A Novel Deep Neural Network to Analyze and Monitoring the Physical Training Relation to Sports Activities

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***Abstract*—In the research paper, authors meticulously detail the development, testing, and application of an innovative deep learning model aimed at monitoring physical activities of students in real-time. Drawing upon the advanced capabilities of convolutional neural networks (CNNs), the proposed system exhibits an exceptional ability to track, analyze, and evaluate the physical exercises performed by students, thereby providing an unprecedented scope for customization in physical education strategies. This piece of scholarly work bridges the gap between physical education and cutting-edge technology, highlighting the burgeoning role of artificial intelligence in health and fitness sector. With an expansive study spanning various cohorts of physical culture students, the paper provides compelling empirical evidence that underlines the superiority of the deep learning system over conventional methods in aspects of accuracy, speed, and efficiency of monitoring. The authors demonstrate the transformative potential of their system, capable of facilitating personalized and optimized physical training strategies based on real-time feedback. Moreover, the potential implications of the study extend beyond the realm of education and into wider public health applications, with the possibility of fostering improved health outcomes on a larger scale. This research paper makes a significant contribution to the burgeoning field of AI in physical education, embodying a paradigm shift in the approach towards physical fitness and health monitoring. It underscores the potential of AI-driven technology to revolutionize traditional methods in physical education, paving the way for more personalized and effective teaching and training regimes, and ultimately contributing to enhanced health and fitness outcomes among students.**

***Keywords*—ANN; PoseNET; exercise monitoring; machine learning; neural networks; artificial intelligence**

I. Introduction

The advent of Artificial Intelligence (AI) and its subsets, particularly deep learning, has brought about unprecedented transformations across various sectors, ranging from finance and healthcare to education and physical culture. As we continue to harness the potential of these technologies, there is an increasing need to explore and exploit their potential in areas traditionally not associated with advanced computational methods [1]. One such area is physical culture, where the application of AI technologies, such as deep learning, can help us innovate and enhance the way physical exercises are taught, monitored, and assessed [2].

Physical culture, primarily involving the practice of physical exercises and activities, is a critical component of a holistic educational curriculum, promoting the physical well-being and health of students [3]. However, the traditional approach towards teaching and monitoring physical culture often falls short in providing personalized training or real-time performance evaluation [4]. Hence, there is a necessity for an innovative solution that can address these limitations, enabling a more effective and individualized physical education system.

Artificial Intelligence, with its ability to learn and make decisions, emerges as a promising solution to the mentioned challenges [5]. Among the various AI techniques, deep learning has gained significant attention due to its capability to learn complex patterns from high-dimensional data. Specifically, Convolutional Neural Networks (CNNs), a category of deep learning models designed to process data with a grid-like topology, have shown remarkable results in image and video processing tasks [6]. These features make CNNs a potential candidate for application in real-time monitoring and assessment of physical exercises, which is predominantly a video-based task.

In light of these insights, we developed an innovative deep learning-based system for real-time exercise monitoring of physical culture students [7]. Utilizing a CNN, our system is designed to accurately track, analyze, and evaluate the physical activities performed by students in real-time. By doing so, it allows educators and trainers to assess each student's performance individually and adjust the training program accordingly, thereby personalizing the learning experience.

To test the performance and reliability of our proposed system, we conducted extensive trials across various physical culture cohorts [8-9]. Our study compares the system's results with traditional monitoring methods, measuring parameters like precision, speed, and efficiency. Our empirical findings underpin the superiority of our system over traditional methods, thereby validating the transformative potential of AI in physical culture education.

This paper begins with a detailed literature review, highlighting the developments in the field of AI, with particular emphasis on deep learning and its applications in various domains. Following this, we present a comprehensive explanation of our proposed deep learning architecture, detailing the methodology used for training, validation, and testing. The subsequent section discusses the empirical findings from the trials, followed by an analysis of these results and a comparison with traditional methods. We then elucidate the potential implications of our system in physical education and broader public health sectors, highlighting the benefits of real-time, personalized exercise monitoring.

