The Realtime Yoga Assistance System

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Jeewaka Perera
Sri Lanka Institute of Information Technology

Sanvitha Kasthuriarachchi
Sri Lanka Institute of Information Technology

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Kanagasunderam Nishanthan
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, SriLanka
nishakanaga0708@gmail.com

Mathyvathana Sivalingam
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, SriLanka
mathyvathanasivalingam@gmail.com

Priyanthi Rajamanoharan
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, SriLanka
riyamano19@gmail.com

Thusara Arulneasan
Department of Information Technology
Sri Lanka Institute of Information Technology
Malabe, SriLanka
thusaraarul2000@gmail.com

Jeewaka Perera
Facaulty of Computing
Sri Lanka Institute of Information Technology
Malabe, SriLanka
jeewaka.p@sliit.lk

Sanvitha Kasthuriarachchi
Facaulty of Computing
Sri Lanka Institute of Information Technology
Malabe, SriLanka
sanvitha.k@sliit.lk

Abstract— **Yoga, an ancient practice originating from India, has gained immense popularity worldwide due to its numerous physical and mental benefits. Through asana and other breathing practices, it is utilized to harmonize the body. The restrictions of standard ways of learning yoga, which frequently relies on hiring instructors or self-learning through reading materials are the issue this study attempts to address. These methods might not be feasible for many people in the present world. Therefore, there is a need to digitalize the yoga learning process, utilizing technology to provide practitioners with scalable and practical ways to practice yoga efficiently. The importance of this study lies in its ability to offer a uniform framework for identifying yoga asanas, facilitating effective instruction, and clear communication. The creation of precise performance tracking, 3D visualization, and recommendation can also improve clients' safety and individualized performance. The web application aims to solve the problem of yoga asana classification and performance tracking by using machine learning algorithms. In the end, the application implemented using modern technologies to achieve accuracy levels of better than 82% for all machine learning models. These results have significant implications for various stakeholders in the field of yoga, including practitioners and instructors.**

Keywords— Convolutional Neural Networ(CNN)), Graph Neural Network(GNN), Long Short-Term Memory(LSTM), Machine Learning(ML), Natural Language Processing(NLP), Pixel-Aligned Implicit Function(PIFu) 3 Dimension(3D), 2 Dimension(2D)

I. INTRODUCTION

In today's fast-paced world, people are seeking ways to maintain a healthy lifestyle amidst their busy schedules. Yoga has emerged as a popular practice for promoting physical fitness, mental well-being, and overall balance[2]. However, not everyone has access to a yoga instructor or the time to attend regular classes[1]. A digital yoga assistant, aiming to make yoga accessible and convenient for individuals of all backgrounds, provides personalized guidance and support to help users achieve their health and wellness goals[9].

One of the primary advantages of a digital yoga assistant is its ability to deliver real-time assistance[13]. With the help of various sensors and motion-tracking devices, the assistant can accurately monitor the user's movements and provide immediate feedback, ensuring that individuals are performing the yoga poses correctly and reducing the risk of injury[5]. By offering real-time adjustments and corrections, the assistant helps users maintain proper form and alignment, maximizing the benefits of their yoga practice.

Recognizing yoga poses accurately and automatically is an essential step toward developing technology that can provide tailored guidance and assistance to yoga practitioners. This research study aims to investigate the process of recognizing yoga poses by collecting images from user input and detecting key points on the body. The recommended approach gives people access to a self-learning program that they can use without an overseer to confirm their actions. Users can measure their performance over the course of a week or month and receive real-time feedback to help them improve.

Asana classifiers track user behavior as they perform an asana, allowing users to determine whether they are performing the asana properly. Speech recognition technology integrated into a yoga aid system allows users to communicate with the digital yoga assistant via speech inputs, improving the system's simplicity and accessibility[10]. Voice recognition technology allows users to communicate with the digital yoga assistant through voice input, collecting keywords from user queries, matching them with a dataset of yoga asanas and their benefits, and utilizing Machine Learning(ML) models to deliver customized recommendations. To enhance the user experience and provide more comprehensive guidance, the digital yoga assistant can utilize 3 Dimension(3D) visualization and voice-based instructions. 3D models of yoga poses can be developed, accurately representing the correct alignment and positioning of the body in each pose. By visualizing the poses in 3D, users can gain a clearer perspective on how their body should be positioned.

