International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
Article Received:30 March 2023 Revised: 22 May 2023 Accepted: 31 May 2023

Smart Yoga Assistant: SVM-based Real-time Pose Detection and Correction System

Deepak Mane[1], Gopal Upadhye[2], Vinit Gite[3], Girish Sarwade[4], Gourav Kamble[5], Aditya Pawar [6]
[1,2,3,4,5,6,]Vishwakarma Institute of Technology, Pune-411037, Maharashtra, India
[1]dtmane@gmail.com
[2]gopalupadhye@gmail.com
[3]vinit.gite19@vit.edu
[4]girish.sarwade19@vit.edu
[5]gourav.kamble19@vit.edu
[6]aditya.pawar19@vit.edu

Abstract: - SVM-based Real-time Pose Detection and Correction System refer to a computer system that uses machine learning techniques to detect and correct a person's yoga pose in real-time. This system can act as a virtual yoga assistant, helping people improve their yoga practice by providing immediate feedback on their form and helping to prevent injury. This paper presents a yoga tracker and correction system that uses computer vision and machine learning algorithms to track and correct yoga poses. The system comprises a camera and a computer vision module that captures images of the yoga practitioner and identifies the poses being performed. The machine learning module analyzes the images to provide feedback on the quality of the poses and recommends corrections to improve form and prevent injuries. This paper proposed a customized support vector machine (SVM) based real-time pose detection and correction system that suggests yoga practices based on specific health conditions or diseases. Paper aims to provide a reliable and accessible resource for individuals seeking to use yoga as a complementary approach to managing their health conditions. The system also includes a practitioner's interface that enables practitioners to receive personalized recommendations for their yoga practice. The system is developed using Python and several open-source libraries, and was tested on a dataset of yoga poses. The hyper parameter gamma tuned to optimize the classification accuracy on our dataset produced 87% which is better than other approaches. The experiment results demonstrate the effectiveness of the system in tracking and correcting yoga poses, and its potential to enhance the quality of yoga practice.

Keyword: - Computer Vision, Machine Learning, Deep Learning, Pose Estimation, Image Classification, Support Vector Machine , Human Pose Estimation, Feature Extraction.

I. INTRODUCTION

Yoga is a traditional Indian practice that has achieved enormous popularity throughout the world because of its many health advantages. As technology has advanced, there has been an increase in interest in employing computer vision to help yoga practitioners do postures correctly. As a result, technologies that detect various yoga poses in real time have been created that can do so accurately. A yoga pose detection system typically uses a camera to capture images or video of a person performing yoga poses. These images are then processed using computer vision algorithms to identify the specific pose being performed. The accuracy of these systems is crucial for ensuring that practitioners are performing poses correctly, as incorrect alignment can lead to injury and decreased effectiveness. Numerous studies on the subject of accurately identifying various yoga poses have been published. These studies examine diverse methods. Some deep learning techniques such as (CNN, ANN, etc.) are frequently used in these articles to identify photos of various poses. In order to train and test the models, they frequently require gathering and annotating enormous datasets of yoga positions.

The yoga classification system we have developed is a powerful tool that can help individuals manage their health conditions and improve their overall wellbeing through the practice of yoga. Our aim is to make yoga more accessible and tailored to specific health needs by suggesting yoga practices that are backed by scientific research and evidence-based practices. The smart yoga tracker contains six common diseases and associated yoga poses that can help, manage or improve the conditions. It includes yoga for diseases like Diabetes, Back Pain, High Blood Pressure, Depression, Heart Pain and Joint Pain. The figure 1 is about system flowchart. In general, yoga position identification is an intriguing area of study that could completely alter the way individuals practice yoga. These

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

technologies can assist practitioners in developing their techniques and lowering the risk of injury by giving real-time feedback on pose alignment.

A. Mediapipe

MediaPipe is an open-source framework developed by Google that helps developers to build real-time computer vision-based applications quickly and easily.

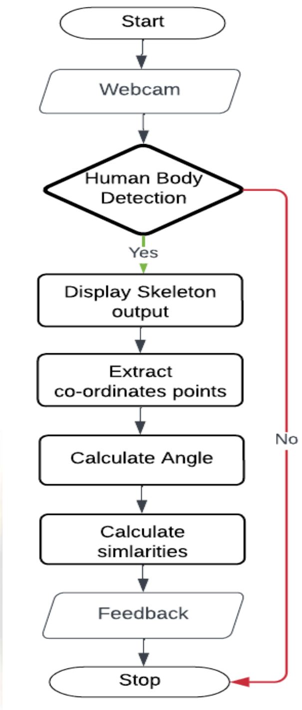

Figure 1. System Flowchart

One of the key features of MediaPipe is its ability to perform pose classification, which involves identifying and classifying the poses of people in images or videos. Pose classification has a wide range of applications, from improving fitness tracking and sports training to enhancing virtual and augmented reality experiences. MediaPipe's pose classification capabilities are based on machine learning models that have been trained on large datasets of labeled images and videos. With MediaPipe, developers can easily integrate pose classification into their applications, allowing them to provide more personalized and engaging practitioners experiences. Figure 2 shows human body coordinates using MediaPipe.

B. SVM (Support Vector Machine)

This is a popular machine learning algorithm used for classification and regression tasks. This algorithm is widely used for applications such as image classification, text classification, bioinformatics, and many others. SVM is a binary classification algorithm, meaning it is designed to separate data into two classes. However, there are several approaches to extend SVM to handle multi-class classification problems. Here are some common methods:

One-vs-One (OvO) approach: In this method, all possible pairs of classes are considered, and a separate binary SVM classifier is trained for each pair. During testing, each classifier predicts a class label for the test instance, and the class which has more votes is chosen for the final prediction. This approach requires training nC2 binary classifiers for n classes.

