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Rapid estimation of elbow joint moment and triceps force during triceps dumbbell kickback

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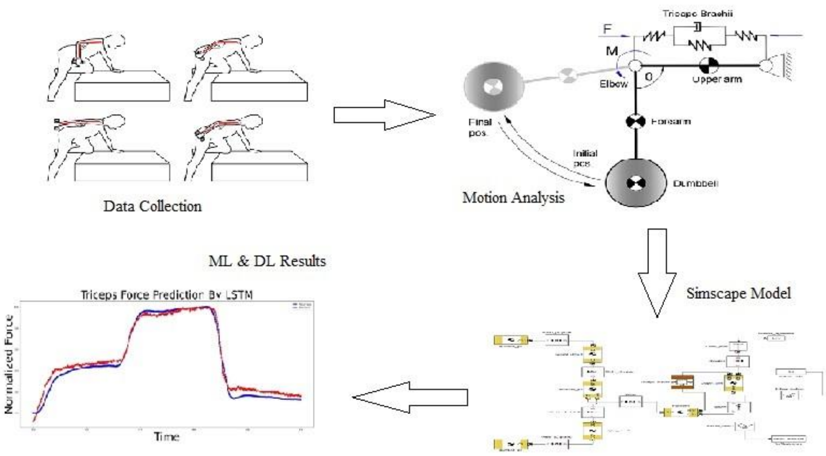
Rapid Estimation of Elbow Joint Moment and Triceps Force During Triceps Dumbbell Kickback

Highlights

- *LSTM achieved the highest accuracy (R = 0.98374) in predicting elbow joint moments.*
- *Kinematic-based models provide a robust alternative to EMG-dependent approaches.*
- *Accurate predictions support real-time control of assistive devices and active orthoses.*

Graphical Abstract

This study evaluates data-driven models for the rapid estimation of elbow joint moments and triceps muscle force during the Rest Pause Triceps Kickback (RPTK) exercise.



Aim

The aim of this study is to develop and evaluate data-driven models for the rapid estimation of elbow joint moments and triceps muscle force during the Rest Pause Triceps Kickback (RPTK) exercise.

Design & Methodology

Fourteen participants performed the Rest Pause Triceps Kickback exercise while kinematic data (time, body and limb masses, elbow angle, and height) were recorded. Seven machine learning and deep learning models were trained on these features and evaluated using MSR, RMSE, MAE, and correlation coefficient (R) to predict elbow joint moments and triceps force..

Originality

The novelty of this study lies in the creation of a unique, time-dependent kinematic and anthropometric dataset for upper limb joint moments and triceps force, collected from 14 female participants during the RPTK exercise.

Findings

The LSTM model achieved the highest predictive accuracy with R = 0.98374, outperforming all other tested algorithms. In descending order, model performance followed: RF, CNN, DT, DNN, SVM, and LR.

Conclusion

The study demonstrates that LSTM-based models can accurately predict elbow joint moments and triceps force, offering a reliable alternative to EMG-based approaches.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Rapid Estimation of Elbow Joint Moment and Triceps Force During Triceps Dumbbell

Araştırma Makalesi / Research Article

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ABSTRACT

Introduction: Understanding the biomechanics of the upper limb is of considerable interest in both clinical and engineering domains. Estimating elbow joint moments and triceps force plays a pivotal role in modelling musculoskeletal function. However, the use of electromyography (EMG) data is often constrained by challenges such as signal noise and calibration complexity. The objective of this study is to determine the elbow joint moment and triceps force during a Rest Pause Triceps Dumbbell Kickback exercise. Methods: This investigation utilized kinematic assessments from a cohort of 14 participants with diverse anthropometric profiles. A range of machine learning and deep learning models were employed to predict joint torque and triceps muscle force, including deep neural networks (DNN), long short-term memory networks (LSTM), convolutional neural networks (CNN), decision trees (DT), linear regression (LR), support vector machines (SVM), and random forests (RF). Model performance was systematically evaluated using multiple statistical metrics: Mean Squared Residuals (MSR), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Correlation Coefficient (R). Results: The analytical outcomes demonstrated that the LSTM model yielded the highest predictive accuracy, achieving a correlation coefficient of R = 0.98374 when six input features (time, mass, forearm mass, upper arm mass, elbow angle, and height) were used. In descending order of R values, the performance of the remaining models was as follows: RF (0.92793), CNN (0.92106), DT (0.88812), DNN (0.75769), SVM (0.70011), and LR (0.44690). These findings underscore the potential of LSTM in capturing the temporal dynamics essential for biomechanical prediction. Conclusion: The findings from this study provide new insights into data-driven biomechanics and suggest that LSTM-based models may offer a promising alternative to EMG-based approaches. Accurate prediction of joint moments has significant implications for the real-time control of assistive technologies, particularly active orthoses in the future.

Keywords: Biomechanical modeling, motion analysis, RPTK, upper limb, deep learning.

1. INTRODUCTION

Understanding the mechanical forces acting on human joints is fundamental to enhancing movement efficiency and maintaining musculoskeletal health. Quantifying joint moments plays a pivotal role in assessing the mechanical stress imposed on joints, which is essential for injury prevention, rehabilitation, and performance optimization. Accurate joint force estimation contributes significantly to post-operative recovery, athletic training refinement, ergonomic workplace design, and the development of prosthetic devices that closely mimic natural limb dynamics. Through the analysis of joint moments, improvements can be made in mobility, occupational safety, and clinical outcomes, thereby positively influencing both health and daily performance.

Direct measurement of joint torques on the limbs is impractical due to the restrictions it imposes on natural movement. As a result, joint moment estimation is typically conducted through computational modeling approaches. These methods often rely on specialized software platforms such as AnyBody [3], OpenSim [2], and MATLAB [1] to simulate and analyze musculoskeletal dynamics. However, the implementation of such techniques necessitates advanced domain-specific knowledge and can be computationally intensive.

In recent years, there has been a growing interest in leveraging artificial intelligence (AI) to address these limitations. AI-based approaches, particularly those employing machine learning (ML), have demonstrated considerable promise in enhancing estimation accuracy while reducing computational burden. The application of ML techniques to predict joint torques is emerging as a viable alternative to traditional biomechanical modeling, offering robust predictive capabilities and wider accessibility. The estimation of elbow moment and triceps force is a crucial aspect in understanding the biomechanics of upper limb movements. In the study by Loss et al., the comparison of muscle force required during elbow flexion exercises highlighted the importance of considering the moment arm of the muscles involved [4]. This emphasizes the need to analyze muscle demand beyond just resistance torque values. Similar to this, Tanaka et al.'s study examined the relationship between the force exerted on the shoulder during pitching and the shoulder's horizontal abduction posture [5]. The findings showed that excessive shoulder horizontal abduction increased the stress on the shoulder, underscoring the importance of proper shoulder positioning in reducing shoulder forces. Modal Pushover Analysis (MPA) was also utilized in the study by Zarfam et al. to estimate the seismic performance of structures with semi-rigid connections [6]. The research highlighted the reliability of MPA in estimating seismic responses in steel frames with varying degrees of fixity, providing valuable insights for structural design and analysis. These studies collectively contribute to the understanding of

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muscle force estimation and structural performance assessment, offering valuable insights for researchers in their respective fields.

