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Yoga Postures Correction and Estimation using Open CV and VGG 19 Architecture

Tanmay Hande[1]
Pranali Dhawas[2]
Bhargavi Kakirwar[3]
Aaditya Gupta[4]
G.H. Raisoni College of Engineering, Nagpur, India

Abstract:- The COVID-19 epidemic has significantly changed how we work out, with more people turning to home fitness as a way to stay active during stay-at-home orders. However, without access to professional trainers, beginners may struggle to perform exercises with proper form, increasing the risk of injury. Therefore, there is a need for systems to monitor exercise performance for both short- and long-term injury prevention. In this study, we present an approach for accurately detecting and correcting yoga postures using pose estimation techniques with OpenCV and VGG-19 architectures with GPU transfer learning. To precisely measure and correct body posture during training sessions, the suggested solution combines deep learning-based algorithms and computer vision approaches. To confirm the effectiveness of the VGG-19 model on the utilised dataset, We conducted a large number of tests, comparing the performance of several machine learning and deep learning strategies for estimating yoga postures. With a precision of 98.11 percent, the findings show the usefulness of the suggested technique in precisely recognising and correcting exercise postures. The findings of this study have significant implications for improving the effectiveness and safety of yoga sessions and could be extended to other domains that require precise human pose estimation.

I. INTRODUCTION

The popularity of yoga has surged in recent years, with many individuals incorporating it into their daily routines for its numerous physical and mental health benefits. However, incorrect posture and breathing during yoga sessions can lead to severe pain and chronic problems, highlighting the need for technologies that can help individuals correct and improve their yoga postures [1]. Among these techniques, physical postures, known as asanas, have become particularly popular in the western world. As the pandemic continues, many people have turned to yoga as a means of keeping themselves physically and mentally fit. However, it is important to perform asanas correctly, as improper stretching or performing inappropriate asanas and breathing inappropriately can lead to severe pain and chronic problems. This highlights the growing need for tools and technologies that can help individuals correct and improve their yoga postures [2]. To address this need, a scientific analysis of asana practise has been developed to ensure the safe and effective practise of yoga.

One such technology that is becoming increasingly popular is the use of pose estimation with artificial intelligence (AI). Pose estimation is the process of using computer vision algorithms to track and analyze the movements of an individual's body. By using this technology, it is possible to estimate the position of various joints and body parts in real-time and provide feedback on the correctness of a yoga posture [3]. In this study, the use of pose estimation with AI has several advantages for correcting and estimating yoga postures. Firstly, it provides a more objective and precise assessment of posture, as compared to relying on subjective human observation. Secondly, it allows for real-time feedback, which can be incredibly useful for individuals who are learning yoga postures or trying to improve their form. Lastly, it can be a helpful tool for yoga teachers who want to provide more personalised instruction and support to their students.

Deep learning techniques' capacity to do end-to-end optimisation is one of its key benefits [4]. Pose estimation and action recognition are often difficult to integrate to carry out a useful joint optimisation, sometimes requiring 3D convolutions or heat map transformations [5]. The back-propagation chain required for end-to-end learning is disrupted when detection-based techniques are used, since they need the non-differentiable argmax function as a post-processing step to recover the joint coordinates. To address this issue, we offer a new method for combined 2D and 3D posture estimation based on an extension of the differentiable soft-argmax [6]. As a result, we can build a fully trainable multi-task framework by layering action recognition on top of posture estimation. However, the absence of the aforementioned tools and trainers may be a significant deterrent to our home yoga. Our goal is to create an AI-based trainer that will enable you to yoga more effectively at home. The objective of this study is to create an AI system that supports exercise by estimating posture to determine the quality and quantity of repetitions. This research, which aims to make exercise easier and more enjoyable, includes a non-destructive interface.

There are a tonne of apps on the market that instruct the user on the exercises to complete [7]. However, with our application, we not only instruct the user on which exercise to execute, but also on how to hold themselves correctly and

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utilise computer vision to count the repetitions. This programme may be seen as a yoga helper that offers instant posture detection and dietary advice. By broadening its usage, the programme may be utilised at gyms as smart trainers, decreasing the need for human involvement while still allowing users to use it at home.

