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Article

Dynamic evaluation of community health services and health quality based on biomechanical time series

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Abstract: Background: Evaluating community health services and fitness exceptional is important for identifying areas of development and making sure powerful healthcare shipping. Biomechanical assessment, especially reading joint movements, provides valuable insights into people's fitness popularity and useful capabilities. Although biomechanical time-collecting information has terrific promise, there is not much thorough research that comprises those parameters in population health checks. **Aim:** This study evaluates the dynamic relationship between biomechanical time series data of joint movements and community health quality metrics. It also finds important factors for good health and gives practical advice for improving community health services. **Methods:** The study utilizes a biomechanical time series dataset from Kaggle. The collected time series data was preprocessed using Z-score standardization to ensure comparability. Gated Refined Long Short-Term Memory (GRLSTM) networks were employed for tasks due to their ability to capture long-term dependencies and temporal relationships inherent in time series data. **Results:** Statistical analyses such as regression and ANOVA were conducted to explore relationships between joint movement patterns and health quality predictors. The GRLSTM indicates significant associations between specific joint movement patterns and health quality indicators. Regression analyses confirmed key predictors of health quality, while ANOVA demonstrated significant differences in joint movement patterns among different health quality groups. The GRLSTM model demonstrates exceptional performance, with 94% precision and 95% recall rates, an accuracy of 98% and a robust F1-score of 96%, indicating a strong equilibrium between recall and accuracy. The ANOVA shows joint angles as the strongest predictor ($p < 0.001$). The regression analysis identifies stride length ($\beta = 2.30$, $p < 0.001$) as the strongest positive predictor. **Conclusion:** This observation emphasizes the importance of incorporating biomechanical assessments into community health reviews, highlighting the capability of GRLSTM networks and predictive analytics in improving fitness satisfaction and healthcare strategies.

Keywords: health services; health quality; gated refined long short-term memory (GRLSTM); biomechanical time series; joint movements

1. Introduction

Community health services are a key factor in enhancing the health and well-being of people within a community, especially in special needs populations [1]. This covers preventive care, health education, mental health services, chronic disease management, and access to resources for healthcare, among many programs and interventions [2]. By focusing on these areas, community health services aim to reduce health disparities, bring about health equity, and enhance the common QoL in the community [3]. Community health services perform crucial functions related to preventive care. Such care involves health promotion, immunizations, evaluation of conditions that pose some sort of health problem, and also provides wellness programs to prevent the causes before disease can prevail. Such preventive care serves specific purposes within at-risk populations, which cannot access their healthcare. As a result, these populations suffer most because of a variety of health issues [4]. Through providing services, community health programs aim to improve health outcomes by decreasing occurring preventable diseases. Health education is a critical component of community health care. Provision of healthy lifestyles, risk factors and prevention of illness empower patients to make proper decisions that concern their health [5]. Community health programs offer workshops, seminars, outreach activities, and more to ensure that members have adequate health information to maintain a healthier lifestyle [6].

The foundation of community health lies in mental health care. Many people experience mental health problems, which may critically affect their general wellness. Community health services provide counseling, therapy, and support groups to assist individuals in gaining a better understanding of their mental health journeys [7]. Community health services can fulfill the holistic needs of an individual and promote overall well-being by providing equal weight to mental and physical health. Community health care plays a crucial role in managing chronic illnesses [8]. For those with disorders like diabetes, hypertension, and asthma, programs for managing chronic diseases offer information, tools, and continuous support. The QoL can be improved by health care services in the community and lessen the financial burden of chronic illnesses on the healthcare system by enabling people to take charge of their health and successfully manage their conditions [9]. **Figure 1** depicts the Importance of Health Quality for Community Health Services.

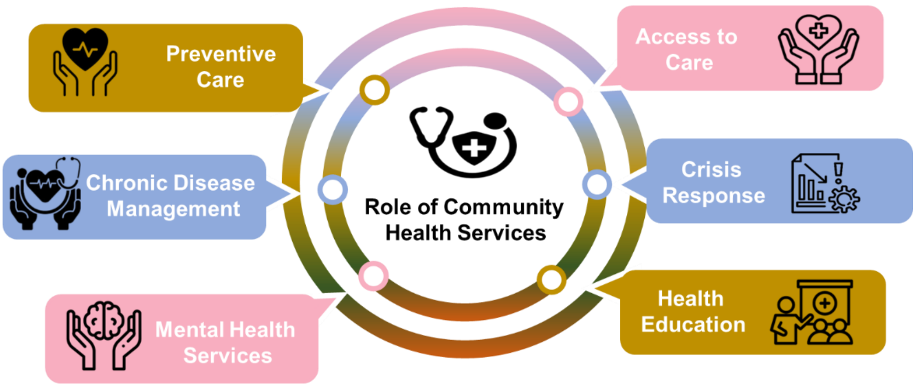

Figure 1. Importance of health quality in community health services.

