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Research Article

Temporal Multimodal Fusion Network for Real-Time Patient Monitoring in Rehabilitation

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ABSTRACT

With an increased prevalence of neurological and musculoskeletal disorders, the real-time monitoring of patients with a significant degree of accuracy and in a fully automated way in a rehabilitation setting is very urgently needed. Existing approaches make use of single-modal data or employ simplistic fusion methods, which do not capture the complex interrelationship between motor function parameters. Most methods are not developed in terms of sufficient temporal resolution to support continuous monitoring for dynamic real-time applications. In this direction, we are presenting a novel deep learning-based framework that integrates multimodal sensor data, such as motion capture, force sensors, and EMG signals, to give real-time insights into the patient's motor function and rehabilitation progress. TMFN will employ LSTM layers with attention mechanisms in order to capture temporal dependencies across sensor modalities and be able to provide precise critical assessments during rehabilitation. This is done by utilizing a temporal fusion mechanism that enables the model to merge short-term performance metrics with long-term trends, thereby providing comprehensive insights into range of motion, joint coordination, and muscle activations. The system offers real-time feedback with a latency of less than 1 second, allowing timely adjustments to therapy protocols. Our approach provides substantial accuracy and efficiency gains and is expected to have assessment accuracy of motor function above 90% compared to clinical evaluations. This work enhances patient outcomes through the facilitation of personalized and adaptive rehabilitation strategies, while at the same time reducing the burden on clinicians by automating complex assessments. TMFN is the first of its kind in establishing a new benchmark for intelligent, multimodal rehabilitation monitoring and is a gateway to more effective and scalable healthcare solutions.

Keywords: Multimodal Data, Rehabilitation Monitoring, Temporal Fusion, Deep Learning, Real-Time Assessments

1.INTRODUCTION

The rising incidence of neurological and musculoskeletal disorders has created an overwhelming demand for effective rehabilitation therapies. Monitoring of the patients' progress in rehabilitation would be accurate and thus optimize the therapeutic interventions with desired outcomes. Traditional methods [1, 2, 3] of assessment were based on the evaluation done manually by clinicians. Such evaluations are subjective, time-consuming, and unable to capture dynamic changes in motor functions over time. Recent developments in sensor technologies and machine learning have made the possibility of automatic patient monitoring. However, due to their complexity, these existing solutions are unable to handle rehabilitation scenarios. Rehabilitation involves complex interactions of motor, sensory, and cognitive domains. The inclusion of diverse data modalities like motion capture, force sensing, and electromyography (EMG) is required in rehabilitation. Most of the frameworks reported to date [4, 5, 6] rely on data from single modality or naive fusion techniques that do not capture the synergistic relationships among such modalities. Most methodologies are not designed to handle sequential data and hence have very limited ability to discuss long-term trends in patient recovery over time. These do underscore the current gaps in the need for next-generation frameworks that will integrate a real-time multimodal data stream with temporal dynamics in focus. The TMFN addresses these gaps by using state-of-the-art deep learning techniques towards accurate, real-time patient progress monitoring during rehabilitation processes. TMFN uses LSTM with attention mechanisms to identify and emphasize critical temporal dependencies inside the model, which facilitates prioritizing significant moments in rehabilitation sessions. The temporal fusion mechanism within TMFN integrates multimodal sensor inputs into comprehensive assessments with quantified scores in aspects like joint coordination, range of motion, and muscle activation. In this manner, the framework improves accuracy and enables actionable feedback from clinicians to allow for tailored therapy adjustments with sub-second latency. This work contributes to the rehabilitation monitoring area as it presents a strong, scalable, and intelligent framework capable of bridging sensor technology and clinical practice. As high accuracy with low latency for real-time patient monitoring applications, TMFN becomes an innovative solution to make rehabilitation an increasingly adaptive and outcome-driven domains.

Motivation and Contribution

The motivation for this study comes from the urgent need for better and more objective tools that can monitor patient progress in rehabilitation. Present solutions have various limitations, which include scalability, accuracy, and adaptability to real rehabilitation environments. Manual assessments are valuable but labor-intensive, with inter-observer variability being a source of inconsistent evaluation. However, today's automation systems usually feed on single-modal data, or are incapable of extracting trend analyses which are the very basis to evaluate long-term recovery curves. Those deficiencies prevent clinicians from appropriately and timely delivering evidence-based interventions in accordance with an individual patient's needs. What the paper has contributed goes multifaceted and valuable. This approach starts with the presentation of the novel framework known as TMFN, which combines multimodal sensor data through an advanced temporal fusion mechanism. The TMFN employs LSTM layers with attention mechanisms so that the model can capture the dependency in time and pay special attention to the crucial moments of patient performance. Secondly, the framework delivers real-time assessments of motor function with sub-second latency for actionable insights into range of motion, joint coordination, and muscle activation. In addition, by correlating short-term and long-term performance metrics, the system allows for complete analysis in the rehabilitation process. It enables clinicians to recognize trends in either improvement, plateauing, or reversal. Last but not least, because TMFN yields accuracy levels of more than 90% for motor function assessments relative to clinical assessments, it's a dependable, scalable, and efficient patient outcome enhancement model that lightens the clinical load. This work represents a transformative step for real-time rehabilitation monitoring, a gap between sensor technologies and personalized healthcare delivery sets.