II. LITERATURE REVIEW

Significant work has been done in this field of real-time yoga assistant in variety of applications and research papers. The primary objective of this proposed research is to build upon the existing body of literature in the field of computer vision for human pose estimation[24]. By thoroughly reviewing and considering the existing research, this study aims to make a significant contribution by improving the current outcomes that can be achieved in this field[7]. The goal is to enhance the accuracy, precision, and overall performance of computer vision algorithms when it comes to estimating human poses[3]. The current research paper is more likely to focus on detecting the pose and visualizing the

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detected pose to the user using Convolutional Neural Networks(CNN) and image processing techniques[13]. Researchers have employed various artificial vision techniques to complement angle calculation in human pose detection[2]. Color segmentation techniques aim to extract human body regions by separating them from the background based on color information. Contour detection methods are used to extract the outlines of the human body, enabling more precise localization of key points[10]. Infrared segmentation techniques utilize infrared sensors to capture depth information, which can help in accurate pose estimation, especially in low-light or occluded environments.

The existing works follow human key points extraction using several open libraries like open Pose, media pipe[20]. Various techniques have been employed for human pose detection, with a primary emphasis on conventional neural networks and image processing methods[11]. These approaches often involve two main steps those are key point extraction and pose estimation. Key point extraction aims to identify specific body joints or landmarks, while pose estimation determines the spatial configuration of these key points to form the overall pose. Open Pose and Media Pipe are widely used libraries that provide pre-trained models and APIs for efficient key point extraction.

Estimating 3D poses from 2 Dimension (2D) images is inherently ambiguous since multiple 3D poses can project onto the same 2D image. Resolving this ambiguity is crucial for accurate pose estimation. Researchers have explored different strategies to address this challenge[18]. One approach is to incorporate 3D information into the estimation process. This can be achieved through multi-view geometry techniques, where multiple images from different viewpoints are used to triangulate the 3D pose. Another approach is to leverage temporal dependencies by considering the sequential nature of human motion[14]. By analyzing the temporal evolution of poses over time, recurrent neural networks, such as Long Short-Term Memory (LSTM) or GRUs, can capture the dynamics and resolve ambiguity. To achieve high-fidelity 3D reconstruction of clothed humans from a single image at 1K resolution. The proposed method utilizes an end-to-end multi-level framework based on the pixel aligned Pixel-Aligned Implicit Function (PIFu) representation, allowing for the retention of detailed information from the high-resolution input without post-processing. By addressing the challenges of unobserved regions, such as the backside, through image-to-image translation networks, the method produces complete reconstructions with consistent levels of detail. This work contributes to advancing the accessibility and quality of high-resolution human digitization, enabling applications in medical imaging and virtual reality[17].

In addition to angle calculation, researchers have explored the use of artificial vision techniques to enhance human pose detection. Color segmentation techniques have been employed to isolate human body regions by distinguishing them from the background based on color information. This enables the extraction of relevant features for accurate pose estimation. Contour detection methods have also been utilized to identify and extract the outlines of the human body, enabling more precise localization of key points. Furthermore, infrared segmentation techniques have been leveraged, making use of infrared sensors to capture depth information. This depth information aids in accurate pose estimation, particularly in challenging scenarios such as low-light conditions or occluded environments[19]. By combining angle calculation with these artificial vision techniques, researchers have made significant advancements in improving the overall effectiveness and reliability of human pose detection systems.

The proposed research aims to contribute to the field of computer vision for human pose estimation by focusing on the detection and visualization of yoga poses using a Graph Neural Network (GNN) to enhance accuracy and precision[9]. The primary objective is to develop a web application that can accurately detect, and track yoga poses in real-time, providing users with feedback on their accuracy[23]. The research will build upon existing literature and techniques in human pose estimation, incorporating artificial vision techniques such as color segmentation, contour detection, and infrared segmentation to improve the reliability of pose detection, particularly in challenging environments[3]. The use of a GNN allows for better modeling of the spatial relationships between body joints and enables more accurate pose estimation. Additionally, the research aims to implement an accuracy calculation mechanism for each yoga pose, enabling users to track their progress and receive personalized feedback[14]. The system will also incorporate voice-based inputs, allowing users to provide instructions or cues for specific poses. To enhance the learning experience, a real-time 3D method will be developed to display the actual and accurate yoga asana poses, providing practitioners with visual guidance and improving their ability to learn and perform yoga poses accurately[22]. By combining advanced computer vision techniques, real-time feedback, and interactive visualizations, this research has the potential to greatly enhance the effectiveness and user experience of yoga practice.