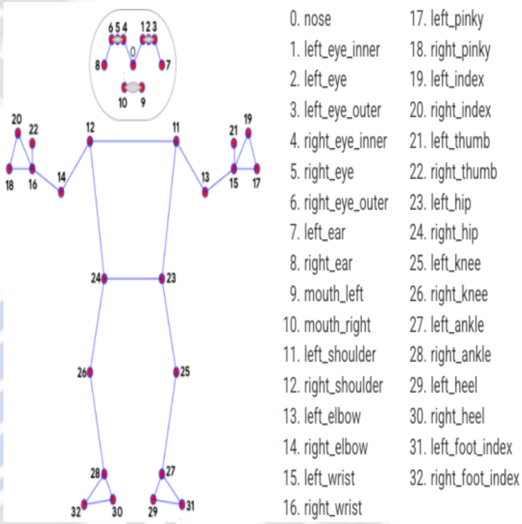

Figure 2. Human body coordinates using Mediapipe

- *One-vs-All (OvA) approach:* In this method, a separate binary classifier is trained for each class, treating all other classes as a single class. During testing, each classifier predicts whether the test instance belongs to its class or not. The class which has a higher confidence score is chosen for final prediction. This approach requires training in binary classifiers for n classes.

The objectives of the paper are,

- To develop yoga, pose prediction and correction systems using SVM and RBF kernels that can accurately predict the yoga poses performed by the practitioners and provide feedback to practitioners to improve their form and posture.
- The system uses a dataset which contains 18 different yoga pose images to train an SVM model. The system then uses the trained model to predict the yoga poses performed by the practitioners in real-time using input from sensors attached to the practitioner's body.
- The system provides corrective feedback to the practitioners based on the difference between the

predicted pose and actual pose, helping the practitioners to improve their form and posture.

- The system's effectiveness is evaluated through a series of experiments, demonstrating its potential as a useful tool for yoga practitioners of all levels.

The overview of this paper is, in section II, the literature survey represented the literature on pose detection and correction systems in the context of yoga practice. It discusses the limitations of existing systems and highlights the need for a more accurate and real-time solution. In proposed architecture section III, explained a detailed explanation of the SVM-based pose detection and correction system. It covers the steps involved in training the SVM model, including data preprocessing, feature extraction, and model selection. It also explains how the model is used in real-time to detect and correct yoga poses. The results of experiments conducted to evaluate the performance of the system represented in section IV. It includes a comparison of the system's accuracy to other models and a discussion of the real-time performance of the system. Conclusion with future direction explained in section V.

II. Literature Survey

Many researchers have proposed real-time systems for detecting and correcting yoga poses using computer vision and machine learning algorithms[11][15]. In March 2022, CNN model was proposed for real-time detection of yoga poses. Different yoga poses were accurately identified in real-time using a webcam, and the outcomes were given in terms of accuracy and real-time performance. The potential of this approach for improving the alignment and safety of yoga poses was highlighted, and future research in personalized pose detection systems and integration of other sensing modalities for a more comprehensive yoga practice was suggested. Additionally, high accuracy score of 0.9958 was achieved by a multilayer perceptron (MLP) for testing datasets with modified features, with lower power consumption compared to CNN and CNN + LSTM [1]. In July 2022, Dr. Maya Bembde and the team had presented a comprehensive survey of different techniques for detecting yoga poses, emphasizing the importance of correct alignment and the potential risks of incorrect posture. Traditional methods for monitoring yoga practice and the limitations of such methods were discussed, and the potential of technology-based solutions was highlighted. Marker-based and marker-less methods are analyzed in detail, with a focus on marker-less methods that rely on computer vision and machine learning. Different techniques were evaluated based on factors such as accuracy, speed, and applicability, and recommendations were provided for future research. [2]. Earlier in December 2021, a real-time system for detecting and correcting yoga poses using PoseNet and KNN algorithms was proposed. The solution was proposed that involves capturing live video footage of a practitioner, processing it using PoseNet, and comparing the estimated pose to a predefined set of correct poses using KNN.

An evaluation of the proposed system was provided, demonstrating its effectiveness in detecting and correcting various yoga poses and comparing it with other pose detection systems. Overall, it has presented a novel system with potential to improve the safety and effectiveness of yoga practice and provides valuable insights for researchers and practitioners interested in developing or using similar systems [3]. We have studied one more system for real-time image detection and classification of yoga poses using deep learning algorithms proposed in April 2022. They had used deep learning models such as VGG-16, InceptionV3, and ResNet-50 to accurately detect and classify different yoga poses.

High accuracy rates of 99.04% for framewise and 99.38% for groups of 12 different people were achieved by the system. A relative analysis with other pose detection systems was presented, highlighting the advantages of their approach [4]. In 2020, CNN , RNN applied to detect the yoga pose[5]. Large yoga pose dataset with 5500 images prepared and applied random forest classifier to classify the pose in 2020[6]. Initially in 2011, patil et al. poposed a a sste to detect the oga poses using SURF algorithm[7]. In 2020, yoga pose detection proposed by variant of deep learning on BODY 25 dataset where image captured by camera and pass through rained model [8]. In 2019, Hybrid CNN plus LSTM model proposed to detect the poses at real time [9]. Recently some researchers used deep learning and its variant used to detect different pattern detection [12][13][14] Overall, this study provides valuable insights for researchers and practitioners interested in developing or using similar systems to improve the safety and effectiveness of yoga practice.

