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Research Article

Deep Learning-Based Classification of Powerlifting Movements Using Mediapipe

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ABSTRACT

The analysis of sports movements is of great importance for optimizing sports performance, minimizing injury risks, and ensuring that athletes work with correct techniques. Powerlifting is a power sport consisting of fundamental movements such as bench press, deadlift, and squat. These movements are inherently complex and challenging to execute. Therefore, it is of great importance to perform these movements with the correct technique and safely. The aim of this study was to classify these movements using deep learning methods to ensure that the basic movements in powerlifting sports (bench press, deadlift, and squat) are applied with correct techniques and to minimize the risk of injury. In this study, feature extraction was performed on powerlifting movements using the deep learning-based SqueezeNet model, followed by classification using machine learning methods. The dataset was compiled from 876 images of bench press, deadlift, and squat movements sourced from various online platforms. Additionally, the dataset was expanded through data augmentation techniques, and key points of posture estimation were added to the images using the Mediapipe library. The obtained datasets were classified using Neural Network, Logistic Regression, Support Vector Machine and Random Forest algorithms and model performances were evaluated using various metrics. The findings revealed that the Neural Network model demonstrated superior performance, achieving the highest accuracy (0.989). Additionally, the integration of pose estimation and data augmentation techniques significantly enhanced classification accuracy and overall model performance. The findings of this study show that deep learning methods are powerful tools in sports movement analysis and can make significant contributions to the evaluation of athletes' performance.

1. Introduction

Sport plays a crucial role in both physical and mental health. Regular exercise offers numerous benefits, such as improved body function, increased muscle strength, weight management and improved flexibility [1]. The positive effects of regular exercise on health have been substantiated by various scientific studies. Warburton et al. reported that aerobic activities improve cardiovascular health, lower blood pressure and stabilize cholesterol levels [1]. Sports activities also provide significant psychological benefits such as reduced stress, improved mental health and increased social interaction [2]. Another study demonstrated that physical activity is effective in preventing obesity and managing body weight [3]. Regular exercise also improves physical functioning by increasing muscle strength, flexibility and coordination. Sport also has numerous positive effects on mental health. Physical activity has been reported to improve concentration, focus and cognitive functioning [4]. Another study found that regular exercise reduces symptoms of depression and anxiety [5]. Sport increases

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overall psychological well-being by strengthening feelings of self-confidence and self-efficacy [6]. Sport has positive effects not only on health and psychology, but also on athletic performance. One study found that regular training improves physical capacities such as endurance, strength and agility [7]. In conclusion, it is clear that playing sports offers multifaceted benefits in terms of health, psychology and performance.

Some sports movements are considered fundamental because they work many muscle groups at the same time. Powerlifting is a strength sport that consists of three fundamental movements: squat, bench press and deadlift. These three fundamental movements engage all major muscle groups in the body. Powerlifting is characterized as a maximal strength sport. Athletes are allowed three attempts per movement category, during which they must lift the maximal load in a single repetition. The highest weights lifted by athletes in each category are totaled to determine their score [8]. The squat is a fundamental lower body exercise that primarily strengthens the quadriceps, glutes, and lower back muscles. The deadlift is known as a basic lower body exercise that works the back, hamstrings and glutes the most. The squat primarily targets the lower body and knee joints, whereas the deadlift primarily targets the torso, hips, and back [9]. Bench press is a basic upper body exercise that intensively works the chest, shoulder and arm muscles [10].

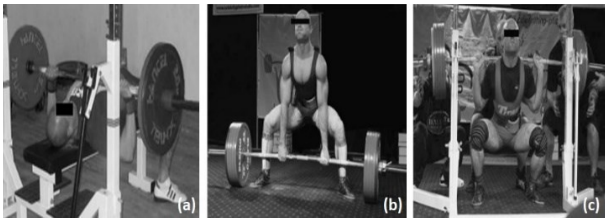

Figure 1. The Fundamental Movements Utilized in Powerlifting a) Bench Press, b) Deadlift, c) Squat [11]

As depicted in Figure 1.a, the bench press is a fundamental sports movement executed by lying supine on a bench and pressing the barbell upward over the chest. The deadlift, illustrated in Figure 1.b, is executed by bending at the hips and lifting the barbell from the ground. The squat, as shown in Figure 1.c, is a fundamental sports movement performed by squatting down and lifting the barbell onto the shoulders. However, it is very important to perform sports movements with the correct technique and safely. Incorrect movement forms increase the risk of injury and negatively affect the performance of athletes [12]. Particularly in high-load movements such as the bench press, squat, and deadlift, proper technique and precision are of paramount importance. Therefore, executing powerlifting movements with correct techniques is critical for minimizing the risk of injury and optimizing athletic performance. Currently, the application of deep learning techniques in the analysis of sports movements is rapidly expanding, enabling the achievement of high accuracy rates.