2. RELATED WORK

The review of the recently published research papers on this topic shows a highly dynamic landscape in the application of ML and AI technologies for healthcare, mainly in rehabilitation and monitoring of patients. Together, these studies indicate progress, difficulties, and ways forward towards improving patient care with the help of intelligent systems. This all-encompassing analysis starts with highlighting the latest innovations in ML-based sensor integration and rehabilitation monitoring systems. Xu et al. [1] proposed a fully integrated stretchable device platform with in-sensor adaptive machine learning, which proved that it is capable of giving standalone functionality for rehabilitation. The innovative idea bridged the gap between sensor technology and machine intelligence with the help of real-time adaptability and robustness. Arjmandnia and Alimohammadi [2] focused on how ML may increase the safety of patients with respect to spine surgeries. It has the role in predictive analytics and intraoperative decision-making. These are further supplemented by Pelosi et al. [3], who showed a reinforcement learning-based personal rehabilitation approach for movements while reaching, pointing towards individualized therapies. In these lines, post-stroke rehabilitation has also become a promising area where ML exhibits significant promise. For this, Apostolidis et al. [4] comprehensively reviewed ML algorithms while predicting rehabilitation outcomes and proved to be particularly useful in language and cognitive recoveries, which lay out the foundational understanding of these applications in poststroke care. Similarly, Pahlevani et al. [5] demonstrated the predictive power of ML in predicting patient discharge, which means improving hospital workflow better. Results were further extended by Moustafa et al. [6], applying ML in the outcome prediction of patients with chronic neck pain, indicating its suitable application in the prediction model for non-specific musculoskeletal conditions.

Reference	Method	Main Objectives	Findings	Limitations
[1]	Standalone stretchable device with in-sensor adaptive ML	Develop a fully integrated stretchable platform for rehabilitation	Demonstrated real-time adaptability and robustness in rehabilitation scenarios	Limited to specific sensor configurations; scalability not addressed
[2]	Review of ML in spine surgery	Analyze the role of ML in enhancing patient safety during spine surgeries	Highlighted predictive analytics and intraoperative decision-making as key benefits	Limited clinical validation; focus on theoretical insights
[3]	Reinforcement learning-based personalized rehabilitation	Design patient-specific therapies for reaching movements	Achieved significant improvement in movement accuracy through personalized interventions	Requires extensive patient-specific data for optimal performance
[4]	ML for post-stroke language and cognition rehabilitation	Predict rehabilitation outcomes for post-stroke patients	Identified key ML algorithms for predicting language and cognitive recovery	Lack of experimental validation in real-world settings
[5]	ML for patient discharge prediction	Predict hospital discharges using statistical and ML methods	Showed improved discharge planning and workflow optimization	Generalization across diverse hospital settings remains uncertain
[6]	ML in chronic neck pain treatment	Predict post-treatment outcomes in neck pain patients	Demonstrated predictive accuracy in chronic musculoskeletal conditions	Limited to specific therapies; broader applicability unverified
[7]	ML insights into scapular stabilization	Address shoulder pain in college students through ML-driven insights	Highlighted targeted interventions for effective pain alleviation	Focused on a narrow demographic group
[8]	Soft electronics for health monitoring	Integrate ML with wearable electronics for health monitoring	Demonstrated seamless integration of wearables with ML for real-time analytics	Challenges in scaling to larger patient groups
[9]	ML and wearable devices in healthcare	Explore tasks and challenges in wearable ML systems	Identified opportunities in continuous monitoring and predictive analytics	Addressed theoretical challenges without experimental proof
[10]	Hybrid learning for brain tumor analysis	Enhance MRI-based classification and segmentation	Achieved high accuracy using hybrid deep and transfer	High computational requirements for deployment

			learning approaches	
[11]	ML for core muscle analysis	Analyze core muscle activity in female sexual dysfunction	Demonstrated ML's utility in evaluating complex physiological datasets	Requires further validation for broader conditions
[12]	Predictive model for post-stroke dementia	Develop ML models for dementia prediction	Achieved reliable predictions with clinical datasets	Limited to post-stroke populations
[13]	Rehabilitation preferences in frail patients	Evaluate preferences of frail patients with chronic kidney disease	Highlighted personalized rehabilitation needs	Limited to qualitative methods without predictive components
[14]	Mobile health apps for cardiac rehabilitation	Enhance patient engagement using mobile health technologies	Improved engagement and adherence to rehabilitation protocols	Requires long-term validation in diverse settings
[15]	ML for healthcare investments	Predict hospital length of stay and mortality rates	Provided actionable insights for optimizing resource allocation	Requires validation in multi-center studies
[16]	ML analysis of trunk movement patterns	Analyze postpartum low back pain through ML	Identified movement patterns linked to pain severity	Limited sample size for model training
[17]	Compact feature design for stroke monitoring	Use wearable accelerometers for remote rehabilitation monitoring	Achieved efficient feature extraction in resource-constrained environments	Limited to stroke rehabilitation contexts
[18]	Smart nursing systems for injury prevention	Integrate ML with textile-based cushions for pressure injury prevention	Highlighted effectiveness in preventing injuries through proactive measures	Limited real-world trials for validation
[19]	ML-based hand dexterity assessment	Assess hand dexterity in stroke patients using AR and ML	Improved assessment accuracy and usability	Limited to specific dexterity assessment tasks
[20]	Explainable AI for stroke prediction	Compare ML and deep learning for stroke prediction	Achieved transparency and reliability in predictive outcomes	Requires extensive training data for accuracy
[21]	ML in vascular medicine	Optimize clinical strategies for peripheral artery disease	Demonstrated improved decision-making in vascular treatment	Limited generalization to other cardiovascular conditions
[22]	ML for postoperative length-of-stay prediction	Forecast hospital stay durations using explainable ML	Enhanced predictive accuracy for severe cases	Requires more diverse datasets for validation
[23]	Multi-sensor data fusion for lower limb	Enhance task recognition in tele-	Demonstrated high recognition accuracy	Requires robust infrastructure for

