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An Evaluation of Yoga and Physiotherapy using Learning Models on Biochemical Perspective of Enhancing Recovery and Wellness

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Abstract

Yoga improves flexibility and strength in the body and mind. This technique may reduce tension and discomfort. Medical or non-medical yoga and physiotherapy may alter the musculoskeletal, visceral, neurological, immunological, and endocrine systems. By merging early well-being practices with modern technology, clinicians may now study the biochemical effects of physiotherapy and yoga and develop more effective retrieval tactics. Deep learning systems, designed to examine and interpret vast amounts of composite data, have helped healthcare professionals identify complicated biochemical reactions that affect recovery. Thus, this research provides an EYPLM-BPERW approach to evaluate yoga and physiotherapy. Deep learning is used to examine the biochemical effects of therapeutic workouts on patient recovery in the EYPLM-BPERW model. The process includes feature extraction, classification, and parameter optimization. EYPLM-BPERW is used with VGG16 model for feature extraction at the primary stage to gather essential spatial characteristics from imaging and motion analysis of physiotherapy and yoga postures. Classification uses the BiLSTM classifier. Finally, the Adam optimizer method optimises the BiLSTM model parameters to improve recovery prediction accuracy. The EYPLM-BPERW model is extensively tested on the benchmark database to prove its classification accuracy. The wide comparing findings showed that EYPLM-BPERW outperformed current techniques.

Keywords: Adam Optimizer, Bidirectional Long Short-Term Memory, Biochemical Perspective, Feature Extraction, Physiotherapy, Yoga.

Introduction

Aging is a natural and irreversible process that results in chronic disease and is virtually paralyzed. It finally causes limited balance and mobility, raises the risk of falls, and harmfully affects the standard of living (1). The capability to carry out activities of daily living (ADL) is basic for elder adults to live independent lives. It needs good balance, muscle strength, and range of motion (ROM). Climbing stairs is a regularly negotiated functional action that is important for self-supporting mobility among the elders (2). The disability for climbing stairs might result in social difficulties for the elders. The risk of falls and injuries is better for those who are unable to independently walk on stairs. Exercise programs connecting muscle consolidation, ROM, and agility exercise have presented improvements in muscle function and decreased the symptoms of different chronic illnesses among aging people (3). Yoga is measured as mind-body training in complementary or alternative medicine that incorporates mental, spiritual, and physical features of an individual's health (4). Its effect contains decreased pain and effectiveness related to osteoarthritic modifications in the body, improved muscle strength, and extension of tight joint arrangements resulting in more flexibility. It improves body awareness and proprioception which increases the balance between the elders (5). Yoga, as an auxiliary treatment and a method of maintaining and promoting well-being, provides an outstanding sample of the mental-physical connection (6). It is recommended that yoga contains different medical and non-medical

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applications in the physiotherapy process. This is mostly qualified to the amount of complexities and multi-dimensionalities of impacts that are superficial in either physiotherapy or yoga exercises as constant procedures (7). The comparisons between physiotherapy and yoga on the intellectual level consist of spiritual, psychological, physiological, educational, and social measurements of human health. Yoga exercises joined with the process of physiotherapy, either in medical or non-medical backgrounds, can affect different body systems and structures (8). This may be advantageous for patients with orthopedic, neurological, psychosomatic, and metabolical illnesses. However, the major power of such activities is that each of the body's measurements (for example; organs, cells, tissues) are affected concurrently inside some complete system (9). The basis for this combination is that physical exercises (asanas) and yoga's philosophy share several main beliefs about the process of physiotherapy. The yoga principles resonate with the ideologies of the physiotherapy process as in their general method concerning the well-being and health of an individual (10). This paper develops an Evaluation of Yoga and Physiotherapy using Learning Models on the Biochemical Perspective of Enhancing Recovery and Wellness (EYPLM-BPERW) methodology. The EYPLM-BPERW model leverages deep learning techniques to analyze the biochemical impact of therapeutic exercises on patient recovery. It comprises three different stages involving feature extraction, classification, and parameter optimizer. At the primary stage, the EYPLM-BPERW technique is applied VGG16 model for the feature extraction process to effectively capture critical spatial features from imaging and motion analysis of physiotherapy and yoga postures. For the classification process, the bidirectional long short-term memory (BiLSTM) classifier is employed. Finally, the BiLSTM model is further optimized utilizing the Adam optimizer algorithm, which fine-tunes the model parameters to enhance accuracy and performance in predicting recovery outcomes. To demonstrate the good classification outcome of the EYPLM-BPERW technique, a huge range of simulations take place on the benchmark database. The paper incorporates many core models for a broader conceptual framework.

