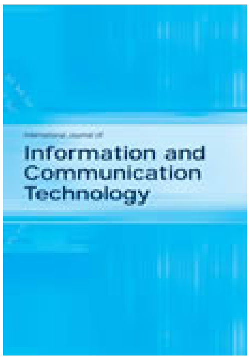

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Xiong Huan

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Patient signal feature extraction technology for intelligent nursing bed

Xiong Huan

School of Medical,
Nanchang Institute of Technology,
Nanchang, China
Email: xh18070111002@163.com

Abstract: The signal of intelligent nursing bed is easily polluted by noise during the acquisition process, so it is necessary to study the noise reduction processing algorithm of the signal. This paper uses deep learning to optimise the bowel sound feature extractor, takes the edge computing system with GPU configuration as the implementation object, and proposes a pre-defecation prediction based on Mobilenet-RF. This paper proposes to use the random forest algorithm to classify the bowel sound signal features extracted by Mobilenet to achieve early classification and prediction of patient characteristics. Furthermore, this paper uses bowel sound signal processing and pre-defecation prediction as cases for experimental analysis. The experimental results show that the Mobilenet-RF algorithm proposed in this paper achieves the highest accuracy of 95.68%. Then, this paper verifies the generalisation ability of the model through multi-dataset experiments, proving the superiority of using random forest for classification.

Keywords: intelligent nursing bed; patient; signals; feature extraction.

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Biographical notes: Xiong Huan is a Master of Education and a Lecturer. She is currently serves as the Director of Academic Affairs at Nanchang Institute of Technology. Her research focuses on nursing education, teaching reform, and interdisciplinary medical fields. She has published papers in core journals, including 'Effects of lobeline alkaloids on the migratory activity of fibroblasts in the cerebral artery adventitia of hypertensive rats' *(Journal of Nanchang University, Medical Science Edition*). She has participated in three provincial and ministerial-level research projects, covering topics such as fragmented information-based teaching and virtual reality technology in nursing education. Recognised for her teaching innovation, she has guided students to win national awards. With experience in both clinical nursing and higher education, she emphasizes the integration of educational technology and interdisciplinary collaboration.

1 Introduction

With the development of sensor technology, Internet technology, and big data technology, people have put forward higher requirements for intelligent and service-oriented medical equipment, which has triggered the technological innovation of unfettered monitoring of physiological signals in the field of medical equipment. At present, many smart devices have been developed. For example, the vest-type respiratory induction plethysmography system uses a pulsed time-sharing excitation solution to solve the contradiction between high signal-to-noise ratio and low system power consumption in polysomnography respiratory induction plethysmography technology. A wristwatch-type sleep monitoring system uses the relationship between blood oxygen saturation, pulse wave, manual signal and respiratory events to indirectly monitor abnormal sleep time and sleep quality. In addition, the belt-type multi-parameter physiological signal monitoring system uses accelerometers, microphones, pressure sensors, ECG electrodes and other acquisition technologies to realise the detection and identification of coughing events during sleep (Akbari et al., 2021). The cap-type wearable physiological information monitoring system monitors physiological information based on reflective blood oxygen, pulse, temperature, acceleration, altitude and other acquisition technologies. Its characteristic is that it uses the same-side blood oxygen transmission monitoring method to replace the bilateral fingernail-type blood oxygen meter monitoring. The micro-motion sensitive mattress-type sleep monitoring system integrates the key technologies of the above systems to achieve long-term, unrestrained sleep monitoring (Che et al., 2021). However, the unrestrained intelligent nursing bed makes up for the shortcomings of the four systems other than the micro-motion sensitive mattress sleep monitoring system, which cause a sense of restraint on the human body and are not conducive to long-term monitoring. In addition, it eliminates the phenomenon of belt slipping and connector falling off during the polysomnography monitoring of respiratory signals. This new unrestrained extraction method can replace the polysomnography, a device that measures the gold standard of sleep quality, to monitor sleep quality, which is convenient for hospitals and families to use, and has a great role in promoting patients' sleep quality monitoring and family healthcare for sleep quality (Harpale and Bairagi, 2021).

It is of great significance to study a signal characteristic analysis equipment combined with intelligent nursing bed for patients' disease treatment and nursing. The project studied a intelligent nursing bed sleep quality monitoring system that can extract physiological signals without restraint. It can monitor respiratory signals and identify sleep apnea, and use the motor of the intelligent nursing bed to generate weak head movements to improve airway obstruction. By identifying the lying position and monitoring the time the same lying position is maintained, it controls the intelligent nursing bed to assist in turning over, getting up, etc., to reduce the occurrence of bedsores and reduce the difficulty of nursing staff. At the same time, it can monitor the activities in the bed and realise the identification and alarm of emergency situations such as accidental falls and no vital signs (Hassan et al., 2023). Furthermore, using physiological signals such as respiration, heart rate, and blood pressure to monitor sleep quality is of great significance for preventing the occurrence of major diseases and improving people's quality of life. Intelligent nursing beds can achieve comprehensive monitoring functions using fewer types of sensors, which has certain engineering application value in reducing the manufacturing cost of intelligent nursing beds. At the same time, the developed smart bed monitoring system can effectively reduce the nursing workload of the guardian and realise the detection of the elderly and disabled people. Different from the remote active monitoring of network cameras, it provides timely and effective protection for the safety of the guardian (Jiang et al., 2021).

This paper uses deep learning to optimise the bowel sound feature extractor, takes the edge computing system with GPU configuration as the implementation object, and proposes a pre-defecation prediction based on Mobilenet-RF, so as to improve the signal processing efficiency and prediction classification effect of intelligent nursing bed. In response to the needs of patient feature extraction, this paper proposes two different bowel sound noise reduction methods based on multi-level filtering and wavelet threshold, and uses different noise reduction methods to process the same bowel sound signal. Moreover, this paper proposes to use the random forest algorithm to classify the bowel sound signal features extracted by Mobilenet to achieve early classification and prediction of patient characteristics. Furthermore, this paper uses bowel sound signal processing and pre-defecation prediction as cases for experimental analysis.

2 Related works

2.1 Research status of intelligent nursing bed

The research of intelligent nursing bed can be divided into two categories, one is to study the mechanical structure design to assist patients in completing various actions, and the other is to use sensor technology to detect the physiological state of human body, including physiological parameters such as heart rate, body temperature and posture movements, etc.

With the development and progress of technology, multifunctional nursing beds have gradually appeared and developed rapidly, and have begun to occupy a place in medical care in developed countries. The intelligent nursing bed produced by Metrocare Company of the United States realises the functions of automatic back lifting and leg bending through the mechanism and size design of each part of the bed body, and has good comfort and functionality. The multifunctional rehabilitation nursing bed produced by HILL-ROM Company of the United States is driven by multiple motors, adopts a detachable guardrail design, and is equipped with functions such as button control, voice control and liquid crystal display. Meanwhile, the original back-knee linkage function can be very convenient to adjust the lying posture of the human body (Khare et al., 2021). Under normal state, the nursing bed is no different from the general nursing bed, but when necessary, the bed body can be changed into a wheelchair, which saves the trouble of frequent movement of the user and facilitates the activities of the patient.