The application of deep learning in sports motion analysis has emerged as a prominent area of research in recent years. In a literature review on machine and deep learning techniques for automatic detection and recognition of sports gestures, Cust et al. emphasize the need to adopt approaches appropriate to the characteristics of these gestures [13]. Ronao, C. A., & Cho, S. B., in a study on deep learning-based human activity recognition using data collected from smartphone sensors, achieved successful results in recognizing sports activities (walking, running, cycling, etc.) [14]. In another study, Wang, P. examined the recognition of sports training actions using deep learning algorithms and suggested the use of these algorithms in action recognition [15]. Pajak, G. et al. examines the performance of deep learning, specifically CNN and ensemble approaches in sports activity recognition using inertial sensor data [16]. Xu, Y. demonstrated that a deep learning-based sports training video classification model offers high accuracy and speed in recognizing training actions [17].

Pan, S. proposes a method for automating basic posture and motion recognition in sports videos, with a particular focus on weightlifting, using deep learning techniques. This method aims to address the challenges faced by traditional target detection and tracking methods (e.g. image distortion, background effect, suddenly changing lighting). The proposed RoI_KP method automatically detects basic postures by fine-tuning region-based classification and convolutional neural networks [18]. Wang, L. et al. developed a big data and deep learning based classification model focusing on automatic understanding of human movements in free gymnastics videos. This model significantly improves the accuracy in the classification of sports videos [19]. Zhao, X., conducted a study aiming to analyze and correct incorrect technical movements in the training of young athletes using deep learning. They developed a model based on convolutional neural networks (CNN) and deep learning (DL) for the detection of incorrect movements during physical education and training process. Simulation results indicate that this method achieves a false movement detection accuracy of 92.16% [20].

In a 2021 study, Ferreira, B. et al. investigated the use of computer vision and deep learning techniques to automatically determine the number of repetitions and the validity of sports movements. In this study, a system for counting and validating exercise repetitions was developed using 2D human posture estimation, and incorrect exercise repetitions were detected. The researchers collected data on five popular CrossFit exercises from more than 130 participants, and the repetition counting and validation module developed with this data was able to take the predicted exercise moments and determine the number of valid repetitions with over 92% accuracy [21]. Chen, K.-Y. et al. conducted a similar study and developed a fitness gesture detection and classification system for home fitness exercisers to prevent injuries caused by faulty movements. The developed system provided real-time detection of 12 distinct fitness movements using YOLOv4 object detection and MediaPipe pose estimation. The results indicated that 98.56% accuracy was achieved in movement type classification, while 92.84% accuracy was recorded in movement completion classification. The system operates in real-time at an average speed of 17.5 FPS. This research led to the development of a highly accurate and efficient fitness motion detection system, utilizing a combination of transfer learning and object detection-pose estimation techniques [22].

A review of the literature reveals that existing studies accurately describe the characteristics of human movements. These studies facilitate the evaluation and correction of incorrect movements in sports training by accurately detecting such movements. In this way, it helps athletes to improve their sports movement techniques. In the literature, deep learning methods have been widely used for analyzing sports movements. However, the majority of these studies have concentrated on sports activities such as walking and running. There is a lack of studies analyzing complex and technical movements such as powerlifting using deep learning methods that achieve high accuracy rates. The primary objective of this study is to analyze and classify powerlifting movements using deep learning techniques with high accuracy. Therefore, this study aims to explore the potential of deep learning-based methods in the analysis of sports movements. This research contributes to the field by providing a novel approach to analyzing powerlifting movements with deep learning, addressing an existing gap in the literature. In practice, this study is expected to contribute to the development of a system that enables athletes and coaches to evaluate performance in a more objective and scientific manner.

