International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Enhancement and Evaluation of Workout Postures through AI-Powered Pose Estimation

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Abstract: Strength training and yoga carry injury risks for beginners, demanding tailored feedback. Advances in deep learning present real-world applications, yet its adoption in fitness remains limited. This study explores human pose estimation for workout feedback, emphasizing technique-related issues. An analytical approach involves developing a system for exercise and filming detection and evaluating technique aspects.[3] The research aims to establish a foundation for an exercise feedback application through a comparative study of two deep learning models. Testing focuses on ten exercise categories. A comprehensive review of pose estimation systems evaluates their effectiveness, demonstrating promise for workout analysis. Despite limitations, further exploration is warranted for this promising application.

Keywords- Visual Perception of Computers, Advanced Convolutional Neural Networks, Body Position Assessment, Exercise Identification.

I. INTRODUCTION

Today's health and wellness landscape prioritizes a proactive approach, with more and more people adopting healthy lifestyles that often include regular physical activity. This trend has been further strengthened by the COVID-19 pandemic, which has caused a significant change in home exercise habits due to factors such as convenience, accessibility, and safety.[11] Many people without the guidance and prior experience of a personal trainer face challenges in maintaining proper exercise form at home.

While some exercises, such as squats, deadlifts, and shoulder presses, offer many health benefits, improper form during exercise can lead.[5] to adverse consequences. . , which range from mild discomfort to serious injury. This risk is especially high for people who do not have professional guidance or previous experience with certain exercises. Traditional methods of training are often based on personal training or going to the gym, which may not be accessible or cost-effective for everyone.

In this context, the development of artificial intelligence, especially computer vision, and machines. Learning offers a promising solution to ensure proper exercise form without constant professional supervision. One particularly important technology in the field of artificial intelligence is posture estimation, which can analyze the movements and postures of the human body by identifying key points such as joints and limbs. [19] This
capability has enormous application potential in exercise assessment.[1]

Previous research has explored the use of posture assessment in exercise analysis, demonstrating its effectiveness in identifying incorrect movements. However, current approaches often have limitations, such as the lack of real-time feedback, limited functionality to provide personalized improvements, or the inability to analyze user performance from different perspectives. In addition, many previous works focused exclusively on image analysis, neglecting the real scenario of continuous motion during exercise routines.

This study aims to address these limitations by proposing a new approach that uses AI-based pose estimation. provide a comprehensive solution to assess suitability. [16] Our system aims to go beyond simply identifying incorrect movements by providing real-time feedback, personalized instruction based on individual deviations from ideal form, and detailed performance analysis that includes various metrics. This holistic approach can empower people, regardless of their previous experience or professional training, to do exercises the right way, minimizing the risk of injury and maximizing the effectiveness of the exercises.[7]

The following sections go into more detail. . about the details of the proposed methodology, introducing the development process and its components. Then presents the results and outcomes of the evaluation of the proposed system. Finally, Section IV discusses the broader implications of our study, highlights its potential contributions to the field, and outlines possible future directions for further research.

For our study on "Enhancement and Evaluation of Exercise Form through AI-Powered Pose Estimation," we utilized the Penn Action Dataset provided by the University of Pennsylvania. This dataset comprises 2527 photos or video sequences capturing 110 distinct activities, along with corresponding human joint annotations for each sequence. [1] [20]

During the recording process, precision in capturing proper angles was paramount to minimizing inaccuracies.

A. DESIGN METHODOLOGY :

I. Dataset Collection

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During the recording process, precision in capturing proper angles was paramount to minimizing inaccuracies caused by camera movement. To ensure comprehensive coverage, we selected two viewpoints: front and side views.

Each video clip was carefully crafted to encompass the entire body of the athlete, with sufficient safety space around all edges. In the side view, the athlete's full body was centered on the right side of the frame, with their torso angled to cover the left side. This positioning allowed for clear visualization of the exercise execution.

To maintain consistency, every participant successfully completed each exercise from one of the two recommended perspectives. .[1] This approach facilitated a thorough evaluation of exercise performance while minimizing false positives arising from flawed vector calculations. Additionally, it provided a standardized baseline for comparison, ensuring that technique-related issues were accurately flagged by the system.