In terms of using sensor technology to monitor the physiological state of the human body, in response to the temperature changes during the formation of pressure sores, Khare et al. (2021) designed an intelligent low-cost nursing bed based on FPGA (piezoelectric material sensor) by monitoring the temperature changes between the patient and the nursing bed. It can be used to prevent pressure sores in clinical environments. Loh et al. (2022) designed an intelligent nursing bed robot system that uses mattresses covered with sensors to recognise posture, which is used for health status monitoring and rehabilitation status evaluation.

The research of unrestrained intelligent nursing bed is particularly important. In view of the current research results and the monitoring needs of the elderly and disabled people, a variety of monitoring methods can be integrated into the electric nursing bed in the smart home environment, so that the multi-functional nursing bed can become a device in the smart home through the network and improve its intelligence.

2.2 Study on physiological signal characteristics

Deep learning is a technology that enables computers to determine nonlinear information from datasets and make corresponding decisions. Due to its strong learning ability and nonlinear feature extraction performance, deep learning models reduce the dependence on manual feature extraction and expert knowledge, which greatly promotes the development of intelligent diagnosis. In medical research, deep learning algorithms have been widely used to diagnose diseases and predict patient physiological conditions. In addition, deep learning algorithms commonly used for medical signal processing can be divided into recurrent neural networks (RNN), autoencoders (AE), and convolutional neural networks (CNN), etc. (Loh et al., 2021).

RNN is a neural network model with memory capabilities that can process sequence data and learn the relationships between sequences. Mahmud et al. (2022) applied the perceptron RNN to the original EEG signal and the corresponding wavelet decomposition features to predict seizures, which proved that this method was feasible. Miltiadous et al. (2021) used Levenberg-Marquardt algorithm to extract ECG features to train RNN to classify normal ECG, congestive heart failure ECG, ventricular tachyarrhythmia ECG and atrial fibrillation ECG, and obtained a classification accuracy of more than 94%.

AE and its variants (denoising autoencoder DAE and sparse autoencoder SAE) are widely used in tasks such as data dimensionality reduction, feature extraction, data denoising, etc. Omidvar et al. (2021) applied stacked sparse autoencoder (SSAE) to EMG control. SSAE can significantly improve the performance of EMG control scheme based on pattern recognition, and has the ability to extract hidden depth information in EMG data, and its performance is better than linear discriminant analysis (LDA) classifier. The ECG automatic processing technique uses DAE to denoise the raw ECG signal, then uses AE to extract features from the denoised data, and finally classifies them by deep neural network DNN. Although it has the problems of long training time and low efficiency, it has achieved good performance in terms of accuracy and sensitivity (Priya et al., 2021).

CNN is a kind of neural network with good local feature extraction and spatial relationship modelling ability. The proposed model is a complete end-to-end structure that classifies EEG signals without any feature extraction (Sharma and Acharya, 2021). The system developed by Subramani and BD (2023) can detect abnormal EEG signals with 79.34% accuracy, 79.64% precision and 78.71% sensitivity. Ullah et al. (2021) proposed a 2D CNN classification network based on ECG time-frequency map, and verified that the CNN classifier using ECG time-frequency map as input can achieve an average accuracy of 99.00% without additional manual preprocessing of ECG signals.

Usman et al. (2021) proposed a method to detect patient feature information using a hybrid convolutional and recurrent neural network, and its accuracy is greater than 93%. Vijayakumar et al. (2021) proposed a CNN to identify patient feature information, and then used Laplacian hidden semi-Markov model to optimise the classification. This method can effectively detect intestinal sounds. Wang et al. (2024) extracted MFCC features from patient feature information data and used them to train neural networks based on LSTM. It is proved for the first time that it is feasible to apply speech recognition methods to intestinal sound detection.

However, due to the variability and complexity of patient feature information, it is more difficult to effectively classify patient feature information than to identify patient feature information. To perform high-precision bowel movement prediction, it is also necessary to develop suitable deep learning algorithms to achieve correct classification of patient feature information.

3 Model construction

3.1 Patient signal feature extraction

The patient characteristic information sound signal is a typical non-stationary signal with sudden characteristics. This section analyses the patient characteristic information sound signal collected in the experiment, and proposes two different patient characteristic information sound denoising methods based on multi-level filtering and wavelet threshold to meet the noise reduction needs of patient characteristic information sound signals in different situations. For the convenience of the following analysis, the collected patient characteristic information sound signal is defined as:

$$x(n),\ n = 1, 2, \ldots, N \tag{1}$$

Among them, N is the number of data points of signal $x(n)$. Since the sampling frequency is 4,000 Hz and the collection time of each segment of patient characteristic information sound data is 1 minute, N is 240,000.

3.1.1 Multi-stage filtering noise reduction method

A method based on multi-stage filtering is proposed to denoise the patient characteristic information sound signal. The low-pass filter has the function of passing low frequency and resisting high frequency. The low-pass filter with a cutoff frequency of 1,000 Hz is selected to complete the denoising of the high-frequency noise signal. The filtered signal can be expressed as:

$$Y(N) = \alpha x(N) + (1 - \alpha) Y(n-1) \tag{2}$$

Among them, α is the filter coefficient, $x(n)$ is the sampled patient characteristic information sound signal, and $Y(n - 1)$ is the last filtered output value. According to the signal characteristics of patient characteristic information tone, a second-order Butterworth high-pass filter with cutoff frequency of 100 Hz is selected to complete low-frequency noise reduction. The Butterworth high-pass filter only needs to be characterised by two parameters, namely filter order and cutoff frequency, and its amplitude square function can be expressed as:

$$|H(j\omega)|^2 = \frac{1}{1 + \left(\frac{\omega}{\omega_c}\right)^{2N}} \tag{3}$$

Among them, N is the order of the filter, ω_c is the cutoff frequency, and ω is the frequency domain parameter of the patient characteristic information sound signal $x(n)$. A three-parameter notch filter is selected to reduce the noise of the patient characteristic information tone, and the processed signal can be expressed as:

$$Y(s) = \frac{s^2 + 2k_2\omega_n s + \omega_n^2}{s^2 + 2k_1\omega_n s + \omega_n^2} x(s) \tag{4}$$

Among them, $x(s)$ is the patient characteristic information sound signal in the frequency domain, k_1 and k_2 are notch factors, and ω_n is the notch frequency.

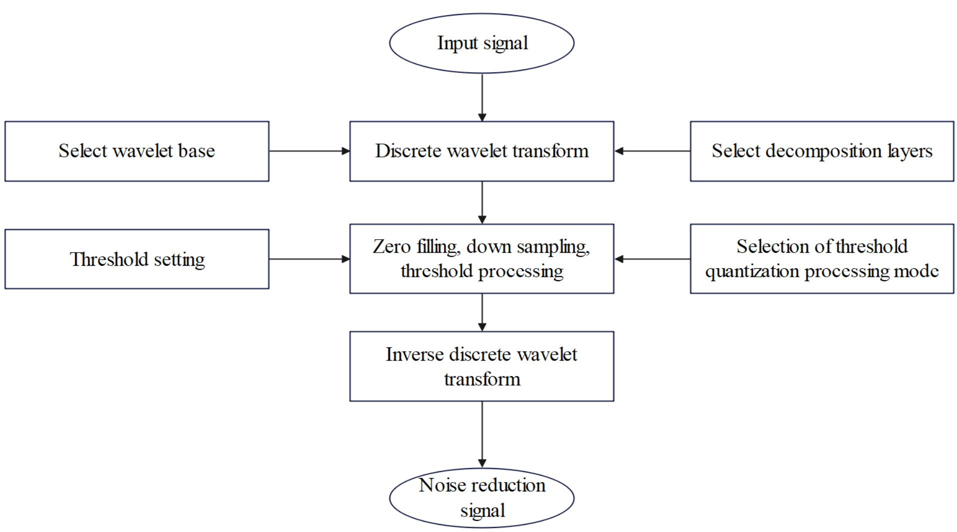
3.1.2 Noise reduction of patient characteristic information sound signal based on wavelet threshold

