Research on human movements push up counter based on media-pipe artificial intelligence

Balde Saido
Tianjin Key Laboratory of Information Sensing and Intelligent Control, Tianjin University of Technology and Education,
Hexi District No. 1310, Tianjin 300222, China
S.ballackchina@gmail.com

Guangda Lu
Tianjin Key Laboratory of Information Sensing and Intelligent Control, Tianjin University of Technology and Education,
Hexi District No. 1310, Tianjin 300222, China
lugd1229@163.com

Zhuanpin Qin
Tianjin Key Laboratory of Information Sensing and Intelligent Control, Tianjin University of Technology and Education,
Hexi District No. 1310, Tianjin 300222, China
13752353890 @163.com

Xianhan Yin
Tianjin Key Laboratory of Information Sensing and Intelligent Control, Tianjin University of Technology and Education,
Hexi District No. 1310, Tianjin 300222, China
1297208559@qq.com

Jianyi Dai
Tianjin Key Laboratory of Information Sensing and Intelligent Control, Tianjin University of Technology and Education,
Hexi District No. 1310, Tianjin 300222, China
121043865@qq.com

Xiaoqian Guo
Tianjin Key Laboratory of Information Sensing and Intelligent Control, Tianjin University of Technology and Education,
Hexi District No. 1310, Tianjin 300222, China
GXQ @qq.com

***Abstract* —This paper introduces a project that integrates pose estimation and deep learning to evaluate exercise performance and provide real-time feedback on repetition counts during workouts. Using machine learning in the fitness sector, the study focuses on accurately tracking and counting exercise repetitions, which is beneficial for physical education and competitive fitness events. The paper presents a novel real-time push-up counting method based on 2D video analysis, utilizing Media-pipe for precise pose estimation and motion analysis. By following the push-up guidelines set by the National Academy of Sports Medicine, the method differentiates between correct and incorrect push-up forms. The experimental results show that the proposed method achieves an accuracy of 90.00%, precision of 91.67%, recall of 91.67%, and an F1-Score of 91.66%. The integration of pose estimation and deep learning in the fitness industry offers new opportunities for improving workout monitoring, ensuring proper form, and optimizing fitness outcomes for individuals of different fitness levels.**

Keywords—Artificial intelligence, push-up counter, Media-pipe, Sport physical fitness.

I. Introduction

The push-up, also known as a press-up in British English, stands as a fundamental calisthenics exercise commencing from the prone position. This exercise involves lifting and lowering the body by utilizing the arm muscles, primarily targeting the pectoral muscles, triceps, and anterior deltoids, while also engaging other muscles like the deltoids, serrate anterior, coracobrachialis, and the core[1]. Push-ups serve as a cornerstone exercise in civilian athletic training, physical education, and military physical conditioning programs. They are often employed as disciplinary measures in military settings, school sports, and certain martial arts practices. Various push-up variations, such as wide-arm push-ups and diamond push-ups, offer targeted muscle engagement and increased difficulty levels, adding versatility and challenge to the exercise routine. These exercises play a crucial role in enhancing overall strength and conditioning across different muscle groups.

The current real-time counter for physical exercise is a research characteristic. The method utilizes pose estimation to monitor person, identify the exercises they are performing, tally the repetitions, and assess the quality of the repetitions. In reference[2], a push-up counting device was examined with the aim of improving count accuracy through the fusion of multiple sensors. Muzakir and Kusmindari created a push-up detector application utilizing an Arduino-based micro-controller. The purpose of this application is to identify nonstandard movements during push-ups and alert users to incorrect push-up habits in order to prevent injuries[3]. Another innovative push-up tracking method involved the utilization of accelerometer and gyroscope data obtained from smartphone sensors. This data was then analyzed using machine learning algorithms to enhance accuracy and efficiency in tracking push-up movements, as detailed in a recent study[4]. The findings from the study indicated that by attaching a smartphone to the upper arm, it was possible to differentiate between accurately performed push-ups and those executed incorrectly. This innovative approach demonstrated the smartphone's capability to effectively discern between correct and incorrect push-up movements, showcasing its potential for fitness tracking applications. Dr. Morris, T. S. Saponas, A. Guillory, and I. Kelner team, develop wearable technology to autonomously monitor and share workout regimens, such as push-ups. Participants wore the device and engaged in repetitive physical activities. Moreover, the device accurately identified and displayed the specific exercises performed by users, along with the number of valid repetitions, leveraging the capabilities of arm-mounted inertial sensors for precise tracking and feedback[5].