The Biopsychosocial Model: stresses how biological, psychological, and social elements impact healing. Biochemical and physiological systems are studied, while stress and mental health affect recovery. Exercise Physiology: knowing biochemical recovery requires knowing exercise-induced muscle repair, inflammation, and adaptation. This research explores biochemical marker changes caused by exercise and their effects on recovery.

Neuromuscular Adaptation**:** The research examines how muscle growth and strength affect recovery. The physiological and biochemical mechanisms of post-exercise recovery are explained by this paradigm. Psychoneuroimmunology (PNI) also illuminates biochemical recovery control. PNI stresses the immunological and neurological systems in healing. This work is important because psychological stress, immunological function, and the neurological system impact recovery results. In the existing study, the current longitudinal research examines the belongings of a tailored mindfulness-based yoga intervention on psychological resilience and SOC in patients of SCI throughout 6 months (11). Yoga presented to the participants of the intervention group weekly 3 times for six months. SOC is estimated by the SOC-13 scale and psychologic resilience by the Connor-Davidson Resilience Scale (CD-RISC). Sizes were captured at post-intervention, baseline, and 6 months of follow-up. Qualitative data obtained over semi-structured interviews and concentration groups provided additional information on psychological advantages arising from the program. The authors of existing article target to present an effective artificial intelligence (AI) model for the estimation of human pose in physiotherapist fitness exercises (12). The research additionally uses a multiple class exercises dataset depending on human skeleton movement pointing to organize the investigational study. The biochemical effects of yoga and physiotherapy must be studied to see how they aid rehabilitation. Yoga affects biological indicators such cortisol, inflammatory cytokines, and Brain-Derived Neurotrophic Factors (BDNF), which reduce stress and promote recovery. However, physiotherapy involves muscle regeneration and functional movement, affecting creatine kinase and muscle protein synthesis. Comparing the biochemical consequences of these two therapies shows their distinct healing processes and therapeutic potential. Traditional recovery measures like the Visual Analog Scale or physiological tests sometimes omit molecular insights that may provide a more complete picture. This dataset includes 133 features originating from the movements of the human skeleton throughout different exercises, leading to higher feature dimensionalities which disturb the performance of human pose estimate through ML and DL algorithms. A new Logistic regression Recursive Feature elimination (LogRF) model has been presented for selecting features. The exiting research examine the efficiency of office and walking on workers' intensity and occurrence of musculoskeletal complaints (MSC), in addition to activation, which includes vigilance and vitalities (13). By the trimester longitudinal randomized experimental designs, 459 office employees from 5 groups have been arbitrarily allocated to both the waitlist control group, the office yoga intervention group, and the walking intervention group. Members in the intervention groups have been trained to separately engage in short-term everyday meetings of the approved activities at the office. Those in the officeyoga group expected video classes for performing the exercises. The exiting research intended to define the knowledge of physical treatment in a mostly lower-income and minority population with cLBP (14). The qualitative research has been set in a randomized control sample for patients with cLBP in city, underprivileged groups. The research utilizes a suitable sample for interviewing 12 members from the 102 who contributed to the PT arm of the testing and then implemented a theatrical study to define their experience. From the study, software has been implemented for the real-time exercise detection posture through the assistance of AI (15). This study substitutes the physiotherapist and offers good real-time feedback on the user's flexion exercise poses and wrist extension. AI is the most common and generally applied approach for real-time image investigation. In real time the user captures at least 1s to implement the exercise posture. The authors of existing article presented Martial Arts and Yoga as a method to retain the balance between body and mind and generate leaders capable of managing workplace pressure. Methods (16). This work accepts the qualitative approaches depending on the content investigation. Outcomes. Martial Arts and Yoga assist in keeping physical and mental balance, improving self-resilience, self-confidence, and self-control, and generating practitioners capable of challenging jeopardized conditions. Therefore, decreases workplace pressure. The authors of existing article contrast and compare the self-actualization theory with the opinions of historic Indian knowledge to generate a method (17). Either idea struggles for an important Self, releasing the possible or the actualization/realization of the accurate Self.

Methodology

This study develops an EYPLM-BPERW methodology. The EYPLM-BPERW model leverages DL techniques to analyze the biochemical impact of therapeutic exercises on patient recovery. It comprises three different stages involving feature extraction, classification, and parameter optimizer. Figure 1 signifies the overall workflow of the EYPLM-BPERW model. This research encompasses four groups:

- Yoga Group: Individuals allocated to this group are provided with a systematic yoga program designed to enhance flexibility, balance, and muscular recuperation.
- Physiotherapy Group: Participants engage in a physiotherapy regimen centered on personalized strengthening and rehabilitation activities.
- Combined Group: Participants in this group get both yoga and physiotherapy sessions to evaluate the synergistic benefits of both therapies on recovery.
- The control group receives no intervention and is evaluated for baseline comparisons with other groups.

