Yoga pose annotation and classification by using time-distributed convolutional neural network

Somashekhar S. Dhanyal, Suvarna S. Nandyal
Department of Computer Science and Engineering, Poojya Doddappa Appa College of Engineering, Kalaburagi, India

Article Info

Article history:

Received Mar 24, 2023
Revised Aug 21, 2023
Accepted Sep 26, 2023

Keywords:

Accuracy
Annotation
Classification
Convolutional neural network
Machine learning
Yoga pose

ABSTRACT

In India, people have been practicing yoga for thousands of years to improve their health and well-being on all levels. As the pace of technological development increases, this presents a great opening for computational probing across all areas of social domains. Nevertheless, it remains difficult to integrate artificial intelligence (AI) and machine learning (ML) methods to an interdisciplinary field like yoga. The proposed study aims to develop a yoga pose annotation and classification for yogasana recognition in real time. The study considers TensorFlow for better implementation of data automation, performance monitoring. TensorFlow yields better numerical computation and hat helps ML and efficiently develops the neural network. The proposed composed of time-distributed convolutional neural network (CNN) through the Softmax function. Also, a poseNet algorithm is considered to estimate the user's real-time yoga pose. The use of a database i.e., poseTrack in the proposed method offers annotation to the evaluation of yoga pose and tracking of it. The performance analysis of the proposed yoga pose annotation and classification model suggests that it offers higher accuracy than traditional, support vector machines (SVM) and K-nearest neighbor (KNN).

Corresponding Author:

Somashekhar S. Dhanyal
Department of Computer Science and Engineering, Poojya Doddappa Appa College of Engineering
Kalaburagi, Karnataka, India
Email: sdhanyalresearch@gmail.com

1. INTRODUCTION

Technological and scientific progress is accelerating at an unprecedented rate, simplifying people's daily lives. Its importance to modern society has become universally recognized [1]. Throughout the healthcare industry and other fields closely associated with it, the impact of computers and technology driven by computing is well-known, just as it is in all other sectors. Other than conventional medicine, many people turn to disciplines like martial art, zumba, and yoga, to improve their health [2], [3]. Yoga, which has its origins in ancient India, is a collection of techniques for improving one's mental, spiritual, and physical well-being. There has been a significant rise in the importance of yoga in the field of medicine [4]. One is physical and emotional well-being, as well as weight, can all benefit from yoga practice. However, yoga should only be done under the guidance of a trained professional, as improper form can cause serious injuries including sprained ankles, neck pain, and muscular pulls [5]. During training, the yoga teacher must make adjustments to the students' postures. Individual practice of yoga is possible only after receiving appropriate training. Nevertheless, in the present day, individuals are more used to staying at home, thus they have switched to doing practically anything online. In light of the aforementioned, a yoga practice that incorporates modern technologies is essential [6], [7]. For this purpose, there are virtual tutoring and smartphone programs available. Both have a great deal of room for improvement in terms of computational power, intelligence, and efficiency [8].

Because of this, yoga postures should be studied scientifically. Using posture identification methods, it was recently discovered that individuals can be helped to achieve more precise yoga postures [9], [10]. Since there are not many datasets available, and because it is hard to identify posture in real-time, posture identification is a difficult task [11], [12]. To address this issue, researchers constructed a massive dataset consisting of a minimum of 5,500 images of ten distinct yoga postures and employed a position estimate algorithm which generates the structure of an individual's body in real-time. Thus, the proposed work aims to work on all the above-mentioned aspects and contributes to the research area.

– The proposed yoga pose annotation model uses time-distributed convolutional neural network (CNN) for yoga pose prediction.
– A model fit generator is used to compare real-time yoga pose with a selected yoga pose by validation of data.
– The use of a database i.e., poseTrack in the proposed method offers annotation to the evaluation of yoga pose and tracking of it.
– Also, the dataset offers detailed and effective yoga annotation of every human pose in the video frame.

The proposed study aims to develop a detection mechanism for yoga asana annotation and classification leveraging data driven analysis and deep feature extraction based approaches. However, in literature there are few recent works carried out in the similar context. This manuscript is categorized as background in section 2 discussing the current state of the art in the research domain along with the contribution of the manuscript. The proposed time-distributed CNN is given discussed is section 3 with blocks involved in it and the algorithm. The results and analysis are discussed in section 4 while the conclusion is in section 5.