Recently, there has been a rise in the use of vision-based technologies in various applications, leveraging advanced computing power and artificial intelligence to enhance their performance[6-7]. Several studies have already been conducted in the human body applications, highlighting advantages such as the relatively low initial cost of cameras, real-time counting systems, and the absence of a need for prior device attachment preparation[8-9]. Despite these advantages, as mentioned, research on vision-based push-up counters is still incomplete. Further studies are needed to explore and optimize the performance of these systems, address potential challenges such as accuracy and robustness in different environments, and enhance user experience. Researchers can focus on refining algorithms, conducting user studies to gather feedback, and testing the technology in various scenarios to ensure its reliability and effectiveness. By addressing these research gaps, vision-based push-up counters can become more reliable and widely adopted in fitness and healthcare applications.

This paper introduces a real-time method for counting push-ups using two dimensional video. The approach leverages Media-pipe to extract multiple joints and links of the human body in each frame, followed by the analysis of key motion features essential for push-up counting. By incorporating the push-up guidelines of the National Academy Sport Medicine, five criteria are established and utilized para-metrically to differentiate between correct and incorrect push-ups. In this particular research project, a grand total of fifty videos recordings capturing push-up exercises were meticulously collected from two distinct angles. These videos were then subjected to a comprehensive analysis focusing on metrics such as accuracy, precision, recall, and F-measure to evaluate the performance and effectiveness of the push-up tracking system. Our primary contribution are as follows:

- Developed real-time push-up counter using 2D video analysis.
- Established five criteria for proper push-up form via NASM.
- High-performance evaluation metrics achieved in the study.
- Integrated AI in fitness industry for monitoring and improving workouts

II. Related Works

There are various methods available for exercise recognition and repetition counting, including the use of a smartwatch, a security camera system, a sensor, or a webcam.

The literature review is organized according to the data modality used for push ups and counting.

III. System Architecture

In order to monitor the number of push-ups performed during the fitness routine, this research employs Media-pipe technology to estimate human pose based on two-dimensional images. Through the analysis of the movement patterns of essential body parts, the study assesses the correctness and errors in push-up form. The system architecture, as depicted in Figure 1, consists of four distinct stages: image acquisition, pose estimation, evaluation of critical motion characteristics, and push-up tallying. Each stage plays a crucial role in the overall process, and the intricate details of their functionalities will be expounded upon in subsequent sections. The utilization of Media-pipe technology allows for the accurate estimation of human pose, enabling a comprehensive analysis of push-up performance. By scrutinizing key motion features, the system can distinguish between correct and incorrect push-up positions, facilitating a detailed assessment of the individual's execution. This systematic approach enhances the precision of push-up counting and evaluation, providing valuable insights for fitness monitoring and improvement.