According to the previous studies, joint moments are frequently estimated using electromyography (EMG) data. Dealing with EMG data presents a number of difficulties, though, such as noise reduction, precise calibration, individual differences in muscle structure, and appropriate electrode implantation. Motion analysis has previously been done using pricy equipment and intricate marker placements [7, 8, 9]. Furthermore, programs like AnyBody and OpenSim are used to compute joint moments [7, 10]. Joint moments are employed by researchers in domains like engineering and have uses in sports, medicine, rehabilitation, and design. Consequently, researchers from many fields should create ML algorithms that are based on joint moment detection and simpler motion analysis in order to produce quick and precise results. Making accurate forecasts with a limited amount of input data is also crucial.

Numerous research works have concentrated on various techniques and technologies for precise estimation of these characteristics. Choi et al. looked into the effects of mechanical assistance on motor function and muscle activation during isometric elbow flexion [11]. The significance of outside help in affecting muscle activity and motor function during particular movements was brought to light by this study. Gaining knowledge about how mechanical aid affects muscle activity can help improve performance and lower the chance of injury. However, in order to forecast joint angles and ground reaction forces during weight lifting jobs, Rakshit et al. created a two-dimensional symmetric maximum weight lifting simulation based on dynamic joint strength [12]. This give us a comprehensive understanding of the biomechanics involved and can be helpful in figuring out the elbow joint moment and triceps force during weightlifting exercises. Using a shear wave tensiometer, Ebrahimi et al. investigated age-related deficits in triceps surae function at different walking speeds [13]. This study sheds light on how the triceps surae muscle modulates force and work, which is crucial for precisely calculating triceps force. Comprehending the impact of age-related alterations on muscle performance helps enhance the approximation of joint moments and forces. Granatosky et al., examined the muscle mechanics of monkeys' feeding and locomotor systems to determine the optimal parameters for various muscle groups [14]. Insights into the biomechanical variations in muscle activity, particularly the triceps muscle, can be gained from this comparative analysis, which is essential for precisely calculating triceps force. To estimate elbow flexion force from EMG inputs, Lu et al. introduced a hybrid Deep Learning (DL) system [15]. This method employed bidirectional long short-term memory networks and convolutional neural networks to increase the accuracy of muscle force estimate, especially triceps force, which is essential for precisely determining the elbow joint moment. Huang et al., concentrated on applying backpropagation neural networks and continuous wavelet transform to estimate elbow joint motion from surface EMG inputs [16]. This method can provide a non-invasive means of measuring the elbow joint's motion as well as the activity of the muscles that contribute to the elbow joint's total moment, like the triceps. In conclusion, measuring the triceps force and elbow joint moment is a difficult but essential component of studying human movement and biomechanics [17, 18]. Researchers can improve the accuracy of forecasting these parameters by utilizing new technologies such as EMG signals, shear wave tensiometers, and DL frameworks. This will lead to a more thorough understanding of human performance and movement [19, 20, 21, 22].

Using AI and ML to measure joint moments takes things to a whole new level of precision and speed. These technologies can analyze movements in real-time, offer personalized insights, and even predict potential issues before they happen, which is invaluable for rehab, sports training, and workplace ergonomics. They handle massive amounts of data effortlessly and can make sense of complex joint mechanics quickly. Moreover, AI allows for non-invasive methods, like using video, to measure movements. As the systems learn and improve over time, they make the process of assessing joint health faster, more accurate, and more efficient than ever before. Recent studies have shown interest in applying machine learning to predict elbow moment and triceps force. To determine the axial capacity of circular and rectangular concrete-filled steel tubular (CFST) columns under centric or eccentric stress situations, Faridmehr et al. created a surrogate machine learning model [23]. The ML model showed superior accuracy compared to traditional design code provisions, offering a simplified approach for generative design in structural engineering. Varma et al. focused on predicting joint moments for walking using a machine learning-based approach that only required kinematic data of subjects [24]. The study aimed to assist therapists in rehabilitation by providing accurate joint moment predictions for patients with neurophysiological conditions. The study also involved the design and feasibility assessment of an active exoskeleton prototype based on the expected joint moments. Using EMG data in conjunction with an Inertial Measurement Unit (IMU) sensor, Sakamoto et al. [25] proposed a machine learning method for predicting Ground Reaction Force (GRF) and Ground Reaction Moment (GRM). The work showed that it was possible to predict GRF using a small number of sensors mounted beneath the knees, emphasizing how crucial EMG data is to precise motion prediction. The creation of a GRF visualization system improved human motion analysis's prediction power even more.

Comprehending human movement and biomechanics requires a grasp of joint moments and muscle forces. Few researches have investigated various techniques and algorithms for precisely estimating these values. Ullauri et al., concentrated on force-controlled elbow exoskeletons in conjunction with EMG-based torque estimate for humans [26]. The study looked at two methods for calculating human elbow joint torque based on muscle activation. The importance of using EMG signals to accurately measure joint torque is shown by this study. Similar to their earlier work [27], Mundt et al. used a feedforward neural network to estimate gait mechanics using measured and simulated IMU data. The study's main goal was to examine lower limb joint moments and 3D joint angles. Using IMU data and artificial neural networks, the researchers were able to provide insights into the evaluation of joint mechanics during walking. This method demonstrates how ML methods may be used to estimate joint parameters. In a work by Hu et al. [28], an enhanced EMG driven neuromusculoskeletal model for elbow joint estimate was covered. The study concentrated on using neural command measures to estimate joint moments and muscle forces. The study intended to improve joint parameter estimation accuracy using EMG data by creating a comprehensive model. This method emphasizes how crucial it is to use neural command data when estimating joint mechanics. Moreover, Taneja et al.'s investigation on parameter identification using feature-encoded physics was concerned with calculating joint moments and muscle forces from data [29]. Accurate estimation of human joint moments was achieved by the researchers through the application of reinforcement learning techniques. This work shows how ML approaches can be used to estimate joint parameters from physiological data. The DL-based sEMG Upper Limb Interaction Force Estimation Framework was examined in a study by Lu et al. [30]. The study's objective was to determine the elbow contact force during isometric contraction using a DL system. By applying DL approaches, the researchers were able to accurately predict the contact forces in the upper limb. This approach shows how joint forces can be estimated using DL algorithms. An investigation into isokinetic elbow joint torque estimation using surface EMG and joint position data was conducted by Luh et al. [31]. The study demonstrated that isokinetic joint torque may be precisely estimated using machine learning approaches. Using a modest sample size, the researchers were able to accurately predict joint torque based on EMG activity and joint position data [32]. The potential of ML methods in calculating joint torques is demonstrated by this work. An interesting area of research in biomechanics and human movement analysis is the assessment of elbow joint moment and triceps force using ML algorithms [33, 34]. Accurate joint parameter estimation has advanced significantly thanks to research using neural command measurements, IMU data, and EMG signals [35, 36]. Artificial neural networks and DL approaches are examples of ML algorithms that have demonstrated significant promise in raising the precision of joint moment and muscle force estimation.