2. LITERATURE SURVEY

Many studies have emphasized the importance of yogasana identification and classification in providing a healthier lifestyle through yoga. There has been a steady increase in the total number of individuals who regularly practice yoga over the past few years. In order to reap the full advantages of yoga, asanas must be practiced correctly. As a result, Devaraju *et al.* [13] have presented a mathematical framework for comprehending the roles played by various muscles during yogasana practice. Muscle activity was captured and analyzed with the use of surface-electromyography (sEMG)-TrignoTM (Delsys Inc.) sensors. Results from the sEMGs reveal that a linear regression model best describes muscle activity at rest and in the ending posture. An early work by Dhanyal and Nandyal [14] has described a dataset to understand the effect of yogasana to deal with muscle disorders. The author has used the support vector machines (SVM) cascade classifier and observed different yogasana postures and obtained a recognition rate of 97%. Similarly, Saud *et al.* [15] have addressed the yoga benefits in musculoskeletal disorders. Islam *et al.* [16] discussed human joint detection by using a Kinect camera in real time for yoga posture recognition. The system monitors the human skeleton movement through a Kinect camera to monitor yoga poses accurately at different angles. Yadav *et al.* [17] has discussed a deep learning mechanism of CNN for real-time yoga recognition. The author has achieved a 99% percentage of posture recognition for 12 yogasana. Similarly, a deep learning approach for yogasana identification is presented by Jose and Shailesh [18]. In this, transfer learning and CNN are used as deep learning techniques and achieved 85% accurate yogasana identification [18].

Cao *et al.* [19], have addressed the real-time pose detection of multiple persons in a single image by using part affinity fields (PAF). The method adapts the greedy bottom-up approach and which yields higher accuracy and efficient pose detection [19]. A self-training approach for yoga posture detection is observed in Chen *et al.* [20] where a fast skeletonization technique is used. Pullen and Seffens [21] explained the gesture analysis for healthy physical life by using a machine learning (ML) approach. An interesting work by Kodama *et al.* [22] has developed a hidden markov model (HMM) of multi-stream type for sign language detection by using a Kinect sensor. The recognition method is able to recognize hand movement and position efficiently [22]. Similarly, a Kinect sensor is used to recognize the yoga poses. The interactive system with the Kinect device recognizes six yoga poses efficiently with higher accuracy of 94.78% [23]. Calin [24] analyzed the gesture variation and pose variation is conducted by using Kinect versions of Xbox 360 and Xbox one. The study uses the ML method to recognize poses and gestures depending on multiple factors like gesture complexity, and pose characteristics. Wang *et al.* [25] also performed an evaluation of pose tracking by using Kinect versions of Xbox 360 and Xbox one for pose tracking of 10 exercises and found Xbox one is more accurate than Xbox 360. The calibration of the Kinect sensor is discussed in Khoshelham and Elberink elaborated on the analysis of depth data accuracy for mapping applications [26]. From the analysis of the existing works, it is observed that very less works have been addressed with yoga pose recognition. Almost all the works have used Kinect sensors for tracking joints and pose recognition which is a bit costlier. The use of time-based CNN is very less in the research area of yoga pose recognition. Less number of works have considered accuracy, precision, and recall as performance matrices for comparison of the research works in yoga pose recognition. A comparative analysis conducted in the proposed work describes the significance of the proposed work over traditional SVM and K-nearest neighbor (KNN) approach-based yoga pose recognition. The next section elaborates on the proposed yoga pose annotation and classification method.

3. PROPOSED YOGA ASANA ANNOTATION AND CLASSIFICATION MECHNAISM

The primary goal of this study is to present a cutting-edge system that combines artificial-intelligence (AI) and computer-vision (CV) methods with the age-old practice of yoga. This system aims to revolutionize the way yoga poses are recognized, classified, and guided, offering practitioners a transformative and personalized yoga experience. The proposed system represents a novel intersection between ancient wisdom and contemporary technology. By harnessing the power of AI, specifically time-distributed CNNs, the system provides real-time feedback, accurate pose recognition, and alignment guidance to practitioners. This fusion of traditional practice and modern innovation is what truly distinguishes our proposed system from existing methods. The proposed study takes on several challenges that are intrinsic to the practice of yoga. One of the fundamental challenges is accurate pose recognition and alignment. Practitioners often struggle to ensure precise posture alignment, which can impact the efficacy of their practice and even lead to potential injuries. By offering real-time feedback on posture alignment, the system mitigates this challenge and promotes safe and effective practice. Another significant challenge lies in the variability of pose execution among different practitioners. Our system addresses this issue by providing standardized recognition and feedback, ensuring consistent pose execution across various practitioners. Furthermore, the system caters to the complexity of dynamic pose transitions. Through the integration of time-distributed CNNs with deep feature extractor model the proposed system captures the temporal nuances of dynamic movements, enhancing the accuracy of pose recognition even during transitions. The proposed study adopts analytical approach in the design and the development process composed of several core components which are highly synchronized to perform for yoga pose classification and its annotation. Figure 1 depicts the proposed system's design in a simplified form.