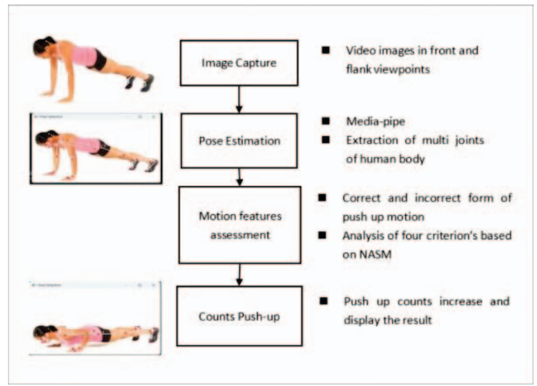


Fig. 1. System Architecture

A. *Image capture*

Two cameras are strategically positioned to record the push-up actions of the individual from both frontal and lateral angles. These cameras are carefully placed to capture a comprehensive view of the subject's head, chest, shoulders, elbows, wrists, waist, knees, and feet during the push-up exercise[10]. The footage obtained from these dual perspectives offers a detailed insight into the subject's form and technique while performing push-ups, as depicted in Figures 3(a) and (b). By utilizing these two camera angles, researchers can analyze the alignment and movement of key body parts throughout the push-up motion, enabling a thorough assessment of the subject's performance. The frontal view provides a clear visualization of the subject's upper body positioning, while the lateral view offers valuable information on the alignment of the subject's entire body during the exercise[11]. This multi-angle approach enhances the accuracy and precision of evaluating push-up form, allowing for a more in-depth understanding of the subject's execution and facilitating targeted feedback for improvement.

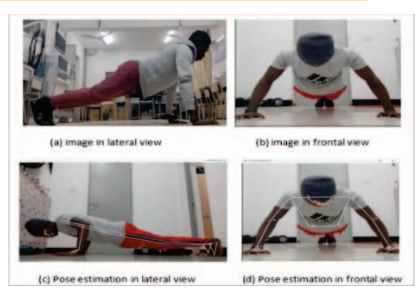


Fig. 2. Original and pose estimated images.

Figure 2. Original and pose estimated images in both lateral and frontal views; (a) an original image in lateral view, (b) an original image in frontal view, (c) a pose estimated image by media pipe in lateral view, (d) a pose estimated image by media pipe in frontal view.

B. Pose estimation

The examines pose is estimated by categorizing the human body into key parts such as the head, shoulders, arms, and feet. To capture and analyze motions during push-ups, each joint of the human body is identified using the Media-pipe algorithm. Media-pipe is a deep learning-based algorithm[12]. It provides valuable information for analyzing various human body movements, such as squat classification[11], injury risk assessment[13], and yoga recognition[14]. Media-pipe utilizes a Bottom-up approach to detect human joints in images and estimate the optimal pose by the connections between the joints. This method maintains accuracy even when human bodies are partially covered and is computationally efficient compared to the Top-down approach[15-17]. Additionally, Media-pipe utilizes a feature map based on the CNN network to generate confidence maps for detecting each joint and determining their relationships. The refined predictions are generated by combining the feature outputs, part confidence maps, and part affinity fields. This process results in the recognition of thirty-two joints the examinee's body, as illustrated in Fig. 2(c) and (d).

C. Key motion features assessment

In accordance with the guidelines provided by the National Academy of Sports Medicine, executing push-ups correctly involves adhering to specific form cues to ensure optimal engagement of the muscles and prevent potential injury. One crucial aspect emphasized by the Academy is the importance of maintaining proper alignment and positioning of key body parts throughout the entire push-up motion.

To consider a push up is standard during the downward phase of the push-up, it is essential to focus on raising both elbows higher than the shoulders. Simultaneously, ensuring that both arms remain straight when pushing back up and maintaining stability throughout the movement. Any deviation from these alignment cues, such as a bent back, arms not fully extended, elbows dropping below shoulder height, or knees bending or making contact with the ground, can compromise the integrity of the push-up and render it incorrect.

The evaluation of standard push-up form based on the alignment of eight key body parts: wrists(x_{wi}, y_{wi}), elbows(x_{ei}, y_{ei}), shoulders(x_{si}, y_{si}), head(x_h, y_h), chest(x_c, y_c), waist(, x_t, y_t), legs(, x_l, y_l), and feet(, x_f, y_f). Each of these body parts plays a crucial role in maintaining proper form and ensuring that the push-up is executed with precision and efficiency. By focusing on the alignment of these key body parts, individuals can not only perform push-ups more effectively but also reduce the risk of strain or injury commonly associated with improper form.