Wavelet transform analysis of patient characteristic information sound signal can be expressed as:

$$WT(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(n) \Psi\left(\frac{n-\tau}{a}\right) dn \tag{5}$$

Among them, a is the frequency expansion of the wavelet function, τ is the time shift, and $x(n)$ is the patient's characteristic information sound signal. The wavelet transform does not use the idea of adding windows, but uses a and τ to provide a 'time-frequency' window that changes with the frequency to achieve localised analysis of the signal. It can not only obtain the information of each frequency component in the signal, but also obtain the time when each component appears.

Figure 1 Wavelet threshold denoising flow chart



Wavelet transform is used to de-noise the patient characteristic information sound signal, and the processing process is shown in Figure 1. Firstly, the wavelet basis function and the number of decomposition layers used by wavelet transform are determined, and the acquired signal is decomposed. Then, the decomposed wavelet coefficients are processed by setting a suitable min value. Finally, based on the processed wavelet coefficients, the effective signal after noise reduction is obtained by reconstruction and restoration.

Common threshold selection methods include fixed threshold estimation and extreme threshold estimation. The method of using a fixed threshold is selected here, which can be expressed as:

$$\lambda = \sqrt{2\log(N)} \tag{6}$$

Among them, λ is the fixed threshold value and N is the signal length.

The hard threshold denoising method is shown in formula (7). When the threshold coefficient of the collected signal is greater than the set threshold, the part of the signal remains unchanged. If it is less than the set threshold, it is set to zero. In terms of mean square error, the hard threshold denoising method is better than the soft threshold, but the denoising signal is prone to oscillation and lacks smoothness.

$$x_\lambda = \begin{cases} x & |x| \geq \lambda \\ 0 & |x| < \lambda \end{cases} \tag{7}$$

Among them, x is the wavelet coefficient and λ is the threshold value.

The noise reduction method of soft threshold is shown in formula (8). When the wavelet coefficient of the collected signal is less than the set threshold, the signal part remains unchanged. If it is greater than the set threshold, the set threshold is subtracted from it. Compared with the hard threshold denoising method, the overall smoothness of the signal after soft threshold processing is better and no additional oscillation will be generated, but a certain deviation will be generated, which will affect the reconstruction of the patient's characteristic information sound signal and cause signal distortion.

$$x_\lambda = \begin{cases} sign(x)\left(|x| - \lambda\right) & |x| \geq \lambda \\ 0 & |x| < \lambda \end{cases} \tag{8}$$

Among them, x is the wavelet coefficient, λ is the threshold value, and *sign*() is the sign function. The above two threshold functions are used to reduce the noise of the patient characteristic information sound signal.

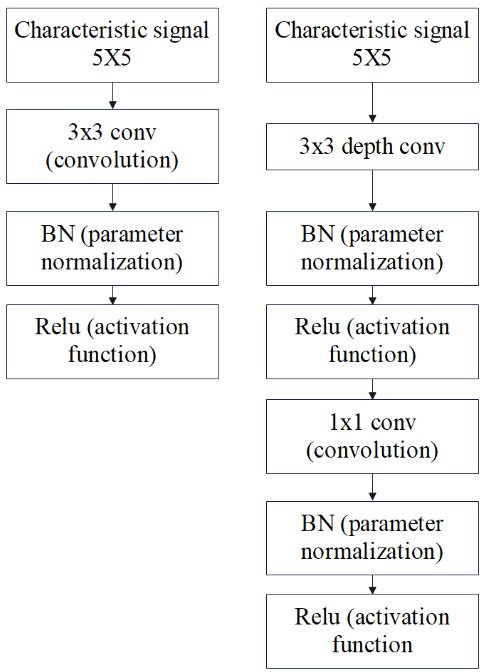
3.2 Automatic feature extraction of patient feature information signals based on Mobilenet

As a typical deep learning algorithm, CNN requires a large number of patient feature information data samples for training in order to effectively perform network functions. However, the sample size of the patient characteristic information dataset is limited by time and volunteer recruitment conditions, and the sample size is difficult to meet the requirements. Mobilenet series algorithms are a high-performance and lightweight way to create neural networks. By lightweighting the model, it can effectively reduce the amount of parameters and calculations of the model and reduce deployment costs. The efficient architecture of the Mobilenet network enables it to operate with Real-time applications in GPU-configured edge computing systems. Therefore, this section studies the model structure of Mobilenet network and its lightweight design method.

3.2.1 Mobilenet-V1 network architecture

Mobilenet is a lightweight neural network that has undergone three iterative development processes to greatly reduce the amount of calculation and model volume while maintaining high accuracy. The convolution method is very similar to the traditional convolution, except that the convolution kernel size of each channel is determined to be $1 \times 1 \times m$, where m is the number of channels of the input signal. If the dimension of the patient feature information input signal is $5 \times 5 \times 3$, and there are three channels in total, then the dimension of the convolution kernel of the point-by-point convolution is $1 \times 1 \times 3 \times n$, where N is the variable of dimension increase or decrease, which can determine the number of channels of the output signal.

Figure 2 Comparison of traditional convolution and deeply separable convolution structures

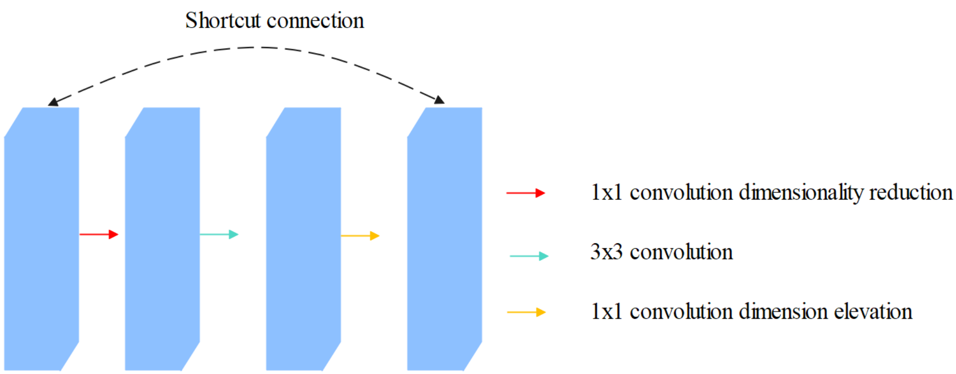


As shown in Figure 2, the left side is the traditional convolution method, and the right half is the combination of deep convolution and point-by-point convolution. Among them, batch normalisation (BN) can normalise model parameters, making the network easier to converge. ReLU is an activation function, which can enhance the ability of nonlinear fitting of the network. As can be seen from Table 1, except for the first layer and the fully connected layer portion, Mobilenet-V1 network structure mainly adopts deep separable convolution to reduce the number of model parameters and the amount of calculation. The entire network framework can be regarded as consisting of multiple deeply separable convolutional layers, and BN operation and ReLU activation function are applied after each convolutional layer to accelerate training and improve model performance.