III. Proposed Architecture

In this paper, a customized SVM classifier is proposed which helps to classify the yoga poses based on joint angles. Proposed approach for classification involves the use of Support Vector Machines (SVM) with the Radial Basis Function (RBF) kernel. The RBF kernel is known for its ability to capture non-linear relationships between data points, which is particularly useful for datasets with complex decision boundaries. The hyperparameter gamma was tuned to optimize the classification accuracy on our dataset. The experimental results demonstrate that our

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

approach achieves a high accuracy of 87%, which outperforms other state-of-the-art methods on the same dataset

SVM is a popular machine learning algorithm that has certain advantages over other classification algorithms for yoga pose classification due to its ability to handle high-dimensional feature spaces, non-linear relationships between variables, and imbalanced datasets. SVM is able to accurately classify yoga poses by effectively handling a large number of features used to describe each pose, modeling non-linear relationships between these features, and handling imbalance. The system will use Mediapipe's pose estimation model to extract the joint keypoints from images or real-time video feed. From the keypoints, the system will calculate the joint angles using trigonometry. The joint angles will be used as features to train the SVM, while the yoga pose labels will be used as classes. It saves the joint angles and yoga pose labels in a CSV file for both training and testing purposes. Preprocess the data by normalizing the joint angles to have zero mean and unit variance. It also divides the data into training sets and testing sets to train and evaluate the SVM algorithm. Once the SVM is trained, use it to classify the yoga poses performed by the practitioners in real-time. If the SVM recognizes the pose, the system will provide feedback to the practitioners on their alignment and form. If the SVM does not recognize the pose, the system will ask the practitioners to try again or provide guidance on how to adjust their pose. The system will provide feedback to the practitioners through a graphical practitioner's interface (GUI) that highlights the joints that need correction or provides textual feedback on how to adjust their pose. System architecture is represented in Figure 3.

Module wise explanation

A. Collection of data

The dataset contains labeled yoga pose images. For each image, the system will extract joint key points using Mediapipe's pose estimation model. Additionally, it will calculate the joint angles from the key points, as these angles will be the main features used for classification. It calculates the joint angles using trigonometry, by finding the angles between pairs of key points. Figure 4 is of Trigonometric formula

For example, to calculate the angle of the knee joint in a yoga pose, it uses the keypoints for the hip, knee, and ankle, and uses the Law of Cosines to calculate the angle between the hip-knee and knee-ankle lines. Once the joint angles and their corresponding labels for each yoga pose are collected, it saves this data in a CSV file. The CSV file should have one row for each image, with the first column containing the label (the name of the yoga pose), and the remaining columns containing the joint angles. Figure 5 shows the table of angle extracted from the image dataset.

Figure 3. System Architecture

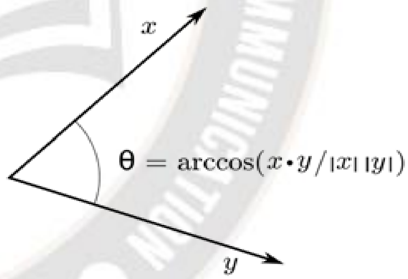

Figure 4. Trigonometry formula

B. Preprocessing

To ready the dataset for SVM training in this research article, several preprocessing steps are required. Firstly, the joint angle extracted from the labeled yoga pose images must be normalized to have zero mean and unit variance. To normalize the data, we can center each value by subtracting its mean and scale it by dividing by its standard deviation. This normalization process ensures that all features are on the same scale and prevents any one feature from dominating the SVM's decision-making process.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

class	left_elbow_angle	right_elbow_angle	left_shoulder_angle	right_shoulder_angle	left_knee_angle	right_knee_angle	left_hip_angle	right_hip_angle
Bow Pose	187.9771376	182.5745048	323.9670807	34.85312462	304.0699258	311.7932436	210.6575968	206.968524
Bow Pose	188.8512433	188.8517051	293.8618313	65.14541552	267.6342423	275.2865908	241.3709743	238.5127691
Bow Pose	185.9076175	188.4004074	292.4006335	61.11217598	266.3835646	262.8749837	250.7540982	244.9045156
Bow Pose	170.6392005	168.6543247	245.9383927	110.5183288	234.7028572	229.2278068	273.4214006	274.5946701
Bow Pose	174.1420408	162.5977854	271.1213203	102.5656109	221.7785429	245.9692872	288.4015315	272.1041884
Bow Pose	99.81057451	101.2050477	251.0990964	106.5615656	253.6719595	250.588466	293.3240098	277.9389876
Bow Pose	156.5906345	156.0548413	233.5134929	127.5457012	233.1742413	233.0052492	290.5685669	285.0915727
Bow Pose	165.2523656	155.2274876	270.6239454	96.11936515	262.4082818	268.2488274	256.670359	251.1120353
Bow Pose	189.5645884	193.4082154	288.6351662	75.98807562	269.8049181	267.3601761	253.5649085	257.6658837
Bow Pose	183.5443064	185.9517746	289.4534743	77.78884567	265.2826673	263.7336601	256.4273307	258.064073
Bow Pose	189.6142581	185.6482474	292.3097372	74.50339388	271.1504744	264.1378522	251.7079452	259.8516661
Bow Pose	191.5393407	210.0873818	291.6321756	59.9099008	262.79017	267.4132299	257.4404789	255.9132201
Bow Pose	184.0920492	207.012111	284.6304772	67.15544687	197.2705415	240.2966775	304.3827918	272.689747
Bow Pose	201.2704355	212.2691929	302.4149433	58.1138677	256.1861239	266.6173105	265.9848321	257.4609242
Bow Pose	196.4704284	181.6523047	295.3768113	99.3118208	250.0717559	258.6173572	281.6392487	278.1656559
Bow Pose	180.5846305	184.3154634	285.6848636	82.43667031	267.6191847	272.553551	258.5879171	258.6360561
Bow Pose	119.8488774	117.193633	214.4468511	143.6580467	264.5085185	265.4971282	281.8293885	280.0193047
Bow Pose	156.4477363	175.9717363	181.0149076	103.8696864	236.8691459	262.8809751	270.9927939	275.0433155
Bow Pose	284.7435628	180.1078338	266.5979842	92.6051329	227.7977867	278.9310603	324.338786	281.7188984
Bow Pose	189.4553362	190.6426241	283.0820657	72.54716834	269.1598726	268.5270046	254.3361595	253.2120798
Bow Pose	189.7485942	182.1992712	281.8511663	76.17438536	265.8794816	272.6623235	264.4160439	257.3682791
Bow Pose	205.2328313	208.3815038	265.0857202	73.77801886	206.735828	248.2397217	297.7523731	271.0630244
Bow Pose	183.0650326	186.8633165	294.4895868	65.13600709	270.4625856	278.2569692	247.1756728	245.778642

Figure 5. Angle extracted from image dataset

In order to evaluate the performance of the model accurately, it is important to partition the dataset into two subsets - a training set and a testing set, with a ratio of 80:20 being commonly employed in such systems. It is crucial that both the training and testing sets have a balanced distribution of yoga poses, to ensure that the SVM can learn to recognize all poses equally well. By following these preprocessing steps, the proposed approach in this paper aims to train an SVM that accurately classifies yoga poses based on the normalized joint angles extracted from labeled images.