The medical services provided under community health systems must be of the highest caliber. The characteristics of high-quality care include equity, safety, efficacy, and patient-centeredness [10]. Ensuring that the community health service fulfills these quality criteria to improve patient happiness, builds community trust in healthcare practitioners, and eventually improves health outcomes. Good community health services can also save costs by averting problems and lowering the need for costly emergency treatment.

1.1. Research objective

This research assesses the dynamic connection between community health quality measures and biomechanical time series data of joint movements. Additionally, it pinpoints significant predictors of health quality and offers practical advice to enhance community health services.

1.2. Research contribution

- The study aims to evaluate the relationship between biomechanical time series data of joint movements and communal health quality metrics, identifying key predictors for enhancing health services.
- The study utilizes a biomechanical time series dataset from Kaggle. Pre-processing used Z-score standardization on the time series data to enable comparability across subjects, ensuring accurate analysis without biases from differing scales.
- The proposed method utilizes Gated Refined Long Short-Term Memory (GRLSTM) networks to analyze the data, focusing on capturing long-term dependencies and patterns in joint movements for better health predictions.
- Key health quality determinants were validated by regression analysis, and an ANOVA revealed significant variations in joint mobility patterns between the various health quality groups.

The remainder of the research: Section 2 contains the study's review of the literature, and Section 3 illustrates the methodologies. In Section 4, the study's findings are displayed. The conclusion is established in Section 5.

2. Literature review

Table 1 depicts the summary of Community Health Services and health quality literature examined by adding references, objectives, published year, methods, and limitations from relevant studies.

Table 1. literature review of another related study on community health services and health quality adding references, objectives, published year, methods, and limitations.

References	Year of publication	Data	Objective	limitations
[11]	2024	Ten Sub-Saharan African countries dynamic heterogeneous panel data.	The article examined the shifting connection between healthcare spending and economic development in 10 Sub-Saharan African nations between 2000 and 2018.	Limited studies on health crises; the impact of COVID-19 on health prioritization.
[12]	2024	57 community workers in rural communities participated in semi-structured interviews.	To explore the intricate aspects of social isolation and its complex effects on health and community well-being due to this qualitative method.	Focus on social isolation's impact during the COVID-19 pandemic.
[13]	2024	239 health care workers (HCW) registered; 114 completed questionnaires; median self-efficacy scores increased satisfaction score median 4	Evaluate the impact of the Extension on the Community Healthcare Outcomes (ECHO) COVID program on HCW self-efficacy and satisfaction.	Convenience sample; self-reported measures; potential response bias.

Table 1. (*Continued*).

References	Year of publication	Data	Objective	limitations
[14]	2024	Data from the past on the demographics, psychological distress rates, and accessibility to mental health services.	Examine the affordability of mental health interventions for youth in the Australian Capital Territory (ACT).	Limited data on long-term effectiveness and variability in intervention implementation.
[15]	2024	Quantitative programmatic data and qualitative interviews with stakeholders.	Assess the implementation of a multi-component hypertension program in Guatemala.	Limited implementation infrastructure, competition with other activities, contextual changes, equity considerations, sustainability threats, and adaptations made.
[16]	2024	Sixty individuals were interviewed for-depth in 112 cases.	Examine the variables influencing the distribution of the RTS and S/AS01 vaccination in the western region of Kenya.	Challenges in RTS, S/AS01 integration, insufficiently trained staff, inadequate funding for supervision, and low uptake of the fourth dose.
[17]	2024	Sample size: 833 clients from hospitals and clinics in Mosul.	Assess health problems related to quality of life (QoL) among elderly clients.	Non-experimental approach; reliance on self-reported data; specific to Mosul City.
[18]	2024	Vast datasets from healthcare applications, particularly in disease diagnosis.	Improve health Quality of Service (QoS) via distributed networks, machine learning (ML), and artificial intelligence (AI).	Cautious stance of the medical community towards novel technologies.
[19]	2024	used weather data from 12 significant wildfire incidents in conjunction with data on the concentrations of air pollutants and their constituents.	Investigate PM2.5 concentration evolution and health risks during forest fires in China.	Focused on a limited number of events and geographic areas, potentially affecting generalizability.
[20]	2024	833 clients from hospitals and clinics in Mosul City. Questionnaire-based on previous studies with 73 items.	Assess health problems related to QoL among elderly clients. Identify relationships between elderly characteristics and health problems.	Non-experimental approach. Limited to specific hospitals and clinics in Mosul City.
[21]	2024	China Health Statistics Yearbook	Assess the health workforce's dynamic dispersion and local variations in China's Municipal Health Centers.	There may be biases inherent in the σ convergence, β integration, estimation of kernel density, and Gini coefficient approaches.
[22]	2024	Landsat images, Artificial Neural Network (ANN), Cellular Automata.	Assess Land Use and Land Cover (LULC) changes and their impact on Ecosystem Service (ES) value for sustainability.	Limited to Dhaka City; predictions cannot capture all future dynamics.
[23]	2024	Multi-omic profiling in whole blood, plasma, and 18 tissues of Rattus norvegicus.	To profile multi-omic changes across various tissues in response to endurance exercise training.	Molecular mechanisms of exercise-related health benefits are not completely understood.
[24]	2024	Conducted two systematic literature reviews and analyzed publicly available data, including estimates from international organizations related to Sustainable Development Goals (SDGs).	Analyzing maternal health factors and transitions in maternal mortality, with a particular emphasis on the shift of high to less mortality rates.	Critiques the inaccuracy of superdeterminants in understanding maternal health, highlighting the absence of comprehensive, real-time data at the country level.