This study's main goal is to predict the triceps brachii force and elbow joint torque during the Reverse Pause Triceps Kickback (RPTK) exercise by assessing the effectiveness of several machine learning and deep learning models. In particular, the analysis combines traditional machine learning methods like Decision Trees (DT), Linear Regression (LR), and Support Vector Machines (SVM) with three deep learning architectures: Deep Neural Network (DNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN). First, while performing the RPTK movement, biomechanical data will be gathered from 14 volunteers that represent a variety of anthropometric characteristics. A comparable biomechanical model will then be built through a dynamic study of the exercise. The primary objective is to assess the prediction accuracy and dependability of these computational models in estimating elbow joint moments in order to ascertain whether they are practical for real-time or nearly real-time biomechanical inference. Furthermore, this study provides a novel dataset on upper limb joint moments that could be validated experimentally in the future and utilized in musculoskeletal modelling research. One of the important contributions of this study is the creation of a unique dataset containing time-dependent kinematic and anthropometric data collected from 14 female participants during the RPTK exercise. While many studies in the literature rely on EMG signals or commercial motion capture systems for joint moment estimation, this dataset was obtained using only a minimum number of markers and a single digital camera. The dataset includes inputs such as elbow angle, individual segment masses, and length information, along with outputs such as elbow moment and triceps force calculated over time. The presentation of individual-specific mass and inertia properties alongside time-dependent motion data makes this dataset suitable for machine learning applications that enable estimation with fewer input variables. In this regard, it constitutes a unique dataset that can be used in musculoskeletal modeling studies, particularly in low-cost or clinical settings.

The estimation of joint moments and muscle forces is crucial for understanding human biomechanics, particularly in athletic training and rehabilitation. While traditional methods like inverse dynamics provide accurate results, they often require extensive data collection and computational resources. Recent advancements in artificial intelligence, specifically ML and DL techniques, offer promising alternatives for rapid and accurate estimation of these biomechanical parameters. In order to estimate elbow joint moments and triceps force during an RPTK exercise, this study compares and uses a variety of machine learning and deep learning techniques, including CNN, DT, LR, SVM, RF, DNN, and LSTM. This makes it unique. This research not only improves the accuracy of biomechanical estimations but also drastically cuts down on computational time and complexity by combining motion analysis data and biomechanical modeling with modern machine learning techniques. This makes it possible for real-time applications in clinical and sports settings.

2. METHODOLOGY

Data collection was the first step in the research, and then motion analysis was performed. A joint-limb model was suggested for the dynamic analysis of the rest RPTK exercise (see Figure 1). The upper arm, forearm, dumbbell, shoulder, and elbow joints make up this model. The joint's kinematic data is one of the parameters that must be understood in order to compute the elbow joint moment using the joint-limb model. Motion analysis is thus carried out to ascertain the angular displacements taking place in the elbow joint. The wrist, elbow, and shoulder regions of the individuals all had passive markers applied to them. Then, tools for MATLAB Simscape Multibody have been created to analyze physical systems of real size dynamically. These instruments are employed in the dynamic analysis of human movements even though they were designed for the analysis of mechanical systems. After the data was ready, ML and DL methods were applied to estimate the elbow joint moment and triceps force in the following stage.

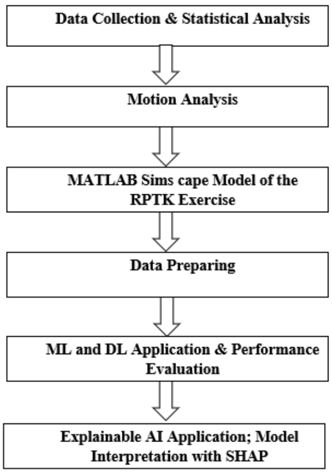


Figure 1. Study flow chart

2.1. Data Collection

The selection of participants (fourteenth female individuals) was carefully made to ensure variation in criteria such as weight, height, and age. In this way, it was aimed to enable the application of machine learning algorithms to individuals with different characteristics. After being made aware of the study, participants gave their consent. One of the key factors influencing joint moments is body weight, and height both have an impact on joint moment through varying joint movement patterns. Table 2 provides comprehensive participant information. The demographic characteristics of the participants indicated a mean age of 23.64 years with a standard deviation of ±1.89 years. The average body mass was recorded at 66 kg, exhibiting a variability of ±19.36 kg, with the maximum and minimum values being 90 kg and 57 kg, respectively. Similarly, the mean stature was measured at 169.21 cm with a standard deviation of ±13.2 cm, ranging between 175 cm and 163 cm, as detailed in Table 1.

2.2. Statistical Analysis

IBM SPSS Statistics version 21 was used to do the statistical analysis of the gathered data. A one-way analysis of variance (ANOVA) and a Tukey post hoc test were used to assess variations in mean values among experimental conditions. By determining the percentage change in each participant's outcomes from the pre-intervention to post-intervention phases, the effectiveness of the intervention was further investigated. In order to ascertain the impact of body mass index (BMI) on the outcomes, an intergroup comparison was required due to the inclusion of multiple BMI categories. According to the one-way ANOVA and the ensuing Tukey test, the joint moment data showed statistically significant differences ($p < 0.05$) between the BMI groups, confirming the suitability of the BMI-based stratification for comparative analysis.

2.3. Analysis of motion through Link-Segment Model

In this study, a joint-limb model as shown in Figure 3 is proposed for the dynamic analysis of the rest RPTK exercise (Figure 2). The model consists of upper arm, forearm and dumbbell segments (body) and shoulder and elbow links (joint). Assuming that the shoulder joint remains fixed during the RPTK exercise, this joint is modeled as a fixed joint. The elbow joint is included in the model in a way that it makes a rotational joint movement on the sagittal plane. Triceps brachii (TB) is represented as a spring and damping element, taking the Hill type muscle model as a reference.

Equation 1 can be used to determine the moment that occurs in the elbow joint in the joint-limb model, which has a single degree of freedom (DOF).

$$\sum_{i=1}^{n} M(t)_i = I_i \cdot \frac{d^2\theta(t)_i}{dt^2} \qquad (1)$$

Here, M is the elbow joint moment, I is the moment of inertia, θ is the angular displacement of the elbow joint, and t is time. Once the joint moment is determined, TB muscle force can be calculated using equation 2.

$$\vec{M}(t) = \vec{F}(t) \cdot d \qquad (2)$$

Here, F represents the TB muscle force and d represents the moment arm distance of the TB muscle relative to the elbow joint.