C. Train SVM

After data preprocessing SVM classifier is trained on training data. It uses the scikit-learn library for it, which makes it easy to experiment with different kernel functions and regularization parameters to find the best model. The SVM will use the joint angles as features and the yoga pose labels as classes. By learning the relationship between the joint angles and the yoga poses, the SVM will be able to recognize new yoga poses based on their joint angles. Choosing an appropriate kernel function is crucial for achieving high classification accuracy in Support Vector Machines (SVM), particularly when dealing with non-linear and intricate data. Here, we present a yoga pose recognition system based on SVM that utilizes the RBF kernel owing to its ability to capture non-linear relationships between the input and output data.We compare the performance of the RBF kernel with other kernel functions such as linear and polynomial kernels, and demonstrate that the RBF kernel outperforms other kernel functions in terms of accuracy and robustness.

The mathematical equation for the RBF kernel.

$$k(x_i, x_j) = exp(-\gamma\|x_i - x_j\|^2) \tag{1}$$

D. Test SVM

After training the SVM, the next step involves evaluating its effectiveness on a separate set of testing data. This evaluation involves computing various metrics such as accuracy, precision, recall, and F1 score, which provide a quantitative measure of the classifier's ability to accurately identify the yoga poses.

*a)Accuracy***:**The accuracy metric quantifies the proportion of accurate predictions made by a model, relative to the total number of predictions made by the model.

*b) Precision:*Precision is a metric that determines the proportion of correctly classified positive instances (yoga poses) to the total number of instances predicted as positive by the model.

*c) Recall:*The recall metric measures the fraction of accurately classified positive instances (yoga poses) relative to the total number of actual positive instances present in the testing set.

*d) F1 score:*The F1 score metric computes the harmonic mean of precision and recall, thereby providing a single combined measure of the model's accuracy and completeness in correctly identifying both positive and negative instances (yoga poses) in the testing set. Figure 6 is about classification reports using the RBF kernel in SVM.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

	precision	recall	f1-score	support
Bow Pose	1.00	0.93	0.96	14
Bridge Pose	0.92	0.96	0.94	23
Cat Pose	0.90	0.64	0.75	14
Cobra Pose	0.84	0.89	0.86	18
Crocodile Pose	0.74	0.79	0.76	33
Diamond pose	0.88	0.88	0.88	17
Downward facing dog Pose	0.88	0.88	0.88	42
Easy pose	0.90	0.75	0.82	12
Extended hands and feet pose	0.94	0.83	0.88	18
Forward Fold	0.81	0.92	0.86	24
Mountain Pose	0.82	0.90	0.86	10
Plank Pose	0.92	0.92	0.92	13
Seated Forward bend Pose	0.83	0.83	0.83	23
Standing forward pose	0.70	1.00	0.82	7
Tree Pose	1.00	0.85	0.92	13
Triangle Pose	0.92	0.85	0.88	13
Upward facing dog pose	0.94	0.94	0.94	18
Warrior Pose	0.88	0.94	0.91	16
accuracy			0.87	328
macro avg	0.88	0.87	0.87	328
weighted avg	0.87	0.87	0.87	328

Figure 6 Classification report

These metrics provide valuable insights into the SVM's performance and its ability to accurately classify and correct yoga poses.

E. Pose Correction

Now that the SVM is trained, it can classify the yoga poses performed by a practitioner in real-time. It uses Mediapipe to estimate the joint keypoints and calculate the joint angles, and then uses the SVM to determine which yoga pose the practitioner is attempting. If the SVM recognizes the pose, we can provide feedback to the practitioners on their alignment and form. If the SVM does not recognize the pose, it asks the practitioners to try again or provide guidance on how to adjust their pose to better match a known pose.

F. Feedback to practitioners

If the SVM determines that a correction is needed, it provides feedback to the practitioners on how to adjust their pose by providing textual feedback such as "Rotate your left foot slightly inward". By giving the practitioners clear and actionable feedback, it will help them improve their form and reduce the risk of injury. The below are the steps for performing yoga pose classification and correction.

- Mediapipe's pose estimation model to extract joint keypoints from images or real-time video feed.
- Calculate joint angles using trigonometry.
- Save joint angles and yoga pose labels in a CSV file for training and testing.
- Preprocess data by normalizing joint angles and splitting into training sets and testing sets.
- Train the SVM model with RBF classifier using joint angles as features and yoga pose labels as classes.

The developed SVM model that can accurately classify yoga poses performed in real-time and offer feedback on the user's alignment and form via a graphical user interface (GUI).The below is the pseudo code for of SVM model

Input: Dataset D

Output: Confusion Matrix, Validation

Train dataset -Split [D, size=0.8]

Test dataset - Split [D, size=0.2]

SVMMultiClassOneVsAlI.train(kernel, gamma, C):

X: Number of Samples

Y: Labels, where Yi € {1, ..., N}

Test the model using "Test dataset"

Calculate the score.

Compute the confusion matrix

About Dataset: To accurately classify yoga poses, it is important to have a diverse and representative dataset that captures the variations in pose execution and context[10]. However, existing datasets for yoga pose classification are limited in size and diversity, and may not be suitable for all use cases [16][17][18][19]. To address this limitation, we developed a custom dataset of yoga poses that is tailored to our specific use case. The dataset consists of 18 yoga poses

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
Article Received:30 March 2023 Revised: 22 May 2023 Accepted: 31 May 2023

images in JPEG and PNG format. The classwise samples represented in table 1.