Additionally, paying attention to the position of the head, chest, waist, legs, and feet helps create a stable and balanced foundation for executing push-ups with control and precision. $\bar{S} \in \{x_{wi}, y_{wi}, x_{ei}, y_{ei}, x_{si}, y_{si}, x_h, y_h, x_c, y_c, x_t, y_t, x_l, y_l, x_f, y_f\}$, These body parts are coordinated and analyzed for changes in video frames using a binary system (0 for left, 1 for right). Five criteria are utilized for quantitative analysis, as detailed below. In Figure 3, illustrates correct and incorrect postures based on these criteria.

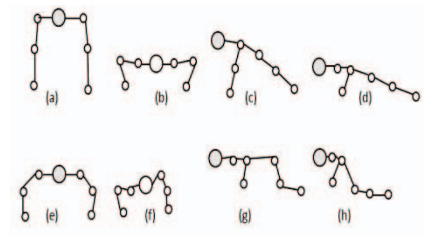


Fig. 3. Correct and incorrect push-up postures.

Figure.3. displays examples of both correct and incorrect postures during push-ups. (a) Demonstrates the correct posture at the highest level in frontal view, while (b) showcases the correct posture at the lowest level in frontal view. (c) Illustrates the correct posture at the highest level in lateral view, and (d) shows the correct posture at the lowest level in lateral view. (e) Depicts an incorrect posture that fails to maintain the proper angle of both elbows, while (f) displays an incorrect posture where the levels of both shoulders are unbalanced. (g) Shows an incorrect posture where the waist is raised and the knee is bent in lateral view, and (h) demonstrates an incorrect posture where the waist is lowered.

The criterion's detailed below:

1. The elbow angles should be less than 90 degrees at the lowest level and greater than 150 degrees at the highest level.

2. The distance between each wrist and shoulder at the lowest level should be less than half of the distance between each wrist and shoulder at the highest level.

3. The distance between the wrists and shoulders should be balanced during push-ups.

4. The waist should remain straight during push-ups, avoiding bending or lowering, and maintain the feet normal distance

5. The knees should be kept straight during push-ups, avoiding bending.

In order to implement these criteria, a parametric classification model is developed. Initially, the elbow angle (θ_{ei}) can be determined by applying the law of cosines as outlined in (1). The distances of wrist-elbow (d_{wei}), elbow-shoulder (d_{esi}), and shoulder-wrist (d_{swi}) can be calculated using the Cartesian coordinates of x_{wi} , y_{wi} for the wrists, x_{ei} , y_{ei} for the elbows, and x_{si}, y_{si} for the shoulders, as demonstrated in equations (2)-(4).

$$\theta_{ei} = \text{acrcos}\left(\frac{d_{wei}^2 + d_{esi}^2 - d_{swi}^2}{2d_{wei}\,d_{esi}}\right) \qquad (1)$$

Where,

$$D_{wei} = \sqrt{|x_{wi} - x_{ei}|^2 + |y_{wi} - y_{ei}|^2}\,, \quad (2)$$

$$D_{esi} = \sqrt{|x_{ei} - x_{si}|^2 + |y_{ei} - y_{si}|^2}\,, \quad (3)$$

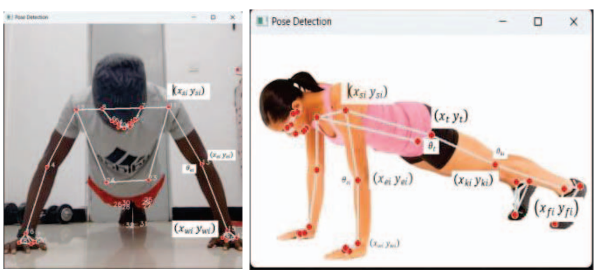
$$D_{swi} = \sqrt{|x_{si} - x_{wi}|^2 + |y_{si} - y_{wi}|^2} \quad (4)$$

