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LogRegression: human action pattern recognition for yoga and kavayat for children

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ABSTRACT

Poses of human pattern recognition through machine learning is an essential facet of several applications, including health, surveillance, and sports analysis. For children yoga and kavayat (mock drill) increases the physical as well as mental health. Through the analysis of motion data this work discriminates between varied actions with high precision, contribution valued insights for monitoring and analysis in real-time. Here, this system that influences technique called as machine learning specifically logistic regression, to precisely discriminate and classify physical action patterns (child pose estimation) of children. Analogous to the propagation of false information, identifying physical actions is essential for upholding integrity and efficiency across various domains. The novel system demonstrates a towering accuracy of 98.00%, highlighting its effectiveness in recognizing and classifying physical action patterns.

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1. INTRODUCTION

In the world of fitness and exercise, doing exercises correctly is super important for getting the results you want and staying safe from injuries. Whether someone is lifting weights, doing yoga, or playing sports or for children doing as yoga and kavayat sometimes it is called as mock drill. Mock drill is retaining children fit and healthy, how move matters a lot. But let's be real, it's not always easy to keep form perfect, especially if don't have someone trained to help. That's where technology can step in to lend a hand. One exciting area is machine learning, which is like smart technology that can learn from lots of data. By studying how we move, these machines can learn to recognize when we're doing exercises right or if we might be at risk of getting hurt. Here stated that how to dives into how this refined technology can give us feedback and guidance as we work on getting fitter and better at what we do.

In the realm of physical fitness, conventional methods of receiving feedback often hinge upon the presence of a qualified trainer who can observe and offer guidance on our exercise techniques. However, the accessibility of personal trainers remains a privilege not afforded to everyone, and even for those who do have access, the limitations of time and availability persist. Herein lies the utility of machine learning technology. Through the utilization of specialized sensors and cameras, these intelligent systems are capable of monitoring our movements and promptly providing feedback on the correctness of our actions. Whether it involves rectifying minor errors in a squat or refining the alignment of a yoga pose, these systems offer instantaneous guidance. What distinguishes these systems is their capacity for continuous learning and adaptation. Over time, they accumulate insights into our unique movement patterns and areas where improvement is needed. Consequently, the feedback dispensed becomes increasingly personalized, akin to the guidance of a seasoned trainer who possesses an intimate understanding of our capabilities and limitations. This personalized feedback not only enhances the efficacy of our workouts but also empowers us with greater autonomy over our fitness endeavors. Apart from giving us feedback during workouts, these smart systems can do a lot more. They can keep track of our progress and tell us how we're improving. They can also warn us if we're at risk of getting hurt, which helps us stay safe in the long run. And if that's not enough, they can even make exercising more fun! By combining with virtual reality or augmented reality, these systems can create exciting virtual worlds for us to train in. It's like playing a video game, but instead of sitting around, we're moving and getting fit. Using machine learning to recognize how we move can make our workouts better and safer. It gives us instant feedback, tracks our progress, and makes exercising more enjoyable. But to make this happen, we need to work together, think about the ethics, and keep improving the technology. With teamwork and innovation, we can make exercising smarter and more fun for everyone.

The use of gyroscopic sensors [1] and accelerometers in mobile based human action recognition, to recognize the accuracy analyzed on the features and discussed the results. Human activity recognition [2] is on condition that different types of sensors being used. This work suffered evaluation and training using a dataset open available. A system utilizes deep learning and computer vision for real-time posture detection supervisory users on the way to accurate postures which comparison with typical yoga poses [3]. Furthermore, amalgamate features this work find path for gym activities from varied posture detection applications onto a combined interface.

Role of camera as a vision-based technique essential for the apprehend the video, which encamps with convolutional neural network (CNN) and convolutional long short-term memory (ConvLSTM) [4]. It proposes the unique method named as logistic regression. Some of the samples from it consider then divide in 2 groups. The novel logistic regression algorithm validates advanced accuracy equated to linear regression [5]. You only look at coefficients (YOLACT)-temporal relation network architecture (TRN) [6] offered and this architecture is precisely intended for actual considerate of hand actions. It merges YOLACT, an instance segmentation methodology uniting in real time a TRN. Most of the hand action understand through the TRN.