2. Material and Methods

In this study, the SqueezeNet model, a lightweight and fast convolutional neural network architecture, was utilized to extract features from Powerlifting images. The extracted features were subsequently input into various machine learning algorithms, including Neural Network, SVM, Logistic Regression, and Random Forest, and the classification results were analyzed in detail. The performance of each model was evaluated using common performance metrics such as Accuracy, F1-Score, and AUC (Area Under the Curve). Figure 2 provides a summary of the data flow and modeling process employed throughout the study.

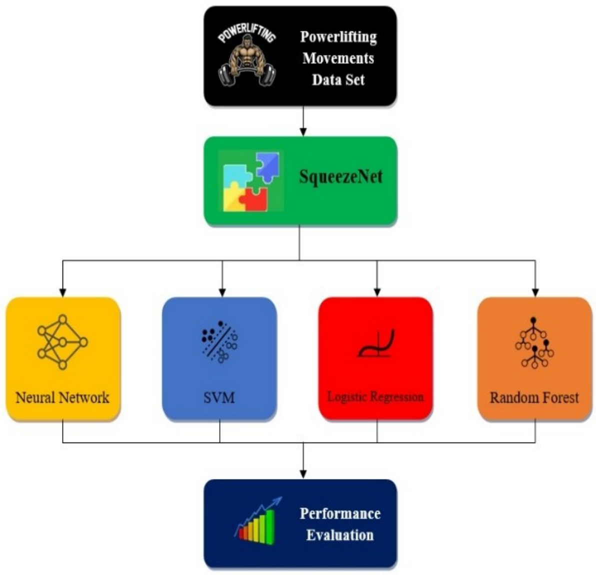

Figure 2. Flowchart of the Modeling Process Used for Classification of Powerlifting Movements

2.1. Data Set

In this study, a dataset containing Powerlifting movements (bench press, squat, deadlift) was compiled from various online sources. As depicted in Figure 3, the original dataset consists of 217 images for the bench press, 359 images for the deadlift, 300 images for the squat, totaling 876 images. Due to variations in the resolution and quality of the images, the first step involved scaling all images to 640x640 pixels.

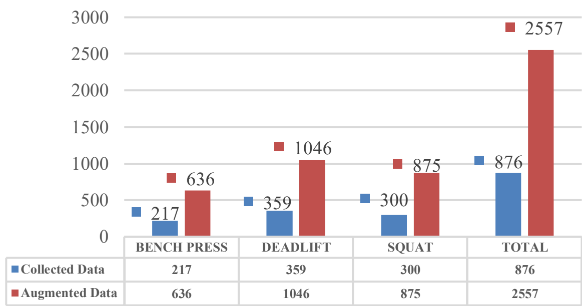

Figure 3. Dataset and Distribution by Category

Data augmentation encompasses techniques used to generate synthetic data by introducing minor variations to the existing dataset. These techniques help to avoid overfitting by increasing the variety of data without changing the model's predictions. Consequently, this enables the model to learn more generalizable features rather than memorizing random patterns [23]. In this study, the rotation method, a common data augmentation technique, was employed. Random rotations ranging from -15° to +15° were applied to the original images. As a result of this process, a total of 2557 images were generated from the original 876 images. Specifically, the number of Bench Press images increased from 217 to 636, Squat images from 300 to 875, and Deadlift images from

359 to 1046. This data augmentation process aims to make the model learn more generalizable and robust features.

2.2. Using Mediapipe Library

Mediapipe is an open-source framework developed by Google and used in image and video processing and media applications. In particular, the framework utilizes deep learning techniques to detect and track objects such as the human body and face. One of the most important features of Mediapipe is its real-time processing capability, making it an ideal solution for interactive applications. Where traditional inverse kinematics approaches fail to address the diversity of human postures, Mediapipe is designed to overcome these limitations. The Mediapipe library has been tested on exercise videos and fall scenarios and demonstrated the ability to run in real-time at 33ms per frame, even on single-board computers without GPUs [24]. The distribution of 33 key points obtained using Mediapipe with these features is given in Figure 4.