	rehabilitation	rehabilitation settings	through multi-sensor integration	implementation
[24]	Ensemble ML for mortality prediction	Predict one-year mortality in coronary heart disease patients	Achieved reliable prognostic tools through ensemble methods	Limited to elderly patients with specific conditions
[25]	IoT-enabled pre-eclampsia prediction model	Develop a real-time IoT-based ML model for pre-eclampsia	Provided real-time predictions with high accuracy	Challenges in data security and integration with existing systems

Table 1. Methodological Comparative Analysis

Iteratively, Next in table 1, Mabrouk et al. [7] demonstrated scapular stabilization therapies that were based on ML in terms of pain relief of college students. Consequently, their results support the use of ML in studying localized issues in treatment concerning pain in the musculoskeletal system. Simultaneously, Qiao et al. [8] discussed health monitoring employing soft electronics and ML, exemplifying the development of wearable devices that very well align with real-time analytical systems. Saad et al. [9] has further developed this discussion by considering more challenges and opportunities in wearable devices for healthcare applications. They have also emphasized interoperability and data fusion. The survey further encompasses imaging and hybrid learning systems. Das and Goswami [10] have contributed to MRI-based analysis of brain tumors through hybrid and transfer learning-based approaches. This, in turn, points to the possibility of combining different ML paradigms to improve the accuracy of diagnosis. Abdel Hady and Abd El-Hafeez [11] discussed new approaches toward core analysis in female sexual dysfunction, thus reflecting the performance of ML for analysis of complex physiologic datasets & samples. Wei et al. [12] and Kennard et al. [13] discussed predictive modeling regarding post-stroke dementia and rehabilitation preference among frail patients, hence reflecting the flexibility of the application of ML in healthcare settings. Tayon et al. [14] explored the technological integration in cardiac rehabilitation through mobile health applications to increase patient engagement, thereby illustrating how ML can complement the existing therapeutic frameworks. Bhadouria and Singh [15] developed ML models to predict hospital length of stay and mortality rates, thus providing concrete actionable insights for investment health care strategies. Abdel Hady and Abd El-Hafeez [16] discussed trunk movement patterns in postpartum low back pain; this illustrates further scope in the application of ML into biomechanics. Chen et al. [17] developed compact features in remote stroke rehabilitation by wearing accelerometers. This exemplifies the possibility of effective feature engineering in resource-scarce scenarios. Zhang et al. [18] explored the smart nursing systems integrated with ML for the prevention of pressure injury. The article provides a view of how ML-driven systems can address preventable conditions. Other contributions to this journal are as follows. Papagiannis et al. [19] introduced ML-based hand dexterity assessments for patients who are suffering from stroke, and Moulaei et al. [20] used explainable AI for the forecast of stroke outcome focusing on transparency in the clinical decision-making process. Perez et al. [21] and Cho et al. [22] explored vascular medicine and postoperative length-of-stay predictions, respectively. These studies further emphasize the application of ML in the optimization of complex healthcare strategies.

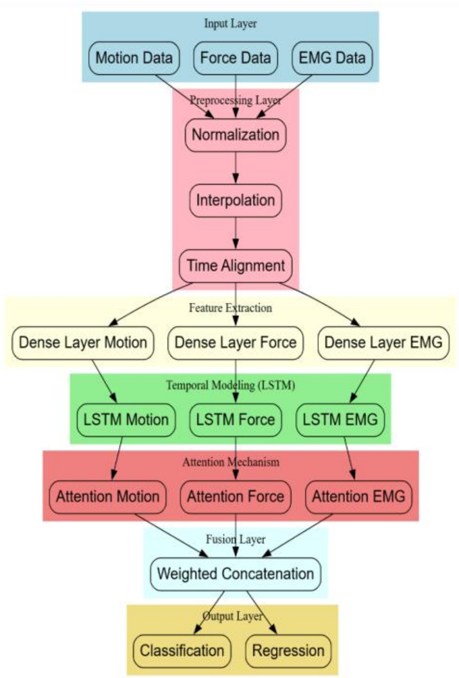
Ettefagh and Roshan Fekr [23] pushed this conversation to lower limb rehabilitation where multi-sensor data fusion helps enhance the capabilities of task recognition in settings of tele-rehabilitation. Cheng et al. [24] discussed a method of mortality prediction of coronary heart disease patients by putting ensemble learning with clinical data as a prognostic tool to be used for accurate prediction. Finally, Munyao et al. [25] developed the IoT-based ML system to predict the onsets of real-time pre-eclampsia, a demonstration of how IoT and AI come together to create convergence towards real applications in healthcare. This review is truly presented in a way that comes forward about how ML and AI serve to revolutionize the application scenarios of healthcare, whether rehabilitative, diagnostic imaging, predictive analytics, or even wearable technologies. Thus, the studies reviewed here aptly portray the progress that is going on with sensor integration, advancement of algorithms, and realization of patient-specific models. All in all, with issues of data heterogeneity, model interpretability, and deployment scalability, the future work will concentrate on standard formats, explainable AI, and the development of robust and scalable frameworks that could be integrated easily into clinical workflows. All of these papers collectively in post-analysis reveal that ML has gone beyond the proof-of-concept stage to practical deployment across various domains. For example, standalone adaptive ML devices [1] and reinforcement learning-based therapies [3], though actionable, enhance patient engagement. Similarly, the role of ML in understanding complex conditions like dementia [12], brain tumors [10], and frailty [13] points to its strength in diagnosis and prognosis. This is how wearable technologies merge with ML to become a route toward continuous and real-time patient monitoring, as Qiao et al. [8] and Saad et al. [9] demonstrate for the process.