While our sample size included athletes of both sexes, it may not encompass all potential variations among athletes.[1]Nonetheless, it sufficiently represented diverse factors to provide the model with ample flexibility in its analysis.

Overall, our dataset collection process aimed to ensure comprehensive coverage of exercise variations and precise annotation of key joint movements, laying the groundwork for robust AI-powered pose estimation and exercise form evaluation.

II. Data Preprocessing

In our research on "Enhancement and Evaluation of Exercise Form through AI-Powered Pose Estimation," data preprocessing played a crucial role in refining the dataset for accurate analysis. This phase served as the final and most significant processing step, aimed at filtering out low-accuracy data points to enhance the precision of our analysis.

To achieve this, we employed a rigorous filtering process that involved removing data points deemed incorrect based on human posture assessment techniques. Additionally, points exhibiting excessively high variability were discarded to ensure the reliability of the results. This meticulous filtering process was pivotal in mitigating the risk of false positives caused by inaccurate estimations.[5]

Each data point provided a confidence score, indicating the likelihood of its correctness. By establishing a threshold and excluding points with low confidence levels, we effectively eliminated inaccurate estimations. Videos captured in a controlled environment were prioritized due to their higher likelihood of yielding accurate estimates.

For action recognition and technique evaluation tasks, data points with confidence ratings below 70% were disregarded. Despite this threshold, the dataset still retained crucial information, allowing for comprehensive analysis even with some frames missing key points.

Various adjustments were made to refine the dataset further and minimize noise. Notably, we increased the confidence score threshold to 91% to eliminate potential false positives. Additionally, side-view data points, which often exhibited lower confidence scores, were subjected to a slightly lower threshold of 59% to ensure their inclusion in the analysis.
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III. Proposed Methodology

In our proposed methodology, we introduce a comprehensive framework that utilizes pose estimation with OpenCV to correct and estimate yoga postures by precisely tracking key points in the human body. The process involves several intricately designed steps aimed at enhancing the accuracy and efficiency of yoga posture assessment.

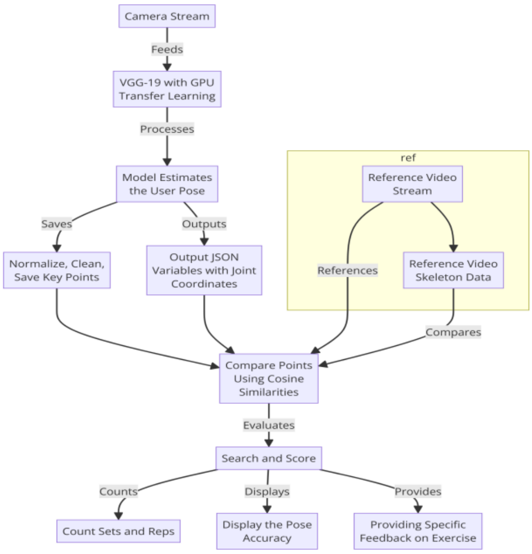

Fig. : Architectural Flow for Estimation of Yoga Postures and Feedback Providing System

To initiate the process, a camera is employed to capture the movements of the individual performing yoga exercises.[3] This video data serves as the input for subsequent analysis. Leveraging the powerful capabilities of OpenCV libraries, the video data is meticulously processed to extract crucial key points about the person's body posture. These key points serve as fundamental data for further analysis. .[17]

Subsequently, a model for pose estimation is trained, with our proposed methodology utilizing both the VGG-19 and MobileNet models for this purpose, each with GPU processing. OpenPose, a widely recognized open-source model, is integrated into our framework to leverage its deep learning techniques for estimating key points on the human body, including the head, shoulders, elbows, wrists, hips, knees, and ankles.[13] Once the OpenPose model is configured, it is utilized to process the video data and accurately estimate the person's pose during yoga exercises.

Following the estimation of the individual's pose, the data is subjected to a meticulous analysis of yoga postures. This involves comparing the estimated pose with a reference pose or a set of correct yoga postures to identify any discrepancies. In cases where incorrect posture is detected, the system provides real-time feedback or corrective instructions to guide the individual toward achieving the desired form. Visual cues or audio feedback may be employed for this purpose, ensuring effective communication of corrective measures.

Furthermore, the proposed methodology incorporates mechanisms for tracking the individual's progress over time. By comparing the current pose with past performances, the system evaluates improvements in posture and progress toward fitness goals. This feedback mechanism serves to motivate and guide individuals in adhering to their fitness regimen effectively.