3.2.2 Mobilenet-V2 network architecture

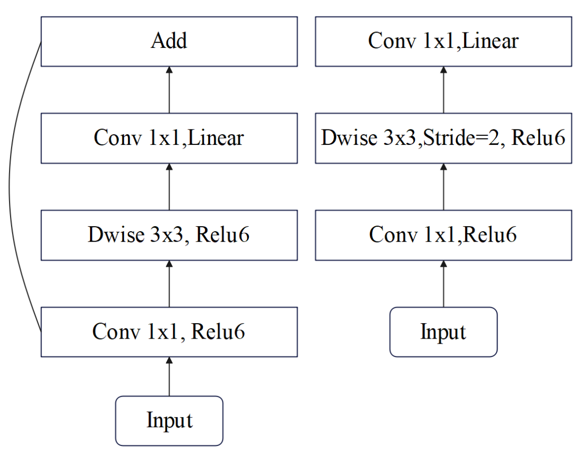
On the basis of Mobilenet-V1, Mobilenet-V2 mainly introduces the reverse residual structure to further optimise the network structure. By using the reverse residual structure, we can not only deepen the number of network layers and enhance the feature expression ability, but also effectively reduce the number of parameters, reduce the computational complexity and improve the running speed and accuracy of the model.

Figure 3 Residual structure (see online version for colours)



The idea of residual error is introduced to solve the problems of gradient disappearance and gradient explosion during model training. It is also applied in other deep learning networks, the most typical of which is the ResNet network. As shown in Figure 3, the residual network structure used by ResNet is a bottleneck structure, which contains three layers of convolution. From the low layer to the high layer, 1 × 1 convolution, 3 × 3 convolution and 1 × 1 convolution are used respectively. The convolution of the first layer realises the dimensionality reduction of the signal, and the convolution of the second layer maintains the signal dimension.

Figure 4 Reverse residual structure

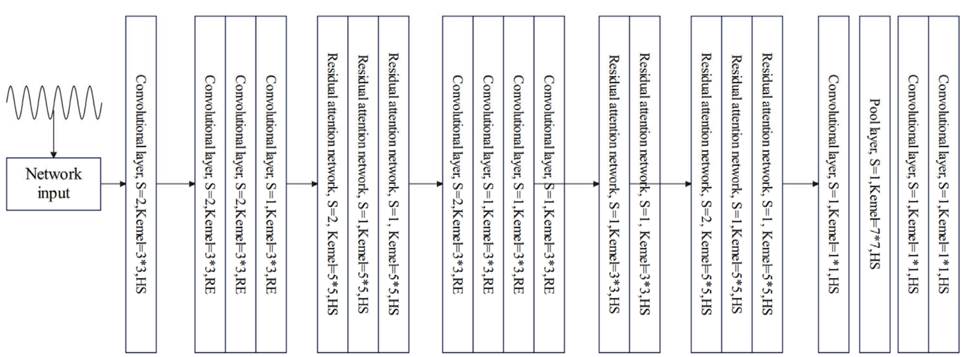


The third layer of convolution realises the dimensionality increase of the signal, and the entire network structure presents a large shape at both ends and a small shape in the middle. The ordinary residual structure is not applicable, so the reverse residual structure is proposed, as shown in Figure 4. The structure also contains three layers of convolution, using point-by-point convolution, depth convolution and point-by-point convolution from the low layer to the high layer. First, the first layer of point-by-point convolution uses a convolution kernel of $1 \times 1 \times N$ to increase the dimension of the signal, N is the dimension after the increase, and then a convolution kernel of $3 \times 3 \times N$ is used to perform deep convolution processing on the signal. Finally, it uses a convolution kernel of $1 \times 1 \times M$ to reduce the dimension, and M is the dimension after the reduction. Since this processing method is exactly the opposite of the ordinary residual structure, it is called the reverse residual structure.

3.2.3 Principle of signal feature extraction based on Mobilenet-V3

Figure 5 is a schematic diagram of the network structure of Mobilenet-V3. In Mobilenet-V3, a calibration mechanism is used to extract patient feature information signal features by accurately modelling the interaction relationship between convolutional feature channels. In addition, a squeeze-and-excitation module (SE), referred to as SE module for short, is also proposed in Mobilenet-V3. As shown in Figure 6, the SE module includes three steps: compression, excitation, and scaling, and the compression method uses global average pooling. If the size of the input signal is $W \times H \times C$, the dimension after compression is $1 \times 1 \times C$. The excitation can be seen as consisting of two fully connected layers, which enhance the correlation between the signal features of each layer, and still obtain the output of $1 \times 1 \times C$. The scaling operation is the multiplication of channel weights. The channel weights calculated by the SE module are multiplied by the two-dimensional matrix of the corresponding channel in the original feature map. By introducing the SE module, Mobilenet-V3 can better improve the model performance while reducing network parameters.

Figure 5 Schematic diagram of Mobilenet-V3 network structure

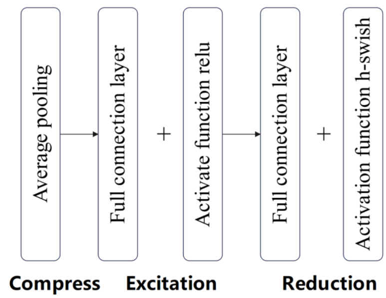


In the process of studying Mobilenet-V3, it is found that swish activation function can effectively improve the accuracy of the network, but swish is too computational and is not suitable for lightweight neural networks. Therefore, Mobilenet-V3 found an alternative activation function h-swish that is similar to the swish activation function but requires much less computation. The calculation formula of this function is as follows:

$$h - swish\left[x(n)\right] = x(n)\frac{\mathrm{Re}LU6\left(x(n)+3\right)}{6} \tag{9}$$

This activation function not only maintains the nonlinear ability and runs fast, but also avoids the loss of numerical accuracy, making it more suitable for use on platforms with average computing power.

Figure 6 SE module in Mobilenet-V3



3.3 RF-based patient feature information signal feature classification algorithm

RF is an ensemble learning algorithm that uses self-service resampling technology to build multiple decision tree models based on training data, and summarises the results of these decision trees through majority voting or averaging for classification or regression.

3.3.1 Decision tree classification principle

Decision tree is the foundation of RF algorithm, and the learning goal of decision tree is to construct a classification model that can complete the correct partition of instance objects and perform the best performance in the sense of loss function.

3.3.1.1 Information entropy and information gain

Decision tree classifies batch data according to information characteristics. Through classification, unordered data can become more ordered. The decision tree defines the information entropy to evaluate the confusion degree of information, which can be expressed by the formula:

$$H(x) = -\sum_{i=1}^{n} p_i \log_2\left(p_i\right) \tag{10}$$

In the formula, x is the subclass of information classification, n is the number of feature subclasses, and p_i is the probability that information is classified into x. If all classifications have been completed, that is, each piece of information has been classified into its own subclass, then the information entropy can be expressed as:

$$H(D) = -\sum_{i=1}^{n} \frac{|c_i|}{|D|} \log_2\left(\frac{|c_i|}{|D|}\right) \tag{11}$$

In the formula, D is the training dataset, $| D |$ is the number of training data, and c_i is the number of patient feature information signals classified into subclass x_i. At this time, $H(D)$ is called empirical entropy.