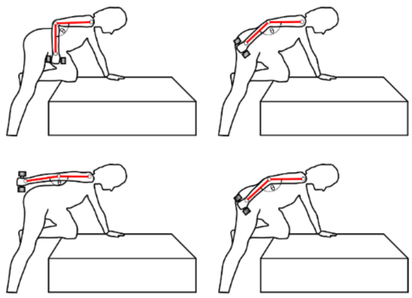


Figure 2. Schematic view of RPTK at a) phase 1, b) phase 2, c) phase 3, and c) phase 4.

Table 1. The demographic details of women subjects. LA, lightly active; MA, moderately active; VA, very active.

Subject/Gender	Mass (kg)	Height (cm)	Age (year)	Dominate Arm	Activity Level
S1/F	76	175	21	Left	MA
S2/F	74	163	20	Right	MA
S3/F	75	175	26	Right	MA
S4/F	90	172	22	Right	LA
S5/F	54	165	23	Right	VA
S6/F	60	170	20	Right	VA
S7/F	57	170	29	Right	VA
S8/F	64	174	25	Right	MA
S9/F	78	170	21	Right	LA
S10/F	59	168	21	Right	VA
S11/F	58	168	28	Right	VA
S12/F	60	168	24	Right	VA
S13/F	63	163	23	Right	MA
S14/F	60	168	28	Right	MA

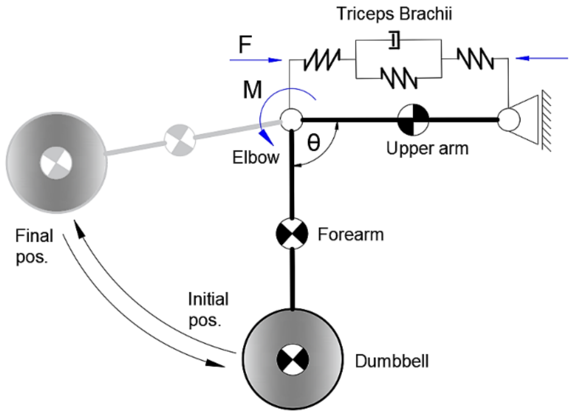


Figure 3. Biomechanical structure of the joint-limb model proposed for analysis of RPTK movement. Θ; elbow joint angle, F; TB muscle strength, M; elbow joint moment.

2.4. Motion Analysis of RPTK Exercise

The kinematic data of the joint is one of the parameters that must be understood in order to compute the elbow joint moment using the joint-limb model. To ascertain the angular displacements taking place in the elbow joint, motion analysis was carried out. The subjects' wrists, elbows, and shoulders were marked passively. Participants performed the movement while leaning on a bench (with their bodies parallel to the ground) at a pace they determined. Using a digital video camera positioned in the sagittal plane, exercise movements were captured at 30 frames per second. Using Kinovea motion analysis software, the pictures were examined, and the elbow joint's angular displacements were computed. Equations 3 and 4 were then used to determine the elbow joint's angular velocity and angular acceleration values.

$$\Omega_n = \frac{\theta_{n+1}-\theta_{n-1}}{2\Delta t} \tag{3}$$

$$\alpha_n = \frac{\omega_{n+1}-\omega_{n-1}}{2\Delta t} \tag{4}$$

Here, t is the time, θ is the angular displacement, ω is the angular velocity, and α is the angular acceleration.

2.5.Determination of Anthropometric Characteristics of Participants

Other parameters that need to be known to calculate the elbow joint moment with the joint-limb model are the mass and inertia properties of the limbs. The results of previous studies were used to determine anthropometric properties. Winter (2009)'s study was used to determine limb lengths and masses [37]. In calculating the moment of inertia of the limbs and the location of the center of mass, Walker et al. (1973) and Chandler et al. (1975)'s studies are taken as reference [38, 39].

2.6. MATLAB Simscape Model of the RPTK Exercise

The dataset collected in this study includes the kinematic and anthropometric data necessary to simulate the biomechanics of the RPTK exercise. The kinematic data comprises angular displacements, angular velocities, and angular accelerations of the elbow joint. These parameters are represented in a time series format, enabling the analysis of joint dynamics throughout different phases of the RPTK movement. Additionally, anthropometric data, including upper arm and forearm mass, center of mass, moment of inertia, and triceps muscle moment arm, were integrated into the dataset. This comprehensive data structure facilitates a biomechanical analysis by relating specific angular positions and velocities to the forces exerted by the triceps muscle during the exercise. Using the obtained dataset, a MATLAB Multibody simulation of the RPTK exercise was conducted. MATLAB Simscape Multibody tools have been developed to perform dynamic analysis of real-size physical systems. Although these tools were developed for the analysis of mechanical systems, they are also used in the dynamic analysis of human movements. The mechanical structure of the joint-limb model and the mass and inertia properties of the participants were modeled with the help of MATLAB Multibody blocks (Figure 4). Here, the shoulder and wrist joints, which are assumed to have no angular displacement, are modeled as "weld joints" (0 DOF). The elbow joint is modeled as a “revolute joint” (1 DOF) so that it rotates on the z axis. After the motion analysis, the elbow joint kinematic data was computed and used to simulate the MATLAB model. Inverse dynamic method was chosen as the analysis mode in the simulation. Thus, the joint moment occurring in the elbow joint during the RPTK exercise was calculated. Then, the muscle force occurring in TB was calculated with the help of equation 2. Based on his research, Sugisaki et al. (2010) provided the moment arm distance of the TB muscle with respect to the elbow joint center [40].

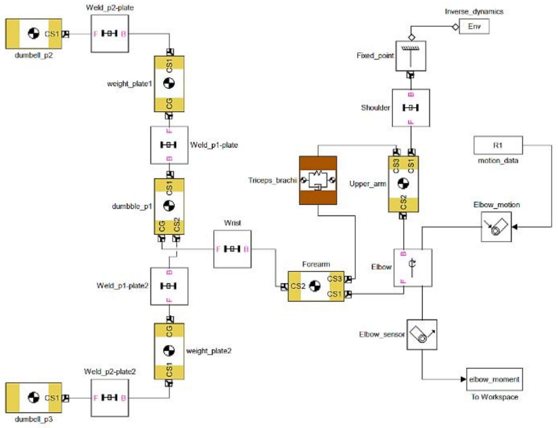


Figure 4. MATLAB Multibody structure of the joint limb model.