This methodology facilitates a comparison of the distinct benefits of yoga and physiotherapy, as well as the synergistic effects of both modalities. The control group establishes a baseline metric to evaluate the effectiveness of the treatments.

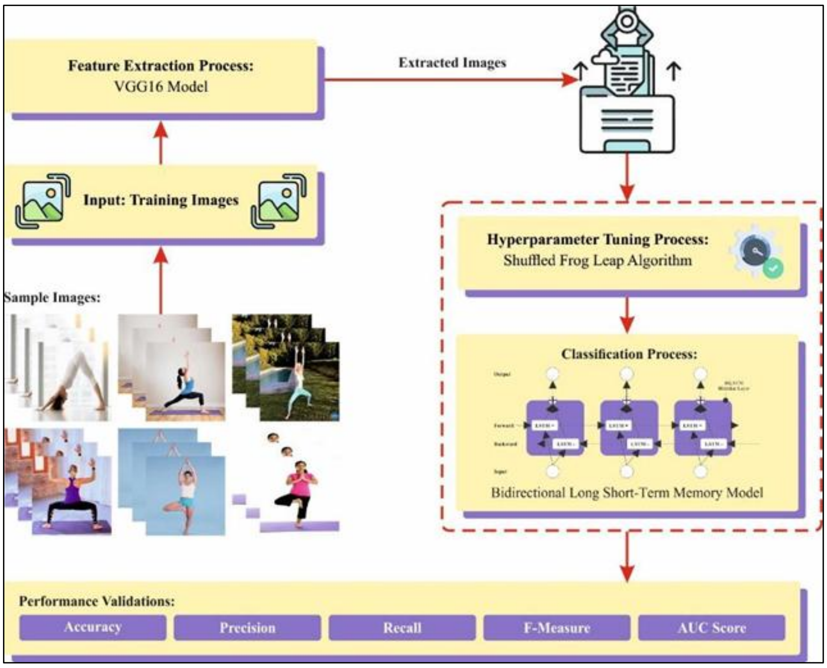

Figure 1: Overall Workflow of EYPLM-BPERW Model

Feature Extraction

At the primary stage, the EYPLM-BPERW technique is applied VGG16 model for the feature extraction process to effectively capture critical spatial features from imaging and motion analysis of physiotherapy and yoga postures. VGG16 is a DCNN method that can obtain higher-level spatial features from yoga posture images (18). These kinds of layers use a learning filter on the images to isolate lower-level data such as forms and edges. Pooling layer down samples feature mapping, lowering spatial outcome while upholding significant features. This aids in retaining model intricacy under the control and averts overfitting. This depth level permits the system to acquire slowly intricate hierarchical domains, terminating in higher-level features that imitate yoga postures. Prior to conducting parametric tests, normality assessments were performed to verify that the data satisfied the prerequisites for parametric analysis. The Shapiro-Wilk test was used to evaluate the normality of the data for each group. Data that did not follow a normal distribution were either converted or analyzed using suitable non-parametric techniques.

In the statistical analysis, we included possible confounding factors, such as dietary behaviors and pharmaceutical therapies that may affect the biochemical markers being studied. The variables were assessed using validated questionnaires and medical records, and their impacts were accounted for by including them as covariates in the statistical models. This method guarantees that the analysis precisely represents the effects of the interventions, free from the influence of extraneous variables. After every layer of convolutional, the non-linear activation function is employed to present non-linearity and upsurge the mode1's capability to acquire intricate patterns. These fully connected (FC) layers generate higher-level feature vectors that gather spatial data linked to the unique yoga position. This vector contains direction, shape, and significant facts about yoga, which makes it beneficial for identifying yoga positions. For each last feature map, the convolutional process covers a dot product amongst the input feature map (Y), weights (V), made with a bias term (a), and an activation function (g) is expressed in Eq. [1]

$$x = g(V^{*}Y + a) \quad [1]$$

Here, x signifies an output of the feature map, V specifies weights, Y denotes an input of the feature map, a means a term of bias. $Max\ pooling$ picks the maximum value of the given feature maps as signified in Eq. [2]

$$X = max(pool(Y)) \quad [2]$$

Here, $pool()$ executes element-wise utmost through a certain area. The design of VGG16's deep allows it to acquire an intricate hierarchy of features, with lower-level edges over higher-level spatial representations of yoga positions. VGG16 was formerly trained on large databases like

ImageNet, which is enhanced near yoga pose recognition by using its feature extraction abilities. VGG16 is deployed well in a range of image classification applications such as extracting yoga position data. Figure 2 represents the structure of the VGG16 model. In the presented research selected a broad sample of individuals by age, gender, and health status to guarantee a representative analysis. Subjects were divided by age (18-30, 31-50, 51+), gender (male and female), and health condition (e.g., hypertension, diabetes, musculoskeletal diseases). The investigation considered these factors to determine their influence on recovery and generalizability.