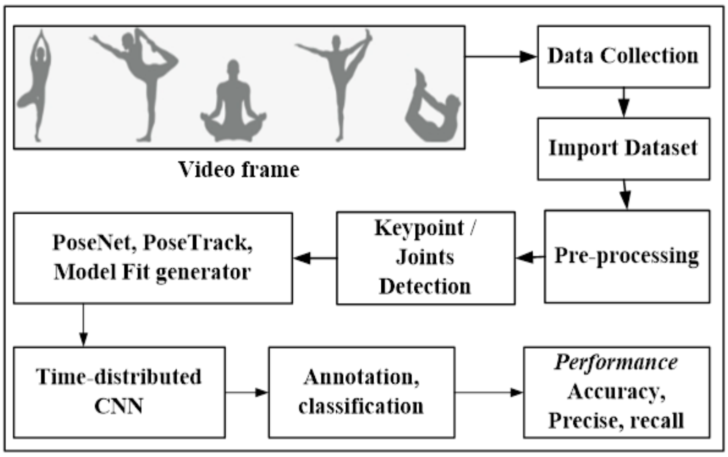

Figure 1. Blocks of proposed yoga annotation and classification mechanism

As shown in the Figure 1, the proposed system initially considers a raw video frame serve as the initial input which comprises a sequence of video frames capturing individuals performing yoga poses. This input raw video frames are prepared by considering several images in sequence. This sequence mimics the scenario and dynamics of real-time yoga practice, capturing the fluidity and transitions of movements. The next module of the proposed system is subjected to extraction of images from each frame that needs to be processed to identify and classify the yoga poses accurately. The collected frames undergo preprocessing to standardize resolution, normalize pixel values, and ensure consistent color channels. This uniformity enhances accurate subsequent analysis. The proposed system then employs the poseNet model to identify key points or joints of the human body. This spatial information forms the basis for pose recognition and classification. Additionally, this phase of the proposed system leverages the PoseTrack database, and the model fit generator to validate and benchmark real-time poses against annotated references. Further, the integration of time-distributed CNNs allows the system to capture temporal patterns, enhancing its ability to classify poses involving dynamic movements. The trained time-distributed CNN classifies recognized poses based on patterns learned during training, providing practitioners with accurate guidance and pose identification. Hence, the research work reported in this manuscript aims to offer an automated system for yoga asana annotation and pose classification that addresses challenges related to pose accuracy, alignment, guidance, personalization, variability, and real-time feedback. By leveraging advance learning methods, it bridges gaps in traditional yoga practice and contributes to safer, more effective, and accessible yoga experiences for practitioners across various skill levels and contexts.

The input dataset images include standing and sitting yoga poses. There is a wide range of hand and leg folds in these positions, making it challenging for classifying and identifying them. The input dataset includes 7 different yoga poses Bhujangasana, Dhanurasana, Gomukhasana, Sukhasana, Tadasana, Trikonasana, and Vajrayana. A pose estimation algorithm is implemented through TensorFlow which takes processed camera images as inputs and yields key point information in real-time. The key points are the joints of humans from yoga poses. In addition, the identified landmarks are combined to calculate 12 unique angles that serve as attributes for classifying and recognizing yoga postures. Openpose is employed to gather the user's yoga video frames and determine the important points (20 joints) using the frame of video acquired by a 1080p Logitech camera, as demonstrated in Figure 2.