For the second criterion, the distance between the midpoint of both wrists and the midpoint of both shoulders, denoted as d_{ws} , is analyzed to minimize variations in individual body structures. This is achieved by measuring the distance at the highest level, highest $-d_{ws}$, and the distance at the lowest posture, lowest $-d_{ws}$, (5) The hand distance(h_d) is then calculated to assess compliance with the second criterion. Moving on to the third criterion, the angles θ_{e0} and θ_{e1} are measured and compared to ensure a balanced difference between them using equation (6)

$$h_d = \text{lowest} - d_{ws} / \text{highest} - d_{ws} \quad (5)$$

$$\delta \geq |\theta_{e0} - \theta_{e1}| \quad (6)$$

For the fourth and fifth criteria, the angles of the knee and feet distance, respectively, are computed using a methodology analogous to that of the elbow angle, as detailed in steps (1)-(4). The coordinates and angles of the main body segments in the subjects are depicted from two distinct perspectives, as illustrated in Figure 4.



(a) Frontal view (b) lateral view

Fig. 4. The coordinates and angles of the main body segments

In this research, each push-up was meticulously analyzed by evaluating its posture at the highest and lowest points. The study utilized five specific criteria to distinguish between correct and incorrect push-ups, with the first three criteria assessed from frontal views and the remaining two from lateral views. Correct and incorrect push-up postures were illustrated in Figures 3(a) to 4(d) for frontal views, and in Figures 3(e) to 4(b) for lateral views. Five parameters were calculated based on these criteria to differentiate between correct and incorrect push-ups, each with defined thresholds detailed in Table 1. Motion data for each criterion was also depicted in Figure 6. The first criterion focused on the angles of the left and right elbows (θ_{e0} and θ_{e1}). Correct push-ups exhibited elbow angles between 40°and 70°degrees at the lowest point, while incorrect push-ups showed angles between 100° and 160° degrees, indicating a partially lowered posture. The study established that a push-up was correct when both elbow angles were below 90°degrees at the lowest point and above 150 degrees at the highest point. The second criterion involved a Hand distance (h_d) parameter with correct push-ups having values between 120cm and 80cm, and incorrect push-ups between 80cm and 60cm. The push-up was considered correct when hand distance was less than 80cm at the lowest point and greater than 120cm at the highest point.

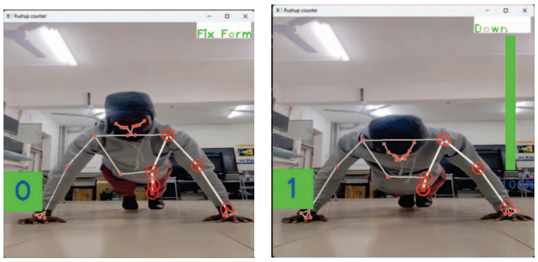
TABLE 1. THE PARAMETERS OF CORRECT AND INCORRECT PUSH-UPS

Criterion	*Parameters*	*Ranges for correct and incorrect push ups*
1	Elbow(θ_{e0} , θ_{e1})	At the lowest level, the elbow angle should be less than 90°, for correct push-ups. At the highest level, the elbow angle should be greater than 150°, for correct push-ups.
2	Hand_distance(h_d)	At the lowest level, an hand distance is variate 80cm to 120cm recommended in correct push up, while at the incorrect push up, an hand distance is variante between 60cm to 80cm .
3	Back_Angle(θ_h)	During correct push- ups the back_angle should be between 150°to 180°while in incorrect form the back_angle is variate 110°~150°.
4	Knee(θ_{k0},θ_{k1})	In incorrect push-ups the knee angle is greater than 10°for incorrect push-ups.while in correct push up the knee angle is less than 10°.
5	Feet_Distance	In incorrect push-ups the feet distance is less than 80cm to 20cm while in correct push up the feet distance is between 40cm to 30cm

The third criterion assessed the back_curve of the upper body with a parameter, where correct push-ups typically had values of 10° degrees or less, while incorrect push-ups exhibited a maximum value of 60° degrees. A push-up was deemed correct when parameter was below 30° degrees. The fourth and fifth criteria evaluated the alignment of the upper and lower body, primarily focusing on the angles of the waist and knee. Correct push-ups had waist angles between 160° and 180° degrees, while incorrect push-ups ranged from 100° to 150° degrees. Similarly, correct knee angles were between 160° and 180° degrees, contrasting with incorrect knee angles of 80° to 150° degrees. Considering potential angle errors due to the estimation of small points for the waist and knee, a push-up was classified as incorrect when the waist angle was less than 150 degrees and when at least one knee angle was below 150° degrees.