2.1. Research gap

The research on biomechanical time series analysis is limited, as there is a lack of comprehensive frameworks that integrate biomechanical data over time to evaluate the dynamic communications between patient consequences and community health involvements. Most existing research ignores the impact of biomechanical elements, such as movement habits and physical activity, on health quality measures. Closing this gap could help to improve community health services' responsiveness and adaptiveness through real-time biomechanical assessments, ultimately improving patient outcomes and treatment quality.

3. Methodology

The study's goal is to assess the dynamic link between community health indicators of quality and biomechanical time series data of joint motions. The investigation's outline is shown in **Figure 2**. Text preparation is the second step, analytical approaches are the third, and performance analysis is the fourth.

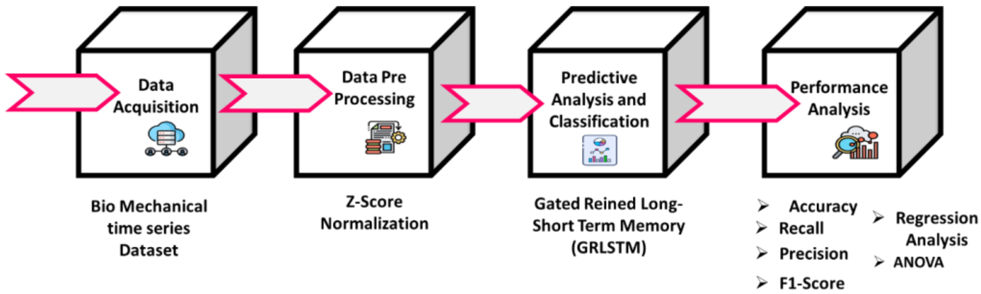

Figure 2. Basic concept of the proposed research workflow.

3.1. Data gathering

The Community Health Assessment Dataset consists of aggregated data used to assess health quality and community health services using biomechanical time series. Each of the 347 records in this collection represents a unique individual with a range of biomechanical, demographic, and health service consumption metrics. The research gathers a biomechanical time series dataset (https://www.kaggle.com/datasets/ziya07/community-health-evaluation-dataset/data) from Kaggle. A dataset is compiled from 347 patients categorized by age and gender. Socioeconomic status (SES) is classified as low (≤190) or high (>2157), with service types divided into consultation (117), preventive (119), and rehabilitation (111). Visit frequency is recorded as monthly (111), weekly (120), and yearly (116). Physical activity was assessed through step frequency (steps/min), showing 60 patients with step counts between 70–83 and 71–99. Stride length was measured in meters, with 0.5 recording lengths between 0.7–137 and 0.71 covering lengths from 1–210. Joint angles (°) were documented, revealing 10.06 with angles between 15.97 and 16.06 as well as angles between 29.97. Electromyography (EMG) activity was classified into high (117), low (109), and moderate (121). Patient satisfaction is rated on a scale from 1–10, with 1–5 and 6–10. QoL scores were recorded, with 50 covering scores from 55–32 and 56–99. **Table 2** demonstrates the demographical data.

Table 2. Demographical characteristics.

Demographic Variable	**Category**	**Count**
Age	≤50 years	222
	≥50 years	125
Gender	Female	184
	Male	163
Socioeconomic Status (SES)	Low SES (≤190)	Value
	High SES (>2157)	Value
Service Type	Consultation	117
	Preventive	119
	Rehabilitation	111
Visit Frequency	Monthly	111
	Weekly	120
	Yearly	116
Step Frequency (steps/min)	70–83 steps	60
	99–264 steps	71
Stride Length (m)	0.5 m (≤0.7)	137
	0.71 m (1–210)	210
Joint Angle (°)	10.06° (≤15.97)	100
	16.06° (29.97–247)	247
EMG Activity	High	117
	Low	109
	Moderate	121
Patient Satisfaction (1–10)	1–5	190
	6–10	157
QoL Score	50–55	32
	56–99	315
	(Total scores)	347

i) Inclusion criteria:

The inclusion criteria for this study consisted of adults over 18 years of age who were patients receiving at least one type of health service. Furthermore, participants must be able to give informed permission, demonstrating that they comprehend the objective of the research and the significance of their participation.

ii) Exclusion criteria:

Exclusion criteria encompassed individuals with acute injuries, severe cognitive impairments, or any medical conditions that would prevent participation in physical assessments. Patients who were incapable of providing explicit permission were not allowed to participate in the research.