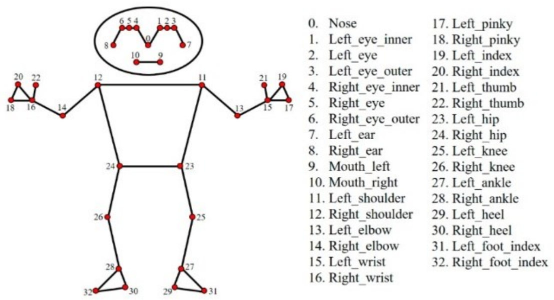

Figure 4. Distribution of 33 key points obtained using Mediapipe.

In this study, Mediapipe library is used to perform 3D pose estimation on 2557 images. The Pose Estimation module of Mediapipe includes an artificial intelligence model capable of estimating the position and posture of the human body with high accuracy. This model enabled the extraction of 3D skeletal data for each image by identifying 33 key points of the human body. In this way, data containing the coordinates of the 33 key points were obtained for each image. As depicted in Figure 5, these key points were superimposed onto each image.

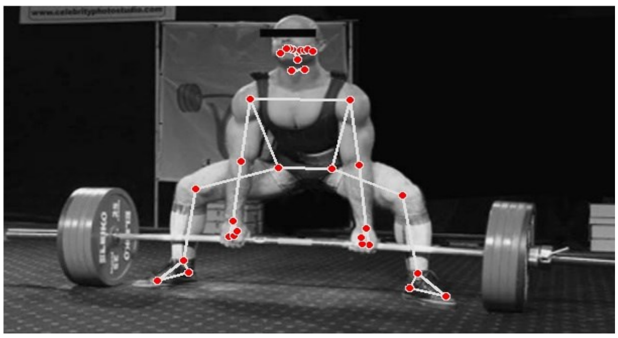

Figure 5. Visualization of the Skeletal Structure with 33 Key Points Identified in the Deadlift Movement Using the Mediapipe Library

2.3. Feature extraction with Deep Learning

SqueezeNet is a low-parameter Convolutional Neural Network (CNN) architecture developed by deep learning researchers, specifically designed for deployment on mobile and embedded devices. Compared to larger models such as AlexNet, this architecture requires significantly less computational overhead while achieving similar levels of accuracy. SqueezeNet is a CNN architecture that achieves AlexNet-level accuracy on ImageNet with 50 times fewer parameters. The basic building block of SqueezeNet is a module called the "Fire Module", which consists of squeeze and expand stages. The Fire Module plays a critical role in reducing the number of parameters of the model by significantly reducing the input channels. The SqueezeNet architecture consists of 8 Fire Modules and the initial and output layers [25].

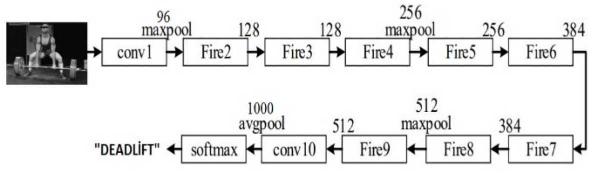

Figure 6. Architectural Structure of the SqueezeNet Model

As shown in Figure 6, SqueezeNet begins with a single initial convolution layer (conv1) followed by 8 "Fire Modules" (fire2-9). At the end of the model, a single output convolution layer (conv10) is present. The number of filters within the Fire Modules increases with the depth of the network, meaning that more filters are employed in the later modules. Furthermore, max-pooling layers are applied after conv1, fire4, fire8 and conv10. These architectural design decisions aim to enable SqueezeNet to achieve AlexNet-level accuracy by significantly reducing the number of parameters. In particular, the Fire Module structure and the strategic positioning of the pooling layers contribute to the realization of this goal. The use of fewer layers in SqueezeNet allows the model to remain lightweight and operate with lower memory requirements [25].

In conclusion, the basic structure of the SqueezeNet architecture, the Fire Module design and the positioning of the pooling layers, is an efficient deep learning architecture that aims to achieve high accuracy while significantly reducing the number of parameters. In this study, 1000 features were extracted for each image from the conv10 layer, one of the final layers of SqueezeNet. These features represent high-level abstractions necessary for deep learning models to effectively interpret the images. However, high-dimensional feature vectors can increase computational complexity and reduce the model's generalization ability. For this reason, the Gini feature selection algorithm was used to select the most meaningful and discriminative features among the 1000 features. At the end of this process, the top 500 features that offer the best performance for the classification process were identified and these features were used in the training and testing phases of the model.