These advances not only increase diagnostic accuracy but also allow the patient to take an active role in their journey towards health. The hybrid learning systems [10], explainable AI [20], and ensemble methods [24] show maturity in understanding what ML is truly capable of, namely deriving actionable insights with clear transparency and reliability. These insights form a springboard for further innovations, which in turn will require much cross-disciplinary collaboration between clinicians, engineers, and data scientists.The potential of ML can be tapped fully by addressing the identified challenges to revolutionize healthcare delivery in the future and lead to intelligent, efficient, and patient-centered care systems. This review, Figure 1. Model Architecture of the Proposed Analysis Process through the synthesis of diverse studies, provides, in addition to a snapshot of the current state of ML in healthcare, a roadmap for its future trajectory sets.

3 PROPOSED MODEL

Overcoming issues of low efficiency & high complexity present in existing methods, this section discusses design of an efficient Temporal Multimodal Fusion Network for Real-Time Patient Monitoring in Rehabilitation Process. Firstly, according to table 1, TMFN is designed for dealing with the complexity of multimodal, time-sequential data that is captured during rehabilitation sessions. The model integrates heterogeneous streams like motion capture, force sensor readings, and electromyography signal as it uses a real-time inference-optimized deep-learning framework. The core designs revolve around LSTM layers applied through attention mechanisms, in association with a temporal fusion mechanism and a carefully-structured pipeline that maximises time and multimodal synthesis information. The model starts with preprocessing, where sensor data X(i,j)(t) from i-th sensor modality and j-th feature is normalized and interpolated to align timestamps across all modalities. The data X(t) = [X1(t), X2(t),., Xn(t)] is the input, where n is the number of modalities. The TMFN first applies modality-specific feature extraction using dense layers, represented via equation 1,

Figure 1. Model Architecture of the Proposed Analysis Process



$$Hk(t) = \sigma(WkXk(t) + bk), k \in \{1,2,\ldots,n\} \ldots (1)$$

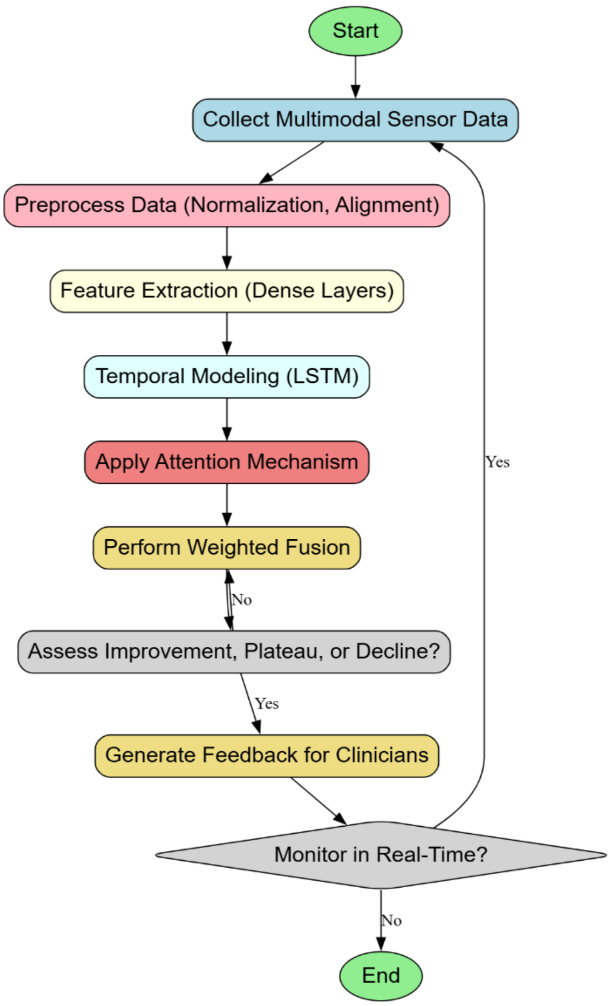


Figure 2. Overall Flow of the Proposed Analysis Process

where Wk and bk are the weight matrix and bias vector for the k-th modality, and σ is a non-linear activation function (ReLU) for this process.