Two separate approaches deep CNN [7]: primarily, until the end of training on the RGB image dataset, engaging transfer learning to classify positions with ImageNet count in number five. Furthermore, control existing qualified (pose estimator) deep convolutional network demonstrate accuracy. Presenting a new way to show the three randomly connected instances combined as a triplet. Which infer the unfamiliar activities and distinguishing characteristics between them [8]. This pioneering method to measure changes in skeleton detection during successive activities is known as skeleton detection technique. It operates to classify velocity levels using nearest neighbor and directs the spatial temporal graph convolutional networks (ST-GCN) model to conclude variations in states [9]. According to Chaudhari *et al.* [10], human joints to identify discrepancies in posture by localizing key points as a model, this practice used in the employs CNN for pose recognition.

Recent progressions in person pose recognition realized complete the entitlement of deep learning techniques [11]. Deep learning has revolutionized pose approximation by approving the growth of tremendously detailed and efficient work that grip multifaceted poses and occlusions. It attempted three tests and trained the framework which distinguishes individually pose of human [12]. It is also supportive in into consistent patterns through the transformation of discrepancies of dissimilar activities. It depicts about activity acknowledgement and processing of image [13]. It receipts single dataset and examines the performance and precision. Frames separated into images. It videopose3D for human activity require the very less data and gives the training for 3D [14]. Exercise based post estimation difficulties can be worked.

One approach [15] utilizes a stateless dynamic length video data input producer, although the other inspects the state dependent capability of recurrent neural network chiefly used in human action recognition. This tactic qualifies the archetypal to fold to excerpt inequitable patterns from previous frames although conserving memory integrity. Various pose estimation frameworks have recently been scrutinized for their efficacy in classifying traditional Indian physical activities. Specifically, Waheed *et al.* [2] using different types of sensors used to recognize the activity of human. The current research builds upon this foundational yardstick by introducing an optimized logistic regression model to enhance pattern recognition accuracy. A mindfulness yoga show to reduce the certain anxiety and physiological arousal (pulse rate) among children with school refusal [16]. According to Wilkin *et al.* [17], executive function of 3- to 7-year children undergo changes and leads to foundation of academics, emotional, and cognitive outcomes. Bazzano *et al.* [18] mindfulness intervention plus combined yoga results into some effects were small and context-dependent that decreases the anxiety and depression. Liu *et al.* [19] focused on 3D pose and mesh recovery methods (single and multi-person), datasets and trends useful if your pipeline considers 3D or depth. Graph convolutional network with 80% accuracy used to extract from emotional features. For action recognition TRN and a face recognition (face recognition backbone-security network (FRB-SN)) based security network for user identification with 91% accuracy and major concern with security and intuitive interaction [20]. Table 1 compare in real time human pose estimation models with single or multi person with different keypoints detection to the system of and then logression with 33 keypoints stated for child pose detection.

Table 1. Human pose estimation models using deep learning

Pose estimation model	Keypoint	Functioning	Approach	Single/many
Openpose	25	Real-time	Bottom-up	Single and many person
Mask-RNN	11	Real-time	Bottom-up	Many person
AlphaPose	12	Real-time	Top-up	Manyperson
Deepcut	17	Real-time	Bottom-up	Many person
Iterative error feedback	13	Real-time	Top-up	Single and many person
LogRegression	33	Real-time	Top-up	Single

2. METHOD

The proposed system is based on apprehending the video frame and detection the correct human action using machine learning approach. Figure 1 illustrate the overall architectural framework of proposed LogRegression system for recognizing yoga and kavayat patterns in children. The flowchart details the sequential stages from video input to final classification performance of the system.