Table 1. Class wise Datset description

Sr No.	Classes	Images
1.	Bow Pose	74
2.	Bridge Pose	129
3.	Cat Pose	89
4.	Cobra Pose	89
5.	Crocodile Pose	83
6.	Diamond Pose	86
7.	Downward Facing Dog Pose	211
8.	Easy Pose	62
9.	Extended Hands And Feet Pose	90
10.	Forward Fold Pose	122
11.	Mountain Pose	53
12.	Plank Pose	67
13.	Seated Forward Bend Pose	127
14.	Standing Forward Pose	40
15.	Tree Pose	66
16.	Triangle Pose	68
17.	Upward Facing Dog Pose	89
18.	Warrior Pose	79

The images are of size (500x500) pixels, and were collected from sources such as YouTube, Yoga websites and stock image websites. The dataset offers a variety of poses and multiple images for each pose, which can be useful for yoga practitioners and computer vision researchers. The poses in our dataset are carefully labeled, ensuring high accuracy and consistency across the dataset. By using a custom dataset, we can ensure that our classification model is optimized for our specific use case and captures the variations in pose execution that are relevant for our application. Additionally, using a custom dataset allows us to incorporate domain-specific knowledge into our model, improving its accuracy and effectiveness. The below figures 7 shows the example of custom dataset

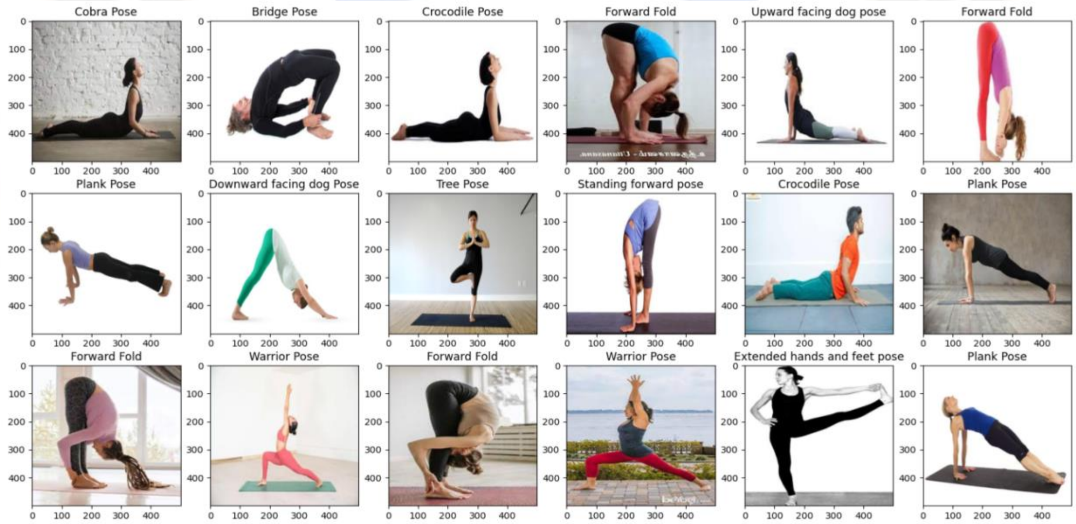

Figure 7 Custom dataset

The below points are the hardware and software requirements that is need to use this system

• We recommend using a computer with a modern processor (Intel i5 or higher). The computer should also have sufficient RAM (at least 8GB) to store and manipulate data.

• To enable the real-time capture of practitioners performing yoga poses, in addition to a computer, we will also require a camera capable of capturing high-quality video. A high-quality camera with a resolution of 1080p or higher is recommended to ensure accurate pose estimation.

• We may also need additional hardware depending on the specific use case of the system. For example, if the system is intended for use in a gym or yoga studio, we may need to mount the camera and computer on a stable surface or stand to ensure they do not move during use

IV. Experiment Results

The paper describes a system for yoga pose classification and correction using computer vision techniques and SVM. The system extracts key points from a yoga pose performed by a practitioner using a webcam and matches them to pre-trained poses using an SVM classifier. Once the pose is classified, if the yoga pose is incorrect the system will give instructions for correction of yoga pose so that they can learn and correct their posture accordingly. The system achieved an accuracy rate of 87%, indicating its potential as a useful tool for yoga practitioners which better than existing approaches. However, limitations and challenges

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

may exist, and further research may be needed to improve the accuracy and usefulness of the system. Figure 9 shows the predicted yoga pose (Easy Pose) with its probability. Figure 10 shows the predicted yoga pose (Tree Pose) with its probability. Figure 11 shows the predicted yoga pose (Diamond Pose) with its probability. Figure 12 shows the predicted yoga pose (Cat Pose) with its probability