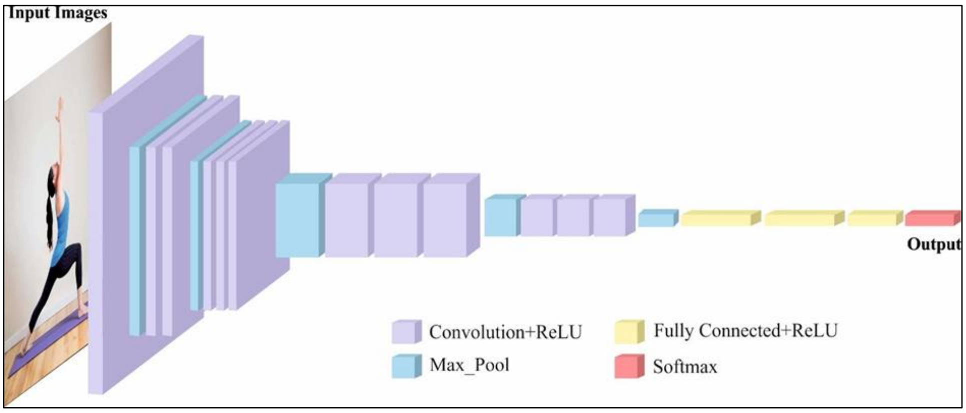

Figure 2: Structure of VGG16 Model

Classification Process

For the classification process, the BiLSTM classifier is employed. This method signifies a kind of RNN structure containing dual networks of LSTM (19). One LSTM handles an input sequence from left to right (forward LSTM), while the other deals with it from right to left (backward LSTM). This bidirectional processing allows BiLSTM to understand sequences more efficiently, rendering it in NLP tasks like entity recognition, sentiment analysis, and machine translation. The authors have presented the LSTM structure to address the problem of vanishing gradient in RNN. Then, Graves and Schmidhuber additionally explored the efficacy of BiLSTMs in tasks like the classification of phonemes and handwriting detection. Their work established the dominance of BiLSTMs over unidirectional methods in capturing rich context data. Therefore, BiLSTMs have arisen as a commonly adopted framework for numerous sequential data analysis tasks, presenting improved performance and robustness. The output of the RoBERTa layer is passed over a layer of dropout in advance being served into the BiLSTM layer. The BiLSTM holds the capability to recollect past data and well achieve long-range dependences in the input. To ensure participant safety, no invasive procedures were involved in this study. Biochemical markers were assessed using non-invasive methods, such as saliva and urine samples, which are safe and non-intrusive ways to collect the necessary data. These samples were analyzed for markers of muscle recovery, inflammation, and other relevant biochemical parameters. So, integrating a BiLSTM as a feature extraction improves the model's accuracy by leveraging both the contextual data from RoBERTa and the long-range dependencies among tokens. The BiLSTM method is termed by the below-mentioned set of Eq. [3].

Input Gate (i_t) :

$$i_t = \sigma\left(W_{ix}^f x_t + W_{ih}^f h_{t-1}^f + W_{ic}^f c_{t-1}^f + b_i^f\right) \odot\sigma\left(W_{ix}^b x_t + W_{ih}^b h_{t+1}^b + W_{ic}^b c_{t+1}^b + b_i^b\right) \quad [3]$$

This formula controls the flow of data into the cell state C_t at time-step t in both backward and forward directions. It unites an input from the forward LSTM $\left(W_{ix}^f x_t + W_{ih}^f h_{t-1}^f + W_{ic}^f c_{t-1}^f + b_i^f\right)$ and the backward LSTM $(W_{ix}^b x_t + W_{ih}^b h_{t+1}^b + W_{ic}^b c_{t+1}^b + b_i^b)$ utilizing an element-wise multiplication. The activation function of sigmoid σ compresses an input to a range between 0 and 1, defining an extent to which every element affects the gate of input. Forget Gate (f_t) are analysed Eq. [4]:

$$f_t = \sigma(W_{fx}^{f} x_t + W_{fh}^{f} h_{t-1}^{f} + W_{fc}^{f} c_{t-1}^{f} + b_f^{f}) \odot\left(W_f^{b_x} x_t + W_{fh}^{b} h_{t+1}^{b} + W_{fc}^{b} c_{t+1}^{b} + b_f^{b}\right) \quad [4]$$

This formulation defines which data from the preceding cell state c_{t-1} must be rejected or forgotten in both the backward and forward directions. It unites the forget gate calculations from the backward and forward LSTMs by employing element-wise multiplication. The below-mentioned formula [Eq 5] upgrades the cell state C_t by uniting data from both directions. It unites the contributions from an input gate in both directions and the $tanh$ activation function of the candidate value.