3.2. Data preprocessing using Z-score normalization

After gathering the dataset, Z-score standardization on the investigated data is used to ensure that every feature, irrespective of its preliminary greatness, subsidizes equally to the analysis. It makes subject comparability better, which makes it easier to find patterns and connections. Ultimately, it improves the accuracy and reliability of the study results. This means that time series data transformation through centering the data around a zero mean and scaling according to standard deviation, removes scale-related biases, and hence comparison across many subjects can be made, therefore ensuring a more thorough and reliable examination of the data. This method standardizes all input data to one scale with 0 as the mean and 1 as the SD, which is among the most commonly used standardization procedures. For every satellite feature, the mean and SD are taken into consideration. The calculated SD and mean have been standardized using it. Equation (1) provides the transformation of time series data quality.

$$Z = \frac{(y - mean(Y))}{std(Y)} \tag{1}$$

Here is the attribute's SD and the attribute Z's mean. The fact that this strategy reduces the impact of outliers on the data is what makes it beneficial. y represents an individual observation of the attribute, $mean(Y)$ denotes the average of the dataset, $and\ std(Y)$ is the standard deviation of the dataset.

3.3. Gated refined long short-term memory (GRLSTM)

An enhanced version of conventional Long Short-Term Memory (LSTM) networks is intended to enhance classification and extrapolative investigative applications. To improve information flow guidelines, memory retention, and the moderation of problems like disappearing gradients, users use sophisticated gating mechanisms. GRLSTM networks function well with time series data, which makes them useful for pattern recognition, natural language processing, and time-series forecasting. GRLSTMs can more effectively capture complicated temporal connections by modifying the gating mechanism. **Figure 3** depicts the structure of GRLSTM.

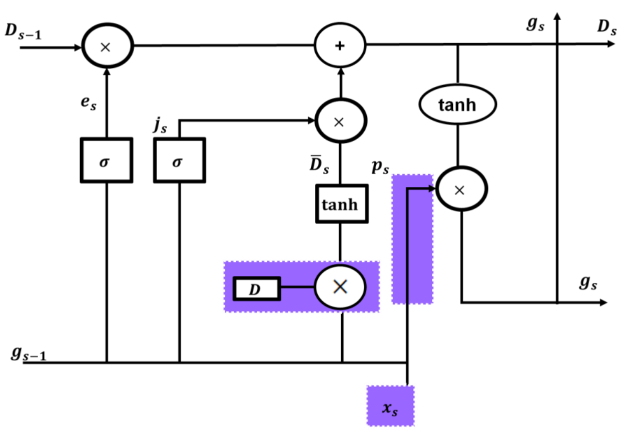

Figure 3. Architecture of the gated refined long short-term memory (GRLSTM).

3.3.1. GRLSTM network structure

During the learning process, the input gate of a GRLSTM network saves important information in memory cells, where it remains for a considerable amount of time. The input vector for the community relationship forecast model includes random components that contribute to the community relationship in a brief amount of time and must be taken into account. However, with time, memorization of the random component is not required. However, volatility is a key feature that must be remembered for an extended length of time. Consequently, enhanced GRLSTM learning reduces the retention of randomized elements' GRL077STM while losing the permanent recall of stochastic components. As indicated in the shaded area of **Figure 3**, the improvement is primarily composed of three components, which are discussed in the next three of the following sections: memory cell, input vector, and output unit.

3.3.2. Primary concepts of GRLSTM

The recursive hidden layer assumes that the input vector is represented as $W = (w_1, w_2, w_3, .., w_{S-1}, w_S)$ and computes the three gates' and memory cells' activation values sequentially based on the time $s = 1 \sim S$. The following is the calculation formula for time s. Equations (2)–(6) indicate the input gate, output gate, memory cell, hidden layer output, and gate of output, respectively, to guarantee precise and effective functioning.

The gate of input:

$$j_s = \sigma(X_{jw}w_s + X_{jg}g_{s-1} + X_{jd}d_{s-1} + a_j) \tag{2}$$

The input gate at time s is given by the Equation (2). In this formula, w_s is a current contribution, j_s is the input gate's activation, g_{s-1} is the previous output, d_{s-1} is the previous memory cell, and a_j is the bias term. The weights for the input, previous output, and previous memory cell are represented by X_{jw}, X_{jg}, and X_{jd}, respectively.