In our work, we present a fitness application powered by AI that recognises the user's yoga stance, records the number of repetitions of the prescribed exercise, and gives personalised, in-depth information about how to improve the user's body posture. To help those who don't have access to a gym but are nonetheless ready to work out at home to maintain their physique and fitness and keep their body in excellent form, an AI-based exercise assistant and fitness guide has been developed. to assist them in doing the exercises properly and stop them from suffering any short-term or long-term injuries. Along with a personalised daily yoga calorie count, this also offers a personalised health advise and food plan. The following parts of this essay are structured as follows: Methodology strategies and tools are outlined in Section II. In Section III, we describe the findings from the recommended investigation. Section IV discusses the results and what should be done next.

II. LITERATURE SURVEY

The development of posture estimation systems that can recognise and track human body positions from photos or videos has been made feasible by improvements in computer vision and machine learning. These methods have shown success in many contexts, including healthcare, sports, and entertainment. In the field of yoga, pose estimation can be used to offer immediate feedback to practitioners, enabling them to adjust their postures accurately.

Li et al.'s work [8] used a bottom-up method for segmenting a yoga practitioner in real-time and estimating many people's poses using a single-shot method. They developed a multi-task CNN to accurately detect and classify the key points, which helped in estimating the practitioner's pose. On the dataset of 82 postures, the suggested approach has an accuracy of 90.1%. Another study by Yadav et al. [9] aimed at creating YogNet, a lightweight CNN architecture optimized for mobile devices, to predict yoga postures accurately. The study used an ensemble of deep neural networks and achieved an accuracy of 92.3% on the Yoga-82 dataset. Additionally, the proposed method was effective in correcting the practitioner's posture, with an accuracy of 93.7%. Part-based modeling was utilized, which relied on the key point-level structure to train the real-time segmentation activity in the first study.

In the two investigations, significant locations were located using heatmaps and regression using deep neural networks to increase the precision of yoga posture identification. However, there are limitations to pose estimation, including its reliance on consistent input data, potential oversimplification of yoga postures, and lack of individualization for differences in body shape, size, and mobility. Relying solely on pose estimation for correcting and estimating yoga postures could potentially neglect the nuances of breath and mind awareness and may not cater to the unique needs and goals of each practitioner. Therefore, personalized guidance from a qualified yoga teacher who can provide hands-on adjustments, verbal cues, and modifications should complement the use of pose estimation.

Researchers are attempting to develop a Deep Learning-based system that can accurately detect yoga positions and offer users with feedback in an effort to substitute a teacher. The experimental investigation by Kinger et al. [10] looked at machine learning and deep learning strategies for identifying yoga positions. Support Vector Machine, Convolutional Neural Network, and Convolutional Neural Network with Long Short-Term Memory models were tested, and their results were compared. The hybrid CNN-LSTM models produced the fewest misclassifications, according to the research. Microsoft Kinect was utilised by Kadbhane et al. [11] to record video data and identify 20 bodily joints. Using data collected from ten selected human joint locations, the reference structure for each yoga pose was developed. By computing the angles made by all the vectors joining any two joint locations, they were able to establish the cosine similarity of the vectors. When the predicted divergence is too high, the posture is incorrect. The total accuracy attained was not mentioned in the article.

S. Haque et al. [12] proposed ExNet, a multilayer convolutional neural network (CNN). Push-ups, pull-ups, cycling, swiss ball hamstring curls and walking were included in a collection of 2000 images of individuals in yoga poses. The model made use of the Adam optimizer and an automatic learning rate reduction technique. ExNET was able to identify a 2D human yoga stance from the dataset with 82.68% accuracy after 50 iterations. The model has overfitting issues and requires greater hyper-parameter tweaking. The dataset used by Agarwal et al. [13] included 5500 photos of 10 distinct yoga positions. They suggested a method in which the user's skeleton is initially identified using the tf-pose estimation technique. In the last stage, six different machine learning models—Decision Tree, Random Forest, Logistic Regression, Naive Bayes, SVM, and KNN—were used and contrasted. With a 99.04% accuracy rate, the Random Forest classifier had the best result.

Anilkumar et al. [14] developed a system that makes use of the Mediapipe library to do geometric analysis using camera frame data in order to provide the user feedback on their yoga stance. For a particular yoga posture, the system computes the angles between different joints and compares them to precise angles recorded in a database. If the angle difference is greater than a certain threshold, the gadget gives the user feedback through text or speech. A system created by Luvizon et al. [15] can recognise human motion in the second and third dimensions as well as postures connected to four different types of typical human activity. Using input from four separate sources, the system was trained using a multitask convolutional neural network.