The angular displacements of the elbow joint were ascertained by utilizing Kinovea motion analysis software to examine the captured images. The participants repeated the RPTK movement (see Figure 2) five times consecutively, and the average of these five repetitions was calculated. Subsequently, equations were employed to calculate the angular velocity and acceleration. This kinematic data forms the basis for further dynamic analysis, providing the necessary parameters to model the physical movements accurately. MATLAB Simscape Multibody tools were utilized to perform the dynamic analysis of the RPTK exercise. These tools, although originally developed for mechanical systems, are also applicable to the analysis of human movements. The mechanical structure of the joint-limb model and the mass and inertia properties of the participants were modeled using MATLAB Multibody blocks.

In the model, the shoulder and wrist joints are treated as “weld joints” with zero DOF, reflecting their assumed lack of angular displacement during the exercise. The elbow joint, however, is modeled as a “revolute joint” with one degree of freedom, allowing rotation around the z-axis. The simulation incorporated the elbow joint kinematic data obtained from the motion analysis. The dynamic analysis employed the inverse dynamic method, enabling the calculation of the joint moment at the elbow during the RPTK exercise. This method is particularly useful for understanding the forces involved in joint movements. The muscular force in the TB was computed using the joint moment data and the TB muscle’s moment arm distance from the elbow joint center. A 14-subject RPTK movement study was conducted to develop the model.

2.7. Preparing Data and Applying ML

This section outlines the procedures undertaken for data preprocessing, followed by a comprehensive explanation of the DL and ML methodologies applied in the study, including the specific adjustments made to model parameters to optimize performance. The dataset, which contains variables as time, mass, forearm mass, upper arm mass, elbow angle, and height, was created using the motion analysis described in the preceding section. Each participant’s data was gathered between 0 and 15 seconds, each individual has a raw size of roughly 470 lines. 6580 raw data points in total were gathered.

2.7.1. Data preparing

Feature normalization represents a critical stage in the data preprocessing pipeline, particularly when the dataset exhibits considerable variability in interquartile range and contains features measured in differing units. Without appropriate normalization procedures, ML algorithms may disproportionately weight features with larger numerical scales, thereby compromising the integrity of the predictive modeling process. To preserve numerical stability and enhance model performance, both ML and DL techniques typically require input features to undergo statistical rescaling. Among the various normalization techniques, the min max scaling method is widely recognized for its ability to adjust feature values within a defined interval commonly between 0 and 1 or -1 and 1 thereby assigning uniform weight to each variable on the same scale [41, 42]. In this investigation, all data inputs were standardized within the 0–1 range using min-max normalization. The transformation process is mathematically depicted in Equation 4, where X denotes the original data value, X max and Xmin refer to the dataset’s maximum and minimum values for the feature X, respectively, and X normalized represents the scaled value confined to the [0,1] interval [43].

$$\text{X normalized} = \frac{\text{X} - X_{\min}}{X_{\max} - X_{min}} \quad (5)$$

2.7.2 ML application

Classification, regression, and decision-making are supervised learning techniques that can be used in a range of fields, including engineering and healthcare [44, 45, 46, 47]. Although deep learning (DL), a sophisticated subclass of machine learning, is very good at solving high-dimensional, complicated problems, it requires large datasets in order to attain the best possible generalization and predictive power. The training procedure can be carried out in supervised, unsupervised, or semi-supervised frameworks, depending on the task’s requirements and the availability of data [48, 49, 50, 51, 52]. The learning efficiency and accuracy of predicted labels are greatly influenced by a number of hyperparameters, including the number of training epochs, the configuration and depth of hidden layers, and the choice of activation functions, since DL architectures are essentially derived from ANNs [48].

In order to estimate the elbow joint moment and triceps force parameters, this study looks at three deep learning algorithms (DNN, LSTM, and CNN) and four supervised machine learning approaches (SVM, DT, RF, and LR). The DL and ML, along with the parameter modifications (Table 2) used for the estimate of the three joints moments, are explained in the next subsections. The following section contains the ML and DL results.

Support Vector Machine (SVM)

One supervised learning technique that can be applied to regression and classification issues is the SVM algorithm. In 1992, SVM was first made available [53]. Researchers from a wide range of fields are becoming more and more interested in it due to its excellent efficacy and feasibility as a ML technique used for regression and classification. On the other hand, the SVM technique stands apart from other ML algorithms for a number of reasons. Structural risk minimization and statistical learning theory guide SVM's operations. This approach reflects an attempt to minimize the maximum possible error during the model's generalization phase, rather than merely optimizing performance on the training dataset. In this context, a hyperplane constructed by the SVM algorithm is identified to separate the data effectively, corresponding to the linear function f(x) as defined in Equation 6, based on the dataset described in Equation 6.

$$P = \{(x_i, d_i)\}_i^n \tag{6}$$

The observation is indicated by n in this case, while the input and output variables are denoted by xi and di, respectively. Finding a function f(x) that is closest to every point is the primary objective [54]. Given a goal function weight vector (w) and a bias (b), we have

$$f(x) = w\phi(x) + b \tag{7}$$

In the same equation, the symbol denotes a high-dimensional space characteristic. It has a nonlinear mapping from the low-dimensional space x [53]. In order to determine the empirical error under a certain loss function and the model's complexity, the regression issue is first reformed into a regularized risk minimization framework. The efficient estimation of the parameters w and b is the goal of this transformation. Equations 7 and 8 provide the mathematical expression for this strategy.

$$Minimize\ \frac{1}{2}w^2 + \mathrm{c}\sum_{i=1}^{\infty}(\delta i - \delta i *) \tag{8}$$

$$f(x, a_i, a_i^*) = \sum_n^i 1(a_i a_i^*)K(x, x_i) + b \tag{9}$$

$$K(x_i, x_j) = \mathrm{e}^{\frac{-||x_i - x_i||}{2\alpha^2}} \tag{10}$$

$\frac{1}{2}w^2$ in this case stands for the regularization. (C 0) is the regularization constant, and the loss function is represented by α and C. The positive slack variables, whose lower and upper excess deviations, are presented by δi , and δi*.

This study assessed a number of kernel functions, such as linear, polynomial, sigmoid, and radial basis function (RBF) kernels, in order to determine which Support Vector Machine (SVM) model was best suited for the dataset. The radial basis function (RBF) kernel, described in Equation 9, was chosen to forecast the joint moments of the ankle, knee, and hip due to its exceptional performance in the particular setting of this investigation.

Linear Regression

A statistical technique called linear regression is used to forecast an answer variable's result by taking into account several explanatory variables. The aim of linear regression is to model the linear relationship between the independent variables x and the dependent variable y under investigation [55]. Fitting a linear equation to the observed data is the process of using linear regression to model the connection between two variables. While the second variable is regarded as a dependent variable, the first is thought to be an explanatory variable (11).

$$Yi = x_i * \beta + \zeta_i \tag{11}$$

where β, or regression coefficients, are a vector of constants (k ∗ 1). Linear relationship with β is taken to hold for all R between 1 and N. In this work, the gathered data (Xi) were subjected to LR to estimate the joints moment (Yi).