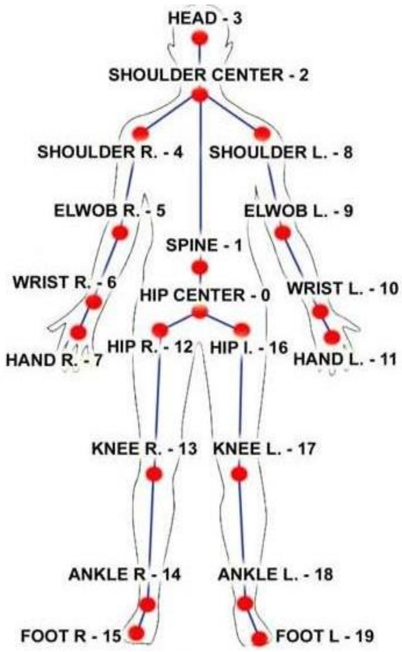

Figure 2. Human skeleton joints [16]

Each joint exhibits information index values in x, y and z coordinates and it represents the status of joints. The yoga pose model is built by taking yoga poses of gymnastics for joint information. The data of these yoga poses are manipulated and build a reference model for yoga pose detection. This model takes the average angular distance of joints which helps in the comparison of input frames. The vector concept with the 3D axis is followed to calculate the angular distance between X, Y, and Z. In the Figure 2, three points like left elbow-9, shoulder left-8, and shoulder center-2, will for an angle C. Further, to calculate the remaining angle 356 (denoted as θ), two vectors 53 (represented as $\overrightarrow{XY}$) and 56 (represented as $\overrightarrow{XZ}$) are formed. Applying the cosine in (1), we can get the angle that exists among the two vectors:

$$\cos\theta = \frac{(\overrightarrow{XY} \times \overrightarrow{XZ})}{(|\overrightarrow{XY}| \times |\overrightarrow{XZ}|)} \tag{1}$$

using the equation, all the angles at points 4, 5, 8, 9, 0, 12, 16, 13, and 17 are calculated. Assume, the calculation of angle 'A' by considering reference angle 'R' and a total number of angles as τ. The average deviation δ of a pose can be given as (2).

$$\delta = \frac{\sum(A-R)}{(|\overrightarrow{XY}| \times |\overrightarrow{XZ}|)} \tag{2}$$

This average deviation (δ) gives the successful recognition of yoga asana and recognition fails if the average deviation (δ) deviates falsely from the usual. The obtained key points are normalized and matched with a prediction model that is composed of time-distributed CNN through the Softmax function. The prediction model also gives the output probability for six classes. The outputs of the prediction model are streamed to the mobile application that guides video-based prediction results and offers the accuracy of a person's yoga pose. In this, a model fit generator is used to compare real-time yoga pose with a selected yoga pose by validation of data. Also, a poseNet algorithm is considered to estimate the user's real-time yoga pose. Using a pose estimation algorithm, the webcam-captured real-time yoga poses are processed. However, the yoga poses with finger positions cannot be processed and compared in the proposed work. The use of a database i.e., poseTrack in the proposed method offers annotation to the evaluation of yoga pose and tracking of it. Also, the dataset offers detailed as well as eand effective yoga annotation of every human video frame.

4. RESULTS AND DISCUSSION

This section presents the outcomes obtained from the application of the proposed method on a diverse range of yoga asana database images and video frames. The method's effectiveness is demonstrated through training sets of yoga poses, highlighting its capabilities in classifying and annotating different poses. The Figure 3 showcases the seven distinct yoga poses, demonstrating the versatility of the proposed method.