D. Push-up counts

As presented in the preceding section, the fulfillment of all five criteria is a prerequisite for the augmentation of the push-up count. Failure to meet any one of the stipulated criteria will result in the count remaining static. Furthermore, the tally of push-up repetitions undergoes revision through a comprehensive analysis of the data acquired during the full range of motion, encompassing both the apex and nadir positions. Subsequently, any rise in the numerical value is visually depicted on the motion screen interface. This systematic approach ensures the accuracy and integrity of the push-up counting mechanism, thereby facilitating precise tracking and evaluation of physical performance. Illustrated in figure 5(a) and (b).



(a) Start push-up (b) update count

Fig. 5. Push-up count update on the screen.

In figure5(a). showed the started position if all condition are meet the system give a feedback down. While in figure5(b). the system examine the movement as explain before then update the count on the screen.

IV. Results And Analysis

A. Experimental environment and experimental evaluation

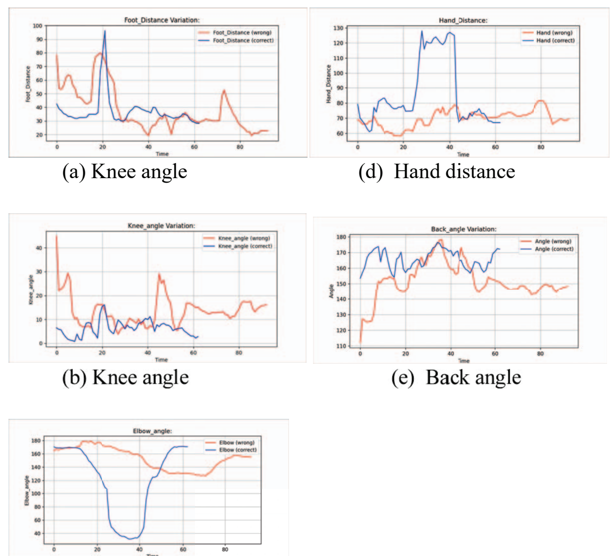
The experimental tested described in the study was meticulously designed to capture and analyze push-up motions with a high level of precision and detail. The utilization of two fixed cameras, each recording at a resolution of 1280 × 720 pixels and a frame rate of 30 Hz, ensured that the movements of the participants were captured accurately from multiple angles. This setup allowed for a comprehensive analysis of push-up postures, enabling the researchers to distinguish between correct and incorrect forms with a high degree of accuracy.

The computational aspect of the experiment was equally sophisticated, with the PC boasting an i7 Intel core processor, 16GB of RAM. This powerful hardware configuration was essential for running complex algorithms such as Media-Pipe, which plays a crucial role in analyzing human movement patterns. By leveraging the computational capabilities of the PC, the researchers were able to process a large volume of data efficiently and derive meaningful insights from the push-up videos captured during the experiment.

The data-set generated from the experiment was substantial, comprising a total of 460,800 samples extracted from fifty (50) push-up videos. Of these samples, 25 showcased correct push-up postures, while 25 displayed incorrect forms. The inclusion of both correct and incorrect examples was crucial for training and evaluating the performance of the proposed method for classifying push-up postures. With twelve individuals participating, including professional instructors and ten examinee, the study befitted from a diverse range of body types and experience levels. The participants heights, ranging from 150 to 180 cm, and ages between 20 and 43, added variability to the data-set, enabling the researchers to evaluate the effectiveness of the proposed method across different demographics.

The division of the push-up videos into two sets one for parametric modeling and the other for testing performance was a strategic approach to validating the proposed method. By using forty (40) videos for modeling and another ten(10) videos for testing, the researchers were able to assess the generalization and accuracy of the classification model. This division ensured that the method was not over fitting to the training data and could effectively classify push-up postures in previously unseen videos.