A. Reaserch Gap

The field of yoga poses classification and feedback systems exhibit several gaps and areas for improvement. One significant gap is the heterogeneity in feature extraction and labeling criteria[16]. Various research studies have employed different criteria such as human joint angles, muscle activations, captured images, or expert annotations for feature extraction and labeling. This heterogeneity can lead to inconsistent results and limit the interpretability and real-world usability of classification models[4].

The products in the market mostly use CNN for pose classification and accuracy checking. Yoga involves a sequence of poses, and the correct execution of one pose often depends on the preceding poses. GNNs can be used to model the relationships and interactions between different poses in a dynamic graph.

Many studies focus solely on pose classification or feedback generation without comparing the user's pose to the ideal pose. This comparison is vital for providing accurate feedback and evaluating the user's performance. While web cameras are commonly used, they can be computationally expensive. Alternatively, wearable sensor devices can be utilized, but this adds to the production and development costs[25].

Existing systems often lack comprehensive feedback and numerical representation of the user's pose performance. Feedback typically revolves around angles and hand-leg positions, making it difficult for users to track their progress accurately. To address this, future systems should incorporate numerical representations to provide a more holistic understanding of the user's performance[17].

Integration of Natural Language Processing (NLP) techniques presents another avenue for improvement. NLP libraries can analyze user queries, identify keywords and intent, and offer relevant recommendations based on a database of yoga poses[8]. Moreover, there is a research gap in the use of 3D visualization techniques in real-time guidance systems for yoga. While real-time guidance systems have been explored, incorporating 3D visualization can provide a more immersive and participatory experience for practitioners[23]. 3D visualization provides a more comprehensive and intuitive representation of faults or errors. Users can see the exact nature and extent of the issue in a way that 2D or text-based feedback cannot convey[].

Addressing the gaps in yoga pose classification and feedback systems requires standardizing feature extraction and labeling criteria, improving accessibility and usability of ML algorithms, ensuring reliable data collection, comparing user poses to ideal poses, exploring cost-effective body joint detection methods, providing comprehensive feedback and numerical representation, advancing NLP capabilities, and investigating the use of 3D visualization techniques[18]. By addressing these gaps, future systems can offer more accurate, personalized, and immersive yoga guidance, ultimately enhancing the practice and benefits of yoga for individuals of all skill levels[26].

TABLE I. RESEARCH GAP ANALYSIS

Features	[12]	[22]	[27]	[8]	[21]	Yogi B
Key point detection	✓	✓	✓	✓	X	✓
Classification Using CNN	✓	✓	✓	✓	X	X
Classification Using GNN	X	X	X	X	X	✓
Real-time 3d modeling	X	X	✓	X	X	✓
Accuracy calculator	X	✓	X	X	X	✓
Suggest yoga pose	✓	X	X	X	✓	✓

III. METHODOLOGY

The methodology used in the development of real time yoga assistance system presented in this study in a analytical way. This section provides insights into the systematic process used to design, implement, and evaluate the system's functionality and performance. Data collection, preprocessing, algorithm selection and development are the important aspects of methodology. This paper aims to provide a clear understanding of the systematic approach used to create an innovative and user-friendly yoga assistance web application. This section will go over the steps we took to ensure the effectiveness and accuracy of our real-time yoga assistant.

A. Data Collection and Analysis

The dataset for this classification pose component was collected from the Kaggle website, an open-source platform that provides a wide range of datasets. The dataset, which was freely available for research, was dedicated to yoga positions. It had an extensive collection of pictures with labels that represented several yoga poses, such as the tree stance, warrior II pose, downward dog pose, goddess pose, and plank pose, among others. These postures represented a variety of typical yoga positions and variants.