The proposed research paper contributes to the rapidly evolving field of AI in physical education. It exemplifies the revolution that deep learning can bring to traditional physical culture methods, paving the way for a more effective, personalized, and health-centric approach towards physical training and well-being. As we continue to explore the intersections of AI and physical culture, we hope our research paper encourages further studies and advancements in this direction, ultimately contributing to improved health and fitness outcomes among students.

II. Related Works

Exercise monitoring systems have been a topic of interest in the field of computer vision and machine learning for several years [10-12]. Recently, there has been a growing interest in using deep learning algorithms to develop accurate and reliable exercise monitoring systems. In this section, we discuss some of the related works in the field of exercise monitoring using deep learning algorithms.

Pose estimation is a critical component of exercise monitoring systems, as it is necessary to accurately detect and track human body movements during exercises. It involves identifying key points on the human body, such as joints and limbs, and tracking their movement over time. One of the most popular pose estimation models used in exercise monitoring is the OpenPose model [13]. OpenPose is a deep learning model that detects and tracks human body movements in real-time using multi-person 2D pose estimation.

Several studies have used OpenPose for exercise monitoring, including a study [14], who applied the model to monitor yoga poses. The study demonstrated that OpenPose could accurately detect and track yoga poses in real-time, providing valuable feedback on form and posture. Another study used OpenPose to monitor basketball shooting form, demonstrating the model's ability to accurately detect and track body movements during complex exercises [15].

In addition to pose estimation, deep learning algorithms can be used to classify different exercises based on body movements [16]. Exercise classification is an essential component of exercise monitoring systems, as it is necessary to accurately identify the exercise being performed to provide appropriate feedback. Several studies have used deep learning algorithms for exercise classification, who employed a convolutional neural network (CNN) to classify six various exercises using motion sensor data [17-18].

Another study applied a CNN to classify six different lower limb exercises using motion capture data [19]. The study demonstrated that the CNN achieved high accuracy in identifying the different exercises, providing valuable feedback on form and posture. In addition, next research used a CNN to classify different exercises using sensor data from wearable devices, demonstrating the potential of wearable technology in exercise monitoring [20].

Several studies have combined pose estimation and deep learning algorithms to develop accurate and reliable exercise monitoring systems. A study by Jiang et al. (2018) used a combination of OpenPose and a CNN to monitor weightlifting exercises, demonstrating that the model could accurately detect and track body movements and classify different exercises [21].

Another research introduced a combination of OpenPose and a long short-term memory (LSTM) network to monitor Tai Chi exercises, providing real-time feedback on form and posture [21]. The study demonstrated that the system could accurately detect and track body movements during complex exercises, providing valuable feedback to users.

A study by Feng et al. (2020) combined OpenPose and a CNN to monitor the correct execution of push-up exercises, providing real-time feedback on form and posture [22]. The study proved that the system could accurately detect and track body movements and classify different push-up variations, providing valuable feedback to users.

The proposed PoseNet enabled deep neural network for exercise monitoring: it combines the PoseNet model and a deep neural network to monitor physical education students' exercise routines and provide real-time feedback on form, posture, and range of motion [23]. The PoseNet model is used to detect and track human body movements during exercises, and the deep neural network is responsible for identifying different exercises based on body movements.

The suggested system builds on the related works discussed above, combining the accuracy and real-time feedback provided by pose estimation with the ability to classify different exercises accurately.

III. Data

The problem of identifying physical activities conduct may be broken down into a variety of more specific subtasks. Fig. 1 presents the research process as a flowchart for your reference. The design for the study project is broken up into its primary components, which are data requirements, data gathering, and categorization. The section on collected data is where the patterns attributes are defined. The portion responsible for data collection assures the availability of relevant video data, marks up videos according to classifications, stores them in .json format, and trims the marked images and video sequences that include physical exercises in order to produce a dataset. Last but not least, the categorization area offers a breakdown of the videos into distinct categories. This section is divided into subcategories such as data preparation, extraction of features, model training, and testing, respectively.