Figure 6, we can observe examples of data showcasing both proper and improper push-up techniques. The visual representation provides clear illustrations of the correct form as well as common mistakes to avoid during push-ups. By studying these examples, individuals can better understand the difference between a well-executed push-up and one that may lead to potential injury or reduced effectiveness.



(a) Knee angle (d) Hand distance

(b) Knee angle (e) Back angle

(c) Elbow angle

Fig. 6. Data example with correct and incorrect push-ups.

B. Analysis of experimental results

The proposed method's effectiveness was assessed through implementation of a machine learning model, specifically a Random Forest Classifier, for classifying correct and incorrect push-up techniques. This matrix was generated by evaluating four essential metrics: true positives(TP, When a push-up is executed correctly, and it is predicted as correct), false positives(FP, When a push-up is executed incorrectly, but it is predicted as correct), false negatives(FN, When a push-up is executed correctly, but it is predicted as incorrect), and true negatives(TN, When a push-up is executed incorrectly, and it is predicted as incorrect). The calculation formula is shown in Equation (7) to (10). By employing this comprehensive evaluation approach, the performance of the method could be thoroughly examined and validated based on its ability to correctly identify true positives, accurately detect false positives, minimize false negatives, and correctly identify true negatives. The Random Forest Classifier provided a structured framework for quantitatively measuring the method's accuracy and reliability in distinguishing between different classification outcomes. Through this rigorous evaluation process, the method's robustness and efficacy in achieving accurate and reliable results were rigorously tested and validated, providing valuable insights into its performance and potential applications in real-world scenarios.

The result of true- positive(TP), false-positive(FP), false-negative(FN), and true-negative(TN) the normalized values from Table 2 were used to calculate accuracy, precision, recall, and F-score according to equations (7) to (10). The computed metrics were then presented in Table 2.

$$\text{Accuracy} = \frac{\text{TP + TN}}{\text{TP+FP+ FN + TN}} \quad (7)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \quad (8)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}} \quad (9)$$

$$\text{F1 - score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision + Recall}} \quad (10)$$

In Table 2, the proposed method achieved an accuracy of 90.00%, with true -positive and true-negative values of 0.623 and 0.230, respectively. Precision quantifies the proportion of correctly predicted positive examples out of all the predicted positives, while recall assesses the fraction of actual positive instances correctly identified by the model. F1-score combines precision and recall into a single metric. The precision, recall, and F1-score values were computed as 91.67%, 91.67%, and 91.66%, respectively. The discrepancy between precision and recall can be attributed to a slightly higher false-positive rate than false-negative by 0.073. This indicates that incorrect push-ups were more frequently classified as correct than vice versa. Future research efforts should focus on enhancing the model's performance.

TABLE 2. THE PARAMETERS OF CORRECT AND INCORRECT PUSH-UPS

Measurements	*Result*	*Performance*	*Result*
True-positive	0.623	Accuracy	90.00%
True-negative	0.230	Precision	91.67%
False-positive	0.080	Recall	91.67%
False-negative	0.071	F-measure	91.66%

V. CONCLUSIONS AND FUTURE WORK

The research conducted a cutting-edge real-time push-up counting experiment using video analysis to classify correct and incorrect push-up forms. Leveraging Media-Pipe, the study meticulously analyzed push-up movements, focusing on key body parts crucial for determining correctness. An extensive dataset of 460,800 samples from fifty push-up videos captured from multiple viewpoints ensured adaptability across diverse individuals. Five essential criteria were defined for classification, including angles of elbows, waist, and knees, and distance ratios during repetitions. The method achieved impressive accuracy and precision scores of 90.00% and 91.67%, highlighting its efficacy in categorizing push-up forms. Future plans include 3D analysis and deep learning integration to enhance performance. This experiment represents a significant advancement in fitness assessment, offering a sophisticated tool for evaluating physical fitness levels and performance in sport settings. The research team's commitment to excellence and innovative approach signal a promising future for revolutionizing physical fitness evaluation.

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