Different variations of each yoga stance were added to assure the dataset's diversity. Yoga asanas can be practiced in a variety of ways, with people using slightly different postures, alignments, or hand positions. These modifications increased the dataset's representation of real-world situations and improved the model's capacity for extrapolating and categorizing asanas correctly.

TABLE II. IMAGE DATASET OVERVIEW

No	Yoga Asana	No of photos	Capacity(MB)
1	**down dog**	**97**	**32.8**
2	**goddess**	**80**	**34.5**
3	**Plank pose**	**115**	**32.1**
4	**Tree pose**	**69**	**37.7**
5	**warrior2 pose**	**119**	**38.4**
	Total	**480**	**175.5**

B. System Overview

To evaluate user input, a combination of NLP and ML approaches is used. approaches is employed to evaluate user input and recommend the most optimal asanas based on their requirements. ML algorithms understand the user's intent and extract relevant keywords, allowing for real-time visualization of outcomes and associated benefits. Keyword extraction is a NLP method that identifies the most essential words or phrases in a text. This approach helps in recommending the most relevant yoga asanas by analyzing the user's input and extracting keywords related to the desired benefits.

The retrieved keywords can be compared to a dataset of yoga asanas and their associated benefits, which includes information about the asana's name, specific benefits, and any tweaks or variants suitable for different practitioners. A real-time suggestion can be generated and shown to the user. NLP can also help users identify the proper asanas for their intended advantages, enhancing their overall health and well-being by optimizing their yoga practice. This approach can help users enhance their overall health and well-being by optimizing their yoga practice.

A maximum classification accuracy of 74.4% was attained during the CNN model's initial training. Even while this accuracy showed the model's potential, it was below the standard that would have allowed for precise and dependable posture estimation in practical situations. The intricate variety of yoga positions and the difficulties in accurately capturing small subtleties in body motions using a typical CNN architecture were blamed for the impediment to reaching a better accuracy. Further research and testing were done in order to examine different machine-learning approaches that would better accommodate the complexity of yoga poses and enhance the overall accuracy of the yoga aid system.

The asana categorization component involved several crucial processes and tools, including obtaining a picture dataset from Kaggle and using Open Pose for multi-individual key point localization. The Open Pose library was used for extraction of 18 keypoints, including the ears, eyes, nose, neck, shoulders, hips, knees, lower thighs, elbows, and wrists.

The preprocessed dataset was used to train the GNN model with the TensorFlow framework. The retrieved keypoints and their related values were used to categorize yoga asanas using the labeled data from the CSV file. The model's parameters were optimized throughout the training phase to increase accuracy and reduce loss. The model was prepared for real-time asana classification after training, using OpenCV to capture a real-time snapshot of the frame and extracting keypoints using computer vision techniques. The trained GNN model processed these extracted keypoints to forecast the appropriate yoga asana based on the user's current stance.

Accuracy checker aims to improve yoga practice by providing real-time feedback and progress tracking to users. It uses ML techniques to receive user input, calculate the accuracy rate of their poses, track their progress over time, and generate a progress report to motivate them. The first step involves using a yoga image dataset, which contains images of various poses. Preprocessing techniques are applied to extract relevant information from these images, which are fed into a pose estimation framework. The extracted key points are arranged sequentially, capturing the coordination of joints and their angles.

The extracted data is saved in a dataset with corresponding yoga pose labels, which serves as the training data for the CNN. The CNN is trained on this dataset to learn patterns and relationships between key points and corresponding yoga poses. By training on a large and diverse dataset, the model can generalize well and accurately classify and detect yoga poses based on the angles of the key points.

When a user interacts with the web application, their input is processed in real-time, and their movements are captured using a camera. The pose estimation framework is used to extract key points from the user's input, and the angles between these points are calculated. The calculated angles are compared with the trained model to determine the accuracy of the pose. If the calculated angles deviate beyond the defined threshold range, the pose is considered inaccurate, and feedback is generated. The application records the time duration of each pose performed by the user, along with the corresponding accuracy results. This data is stored in a database for further analysis and tracking of the user's progress. LSTM is employed to analyze the progress over time, capturing and analyzing sequential data. The web app generates a progress report that showcases the user's performance and improvement over time, serving as a motivational tool to encourage users to continue practicing and strive for better accuracy and alignment in their yoga poses.

