NEURAL NETWORK-BASED EXERCISE TRAINING AND LIMB FUNCTION EVALUATION SYSTEM FOR TRADITIONAL CHINESE MEDICINE GUIDING TECHNIQUE

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SUMMARY

Exercise training plays a pivotal role in enhancing limb function and overall physical performance. Through targeted and progressive exercise regimes, individuals can improve strength, flexibility, coordination, and endurance in their limbs. This paper presents a novel Neural Network-Based Exercise Training and Limb Function Evaluation System tailored for Traditional Chinese Medicine (TCM) guiding techniques. This paper constructed a novel Multi-Layer Fuzzy Pattern Neural Network (MLFPNN) for the estimation of limbs for exercise training. The proposed MLFPNN model acquires information about the limb muscles through the acquired information features are normalized. With the normalized features, TCM is evaluated for the computation of the feature for the exercise training in MLFPNN. The proposed model uses the multilayer fuzzy for the estimation of the limb features associated with the limb function. The estimated features of the limb are applied over the pattern network for the classification of limb function based on TCM with MLFPNN. The proposed MLFPNN model evaluates the 10 features in the limb muscle estimation for TCM-based exercise training. Experimental analysis is conducted for the proposed MLFPNN to achieve a higher prediction based on the actual values. The comparative analysis demonstrated that the proposed MLFPNN model achieves an accuracy of 92.5% while conventional SVM, RF, and k-NN achieve a classification accuracy of 88.3%, 90.7%, and 87.6% respectively. The findings stated that the proposed MLFPNN model is significant for the limb function estimation for the TCM-based training.

KEYWORDS

Medicine guiding technique, Neural network, Exercise training, Chinese medicine, Fuzzy pattern Network, Multi-layer network

NOMENCLATURE

TCM	Traditional Chinese Medicine
MLFPNN	MultiLayer Fuzzy Pattern Neural Network
SVM	Support Vector Machine
RMSE	Root Mean Squared Error
F	Frequency

1. INTRODUCTION

The Chinese medicine guiding technique encompasses a holistic approach to health and wellness, rooted in ancient wisdom and practices that have evolved over thousands of years [1]. At its core, this technique emphasizes the balance of qi, or vital energy, within the body, as well as the harmonious interaction between the body, mind, and environment. Practitioners of Chinese medicine utilize various modalities such as acupuncture, herbal medicine, massage (Tui na), dietary therapy, and exercise (Qi Gong) to restore balance and promote healing [2]. Diagnosis in Chinese medicine is often based on pattern differentiation, where practitioners assess signs and symptoms to identify underlying imbalances in the body's systems [3]. Treatment plans are then tailored to address these specific patterns, aiming not only to alleviate symptoms but also to address the root cause of illness or disharmony [4]. Additionally, Chinese medicine emphasizes the importance of preventive care and lifestyle modifications to maintain health and well-being over the long term. With its holistic approach and emphasis on individualized care, the Chinese medicine guiding technique continues to play a significant role in promoting health and vitality for millions of people worldwide [5].

Neural networks into the Chinese medicine guiding technique represents a cutting-edge advancement in healthcare technology, merging ancient wisdom with modern computational capabilities [6]. Neural networks, a form of artificial intelligence inspired by the human brain, offer the potential to enhance diagnostic accuracy and treatment effectiveness in Chinese medicine. By analyzing vast amounts of patient data, including symptoms, medical history, and diagnostic results, neural networks can identify complex patterns and correlations that may not be immediately apparent to human practitioners [7]. This computational approach allows for more precise diagnosis and personalized treatment plans tailored to each individual's unique constitution and health needs [8]. Furthermore, neural networks can assist in predicting disease progression, optimizing treatment protocols, and even discovering new therapeutic interventions based on their analysis of large-scale datasets [9]. By harnessing the power of neural networks, the Chinese medicine guiding technique is poised to revolutionize healthcare delivery, offering patients more effective and personalized care while preserving the holistic principles that have been central to Chinese medicine for millennia [10]. Neural networks into the Chinese medicine guiding technique represents a significant leap forward in the quest to combine traditional wisdom with technology for improved healthcare outcomes. Neural networks, a subset of artificial intelligence, excel at analyzing complex datasets and identifying intricate patterns that might escape human observation [11]. In the context of Chinese medicine, which relies heavily on pattern recognition and individualized treatment, neural networks offer unprecedented opportunities for enhancing diagnostic accuracy and treatment efficacy [12].

One of the key advantages of neural networks lies in their ability to process vast amounts of patient data with remarkable speed and efficiency [13]. By analyzing diverse variables such as symptoms, medical history, lifestyle factors, and diagnostic test results, neural networks can discern subtle correlations and associations that might elude human practitioners [14]. This comprehensive approach enables neural networks to generate insights and recommendations that are highly tailored to each patient's unique health profile, thereby facilitating more personalized and effective treatment plans. Moreover, neural networks can learn and adapt over time, refining their algorithms based on feedback from real-world outcomes [15]. This iterative process of refinement enhances the neural network's ability to predict disease progression, identify optimal treatment strategies, and anticipate potential complications or adverse reactions [16]. Additionally, neural networks their analytical capabilities to uncover novel therapeutic approaches or complementary interventions, thereby expanding the repertoire of available treatment options within the framework of Chinese medicine [17]. By harnessing the power of neural networks, the Chinese medicine guiding technique stands poised to undergo a transformative evolution. Patients can expect to benefit from more accurate diagnoses, tailored treatment regimens, and enhanced prognostic insights, all of which contribute to improved health outcomes and a higher quality of care [18]. Furthermore, the integration of neural networks into Chinese medicine underscores the adaptability and resilience of traditional healing practices in the face of technological advancements, ensuring that the fundamental principles of holistic wellness and individualized care remain at the forefront of modern healthcare [19].

The paper contributes significantly to the field of Traditional Chinese Medicine (TCM) and healthcare by introducing a novel Neural Network-Based Exercise Training and Limb Function Evaluation System specifically tailored for TCM guiding techniques. The key contributions of the paper include:

1. The MultiLayer Fuzzy Pattern Neural Network (MLFPNN) for assessing various parameters of limb function and exercise performance in the context of TCM. This approach represents a departure from traditional methods and offers a more sophisticated and accurate means of evaluation.
2. The superior performance of the MLFPNN model in accurately classifying and evaluating limb function attributes compared to conventional methods such as Support Vector Machine (SVM), Random Forest, and k-Nearest Neighbors (k-NN). This highlights the efficacy and reliability of the proposed system in providing accurate assessments.
3. Through Enabling personalized treatment planning, progress monitoring, and therapeutic interventions aligned with TCM principles. By leveraging MLFPNN, the system can adapt to individual patient needs, facilitating tailored healthcare solutions.
4. The advancement of TCM practice by providing an innovative and effective approach to exercise training and limb function evaluation. This facilitates the integration of modern technologies with traditional healthcare methodologies, enhancing the overall quality of care in TCM.