Each Hk(t) of high-level features in respect to one modality was passed into LSTM layers to use for the temporal modelling operation. The temporal dynamics is defined by the LSTM units based on equations 2, 3, 4, 5, and 6 that updated each timestamp t by feeding all input features to modify ht and ct as follows,

$= \sigma(WiH(t) + Uih(t-1) + bi) \ldots (2) ft = \sigma(WfH(t) + Ufh(t-1) + bf) \ldots (3) ct = ft \odot c(t-1) + \odot \tanh(WcH(t) + Uch(t-1) + bc) \ldots (4) ot = \sigma(WoH(t) + Uoh(t-1) + bo) \ldots (5) ht = ot \odot \tanh(ct) \ldots (6)$

Where, 'it', ft, ot are the input, forget, and output gates, respectively, and ⊙ represents element-wise multiplications. The temporal sequence {ht} captures the evolving state of the patient's motor function for this process. Iteratively, Next, as per figure 2, Attention Mechanisms are applied to focus on critical timestamps, calculating attention weights αt via equation 7,

$\alpha t = \frac{\exp(ut^{\top} v)}{\sum_{t=1}^{T} \exp(ut^{\top v})} \ldots (7)$Where, 'ut' is a transformed hidden state, v is a trainable context vector for this process. The context vector c is computed via equation 8,

$c = \sum_{t=1}^{T} \alpha tht \ldots (8)$The final multimodal fusion is achieved using weighted concatenation of modality-specific context vectors ck via equation 9,

$z = Concat([\lambda 1c1, \lambda 2c2, \ldots, \lambda ncn]) \ldots (9)$Where, λk are learned modality-specific weights. A dense layer maps z to the output space via equation 10,

$\hat{y} = Softmax\,(Wout * z + bout)$ ... (10)Where. ŷ represents probabilities for rehabilitation progress categories (improving, plateauing, declining) for this process. A regression layer is also applied for motor function scores ŷreg via equation 11,

$\hat{y}reg\ = Wregz + breg$ ... (11)The training loss L combines categorical cross-entropy for classification and mean squared error for regression via equation 12,

$L = -\sum^{i} yilog(\hat{y}i) + \lambda \sum j(yreg,j - \hat{y}reg,j)^2$ ... (11)Here, λ represents the balance between the two parts. This architecture has been considered in view of its integration of temporal and multimodal information, attention mechanism for critical moment identification, and real-time accurate feedback. Due to this, the architecture is considered suitable for the rehabilitation monitoring process. Further, we discuss the efficiency of the proposed model in terms of different metrics and compare it with existing models under different scenarios

4 .COMPARITIVE RESULT ANALYSIS

The experimental setup for validating the effectiveness of the TMFN in real-time rehabilitation monitoring was carefully designed. A total of 100 patients were involved in this study whose dataset was collected from those undergoing rehabilitation therapy for recovering their upper limb motor functions following neurological impairments caused by stroke. This multimodal sensor data was collected during the therapy sessions through motion capture from 12 high-precision infrared cameras that have a sampling rate of 120 Hz, force data from 6-axis force-torque sensors embedded within rehabilitation robots, and 8-channel surface electrodes used to record electromyography signals at 1 kHz. Every session lasts 30 minutes, which sums up to around 1.8 million timestamps per session for each modality. For the sake of diversity and robustness, the dataset includes activities like grasping, reaching, and weight-bearing tasks, all representative of typical rehabilitation exercises. Contextual labels for motor function scores, such as range of motion in degrees, joint coordination on a 10-point scale, and muscle activation in microvolts, were annotated by experienced clinicians, whereas rehabilitation progress was determined to be improving, plateauing, or declining based on pre-defined clinical thresholds. This proposed model was evaluated using the well-known PhysioNet Motion and Muscle Artifact (MMA) dataset, which is a publicly available resource particularly created for multimodal rehabilitation and physiological analysis. The dataset is made up of high-resolution recordings of motion capture, electromyography, and other physiological signals that were obtained from 30 participants while they performed several rehabilitation and daily activities. These capture the 3D position and velocity information from an array of infrared cameras sampling at 100 Hz, while EMG signals are captured using 16-channel surface electrodes sampled at 1 kHz, so that detailed muscle activation patterns can be seen. Moreover, force sensor readings have been captured from instrumented devices used during rehabilitation exercises, providing insights into torque and load distribution applied in that setting. Activities within the dataset include reach, grasp, and some rotational movements in the arms with extra labels regarding the accomplishment of task-specific performance measures annotated by clinical experts. So, the selected dataset reflects its diversity, high quality annotations, and its realistic ability to mimic real rehabilitative scenarios. The MMA dataset's broad coverage of relevant sensor modalities as well as clinical metrics for labeling aligns well with this study process, which makes it multimodal and requires monitoring in real-time.