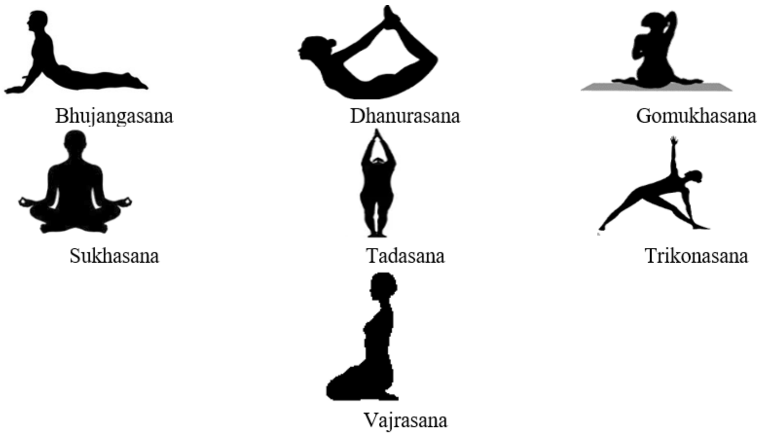

Figure 3. Seven different asanas under consideration

As shown in Figure 3, the proposed study concentrates on seven asanas to treat muscular disease. The first yoga sana under consideration is Bhujangasana also recognized as the cobra pose. This asana entails elevating the upper body while executing backbends. By arching the spine and raising the chest as depicted in Figure 3 Bhujangasana enhances spinal flexibility and strengthens the back muscles. It is known to alleviate muscular stiffness and improve posture, offering relief to individuals afflicted by muscular ailments. The second asana is Dhanurasana exhibiting a bow-like shape. This asana requires bending the body backward and gripping both feet with the hands. This pose actively stretches and engages the muscles of the back, thighs, and arms. Dhanurasana promotes enhanced muscular strength and flexibility, making it a valuable practice for individuals with muscular issues seeking to address imbalances and discomfort. The third asana under consideration is Gomukhasana also known as cow face pose. The Gomukhasana involves intertwining the arms behind the back while positioning either the right or left foot under the corresponding buttock. This asana effectively stretches the shoulders, chest, and hips. Its therapeutic benefits include easing muscular tension, particularly in the shoulders and upper body. The Sukhasana is characterized by a comfortable seated position with hands resting on the lap or knees and feet placed beneath the knees. This pose facilitates relaxation and tranquility, promoting a sense of ease within the muscles. It serves as an excellent starting point for individuals dealing with muscular stress, gradually aiding in its reduction.

The next Tadasana is called as Mountain Pose which involves grounding both feet while extending the arms upward. This pose enhances overall body alignment, fostering muscular balance and coordination. By engaging various muscle groups, Tadasana contributes to muscle toning and reinforcement, beneficial for individuals addressing muscular weaknesses. Trikonasana (Triangle Pose) executed by extending both legs wide and forming a 90-degree angle between the upper and lower body. The Trikonasana engages the legs, hips, and core muscles. Its stretching properties alleviate muscular tension and improve flexibility, making it instrumental in maintaining muscle health. Vajrasana refers to Thunderbolt Pose a seated Vajrasana, which requires kneeling and lowering the back while resting the buttocks on the heels. This pose supports digestion and relieves tension in the lower body muscles. Its calming effect on the muscles makes it beneficial for individuals seeking relief from muscular discomfort. Each of these yoga asanas offers unique benefits to individuals grappling with muscular diseases. By incorporating them into a comprehensive practice, individuals can enhance their muscular strength, flexibility, and overall well-being. The model performance is evaluated by considering training accuracy against epochs as shown in Figure 4 where accuracy increases with an increase in epochs which represents the fast learning of the network. The outputs obtained for a proposed model with annotation is elaborated in Figure 4.

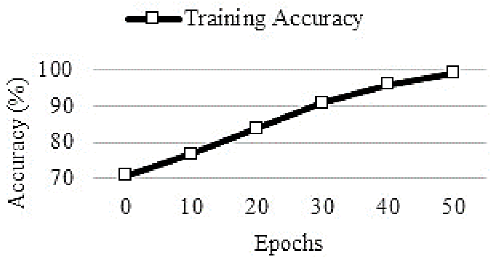

Figure 4. Training accuracy analysis

The next performance analysis is carried out regarding assessing the effectiveness of the proposed distributed CNN model towards yoga pose classification and annotation. Here, the annotation refers to the process of labeling or marking specific characteristics or attributes of yoga poses in the collected video frames. This labeling provides essential contextual information about the poses and their features, allowing the system to recognize and classify them accurately. In the proposed system, annotation involves associating each video frame or sequence of frames with metadata that describes the yoga pose being performed. This metadata could include information such as the name of the pose, the position of key body joints, the orientation of the body, and any other relevant details that differentiate one pose from another. The following subsection provides an analysis of the outcome regarding each seven types of yoga poses.

4.1. Analysis of input images

The Table 1 illustrates the performance analysis conducted on an input image featuring the Bhujangasana (Cobra Pose). This analysis showcases the accuracy of the proposed model in correctly predicting the type of yoga pose from an image and providing a comprehensive annotation that encompasses key information for practitioners. The Bhujangasana is a versatile pose that caters to a wide age range, encompassing individuals from 3 to 50 years of age. This inclusivity highlights the pose's gentle nature and its potential to benefit practitioners across different life stages. The benefits suggested by model for this asana holds promising outcome. The output generated by the annotation process holds profound significance for practitioners. It offers real-time guidance and accurate feedback, thereby enriching the practitioner's yoga experience. With this insight, practitioners can fine-tune their poses, optimize alignment, and derive enhanced benefits from their yoga practice. This real-time feedback mechanism plays a pivotal role in nurturing practitioners' overall well-being and yoga journey. Similarly, the results for Tadasana and Trikonasana has been shown in Tables 2 and 3. The results show the suitable age and benefits of doing the yoga pose.