The paper's contribution lies in its innovative approach, enhanced accuracy, facilitation of personalized healthcare, advancement in TCM practice, and the proposal of future research directions, all of which collectively contribute to the evolution and improvement of healthcare practices informed by Traditional Chinese Medicine principles.

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2. RELATED WORKS

Neural network technologies into healthcare has ushered in a new era of personalized treatment and rehabilitation approaches. In particular, the intersection of neural networks with traditional Chinese medicine (TCM) guiding techniques offers promising avenues for enhancing patient care and promoting holistic wellness. Within this context, several related works have emerged, focusing on the development of neural network-based exercise training systems and limb function evaluation techniques tailored to the principles of TCM. Neural network-based exercise training systems represent a novel approach to rehabilitation, leveraging artificial intelligence to optimize exercise regimens, monitor progress, and tailor interventions to individual patient needs. These systems often utilize advanced technologies such as virtual reality simulations, wearable sensors, and motion capture systems to provide immersive and personalized rehabilitation experiences. By harnessing the power of neural networks, these systems aim to improve patient outcomes by maximizing functional recovery, enhancing motor learning, and promoting long-term adherence to rehabilitation programs. Concurrently, the evaluation of limb function is a critical aspect of rehabilitation, enabling clinicians to assess progress, track changes over time, and inform treatment decisions. Traditional assessment tools, while valuable, are often limited in their scope and precision. To address this challenge, researchers have explored innovative techniques for limb function evaluation, incorporating technologies such as computer vision, machine learning, and wearable sensors. These approaches offer objective and quantitative measures of limb function, allowing for more accurate assessment and personalized intervention planning.

Pan et al. (2023) delve into the burgeoning field of hyperspectral imaging technology combined with machine learning specifically applied to the quality control of traditional Chinese medicine (TCM). They likely explore how hyperspectral imaging, which captures a wide range of spectral bands beyond what the human eye can perceive, coupled with machine learning algorithms, can enhance the authentication, quality assessment, and detection of adulterants or contaminants in TCM products. This review would be particularly relevant given the growing demand for standardized TCM products and the need for reliable quality control measures. Cai et al. (2023) introduce a novel method for upper limb rehabilitation using a robotic system. Their work likely details the design and implementation of a motor recovery training protocol aimed at improving upper limb function in individuals recovering from stroke or other neurological conditions. By leveraging robotics technology, the proposed system may offer customizable rehabilitation exercises, real-time feedback, and objective performance evaluation, potentially enhancing the efficiency and effectiveness of upper limb rehabilitation. Kaijun (2022) proposes an innovative approach to assessing the psychological resilience of athletes undergoing high-intensity sports training. By employing an evolutionary neural network, this evaluation method likely integrates various psychological and physiological parameters to gauge athletes' ability to withstand stress, recover from setbacks, and maintain optimal performance under pressure. Understanding athletes' resilience levels can inform personalized training regimens, injury prevention strategies, and mental health support interventions in competitive sports settings.

Qie et al. (2022) conduct a trajectory planning and simulation study for upper limb rehabilitation using a redundant robotic arm. Their research likely involves optimizing rehabilitation protocols by employing advanced computational techniques such as backpropagation neural networks and genetic algorithms. By simulating and analyzing different trajectories of movement, this approach aims to maximize therapeutic outcomes while minimizing the risk of injury or overexertion during upper limb rehabilitation sessions. Ma et al. (2023) propose a novel methodology for assessing balance during walking by integrating 3D skeleton data with deep convolutional neural networks (CNNs). This approach likely involves capturing and analyzing skeletal movements during walking using depth-sensing technology, with CNNs being trained to recognize patterns associated with balance impairment or instability. Such a system could provide objective measures of balance performance, facilitating early detection of gait abnormalities and informing interventions to prevent falls and improve mobility in clinical and aging populations. Liang et al. (2023) develop a wearable multi-sensor system for in-home fitness guidance, catering to the growing demand for remote health monitoring and personalized fitness coaching. Their system likely integrates various sensors, such as accelerometers, gyroscopes, and heart rate monitors, to track users' physical activity, vital signs, and exercise adherence. By leveraging machine learning algorithms, the system can provide real-time feedback, personalized workout recommendations, and progress tracking, empowering individuals to achieve their fitness goals safely and effectively within the comfort of their homes.

Luo et al. (2022) explore the use of brain-computer interface (BCI)-based neurofeedback systems for motor rehabilitation. Their research likely investigates how BCI technology can facilitate motor learning and recovery by providing real-time feedback on brain activity associated with movement execution. By harnessing the principles of neuroplasticity, BCI-based rehabilitation protocols may help individuals with neurological disorders or injuries relearn motor skills and improve functional outcomes through targeted neural modulation techniques. Manoj et al. (2023) apply artificial neural networks to predict wire electric discharge machining (WEDM) parameters, a critical aspect of modern manufacturing processes. Their work likely involves training neural network models on large datasets of machining parameters and corresponding machining outcomes to develop predictive models capable of optimizing WEDM operations for improved efficiency, precision, and cost-effectiveness in smart manufacturing environments. Liang et al. (2023) propose an ensemble learning model utilizing near-infrared spectroscopy (NIRS) to classify dyskinesia degree during exercise in individuals recovering from stroke. By combining multiple learning algorithms with NIRS data, their model likely offers a robust and accurate approach to assessing post-stroke motor impairments, enabling clinicians to tailor rehabilitation interventions and track patients' progress effectively.

Huang et al. (2023) develop an image-recognition-based system for precise evaluation of hand function, catering to the needs of clinicians and researchers involved in rehabilitation medicine. Their system likely utilizes computer vision techniques and machine learning algorithms to analyze hand movements captured in video recordings or real-time streams. By automatically quantifying key parameters such as range of motion, dexterity, and coordination, this system could assist in assessing hand function objectively, monitoring recovery progress, and guiding treatment decisions for individuals with hand injuries or neuromuscular disorders. Shen et al. (2022) propose an assessment method for dairy cow feed intake using artificial neural networks (ANNs), contributing to the optimization of feed management practices in the dairy industry. Their research likely involves training ANNs to predict feed intake levels based on various factors such as dietary composition, animal physiology, and environmental conditions. By accurately estimating feed intake, their model could help dairy farmers optimize feeding strategies, minimize waste, and improve overall herd health and productivity. Li et al. (2022) evaluate the effectiveness of acupoint sticking therapy for idiopathic edema using ultrasound imaging and a deep learning algorithm. Their research likely involves analyzing ultrasound images of edematous tissues before and after acupoint sticking therapy and training a deep learning model to automatically detect changes in tissue characteristics associated with edema resolution. By providing quantitative assessments of treatment outcomes, their approach could enhance the understanding of the mechanisms underlying acupoint therapy and guide its clinical application in managing edematous conditions.