Random Forest

The main benefit of the RF algorithm is its adaptability to both regression and classification problems, which are essential to many contemporary machine learning frameworks. RF creates a "forest" consisting of several DT, which may be trained using the "bagging" technique. Each leaf node in a DT represents the choice made after considering all relevant data, and it correlates to a particular class label. A DT's internal nodes each represent a "test" that has been run on an attribute, and the branches show the test's result. Nodes that are leaf nodes are those that have no children. The bagging technique's fundamental idea is that combining several

Table 2. ML algorithms parameters.

Algorithm	Parameter
SVM	radial basis function (RBF) kernel
LR	β between 1 and N
RF	depth of 150
DT	depth of thirty
DNN	6-4-2 layers, and 6-4-1 layers. Relu, and linear activation
CNN	4-2-2 layer, and 4-2-1 layers. Relu activation function
LSTM	100-70-2 layers, and 100-70-1 layers. Relu activation function

models improves performance as a whole. RF combines the results of numerous decision trees to classify or predict the value of a target variable in regression. In other words, after processing an input vector that contains values of different features from a specific training set, RF creates several regression trees and then averages the predictions made by these trees. Equations 12 and 13 describe the RF regression equation in full.

$$Regression = \sum(y_i - y_l)^2 + (y_i - y_i)^2 \quad (12)$$

$$Gini = N_i \sum_{k=1}^{k} pkl(1 - pkl) + N_r \sum_{k=1}^{k} pkr(1 - pkr) \quad (13)$$

The variables yi and yr in the equation above represent the average of the data at the left and right nodes, respectively. In the second equation, the variables Ni and Nr stand for the number of items in the left and right nodes, respectively. In this work, RFs were constructed with a maximum depth of 150 to determine the moment of the three joints.

Decision Tree

A decision tree is presented by including the Iterative Dichotomiser 3 (ID3) algorithm [56]. A decision tree is constructed by ID3 starting at the top. Equation 14 provides the DT formula. A decision tree is a tree-structured decision-making procedure. Its four components are a root, internal nodes, branches, and leaf nodes [57]. The classes are connected by the root of a tree, whose internal leaves represent processes, branches represent results, and leaf nodes represent the classes. Classification is based on the pathways from the root to the leaves.

$$E(S) = -P(+) * log\, p(+) - p(-) * \log p\,(-) \quad (14)$$

In this context, the probability of a positive class is represented by p+, the probability of a negative class by p−, and S denotes a subset of the training examples. For this study, the DT model was constructed with a maximum depth of thirty, specifically designed to estimate the moments of the three target joints.

Deep Neural Network (DNN)

The architecture typically comprises input, hidden, and output layers, which are standard components in backpropagation algorithms. Both the training and testing phases are structured around simplified representations of biological neural networks, which are inspired by the functioning of the human brain. Essentially, this algorithm aims to replicate the operational processes of the biological nervous system. Like a biological system, it seeks to understand the systems before extrapolating the results. Its exceptional capacity to predict complex and nonlinear systems makes it widely used in many different fields.

Multiple feed-forward neural networks were employed in this work. One method that was frequently used to train multiple-layer perceptrons was the backpropagation algorithm. By tackling the intricate relationship between input and output data, the weight values of the multilayered layer perceptron are modified. The general output and error functions are shown in equations 15 and 16 below [58].

$$Y_i = \mathrm{f}\left(\sum_{i,j=1}^{L,m}(w_i . x_i)\right) \quad (15)$$

$$E = \frac{1}{N}\left(\sum_{i=1}^{N}(D_i - y_i)^2\right) \quad (16)$$

The model architecture for this study is defined by input, output, and two hidden layers, with configurations of 6 (6 inputs) – 6 – 4 – 2 (2 outputs: joint moment and triceps force) and 6 (6 inputs) – 6 – 4 – 1 (1 output: either joint moment or triceps force). The output layer employed a linear activation function, while the hidden layers utilized Rectified Linear Unit (ReLU) activation functions. Additionally, the Adam optimizer was specified for training, along with early termination criteria and a total of 200 training epochs.

CNN

In practically every field, from cyber security and human activity detection to electronic health records, time series are a given. This latter definition defines time series prediction as the process of training a predictor on a set of numerous Xs and their associated values Ys so that, at the end of the test, it can predict the value of an unknown time series with accuracy. CNNs are DL algorithms that process data with a grid layout. CNNs are DL algorithms that are used to handle data that is connected either spatially or temporally. CNNs are similar to other neural networks, but they are more sophisticated since they employ many convolutional layers. The four main components of the CNN network are the input layer, convolutional layer, pooling layer, and fully connected layer. Equation 17 states that W_i is the weight, b_i is the offset, and ρ is the rectified linear unit. The convolutional layer retrieved feature H_i feature map.

$$H_i = \mathrm{p}(H_i W_i + b_i) \quad (17)$$

The CNN time series model used to predict joint moments was composed of an output layer (two neurons for two phases and one neuron for another phase), a fully connected layer with relu activation function, a pooling layer of size two, a one-dimensional convolutional layer, an input layer (six neurons), and an output layer. To anticipate joint moments, 200 iterations of the Adam optimizer and MSE were employed.

LSTM

LSTM is particularly effective for predicting future values, such as inventory levels, based on historical data. It was specifically designed to address the issues of long-term dependency and the vanishing gradient problem, which are common challenges in traditional RNNs. By maintaining an internal state, LSTMs can store and process information from previous time steps, making them well-suited for sequence data modeling. An LSTM contains several memory blocks, with two key states the hidden state and the cell state that are transferred and updated as data flows through the network. These states carry information to subsequent blocks, allowing for the retention or overwriting of data from earlier time steps. LSTMs utilize gates, a learning mechanism that determines which information should be retained or discarded within the sequence. Specifically, LSTMs feature three types of gates: input, forget, and output. Which data from the prior time step should be removed from the cell state is determined by the forget gate. As stated in Equation 18, a sigmoid activation function in the forget gate generates a value between 0 and 1, where 0 signifies discarding the information and 1 indicates retaining it, using the current input Xt and the prior output Y t−1.

$$f_t = \sigma(W_f.X_t + V_f.Y_{t-1} + W_c.C_{t1} + b_f) \quad (18)$$

where W_f, V_f , and W_c are weight matrices and b_f is a bias vector. Usually taught during training, these components initialize with random integers. C_{t1} represents the condition of the memory cells at time t-1. The goal of the input gate is to identify the updated value in the cell state. Next, a vector of brand-new candidate values C_{t1} is provided by a tanh layer. The constitutive equations (19 and 21) for these processes are given as follows.

$$i_t = \sigma(W_i.X_t + V_i.Y_{t1} + W_c.C_{t1} + b_i) \quad (19)$$

$$C_t = tanh(W_c.X_t + V_c.Y_{t1} + b_c) \quad (19)$$

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (21)$$

where the weight matrices are W_i, V, V_c and the bias vectors are b_i, b_c. These components are also taught and initialized with random integers during the training process. It is the input gate's output. Finally, Equations 22 and 23 are used to estimate the output of each repeating LSTM module.

$$O_t = \sigma(W_o.X_t + V_o.Y_{t1} + W_c.C_{t1}.b_o) \quad (22)$$

$$Y_t = O_t.\tanh(C_t) \quad (23)$$

LSTM comes in three varieties: stacked, vanilla, and bidirectional. The current study used stacked LSTM with two LSTM layers, the layers contain 100 and 70 neurons respectively, and an output layer with two neurons for each of first phase and one neuron for the second phase. For the elbow joint moment and triceps force prediction, the following settings were set: Adam optimizer, Relu activation function for the two hidden layers, and 200 epochs.