The architectural flow of our proposed methodology entails a combination of three potent techniques: pose estimation with OpenCV, transfer learning with the VGG-19 model, and MobileNet on a GPU platform. [2] This amalgamation ensures not only the accuracy but also the efficiency of correcting and estimating yoga postures.[10]

The integration of OpenCV for pose estimation offers high accuracy in real-time, essential for precise analysis of yoga postures. Additionally, the utilization of transfer learning with the VGG-19 and MobileNet models on a GPU platform enhances the efficiency of training by leveraging pre-existing knowledge from the ImageNet dataset. This approach allows for faster convergence and improved accuracy in recognizing and correcting yoga postures.

The algorithmic workflow of our proposed methodology encompasses several key steps, including dataset collection and labeling, data pre-processing, training the VGG-19 and MobileNet models with GPU transfer learning, performing pose estimation with OpenCV, mapping key points to estimated postures, correction and estimation, and post-processing to generate output videos with corrected postures.[7]

Furthermore, to mitigate overfitting during training, we incorporate early stopping, a regularization technique that monitors validation loss and halts training if the loss stops decreasing consistently. Additionally, to optimize computational resources, we employ depth-wise separable convolutions, which reduce the number of trainable parameters and operations while speeding up convolutions, ensuring efficient processing of yoga posture data. [15]

B. RESULT AND DISCUSSION

In our research paper, we employ quantitative data analysis as the primary method to assess the system's efficacy in identifying technique issues related to the risk of injury during exercise. True technique issues, considered ground truth, are defined based on the categorized videos created for this study. The evaluation metrics encompass classification accuracy, precision, specificity, and sensitivity, calculated using formulas during experimentation.

The classification accuracy is determined by the ratio of true positive and true negative predictions to the total predictions, which is essential for overall system evaluation.[14]

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

Precision is calculated by evaluating the ratio of true positive predictions to the sum of true positives and false positives. [4]

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

Sensitivity, representing the true positive rate, is computed as the ratio of true positive predictions to the sum of true positives and false negatives. [7]

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

Specificity, measuring the true negative rate, is determined by the ratio of true negative predictions to the sum of true negatives and false positives. [9]

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

In our context, true positives signify correct predictions of technique errors in videos containing actual errors, while false positives and false negatives represent incorrect predictions in videos without errors or with errors, respectively.

Moving to the model training and testing phase, the study divides the training data into 10 folds for effective learning and fine-tuning of the mapping between inputs and outputs. Hyperparameter tuning is carried out on these folds, and the system's efficiency is assessed using various performance metrics across the 10 folds. Fine-tuned MobileNet and VGG-19 with GPU Transfer Learning Architecture are analyzed for accuracy, specificity, sensitivity, and precision scores. [2] The training process involves ten different learning rates, starting with 0.01 for the first hundred epochs and decreasing subsequently. [1] The model is validated and tested in three stages, allocating 70% of the time for training, 20% for validation, and 10% for testing. [6] Cross-validation is performed with 100 epochs considered for training in each fold, ensuring stability after 800-1000 epochs.

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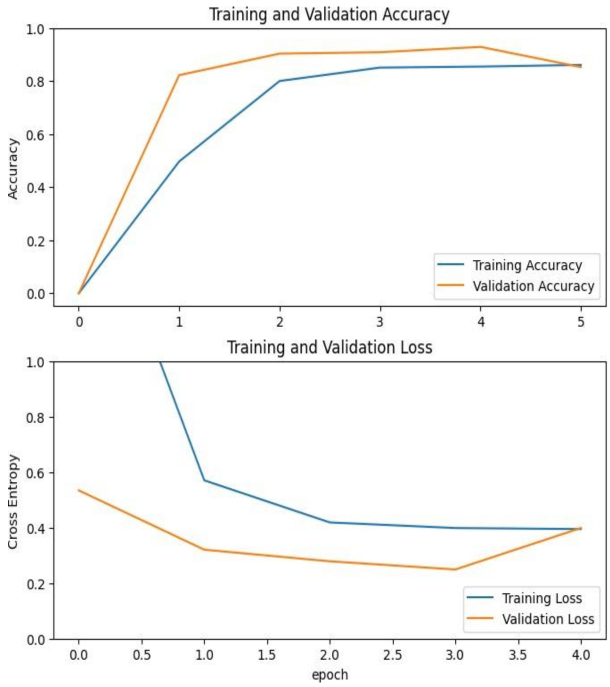