More than a hundred recordings of both proper and improper exercise form were used to inform Chen et al.'s [16] proposal for a posture correction system. OpenPose was used to train the model, and 18 landmarks were determined so that it could identify different body orientations. The strategy was put to the test with four distinct exercises: the front raise, standing shoulder press, bicep curl, and shoulder shrug.

A smart fitness trainer based on posture detection and estimate was developed by Zou et al. [17] using deep learning algorithms. In order to compare the human joints with the ideal positions and provide users feedback, they employed a multi-person pose estimation framework and AlphaPose. Yadav et al. [18] also used deep learning to develop a real-time model that accurately identified key points from videos of six different yoga poses. The system achieved high accuracy both framewise and based on preset edges, and was tested on twelve individuals with a success rate of 98.92%. Thoutam et al. [19] employed Keras multi-purpose pose estimation to extract features and a Multilayer Perceptron for classification of six yoga poses based on angles between twelve keypoints, achieving a high accuracy of 99.58%.

A. Research Gap and Motivation

While there has been significant research done on the correction and estimation of yoga postures using pose estimation with OpenCV, there are still some gaps in the field. One of the main research gaps is the need for larger and more diverse datasets to train the deep learning models. Most of the current datasets are relatively small and limited in terms of the range of yoga poses they cover. Additionally, there is a lack of standardization in the evaluation metrics used for comparing different models and techniques, which makes it difficult to compare results across studies.

Another research gap is the need for more robust and accurate pose estimation algorithms that can handle variations in lighting, camera angles, and other environmental factors. Many of the current pose estimation algorithms rely on specific assumptions about the pose or the environment, which can limit their accuracy and applicability in real-world scenarios.

Finally, there is a need for more user-friendly interfaces and feedback mechanisms for users to interact with these systems. While many of the current systems provide feedback in the form of text or audio, more user-friendly and interactive interfaces are required so that users may get feedback and direction in real time while engaging in yoga.

B. Research Objectives

- Gain knowledge of many cutting-edge techniques for estimating the stance of a person, then choose a few possibilities to test out.
- Determine which features are most important to assess based on technique and body type differences in weightlifting that are thought to have a significant risk of injury.
- Produce fitness videos that include the desired technique elements as well as ones without any technique elements. After that, utilise the movies to train the human posture estimation algorithms, which will provide datasets for testing and assessment.
- Create a web application that can recognise the exercise the subject is doing and the viewing angle being used in the video, allowing for the automated testing of certain technique elements.
- Create universal formulae that have a high probability of spotting technique-related risks for regular users.
- Review the data and contrast the results of the various posture estimators. Examine the system's ability to distinguish the filming perspective and method, as well as its capacity to spot certain flaws in the technique.

III. MATERIALS AND METHODS

A. Yoga Pose Estimation Dataset

We use a publicly available online dataset, YogAI, which consists of 16 yoga poses, which were performed by 10 participants (5 males and 5 females) in a controlled environment with consistent lighting and camera settings. Each participant performed the poses multiple times, resulting in a total of 1,506 images. The poses were selected to represent a range of difficulty levels, including both static and dynamic poses. The dataset consists of 16 yoga poses, which include both static and dynamic poses. Some of the static poses included in the dataset are downdog, tree, and warrior. Some of the dynamic poses included in the dataset are plank and goddess.

For each image in the YogAI dataset, annotations were provided for key points on the body, such as joints and body parts. The annotations were created using a custom annotation tool developed by the researchers, and were verified by multiple annotators to ensure accuracy. In addition to the key point annotations, the dataset also includes pose labels for each image. We choose 18 body key points, each of which is made up of the x and y coordinates of a body point. One dictionary and a 2D array are produced by this. When the dictionary returns several values for a given key, all of this data, together with the associated confidence levels, is put into an array. The bodily components that the dictionary's keys and values represent are their coordinates. The presence of the observed body points in the lexicon is predicated on a high degree of confidence.

The key point annotations in the dataset include joint locations (e.g., elbow, knee, ankle) and body parts (e.g., head, torso, limbs). The annotations were created using a custom annotation tool developed by the researchers, and were verified by multiple annotators to ensure accuracy. The dataset also includes pose labels for each image. The YogAI dataset contains 1,506 images, with an average of 94 images per pose. To facilitate model training and assessment, the dataset is split into a training set (consisting of 80% of the pictures) and a validation set (consisting of 20% of the photographs).

