x_{d,e+m} \tag{4}$$

where W is the number of channels in this layer and m is the number of neurons in each channel [17]. The convolution result introduces nonlinearity through the activation function. The activation function used in this paper is Relu.

The pooling layer is often inserted behind the convolution layer. The purpose of this layer is to reduce the number of features, thus reducing the parameters required by the network, the amount of calculation of network training, and also avoiding over-fitting. In practical application, the most commonly used method is maximum pooling.

The fully connected layer integrates highly abstracted features after multiple convolutions. When solving multi-classification problems, the softmax layer is enabled to output the probability of each class.

The proposed CNN model for detecting lower limb paraparesis is shown in the Fig. 7. The first layer is the input layer, whose input signal is the wireless sensor signal after calibration. The proposed network architecture consists of two convolution layers and two pooling layers. In the first convolution layer, we use 100 filters with 10 lengths and output 100 feature maps after convolution. In order to introduce nonlinearity, sparsity, and greatly increase the training speed, all the feature maps are corrected by Relu. The pooled layer

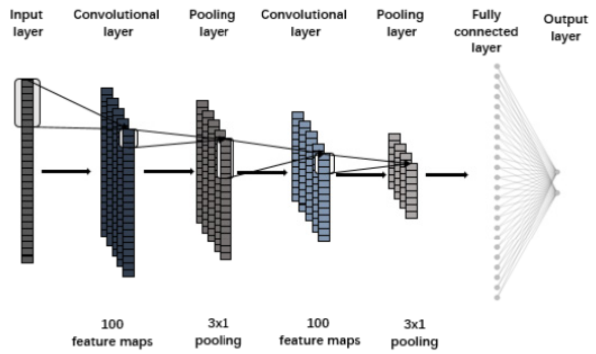

FIGURE 7. The architecture of the proposed model.

(3×1) after the activation layer subsamples the corrected feature map, reducing the amount of data while retaining useful information. To reduce the risk of overfitting, we randomly discard some of the neurons with a 50% probability after the sampling layer and the fully connected layer. The second convolutional layer and the pooled layer are identical in structure to the first convolutional layer and repeat the process of the first convolutional layer and the pooled layer. In the fifth layer of the model is a fully connected layer, which integrates highly abstracted features after multiple detections and maps them into a 1-D vector. The output layer is the number of classes to be identified. In this study, we aimed to screen patients suspected of paralyzed lower limbs. So the output layer has two neurons. The probability of each class output by the softmax function. Thereby detecting whether the patient has early paraparesis. In this study, the cross-entropy loss function and the Adam algorithm are used to update the weight of the neural network [18]. The Adam optimization algorithm is an extension of the stochastic gradient algorithm. Adam designs an adaptive learning rate for different parameters by calculating the first moment and second order estimation of the gradient. Compared to the stochastic gradient algorithm, Adam requires less resources and makes the model converge faster. The number of iterations in training is set to 50 small batches of data 25. Among them, the number of training samples and test samples are 70% and 30% of the total number of samples.

VI. RESULTS AND DISCUSSION

A. BARRE TEST RESULTS

All volunteers performed the task as described in Section I. The Fig. 8. (a) shows the amplitude data of the channel frequency response of the normal participants that were continuously acquired during the experiment. At the beginning of the experiment, the volunteers prone and flexed their knees to a vertical position and maintained this posture. It can be clearly seen that the amplitude of the carrier wave in the red frame region exhibits short-term up and down fluctuations which shows that our system detects knee flexion. And because the normal participants can maintain this pose for a long time, the amplitude data in the green frame area remains stable.

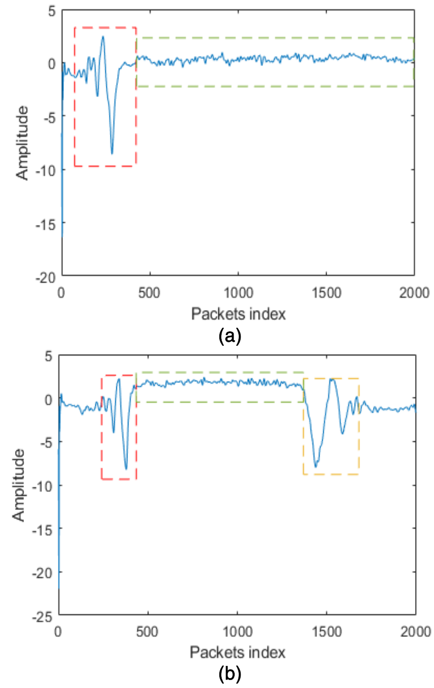

FIGURE 8. (a) WCI amplitude of the healthy participant Barre test. (b) WCI amplitude of the patient Barre test.