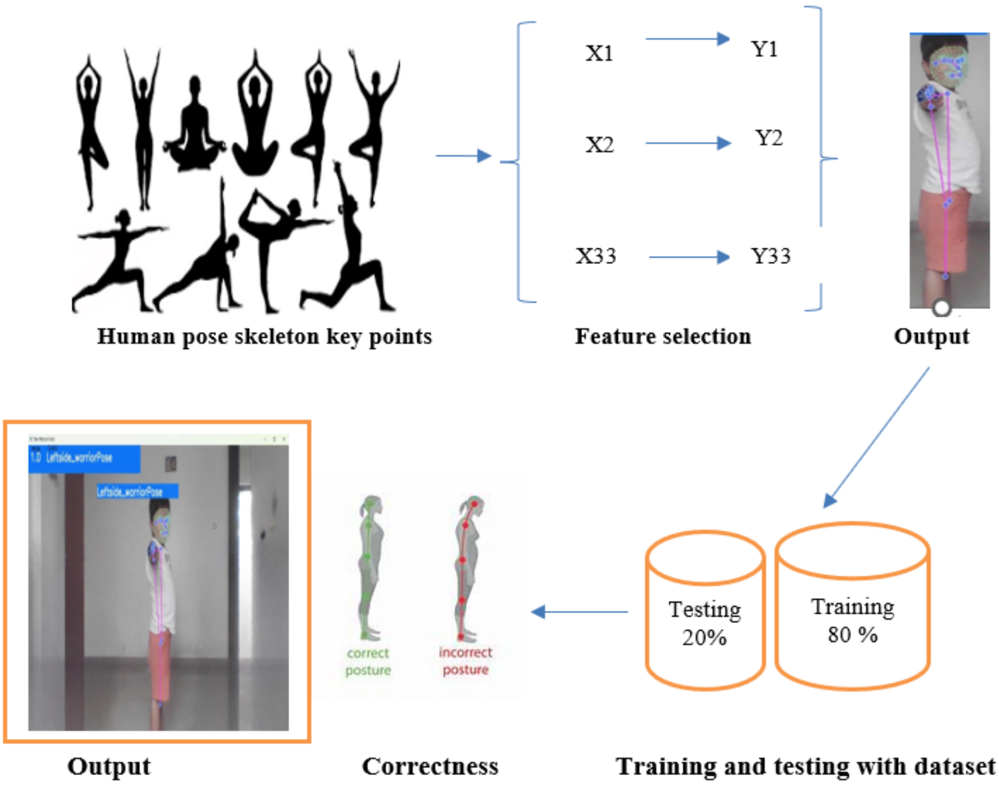

Figure 1. Workflow diagram of proposed LogRegression system

2.1. Architecture

This is proposed workflow diagram to illustrate the Figure 1, which highlight the dataflow and integration of each component as follows:

i) Input: the input to the system is a live data of user's body points. The dataset contains samples of various physical activities performed by the children. The data is captured by camera.
ii) Preprocessing: the raw data is pre-processed to eradicate noise and inappropriate information. This includes techniques such as filtering, normalization, and segmentation to isolate individual activities. Preprocessing is done to emphasize the significance of data quality.

iii) Feature extraction: it includes transforming and selecting unprocessed data hooked on valuable and insight features may routine that machine learning models for correct acknowledgement of person activity. Relevant features capture information for action recognition. The system uses coordinates allocated on the body and face of the practitioner to detect the poses. A dataset of child (yoga and kavayat) poses with corresponding coordinates for each pose with keypoints.
iv) Classification using logistic regression algorithm: logistic regression is used for classification of multiple tasks. It models the probability of each class using a logistic function and makes predictions based on the probability scores. The dataset was preprocessed, and logistic regression was trained to classify the poses depend on the obtained features.
v) Detect human activity: after training of logistic regression model, it can be used to classify new instances of sensor data into different activity classes. The model predicts the greatest possible activity worked on the extracted features and learned parameters.
vi) Evaluation: metrics like accuracy are used to evaluate the performance of the model, offering insights into its ability to accurately classify various activities.

2.2. Proposed algorithm

Logistic regression: this algorithm which classifies the tasks in binary numbers. Group of input features $x_{1,}x_2, x_3, \ldots, x_n$. Output will be given in the combination of 0 and 1.
Given a dataset with input features x and binary labels y, y is either 0 or 1 and, x is a vector of size n.
Initialize the weights w and bias p to 0's or minor random values.
Compute the sum of the products of corresponding weights and input features as in (1).

$$S = w_1p_1 + w_2p_2 + \cdots + w_np_n + c \quad (1)$$

Apply and calculate the logistic (sigmoid) function to the linear combination to get the predicted probability. Determine the loss, or error, by comparing the predicted probability to the actual label, typically using a loss function like binary cross-entropy. Update the bias and weight to minimize the loss function using gradient descent as in (2).

$$w_j = w_j - \alpha \frac{\delta R}{\delta w_j} \quad (2)$$

Repeat steps the sum of product and update the bias and weight for a quantified number of iterations or until convergence. Use the trained weights and bias to predict outcomes for new data, achieved by applying the logistic function to the sum of the products of input features and their corresponding weights.