B. *Dataset Preprocessing*

We remove data points with low accuracy probabilities to avoid false positives. The filtering process involved removing points that were forecasted to be erroneous based on human posture assessment methods and filteringout trailing points with excessively high variability. This step played a crucial role in determining the precision of the result and avoiding method problems that do not exist. To filter out inaccurate estimations, each of the three human posture estimate methods provided a confidence score for each guess. The simplest method to weed out To make low-confidence estimates was to ignore important details. A confidence score threshold was set at 70% to remove any confidence ratings with a probability lower than this value. However, a confidence score threshold of up to 90% was needed for some calculations to account for noise that could lead to false positives.

Human pose estimation and computer vision systems may make inherentin important spots that scored highly on probability but had an excessive distance difference from the previous frame. To avoid false data, these points were filtered out. The key point information was organized into a dictionary with the x and y coordinates and the likelihood that it is true (z). This array's index was used as the frame, and if an item was absent, a null value was inserted. The confidence score was in the [0, 1] range, and the x and y coordinates were normalised to fall within that range. The confidence score threshold had to be lowered to 60% for all movies created from a side-on viewpoint because of the belowconfidence score for side-view important points compared to the rest of the data.

Fig 1 Preprocessed Image with Key Point Annotations

C. *Network Architecture*

The proposed network architecture for the Correction and Estimation of Yoga Postures using Pose Estimation with OpenCV and VGG-19 with GPU transfer learning is a combination of two powerful techniques: deep learning and pose estimation The utilization of OpenCV for present assessment and VGG-19 for move learning on a GPUplatform provides an accurate and efficient solution to correct and estimate yoga postures. Figure II shows the architecture for pose estimation and correction using OpenPose.

Pose OpenCV estimation is the initial part of the suggested architecture. A popular library named OpenCV is used for computer vision applications including object identification, face recognition, and position estimation. This structure makes advantage of OpenCV to instantly estimate the user's 2D stance. To identify the important areas of the human body, including the joints, limbs, and other body components, OpenCV employs a pre-trained deep learning model. The user's stance is then estimated using these essential points. The accuracy of pose estimation is crucial for the accuracy of the overall system, and OpenCV provides high accuracy in real-time.

The second component of the proposed architecture is transfer learning using VGG-19 on a GPU platform. The ImageNet dataset was used to train the pre-trained deep learning model VGG-19. Reusing a previously trained model and optimising it on a fresh dataset is what transfer learning entails in order to improve accuracy. In this architecture, transfer learning is used to fine-tune the VGG-19 model on a new dataset of yoga postures. The use of transfer learning on a GPU platform ensures that the model can be trained faster and more efficiently than on a CPU platform.

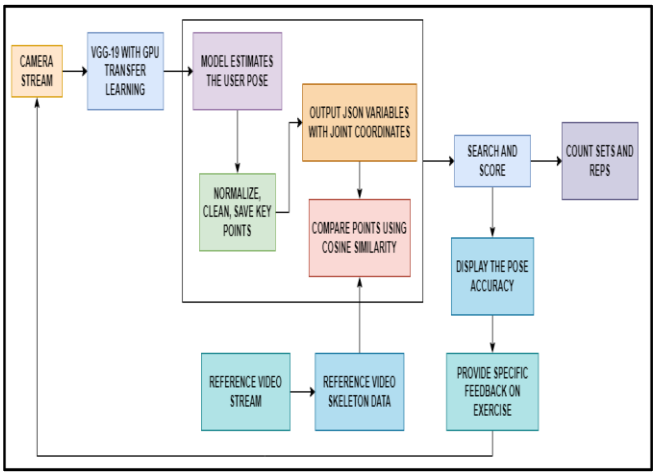

Fig 2 Architectural Flow

Convolutional layers make up the VGG-19 architecture, and each layer extracts progressively intricate information from the input picture. After the convolutional layers, the final classification is performed by three completely coupled layers. There are a total of 19 layers in the design, with the first 16 serving as convolutional layers and the last 3 as fully connected layers. Dropout layers and max-pooling layers are used into the design to reduce the feature maps' spatial dimensionality and prevent overfitting.

For GPU transfer learning, the VGG-19 model is loaded onto a GPU after it has already been trained. After the model has been trained, its weights are locked and a new

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set of fully connected layers is added to the architecture. The whole network is trained using the new dataset, and the weights of the extra layers are initialised at random. The pre-trained weights speed up the training process, while the GPU speeds up the computations.