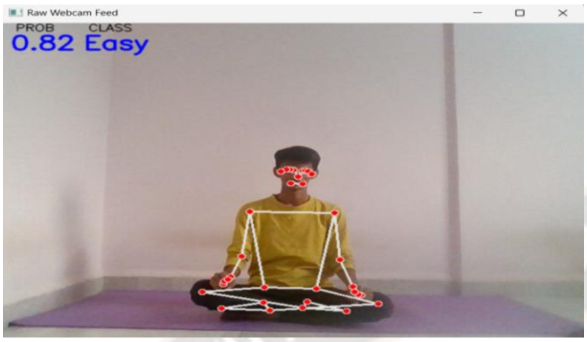

Figure 9. Easy Pose

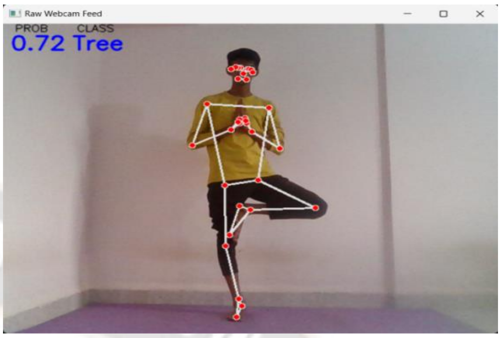

Figure 10. Tree Pose

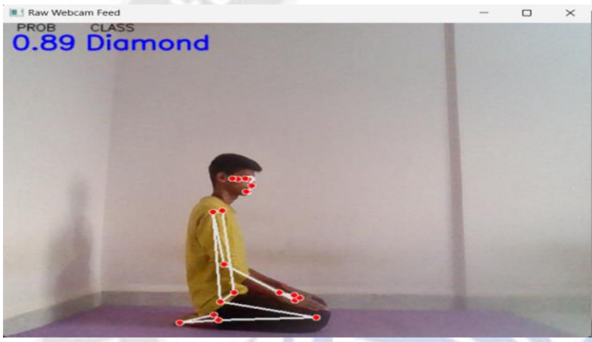

Figure 11. Diamond Pose

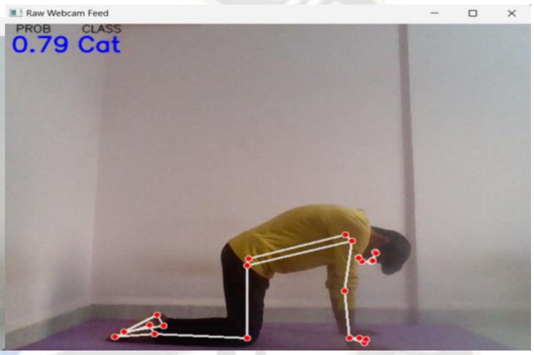

Figure 12. Cat Pose

- The below Figure 13 shows the correction system for downward facing dog pose. In the black window it shows the angle adjustment for downward facing dog pose.

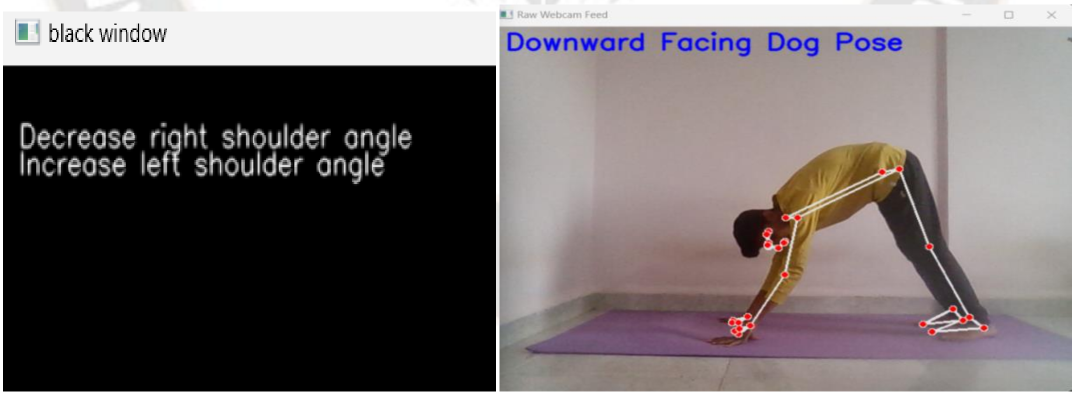

Figure 13. Downward Facing Dog Pose Correction

- Below figure 14 shows the correction system for Mountain pose. In the black window it shows the angle adjustment for mountain pose.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

Figure 14. Mountain Pose Correction

- The below figure 15 shows the correction system for Triangle pose. In the black window it shows the angle adjustment for triangle pose.

Figure 15. Triangle Pose Correction

- The below figure 16 shows the correction system for Warrior pose. In the black window it shows the angle adjustment for warrior pose.

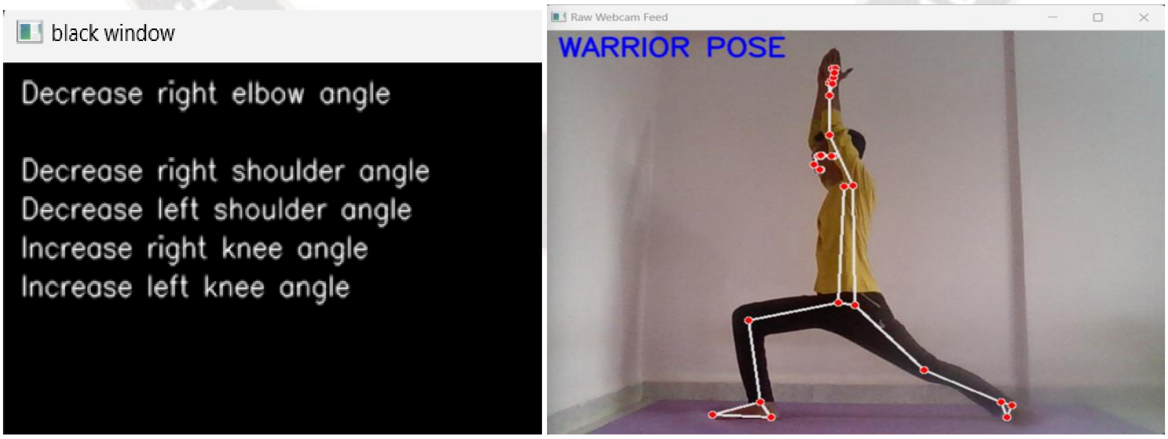

Figure 16. Warrior Pose Correction

In Figure 17 illustrates the confusion matrix generated by the Support Vector Machine (SVM) classifier, which summarizes the classification outcomes for each class. The matrix represents the number of instances classified into each class, with the true labels displayed on the y-axis and the predicted labels on the x-axis. The diagonal cells of the matrix represent the number of correctly classified instances for each class, while the off-diagonal cells

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6997
***Article Received**:30 March 2023 **Revised**: 22 May 2023 **Accepted**: 31 May 2023*

indicate misclassifications. By examining the confusion matrix, we can assess the performance of the SVM classifier and calculate various performance metrics such as precision, recall, and F1-score. Accuracy of different ML algorithms is represented in Figure 18.