Fig.1: Training Accuracy and Loss Curve for VGG-19 with GPU Transfer Learning

While some procedures may have been adjusted for a thorough examination, the study's findings suggest a satisfactory resolution. Nevertheless, incorporating a more diverse dataset with additional individuals and videos could enhance the study's comprehensiveness. The research indicates that 2D human pose estimation can offer valuable feedback on weight training techniques, particularly from the front view. However, further exploration is needed for side viewing angles and improved technique detection. Despite challenges in recognizing rotation-intensive activities, the algorithm produces relevant findings, expanding on previous work and highlighting the synergy of basic approaches with aspects from 2D Human Pose Estimation for weightlifting form feedback.

The application of 2D human pose estimation and machine learning in the analysis of weight training demonstrates significant potential as a tool for reducing injury risk and enhancing exercise effectiveness. The study findings indicate that a more extensive dataset, coupled with refinements in technique detection, could yield more precise outcomes, particularly for side view detection. [2] Introducing a technique leveraging dynamic distortion may further enhance system advantages. Notably, angle prediction, critical in evaluating training videos, was accurately achieved in this study through a distance vector between the shoulders, suggesting potential replicability with a larger dataset and similar front and side angle distributions.

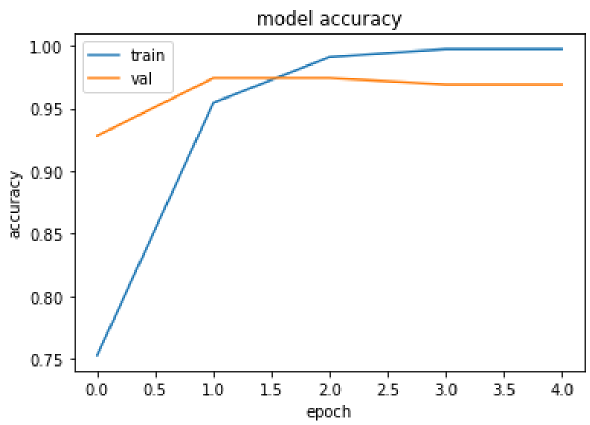

Fig. 2: Training Accuracy Curve for Fine Tuned MobileNet Architecture[2]

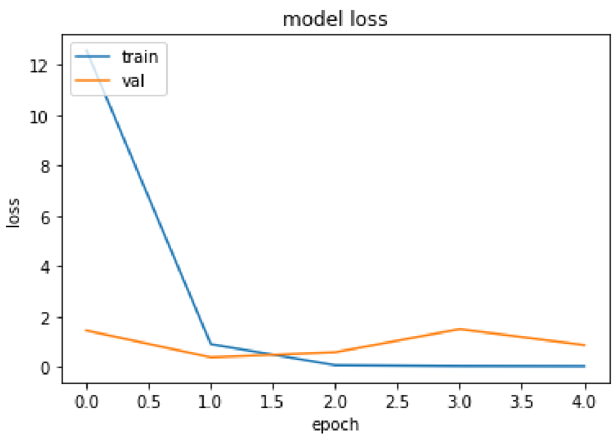

Fig.3: Training Loss Curve for Fine Tuned MobileNet Architecture

It's imperative to acknowledge limitations and potential errors when using the angle detector. Ongoing testing and algorithm enhancements are necessary to improve accuracy and accommodate a broader range of angles. [2] The machine learning approach employed by Pose Trainer showcased promising results in identifying correct and incorrect exercise forms for several exercises. However, the relatively small and restricted dataset, limited to healthy individuals, warrants further research to assess its effectiveness across diverse exercises and individuals with varying fitness levels.