2.4. Machine Learning Algorithms

In this study, widely utilized machine learning algorithms, including Neural Networks, Logistic Regression, SVM, and Random Forest, were employed.

Neural Networks are computational models that function similarly to neurons and synaptic connections in the brain [26]. Deep learning architectures consisting of multiple layers, trained with back-propagation algorithms, provide high success in complex problems such as image, voice, language processing [27]. Combines feature extraction and classification and includes a large number of parameters, can learn more powerful representation [28].

Logistic Regression is a linear classification algorithm and is often used for binary classification problems [29]. By utilizing a linear combination of independent variables, it calculates the probability of the dependent variable and predicts class labels. The parameters of Logistic Regression are learned through optimization techniques, including gradient descent. This algorithm is particularly effective when classes can be clearly separated from each other [30].

Support Vector Machine (SVM) is an algorithm applicable to both classification and regression tasks. Its main goal is to find the optimal separating hyperplane between classes. SVM is also capable of solving non-linear problems using kernel functions [31]. It is robust to outliers and noise, and is effective for high-dimensional data [32].

Random Forest is an ensemble learning algorithm that combines a large number of decision trees [33]. Each tree is trained on a random subset of the training data and the final classification or regression prediction is made based on the majority of the results. Random Forest is robust to outliers, noise and overfitting problems, and is also notable for its ability to perform variable importance ranking [34].

2.5. Performance Metrics

One of the main methods used to evaluate the performance of machine learning models is confusion matrix analysis. The confusion matrix provides a summary of the accuracy of the model's predictions across various categories and includes four key components: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

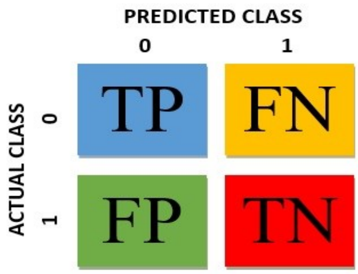

Figure 7. Confusion Matrix for Binary Classification

True Positives (TP): Instances that the model correctly predicts as positive outcome. True Negatives (TN): Instances that the model correctly predicts as negative outcome. False Positives (FP): Instances where the model incorrectly predicts a positive outcome (Type I error). False Negatives (FN): Instances that the model incorrectly predicts as negative outcome (Type II error). Various performance metrics can be derived from the confusion matrix, as presented in Table 1 [35].

Table 1. Performance Metrics and Corresponding Formulas

Performance Metric	Formula
Accuracy(CA): The ratio of correctly classified samples to total samples.	$\frac{TP+TN}{TP+TN+FP+FN}x100$
Precision(Prec): Indicates how many of the samples predicted positive are actually positive. It is important for situations that aim to reduce the rate of false positives.	$\frac{TP}{TP+FP}$
Recall or True Positive Rate: Shows how many true positive samples are correctly predicted. Refers to the model's ability to capture the positive class.	$\frac{TP}{TP+FN}$
F1-Score: The harmonic mean of Precision and Recall metrics and may be a more meaningful measure, especially in imbalanced datasets.	$2x\frac{Precision\ x\ Recall}{Precision+Recall}$
Matthews Correlation Coefficient (MMC): MCC is a powerful performance metric used in classification problems and measures the overall accuracy of a classifier by taking into account all complexity matrix components (TP, TN, FP, FN). MCC is considered an important metric, especially in imbalanced datasets. Its value ranges from -1 to +1, with +1 indicating perfect classification, 0 indicating random prediction, and -1 indicating completely incorrect prediction.	$\frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

AUC - Area Under the Curve: AUC is a metric that indicates the overall performance of the classifier and takes a value between 0 and 1. Values closer to 1 represent better classification performance.

3. Results

This study demonstrates that sports activities can be successfully recognized using deep learning techniques, enabling detailed analysis of associated movement techniques. The datasets used in the study consist of 876 images for the analyses in Table 2 and Table 4, and 2557 images obtained with data augmentation techniques for the analyses in Table 3 and Table 5. Eighty percent of the data was allocated for model training and twenty percent for testing. After the data sets were separated by random sampling method in each iteration, each model was trained 10 times and test results were obtained. The training and testing processes of the model were carried out on a computer with Intel(R) Core (TM) i3-4000M CPU @ 2.40GHz, 8GB RAM, AMD Radeon R5 M230 Series graphics card.