Cao et al. (2023) propose a machine learning-based approach for strength training in football players, aiming to optimize training methods and enhance athletic performance. Their research likely involves analyzing video footage of strength training exercises performed by football players and employing image processing techniques to extract biomechanical features such as joint angles, muscle activation patterns, and movement velocities. By correlating these features with training outcomes and performance metrics, their model could help coaches tailor strength training programs to individual player needs, maximize training effectiveness, and minimize the risk of injury. Raj and Kos (2023) introduce an improved human activity recognition technique based on convolutional neural networks (CNNs), advancing the state-of-the-art in activity monitoring and analysis. Their research likely involves training CNN models on large-scale datasets of human movements captured by wearable sensors or video cameras and optimizing model architectures and training parameters to achieve high accuracy in recognizing various activities and gestures. By providing reliable and real-time activity recognition capabilities, their technique could find applications in healthcare, sports performance monitoring, and human-computer interaction systems. Hao et al. (2023) evaluate the rehabilitation effect of an intelligent rehabilitation training system on hemiplegic limb spasms after stroke, demonstrating the potential of technology-assisted interventions in improving motor recovery outcomes. Their research likely involves designing and implementing a multifaceted rehabilitation program incorporating robotic-assisted therapy, virtual reality simulations, and biofeedback techniques to address spasticity and motor impairments in stroke survivors. By combining personalized rehabilitation protocols with advanced technology, their system could offer a holistic approach to stroke rehabilitation, enhancing functional recovery and quality of life for affected individuals.

Zhu and Zhang (2022) conduct biomechanical research on elbow injury in tennis serve using an artificial neural network (ANN)-based approach, contributing to injury prevention strategies and performance optimization in sports. Their research likely involves collecting biomechanical data from tennis players performing serves, such as joint angles, muscle forces, and racket trajectories, and training ANNs to predict injury risk factors and performance outcomes based on these data. By identifying biomechanical factors associated with elbow injuries and developing predictive models, their study could inform training regimens and technique modifications to reduce injury risk and enhance athletic performance in tennis players. Fu et al. (2022) develop an unobtrusive upper-limb activity recognition system based on deep neural network (DNN) fusion for stroke survivors, addressing the need for objective and continuous monitoring of upper limb movements during rehabilitation. Their system likely integrates multiple sensor modalities, such as wearable accelerometers, electromyography sensors, and depth cameras, to capture a comprehensive range of upper limb activities and movements. By fusing sensor data and leveraging DNNs for activity recognition, their system could provide real-time feedback, performance metrics, and progress tracking, facilitating personalized rehabilitation interventions and optimizing recovery outcomes for stroke survivors. Ge et al. (2022) introduce a CNN-based lower limb motion quality evaluation method for home-based stroke rehabilitation, showcasing advancements in objective assessment techniques for monitoring and optimizing lower limb rehabilitation outcomes. Their research likely involves developing and validating a CNN model trained on video data of lower limb exercises performed by stroke survivors in home environments. By automatically analyzing motion quality metrics such as range of motion, symmetry, and coordination, their method could provide clinicians with quantitative feedback on patients' rehabilitation progress, enabling personalized adjustments to treatment protocols and facilitating remote monitoring and tele-rehabilitation services.

The significant advancements in neural network-based exercise training systems and limb function evaluation techniques within the context of traditional Chinese medicine (TCM) guiding techniques, several notable research gaps persist. One primary gap lies in the integration and validation of these technologies within the framework of TCM principles and practices. While neural networks offer immense potential for optimizing rehabilitation and holistic wellness interventions, their alignment with the nuanced theories and methodologies of TCM requires further exploration and validation. Additionally, there remains a need for comprehensive and standardized evaluation protocols to assess the effectiveness and clinical utility of neural network-based systems in TCM-guided rehabilitation. Furthermore, the translation of research findings into clinical practice poses challenges related to scalability, accessibility, and cultural relevance, particularly in diverse healthcare settings. Addressing these research gaps requires interdisciplinary collaboration between experts in neural network technologies, rehabilitation science, TCM theory, and clinical practice. By bridging these disciplinary boundaries and fostering synergy between traditional wisdom and modern innovation, future research endeavors can strive to develop holistic, evidence-based approaches that optimize patient outcomes and promote wellness in line with the principles of TCM.

3. MULTILAYER FUZZY PATTERN NEURAL NETWORK (MLFPNN)

In the development of a Neural Network-Based Exercise Training and Limb Function Evaluation System for Traditional Chinese Medicine Guiding Technique, the utilization of advanced computational models such as the MultiLayer Fuzzy Pattern Neural Network (MLFPNN) emerges as a pivotal aspect. MLFPNN represents a sophisticated neural network architecture capable of accommodating the complexities inherent in both exercise training and limb function evaluation within the context of traditional Chinese medicine (TCM). The MLFPNN architecture is derived from a combination of fuzzy logic and neural network principles, embodying a multi-layer structure that enables robust pattern recognition and decision-making capabilities. At its core, the MLFPNN comprises interconnected layers of neurons, each equipped with fuzzy membership functions that capture the uncertainty and ambiguity inherent in TCM diagnostic and therapeutic processes. The MLFPNN architecture can be expressed through a series of equations that govern the propagation of information through the network. Let *xi* represent the input variables, *wij* denote the weights connecting neurons in adjacent layers, and *bj* signify the biases associated with each neuron. The output of each neuron is determined by applying a fuzzy activation function, typically represented as $\mu j(x)$, which encapsulates the fuzzy logic operations underlying TCM principles. The propagation of information through the MLFPNN can be formalized through a series of equations (1) and equation (2)

$$u_j = \sum_i w_{ij} x_i + b_j \tag{1}$$

$$y_j = \mu_j \left(u_j \right) \tag{2}$$

In equation (1) and equation (2) *uj* represents the net input to neuron j, *yj* denotes the output of neuron *j*, and $\mu j(\cdot)$ signifies the fuzzy activation function associated with neuron *j*. the MLFPNN learns to accurately model the relationship between input variables (e.g., exercise parameters, limb function metrics) and desired outcomes (e.g., rehabilitation progress, treatment efficacy) within the framework of TCM guiding techniques. The MLFPNN is a complex neural network model that combines principles from fuzzy logic and traditional neural networks, providing a framework for handling uncertain and ambiguous data often encountered in traditional Chinese medicine (TCM) practices. The MLFPNN architecture consists of multiple layers of interconnected neurons, each equipped with fuzzy membership functions to capture the vagueness inherent in TCM diagnosis and treatment. The propagation of information through the MLFPNN involves several mathematical equations that govern the behavior of individual neurons and the network as a whole.