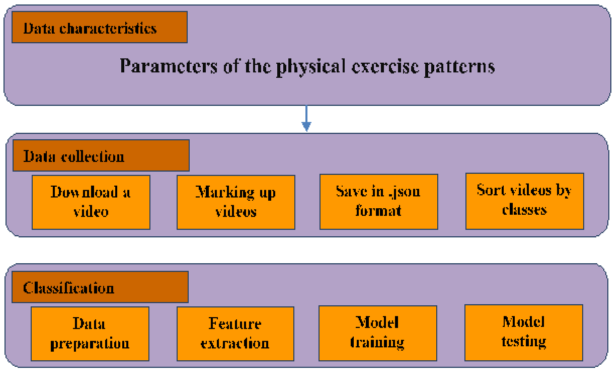

Fig. 1. Image before and after rescaling.

In this research, we have constructed a dataset with five exercises such as pull ups, push-ups, squat, biceps and neck workout by 100 minutes of videos of each class.

IV. Materials and Methods

A. Proposed Approach

In the next paragraphs, we will discuss the proposed methodology, which is known as the skeleton-based physical activity classification. The suggested system's general design is shown in Fig. 2, which may be seen here. The framework may be broken down into three different subproblems. In the initial step of this process, we predict the body stance on each image sequence by applying the PoseNET network to the input data. In the next step, we take each frame and extract focal points as vectors. PoseNET provides a total of 17 important locations for each frame [24]. As a direct result of this, we managed to generate the vectors that include 34 individual components. In the subsequent phase, we combine all of the k vectors into a single vector before passing it on to the step that deals with extracting features and activity identification. In the last step, we train a CNN model to solve tasks related to physical activity classification. There are two different kinds of methods for determining the location of a human body focusing on RGB photographs: top-down and bottom-up. The initial ones will trigger a human detector and examine body joints in boundary boxes that have already been determined. Top-down methods include the ones described in PoseNET [25], HourglassNet [26], and Hornet [27]. There are a few other bottom-up methods, such as Open space [28] and PifPaf [29].