In recent years, advancements in computer vision have led to the development of PIFu technology, which uses deep learning algorithms to generate high-quality 3D models from single 2D images. The methodology involves data collection and preparation, training the PIFu network, and constructing 3D models from new, unseen 2D images. The PIFu network predicts per-pixel depth and occupancy values for new images, which are then used to generate a 3D point cloud representation of the object or scene depicted in the image. Surface reconstruction techniques, such as Poisson surface reconstruction or Marching Cubes algorithm, are applied to the generated point cloud, resulting in a complete and textured 3D model.

Treatment mapping is performed to assign colors to the surface of the 3D model, which involves projecting the 2D image onto the 3D mesh using UV mapping techniques. The accuracy and quality of the reconstructed 3D models depend on factors such as the quality and diversity of the training dataset, the architecture and parameters of the PIFu network, and the effectiveness of surface reconstruction and texture mapping techniques.

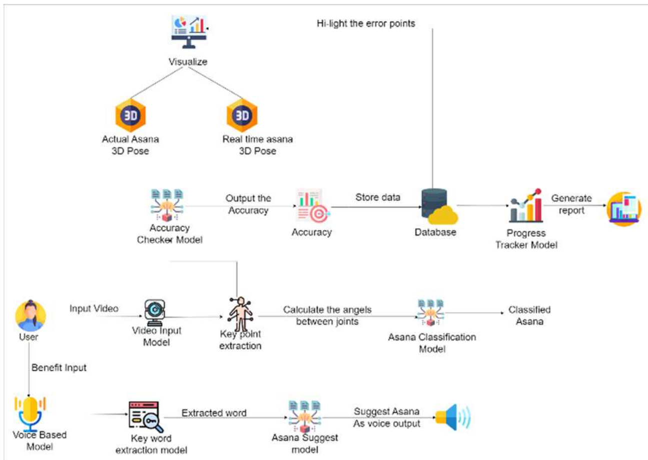

Fig. 1. System Overview Diagram

IV. Result and Discussion

The main component of the proposed system yields various results that contribute to an enhanced yoga experience. Firstly, the yoga classification component utilizes a GNN for model training, achieving an impressive accuracy rate of 95.9% with a loss of 12%. This trained model is capable of accurately classifying different yoga poses. The classified yoga pose is then communicated to the user through both voice and text outputs, ensuring clear understanding and guidance. And for more helpful things to guide the user, the system offers YouTube videos to learn.

```
Epoch 47/200
19/37 [==============>...............] - ETA: 0s - loss: 0.1162 - accuracy: 0.9638
Epoch 47: val_accuracy did not improve from 0.99020
37/37 [==============================] - 0s 4ms/step - loss: 0.0953 - accuracy: 0.9740
902
```

Fig. 2. Classification Component Accuracy

In addition, the yoga pose accuracy checker component focuses on evaluating the accuracy of a user's yoga performance. The model has been trained by getting the average for each key point angle from the dataset. The model training process for this component achieves an outstanding accuracy of 98.88%. By comparing the detected angles of the user's pose with the calculated angles from the trained model, an accurate assessment of the user's performance is obtained.

Then the results of the accuracy will be portrait in the graph view along with the time. This information is crucial for providing feedback and suggestions for improvement.

```
multiclass logloss accuracy 0.9887218045112782
multiclass error accuracy 0.9887218045112782

roc_score(mlogloss): 0.9923379305770279
```

Fig. 3. Accuracy Checker Component Accuracy

Furthermore, the yoga recommendation component employs ML techniques to train a model that attains an accuracy rate of 84.9%. Based on user input and preferences, this trained model recommends suitable yoga poses. The recommendations are delivered to the user through a voice-based output, providing personalized guidance and facilitating their yoga practice. Analyzing user voice-based input, the keywords emerged as prominent concerns. Based on model training and recommendations, practicing yoga asanas to alleviate stress and improve flexibility. Asanas have been known to effectively address these specific needs, contributing to overall well-being.

```
Model accuracy          : 0.8489304812834224
Accuracy in Percentage  : 84.9%
              precision    recall  f1-score   support

           0       0.93      0.96      0.94      2131
           1       0.94      0.90      0.92      1609
```