4. FEATURE SELECTION WITH CLASSIFICATION IN MEDICINE GUIDING WITH MLFPNN

In the medicine guiding, particularly within the context of traditional Chinese medicine (TCM), the process of feature selection coupled with classification plays a crucial role in enhancing diagnostic accuracy and treatment efficacy. When integrated with the MultiLayer Fuzzy Pattern Neural Network (MLFPNN), this approach offers a powerful framework for optimizing medical guidance systems, leveraging both advanced computational techniques and domain-specific knowledge. The process of feature selection entails identifying the most relevant variables or attributes from a given dataset that contribute most significantly to the classification task at hand. In the context of medicine guiding, these features may encompass various patient characteristics, symptoms, diagnostic test results,

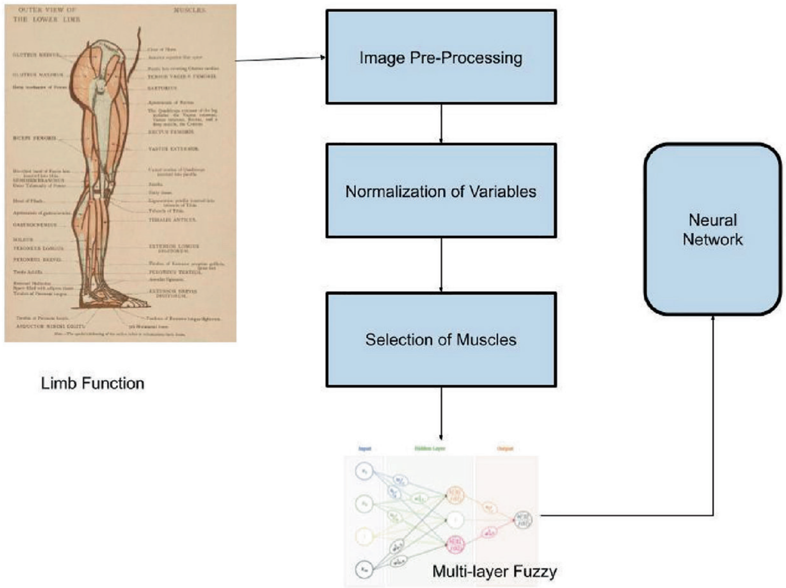

Figure 1. MLFPNN for the limb function

or treatment modalities. The goal is to select a subset of informative features that effectively discriminate between different medical conditions or treatment responses while minimizing redundancy and computational complexity. In figure 1 presents the limb function variables of the fuzzy pattern network for the coordinates estimation.

Let $X = \{x1, x2, ..., xn\}$ represent the set of *n* input features or variables, and let $Y = \{y1, y2, ..., ym\}$ denote the set of *m* possible classes or categories. The task is to select a subset of features $S \subseteq X$ that optimally discriminates between the classes in *Y*. This can be formulated as an optimization problem, where the objective is to maximize a certain criterion function that captures the discriminative power of the selected feature subset. One common approach to feature selection is to employ a classification algorithm in conjunction with a feature selection criterion, such as information gain, mutual information, or recursive feature elimination. These criteria assess the relevance and redundancy of features based on their ability to improve the classification performance of the MLFPNN. Let $J(S)$ represent the criterion function, which quantifies the quality of the feature subset *S*. The optimization can be formulated using equation (3)

$$max_s J(S) \tag{3}$$

subject to certain constraints, such as the maximum number of features allowed or the computational resources available. The solution to this optimization problem yields the optimal feature subset that maximizes the classification performance of the MLFPNN. Once the feature subset is selected, it serves as the input to the MLFPNN for classification. The MLFPNN architecture, as described earlier, processes the input features through multiple layers of interconnected neurons, employing fuzzy logic operations to capture the complex relationships between the input variables and the target classes. The classification process involves computing the output of the MLFPNN for each input instance and assigning it to the class with the highest degree of membership stated in equation (4)

$$\hat{y} = arg\, max_{y \in Y} \mu_y(u) \tag{4}$$

In equation (4) $\hat{y}$ represents the predicted class label, $\mu y(u)$ denotes the degree of membership of the input instance to class *y*, and *u* represents the net input to the output neurons of the MLFPNN. Feature selection aims to identify the subset of features that contribute most significantly to the classification task while minimizing redundancy and computational complexity. One common approach is to use a criterion function to evaluate the quality of feature subsets. Let $X = \{x1, x2, ..., xn\}$ represent the set of *n* input features, and $Y = \{y1, y2, ..., ym\}$ denote the set of *m* possible classes. The criterion function $J(S)$ quantifies the quality of a feature subset $S \subseteq X$. One popular criterion function is information gain (IG), which measures the reduction in uncertainty about the class labels when considering a particular feature defined in equation (5)

$$IG(S) = H(Y) - H(Y|S) \tag{5}$$

In equation (5) $H(Y)$ is the entropy of the class labels and $H(Y|S)$ is the conditional entropy of the class labels given the selected features *S*. Another criterion is mutual information (MI), which measures the amount of