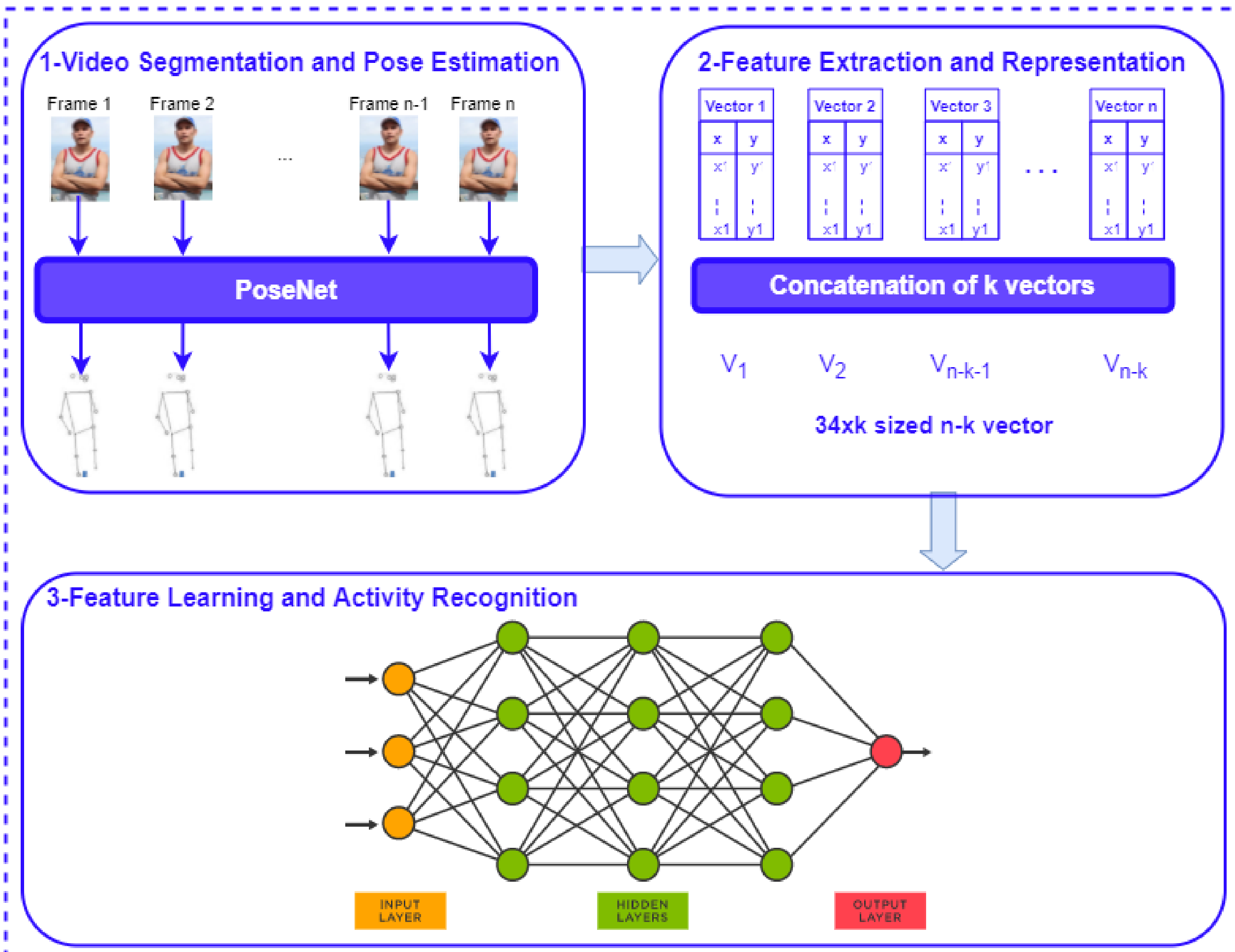

Fig. 2. The proposed framework architecture.

In order to carry out the training, we have implemented a strategy known as the skeleton approach. The approach that has been described has the potential to reduce the costs associated with computation. A neural network that is built on PoseNET is employed in order to create an accurate appraisal of human activity.

Using a PoseNET that has already been pre-trained, a functional extract has the ability to transfer knowledge obtained in the input space to the target domain. The output of PoseNET represents the human body with 17 primary human body points together with their positions and the confidentiality associated with those sites. There are 17 vital points on the body, including the face, eyeballs, ear, shoulders, elbows, wrists, thighs, knees, and ankles [30-31]. Fig. 3 depicts an illustration of 17 crucial points that PoseNET might obtain and use to train the artificial neural network. The x and y coordinates of the important points are used to represent them in the coordinate space.

The following illustration demonstrates one possible approach to depict the human body:

$$r_b(x_i;\theta), \tag{1}$$

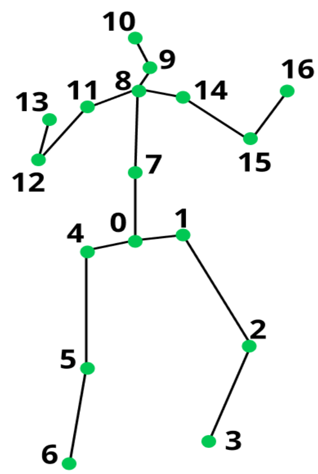

Fig. 3. PoseNET key points.

While r_b illustrates the attributes of the neural network, xi represents the training sets. In order to categorize the illustration of the human body, $r_b(x_i;\theta)$, , a layer of a completely linked neural network is introduced. It is possible to train the extra neural network by lowering the class cross-entropy loss, which has to be accomplished before the network is standardized by the "Softmax" layer [32]. Fig. 4 presents an overview of the structure of the PoseNET-based network. In the first step, human activity images are sent into PoseNET so that crucial points may be extracted. Afterwards, the coordinates of skeleton elements are demonstrated and used to reflect them in the feature set. Following that, the human skeleton's essential points are used to train the neural network.