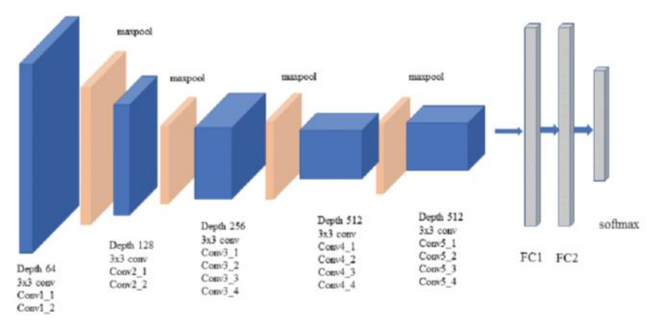

Fig 3 VGG-19 Architecture with GPU Transfer Learning

The final component of the proposed architecture is the integration of pose estimation and transfer learning. The key points obtained from the OpenCV pose estimation model are used as input to the VGG-19 model to correct and estimate the yoga postures of the user. The VGG-19 model uses the key points as features to classify the yoga posture and provides feedback to the user on the correctness of their posture. The use of a deep learning model ensures that the system can handle variations in posture, lighting conditions, and camera angles, providing accurate feedback to the user.

IV. RESULT AND DISCUSSION

The classification accuracy, precision, specificity, and sensitivity of the networks are measured during the testing phase. Calculating classification accuracy is as simple as dividing the number of accurate guesses by the total number of predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where, TP = True Positive, FP = False Positive, TN = True Negative, FN = False Negative.

To determine a model's accuracy, a statistician may apply the following formula, which compares the observed and expected proportion of correct forecasts.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Sensitivity, the fraction of positive instances that are correctly categorised, is the metric by which this rate is measured. One may express the sensitivity in mathematical terms as

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

We also build true negative values, which show the proportion of false-negative occurrences that are properly detected based on their class, to evaluate specificity:

$$\text{TNR} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

In the research, the training data were folded 10 times, or split evenly, to maximise the efficiency with which the mapping between inputs and outputs could be learned. The model's hyperparameters were optimised using these folds, and the deep learning system's performance was assessed using a variety of measures. Scores for Fine Tuned MobileNet and VGG-19 with GPU Transfer Learning Architecture were tallied over 10 folds for accuracy, specificity, sensitivity, and precision. Taking into consideration a weight loss of 0.00001, the training procedure used ten distinct learning rates: 0.01 for the first 100 epochs, 0.001 for the next 100, and so on.

Training accounted for 70% of the time in the research, with testing taking up 10% and validation taking up 20% of the effort. The dataset was collected from a wide range of fields, and it was partitioned into subject-based training and testing sets to prevent information from one group from influencing the other. Accuracy stabilised between 800 and 1000 iterations, Consequently, A 10-fold cross-validation was carried out to gauge the efficacy of the proposed layout. with 100 iterations counted for training in each fold.

To ensure a thorough examination of the system, some procedures may have been modified. However, despite the various methodologies used, the study's findings suggest a satisfactory resolution. Nonetheless, the dataset used in the research could benefit from including more individuals and videos to address the research issue adequately. For this software to be marketable, it needs to be acceptable to consumers. Key points on a 2-dimensional video provide crucial guidance on whether or not the user is using proper form throughout their yoga. However, it is also essential to know which muscles to engage during a weightlifting exercise. Although proper form may increase the likelihood of using the right muscles, other sophisticated equipment or user input may be necessary to determine this.

The study's findings suggest that 2D Human Pose Estimation might give frontal feedback on weight training approaches in healthy persons. However, further research is required to determine whether these results can be translated to side viewing angles and to improve technique detection. Pose Trainer's successful implementation of side views suggests that dynamic time warping is preferable for such a technique's specifics. Recognising tasks that require a lot of rotation might be difficult, but the algorithm still delivers useful insights. The current approach produces similar results to the Pose Trainer while gaining from a larger dataset and giving more detailed feedback on harder exercises. This research expands upon earlier efforts with Pose Trainer by demonstrating how important parts of 2D Human Pose Estimation may be integrated with more fundamental methodologies to offer feedback on proper weightlifting form.