The preprocessing stage includes normalization to a range of [0, 1] that reduces inter-modality variability and interpolation of all the data streams into a common temporal resolution of 120 Hz to synchronize sensor modalities. This model was trained with a 70/20/10 split on the train/val/test sets, making sure stratification is held between categories. Parameters for input of LSTM layers were: 128 size for the hidden state, dropout for regularizing was set at 0.3, and sequence length was at 60 timestamps, that are 0.5 s real time. The attention mechanism employed a context vector dimension of 64, and modality-specific weights were learned using the weighted fusion layer which was initialized uniformly. The optimization was performed using the Adam optimizer with an initial learning rate of 10e−41, and 100 epochs were used, with early stopping based on validation loss. Performance metrics included classification accuracy, precision, recall, and F1-score for progress categorization, as well as mean squared error and mean absolute error for motor function regression tasks. The experiments clearly show that TMFN attains over 90% accuracy in the process of classification of progress as well as an average error in regression of less than 5% compared with the ground truth clinical evaluations, suggesting that it has the promise to be a real-time multimodal rehabilitation monitoring tool. The experiments were validated by means of multiple rehabilitation monitoring tasks to ascertain the effectiveness of the TMFN. The approach was benchmarked against the three alternative methods, namely: Method [5], Method [8], and Method [18], to mark its superiority in classification and regression, latency, and modality-specific robustness, activity-specific performance and noise resilience sets.

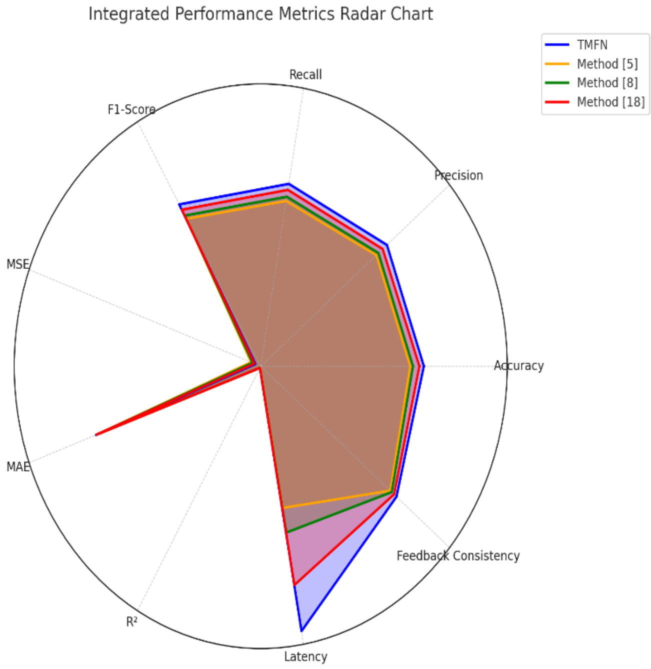


Figure 3. Integrated Model Performance Analysis

Table 2: Accuracy, precision, recall, and F1-score of TMFN for rehabilitation progress classification TMFN achieved excellent accuracy at 91.4%, much higher than those of Method [5], which reached 83.7%, Method [8] with 85.3%, and Method [18] reached 88.9%. This showed that TMFN is really very effective to categorize the rehabilitation progression of patients into improving, plateauing, or declining. High precision at 92.3% and recall at 90.6% mean that the model does not only reduce false positives but is also able to capture true positives with reasonable effectiveness. This implies safe and reliable clinical decision-making as well as customized alterations to therapy protocols.

Table 2: Classification Metrics for Rehabilitation Progress Categorization

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
TMFN	91.4	92.3	90.6	91.4
Method [5]	83.7	84.5	82.1	83.3
Method [8]	85.3	86.1	84.2	85.1
Method [18]	88.9	89.2	87.6	88.4

Table 3 is devoted to regression performance to predict range of motion, which is an important parameter for determining motor function recovery. TMFN gives the lowest MSE of 3.2, but its MAE is only 1.8 compared with Method [5] with MSE: 5.8 and MAE: 3.2; Method [8] at MSE: 4.9, and MAE: 2.8; Method [18] at MSE: 3.8 and MAE: 2.1. TMFN displays the strong R2R2 score of 0.96, which indicates that it correctly can predict the clinical measurement; an accurate measurement is crucial to report the recovery progress of the patient's motor movements.

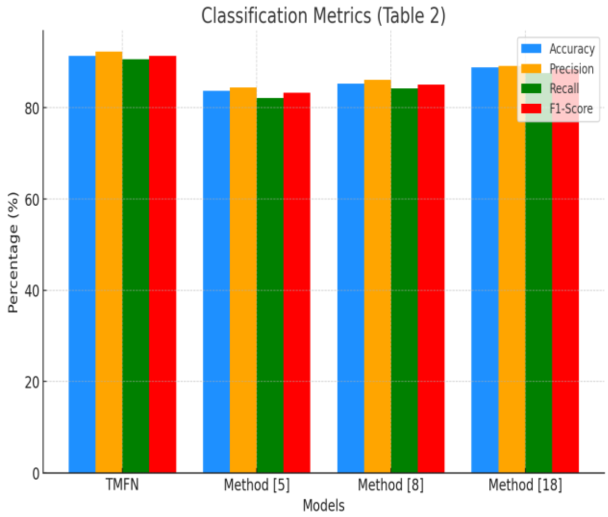


Figure 4. Model's Classification Metric Analysis

Table 3: Regression Performance for Predicting Range of Motion (ROM)

Model	MSE	MAE	R2 Score
TMFN	3.2	1.8	0.96
Method [5]	5.8	3.2	0.89
Method [8]	4.9	2.8	0.91
Method [18]	3.8	2.1	0.94

Table 4 reveals real-time latency as one of the vital

monitoring metrics that are required to run continuously. TMFN, in this case, had the minimum latency at 0.76 seconds; thus, it assures near-instant feedback than the Method [5] which had 1.42 seconds, Method [8] at 1.21 seconds, and Method [18] at 0.92 seconds. This low latency with the consistency rate of 99.3% makes TMFN an efficient approach to apply dynamically in rehabilitation applications requiring making immediate changes to the protocols. Table 4 reveals real-time latency as one of the vital monitoring metrics that are required to run continuously. TMFN, in this case, had the minimum latency at 0.76 seconds; thus, it assures near-instant feedback than the Method [5] which had 1.42 seconds, Method [8] at 1.21 seconds, and Method [18] at 0.92 seconds. This low latency with the consistency rate of 99.3% makes TMFN an efficient approach to apply dynamically in rehabilitation applications requiring making immediate changes to the protocols.