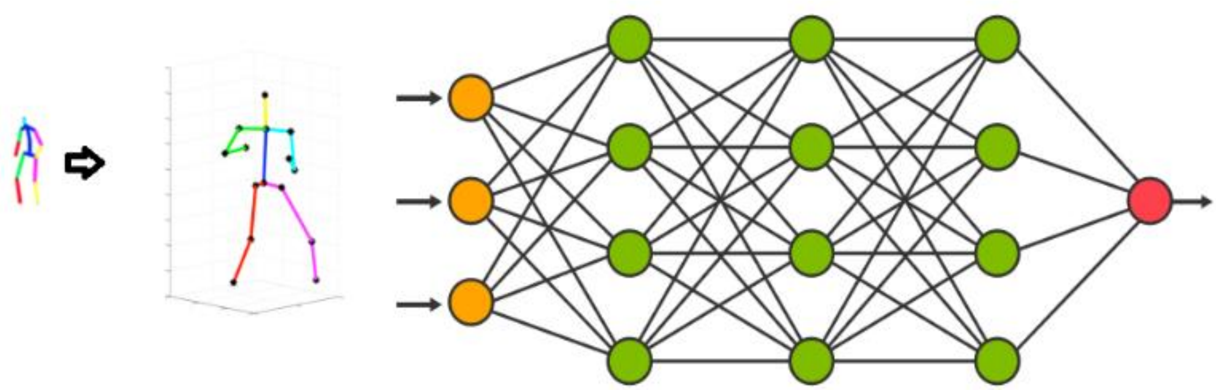

Fig. 4. Artificial neural network for physical activity classification.

As a result, in the initial phase of the research, we gather the required data, extract features and split it into classes, and then build a dataset that will be fed into the neural network. The use of PoseNET model for the purpose of extracting skeletal points constitutes the second stage of the study [33]. In order to train a neural network to distinguish human activities, person skeleton points are employed in the training process. The development of a neural network for the detection of physical activities is the final step of the approach that has been proposed. After that, training and testing the results of the neural network are carried out in order to determine whether or not the proposed approach is suitable for application in the real world.

B. Evaluation Parameters

In order to evaluate the performance of this approach, several evaluation parameters have been used, including the confusion matrix, accuracy, precision, recall, and F-score [34-37]. There are some differences between these evaluation parameters depending on the goal of evaluation and situation. Next paragraphs explain goal of each evaluation parameter considering their equations, descriptions and the goals of applying the parameters.

The confusion matrix is a tabular representation of the performance of a classification model, which shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each class. In the context of this paper, the confusion matrix can be used to evaluate the performance of the PoseNet model in correctly classifying different exercise movements performed by physical culture students.

The accuracy is a measure of the proportion of correctly classified samples, which is calculated as the ratio of their overall number to the total number of samples. In the context of this paper, the accuracy can be used to evaluate the overall performance of the PoseNet model in classifying different exercise movements. Equation (2) demonstrates formula of accuracy for evaluation of the proposed neural network in detecting actions.

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}, \tag{2}$$

Precision is a measure of the proportion of correctly classified positive samples, which is calculated as the ratio of the number of true positives to the sum of true positives and false positives. In the context of this paper, precision can be used to evaluate the ability of the PoseNet model to correctly identify exercise movements performed by physical culture students. Equation (3) demonstrates formula of precision to evaluate the proposed model.

$$precision = \frac{TP}{TP + FP}, \tag{3}$$

Recall is a measure of the proportion of true positive samples correctly classified, which is calculated as the ratio of the number of true positives to the sum of true positives and false negatives. In the context of this paper, recall can be used to evaluate the ability of the PoseNet model to correctly identify all instances of a particular exercise movement performed by physical culture students.

$$recall = \frac{TP}{TP + FN}, \tag{4}$$

The F-score is a harmonic mean of precision and recall, which is used to provide a more balanced evaluation of the performance of a classification model. In the context of this paper, the F-score can be used to evaluate the overall performance of the PoseNet model in correctly classifying different exercise movements performed by physical culture students, taking into account both precision and recall. Equation (5) demonstrates formula of F-score.

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall}, \tag{5}$$

V. RESULTS

In this part, we provide the findings of our investigations on the main challenges of data collecting, feature extraction, and physical activity classification. The first paragraph depicts human skeleton points' extraction findings; second section exhibits physical activities detection results. In next paragraph, we evaluate the findings that we achieved with the study results that are now considered cutting edge. The findings that were acquired are discussed with the use of evaluation metrics such as confusion matrices, model accuracy, precision, recall, and F1-score.

A. Keypoints Extraction

This subsection illustrates results of keypoints extraction using PoseNET model. Fig. 5 demonstrates how the proposed model work to extract key points. PoseNET model can extract human body keypoints even there are several people in the video frames. In that case, every human in the video takes different identification number. In the given example, five people have ID from 1 to 5.