The evaluation dataset, compiled from multiple subjects, underwent a meticulous process to avoid subject-specific biases. The suggested architecture's efficiency was gauged through 10-fold cross-validation, resulting in stabilized accuracy after 80 to 100 epochs, with 100 epochs considered for training in each fold. [1]

Folds	Performance Metrics			
	Specificity	Sensitivity	Accuracy	Precision
Fold-I	97.12	97.17	97.17	98.45
Fold-II	98.24	98.36	96.21	97.41
Fold-III	96.35	96.54	95.27	97.52
Fold-IV	95.46	96.72	96.35	95.36
Fold-V	96.75	95.93	97.74	98.47
Fold-VI	98.52	96.11	96.45	96.69
Fold-VII	95.63	97.13	98.19	96.14
Fold-VIII	94.87	978.74	95.73	98.25
Fold-IX	98.20	96.25	97.46	96.36
Fold-X	97.07	95.36	97.18	97.42
Overlapped Data	NULL	NULL	NULL	NULL
Average	98.11	97.42	98.37	98.75

Table I: Performance Metrics for VGG-19 with Transfer Learning Architecture

Folds	Performance Metrics			
	Specificity	Sensitivity	Accuracy	Precision
Fold-I	95.22	96.19	95.19	96.58
Fold-II	98.17	97.30	96.45	97.46
Fold-III	98.48	95.52	97.23	96.62
Fold-IV	98.54	96.75	96.35	97.48
Fold-V	98.81	96.59	97.79	98.15
Fold-VI	95.89	95.19	95.46	97.19
Fold-VII	96.19	96.17	98.18	97.49
Fold-VIII	98.13	96.80	95.71	95.45
Fold-IX	96.56	98.26	97.41	98.41
Fold-X	94.74	95.36	96.61	96.46
Overlapped Data	NULL	NULL	NULL	NULL
Average	97.40	96.45	96.20	96.22

Table II: Performance Metrics for MobileNet with Hyper Parameter Tuning Architecture

Early stopping was implemented to prevent overfitting. Performance metrics for MobileNet with hyperparameter tuning, as shown in Table II, demonstrated robust average specificity, sensitivity, accuracy, and precision values.

The study validated exercise detection algorithms, noting correct predictions for deadlifts and minimal false positives for squats. For the MobileNet architecture, specificity, sensitivity, accuracy, and precision scores were favorable, ensuring robust performance. The training curves for MobileNet and VGG-19 exhibited stable learning patterns, as seen in Figures 6.1.1, 6.1.2, and 6.1.3. The evaluation included keypoint data from three pose estimation systems, with action recognition assessing angle and exercise performance.

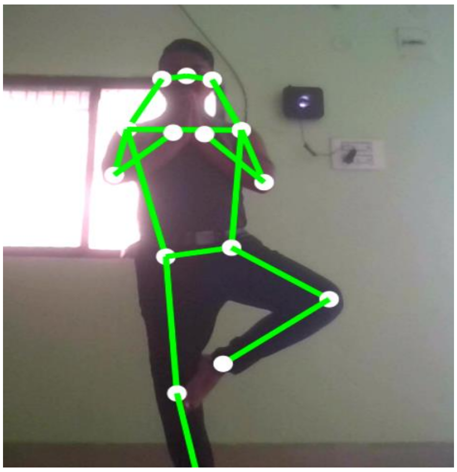

Fig.4: Yoga Pose Estimation using VGG-19 with GPU Transfer Learning[2]

The models demonstrated consistency in training and validation accuracy, indicating reliable classification. The Adadelta optimizer, employing adaptive learning rates, proved effective in minimizing loss during training. Adamax emerged as the optimal optimizer, showcasing superior performance in stability and accuracy over others in the testing dataset.

Optimizer	30 Epochs	75 Epochs	150 Epochs	300 Epochs
SGD	16.68 ± 0.19	12.63± 0.12	14.04± 0.21	14.53± 0.12
Adam	15.88 ± 0.17	11.45 ± 0.06	13.07 ± 0.14	12.35 ± 0.06
Adadelta	18.49 ± 0.16	12.37 ± 0.15	15.14 ± 0.16	13.37 ± 0.15
Adagrad	17.51 ± 0.4	15.41 ± 0.20	14.06 ± 0.18	15.21 ± 0.20
AdamW	14.35 ± 0.12	13.67 ± 0.17	13.12 ± 0.10	12.67 ± 0.17
Adamax	11.65 ± 0.05	7.86 ± 0.19	9.02 ± 0.21	9.86 ± 0.19

Table III: Performance of Different Optimizers on Test Data

In conclusion, while market acceptance is pivotal for software usability, 2D video analysis provides valuable insights into exercise form. Notably, tracking muscle engagement requires advanced equipment or user feedback, presenting an avenue for further research in refining exercise assessment methods.