Cell State Update (C_t) shown in Eq. [5]:

$$C_t = f_t \odot C_{t-1} + i_t \odot tanh\left(W_{cx}^{f} x_t + W_{ch}^{f} h_{t-1}^{f} + b_c^{f}\right) + i_t \odot tanh\left(W_{cx}^{b} x_t + W_{ch}^{b} h_{t+1}^{b} + b_c^{b}\right) \quad [5]$$

Output Gate (o_t) :

$$o_t = \sigma\left(W_{ox}^{f} x_t + W_{oh}^{f} h_{t-1}^{f} + W_{oc}^{f} c_t^{f} + b_o^{f}\right) \odot\sigma\left(W_{ox}^{b} x_t + W_{oh}^{b} h_{t+1}^{b} + W_{oc}^{b} c_t^{b} + b_o^{b}\right) \quad [6]$$

Eq. [6] adjusts which parts of the cell state C_t must be employed to calculate the hidden layer (HL) h_t at the present time-step t in both the directions. It merges output gate calculations from both directions utilizing element-wise multiplication. Eq. [7] computes the HL h_t by using an output gate to the hyperbolic tangent of the cell state C_t.

Hidden State (h_t) :

$$h_t = o_t \odot tanh(C_t) \quad [7]$$

Output (y_t) shown below Eq. [8]:

$$y_t = Softmax\left(W_{hy} h_t + b_y\right) \quad [8]$$

The Eq. [8] creates a prediction of output at time-step t by employing an activation function Softmax to the linear transformation of the HL h_t. Yoga and physiotherapy have showed promise in aiding rehabilitation, but sustainability and accessibility are still vital. Community yoga may be a cost-effective and sustainable rehabilitation method. The absence of skilled teachers in certain places may restrict its accessibility. Physiotherapy is beneficial but needs frequent trips to healthcare institutions, making it less accessible to rural and marginalized populations. A combined strategy that includes yoga, physiotherapy, and remote alternatives like tele-rehabilitation might improve accessibility and long-term involvement.

Hyper Parameter Tuning Process

Finally, the BiLSTM model is further optimized utilizing the Adam optimizer algorithm, which fine-tunes the model parameters to enhance accuracy and performance in predicting recovery outcomes (20). Adam optimizer algorithm is a highly effective stochastic optimizer model, which attains excellent performance while using only 1st-order gradients and protecting memory. It achieves this by dynamically computing the adaptive rate of learning for every parameter, trusting on assessments of the 1st and 2nd moments of the gradients. The abbreviation "Adam" signifies adaptive moment assessment, which merges the powers of dual renowned models such as AdaGrad, which is recognized for its efficacy with sparse gradients, and RMSProp. In our description, we determine clear relations between Adam and other stochastic optimizer models. One major benefit of Adam is its capability to uphold steady levels for parameter upgrades, despite gradient rescaling. Furthermore, the sizes of steps are nearly assured by the step size hyperparameter. Unlike a few models, Adam does not require a stationary objective, permitting it to adjust flexibly to developing scenarios. Moreover, it accurately grips sparse gradients and essentially presents a method of step-size annealing. Adam optimizer algorithm upholds a set of adaptive rates of learning for every parameter in the method. Let θ signify the parameter to be enhanced, and g_T represents the gradient of the objective function with esteem to θ at time-step t. The ADAM upgrade regulation can be signified as below:

Initialize each of

- Time-step t= 0.
- the 1st moment vector (m) with zeros
- the 2nd moment vector(v)with zeros
- the parameters to be improved (θ).

If the stopping criterion is not met, do

- Increase the time-step (t).
- Calculate the gradients (g) of the objective function with esteem to the parameters.
- Upgrade the 1st moment estimations are Eq. [9]:

$$m_t = \beta_1 m_{(t-1)} + (1-\beta_1)g_t \quad [9]$$

- Upgrade the 2nd moment estimations are Eq. [10]:

$$v_t = \beta_2 v_{(t-1)} + (1-\beta_2)g_{t^2} \quad [10]$$

Pay for the bias of the initial moment estimations, ADAM uses bias correction given below Eq. [11] and Eq. [12]:

$$m = \frac{m_t}{1-\beta_1^t} \quad [11]$$

$$V = \frac{v_t}{1-\beta_2^t} \quad [12]$$

Whereas, (t) denotes the present time-step. These bias-corrected moment evaluations are then employed in order to upgrade the parameters are shown in Eq. [13]:

$$\theta = \theta - \left(\alpha \frac{\widehat{m}}{\sqrt{v}+\varepsilon}\right) \quad [13]$$

The Adam optimizer algorithm originates an FF to attain enhanced classifier efficiency. It defines a positive number to characterize the superior performances of the candidate solution. In this work, the reduction of the classifier rate of error is considered as FF, as shown in Eq. [14].

$$fitness(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{no.of\ misclassified\ instances}{Total\ no.of\ instances} * 100 \quad [14]$$

This study's results have substantial practical consequences for clinical practice: **Rehabilitation Facilities:** The biochemical indicators developed in this research help evaluates the efficacy of rehabilitation therapies. Monitoring alterations in inflammation and muscle repair indicators may assist healthcare professionals in assessing the recovery trajectory of patients receiving physiotherapy or other therapeutic treatments.