Table 1. Result for input yoga asana: Bhujangasana

Input yoga asana: Bhujangasana	Annotation result
	Name of asana: Bhujangasana (Cobra Pose) Suitable age: recommended for individuals aged 3 to 50 years Benefits: Improves digestion Improves liver functioning Improves kidney functions Improves tone of the body Improves spinal nerves

Table 2. Result for input yoga asana: Tadasana

Input yoga asana: Tadasana	Annotation result
	Name of asana: Tadasana Suitable age: recommended for individuals aged 3 to 70 years Benefits: Increases stability Improves tone core muscles

Table 3. Result for input yoga asana: Trikonasana

Input yoga asana: Trikonasana	Annotation result
	Name of asana: Trikonasana Suitable age: recommended for individuals aged 3 to 70 years Benefits: Improves spine Improves hamstrings Increases stability in neck and shoulder region

4.2. Comparative study

The comparative analysis of the proposed CNN model is conducted with traditional SVM [27], and YoNet [28] for accuracy, precision, and recall. The following Figure 5, indicating the comparative analysis suggests that the proposed CNN model offers higher accuracy than traditional, SVM and KNN. The performance analysis of the proposed time distributed CNN for yoga pose recognition is conducted with existing research works like Islam *et al.* [16] and Jose and Shailesh [18]. Table 4 gives the performance analysis which suggests that the proposed method is more accurate than existing methods. The comparative study highlights three different image classification methods and their respective techniques and accuracies. Islam *et al.* [16], combined a CNN with data from the Kinect sensor, achieving a 97% accuracy in classifying instances. Jose and Shailesh method [18] involved a CNN with transfer learning, resulting in an 82% accuracy for identifying instances. The proposed method introduced a unique "Time Distributed CNN" technique, achieving an impressive 99.38% accuracy in recognizing instances. Accuracy indicates how well a model performs, with higher values indicating better performance. However, considering factors like dataset size, diversity, and potential biases is essential for a comprehensive evaluation of a method's effectiveness.

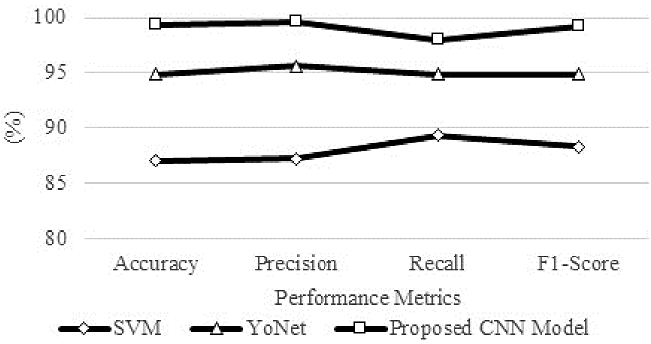

Figure 5. Comparative analysis

Table 4. Performance analysis of the proposed method

Method	Technique adapted	Accuracy
Islam *et al.* [16]	CNN+ Kinect	97%
Jose and Shailesh [18]	CNN + transfer learning	82%
Proposed method	Time distributed CNN	99.38%

5. CONCLUSION

With the increased cost of medications and treatment, there is a need for alternative ways to overcome these health concerns. Originally developed in India, yoga is a set of techniques for improving one is health on all levels. However, yoga needs proper guidelines from the trainer and it can be avoided by a computational mechanism that helps everyone to perform proper yoga practices. Thus, the proposed study aims to develop a yoga pose annotation and classification for yogasana recognition in real-time. The study considers TensorFlow for better implementation of data automation, and performance monitoring. TensorFlow yields better numerical computation that helps ML and efficiently develops the neural network. The proposed composed of time-distributed CNN through the Softmax function. Also, a poseNet algorithm is considered to estimate the user's real-time yoga pose. The use of a database i.e., poseTrack in the proposed method offers annotation to the evaluation of yoga pose and tracking of it. The model performance is evaluated by considering training accuracy against epochs which represents the fast learning of the network. The validation analysis is developed CNN model is learning and efficiently working. The performance analysis of the proposed yoga pose annotation and classification model suggests that it offers higher accuracy than traditional, SVM and KNN. According to the findings, the suggested approach is able to detect the yoga position with an accuracy of 99.38%, significantly better than the state-of-the-art approaches. The suggested annotation method can be applied on data provided by a normal RGB camera, making the use of Kinect or additional specialized gear for Yoga position identification.