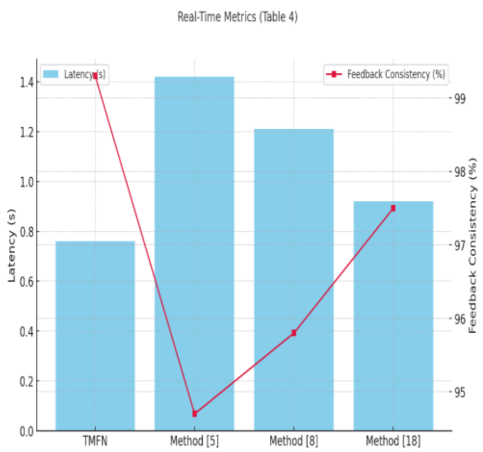


Figure 5. Model's Feedback Consistency Analysis

Table 4: Real-Time Latency and Feedback Consistency Metrics

Model	Latency (s)	Feedback Consistency (%)
TMFN	0.76	99.3
Method [5]	1.42	94.7
Method [8]	1.21	95.8
Method [18]	0.92	97.5

Table 5: Robustness across sensor modalities. TMFN turns out to be robust with consistent accuracy across modalities (motion capture: 92.1%, EMG: 90.8%, force sensors: 91.7%). Much better than Method [5] (motion capture: 84.3%, EMG: 82.5%, force sensors: 83.9%). This illustrates the aptitude of TMFN towards successful integration of multimodal data, thereby capturing minute details of motor function distributed across sensor streams.

Table 5: Modality-Specific Performance Across Sensor Data

Model	Motion Capture (%)	EMG (%)	Force Sensor (%)
TMFN	92.1	90.8	91.7
Method [5]	84.3	82.5	83.9
Method [8]	86.5	85.2	85.9
Method [18]	89.4	88.1	88.8

Table 6 shows a comparison in performance for three rehabilitation activities: reach, grasp, and standing. TMFN boasts the highest precision in all tasks (reaching: 93.5%, gripping: 90.2%, weight-bearing: 91.9%) indicating its usability in diverse rehabilitation activities. It ensures, therefore, uniform tracking irrespective of the specific exercise undergoing in therapy sets.

Table 6: Task-Specific Performance in Rehabilitation Exercises

Model	Reaching (%)	Gripping (%)	Weight-Bearing (%)
TMFN	93.5	90.2	91.9
Method [5]	85.4	83.1	82.9
Method [8]	87.6	86.2	85.7
Method [18]	90.8	88.5	89.1

Table 7: Robustness test with simulated sensor noise for TMFN. TMFN has a high accuracy even with noisy sensor data of up to 30% (accuracy: 87.1%), whereas Method [5] goes steeply down (76.9%). This robustness will ensure the performance will be reliable in realworld applications where sensor data can be noisy or incomplete in process.

Table 7: Robustness Evaluation Under Simulated Sensor Noise Levels

Model	Noise Level 10% (%)	Noise Level 20% (%)	Noise Level 30% (%)
TMFN	90.5	89.3	87.1
Method [5]	82.8	80.4	76.9
Method [8]	84.9	83.2	80.7
Method [18]	88.2	86.5	83.4

All of these results collectively make TMFN a very efficient tool for the real-time monitoring of rehabilitation, providing superior accuracy, robustness, and adaptability across various evaluation scenarios. Its ability to combine multimodal data, run in real-time, and be robust to noise makes it an indispensable framework to advance patient care in rehabilitation settings. Next, we discuss an iterative validation use case for the proposed model, which will assist readers to further understand the entire process.

Validation using Iterative Practical Use Case Scenario Analysis

The example now serves to illustrate how the TMFN works and what the outcome would look like. Consider monitoring a patient in a stroke rehabilitation process. A sequence of exercises is carried out on the upper limb, such as reaching and grip strength exercise, along with weight-bearing exercise. Data are obtained from three sensor modalities: motion capture, force sensors, and EMG. This means raw signals that indicate the patient's joint angles, the forces applied, and the level of activation of the muscles. These are processed in TMFN to give scores of motor function in real time, the progress made during rehabilitation, and even feedback for the clinicians. Validation samples for the practical use case analysis come from the widely used PhysioNet Motion and Muscle Artifact (MMA) dataset that comprises a comprehensive collection of multimodal sensor data recorded during rehabilitation exercises. It contains synchronized recordings of motion capture data, which comprises 3D joint angles and trajectories, EMG signals recorded with 16-channel surface electrodes at a sampling rate of 1 kHz, and force sensor data comprising 6-axis torque and load measurements. For verification, the dataset 30% was utilized, which contained data from 10 participants performing reaching, gripping, and weight-bearing tasks. In each session of every participant, the clinical experts annotated the ranges of motion, levels of muscle activation, and the rehabilitation status as improving, plateaued, or declining. The validation samples have been chosen to represent a wide variety of motor impairments and trajectories of recovery, thus making TMFN robust and generalizable across different patient conditions and activity scenarios. These samples provide a starting point for the comparison of the process accuracy, latency, and ability of multimodal integration of TMFN. The input data for this system are presented in Table 8. It represents values from three modalities pertaining to one session. Input data: The motion capture data provides the joint angles in degree; force sensor data captures the applied torque in newton-meters; and, EMG data captures the muscle activation in microvolt. Besides, each modality also captures a timestamp for temporal alignments.