Physical Recuperation: In sporting contexts, understanding the metabolic alterations linked to recovery may inform training and recuperation techniques. The study's results may inform the customization of recovery regimens according to individual metabolic reactions to exercise, enhancing performance and minimizing injury risk.

The findings from this research may guide the creation of individualized treatment strategies for people with chronic pain. By integrating biological indicators into recovery assessments, healthcare practitioners may discern individuals' particular recovery requirements and modify their treatment strategies appropriately.

Results and Discussion

In this section, the progressive simulation of the EYPLM-BPERW technique can be inspected under the Yoga Poses dataset (21). The dataset contains 500 images under 5 classes as exemplified in Table 1. Figure 3 depicts the sample images.

Table 1: Details of Dataset

Yoga Poses	No. of Images
Down Dog	100
Goddess	100
Plank	100
Tree	100
Warrior 2	100
Total Images	500

Figure 3: Sample Images

Table 2 and Figure 4 demonstrate the classifier results of the EYPLM-BPERW system in terms of 70%TRAPH and 30%TESPH. The results suggest that the EYPLM-BPERW technique appropriately identified the instances. With 70%TRAPH, the EYPLM-BPERW method provides average$accu_y$, $prec_n$, $reca_l$, $F_{measure}$, and AUC_{score} of 93.83%, 84.79%, 84.62%, 84.64%, and 90.38%, respectively. Simultaneously, with 30%TESPH, the EYPLM-BPERW system gives average$accu_y$, $prec_n$, $reca_l$, $F_{measure}$, and AUC_{score} of 96.27%, 91.00%, 90.59%, 90.67%, and 94.13%, individually. One weakness of the research is the very small sample size, which may influence the generalizability of the results. Moreover, we did not include specific confounding factors, such drug consumption or genetic predisposition that might affect the recovery results. The brief period of the trial constrains our capacity to evaluate the long-term benefits of yoga and physiotherapy. Future research should focus on including bigger, more varied sample groups and investigating the long-term benefits of yoga and physiotherapy. Furthermore, research might investigate the synergistic advantages of amalgamating these two therapies across diverse patient groups, including those with chronic illnesses, and assess the practicality of including remote or virtual rehabilitation alternatives to enhance accessibility.

Table 2: Comparative Analysis of EYPLM-BPERW Technique under 70%TRAPH and 30% TESPH

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$	AUC_{score}
TRAPH (70%)					
Down Dog	96.00	92.54	87.32	89.86	92.77
Goddess	96.29	88.41	92.42	90.37	94.80
Plank	92.29	82.54	76.47	79.39	86.28
Tree	93.14	83.56	83.56	83.56	89.61
Warrior 2	91.43	76.92	83.33	80.00	88.43
Average	**93.83**	**84.79**	**84.62**	**84.64**	**90.38**
TESPH (30%)					
Down Dog	94.67	83.87	89.66	86.67	92.76
Goddess	96.00	93.75	88.24	90.91	93.26
Plank	97.33	91.18	96.88	93.94	97.17
Tree	98.00	100.00	88.89	94.12	94.44
Warrior 2	95.33	86.21	89.29	87.72	93.00
Average	**96.27**	**91.00**	**90.59**	**90.67**	**94.13**