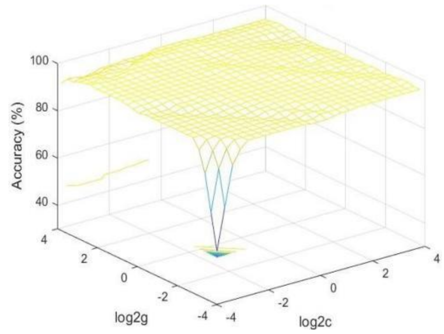

Fig.5: Accuracy Curve Across 10-Fold Cross Validation for VGG-19

The outcomes underscore the potential success of 2D human pose estimation in offering feedback on weight training techniques, particularly from a front-view angle for healthy individuals. The positive results from the Pose Trainer on side-view angles suggest dynamic time-warping as a preferable option for such technique aspects. While detection for rotation-intensive exercises remains challenging, partial success was achieved. [3]

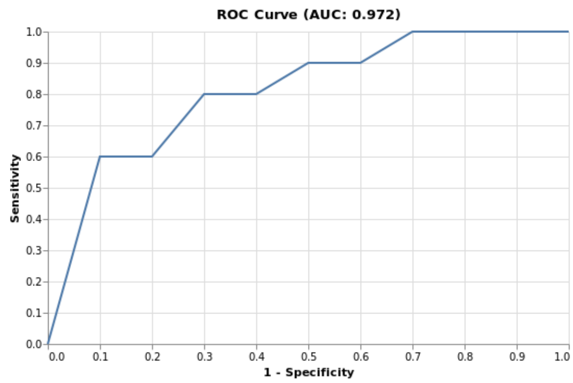

Fig.6: ROC Curve Across 10-Fold Cross Validation for VGG-191

In addition to achieving high accuracy in weightlifting technique classification, market acceptance is integral to user adoption. The study illuminates the efficacy of 2D human pose estimation in providing valuable feedback on weightlifting form, emphasizing the importance of additional tools for determining muscle engagement accurately.[1]

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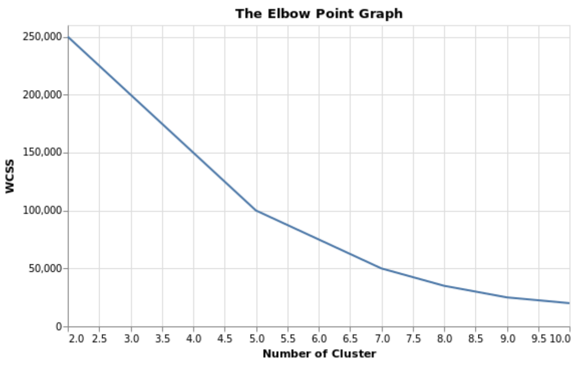

Fig.7: Elbow Point Graph

The research indicates a higher success rate in detecting weightlifting techniques from front-view angles compared to side views. Further research is imperative to ascertain the transference of success from front-to-side views. Dynamic time warping emerged as a potential solution for side-view technique aspects, demonstrating partial success for rotation-centric exercises.

Activity	True Positives	False Positives
Adho Mukha Svanasana	0.98	0.02
Tadasana	0.98	0.02
Vrikshasana	0.97	0.03
Natarajasana	0.98	0.02
Padmasana	0.96	0.04
Paschimottanasana	0.97	0.03
Salabhasana	0.96	0.04
Trikonasana	0.98	0.02

Table IV: True Positive and False Positive Classification for Test Dataset using MobileNet Architecture

Table IV details the classification rates for each activity, highlighting the model's performance in incorrectly classifying data samples. [10]Pose Trainer's machine learning approach yielded positive results, especially for front raises. Despite a small dataset, the bicep curl detector demonstrated an 80% detection rate for flawed executions, emphasizing dynamic time warping's potential efficacy.

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The study compared the proposed technique with Pose Trainer, revealing similar outcomes on a larger dataset and more complex exercises. Challenges arose from disparate data presentation methods, with Pose Trainer focusing on overall correctness while the study delved into individual technique aspects. The angle detector's limitation to the front or side views may introduce inaccuracies for exercises with substantial rotations.