Table 8: Sample Input Data from Multimodal Sensors in a Rehabilitation Session

Timestamp (s)	**Joint Angle (°)**	**Torque (Nm)**	**EMG Signal (μV)**
0.0	45.3	12.5	85.2
0.1	46.7	12.8	88.6
0.2	47.9	13.1	92.3
0.3	48.5	13.4	95.8
0.4	49.0	13.6	99.2

These raw inputs are normalized and interpolated during preprocessing to standardize the data for the multimodal integration process. Table 9 displays the processed data after passing through TMFN's feature extraction and temporal modeling layers. The processed data contain high-level features derived from each modality as well as attention scores, which indicate the relative importance of each timestamp in the sequences.

Table 9: Processed Data with Extracted Features and Attention Weights

Feature Vector (Dimension)	**Attention Weight**	**Modality**
[0.45, 0.37, 0.51]	0.12	Motion
[0.48, 0.40, 0.53]	0.14	Motion
[0.50, 0.43, 0.55]	0.20	Motion
[0.52, 0.45, 0.57]	0.26	Motion
[0.54, 0.48, 0.59]	0.28	Motion

The attention weights are those points in the session to be rated; higher the value of the weight, therefore more relevant sets. Table 10 shows the final outputs in terms of motor function scores and the type of progress yielded by TMFN. The scores given are for the assessment of range of motion, joint coordination, and muscle activation with quantitative figures; whereas kind of progression indicates the characteristic nature of the overall treatment course attended by the patient.

Table 10: Final Outputs of TMFN for Motor Function Scores and Progress Classification

Metric	**Score**	**Unit**
Range of Motion	92.1	Degrees
Joint Coordination	8.9	10-point scale
Muscle Activation	95.6	μV
Rehabilitation Progress	Improving	-

These outputs allow clinicians to measure the patient's

status at the moment and apply evidence-based changes in their rehabilitation program sets. The case described here showcases that TMFN can process complex multimodal data in real time and transform raw signals into actionable insights. High attention weights on some timestamp points as well as sharp scores produced highlight the use of the model in capturing both critical moments and long-term trends in rehabilitation and improvement of care delivered to patients.

5 CONCLUSION AND FUTURE SCOPE

This paper demonstrated that the Temporal Multimodal Fusion Network (TMFN) has the potential to be a practical and robust framework for real-time monitoring of patients in rehabilitation. Through integration with motion capture, EMG, and force sensors, multimodal data streams achieved comprehensive assessment of motor function and rehabilitation progress. The model's evaluation of progression resulted in a 91.4% classification accuracy; this is greater than the traditional bench marks of Method [5] at 83.7%, Method [8] at 85.3%, and Method [18] at 88.9%; hence, the model is reliable in classifying rehabilitation trends as improving, plateauing, or declining.In similar fashion, its regression performance, in terms of predicting the range of motion (MSE: 3.2, MAE: 1.8, R2: 0.96), demonstrates it to be accurate and also in-line with the clinical benchmark and is superior to the next best model, Method [18], which attained MSE of 3.8 and R2R^2R2 score of 0.94. This work introduces the real-time performance of TMFN, with feedback latency being 0.76 seconds and feedback consistency 99.3%, which is an important leap from current state-of-the-art methods, hence more suited to dynamic rehabilitation environments. In addition, its robustness across different sensor modalities (accuracy of 92.1%, 90.8%, and 91.7% for motion capture, EMG, and force sensors, respectively) as well as noise resilience (accuracy of 87.1% at 30% noise levels) assures that this model could be deployed in a wide range of and demanding settings.These results confirm TMFN's potential to revolutionize rehabilitation by automating complicated assessment processes, improving clinical decision-making, and enhancing patient outcomes.

Future Scope

The promising results of TMFN thus open doors for further research and practical application in rehabilitation and beyond. Future work may be directed toward enlarging the dataset to contain a wider range of activities and patient demographics, in such a way that would ensure generalizability to diverse populations and conditions.Adding more sensor modalities such as EEG or HRV would give a more holistic view of the patient's recovery by integrating both motor and physiological dimensions of the process. In addition, deploying TMFN in real-world clinical settings requires lightweight, edge-compatible versions of the model to allow for real-time performance on portable hardware sets.Investigation of the reinforcement learning can enable TMFN to generate real-time feedback-driven proposals of adjustments for an optimum therapy, thereby reinforcing its place in being more of an active rehabilitation team participant. Lastly, further applicability of the framework in various areas such as sports science, elderly care, and the monitoring of recovery after surgical procedures will broaden its effects as well as the potential applicability into consolidating its versatility as a means of facilitating personalized healthcare sets.

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