In order to evaluate whether the classification method is effective and distinguish the changes in information before and after classification, the concept of information gain is defined. That is, the information entropy difference between feature A and the patient's feature information signal before and after classification can be expressed as:

$$g(D, A) = H(D) - H\left(D \mid A\right) \tag{12}$$

$g(D, A)$ is the information gain of information feature A to dataset D, $H(D \mid A)$ is the conditional entropy, which refers to the information entropy of the classification of feature A in dataset D under given conditions, which can be expressed as:

$$H(D|A) = \sum_{i=1}^{n} p_i H\left(D|A = x_i\right) \tag{13}$$

p_i is the probability that feature A is classified into subclass x_i.

There is no relative comparison relationship between the information gains of different datasets, and the information gain ratio can effectively avoid the above problems, which is more beneficial as the basis for selecting nodes in the process of decision tree generation, and can be expressed as:

$$g_R(D, A) = \frac{g(D, A)}{H(D)} \tag{14}$$

3.3.1.2 Generation of decision tree

The decision tree selects the best classification method from multiple classification features to divide data, forming two or more leaf nodes, and then continues to classify from each leaf node in the same classification method until it can't continue to classify.

3.3.1.3 Decision tree pruning

The problem of over-fitting is essentially over-classification of the training dataset, and pruning and transformation operations are performed on the basis of decision tree generation, thus reducing the complexity of the tree.

In order to express the complexity of decision tree, the loss function of decision tree is introduced, which is beneficial to the realisation of pruning. The loss function of the decision tree can be defined as:

$$C_\alpha(T) = \sum_{t=1}^{|T|} N_t H_t(T) + \alpha|T| \tag{15}$$

Among them, T is the leaf node of this sub-tree, $| T |$ is the number of leaf nodes, N_t is the number of training samples contained in the leaf node, $H_t(T)$ is the entropy of the i^{th} leaf node, and α is the penalty factor. The loss function can also be expressed as:

$$C_\alpha(T) = C(T) + \alpha|T| \tag{16}$$

Among them, $C(T)$ represents the fitting degree of the decision tree to the training samples:

$$C(T) == \sum_{i=i}^{|T|} N_i H_i(t) = -\sum_{i=i}^{|T|} \sum_{k=1}^{K} N_{ik} \log \frac{N_{ik}}{N_i} \tag{17}$$

The loss function can be expressed as:

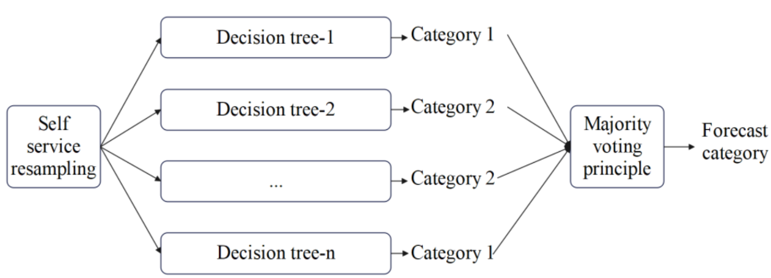
$$C_\alpha(T) = -\sum_{i=i}^{|T|} \sum_{k=1}^{K} N_{ik} \log \frac{N_{ik}}{N_i} + \alpha |T| \tag{18}$$

After determining the penalty factor α, the model with the smallest loss function is selected. Pruning the decision tree by the loss function can balance the overfitting and underfitting, and obtain a decision tree with appropriate fitting degree.

3.3.2 RF algorithm based on decision tree construction

RF algorithm is a typical ensemble learning algorithm based on bagging ensemble framework with decision tree as learner. Figure 7 shows the construction process of RF. Based on the self-service sampling method, sub-samples are selected from the sample pool and can be used for the training and learning of each decision tree. In RF algorithm, the learning between all decision trees is independent of each other and processed in parallel. The output results of all decision trees are summarised by voting method. Voting methods are divided into soft voting and hard voting. In soft voting, the output results of their respective decision trees are weighted and averaged, while the hard voting results follow the rule that the minority obeys the majority. This paper chooses to adopt hard voting for summary.

Figure 7 Construction process of RF



3.4 Mobilenet-RF-based pre-defecation prediction algorithm

Mobilenet is a lightweight designed neural network that can be directly used to achieve classification, but the performance of the model is difficult to optimise and adjust after training. Combining Mobilenet and RF, a pre-defecation prediction algorithm based on Mobilenet-RF is designed. The overall architecture is shown in Figure 8.

Figure 8 Overall architecture of Mobilenet-RF

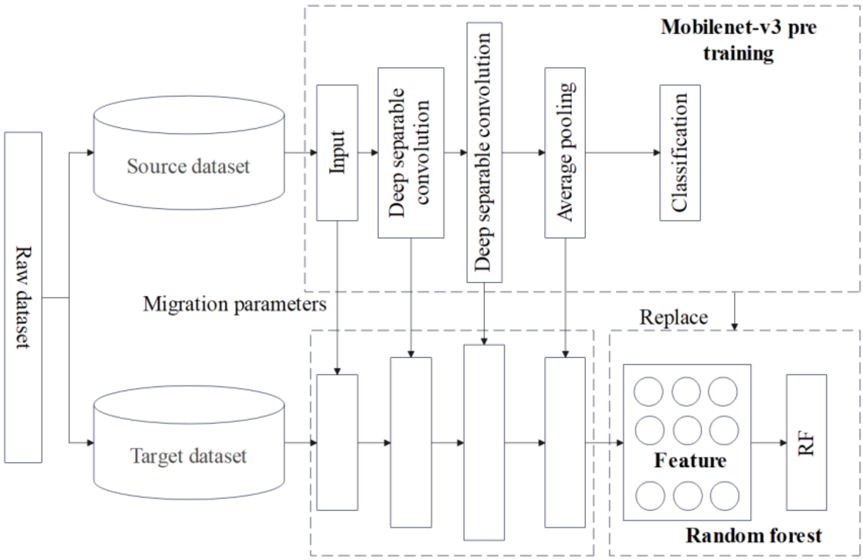
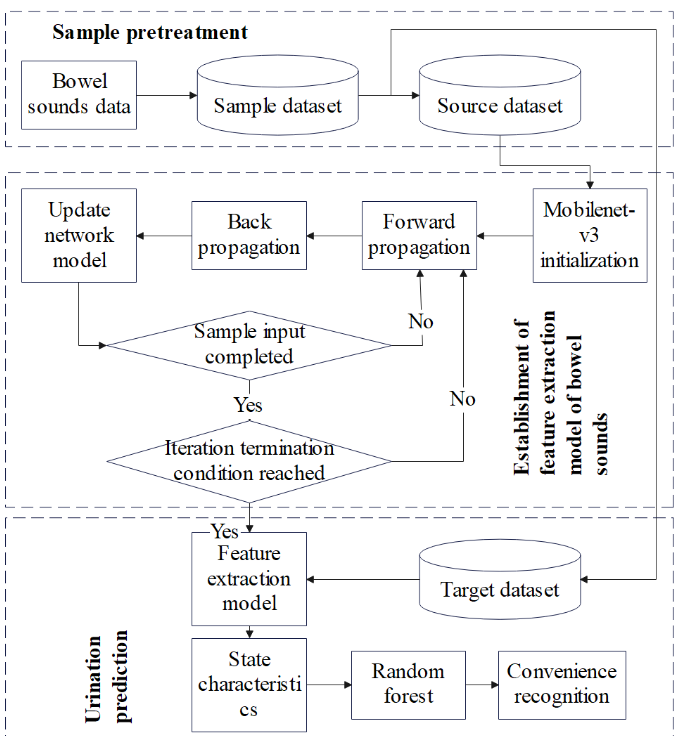


Figure 9 Flowchart of pre-defecation prediction algorithm based on Mobilenet-RF



A pre-defecation prediction algorithm based on Mobilenet-RF is proposed (Figure 9):

Step 1 Each patient characteristic information data is divided into 6 segments, each segment of patient characteristic information signal is 10 seconds long, and each data is constructed as a matrix of 200 × 200 to construct a sample dataset.