Confidence scores were identified as a potential error source, influenced by varying scales across systems. Dataset constraints, featuring only healthy, amateur lifters, may not represent diverse body types or physical abilities. The proposed action recognition system and technique evaluation system demonstrated promise but faced limitations in angle detection precision and shoulder distance calculations.

A methodology for correcting and estimating yoga postures using pose estimation with OpenCV and VGG-19 with GPU transfer learning was presented.[8] Deep learning models, including VGG-19, AlexNet, and MobileNet, underwent transfer learning for optimal performance. VGG-19, further enhanced with GPU transfer learning, outperformed bench-marking models. Evaluation metrics demonstrated superior accuracy, precision, recall, and F1 score. Real-world testing validated the system's real-time posture detection and correction capabilities, providing valuable feedback for form improvement and injury risk reduction.

CONCLUSION

This study leveraged human pose estimation techniques to identify and address methodology issues in everyday workout routines. Our findings suggest that human pose estimation has the potential to evaluate a wide array of fitness training methods across diverse user profiles, exercises, and technique challenges. By evaluating various human pose estimation methods on a limited sample size, we uncovered insights into their efficacy in detecting technique flaws in weightlifting from multiple-dimensional views. [1]

While our results may not be fully generalizable due to the limited dataset, this methodology offers a contemporary perspective by comparing similar approaches among users with diverse body types and pose estimation techniques. By accounting for variances, our findings can be extrapolated to make informed deductions about weightlifting techniques. [1]

Unlike previous research, which often relied on depth cameras or multiple sensors to gather three-dimensional data, our study utilized only a single RGB camera to capture the subject's position. [1][3]This approach offers a more accessible solution, potentially requiring nothing more than a user's smartphone camera.

Despite the algorithm's superior performance in estimating video frames from frontal views compared to side views, our study highlights the need for further refinement in pose detection and angle calculation for side-view videos. [1] Future research

endeavors should focus on addressing this challenge to enhance the algorithm's overall effectiveness.
In conclusion, our study underscores the promising role of AI-powered pose estimation in improving exercise form evaluation. By offering insights into technique flaws and providing actionable feedback, this technology has the potential to revolutionize the way individuals approach fitness training, promoting safer and more effective workout routines. [12]

REFRENCES

[1] H. Xiong. S. Berkovsky, R. V. Sharan, S. Liu, and E. Coiera, "Robust vision-based workout analysis using diversified deep latent variable model," in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC), pp. 2155-2158, 2020.

[2] S. Yadav, A. Singh, A. Gupta, and J. Raheja, "Real-time yoga recognition using deep learning, Neural Computing and Applications, vol 31, pp. https:/link.springer.com/article/10.1007/900521-019, 122019

[3] Y. Gu, S. Pandit, E. Sarape, T. Nordahl, T. Ellis, and M. Betke, "Home- based physical therapy with an interactive computer vision system," in 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), pp. 2619-2628, 2019

[4] C. Huang, Y. Z. He, and C.-C. Hei, "Computer-assisted yoga training system, Multimedia Tools and Applications, vol. 77, 09 2018.

[5] P. Keshari, "Wrong posture detection using, opencv and support vector machine." 01 2020.

[6] A. Nagarkoti, R. Teotia, A. K. Mahale, and P. K. Das, "Real-time indoor workout analysis using machine learning amp; computer vision, in 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1440-1443, 2019.

[7] Y. Agmwal, Y. Shah, and A. Sharma, "Implementation of machine. learning technique for identification of yoga poses, in 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), pp. 40-43, 2020,

[8] Z. Can, G. Hidalgo, T. Simon, S. Wei, and Y. Sheikh, "Open-pose: Real-time multi person 2d pose estimation using part affinity fields," IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 43, pp. 172- 186, jan 2021.

[9] D. Kumar and A. Sinha, "Yoga pose detection and classification using deep learning. International Joumal of Scientific Research in Computer Science Engineering and Information Technology, 11 2020

[10] G Chiddarwar, A. Ranjanc, M. Chimdhe. R. Deodhar, and P Gangamwar, "Ai-based yoga pose estimation for android application," International Journal of Innovative Science and Research Technology, val 5. pp. 1070-1073, 10 2020.

