Yoga Using Intelligent Internet of Things

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The detection and monitoring of the yoga postures are possible with the Intelligent Internet of Things (IIoT), which is the integration of intelligent approaches (machine learning) and the Internet of Things (IoT). Considering the increment in yoga practitioners, the integration of IIoT and yoga has led to the successful implementation of IIoT-based yoga training systems.

Keywords: future intelligence ; health intelligence ; IoT ; IoMT ; medical intelligence ; exercise

1. Sensor-Based Approach

Multiple sensors are used to detect yoga postures, including wearable and infrared sensors, which are explained below.

1.1. Wearable Sensor

Wearable sensors are small, lightweight, cheap, and portable medical devices that can acquire numerous daily data without disturbance. Wearable devices are considered a better approach for monitoring and detecting yoga positions. Pal et al. [1] used a smart belt to analyze the performance of yoga. Pauranik and Kanthi [2] designed wearable devices to monitor heart rate, yogic breathing, and posture. Ashish and Hari [3] designed a wearable-based yoga help system that can guide practitioners without requiring a trainer.

1.2. Infrared Sensors

Infrared sensors are also widely used for the detection and monitoring of yoga through the privacy-preserving approach [4]. The infrared sensor-based Infinity Yoga Tutor was designed by Rishan et al. [5], and it can identify the yoga posture and guide the practitioner through visual information. The system uses CNN and LSTM to learn and predict the yoga posture and is also able to capture the movement of the practitioner [6]. A self-assistance-based yoga poses recognition and real-time feedback system using an infrared sensor is designed in [7]. The deployed system can also identify the hand gestures, commonly named yogic mudra. The system uses machine learning-based XBoost and random CV as a learning approach. Experimental results show the system was able to detect yoga postures with high accuracy. YogaNet is designed in [8], which is based on CNN and LSTM, which can detect the yoga postures and also provides feedback for the correction.

1.3. RFID

The progress on RFID technology has enabled many human action recognition tasks. The use of active and passive tags has overcome the limitations of the RFID that existed initially. Yoga posture detection using RFID has been a common practice. Sun [9] implemented an RFID-based yoga mat that can detect and estimate yoga postures. The method deploys deep learning as the learning approach to predict yoga postures. Yao et al. [10] deployed an RFID-based human activity recognition system to detect human postures. The experimental analysis shows that the method was able to detect multiple postures with high accuracy. A system in [11] is designed to detect yoga postures based on RFID. Along with the detection of poses, this method also evaluates the stress levels in the practitioner.

1.4. Smart Mat

The mat is a convenient tool for the practitioner to practice yoga. There have been numerous attempts made at the detection of yoga using the smart mat. A smart mat is a mat that uses intelligent techniques and sensors, taking data from practitioners and learning from them to make a prediction. The design of the smart mat strategy is still in its infancy as tremendous research is required before deploying them. Smart mats are usually designed by implementing numerous sensors in the mat, where force-resistive sensors (FRs)are the common practices [12]. Chinnaaiah et al. [13] deployed FSRs to design the smart yoga mat. The smart mat was only able to detect the lying and sitting yoga postures. Standing yoga postures were not detected using FSR sensors. The smart prayer mat is designed in [14], wherein arrays of FSRs were used to detect the prayer.

2. Vision-Based Approach

The vision-based approach relies on the camera for the input, which is further processed using intelligent approaches for the detection of the yoga postures [15][16]. The intelligent approaches used in vision-based approaches are machine learning, deep learning, and hybrid approaches, the comparison of which is shown in **Table 1**.

Table 1. Detection of yoga using various IIoT approaches and their comparison.