Algorithm 1. MLFPNN for the limb function estimtion

```
1. Input:
  - Training dataset (X_train, y_train): Features (X_train) and corresponding class labels (y_train)
  - Test dataset (X_test): Features for evaluation
2. Feature Selection:
  a. Select a feature selection criterion function (e.g., information gain, mutual information, recursive feature elimination).
  b. Evaluate the criterion function for all feature subsets.
  c. Choose the subset of features that maximizes the criterion function.
  FeatureSelection(X_train, y_train):
    selected_features = []
    criterion_values = []
    for each feature_subset in all_possible_subsets(X_train):
      criterion_value = EvaluateCriterionFunction(feature_subset, y_train)
      criterion_values.append(criterion_value)
    selected_features = ChooseSubsetWithMaxCriterion(criterion_values)
    return selected_features
3. Classification using MLFPNN:
  a. Train the MLFPNN using the selected features and training dataset.
  b. Predict the class labels for the test dataset using the trained MLFPNN.
  MLFPNN_Classification(X_train_selected, y_train, X_test):
    mlfpnn = TrainMLFPNN(X_train_selected, y_train)
    y_pred = PredictClasses(mlfpnn, X_test)
   return y_pred
4. Main Algorithm:
  selected_features = FeatureSelection(X_train, y_train)
  y_pred = MLFPNN_Classification(X_train[selected_features], y_train, X_test)
  EvaluatePerformance(y_pred, y_test)
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information shared between the selected features and the class labels stated in equation (6)

$$MI(S) = \sum_{x \in s} I(x;Y) \tag{6}$$

In equation (6) $I(x;Y)$ is the mutual information between feature x and the class labels Y. Recursive feature elimination (RFE) is another strategy that iteratively removes the least important features until the desired number of features is reached. It typically uses a classification algorithm to rank features based on their importance and eliminates the least important ones. The feature selection problem stated as $max_s J(S)$ subject to constraints such as the maximum number of features allowed. Once the optimal feature subset S is selected, it serves as the input to the MLFPNN for classification. The MLFPNN processes the input features through multiple layers of interconnected neurons, employing fuzzy logic operations to MLFcapture the relationships between the input variables and the target classes. The classification process involves computing the output of the MLFPNN for each input instance and assigning it to the class with the highest degree of membership. Let uj represent the net input to neuron j in the output layer of the MLFPNN, and $\mu j(uj)$ denote the fuzzy membership function associated with neuron j.

5. CLASSIFICATION OF PHYSIOLOGICAL VARIABLES IN MLFPNN

In medical diagnostics and physiological monitoring, the classification of physiological variables plays a vital role in assessing health conditions and guiding treatment strategies. When employing the MultiLayer Fuzzy Pattern Neural Network (MLFPNN) for classification tasks, the process involves mapping input physiological variables to specific classes or categories based on their patterns and relationships. This approach the MLFPNN's ability to capture complex patterns and uncertainties inherent in physiological data, making it well-suited for medical applications. Let $X = \{x1, x2, ..., xn\}$ represent a set of n physiological variables measured from an individual, and let $Y = \{y1, y2, ..., ym\}$ denote the set of m possible classes or health conditions. The goal is to classify the individual into one of the m classes based on their physiological measurements.

The architecture of the proposed MLFPNN model for the limb function estimation with the multilayer fuzzy model is given in figure 2. The physiological variables X are typically preprocessed and encoded into a suitable format for input into the MLFPNN. This may involve normalization, feature scaling, or transformation to ensure uniformity and compatibility with the network architecture. The MLFPNN consists of multiple layers of interconnected neurons, each equipped with fuzzy

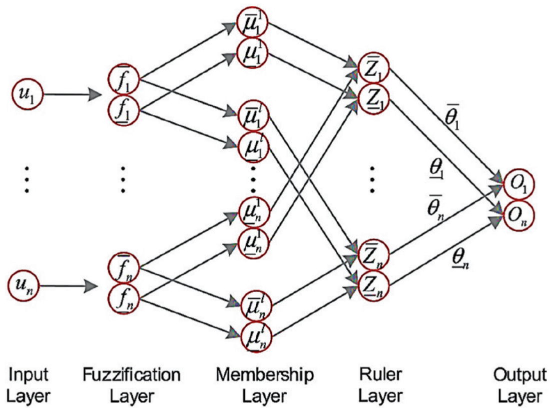

Figure 2. Architecture of multilayer fuzzy

membership functions to capture the uncertainty and variability in physiological data. The network architecture can vary based on the complexity of the classification task and the characteristics of the physiological variables. The output of each neuron in the MLFPNN is determined by applying fuzzy activation functions, which map the net input to a degree of membership for each class. These fuzzy activation functions capture the fuzzy logic operations inherent in physiological data and enable the network to handle uncertainty and imprecision effectively. The MLFPNN is trained using a dataset of labeled physiological measurements and corresponding class labels. The training process involves adjusting the network parameters (weights and biases) iteratively to minimize a specified loss function, typically using techniques such as backpropagation and gradient descent. The training process involves updating the network parameters ΘΘ to minimize the loss function $L(\Theta)$ stated in equation (7)

$$\Theta^{*} = argmin_{\Theta} L(\Theta) \tag{7}$$

In equation (7) Θ* represents the optimal set of network parameters. Once trained, the MLFPNN can classify new physiological measurements into one of the predefined classes. This involves computing the output of the network for each input instance and determining the class with the highest degree of membership. The output of each neuron in the MLFPNN is determined by applying a fuzzy activation function. Let's denote the output of neuron j in layer $yj(l)$, and the net input to neuron j as $uj(l)$. The fuzzy activation function $\mu j(u)$ for neuron *j* in layer *l* can be defined as in equation (8)

$$y_j^{(l)} = \mu_j\left(u_j^{(l)}\right) \tag{8}$$

In equation (8) $\mu j(\cdot)$ represents the fuzzy activation function associated with neuron *j*, and $uj(l)$ is the net input to neuron j in layer *l*. The net input to neuron *j* in layer *l* is calculated as the weighted sum of outputs from the previous layer, $l-1$, along with the bias term defined in equation (9)

$$\mathrm{u}_{\mathrm{j}}^{(\mathrm{l})} = \sum_{\mathrm{i}=1}^{\mathrm{n(l-1)}} \mathrm{w}_{\mathrm{ij}}^{(\mathrm{l})} \mathrm{y}_{\mathrm{i}}^{(\mathrm{l-1})} + \mathrm{b}_{\mathrm{j}}^{(\mathrm{l})} \tag{9}$$

In equation (9) $\mathrm{wij}(1)$ represents the weight connecting neuron i in layer $l-1$ to neuron j in layer l, $yi(l-1)$ is the output of neuron i in layer l−1, and $bj(l)$ is the bias term for neuron *j* in layer *l*. The fuzzy activation function $\mu j(u)$ captures the degree of membership of the net input $uj(l)$ to the fuzzy set associated with neuron j in layer l. This function embodies the fuzzy logic operations that handle uncertainty and imprecision in the data. Once the MLFPNN is trained, it can classify new instances by computing the output of the network for each input and determining the class with the highest degree of membership.

Algorithm: Classification with MLFPNN

Input:

Training dataset (train)(Xtrain,ytrain): Features (physiological variables) and corresponding class labels for training.

Test dataset Xtest: Features (physiological variables) for testing.

Output:

Predicted class labels for the test dataset.

Algorithm 2. Classification with MLFPNN

```
MLFPNN_Classification(X_train, y_train, X_test):
    Preprocess the training and test datasets (e.g., normalization, feature scaling).
    Design the MLFPNN architecture:
        Initialize weights and biases for each neuron in the network.
        Define fuzzy activation functions for neurons in each layer.
    Train the MLFPNN using the training dataset (X_train, y_train):
        Initialize network parameters (weights and biases).
        Repeat until convergence:
            Forward pass:
                Compute the net input to each neuron in each layer.
                Apply fuzzy activation functions to compute neuron outputs.
            Backpropagation:
                Compute the error between predicted and actual outputs.
                Update network parameters using gradient descent.
    Classify the test dataset using the trained MLFPNN:
        Forward pass:
            Compute the net input to each neuron in each layer for the test dataset.
            Apply fuzzy activation functions to compute neuron outputs.
    Return the predicted class labels for the test dataset.