Step 2 The patient characteristic information dataset is divided into a source dataset and a target dataset. The source dataset consists entirely of characteristic information signals of patients without defecation urge, which are labelled as ‘0’, and the target dataset consists of characteristic information data of patients with and without defecation urge with balanced sample sizes, where the characteristic information signal of patients without defecation urge is labelled as ‘0’ and the characteristic information signal of patients with defecation urge is labelled as ‘1’.

Step 3 The Mobilenet network is trained based on samples in the source dataset to build an automatic feature extractor for patient characteristic information signals.

Step 4 While keeping the network parameters of Mobilenet unchanged, it is migrated to the target dataset, and the input vector of the Softmax layer in the Mobilenet network is used as the extracted patient feature information feature to construct a feature set for pre-defecation prediction.

Step 5 The patient feature information extracted by Mobilenet is input into the RF model to achieve pre-defecation prediction. The RF algorithm has the advantages of strong anti-interference ability, fast training speed, and good classification effect, which can further improve the accuracy and robustness of pre-defecation prediction.

The necessity of intelligent nursing beds is reflected in their breakthrough of the application limitations of traditional medical equipment through multimodal sensorless monitoring technology: compared with contact devices, based on the depth pressure sensing matrix (a non-contact sensing system fused with millimetre wave radar, combined with dynamic baseline calibration algorithm, it can achieve micrometer level body motion capture within a suspension detection distance of 0.5–2 cm. Combined with the transfer learning model of the patient’s exclusive physiological feature library, even in the face of the signal-to-noise ratio loss caused by indirect sensor contact, it can still extract the phase synchronisation features of heart rate variability through spatiotemporal feature fusion technology. Its continuous monitoring mode can capture early compensatory signs that are easily missed by traditional devices. This all-weather, interference free intelligent monitoring not only avoids the risk of skin damage caused by electrode patches, but also achieves early warning value that traditional single parameter devices cannot achieve through multidimensional sign correlation analysis.

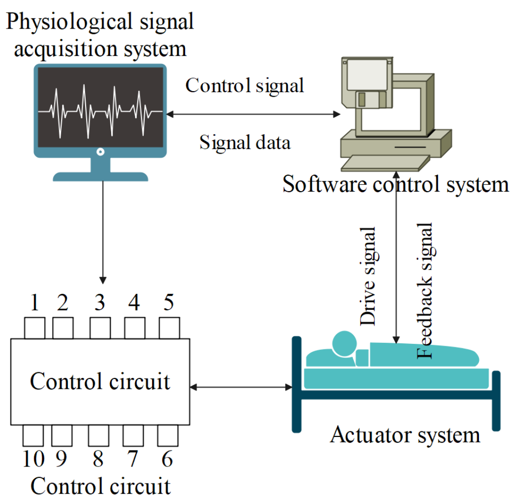
4 Test

4.1 Test methods

The data processing algorithm is compiled in MATLAB R2019b software, and the running environment is Intel (R) Xeon (R) CPU, 96GB RAM, and Windows 10 system.

The overall architecture of the defecation nursing experimental platform built in this paper is shown in Figure 10, including physiological signal acquisition system, actuator system and software control system. Among them, the software control system can control the physiological signal acquisition system in real time, communicate with the sensor that collects physiological signals through Bluetooth, control the start and stop of signal acquisition, and carry out noise reduction processing and consciousness change on the collected physiological signals.

Figure 10 Nursing experimental platform (see online version for colours)



To address the modelling challenges caused by individual signal differences, the intelligent nursing bed system can adopt an evolutionary architecture of 'federated meta learning + dynamic feature decoupling' to achieve adaptive optimisation:

1 Hierarchical feature modelling: universal feature layer: aggregating data from multiple medical institutions through a federated learning framework (with privacy preserving model parameter transmission), training a transformer-based meta feature extractor, and capturing time-frequency common patterns of signal features across patients.

   Build a personalised feature layer using dynamic network technology, deploy deformable convolution kernels on edge devices, and automatically adjust feature response weights based on real-time monitoring data.

2 Self supervised calibration mechanism: design a physiological signal decoupling loss function, utilising the 24-hour monitoring data during the initial admission period By comparing and learning to separate device noise and physiological signals, a variational autoencoder (VAE) is constructed to establish a patient specific intestinal motion baseline pattern, and an implicit correlation model between pulse wave transit time (PTT) and intestinal sounds is developed.

3 Incremental evolutionary architecture: using neural architecture search (NAS) to construct dynamic decision trees, pre training Meta learning models, online knowledge distillation modules, continuously absorbing new patient features, setting

up feature drift detectors, and triggering model fine-tuning when cosine similarity <0.85.

4 Equipment collaborative verification: establish a multi-sensor cross validation mechanism, verify the temporal consistency between body motion signals and patient characteristic signals using millimetre wave radar, and detect the energy distribution of abdominal deformation through a flexible piezoelectric sensor array.

The intelligent nursing bed system built in this paper can automate the entire process from the collection and monitoring of physiological parameters to the treatment and collection of waste, thereby facilitating the operation of the nursing bed by non-professionals such as medical staff and family members in clinical auxiliary nursing work.

The dataset s used in this article include: MIMIC-III intensive care dataset, Diabetes Diabetes dataset, eICU-demo dataset, and Glioma-MDC2025. Then, the bowel sound data of different patient types are analysed to explore the effectiveness and generalisation ability of the model.

In response to the reliability issue of feature extraction caused by physiological signal interference in patients, this paper adopts a hybrid optimisation scheme combining multimodal signal separation technology and deep learning: firstly, the improved FastICA algorithm is used to separate the mixed signal, and the DnCNN network is used for end-to-end noise reduction; Then, an enhanced version of the MobileNet RF model is constructed, incorporating channel attention mechanism and adversarial training module to enhance feature selectivity; Finally, a double-layer stacking classifier (RF+LightGBM) is established and an uncertainty quantisation mechanism is introduced to filter low-quality predictions through dynamic confidence thresholds. Simultaneously developing an online learning system to achieve continuous model optimisation, this solution can reduce false alarm rates by over 60% in interference environments while maintaining the original 95.68% accuracy.

To address the bottleneck of multimodal real-time processing for edge devices, a collaborative optimisation strategy of ‘computational topology reconstruction + spatiotemporal resource scheduling’ is adopted to systematically solve the problem of resource constraints.