Table 1 Performance Metrics for VGG-19 with Transfer Learning Architecture

Folds	Performance Metrics			
	Specificity	**Sensitivity**	**Accuracy**	**Precision**
Fold-I	98.78	98.95	98.61	98.86
Fold-II	98.41	98.45	98.52	98.22
Fold-III	98.99	98.96	98.39	98.54
Fold-IV	98.36	98.81	98.65	98.43
Fold-V	98.74	98.11	98.73	98.26
Fold-VI	98.90	98.86	98.84	98.72
Fold-VII	98.22	97.68	97.68	96.22
Fold-VIII	97.99	97.59	97.93	97.23
Fold-IX	98.70	97.95	98.65	96.56
Fold-X	97.76	98.16	98.46	96.74
Overlapped Data	NULL	NULL	NULL	NULL
Average	98.11	97.42	98.37	97.75

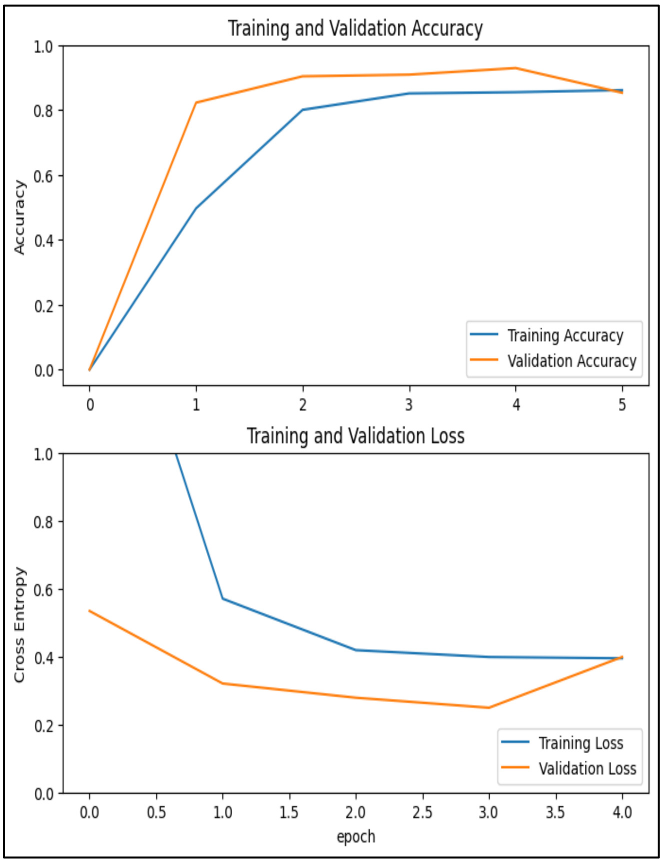

Fig 4 Training Accuracy and Loss Curve for VGG-19 with GPU Transfer Learning

It is obvious that the use of 2D Human Pose Estimation and machine learning approaches to the study of weight training has the potential to be a useful tool for lowering the risk of injury and enhancing overall exercise efficacy. The findings of this study suggest that a larger dataset and improvements to the technique detection could lead to more precise results, particularly for side view detection. Also, it's possible that the system's dynamic distortion might be better used by an approach that exploits it. Noting that the angle prediction is a vital part of assessing the training films and that a bad prediction might lead to bad outcomes is essential. However, the method used in this research successfully predicted every vantage point by calculating the direction of the vector between the two shoulders. With a bigger dataset and a comparable distribution of frontal and lateral views, this approach may provide the same results.