Figure 2 illustrates the dataset compiled for this study, which distinguishes between the high-precision static requirements of yoga and the coordinate-based movements of kavayat (drill). While yoga poses emphasize maintaining specific joint angles, kavayat actions are characterized by rapid transitions between standard positions. Table 2 illustrates the different techniques used with the dataset and the accuracy of the model. To ensure a balanced classification, the logistic regression model was trained on standardized feature vectors extracted from MediaPipe, allowing the system to differentiate between the subtle angular deviations in yoga and the distinct spatial shifts in school drills.

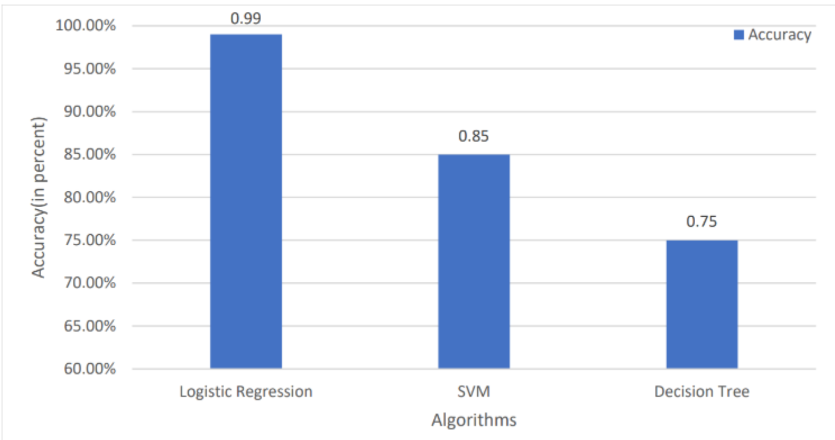

Figure 2. Comparison of exercise poses data

Table 2. Model settings with dataset used with accuracy

Year	Training model	Technique used	Dataset used	Accuracy (%)
2024	Machine learning	Logistic regression	Real time dataset used made by HD camera	99.00
2023	Deep learning	BlazePoseGHUM 3D [21]	RGB image dataset	96.90
2023	Deep learning	MoveNet [22]	Self-collected dataset by HD cam	83.00
2022	Deep learning	PoseNet [23]	COCO and MPII human pose dataset	97.60
2022	Deep learning	CNN-LSTM [24]	Innovative data collect by Kinect sensor	90.18
2020	Machine learning	DenseNet [25]	YOGA-82S,82 instance	91.44

3. RESULTS AND DISCUSSION

For the detection of human action recognition, a camera is utilized. The system processes a live dataset to detect human poses. The camera employed can be embedded in a laptop or an external camera can be used. It identifies the output of live poses by comparing them with original dataset. Additionally, the system provides the name of the activity being performed.

Few samples depicted in real-time operational capability of the system is demonstrated like Figure 3 which illustrates the 'standing drill front' (kavayat), Figure 4 leftsize warrior pose, Figure 5 seated size stretch recognition using a live camera feed. As the child performs the drill, the system utilizes a frame-by-frame processing approach to overlay 33 skeletal landmarks on the human subject. The real-time interface provides immediate feedback by calculating the spatial coordinates of the limbs. For the standing drill, the logistic regression model specifically monitors the vertical alignment of the torso and the proximity of the arms to the lateral midline. This visualization confirms that the model can maintain tracking stability and classification accuracy even under varying lighting conditions and background noise typical in front of the camera.