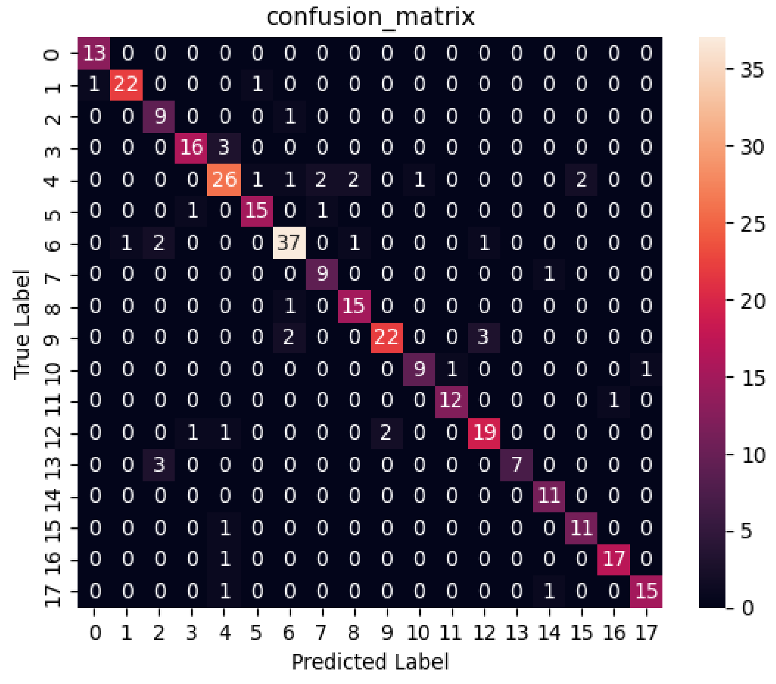

Figure 17. Confusion Matrix for each class

TBALE 2. RESULT COMPARISON WITH EXISTING METHODOLOGY WITH 18 YOGA POSES

Sr. No	Model	Accuracy
1	Logistic Regression	72.25%
2	Ridge Classifier	51.52%
3	Random Forest	85.60%
4	Gradient Boosting Classifier	84.75%
5	**Proposed SVM model**	**87%**

Table 2. about comparison of SVM with different machine learning models and with its accuracy. Figure 8 graph displays the accuracy of each algorithm as a percentage, with the x-axis representing the models, and the y-axis representing accuracy. As we can see in the bar graph, the accuracy of the SVM model is higher compared to other classification algorithms. This is due to the fact that SVMs can handle complex data with non-linear decision boundaries by mapping data to a higher-dimensional space and finding the optimal hyperplane that maximizes the margin between classes. In contrast, logistic regression, ridge classifier, random forest and gradient boosting classifier may not be able to handle such complexities. Furthermore, SVMs are less prone to overfitting compared to other algorithms, which means they generalize well to new, unseen data. This is because SVMs aim to find the maximum margin hyperplane that separates the classes, rather than fitting the data closely, as is the case with some other algorithms. Overall, based on the accuracy shown in the bar graph, we can conclude that customized SVM is a reliable classification algorithm and may be a good choice when dealing with complex, high-dimensional data with non-linear boundaries.

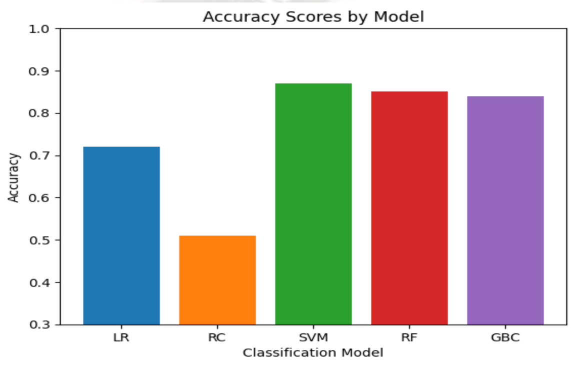

Figure 18. Accuracy of different ML algorithms

V. CONCLUSION

This paper proposed a SVM based smart yoga assistant for yoga poses classification and correction using computer vision techniques and SVM holds great potential for enhancing the practice of yoga, particularly for individuals with specific health conditions or diseases. By incorporating a database of yoga poses tailored to specific health concerns, such as arthritis or chronic pain, the system tries to provide more feedback and support to practitioners. Performance evaluation done on yoga poses dataset which produced 87% accuracy rate by the system in classifying yoga poses suggests that it can accurately identify and provide guidance on specific poses that may be beneficial for individuals with certain health conditions. However, the system may still have limitations and challenges in accurately classifying poses for individuals with unique health conditions or physical limitations. Therefore, further research and development may be necessary to ensure the accuracy and usefulness of the system for a wider range of health conditions. Overall, the incorporation of specific yoga poses for disease management into a yoga pose classification and correction system can greatly benefit individuals seeking to improve their health and well-being through yoga. The availability of a good and diverse dataset is critical for building any machine learning model. In the case of yoga pose classification, obtaining a comprehensive and diverse dataset with multiple variations of each pose was a challenging task. Before feeding data to the SVM model, it needs to be preprocessed, which involves cleaning, normalization, and feature extraction. Extracting features that represent the poses accurately can be difficult due to the nature of the data. Tuning the SVM model was a challenge. The optimal parameters for the model, such as the kernel function and regularization parameters may be difficult to determine, and different parameters may be more or less effective for different poses. Additionally, selecting the appropriate evaluation metrics and optimizing them was a challenging part. There are several avenues for future research and development in the area of yoga pose classification and correction using SVM, particularly with regards to incorporating yoga poses tailored to specific health conditions or diseases. One potential direction for future work is to expand the database of yoga poses included in the system to encompass a wider range of health concerns and conditions. This would involve researching and identifying yoga poses that are beneficial for individuals with specific health conditions, such as diabetes or heart disease, and incorporating them into the system's database. Also to develop more personalized feedback and guidance for practitioners based on their individual health conditions and goals. This could involve incorporating machine learning algorithms that adapt to practitioners' progress and provide feedback that is tailored to their unique needs.