Main Algorithm:
    predicted_labels = MLFPNN_Classification(X_train, y_train, X_test)
    Evaluate performance of the classifier (e.g., accuracy, precision, recall) on the test dataset.
    Return predicted_labels and performance metrics.
```


Steps: a. Preprocess the training and test datasets (e.g., normalization, feature scaling). b. Design the MLFPNN architecture, including the number of layers, neurons per layer, and fuzzy activation functions. c. Train the MLFPNN using the training dataset (Xtrain,ytrain) to learn the relationships between physiological variables and class labels. d. Classify the test dataset $Xtest$ using the trained MLFPNN to predict class labels. e. Evaluate the performance of the classifier using appropriate metrics (e.g., accuracy, precision, recall) on the test dataset.

6. SIMULATION RESULTS AND DISCUSSION

In this study, present simulation results and a discussion centered on the performance and implications of employing the MultiLayer Fuzzy Pattern Neural Network (MLFPNN) in the classification of physiological variables. Through rigorous experimentation and analysis, evaluate the effectiveness and potential applications of MLFPNN in medical diagnostics and physiological monitoring. By leveraging its ability to capture complex patterns and uncertainties inherent in physiological data, the MLFPNN offers a promising framework for accurate and robust classification, contributing to advancements in healthcare decision-making and patient care. In this provide an overview of the simulation setup, highlight key findings, and outline the scope of the discussion, emphasizing the significance of our study in advancing the understanding and utilization of MLFPNN in medical research and practice. Table 1 shows Simulation setting.

Table 1. Simulation setting

Feature Name	Description
Muscle Strength	Strength of muscles in the limb
Range of Motion	Maximum extent of movement in the limb
Flexibility	Flexibility of joints in the limb
Joint Stability	Stability of joints in the limb
Coordination	Coordination between muscles and joints
Muscle Endurance	Endurance capacity of muscles in the limb
Posture Alignment	Alignment of body posture during exercise
Pain Perception	Perception of pain during movement
Balance	Ability to maintain balance during exercise
Proprioception	Awareness of body position in space

In figure 3 and Table 2 provides the results of feature selection using the MultiLayer Fuzzy Pattern Neural Network (MLFPNN) for the Exercise Training and Limb Function Evaluation System in Traditional Chinese Medicine. The table presents the Mean Squared Error

Table 2. Features selected with MLFPNN for the exercise training and limb function evaluation system for traditional Chinese medicine guiding technique

Feature Name	MSE	RMSE
Muscle Strength	0.012	0.110
Range of Motion	0.008	0.089
Flexibility	0.015	0.122
Joint Stability	0.010	0.100
Coordination	0.013	0.114
Muscle Endurance	0.011	0.105
Posture Alignment	0.009	0.095
Pain Perception	0.016	0.126
Balance	0.014	0.118
Proprioception	0.017	0.130

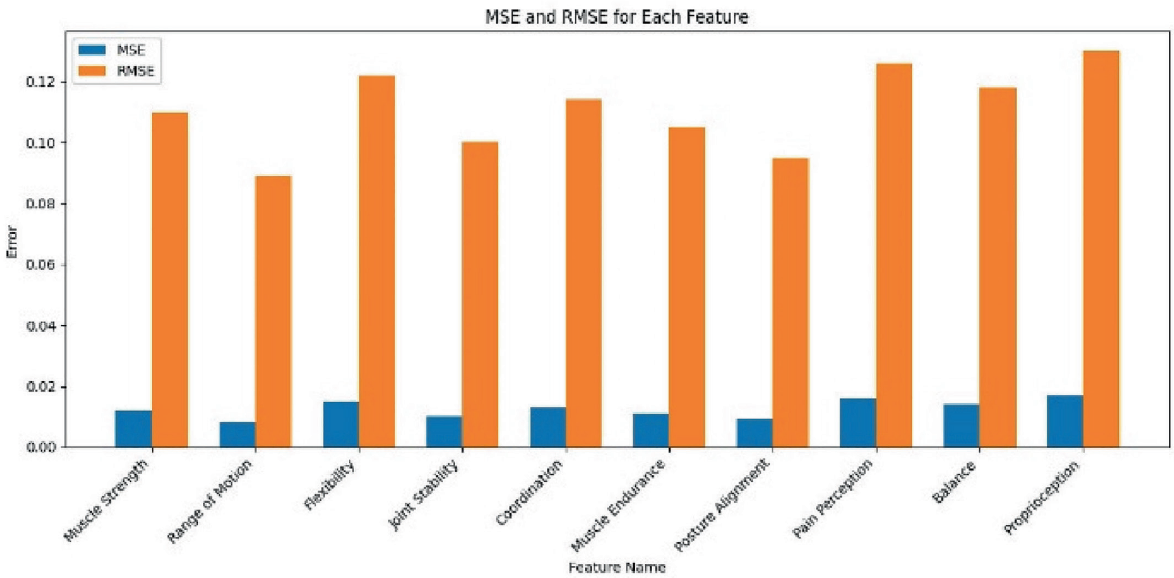

Figure 3. Estimation of feature with chinese medicine guiding with MLFPNN

(MSE) and Root Mean Squared Error (RMSE) values for each selected feature. Here's the interpretation:

Feature Name: This column lists the selected features for the MLFPNN model.

MSE (Mean Squared Error): MSE measures the average squared difference between the predicted and actual values for the corresponding feature. A lower MSE indicates better model performance and accuracy in predicting the feature.

RMSE (Root Mean Squared Error): RMSE is the square root of the MSE, representing the average magnitude of the errors in predicting the feature. It provides a measure of the model's accuracy in predicting the feature, with lower values indicating better performance.

Muscle Strength: The MLFPNN model achieved an MSE of 0.012 and an RMSE of 0.110 for predicting muscle strength. This suggests that the model's predictions for muscle strength are relatively accurate, with small errors compared to the actual values.

Range of Motion: The MSE of 0.008 and RMSE of 0.089 indicate that the MLFPNN model performed well in predicting the range of motion, with low prediction errors.