Firstly, construct a three-level processing pipeline as follows:

1 Sensor level preprocessing: deploy CNN-LSTM hybrid model compression to FPGA, use OpenCL to achieve < 5 ms delay, adaptively adjust ADC sampling bit width based on signal variance (12 bit to 8 bit controllable attenuation).

2 Edge node feature extraction: construct a multimodal shared base model (MM-BERT) to obtain physiological signal modalities through depthwise separable convolution and dilated temporal convolution Split the complete model into mandatory modules (Always-0n) and on-demand loading modules (On Demand).

3 Device cluster federated computing: establish a dynamic DAG task scheduler and achieve cross bed computing power sharing through ZigBee+UWB dual-mode communication for critical path acceleration. Enable GPU hard decoding (NVIDIA Jetson Nano) for core indicators such as gastrointestinal motility index.

Next, perform dynamic scheduling of spatiotemporal resources

1 Time dimension optimisation: develop a circadian rhythm perception scheduler that automatically switches to low-power mode during non rapid eye movement periods Based on the phase space reconstruction prediction algorithm, the resolution of the millimetre wave radar is automatically improved (0.5 mm → 0.1 mm) during the precursor period of defecation.

2 Spatial dimension optimisation: deploy a feature gating network based on attention mechanism to perform spatial coding on redundant body motion signals (reducing computational complexity by 40%) to construct an abdominal quadrant energy map, and only perform full precision calculations on high probability activity areas.

To address the challenges of modelling and clinical verification of low-level signals, a collaborative approach of ‘physical sensing enhancement + digital twin verification’ can be used. Firstly, a quantum level magnetic shielding array (0.1pT/√ Hz) and a biomimetic MEMS sensor (60 dB gain) are used to improve signal quality; Secondly, construct a dual channel interpretable model that integrates fluid dynamics simulation and clinical auscultation features; Finally, reliability is ensured through a three-level validation system (biomimetic model → animal experiment → double-blind clinical trial).

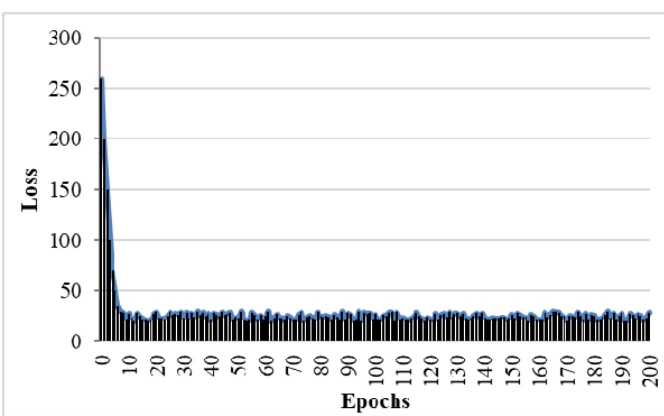
4.2 Results

The calculation time spent by the three noise reduction algorithms in three noise reduction processes is shown in Table 1.

Table 1 Comparison of calculation time of three noise reduction algorithms

Noise reduction algorithm	*Calculation time (s)*			*Average computation time (s)*
	1	*2*	*3*	
Multi-stage filtering noise reduction	0.2418	0.2372	0.2262	0.2351
Hard threshold noise reduction	1.3621	1.349	1.3479	1.353
Soft threshold noise reduction	1.3252	1.3218	1.3203	1.3224

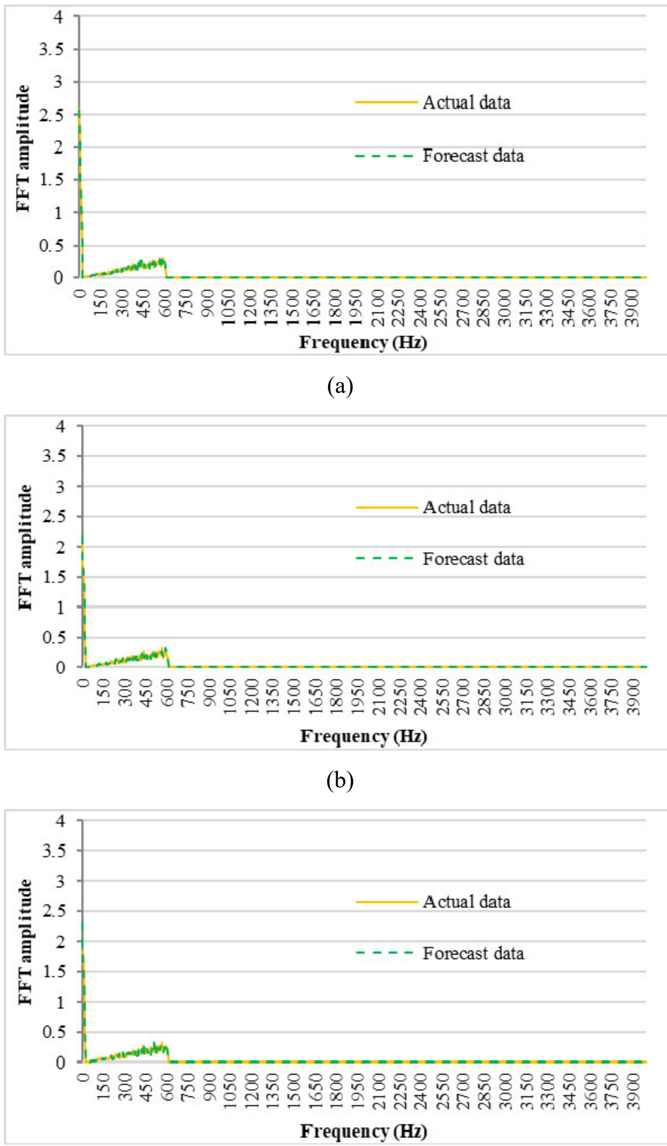
Figure 11 Loss diagram of data enhancement (see online version for colours)



In order to achieve small sample bowel sound data enhancement, a total of 200 sets of preprocessed bowel sound data are used in the real bowel sound dataset. After

200 rounds of training, the 1oss of the network model reaches the minimum, and the loss image of the training process is shown in Figure 11.

Figure 12 Comparison diagram between real data and generated data, (a) group 1 (b) group 2 (c) group 3 (see online version for colours)



(a)

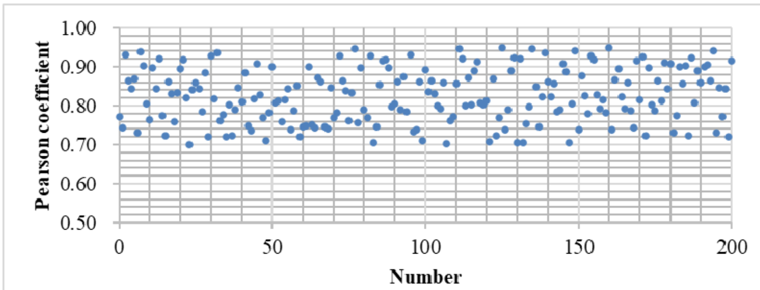
(b)

(c)

In order to more intuitively compare the real bowel sound data with the data generated by the prediction algorithm in this paper, three groups of real data and generated data are randomly selected, and their comparison images are shown in Figure 12.

In order to visually show the quality of all the data generated in this paper, the Pearson correlation coefficients of 200 sets of generated data are plotted into a scatter plot, as shown in Figure 13.