For future work, there is room for expansion in the number of asanas available and the size of the collection that comprises both still images and moving ones. The method can also be deployed on a mobile platform for on-the-go forecasting and self-improvement. This study demonstrates the viability of activity identification techniques in practical settings. The same method can be applied to the identification of postures in other contexts, and such as sports.

REFERENCES

[1] F. Zhang, X. Zhu, and C. Wang, "A comprehensive survey on single-person pose estimation in social robotics," *International Journal of Social Robotics*, vol. 14, no. 9, pp. 1995–2008, Oct. 2022, doi: 10.1007/s12369-020-00739-5.

[2] S. Haque, A. S. A. Rabby, M. A. Laboni, N. Neehal, and S. A. Hossain, "ExNET: deep neural network for exercise pose detection," in *Communications in Computer and Information Science*, vol. 1035, Springer Singapore, 2019, pp. 186–193.

[3] P. Szczuko, "Deep neural networks for human pose estimation from a very low resolution depth image," *Multimedia Tools and Applications*, vol. 78, no. 20, pp. 29357–29377, Mar. 2019, doi: 10.1007/s11042-019-7433-7.

[4] S. Patil, A. Pawar, A. Peshave, A. N. Ansari, and A. Navada, "Yoga tutor: visualization and analysis using SURF algorithm," in *Proceedings-2011 IEEE Control and System Graduate Research Colloquium, ICSGRC 2011*, Jun. 2011, pp. 43–46, doi: 10.1109/ICSGRC.2011.5991827.

[5] W. Gong *et al.*, "Human pose estimation from monocular images: a comprehensive survey," *Sensors (Switzerland)*, vol. 16, no. 12, p. 1966, Nov. 2016, doi: 10.3390/s16121966.

[6] G. Ning, P. Liu, X. Fan, and C. Zhang, "A top-down approach to articulated human pose estimation and tracking," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11130, pp. 227–234, 2019.

[7] A. Gupta, T. Chen, F. Chen, and D. Kimber, "Systems and methods for human body pose estimation," *Systems and methods for human body pose estimation. U.S. Patent 7, 925, 081*, 2011.

[8] H. Sidenbladh, M. J. Black, and D. J. Fleet, "Stochastic tracking of 3D human figures using 2D image motion," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 1843, Springer Berlin Heidelberg, pp. 702–718, 2000.

[9] A. Agarwal and B. Triggs, "3D human pose from silhouettes by relevance vector regression," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2, 2004, doi: 10.1109/cvpr.2004.1315258.

[10] M. Li, Z. Zhou, J. Li, and X. Liu, "Bottom-up pose estimation of multiple person with bounding box constraint," in *Proceedings - International Conference on Pattern Recognition*, Aug. 2018, pp. 115–120, doi: 10.1109/ICPR.2018.8546194.

[11] N. B. Nordsborg, H. G. Espinosa, and D. V. Thiel, "Estimating energy expenditure during front crawl swimming using accelerometers," *Procedia Engineering*, vol. 72, pp. 132–137, 2014, doi: 10.1016/j.proeng.2014.06.024.

[12] P. F. Pai, L. H. C. Liao, and K. P. Lin, "Analyzing basketball games by a support vector machines with decision tree model," *Neural Computing and Applications*, vol. 28, no. 12, pp. 4159–4167, Apr. 2017, doi: 10.1007/s00521-016-2321-9.

[13] V. Devaraju, A. Ramesh, K. Alva, V. Debur, and S. Omkar, "A mathematical method for electromyography analysis of muscle functions during yogasana," *International Journal of Yoga*, vol. 12, no. 3, p. 240, 2019, doi: 10.4103/ijoy.ijoy_63_18.

[14] S. S. Dhanyal and S. Nandyal, "A dataset to find effect of yogasan on muscular disorder," *International Journal of Advanced Research in Engineering and Technology*, vol. 12, no. 6, pp. 1–10, 2021, doi: 10.34218/IJARET.12.6.2021.001.

[15] A. Saud *et al.*, "Harnessing the benefits of yoga for myositis, muscle dystrophies, and other musculoskeletal disorders," *Clinical Rheumatology*, vol. 41, no. 11, pp. 3285–3297, Jul. 2022, doi: 10.1007/s10067-022-06280-2.

[16] M. U. Islam, H. Mahmud, F. Bin Ashraf, I. Hossain, and M. K. Hasan, "Yoga posture recognition by detecting human joint points in real time using microsoft kinect," in *5th IEEE Region 10 Humanitarian Technology Conference 2017, R10-HTC 2017*, Dec. 2018, pp. 668–673, doi: 10.1109/R10-HTC.2017.8289047.