The Fig.8 (b) shows the carrier amplitude data collected from participants with simulated paraparesis. As described above, when the knee flexion is performed, the moving lower limb is regarded as an obstacle and hinders the propagation of the wireless signal. When the received signal collected by the receiving end receives interference, the amplitude will fluctuate up and down. Participants hold the pose for several seconds, during which there is no moving object between the receiver and the transmitter. Therefore, this state can be considered as a static environment. There is no interference in the process of wireless signal transmission, so the amplitude in the green frame region remains stable. However, patients with lower limb paraparesis could not maintain this posture for a long time and the affected limbs will gradually sag. As shown by the amplitude of the yellow box area, the drop of the affected limb interferes with the propagation of wireless signals, resulting in amplitude fluctuations.

B. MINGAZZINI TEST RESULTS

All volunteers performed the experiment as described in Section I. The wireless signal information of the healthy participant performing the Mingazzini test collected by the receiver is shown in the Fig. 9(a). At the beginning of the implementation of the Minkasini test, the Volunteers lie on their backs and bend their knees at right angles. As shown in the red area, the knee bend affects the propagation of wireless signals resulting in short fluctuations in amplitude. Normal volunteers can maintain this knee posture for a longer period of time. Therefore, the subsequent waveform will remain stationary as shown in the green box area. At the beginning of the

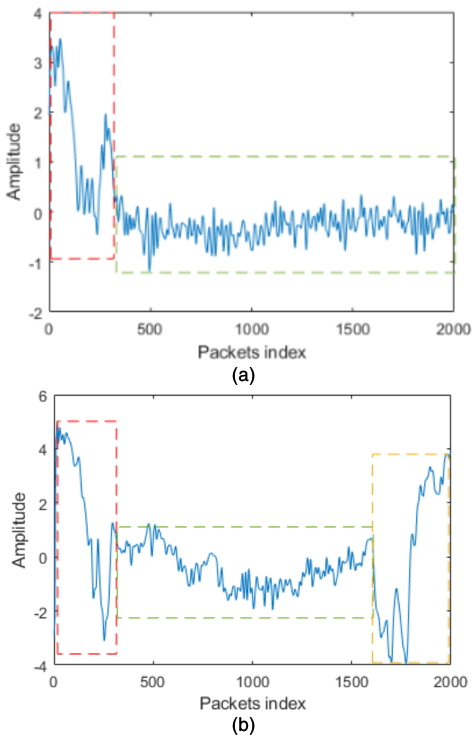

FIGURE 9. **(a) WCI amplitude of the health participant Mingazzini test. (b) WCI amplitude of the patient Mingazzini test.**

detection of lower extremity palsy volunteers. The wireless signal fluctuates due to the influence of the knee flexion. The volunteer then keeps the position for a few seconds. The static state does not interfere with wireless signal, so the carrier amplitude in the green frame region does not fluctuate significantly. However, after a period of time, the lower limb paraparesis patients could not maintain this posture for a long time, making the lower leg of the paralytic side gradually fall. This behavior results in a change in the wireless channel leading to a short fluctuation in the amplitude as shown in the yellow box.