The output gate:

$$e_s = \sigma(X_{ew}w_s + X_{eg}g_{s-1} + X_{ed}d_{s-1} + a_e) \tag{3}$$

The output gate at time s is calculated as Equation (3). Here, e_s is the output gate's activation, w_s is the current input, g_{s-1} is the previous output, d_{s-1} is the previous memory cell, and a_e is the bias term. The weights associated with the input, previous output, and previous memory cell are X_{ew}, X_{eg}, and X_{ed}, respectively.

The memory cell:

$$d_s = e_s \odot d_{s-1} + j_s \odot \varphi(X_{dg}g_s + X_{dw}w_s + a_d) \tag{4}$$

The memory cell value at time s is defined by Equation (4). In the equation, X_{dw} is the memory cell value, g_s, and $X_{dw}$is input &output gate's activation, d_{s-1} is the previous memory cell, and g_s is the current output. The bias for the memory cell is a_d, with weights X_{dg} and X_{dw} for the current output and input, respectively.

The hidden layer output:

$$p_s = \sigma(X_{pw}w_s + X_{pg}w_{s-1} + X_{pd}d_{s-1} + a_p) \tag{5}$$

The hidden layer output at time s is given by Equation (5). Here, p_s is the output of the hidden layer, w_s is the current input, d_{s-1} is the previous memory cell, and a_p

is the bias term. The weights for the input, previous output, and previous memory cell are X_{pg}, X_{pw}, and X_{pd}, respectively.

The gate of output:

$$g_s = p_s \odot \varphi(d_s) \tag{6}$$

The network output at time s is calculated as Equation (6). In this formula, g_s is the final output, p_s is the hidden layer output, and d_s is the memory cell value. This equation combines the hidden layer output and memory cell using the activation function to produce the network output.

3.3.3. Input vector

In many different fields, including meteorological conditions, economic indicators, and health measurements, a signal is represented by a one-dimensional time series. Most statistical model-based predictive analytic approaches use the data from a sliding community as the input vector, as Equation (7) illustrates. This is commonly done to create a multi-dimensional sample. The input vector is m-dimensional w_s if the current time is s and the sliding time width is m.

$$w_s = (O_{s-m+1}, O_{s-m+2}, \ldots, O_s) \tag{7}$$

In this equation, w_s is an mmm-dimensional vector made up of the current and previous observations from a time series. The observations O_{s-m+1}, O_{s-m+2},…, O_s represent data points within a sliding window of size mmm.

The decomposition findings are decided depending on the type of link that is hidden in the original signal. Consequently, the prediction model can accept as input the multi-dimensional sample made up of three decompositions, with the input sample at time s. The anticipated value is the result of the prediction model. Initially, the projection model recognizes and detects similarities in the input vectors before the network model can make predictions. The input and output vectors are then mapped. It is a difficult challenge to find the mode of the present time point in an input vector consisting of data gathered across time. It helps the network learning process to find a vector that can represent the characteristics of the signal, leading to the establishment of a more accurate prediction model.

3.3.4. Memory cell

An additional parameter called C is included in the memory cell's input to impede the effect of accidental elements regarding memory retention patterns. Next, switch the formulation of $d_s$from Equations (4)–(8).

$$d_s = e_s \odot d_{s-1} + j_s \odot \varphi\left(X_{dg} g_s + X_{dw}(w_s.C) + a_d\right) \tag{8}$$

where C is the suppression parameter for the random component, $C = (11\ \alpha), 0 \leq \alpha \leq 1$. It is evident based on the three-layer decomposing result, which shows that the third layer component's random amount is predominant. However, since the third layer's element is permitted into the storage cell, it needs to be increased by e, the first two tiers of components can go straight to long-term memory, $and\ C$ is intended to be $(11\ \alpha)$. Because $0 \leq \alpha \leq\ 1$, the haphazardelement's value is repressed. The value of α is determined by the number of random components in the signal (Equation (9)).

$$\alpha = 1 - Err * 10 \tag{9}$$

where, $Err = \begin{cases} 0{,}1\ MAPE > 10\% \\ MAPE\ 0 < MAPE < 10\% \end{cases}$

Equation (10) establishes Mean Absolute Percent Error (MAPE) as follows:

$$MAPE = \frac{1}{M}\sum_{s=1}^{M}\frac{|O_s^x - O_s^e|}{\bar{O}^x} \tag{10}$$

The actual and predicted relationship at time s is represented by the predictors O_s^x, O_s^x, and O_s^e, where M is the quantity for the specimens. The value of e should be modest when the degree of unpredictability is high. For instance, the third-layer element containing the element of randomness would be removed instead of stored in permanent memory if α were meant to be 0. A significant value of one can be designed for when the signal's unpredictability is low. If $e = 1$, the third-layer component would accomplish full reach into long-term memory. There isn't yet a recognized indication to calculate the unpredictability of the signal. Thus, this research proposes an approximation pointer for unpredictability constructed on past prediction mistakes. Unpredictability characterizes true random behavior. The strength of the arbitrary amount within the indication would determine how inaccurate the prediction would be. Therefore, a measure can be defined using the predicted error.