In this study, it was found that the combination of image and skeletal data, as well as data augmentation techniques, significantly improved the model performance. In addition, the choice of the deep learning algorithm used has a significant impact on the classification results. The results obtained throughout the study are presented in step-by-step tables. Table 2 provides a summary of the analysis results using the initial dataset (876 images).

Table 2. Results with the initial data set

Model	AUC	CA	F1	Prec	Recall	MCC
Neural Network	**0.988**	**0.925**	**0.923**	**0.922**	**0.925**	**0.886**
Logistic Regression	0.987	0.923	0.921	0.920	0.923	0.882
SVM	0.986	0.921	0.919	0.919	0.920	0.879
Random Forest	0.932	0.804	0.803	0.806	0.808	0.700

As presented in Table 2, the Neural Network model demonstrated the best performance, achieving an accuracy (CA) of 0.925 and an AUC value of 0.988, while the Random Forest model exhibited comparatively lower performance relative to the other algorithms. Figure 8 shows the ROC (Receiver Operating Characteristic) curves of different machine learning models trained using the baseline dataset for Bench Press, deadlift and Squat movements respectively.

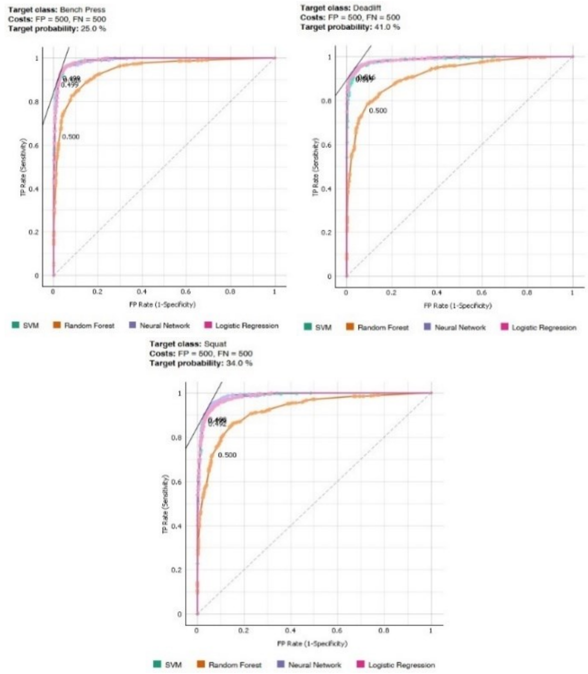

Figure 8. ROC Curves for the Initial Data Set

Figure 8 compares the ROC curves of Neural Network, Logistic Regression, SVM and Random Forest models. Neural Network and Logistic Regression models show the best performance with high AUC values.

Table 3 summarizes the results of the analyses performed using the expanded dataset of 2557 images obtained through the data augmentation process.

Tablo 3. Results with augmented data set

Model	AUC	CA	F1	Prec	Recall	MCC
Neural Network	**0.999**	**0.983**	**0.983**	**0.983**	**0.982**	**0.974**
Logistic Regression	0.998	0.977	0.977	0.977	0.976	0.964
SVM	**0.999**	0.974	0.974	0.973	0.975	0.961
Random Forest	0.967	0.875	0.875	0.876	0.874	0.809

The results in Table 3 show that the model performance improves significantly by increasing the data set. The Neural Network model emerges as the best-performing model, achieving an accuracy (CA) of 0.983. It is evident that the application of data augmentation techniques leads to increased model accuracy and improved classification performance. While the Random Forest model exhibited inferior performance compared to the other algorithms, it nonetheless demonstrated improved results with the expanded dataset.

Figure 9 compares the ROC curves of various machine learning models trained on the dataset obtained through the data augmentation process. The Neural Network and SVM models exhibit the best performance, reflected in their high AUC values.