Figure 3. Standing drill front

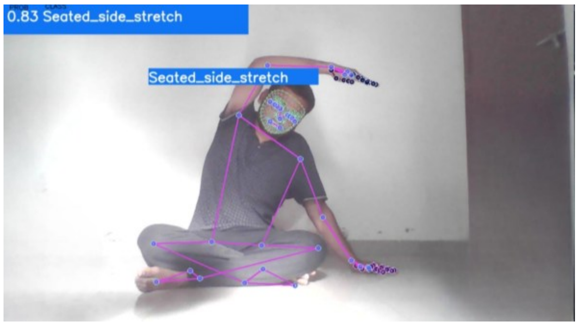

Figure 4. Leftsize warrior pose

Figure 5. Seated size stretch

3.1. Comparison of exercise data

The logistic regression model achive the significanlt outperforming 99% accuracy when comparing with other support vector machine attin the 85% and decision tree 75% while handling the variations of the pose patterns as shown in the Figure 2. The superior performance logistic regression effectively handles linearly separable features derived from the normalized poses key points. It works excellent in the real time pose classification work.

3.2. Proposed mathematical modelling

This system uses the machine learning algorithm as a logistic regression. Outcome measure in form of 0 and 1. Log function find probabilities in relations of 1 and 0. The hypothesis function given by logistic regression as in (3).

$$h_\theta(p) = \frac{1}{1+e^{\theta^T p}} \tag{3}$$

Where T is feature vector, $h_\theta(p)$ is based probability, θ is parameters of vectors (weights) connected with every feature, e is logarithm base upon outcome the values of θ, logistic regression model is trained.

In logistic regression, the cost function is defined by the log-likelihood function as in (4).

$$R(\theta) = -\frac{1}{n}\sum_{j=1}^{n}\left[-q^{(j)}\, log(h_\theta\,(p^{(j)})) + (1-q^{(j)})\, log(1-h_\theta\,(p^{(j)}))\right] \tag{4}$$

Where R is a loss function, θ is the parameter vector that defines the weights of the model, n is the size of sample in the dataset, $q^{(j)}$ is the actual label of the jth sample, $h\theta(p^{(j)})$ is the foreseen probability of the jth sample belonging to the positive class, $p^{(j)}$ is the jth sample in the dataset.

3.3. Data collection protocol

A Logitech C920 HD Pro RGB camera mounted, grasping videos at a frame rate of 30 FPS and resolution of 1920×1080 pixels. Participants positioned about 2.5 to 3.0 meters out of sight from camera with modifications completed for single person to guarantee the complete body points can visible. The camera height of around 1.2 meters on tripod so that the participants in the proper middle. The participants taught to stance on a noticeable location on the floor to continue reliable distance and aligning with the camera. Every participant performed sequence action of yoga and kavayat drills (total 10 classes). Movement executed three periods per posture/exercise to account for intra-participant variability. Data gaining conducted in a precise inside setting to decrease contextual and lighting inconsistency. To avoid visual distractions during landmark detection, recordings were performed against a plain, texture-free wall with uniform ambient lighting that minimized shadows. Super vision staff confirmed that movements directed carefully, with satisfactory break between duplications. Motion fitting garments used so do not obstruct the joints visibility.

Table 3. Dataset statistics

Parameter	Illustrative value
Total participants (N)	N =120
Videos per participant	10 videos per participant
Overall video count	1,200 videos
Extracted frames	≈11,500 frames
Definition of a sample	1 sample =1 frame (pose instance)

4. CONCLUSION

Yoga and kavayat for children leveraging the study developed, capable of real-time action recognition, providing feedback sound by way of the predicted exercise name. By successfully implementation of this intelligent system capable of recognizing human actions in front of the camera, this work led to the way for revolutionary applications in the field of holistic and personal well-being. This application not only enhances the fitness experience for individuals but also holds promise for applications in sport, healthcare, and personal training. The implemented system is for single user at a moment capture with MediaPipe Framework with logistic regression algorithm. This technology-guided human movement, augment its engage and make it more enjoyable. This work can be extended to support many users simultaneously, enabling group workouts or competitive scenarios. Integration with virtual reality or the possible to upgrade the end user experience with superior technology called as augmented reality.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data used in this study are available from the corresponding author [VB], upon reasonable request. Owing to privacy concerns and ethical obligations, the dataset, which includes participant exercise videos and pose frame extractions, is not publicly accessible.

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