Figure 13 Scatter plot of Pearson correlation coefficient (see online version for colours)



In order to evaluate the performance of the proposed MOBILENET-RF method, a set of comparative experiments is designed. This paper uses the MIMIC-III intensive care dataset, Diabetes diabetes dataset, eICU-demo dataset, and Glioma-MDC2025 test sets into four models for classification, and the learning rate is set to 0.002.

In order to more intuitively reflect the accuracy change process in network training, the classification precision of the four test sets in the four models is shown in Table 2.

Table 2 Precision of each dataset

	LSTM	*CNN*	*CNN+BiGRU*	*MOBILENET-RF*
MIMIC-III	78.71%	80.69%	86.13%	91.08%
Diabetes	91.08%	79.70%	73.76%	95.04%
eICU-demo	81.68%	85.14%	72.27%	92.57%
Glioma-MDC2025	85.64%	82.17%	69.30%	91.58%
Average value	84.27%	81.92%	75.36%	92.57%

Specificity and sensitivity tables are shown in Table 3.

Table 3 Specificity and sensitivity table

	TP quantity	*TN quantity*	*FP quantity*	*FN quantity*	*Specificity*	*Susceptibility*
MIMIC-III	54	128	12	6	91.43%	90.00%
Diabetes	55	135	5	5	96.43%	91.67%
eICU-demo	52	133	7	8	95.00%	86.67%
Glioma-MDC2025	55	128	12	5	91.43%	91.67%
Average value	54	131	9	6	93.57%	90.00%

Since Mobilenet-V3 is divided into two versions, Mobilenet-V3_ Large and Mobilenet-V3_Small, the classification precision of the proposed method under the two versions is compared. They are compared with directly using Mobilenet-V3 for prediction and two commonly used deep learning methods, CNN and LSTM, and the results are shown in Table 4.

Table 4 Test results of different methods

Classifier	*Training set accuracy*	*Test set accuracy*
Large	98.50%	95.45%
Large+RF	98.90%	95.68%
Small	96.86%	91.65%
Small+RF	99.00%	92.37%
CNN	93.71%	61.82%
LSTM	95.84%	53.77%

4.3 Analysis and discussion

In Table 1, the computational cost of the two denoising algorithms based on wavelet threshold is higher than that of the denoising algorithms based on multi-level filtering, which shows that the denoising algorithms based on multi-level filtering have better real-time performance than the denoising algorithms based on wavelet threshold.

In practical applications, if better noise reduction effect is needed and the information of bowel sound signals needs to be retained as much as possible, and the real-time requirements are not particularly high, wavelet noise reduction based on soft threshold can be used first. If a stronger noise reduction effect is needed and the real-time requirements are not particularly high, wavelet noise reduction based on hard threshold can be used first. If the noise reduction effect is not particularly high, but the real-time requirements are higher, the filtering noise reduction algorithm can be used first.

From the comparison chart of real data and generated data, we can see that the generated bowel sound data retains most of the morphological features of the real bowel sound data, but is not exactly the same as the real data, and has differences in details. This is because after the encoder reduces the dimension of the data, the variational autoencoder adds a noise regularisation term to the training process. This operation enables VAE to not only learn potential attributes in the probability distribution, but also avoid overfitting in the training process and ensure that its hidden variables have good properties for generating new samples.

Among the 200 sets of data in Figure 15, the maximum Pearson correlation coefficient is 0.9413 and the minimum is 0.701245. The average Pearson correlation coefficient of the population is 0.8235, and the overall level is extremely strong correlation. Moreover, all the Pearson coefficients are above 0.7. The Pearson coefficient diagram of these 200 groups of data shows the performance of the proposed bowel sound data increasing algorithm, which shows that the correlation coefficient analysis of the four groups randomly selected earlier is reliable, and preliminarily verifies the validity of the generated data.

In Figure 16, the average accuracy of all three comparison methods is lower than that of MOBILENET-RF. In this experiment, CNN, LSTM, CNN + BiGRU are not satisfactory in the classification of bowel sounds data, and they can't effectively classify bowel sounds with and without bowel intention. In other words, MOBILENET-RF has better performance. The average accuracy of this method for all classification tasks is about 94.4%.

In Table 2, the accuracy rate of CNN is relatively stable on different test sets, but the highest accuracy rate is not high, only 85.14%. The results of LSTM and CNN + BiGRU are not ideal, and the accuracy fluctuates greatly on the six test sets. However, the classification effect of the proposed method in this paper is better than that of the three comparison methods on the four test sets. Therefore, the feasibility of using the MOBILENET-RF classification method is confirmed.

The Diabetes dataset has the highest specificity (96.43%), while the eICU-demo specificity is slightly less (95.00%). The average specificity is 93.57%, indicating that these datasets have high accuracy in judging negative cases as a whole. Sensitivity: The Diabetes dataset has the highest Sensitivity (91.67%), followed by MIMIC-III and Glioma-MDC202 (both 90.00%), while eICU-demo has the lowest Sensitivity (86.67%). Number of TPs and TNs: The number of TPs and TNs is high for all datasets, indicating that the model performs well in correctly identifying and classifying positive and negative samples. Number of FPs and FNs: The number of FPs and FNs is relatively small. In particular, the Diabetes dataset has the least number of FPs (5), indicating fewer false positives. Overall, the proposed method has high specificity and sensitivity and is more reliable in the problem of bowel sound classification.

In Table 4, Mobilenet-RF achieves the best classification effect on the test set when using Mobilenet-V3 _ Large, which can achieve an accuracy rate of 96.65%. In addition, using the random forest algorithm to classify the features extracted by Mobilenet-V3 can achieve better classification results than using Mobilenet-V3 directly.

In general, the automatic feature extraction model of bowel sound signals built using the lightweight neural network Mobilenet can effectively avoid overfitting while reducing model parameters and improving computational efficiency. By inputting the features extracted by Mobilenet into four other classification models, it can be seen that the proposed Mobilenet-RF algorithm achieves the highest accuracy of 95.68%, proving the superiority of using random forest for classification.

5 Conclusions

This paper optimises the bowel sound feature extractor with the help of deep learning, and uses an edge computing system with GPU configuration as the implementation object, and proposes a pre-defecation prediction based on Mobilenet-RF. This method uses the lightweight neural network Mobilenet to establish an automatic feature extraction model for bowel sound signals, and inputs the extracted signal features into the random forest for classification to complete the pre-defecation prediction function. Through experimental analysis, we can see that the automatic feature extraction model of bowel sound signals built with lightweight neural network Mobilenet can effectively avoid overfitting while reducing model parameters and improving computational efficiency. By inputting the features extracted by Mobilenet into four other classification models, this paper found that the Mobilenet-RF algorithm proposed in this paper achieved the highest accuracy of 96.65%, proving the superiority of using random forest for classification.

Two different bowel sound signal reduction methods proposed in this paper can meet the demand of noise reduction in the experimental acquisition process, but in the actual bowel sound signal acquisition process, there are more complicated situations that will lead to the generation of noise, such as human movement, speech, electromagnetic interference of other equipment, etc. These noises will affect the final prediction accuracy before defecation, so further research is needed on bowel sound noise reduction algorithms with stronger noise reduction capabilities and better real-time performance.

Declarations

All authors declare that they have no conflicts of interest.

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