3.3.5. Network output

The output of the GRLSTM g_s is limited to networking storage d_s, according to Equations (5) and (6). Given that the alteration to the GRLSTM memory suppresses the random component d_s, the information remembered in d_s is incomplete. The output would be deficient in the portion of the signal that is random if the network output were to be produced by using Equations (11) and (12). Ignoring the random component in the forecast result would be incorrect because unpredictability is a component of the signal as well.

$$p_s = X_{pw}w_s + a_p \tag{11}$$

$$g_s = p_s \odot \varnothing(d_s) \tag{12}$$

The main modification made to Equation (12) from Equation (5) is the elimination of the sigmoid operation, which permits the preservation of the data in w_s. This means that even if the random component is not entirely recorded in d_s, all of the data about the signal's properties, including unpredictability, are saved in p_s. Specifically, the present randomized element can be learned and considered in the forecasting production, regardless of whether the element of chance should be suppressed in long-term storage. The 3-layer decomposition breaks down the signal to produce a 3D vector that is the input w_s for the GRLSTM. The network's current output, w_s, has its random component muted by multiplying it by C. The memory cell is then updated to D_s after being compared and calculated with the prior cell state, D_{s-1}. Lastly, using $w_s$andd_s as inputs, Equations (11) and (12) compute the output of the GRLSTMg_s. Another fundamental component of the signal is randomness. C prevents potential patterns in the element of chance from being erased by keeping it hidden rather than deleting it from persistent memory. In addition, unpredictable components are retained in short-term storage to maintain the intrinsic volatility of the outcome.

The way that signal is generated determines how the GRLSTM structure is improved and broken down. It should be mentioned that systems of a different kind, including vibration signals and voice, are not appropriate for the suggested strategy. The long-term random component impacts in detection should not be repressed, as it can contain numerous eigenvalues in the high-frequency vibration signal. The kind of system will determine which prediction model is employed; for communications or comparable structures, the GRLSTM is a useful tool.

3.4. Statistical analysis

The statistical analysis conducted using GRLSTM revealed significant associations between specific joint movement patterns and health quality indicators. Regression analyses were employed to identify key predictors of health quality, highlighting the importance of certain movement characteristics in determining overall health. Additionally, ANOVA tests demonstrated significant differences in joint movement patterns across various health quality groups, suggesting distinct patterns associated with different levels of health. These findings underscore the critical role of joint movement in health assessment, providing insights into how movement patterns can influence overall well-being.

4. Performance analysis and discussion

An HP brand system with an Intel Core i9-12900 processor, an Intel Core i7-13700 CPU type, 3.50 GHz clock speed, 64 GB RAM, Windows 11 Home operating system, Python version 3.10.0, and a 16 MB L3 cache size is described in **Table 3**, along with the hardware and software components of the computer.

Table 3. Experimental setup.

Parameter	Setup
Processor Model	Intel(r) Core(tm) i9-12900
Brand	HP
CPU Type	Intel Core i7-13700
Clock Speed	3.50 GHz
Memory (RAM)	64 GB
Operating System	Windows 11 Home
Python Version	3.10.0
L3 Cache Size	16 MB

4.1. Accuracy

Accuracy in health assessment refers to how efficiently a model or an evaluation system correctly identifies the actual health outcomes or service efficacy based on the total number of assessments. Accuracy is also a basic statistic, which is defined as the percentage of correctly identified examples in a dataset relative to all occurrences.

High accuracy would mean that the rating is valid and may differentiate between various types of health service outcomes, allowing the expert community health practitioners to make informed decisions. The proposed GRLSTM model achieves a high accuracy of 98%.

4.2. Precision

Precision is a metric that quantifies the number of true positive results divided by the sum of true positive and false positive results. In community health services evaluation, precision is crucial when the focus is on ensuring that the services identified as effective are truly effective. When a community health service is anticipated to enhance health quality, a high precision score suggests that this is likely to happen. To ensure that resources are dedicated to truly beneficial initiatives, this indicator helps decrease the frequency of false positives. The GRLSTM model has a 94% accuracy rate.