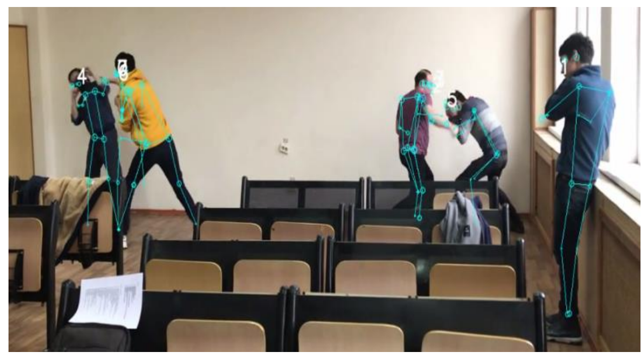

Fig. 5. Keypoints extraction from video.

B. Physical Activity Classification

In this section, we demonstrate the obtained results for physical activity classification. Fig. 6 and Fig. 7 present model accuracy and model loss. Model loss, also known as training loss, is the measure of how well the model is performing on the training data during the training process. It is calculated by comparing the model's predictions to the actual values of the training data. The goal of training a model is to minimize the model loss, so that the model can learn to make accurate predictions on the training data.

Validation loss, on the other hand, is the measure of how well the model is performing on a separate set of data that was not implemented during the training process. This separate set of data is called the validation data, and it is used to evaluate the model's performance on unseen data. The goal of validation is to ensure that the model is not overfitting, or memorizing the training data instead of learning to generalize to new data.

Fig. 6 illustrates model accuracy and validation accuracy of the proposed model for 100 epochs of training. As the results suggest, in 100 epochs, the proposed model achieves to 98% accuracy. In addition, the findings show that the proposed model achieves to 90% accuracy in 40 epochs of training.

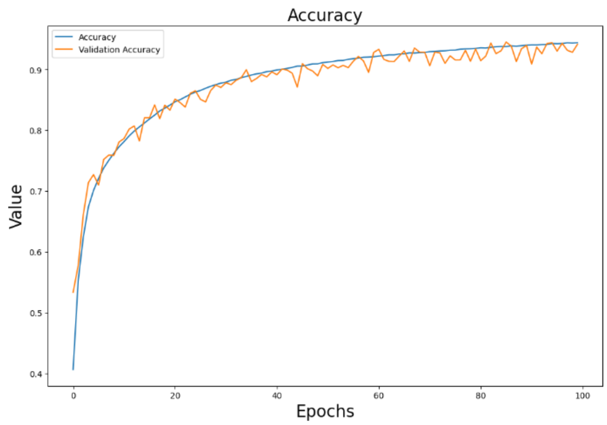

Fig. 6. Model accuracy.

Fig. 7 demonstrates model loss and validation loss for 100 learning epochs. As the results show, in 100 epochs the model loss achieved to 0.2. Also, should be noted that the proposed system works in real-time.

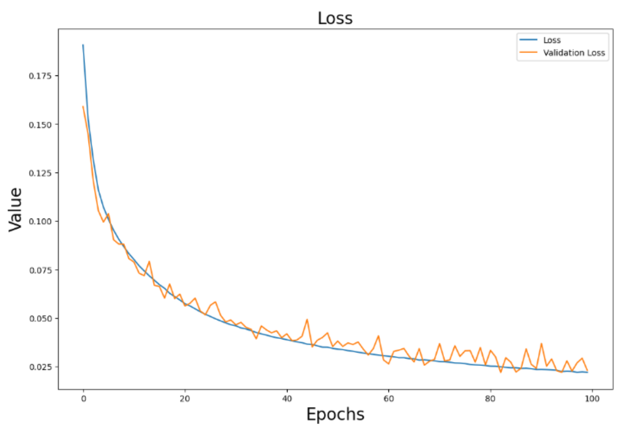

Fig. 7. Model loss.

Fig. 8 illustrates an example of biceps monitoring. The proposed framework works by indicating the angles. If the angle is less than 30, the counter will be incremented.

Fig. 8. Biceps monitoring.

Fig. 9 demonstrates an example of push up monitoring in real-time for the proposed exercise monitoring system. Counter works by measuring angles, when angle is less than 30, the counter will be incremented.