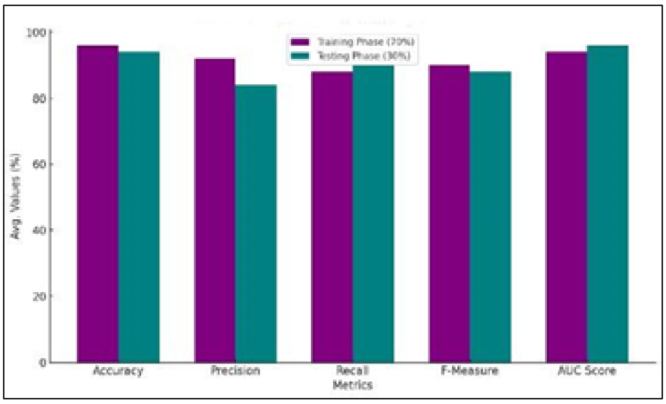

Figure 4: Average of EYPLM-BPERW Method under TRAPH of 70% and TESPH of 30%

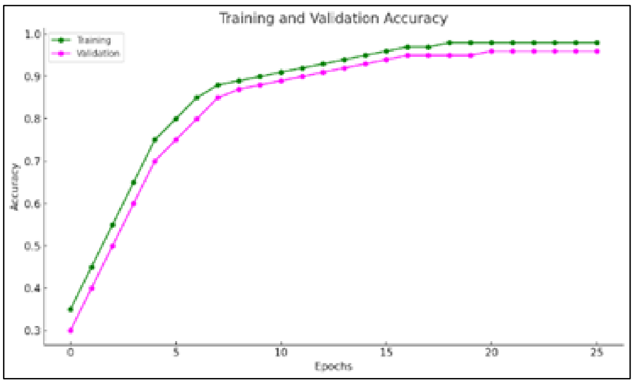

Figure 5: $Accu_y$ Curve of EYPLM-BPERW Method

In Figure 5, the training $accu_y$ (TRAAC) and validation $accu_y$ (VLAAC) outcomes of the EYPLM-BPERW approach are portrayed. The $accu_y$values are computed for an interval of 0-25 epoch counts. The figure discovered that the TRAAC and VLAAC values show increasing tendencies that indicate the abilities of the EYPLM-BPERW methodologies with enhanced outcomes through several number of iterations. Also, the TRAAC and VLAAC stay adjacent across the epoch counts that specify least overfitting and establish greater performance of the EYPLM-BPERW algorithm, encouraging reliable prediction on unidentified instances. In Figure 6, the TRA loss (TRALS) and VLA loss (VLALS) graph of the EYPLM-BPERW technique is determined. The loss values are calculated for an interval of 0-25 epochs. It is stated that the TRALS and VLALS values established a declining trend, informing the capabilities of the EYPLM-BPERW algorithm in balancing a trade-off amongst data fitting and generalization.

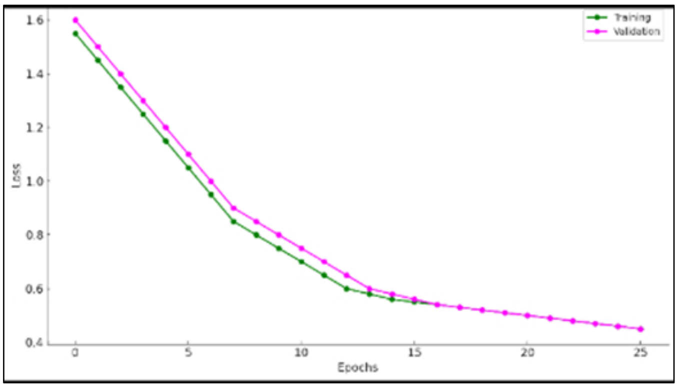

Figure 6: Loss Curve of EYPLM-BPERW Method

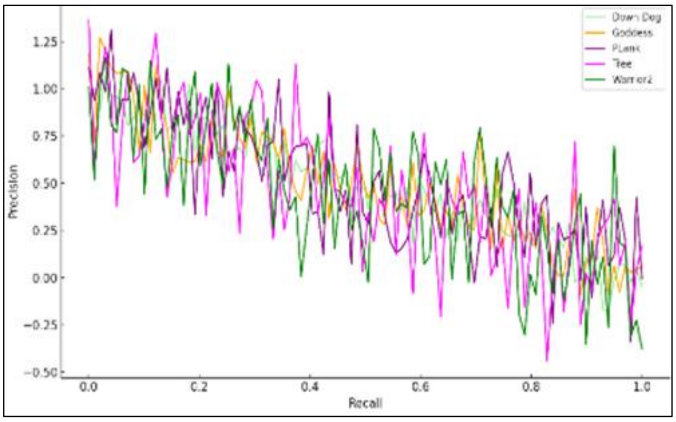

Figure 7: PR Curve of EYPLM-BPERW Method

In Figure 7, the precision-recall (PR) investigation examination of the EYPLM-BPERW algorithm provides an analysis of its outcomes by plotting Precision against Recall for all five classes. This figure displays that the EYPLM-BPERW technique continually attains better PR performances through numerous classes, demonstrating its proficiency to keep a major part of true positive predictions among each positive prediction (precision) but additionally seizing a larger amount of actual positives (recall). In Figure 8, the ROC inspection of the EYPLM-BPERW algorithm is examined. The outcomes showed that the EYPLM-BPERW technique attains improved ROC results across every class, establishing important capabilities of differentiating the class labels. These consistent tendencies of enhanced values of ROC across several class labels represent the effective performance of the EYPLM-BPERW algorithm on predicting classes, underlining the stronger nature of the classifier process.