4.3. Recall

The proportion of true positives and false negatives to real positive outcomes is called recall, or sensitivity. Recall in the assessment of community health services denotes the evaluation framework's capacity to pinpoint every situation in which improvements in health quality take place. In public health settings, a high recall rate indicates that the predictive system can identify the majority of real positive instances. This helps to prevent the underutilization of valuable interventions, particularly for marginalized groups. The GRLSTM model's recall rate is 95%.

4.4. F1-Score

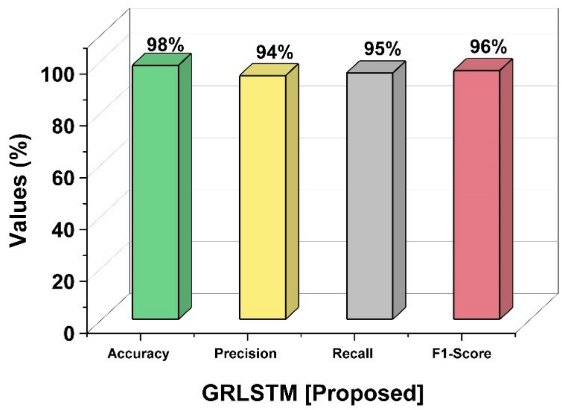

Figure 4. Graphical outcomes of the proposed method.

The mean of the harmonics of each of these measures provides the F1-score, which regulates recall and accuracy. In the context of dynamic assessment of network health offerings and health exceptional, the F1-score is especially applicable when there is an unequal distribution of classes, which includes when effective offerings are rare relative to ineffective ones. An evaluation model is considered strong as a degree of overall performance if it retains both high accuracy and takes into account, as shown by a high F1 rating. For network fitness experts who need to maximize provider delivery while making sure that excellent enhancements are precisely recognized and put into use, this measure is important. The GRLSTM model has an F1 score of 96%. The suggested method's graphical results are shown in **Figure 4.**

Other traditional measures of community health and fitness quality are usually based on static, self-reported data or periodic assessments that may not capture real-time or dynamic changes in health status. Such approaches lack precision because they do not account for biomechanical parameters like joint movements or stride length, which were crucial for assessed functional health. Traditional statistical methods might also not handle the complexities of intricate time-dependent data patterns and therefore are less likely to find the subtlety or trends in long-term developments. In turn, such approaches would neglect crucial predictors of health quality, thus having less effective healthcare interventions and strategies. The issues overcome to novel approach as the study integrates biomechanical assessments into community health evaluation, enhancing the precision of health quality predictions. In this study, the potential of GRLSTM networks in capturing complex temporal relationships in data is effectively presented, leading to greater accuracy in health insights. This approach supports targeted data-driven improvements in healthcare delivery and fitness strategies.

4.5. Analysis of variance (ANOVA) test

Table 4. Outcomes for joint movement patterns between different health quality groups.

Source of Variation		The sum of Squares (SS)	df	Mean Square (MS)	F	*p*-value
Quality of Life (QoL)	Joint Angle	280.40	1	280.40	22.00	<0.001
	Step Frequency	150.70	1	150.70	11.50	0.0015
Patient Satisfaction	Joint Angle	400.50	1	400.50	31.50	<0.001
	Step Frequency	250.90	1	250.90	19.00	<0.001
Total		1283.50	3			

Note: SS-Sum of Squares, DF-degrees of freedom, MS-Mean Square.

Analysis of Variance (ANOVA) is an effective statistical method used to evaluate whether or not there are sizable variations among the methods of 3 or more unbiased companies. It is particularly helpful in experimental designs when scientists need to know how one or more independent factors affect a dependent variable. Consider that ANOVA was hired to research the connection among joint motion styles (mainly joint angles and step frequencies) and numerous fitness indicators, which include patient desire and QoL. Joint motion patterns are vital in determining the physical and mental well-being of individuals, mainly in scientific settings. Understanding how special aspects of joint motion relate to health results can provide insights into effective interventions and therapeutic strategies. The ANOVA can decide if precise joint movement patterns substantially affect fitness fine indicators, thereby guiding healthcare professionals in their practices. **Table 4** summarizes the ANOVA results analyzing the influence of joint movement patterns on health quality indicators, specifically focusing on how joint angles and step frequencies impact patient satisfaction and QoL. The analysis provides a breakdown of the sources of variation, the sum of squares, degrees of freedom, mean squares, F-values, and associated p-values.

With an F-value of 22.00 for QoL and 31.50 for patient satisfaction, the joint angle is reported as a strong factor in that it has the maximum influence on both QoL and patient satisfaction indicators. The $p < 0.001$, confirms that this association is statistically significant, as the health outcomes of the patients are significantly affected due to different joint angle patterns. Although step frequency has a highly significant effect both on QoL and patient satisfaction, with $p-\text{values} < 0.001$ and 0.0015, respectively, its influence is relatively much weaker than that of joint angle, as indicated by lower F-values of 11.50 for QoL and 19.00 for patient satisfaction. Therefore, joint angles are significant indicators of health quality parameters. This may lead health service providers to target the optimization of joint movement for better patient satisfaction and the QoL.