[11] Bodhe, R., Sivakumar, S., Sakarkar, G. et al. Outdoor activity classification using smartphone based inertial sensor measurements. Multimedia Tools App (2024). https://doi.org/10.1007/s11042-024-18599-w

[12] F. Sajjad. A. F. Ahmed, and M. A. Ahmed, "A study on the kaming learning based human pose recognition," in 2017 9th IEEE-GCC Conference and Exhibition (GCCCE), pp. 1-8, 2017.

[13] H.-T.Chen, Y Z. He, and C.-C. Hrit "Computer-assisted yoga training system," Multimedia Tools and Applications, vol 77, no. 18, pp. 23969- 23991, 2018

(14) S. Jam, A. Rustagi, S. Saurav, R. Saini, and S. Singh, "Three dimensional CNN-inspired deep learning architecture for Yoga pose recognition in the real-world environment, Neural Computational Intelligence and Neuroscience, Computing & Applications, vol. 33, no. 12, pp. 6427-6441,2021

[15] Mais Yasen and Shaidah Jusch. "A systematic review on hand gesture recognition techniques, challenges and applications". In: Peer) Computer Science 5 (2019), e218

[16] H. Tang, Q. Wang and H. Chen, "Research on 3D Hunan Pose Estimation Using RGBD Camera," 2019 IEEE 9th International Conference on Electronics Information and Emergency Communication (ICETEC), 2019, pp. 538-541, doi: 10.1109/1CEIEC 2019.8784591.

[17] GR.S. Murthy and R.s Jadon. "A review of vision based land gesture recognition". In: International Journal of Information Technology and Knowledge Management 2 (Aug 23, pp. 405-410

[18] Santiago Riofrio et al "Gesture Recognition Using Dynamic Time Warping and Kinect: A Practical Approach. In: Nov, 2017, pp. 302-308. doi: 10.1109/INCISCOS.2017.36.

[19] Zhe Cao et al. "OpenPose: Realtime Multi-Person 20 Pose Estimation. Using Part Affinity Fields". In: IEEE Transactions on Pattern Analysis and Machine Intelligence 43.1 (2021) pp. 172-186 dor: 10.1109/TPAML2019.2929257.

[20] T. 1. Manca, Y. Z. Jembre, H. T. Weldegebriel, 1. Chen, C. Huang and C. Yang, "The Progress of Human Pose Estimation: A Survey and Taxonomy of Models Applied in 2D Human Pose Estimation," in IEEE Access, 133330-133348, 2020 doi: 10.1109/ACCESS 2020 3010248. vol

[21] Y. Cheng, P. Yi, R. Liu, J. Dong, D. Zhou and Q. Zhang, "Human-robot Interaction Method Combining Human Pose Estimation and Motion Intention Recognition," 2021 IEEE 24th International Conference Computer Supported Cooperative Work in Design (CSCWD) 2021, pp. On 958-963, doi: 10.1109/CSCWD49262 2021.9437772

[22] Imam Riadi, Sunardi Sunaidi, and Arizona Firmansyah. "Forensic Investigation Technique on Android's Blackberry Messenger using NIST Framework. In: International Journal of Cyber-Security and Digital Forensics 6 (Oct. 2017), pp. 198-205,

[23] Henrik Sj oberg et al. "Content Validity Index and Reliability of a New Protocol for Evaluation 1 of Lifting Technique in the Powerlifting Squat and Dead lift. In Journal of Strength and Conditioning Research (Sept. 2018). doi: 10 1519/ JSC 0000000000002791

[24] Zhe Cau et al. "OpenPose: Realtime Multi-Person 20 Pose Estimatiom using Part Affinity Fields" in: (Dec. 2018)

[25] Bajaj, Nidhi & Kshirsagar, Pravin & Akojwar, Sudhir (2018) A hybridized neural network and optimization algorithms for prediction and classification of neurological disorders. International Journal of Biomedical Engineering and Technology. 28. 307, 10.1504/UBET.2018.10017200.

[26] Kshirsagar. Pravin & Akojwar. Sudhir (2016). Hybrid Heuristic Optimization for Benchmark Datasets, International Journal of Computer Applications. 146. 11-16, 10.51200jca2016910853

[27] Dataset : https://www.kaggle.com/datasets/niharika41298/yoga-poses-dataset/data