References	Approaches	Descriptions
[1][2][3][4][5][7][8][9][10][11][12][13][14]	**Sensor-based approach**	**Multiple sensors are used to detect yoga postures, including wearable, infrared sensors, RFID, and smart mat.**
[15][16]	**Vision-based approach**	**Relies on the camera for the input, which is further processed using intelligent approaches for the detection of the yoga postures.**
[17]	**Logistics regression**	**An extension of ordinary regression; it is a powerful and popular technique for supervised classification for modeling a dichotomous variable for an associated label.**
[18]	**Adaboost**	**An ensemble method to combine weak classifiers to create a powerful classifier. To attain high accuracy for the model, it continues to add learners until a robust classifier is reached.**
[19][20][21]	**Random forest**	**In RF, each tree is reliant on values from a random vector that was randomly sampled and had a uniform distribution across all of the forest trees.**
[22]	**Support vector machine (SVM)**	**It has two classifiers and is an SVM classifier. Nonetheless, a multiclass SVM is widely used because most issues involve multiple classes.**
[23][24]	**K-nearest neighbor (KNN)**	**KNN saves all potential examples and categorizes them according to their similarities. It is primarily used with the pattern recognition method.**
[25]	**Deep learning-based methods**	**Deep learning is essentially based on ANN and it can be compared to the human brain.**
[26][27][28][29]	**AutoEncoder**	**A rich and versatile framework for discovering the salient features of data in an unsupervised manner. Used to drive the learning of a deep illustration of the volumetric human body structure.**
[22][30][31]	**Convolutional neural networks (CNN)s**	**A great choice because they have proven to have a significant amount of potential for pose classification tasks. They can be trained directly on pictures or on key human skeleton joint locations.**
[32]	**Recurrent neural networks (RNNs)**	**RNNs are useful for processing sequential data since they preserve a neuron's prior data. RNNs have difficulty remembering the initial steps necessary to forecast the current task when there are too many intermediate steps in a yoga asana.**
[33]	**Long short-term memory (LSTM)**	**A well-known RNN called an LSTM has the ability to naturally remember knowledge or data for sufficient lengths of time. The LSTM algorithm employs three gates: input, update, and forget. Resultantly, an LSTM will selectively ignore or recall the learned information.**
[34][35][36][37][38]	**Deep neural networks (DNNs)**	**DNNs have demonstrated exceptional performance on visual classification functions. DNNs can capture the complete context of every body joint since each joint regressor uses the entire image as a signal.**
[39][40][41][42][43][44][45][46][47]	**Hybrid approaches**	**Several algorithms make use of hybrid models. For example, SVM and Inception V3 are hybrid algorithms. Another study classified data using a hybrid 798 CNN–LSTM layer after extracting key points using OpenPose.**

Several algorithms make use of intelligent and hybrid models. The most important is [39], which proposes a hybrid approach that combines two algorithms, SVM and Inception V3. Before categorization, the posture dataset normalized and enhanced the images. The picture dataset was then submitted for modeling training and validation after its features were chosen using the LASSO FS technique. In order to facilitate hybridization, the Inception V3 TL model's final layer was swapped out for an SVM classifier in the investigation.

Using portable systems and intelligent technology to anticipate and manage human health is an essential feature of smart cities. Consequently, posture recognition in this research is accomplished using multisensory and LoRa technology. The two benefits of the LoRa WAN are its low-cost and wide range of communication. These two technologies—multisensory and LoRa—are combined to create comfortable wearable apparel in any setting. Due to LoRa's low transmission frequency and small data transfer size, multiprocessing was used in this investigation. RF is considered for data processing, feature extraction, and selection, whereas sliding windows are utilized for multiprocessing. The three testers from a group of 500 datasets are employed to enhance functionality and accuracy [40]. In addition to body language, nonverbal communication techniques also include gestures and postures. This research uses augmented reality and cutting-edge body tracking techniques to identify stagnant posture. Moreover, Kinect body position sensors and unsupervised machine learning are applied to detect group participation and learning [41]. Posture detection has made it feasible to practice yoga correctly. There are only a few datasets and a real-time basis, so posture detection is challenging. A sizable data collection with at least 5500 images of different yoga postures was produced to solve this problem. The tf-pose estimation method was employed for posture detection, which shows the human body's skeleton in real time. Many ML algorithms employ the tf-pose skeleton as a feature to extract the locations of the human body joints (KNN, logistic regression, SVM, NB, DT, and RF). The RF model has the greatest level of accuracy [42][43][44][48]. Another posture issue that impacts people is that they spend most of their time sitting down.

In addition, [45][46] created a hybrid machine learning strategy for posture recognition by fusing deep neural networks with conventional machine learning techniques. Combining the weight that the deep learning method has learned with the standard model's forecast yields the final class prediction. Another study [47] classified data using a hybrid CNN–LSTM layer after extracting key points using OpenPose. A total of 88 videos of six distinct yoga stances were used to construct the model.

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