In this study, regression techniques were employed to quantify the triceps force and elbow joint moments. The analyses were performed utilizing the Python programming language, along with its associated libraries, such as TensorFlow, scikit-learn, and Keras, which provide powerful tools for implementing machine learning models. Time, mass, elbow angle, height, forearm mass, and upper arm mass were all included in the training data. For the initial training phase, there were six inputs in total. The "split" function was then used to divide the data, with 30% going to validating and testing and 70% going to training.

3. RESULTS

Performance measures included the Correlation Coefficient R, MAE, RMSE (a statistic based on the sample standard deviation of the differences between the predicted and observed values), and MSE. Using 6 inputs (time, mass, forearm mass, upper arm mass, elbow angle, and height) during the training and testing phases of ML and DL algorithms had a positive effect on the results for SVM, DT, RF, LSTM, LR, CNN, and DNN. The success of the algorithms is shown in Tables 3 to 5.

Examining Tables 3–5 reveals that the LSTM algorithm has the best success rate when estimating with 6 inputs and 1 output. On the other hand, R > 0.90 is the prediction success for the RF, and LR algorithms. The LSTM algorithm outperforms the other algorithms in this dataset by a wide margin. The RF algorithm produced predictions with the highest success rates (R > 0.98) for the elbow and triceps force using seven input and one output dataset. The results show that LSTM, RF, and CNN all have success rates of R > 0.98, and R > 0.98 when it comes to elbow joint and triceps force evaluation. Both the CNN and DNN algorithms have significantly poor prediction success in the dataset with 6 inputs and 2 outputs. As the number of inputs decreases, these algorithms lose their effectiveness. The study's findings show that, regardless of the amount of input and output variables taken into account, the LSTM, RF, and DT algorithms produced the best predictions for triceps force and lower extremity joint moments.

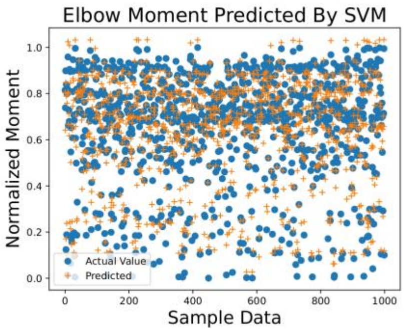
A comparison of the values calculated using different methods, and the joint moment and triceps force computed using MATLAB Simscape tools is presented in Figures 5 (a-g) and Figure 6 (a-g). The normalized form of the joint moments is provided. The distribution of the estimated and computed joint moment and triceps force for a person chosen at random is shown in the figures.

Out of the seven distinct ML algorithms that were analyzed in this research, the combined moment

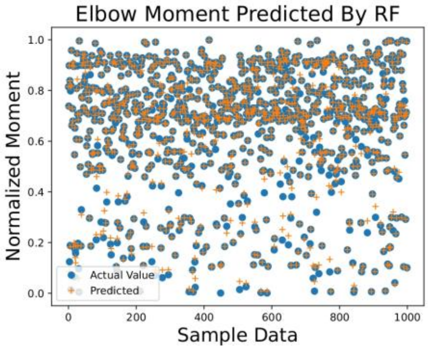
Table 3. Evaluation for the 6 inputs and 2 outputs (elbow and triceps force)

Algorithm	MAE	RMSE	MSE	R
RF	0.070463672	0.092128776	0.008487711	0.927935355
SVM	0.147912486	0.168935022	0.028539042	0.757690165
LR	0.083836454	0.096422729	0.009297343	0.921061205
DNN	0.163399105	0.187935139	0.035319616	0.700119911
DT	0.888121698	0.013176929	0.114790806	0.09392364
CNN	0.224973142	0.255231176	0.065142953	0.446905811
LSTM	0.035951125	0.043750133	0.001914074	0.983748614

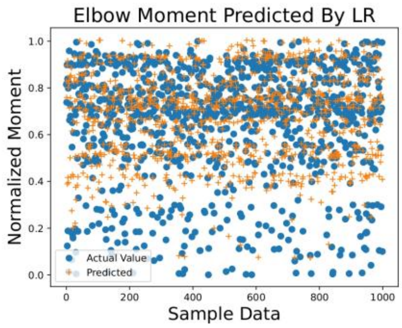
predictions made by the LSTM, RF, and DT algorithms were more successful. Figures A1-A14 in the appendix demonstrate the precise estimation of joint moments achieved through a simplified motion analysis technique, utilizing fewer input variables.



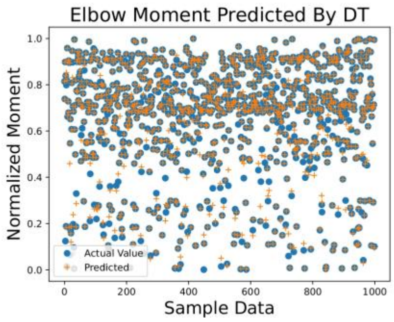
a- Elbow moment predecited using SVM.