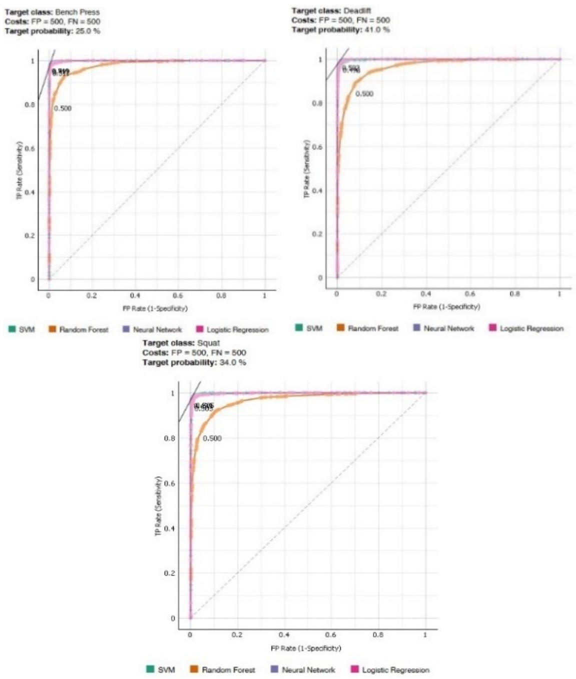

Figure 9. ROC Curves for the Augmented Data Set

Table 4 provides a summary of the analyses conducted using the initial dataset for pose estimation with Mediapipe. This dataset was generated by applying pose estimation to the base dataset of 876 images and overlaying the key points onto each image. Pose estimation for each image was performed using the Mediapipe library, with the resulting estimations superimposed onto the images.

Table 4. Results obtained using the initial dataset for posture estimation with Mediapipe.

Model	AUC	CA	F1	Prec	Recall	MCC
SVM	0.982	**0.919**	**0.919**	**0.921**	**0.918**	**0.877**
Neural Network	**0.984**	0.916	0.915	0.913	0.917	0.873
Logistic Regression	0.982	0.909	0.906	0.905	0.907	0.861
Random Forest	0.922	0.795	0.797	0.836	0.825	0.696

The results in Table 4 show that the model performance is slightly degraded compared to the augmented dataset in Table 2 when the data obtained by predicting posture on the base dataset is used. The SVM model emerges as the best-performing model in this classification task, achieving a CA of 0.919. Although posture estimation results in a minor decrease in model accuracy, the models continue to perform at a reasonable level.

Figure 10 compares the ROC curves of various machine learning models trained on the dataset with Mediapipe posture prediction. The SVM and Neural Network models exhibit the best performance, reflected in their high AUC values.

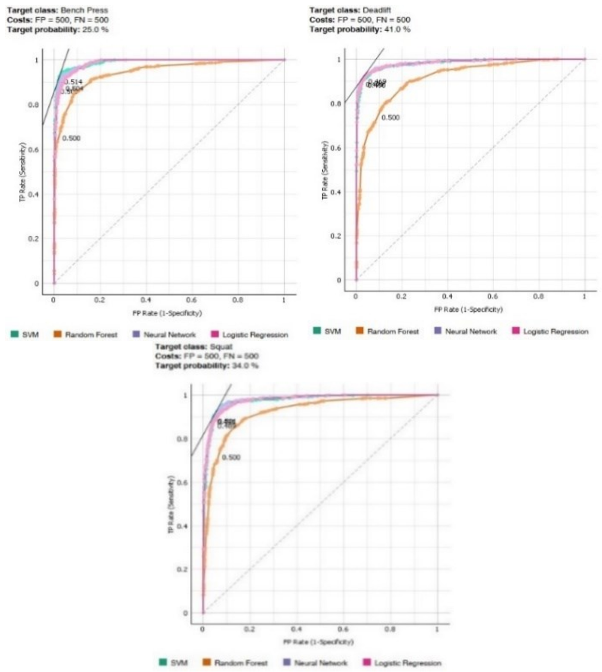

Figure 10. ROC Curves for the Dataset Used in Posture Estimation with Mediapipe

In this study, the analysis of the augmented dataset, obtained by combining posture estimation and data augmentation techniques, demonstrates significant improvements in the recognition of sports activities. Posture estimation enables the detection of various key points on the human body, which are then input into deep learning models. Following the application of pose estimation to the baseline dataset, the dataset was expanded using data augmentation techniques, and machine learning models were subsequently trained on this new dataset. Table 5 provides a summary of the results of these analyses.

Table 5. Results Using the Augmented and Pose Estimation Dataset".