REFERENCES

[1] Anand Thoutam, V., Srivastava, A., Badal, T., Kumar Mishra, V., Sinha, G.R., Sakalle, A., Bhardwaj, H., & Raj, M. (2022). Yoga Pose Estimation and Feedback Generation Using Deep Learning. Computational Intelligence and Neuroscience, 2022.

[2] Dr. Maya Bembde et al., “Yoga Posture Detection and Correction System”, International Journal of Advanced Research in Science, Communication and Technology , Vol 2, Issue 1, July 2022.

[3] U. Bahukhandi and S. Gupta, "Yoga Pose Detection and Classification Using Machine Learning Techniques," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 03, no. 12, pp. 1-8, Dec. 2021, e-ISSN: 2582-5208

[4] Mr. Kunal Verma, Mr. Dharmesh Dhabliya. (2015). Design of Hand Motion Assist Robot for Rehabilitation Physiotherapy. International Journal of New Practices in Management and Engineering, 4(04), 07 - 11. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/40

[5] Bhosale, Varsha & Nandeshwar, Pranjal & Bale, Abhishek & Sankhe, Janmesh. (2022). Yoga Pose Detection and Correction using Posenet and KNN. International Research Journal of Engineering and Technology, vol. 9, issue 4, April 2022.

[6] Kumar, Deepak & Sinha, Anurag. (2020). Yoga Pose Detection and Classification Using Deep Learning. International Journal of Scientific Research in Computer Science Engineering and Information Technology. 10.32628/CSEIT206623.

[7] S. Patil, A. Pawar, A. Peshave, A. N. Ansari and A. Navada, "Yoga tutor visualization and analysis using SURF algorithm," 2011 IEEE Control and System Graduate Research Colloquium, Shah Alam, Malaysia, 2011, pp. 43-46, doi: 10.1109/ICSGRC.2011.5991827.

[8] Dwarkanath Pande, S. ., & Hasane Ahammad, D. S. . (2022). Cognitive Computing-Based Network Access Control System in Secure Physical Layer. Research Journal of Computer Systems and Engineering, 3(1), 14–20. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/36

[9] Y. Agrawal, Y. Shah and A. Sharma, "Implementation of Machine Learning Technique for Identification of Yoga Poses," 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), 2020, pp. 40-43, Doi: 10.1109/CSNT48778. 2020.9115758.

[10] F. Rishan, B. De Silva, S. Alawathugoda, S. Nijabdeen, L. Rupasinghe and C. Liyanapathirana, "Infinity Yoga Tutor: Yoga Posture Detection and Correction System," 2020 5th International Conference on Information Technology Research (ICITR), 2020, pp. 1-6,Doi: 10.1109/ICITR51448.2020.9310832.

[11] Santosh Kumar Yadav1, Amitojdeep Singh2, Abhishek Gupta2, Jagdish Lal Raheja1,” Real-time Yoga recognition using deep learning,” 9 May 2019 Springer-Verlag London Ltd., part of Springer Nature 2019.

[12] Smit, S., Popova, E., Milić, M., Costa, A., & Martínez, L. Machine Learning-based Predictive Maintenance for Industrial

Systems. Kuwait Journal of Machine Learning, 1(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/139

[13] Manisha Verma1, Sudhakar Kumawat2, Yuta Nakashima1 , Shanmuganathan Raman2," Yoga-82: A New Dataset for Fine-grained Classification of Human Poses," CVPR2020 IEEE.

[14] Nagalakshmi Vallabhaneni, Dr. P. Prabhavathy," The Analysis of the Impact of Yoga on Healthcare and Conventional Strategies for Human Pose Recognition," 27 January 2021, Turkish Journal of Computer and Mathematics Education.

[15] Bhujbal, A., & Mane, D.T. (2019). A Survey On Deep Learning Approaches For Vehicle And Number Plate Detection. International Journal of Scientific & Technology Research, 8, 1378-1383.

[16] D.T. Mane, U.V. Kulkarni (2018).Modified Fuzzy Hypersphere Neural Network for Pattern Classification using Supervised Clustering, Procedia Computer Science, Volume 143, 2018, Pages 295-302, https://doi.org/10.1016/ j.procs.2018.10.399.

[17] Mane, D.T., Kumbharkar, P.B., Dhotre, P.S., Borde, S. (2021). Vehicle-Type Classification Using Customized Fuzzy Convolutional Neural Network. In: Bhateja, V., Satapathy, S.C., Travieso-González, C.M., Aradhya, V.N.M. (eds) Data Engineering and Intelligent Computing. Advances in Intelligent Systems and Computing, vol 1407. Springer, Singapore..

[18] Fatima Abbas, Deep Learning Approaches for Medical Image Analysis and Diagnosis , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[19] Abarna, S., Radhika Rani, V., & Dhanalakshmi, P. (2021). A Review of Machine Learning Technique for Yoga Posture Classification. International Research Journal of Engineering and Technology (IRJET), Nov 2021.

[20] Mediapipe - Pose landmark Detection [online], Available: Pose landmarks detection task guide | MediaPipe | Google Developers

[21] Yoga Poses for Diabetes (https://www. medicalnewstoday.com /articles/317381#poses)

[22] Singh, P. ., & Sharma, D. V. . (2023). Pre-Processing of Mobile Camera Captured Images for OCR . International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 147–155. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2518

[23] Yoga Poses for Back Pain (https:// rajyogarishikesh.com/yoga-for-back-pain.html)

[24] Yoga Poses for Depression (https:// www.stylecraze.com/ articles/yoga-poses-that-will-help-you-fight-depression/)