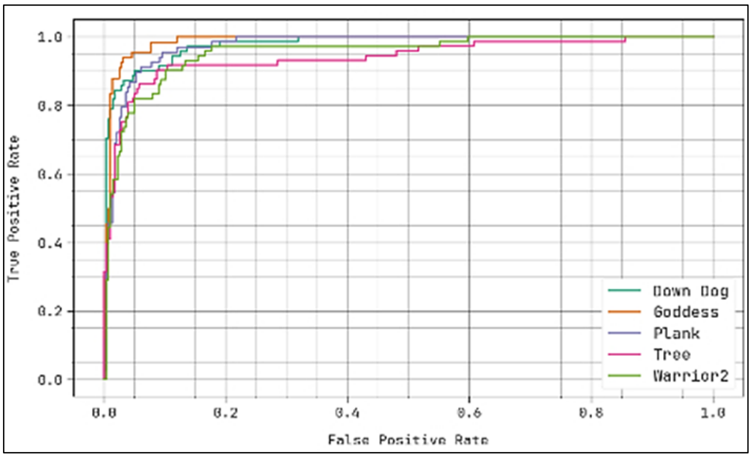

Figure 8: ROC Curve of EYPLM-BPERW Method

Table 3: Comparative Analysis of EYPLM-BPERW Model with Existing Approaches

Methodology	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$
LSTM Classifier	92.26	89.44	87.69	80.80
Random Forest	89.47	80.06	89.48	80.83
XGBoost Model	89.69	87.22	84.91	89.59
AlexNet Algorithm	91.29	80.66	87.50	82.15
InceptionV3 Model	92.50	80.19	85.95	88.48
MLP Algorithm	94.13	83.63	82.44	84.99
EYPLM-BPERW	96.27	91.00	90.59	90.67

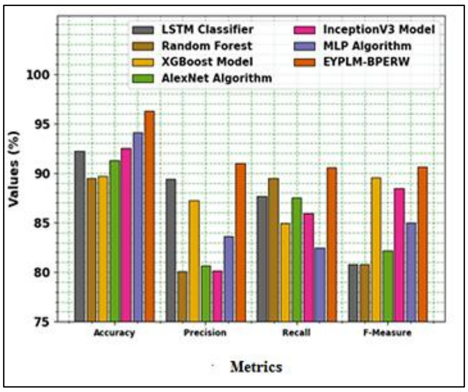

Figure 9: Comparative Analysis of EYPLM-BPERW Model with Existing Approaches

Table 3 and Figure 9 inspect the comparative outcomes of the EYPLM-BPERW approach using the recent approaches. The results underscored that the LSTM, RF, XGBoost, and AlexNet techniques have stated poor performance. In the meantime, InceptionV3, and MLP methods have gained adjacent outcomes. Additionally, the EYPLM-BPERW methodologies described better performance with higher$prec_n$, $reca_l$, $accu_y$, and $F_{measure}$ of 91.00%, 90.59%, 96.27%, and 90.67%, respectively.

Table 4 represents the comparative outcome of EYPLM-BPERW model under normal and yoga groups. The table values show that the EYPLM-BPERW model has obtained effective outcomes. When compare the reduction of percentage in pain and stiffness at 6 months in normal and yoga groups, we got significant improvement in yoga group as compared to normal group.

Table 4: Comparative Outcome of EYPLM-BPERW Model under Normal and Yoga Group

Group	Improvement In Pain and Stiffness At 6 Weeks (%)	Improvement In Pain and Stiffness At 3 Months (%)	Improvement In Pain and Stiffness At 6 Months (%)	Improvement In Function At 6 Months (%)
Normal	19.78	14.16	10.75	25.15
Yoga	26.44	33.97	50.04	64.92

Conclusion

This study develops an EYPLM-BPERW methodology. The EYPLM-BPERW model leverages DL techniques to analyze the biochemical impact of therapeutic exercises on patient recovery. It comprises three different stages involving feature extraction, classification, and parameter optimizer. At the primary stage, the EYPLM-BPERW technique is applied VGG16 model for the feature extraction process to effectively capture critical spatial features from imaging and motion analysis of physiotherapy and yoga postures. For the classification procedure, the BiLSTM classifier is employed. As a final point, the BiLSTM model is further optimized utilizing the Adam optimizer algorithm, which fine-tunes the model parameters to enhance accuracy and performance in predicting recovery outcomes. To demonstrate the good classification outcome of the EYPLM-BPERW technique, an extensive range of experimentations take place on the benchmark database. The extensive comparative results ensured the betterment of the EYPLM-BPERW technique over the recent methods.

Abbreviations

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Author Contributions

Jackson SJ: Data curation, Conceptualization, Investigation, T.Parasuraman: Data curation, Conceptualization, Investigation, P. Karthikeyan: Formal Analysis, S. Jayaraman: Investigation, JPD Srinivasan: Methodology, K. Vishnuvardan Reddy: Writing, S. Indumathi: validation.

Conflict of Interest

The authors have expressed no conflict of interest.

Ethics Approval

Not Applicable.

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