C. INFLUENCE OF WAVELET DECOMPOSITION LEVEL

This paper uses wavelet decomposition to de-noise wireless signals. Wavelet decomposition has non-smoothness that causes the wavelet to remove the noise of the signal, preserving the abrupt portion of the wanted signal, regardless of their frequency range. Wavelet decomposition level is an important factor affecting the result of noise removal. Therefore, it is important to determine decomposition level. If the number of decomposition layers is too small, the decomposed signal may still contain noise. The results of the experiments are not satisfactory. Similarly, if the number of decomposition layers is too large, the filtering effect is improved and the amount of calculation is increased. The most important point is that it filters out signals with a large number of features. Excessive number of decomposition layers can also lead to a decrease in recognition accuracy. The wavelet decomposition of the collected wireless signals from first to fourth levels is carried out in this paper. Our goal is to determine the appropriate decomposition level that will help diagnose lower limb paraparesis. The Fig.10. Shows the effect of different wavelet decomposition levels on the performance of the proposed CNN model:

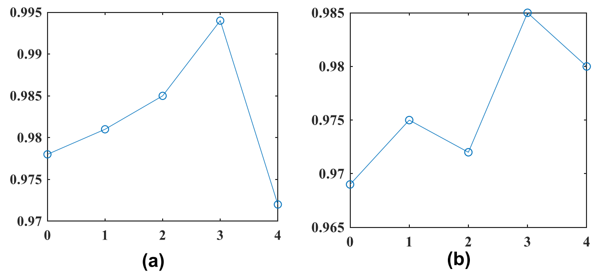

FIGURE 10. **(a) Comparison of different wavelet decomposition levels in Barre datasets. (b) Comparison of different wavelet decomposition levels in Mingazzini dataset.**

The Fig.9 shows the variation of the Barre test and Mingazzini test detection accuracy with the number of wavelet decomposition layers. From the above figure, the results show that with the increase of wavelet decomposition levels, the accuracy of paraparesis detection increases, and then decreases with the increase of decomposition levels. Moreover, we found that the proposed model can achieve higher accuracy when processing the original experimental data. The average accuracy of the Barre and Mingazzini experiments was 97.8% and 96.9%, respectively. Our CNN model uses three-level wavelet decomposition to demonstrate the high performance of Mingazzini and Barre experimental data. The accuracy in the Barre test is 99.4%, and the average accuracy of the Mingazzini test is 98.5%.

D. COMPARED WITH MACHINE LEARNING

In order to evaluate the performance of our proposed CNN model, Machine learning algorithms such as SVM and KNN are used to compare with our model. The performance metrics recall, precision, accuracy and F-measure.

In the SVM-based classification model, hyperparameter optimization is the key to achieving high accuracy. Therefore, we performed a grid search regularization parameter (C)1 to 100 and gamma parameter (γ) 0.001 to 1 to obtain the lowest error rate. The radial basis function (RBF) is used as the kernel function of SVM. K-NN is a commonly used method of supervised learning. It classifies based on the similarity between the predicted object and the known object. The key to the K-NN algorithm is to choose a suitable K value, which is the neighboring number. In this study, the value range of K value is [1, 10]. We traverse all values in the value range of K value to minimize the error rate of the result.

In this paper, in order to objectively compare the performance of each model, all classifiers process the same patient data and normal person data. Specifically, we did not extract features from the preprocessed data. The preprocessed data is directly imported into each classifier. It is worth emphasizing that the advantage of our proposed model is that it does not

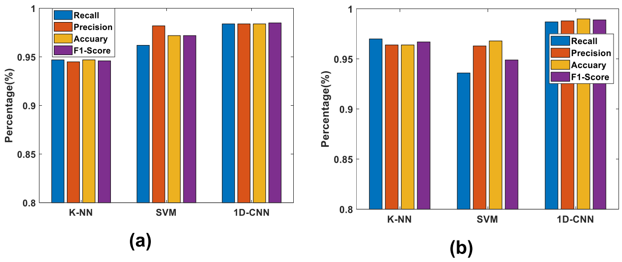

FIGURE 11. **(a) Comparative analysis of Barre dataset. (b) Comparative analysis of Mingazzini dataset.**