Model	AUC	CA	F1	Prec	Recall	MCC
Neural Network	**1.000**	**0.989**	**0.989**	**0.989**	**0.990**	**0.983**
SVM	0.999	0.980	0.981	0.981	0.981	0.969
Logistic Regression	0.998	0.978	0.977	0.977	0.978	0.967
Random Forest	0.975	0.894	0.894	0.896	0.892	0.837

The results presented in Table 5 are obtained by pose estimation on a dataset that was expanded from 876 images to 2557 images through data augmentation. These results show a significant improvement in the performance of the model. The Neural Network model improves from an initial accuracy of 0.925 to an accuracy (CA) of 0.989, from an AUC of 0.988 to an AUC of 1,000 and still emerges as the best performer in this classification task. The combination of pose estimation and data augmentation techniques significantly improved the classification accuracy and overall performance of the model.

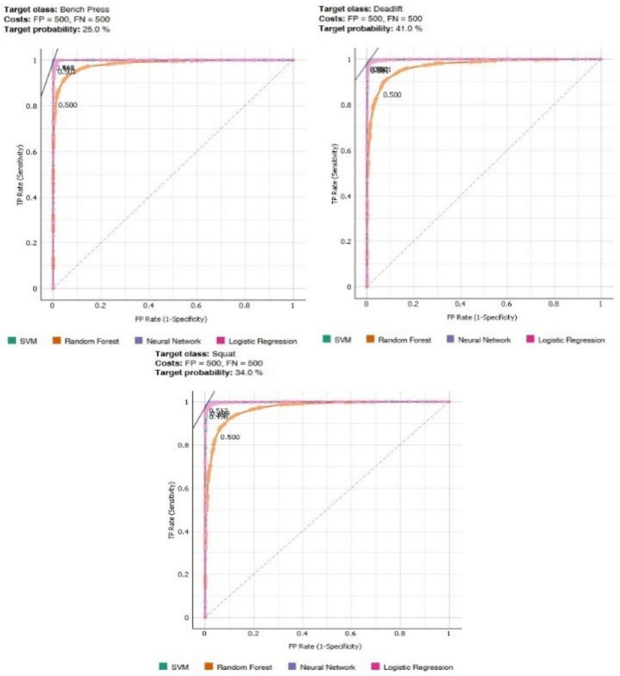

Figure 11. ROC Curves for the Augmented and Pose Estimation Data Set

Figure 11 compares the ROC curves of various machine learning models trained on the augmented dataset enhanced with pose estimation. The Neural Network model performs near-perfectly in terms of area under the ROC curve (AUC), making it the best model for this classification task. Upon analyzing the results, it is evident from Table 5 and Figure 11 that the posture prediction technique with Mediapipe significantly enhances model performance as the dataset size increases. Compared to the baseline dataset, the combination of pose estimation and data augmentation techniques resulted in significant improvements in classification accuracy and other performance metrics.

4. Conclusions

This study deals with the classification of powerlifting movements using deep learning methods and the results obtained with high accuracy rates show that these methods can be a powerful tool for sports movement analysis. The high performance observed indicates that the model is suitable for real-world applications, as deep learning models can effectively recognize sports movements, playing a crucial role in the evaluation of athletes' performance. These findings suggest that deep learning methods can find a wider application area in sports sciences.

There are several critical areas where this study could be extended and further developed. First, expanding the datasets used and including data from different sports can improve the generalizability and reliability of the models. For instance, recognizing a broader range of sports movements, including more complex patterns, could test the limits of deep learning models and contribute to the body of knowledge in this field. Furthermore, the development of real-time motion recognition and analysis systems can be adapted for use in mobile devices and wearable technologies. Such applications could assist athletes in optimizing their performance by providing instant feedback during training. Another critical research direction involves comparing different deep learning architectures and algorithms to assess their impact on sports motion analysis. Specifically, hybrid models that combine deep learning methods could be developed to further enhance model performance.

In conclusion, the findings of this study indicate that analyzing sports movements using deep learning can be valuable not only for evaluating athletic performance but also for injury prevention and monitoring rehabilitation processes. Detecting and correcting improper movements in athletes can minimize the risk of injury and safeguard the long-term health of athletes. In summary, this study has shown that power sports movements such as powerlifting can be successfully analyzed with deep learning techniques and that these methods can play an important role in sports science in the future. Ongoing research in this area will contribute to the development of next-generation tools that can assist athletes in better understanding and enhancing their performance.

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