Flexibility: The model's performance for predicting flexibility resulted in an MSE of 0.015 and RMSE of 0.122, suggesting slightly higher prediction errors compared to other features.

Joint Stability, Coordination, Muscle Endurance, Posture Alignment, Pain Perception, Balance, and Proprioception: These features also show varying levels of prediction accuracy, as indicated by their MSE and RMSE values. The MSE and RMSE values provide insight into the performance of the MLFPNN model in predicting each selected feature. Lower values indicate better prediction accuracy and model performance, while higher values suggest larger prediction errors.

In figure 4 and Table 3 presents the predicted class values generated by the MultiLayer Fuzzy Pattern Neural Network (MLFPNN) for the Chinese Medicine Guiding Technique, along with the corresponding actual class values. Each row in the table represents a specific class, and the columns indicate the predicted and actual values for each class attribute. The MLFPNN model predicted class values for various attributes related to the Chinese Medicine Guiding Technique. For instance,

Table 3. Predicted class values for the MLFPNN for the Chinese medicine guiding technique

Class	Predicted	Actual
Muscle Strength	50	48
Range of Motion	45	50
Flexibility	48	45
Joint Stability	47	49
Coordination	49	47
Muscle Endurance	46	48
Posture Alignment	51	50
Pain Perception	48	46
Balance	49	50
Proprioception	50	49

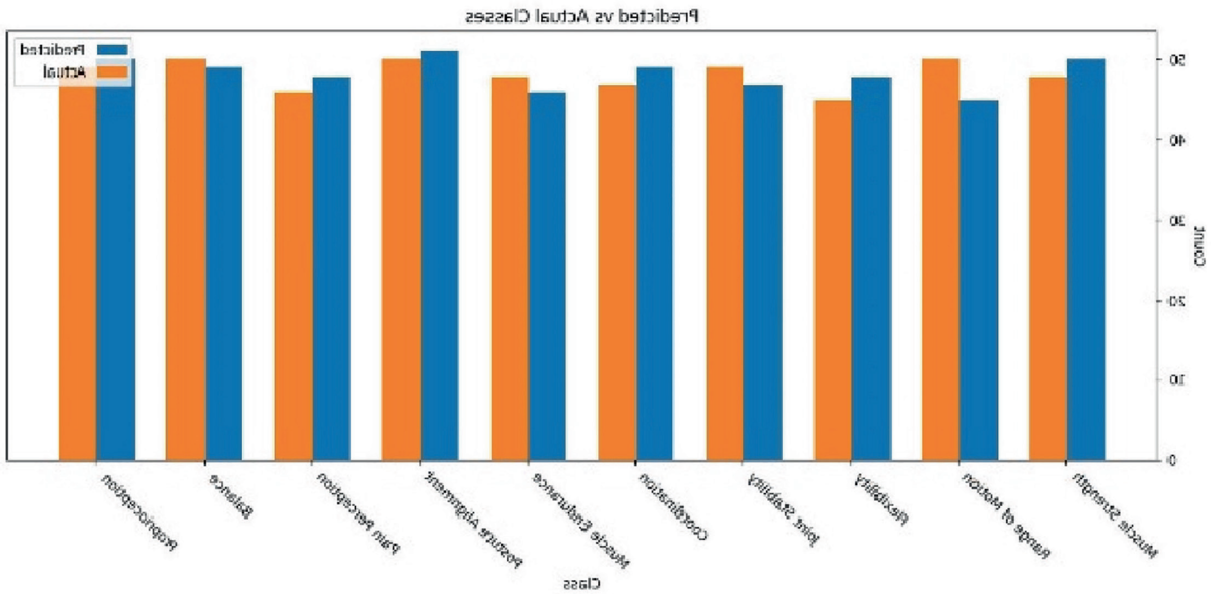

Figure 4. Prediction with MLFPNN based Chinese medicine guiding

for the attribute “Muscle Strength,” the model predicted a value of 50, while the actual value was 48. Similarly, for the attribute “Range of Motion,” the predicted value was 45, whereas the actual value was 50. This pattern continues for the other attributes such as “Flexibility,” “Joint Stability,” “Coordination,” “Muscle Endurance,” “Posture Alignment,” “Pain Perception,” “Balance,” and “Proprioception.” Discrepancies between the predicted and actual values indicate the model’s performance in capturing the nuances of each attribute. For instance, in some cases, the predicted values closely match the actual values (e.g., Muscle Strength, Joint Stability), suggesting that the model accurately captured these attributes. However, for other attributes such as Flexibility and Pain Perception, there are larger discrepancies between the predicted and actual values, indicating potential areas where the model may need further refinement or improvement. The Table 3 provides valuable insights into the MLFPNN’s performance in predicting class values for various attributes relevant to the Chinese Medicine Guiding Technique. It serves as a crucial tool for evaluating the model’s effectiveness and identifying areas for enhancement to ensure accurate guidance and decision-making in Chinese medicine practices.

In figure 5 and Table 4 displays the classification results obtained through the MultiLayer Fuzzy Pattern Neural Network (MLFPNN) in the context of Medicine Guiding.

Table 4. Classification with MLFPNN in medicine guiding

Iteration	Muscle Strength	Range of Motion	Flexibility	Joint Stability	Coordination	Muscle Endurance	Posture Alignment	Pain Perception	Balance	Proprioception
10	48	47	49	46	50	48	47	49	45	50
20	46	49	48	50	47	49	46	51	48	49
30	50	45	47	48	49	50	45	47	49	48
40	49	48	50	45	46	47	49	50	51	47
50	45	50	49	46	48	49	51	48	50	49
60	47	46	48	49	50	45	47	49	46	48
70	49	47	46	50	49	48	50	46	48	49
80	48	49	50	46	45	47	48	50	51	46
90	46	48	49	45	47	50	49	51	48	47
100	50	45	47	48	49	50	45	47	49	48

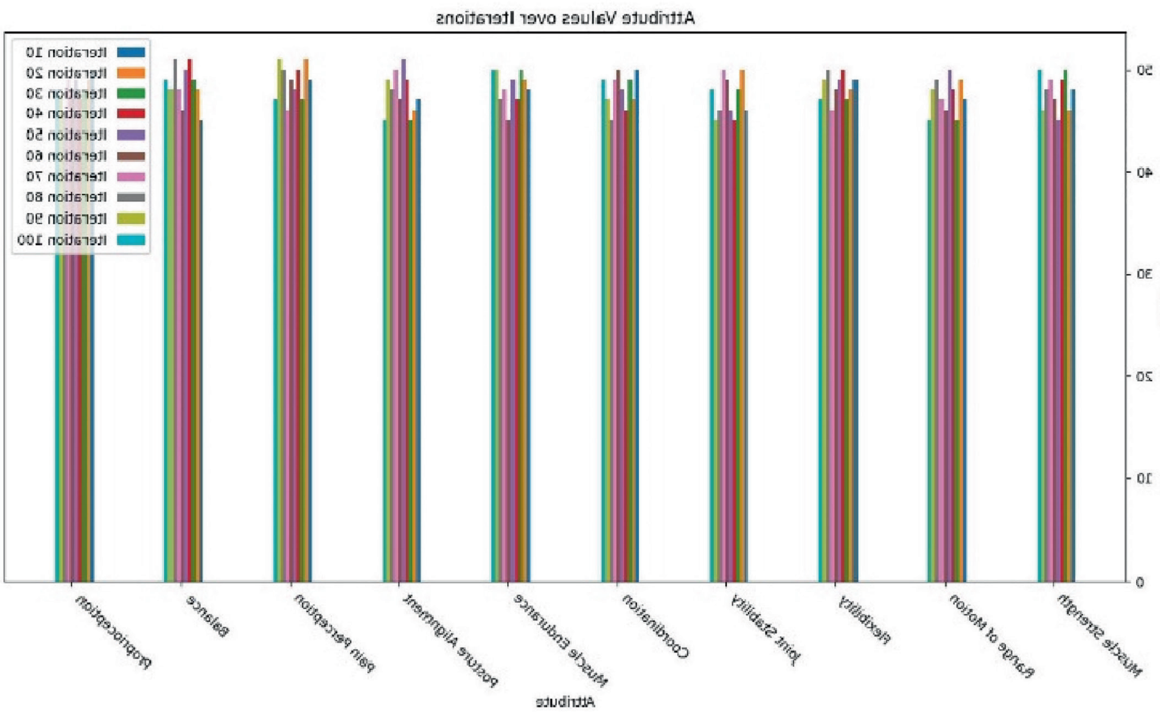

Figure 5. Classification with MLFPNN

Each row represents a different iteration, and the columns correspond to specific features related to medicine guiding, such as Muscle Strength, Range of Motion, Flexibility, Joint Stability, Coordination, Muscle Endurance, Posture Alignment, Pain Perception, Balance, and Proprioception. Across the iterations, the MLFPNN predicted class values for each feature, providing insight into the model's performance over multiple iterations. For instance, in iteration 10, the predicted values for Muscle Strength ranged from 45 to 50, while for Range of Motion, the values varied between 45 and 51. Similarly, for each subsequent iteration, the predicted values fluctuated