Fig. 4. Recommendation Component Accuracy

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   GITLENS

[Running] python -u "c:\Users\Thusara Arulnesan\Desktop\RP-my\23-217\app.py"
Listening...
Voice input: I want a relax
Keywords found: relax

[Done] exited with code=0 in 11.805 seconds
```

Fig. 5. Figure 5: Accuracy Checker Output

The PIFu network's occupancy predictions allow for the creation of 3D models that are impenetrable and sturdy. The occupancy values distinguish each pixel as belonging to the object or the background, enabling accurate surface geometry extraction. This improves the reconstructed 3D models' quality and makes it possible to depict and analyze the items or situations of interest more precisely. Another noteworthy outcome is the capacity of PIFu technology to produce textured 3D models. The 3D meshes were colored according to the 2D photos, giving the rebuilt models a realistic appearance and visual accuracy. From the real-time capturing of human body using computer vision technology to track the user's body movements through a webcam or camera feed. It identifies key joint points, such as hands, head, and feet, and provides real-time feedback and instructions on correct yoga poses and alignment. This model analyzes the user's movements, compares them to predefined yoga poses, and offers visual and audio cues to help users improve their form and maximize the benefits of their yoga practice, creating an interactive and informative yoga coaching experience. A visually pleasing depiction of the objects or sceneries in the 3D realm is provided by the texture mapping technique, which successfully transfers the visual information from the 2D photographs.

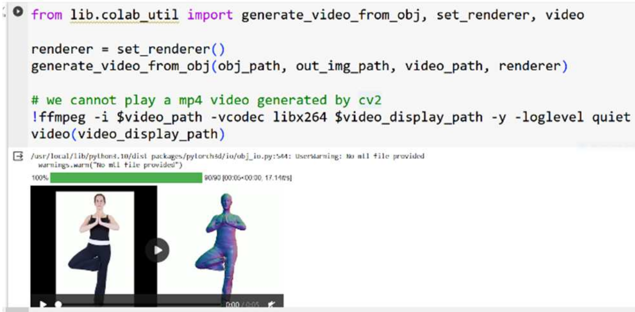

Fig. 6. 3D modeling

V. Conclusion

A real-time yoga assistant application has the potential to support beginners in their practice by utilizing ML and incorporating technologies like GNN, CNN , NLP and Pixel aligned Implicit Function. This application accurately recognizes and identifies yoga poses, offering valuable feedback and suggestions to improve technique and alignment. Voice-based feedback enhances the user experience, and the web app can monitor accuracy improvement over time[08]. It can analyze historical data and provide personalized reports on performance, motivating users to continue practicing. 3D visualization is more efficient than 2D images or videos, providing a more immersive and accurate representation of poses. The integration of open libraries like Open Pose, Media Pipe, and TensorFlow streamlines the development process and enhances efficiency[20]. This real-time yoga assistant web application offers a user-friendly and personalized experience, promoting proper alignment and technique, and contributing to the overall health and well-being of individuals practicing yoga. Further research and development are needed to refine and optimize the system's performance, including training ML models on diverse datasets and user feedback[29].

VI. Future Work

This study highlights the potential for further research and development in categorizing yoga asanas when multiple users are engaged in exercise. The current classification approach considers only five distinct asanas, but there is room for expansion by incorporating a wider variety of asanas. This could be achieved by gathering a larger dataset of asanas performed by multiple users and using ML methods like ensemble models.

A mechanism must be developed to calculate accuracy throughout a series of asanas performed by various users. This comprehensive examination can help practitioners improve their practice and achieve better alignment and balance. Extending the recommendation system for medical issues could expand the system to include an extensive database of medical disorders and yoga asanas. This would allow the system to offer personalized recommendations based on users' individual health needs.

An algorithm could recommend yoga asanas that match and improve athletic performance by considering the unique physical demands and requirements of various sports. This would involve collaborating with coaches and athletes to identify the best postures for enhancing flexibility, strength, balance, and injury prevention in specific sports activities.

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