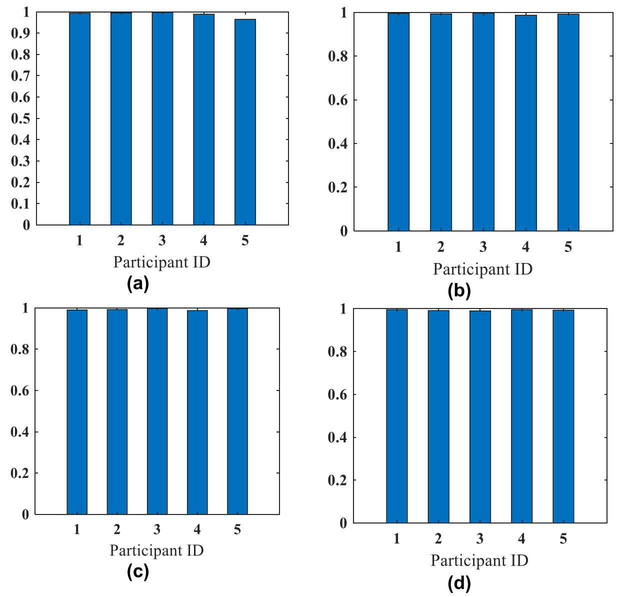

FIGURE 12. **(a) Diagnostic accuracy of patients in the Barre test. (b) Diagnostic accuracy of healthy people in the Barre test. (c) Diagnostic accuracy of patients in the Mingazzini test. (d) Diagnostic accuracy of healthy people in the Mingazzini test.**

require artificial feature extraction. The Fig.11 shows the results of each classifier. We can find that the performance of the CNN-based classification model proposed in this paper is better than other classification models. In the Barre test data, k-NN has the poorest classification performance. In contrast, compared with the K-NN classification model, the recall rate of the CNN-based classification model increased by 3.7%, the precision increased by 4%, the accuracy increased by 3.7 %, and F1-score increased by 3.9%. In the Mingazzini test, the SVM-based classification model shows the poorest performance. Compared with the CNN model proposed in this paper, the recall rate of our model increased by 5.1%, precision increased by 3%, accuracy increased by 4%, and F1-score increased by 4%. All in all, the proposed model has better performance on various performance indicators and is more suitable for detecting lower limb paraparesis than other models.

E. PARTICIPANT DIAGNOSIS

In this experiment, there were 10 participants, 5 are lower extremity patients and 5 are healthy participants. All participants conducted the Barre test and the Mingazzini test. The Fig.12 show the results of the classification of the positive and negative participants in the Barre test. The (c) and (d) show the results of the classification of the positive and negative participants performing the Mingazzini test. The average accuracy of the proposed model for the positive participants who performed the Barre experiment is 98%, and the average recognition accuracy for healthy participants is 99.3%. The average accuracy of the proposed model for the Mingazzini test is 99.2%. The average recognition accuracy for healthy people is 99.2%. The experimental results are encouraging that the average accuracy of our system is almost 99%.

VII. CONCLUSION

Lower limb paraparesis affects patient standing posture and walking style etc. and also effect quality of life of the patient. It can cause serious harm to the patient's mind and bring a small burden to the family and society. In this article, early detection of paraparesis of the lower extremities to improve the accuracy of prediction. A non-contact detection system driven based on wireless channel information is designed to diagnose paraparesis. We obtain the wireless channel information of the physical layer through the continuous detection channel. Make full use of the advantages of WCI to perceive the information of volunteers' buckling behavior. The noise corresponding to the channel is removed using a Hampel filter and a wavelet hard threshold filter. In particular, the advantages of OFDM multi-carrier modulation are used to rapidly increase data samples. In order to improve the accuracy of recognition, 1D-CNN is used to automatically extract features of wireless signals and detect paraparesis.

The experimental results show that our method is reliable and accurate. Two tests (Barre/Mingazzini), which are widely used in the clinic, are considered in this paper. The experimental results show that the accuracy of the original data recognition after 3 levels of wavelet hard threshold filtering is 2% higher than that of the original data. The performance we obtained in our experiments is a sensitivity of 99% and a specificity of 98%. Compared with other state-of-the-art models, the proposed 1D-CNN model has improved performance by 3%.

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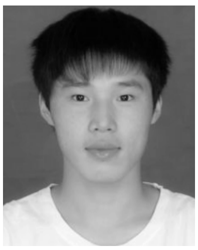

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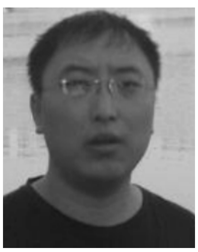

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