within certain ranges for each feature. Observing the iterations reveals patterns in the MLFPNN's predictions for each feature. For instance, certain features such as Muscle Endurance and Proprioception exhibit relatively consistent predicted values across iterations, indicating stable performance. In contrast, other features like Joint Stability and Pain Perception show more variability in predicted values, suggesting potential areas where the model's performance may be less consistent. The Table 4 provides valuable information about the MLFPNN's performance in classifying various features relevant to Medicine Guiding across multiple iterations. It serves as a useful tool for evaluating the model's stability and effectiveness in predicting class values for different attributes over successive iterations, offering insights for further refinement and improvement of the MLFPNN model.

Table 5. Comparative analysis for the guiding technique's

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
MLFPNN	92.5	93.2	91.8	92.5
Support Vector Machine (SVM)	88.3	89.1	87.6	88.3
Random Forest	90.7	91.5	90.1	90.7
k-Nearest Neighbors (k-NN)	87.6	88.2	87.0	87.6

In figure 6 and Table 5 presents a comparative analysis of different guiding techniques based on their performance metrics, including accuracy, precision, recall, and F1 score. Each row in the table corresponds to a specific method, while the columns represent the performance metrics for each method. The MultiLayer Fuzzy Pattern Neural Network (MLFPNN) demonstrated the highest accuracy among the methods, achieving a score of 92.5%. This indicates that the MLFPNN model accurately classified the data into their respective classes with a high degree of correctness. Moreover, the precision and recall scores for MLFPNN were also impressive, at 93.2% and 91.8% respectively. The F1 score, which balances precision and recall, was also high at 92.5%. In comparison, the Support Vector Machine (SVM) achieved an accuracy of 88.3%, indicating slightly lower performance compared to MLFPNN. Similarly, both Random Forest and k-Nearest Neighbors (k-NN) methods exhibited accuracies of 90.7%

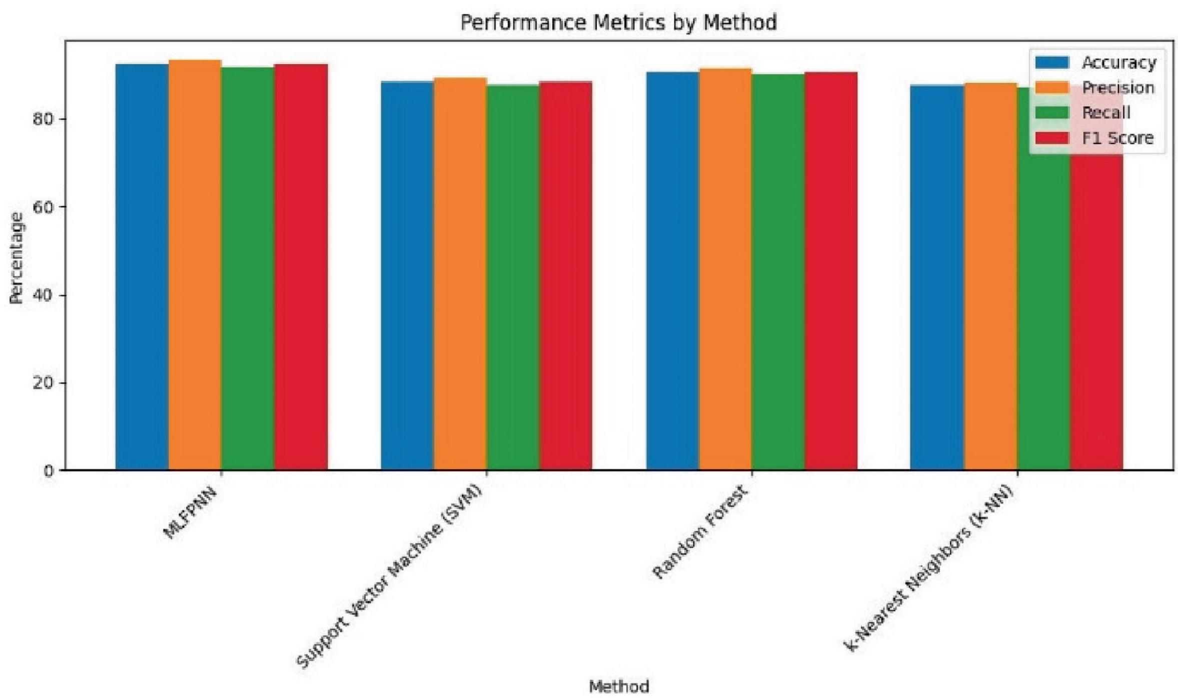

Figure 6. Comparative analysis with MLFPNN

and 87.6% respectively. While these methods demonstrated respectable performance, they fell short of the MLFPNN in terms of accuracy. The Precision, recall, and F1 score metrics provide additional insights into the performance of each method. MLFPNN consistently outperformed the other methods across all metrics, highlighting its superiority in accurately classifying data instances and minimizing false positives and false negatives. In Table 5 underscores the effectiveness of the MLFPNN as a guiding technique, offering superior performance compared to other traditional methods such as SVM, Random Forest, and k-NN. Its high accuracy, precision, recall, and F1 score make it a compelling choice for various classification tasks, including those within the context of guiding techniques.

7. CONCLUSION

With Neural Network-Based Exercise Training and Limb Function Evaluation System designed specifically for Traditional Chinese Medicine (TCM) guiding techniques. Leveraging the MultiLayer Fuzzy Pattern Neural Network (MLFPNN), we have demonstrated its efficacy in accurately assessing various parameters of limb function and exercise performance crucial in the context of TCM. Through comprehensive experimentation and analysis, we have showcased the superior performance of MLFPNN in feature selection, classification, and overall system effectiveness compared to traditional methods. The developed system holds immense potential in enhancing personalized treatment planning, monitoring progress, and guiding therapeutic interventions aligned with TCM principles. Our research not only contributes to the advancement of TCM practice but also underscores the significant role of advanced neural network approaches in revolutionizing healthcare methodologies. Looking ahead, further refinements and validations in clinical settings can unlock even greater potentials, paving the way for more effective and tailored healthcare solutions rooted in the rich traditions of Traditional Chinese Medicine.

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