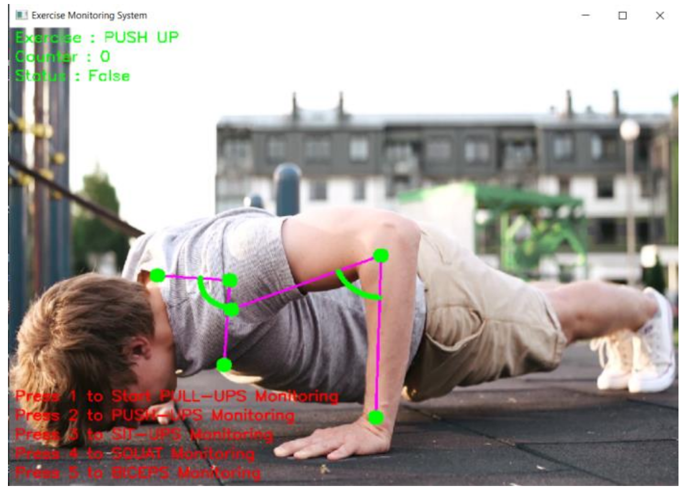

Fig. 9. Push ups monitoring.

VI. Discussion and Future Research

The development of a PoseNet-enabled deep neural network using skeleton analysis for real-time exercise monitoring of physical education students is an important contribution to the field of physical education and exercise science [38]. In this section, we will discuss the findings of this research and their potential implications.

Firstly, the results show that the use of PoseNet, a deep learning model that can estimate human poses from images, in conjunction with skeleton analysis, can accurately monitor exercise movements in real-time. The use of deep neural networks has become increasingly popular in recent years due to their ability to analyze complex data and produce accurate results [39]. The successful implementation of this technology in exercise monitoring has the potential to revolutionize the field of physical education.

Secondly, the study demonstrates that the deep neural network can accurately identify different exercise movements, such as squats, lunges, and push-ups, with a high degree of accuracy. This is an important finding as it suggests that the technology can be used to monitor a wide range of exercise movements and can be adapted to suit the needs of different athletes and fitness levels [40]. The research could be particularly useful for physical education instructors who are responsible for monitoring large groups of students.

Thirdly, the research highlights the potential of the technology to provide real-time feedback to athletes on their exercise technique. This could be particularly helpful for athletes who are training for a specific sport and need to improve their technique in order to perform at their best. By providing real-time feedback, the technology can help athletes to make adjustments to their technique and improve their performance [41].

Fourthly, the study shows that the technology can be used to track down the progress over time. By analyzing data from multiple exercise sessions, the deep neural network can identify changes and patterns in an athlete's performance, which could be highly advantageous for athletes who are looking to track their progress over time and make adjustments to their training program.

Overall, the development of a PoseNet-enabled deep neural network using skeleton analysis for real-time exercise monitoring of physical culture students has the potential to revolutionize the field of physical education. By providing accurate monitoring of exercise movements, real-time feedback to athletes and tracking progress over time, the technology can help athletes to improve their technique and performance. Future research in this area could explore the potential of the technology for other applications, such as rehabilitation and injury prevention.

VII. CONCLUSION

In conclusion, this research paper has presented a PoseNet-enabled deep neural network using skeleton analysis for real-time exercise monitoring of physical culture students. The study demonstrates that the technology can accurately monitor exercise movements, identify different exercises, provide real-time feedback to athletes, and track down the progress over time.

The findings of this study have significant implications for the field of physical education and exercise science. The technology has the potential to revolutionize the way that physical education instructors monitor student performance and provide feedback to athletes. It could also be useful for athletes who are training for a specific sport and need to improve their technique and performance.

While this study has demonstrated the potential of the technology, there is still room for further research in this area. Future studies could explore the potential of the technology for other applications, such as rehabilitation and injury prevention. Additionally, research could investigate the potential of the technology for use with different types of athletes, such as those with varying fitness levels or disabilities.

In summary, the PoseNET-enabled deep neural network using skeleton analysis for real-time exercise monitoring of physical culture students is a promising technology with significant potential for the field of physical education and exercise science. Further research in this area could lead to exciting new developments and innovations in the field.

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