4.6. Regression analysis

A regression evaluation is carried out to identify big predictors of fitness quality ratings among a number of the participants. The following predictors were covered in the model: joint perspective, stride length, step frequency, EMG activity, gender, and age. The consequences exhibit that joint perspective and stride length are vastly advantageous predictors of health satisfaction, while step frequency has a negative association. Additionally, older age (≥ 50 years) is observed to negatively affect fitness best ratings, indicating that increased age correlates with decreased QoL assessments. **Table 5** gives the effects of the regression analysis, figuring out the coefficients, popular errors, t-statistics, and p-values for various predictors of health satisfactory scores. The predictors protected are joint perspective, stride length, step frequency, EMG pastime, gender, and age. Significant predictors are highlighted, indicating their effect on health quality outcomes. Positive coefficients suggest a direct relationship with fitness great ratings, whilst bad coefficients imply an inverse courting.

Table 5. Regression analysis results for predictors of health quality.

Predictor Variable	Coefficient (β)	Standard Error (SE)	*t*-Statistic	*p*-value
Intercept	10.50	1.45	7.24	<0.001
Joint Angle (°)	0.45	0.12	3.75	<0.001
Stride Length (m)	2.30	0.55	4.18	<0.001
Step Frequency (steps/min)	−0.05	0.02	−2.50	0.013
EMG Activity (High)	1.10	0.49	2.24	0.025
Gender (Male)	−0.60	0.40	−1.50	0.135
Age (≥50 years)	−0.80	0.35	−2.29	0.023

The intercept ($\beta = 10.50, p < 0.001$) is the zero-based health quality score when all predictors are at zero, a reference point for each predictor's impact. A positive coefficient is seen for joint angle, $\beta = 0.45, p < 0.001$. This suggests that the bigger the joint angle, the higher the scores of health quality, probably due to increased flexibility and range of movement.

The impact of stride length on quality health is positive and the largest in all variables, where the coefficient is $\beta = 2.30$ with a $p < 0.001$. This means strides taken are significantly associated with high QoL scores, which therefore stresses a proper stride length role in mobility and general physical well-being. A negative coefficient is obtained for step frequency ($\beta = -0.05, p = 0.013$), which means an inverse relationship with health quality: higher step frequency corresponds with lower health quality scores. Probably fast and quick steps don't serve well in health. Maybe it is a case of increased strain or less effective movement patterns.

Higher EMG activity correlates with better health quality scores; that is, active engagement of the muscle positively relates to fitness and well-being ($\beta = 1.10, p = 0.025$). Gender, especially male, has a weak negative relationship with health quality ($\beta = -0.60$), but this is not statistically significant at $p = 0.135$. This therefore means that gender does not play a significant role in the health quality outcomes for this model. Age negatively correlates with quality of health with a coefficient of $\beta = -0.80$ and $p = 0.023$, suggesting that advanced age is correlated with health quality ratings of lower degree. This is because there is a reduction in people's mobility and fitness during old age; therefore, interventions should thus be tailor-made for elderly populations.

The **Table 5** regression analysis shows the effects of physical factors, such as stride length and joint angles on health quality. Overall, these result in quality-of-life improvements and better patient satisfaction. These results thus give practicing health professionals elements for action to improve health outcomes on the basis of their embodied character.

5. Conclusion

Critical insights into the efficacy and responsiveness of fitness remedies are revealed through the dynamic evaluation of community health offerings and health quality, that is based on biomechanical time series analysis. Combining biomechanical data makes it possible to identify trends and changes that influence health outcomes, leading to a deeper understanding of network fitness dynamics. To initiate modifications to fitness services that can improve quality and accessibility, this approach highlighted the need for real-time tracking and evaluation. The GRLSTM model validated spectacular performance metrics, attaining an accuracy of 98%. It recorded precision and recall of 94% and 95%, respectively. Additionally, the method's F1-score was cited as 96%, indicating a strong balance between precision and recall. The ANOVA and regression analyses displayed that joint angles are the most powerful predictor of both patient pleasure and QoL, with vast F-values and p-values (<0.001). Regression consequences show stride length as the maximum effective predictor of health pleasantness ($\beta = 2.30$, $p < 0.001$), at the same time as step frequency and older age are negatively associated with health outcomes.

Limitations and future scope: A research drawback is its dependence on sure biomechanical measurements, which couldn't safely represent the intricacy of network health dynamics. To improve the reliability and generalizability of the results, future studies should investigate the incorporation of different populations and more health markers. Including longitudinal research can broaden the focus and shed more light on the long-term impacts of community health services on the standard of overall health.

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