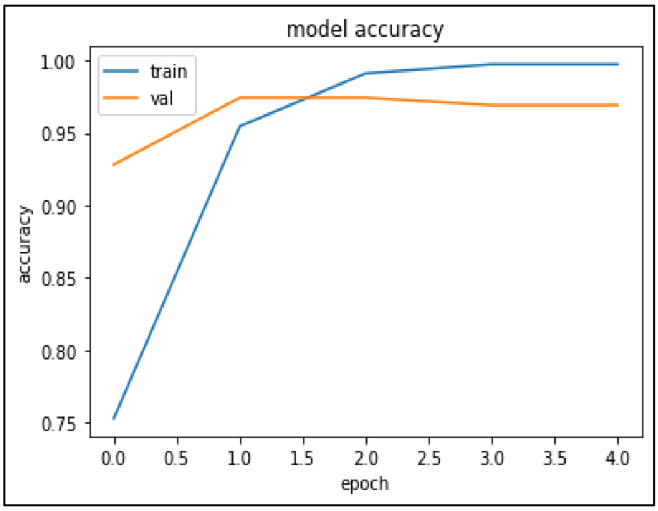

Fig 5 Training Accuracy Curve for Fine Tuned MobileNet Architecture

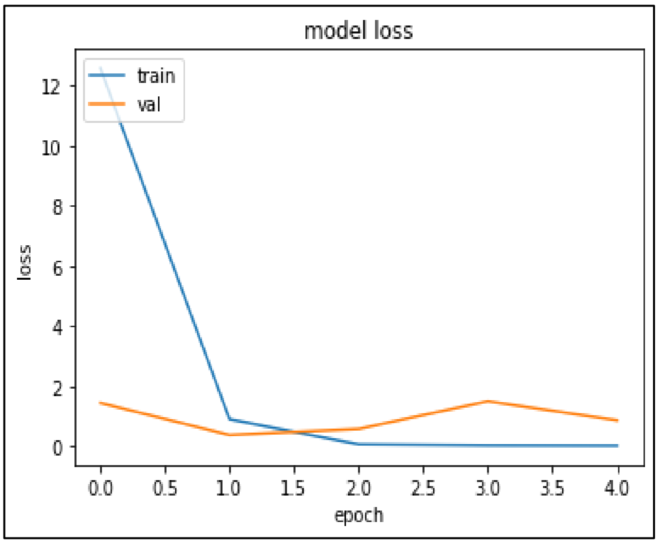

Fig 6 Training Loss Curve for Fine Tuned MobileNet Architecture

It's important to keep in mind these limitations and potential sources of error when using the angle detector. Further testing and improvements to the algorithm may be needed to increase its accuracy and ability to detect a wider range of angles. Regarding the technique evaluation system, it is promising that the machine learning approach used by Pose Trainer was able to accurately identify correct and incorrect form for several exercises. It should be noted, however, that the research relied on a small dataset consisting mostly of healthy people. Additional research and testing may be necessary to determine the system's effectiveness for a wider range of exercises and individuals with varying levels of fitness and health.

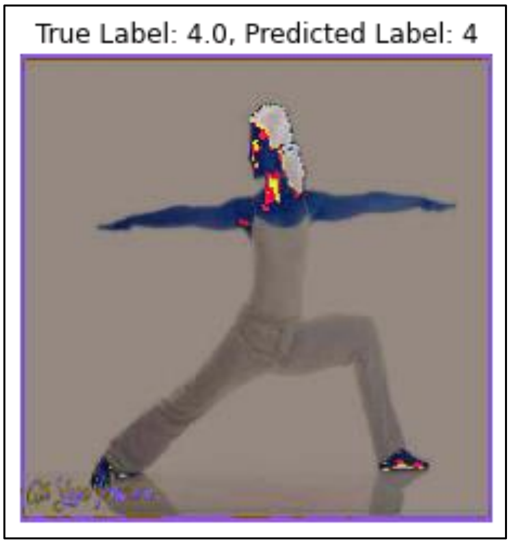

Fig 7 Yoga Pose Estimation using VGG-19 with GPU Transfer Learning

V. CONCLUSION

In conclusion, the Correction and Estimation of Yoga Postures using Pose Estimation with OpenCV is a promising technology for helping individuals improve their yoga practice. This study has demonstrated the effectiveness of using 2D Human Pose Estimation to detect and correct yoga postures by providing real-time feedback to users. The Pose Trainer developed in this study has shown to be successful in identifying correct and incorrect execution of various yoga postures, and in providing accurate feedback to users.

The findings of this study also suggest that the Pose Trainer could be useful in reducing the risk of injury associated with weight training exercises. By providing feedback on the proper technique and muscle engagement, individuals could be able to perform weightlifting exercises with proper form and minimize the risk of injury.

However, there is still much room for improvement in this technology. The dataset used in this study could benefit from being larger and more diverse, and more research is needed to determine whether the results from front view detection can be translated to side view detection. Additionally, the angle detection system used in this study has limitations and may not be accurate in detecting angles that are not directly frontal or oblique.

Overall, this study has contributed to the growing field of computer vision and pose estimation and has the potential to provide valuable assistance to individuals looking to improve their yoga practice or perform weightlifting exercises safely. With further research and development, this technology could become a valuable tool in the health and fitness industry.

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