[17] S. K. Yadav, A. Singh, A. Gupta, and J. L. Raheja, "Real-time yoga recognition using deep learning," *Neural Computing and Applications*, vol. 31, no. 12, pp. 9349–9361, May 2019, doi: 10.1007/s00521-019-04232-7.

[18] J. Jose and S. Shailesh, "Yoga asana identification: a deep learning approach," *IOP Conference Series: Materials Science and Engineering*, vol. 1110, no. 1, Mar. 2021, p. 012002, doi: 10.1088/1757-899x/1110/1/012002.

[19] Z. Cao, T. Simon, S. E. Wei, and Y. Sheikh, "Realtime multi-person 2D pose estimation using part affinity fields," in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, Jul. 2017, pp. 1302–1310, doi: 10.1109/CVPR.2017.143.

[20] H. T. Chen, Y. Z. He, C. C. Hsu, C. L. Chou, S. Y. Lee, and B. S. P. Lin, "Yoga posture recognition for self-training," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 8325 LNCS, no. PART 1, Springer International Publishing, 2014, pp. 496–505.

[21] P. Pullen and W. Seffens, "Machine learning gesture analysis of yoga for exergame development," *IET Cyber-Physical Systems: Theory and Applications*, vol. 3, no. 2, pp. 106–110, May 2018, doi: 10.1049/iet-cps.2017.0027.

[22] T. Kodama, T. Koyama, and T. Saitoh, "Kinect sensor based sign language word recognition by mutli-stream HMM," in *2017 56th Annual Conference of the Society of Instrument and Control Engineers of Japan, SICE 2017*, Sep. 2017, pp. 94–99, doi: 10.23919/SICE.2017.8105627.

[23] E. W. Trejo and P. Yuan, "Recognition of yoga poses through an interactive system with kinect device," in *2018 2nd International Conference on Robotics and Automation Sciences, ICRAS 2018*, Jun. 2018, pp. 12–17, doi: 10.1109/ICRAS.2018.8443267.

[24] A. D. Calin, "Variation of pose and gesture recognition accuracy using two kinect versions," *In 2016 International Symposium on Innovations in Intelligent Systems and Applications (INISTA),* Aug. 2016, doi: 10.1109/INISTA.2016.7571858.

[25] Q. Wang, G. Kurillo, F. Ofli, and R. Bajcsy, "Evaluation of pose tracking accuracy in the first and second generations of microsoft kinect," in *Proceedings - 2015 IEEE International Conference on Healthcare Informatics, ICHI 2015*, Oct. 2015, pp. 380–389, doi: 10.1109/ICHI.2015.54.

[26] K. Khoshelham and S. O. Elberink, "Accuracy and resolution of kinect depth data for indoor mapping applications," *Sensors*, vol. 12, no. 2, pp. 1437–1454, Feb. 2012, doi: 10.3390/s120201437.

[27] D. Mane, G. Upadhye, V. Gite, G. Sarwade, G. Kamble, and A. Pawar, "Smart yoga assistant: SVM-based real-time pose detection and correction system," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 7, pp. 251–262, Jul. 2023, doi: 10.17762/ijritcc.v11i7s.6997.

[28] F. B. Ashraf, M. U. Islam, M. R. Kabir, and J. Uddin, "YoNet: a neural network for yoga pose classification," *SN Computer Science*, vol. 4, no. 2, Feb. 2023, doi: 10.1007/s42979-022-01618-8.

BIOGRAPHIES OF AUTHORS

Somashekhar S. Dhanyal has Bachelor degree in Information Science and Engineering and Master's degree in Computer Science. Presently working as assistant professor Department of CSE (AI & ML) at B. L. D. E. A's V. P. Dr. P. G. Halakatti College of Engineering and Technology Vijayapur Karnataka, India. Areas of interest include image processing. Pubications: 04 number of paper publications in national and international conferences and journals. He can be contacted at email: sdhanyalresearch@gmail.com.

Dr. Suvarna S. Nandyal has Bachelor degree in computer science and Master's degree in Computer Science from VTU Belgaum, Karnataka, India. Completed Ph.D. in Image Processing domain, from JNTU Hyderabad. Working as Professor in Computer Science and Engineering. Areas of interest include image processing, data mining, cloud computing, and computer networks. Teaching Experience: 28 years, more than 100 number of paper publications in national and international conferences and journals She can be contacted at email: suvarna_nandyal@yahoo.com.