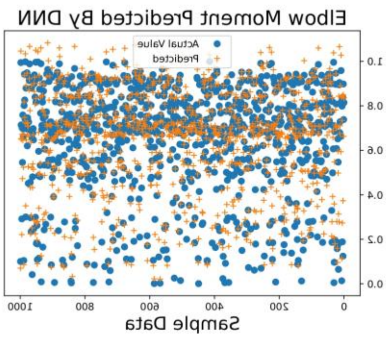
b - Elbow moment predecited using RF



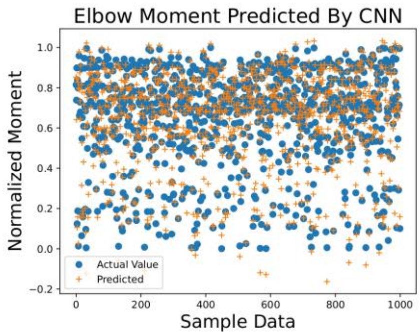
c - Elbow moment predecited using LR



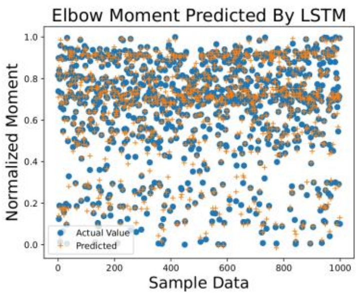
d - Elbow moment predecited using DT.



e - Elbow moment predecited using DNN

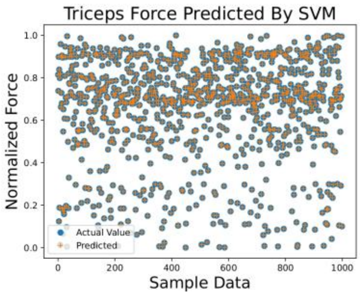


f - Elbow moment predecited using CNN

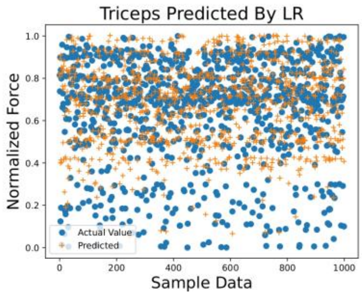


g - Elbow moment predecited using LSTM

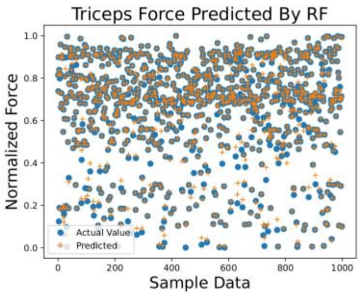
Figure 5. Elbow moment comparison of different algorithms



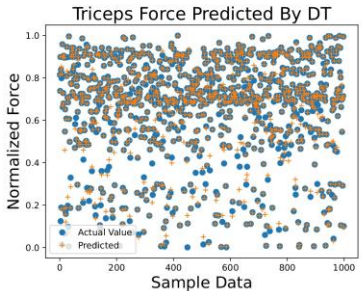
a- Triceps Force predecited using SVM



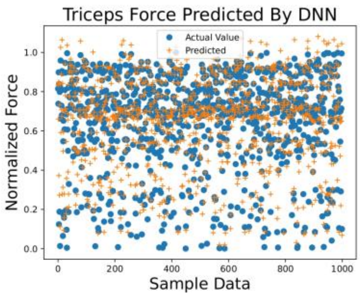
b - Triceps Force predecited using LR



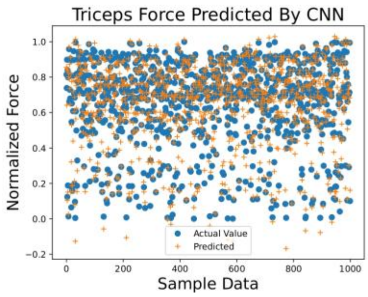
c - Triceps Force predecited using RF



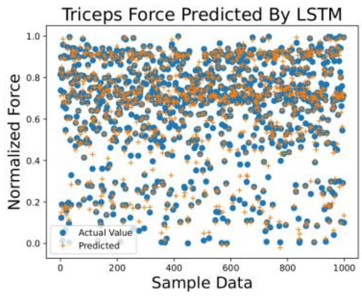
d - Triceps Force predecited using DT.



e - Triceps Force predecited using DNN



f - Triceps Force predecited using CNN



g - Triceps Force predecited using LSTM

Figure 6. Triceps force comparison of different algorithms

4. DISCUSSIONS

Bulanık mantık, The research of the RPTK exercise through dynamic analysis requires a comprehensive joint limb model that includes the upper arm, forearm, and dumbbell segments. This model is crucial for understanding the biomechanics involved in the exercise, particularly focusing on the shoulder and elbow joints. The joint limb model, as described, comprises the upper arm, forearm, and dumbbell segments. The shoulder joint is assumed to remain fixed during the RPTK exercise, allowing it to be modeled as a fixed joint. This assumption simplifies the analysis by focusing solely on the rotational movement of the elbow joint on the sagittal plane. The TB muscle is modeled using a spring and damping element, referencing the Hill type muscle model. This approach effectively captures the mechanical properties of the muscle during exercise, allowing for an accurate simulation of muscle dynamics.

To calculate the elbow joint moment, precise kinematic data is essential. This data includes angular displacements, velocities, and accelerations of the elbow joint, which were obtained through motion analysis. Participants in the study performed the RPTK exercise while leaning on a bench, with their bodies parallel to the ground. Passive markers placed on the shoulder, elbow, and wrist areas facilitated the capture of movement data. The exercise was recorded using a digital camera at 30 frames per second, positioned in the sagittal plane to ensure accurate capture of the joint movements.

The elbow joint moment and triceps force were assessed using seven distinct algorithms: CNN, DT, LR, SVM, RF, DNN, and LSTM networks. Four statistical metrics were utilized to evaluate the model performance. The LSTM algorithm demonstrated the highest accuracy in predicting triceps force and elbow joint moments when six input variables were employed, achieving an R-value of 0.983375. In comparison, the performance of the other algorithms yielded lower R-values of 0.92794 (RF), 0.92106 (CNN), 0.88812 (DT), 0.75769 (DNN), 0.7001 (SVM), and 0.44690 (LR). This study presents a valuable methodology for quantifying joint moments during walking, which could enhance rehabilitation programs for individuals recovering from joint-related diseases or injuries. The robustness of the data is assured through the application of multiple algorithms and statistical measures, with the outstanding performance of the LSTM algorithm suggesting its potential for future research in this domain.

Recent studies have demonstrated significant advancements in the prediction of joint moments and muscle forces using ML [59]. This discussion contrasts and compares findings from various studies and highlights a novel approach to predicting elbow moments and triceps force during the RPTK exercise. In order to evaluate the axial capacity of steel tube columns loaded with concrete, Faridmehr et al. created a surrogate machine learning model, which they found to be more accurate than conventional techniques [22]. While their focus was on structural engineering, the principles of using ML to simplify complex predictions are relevant to biomechanics. Similarly, Varma et al. applied ML to predict joint moments during walking, utilizing kinematic data to aid rehabilitation [23]. Their research extended to the design of an active exoskeleton prototype, showcasing the practical applications of accurate joint moment predictions. Sakamoto et al. introduced a method combining EMG data with IMU sensors to predict ground reaction forces and moments [24]. Their work underscored the feasibility of using limited sensor inputs to achieve accurate motion predictions, a crucial consideration for practical applications in motion analysis and rehabilitation.

Table 4. Performance evaluation for the 6 inputs and 1 output (elbow)

Algorithm	MAE	RMSE	MSE	R
RF	0.074719134	0.093554704	0.008752483	0.925687322
SVM	0.148858056	0.170387871	0.029032026	0.753504495
LR	0.029142609	0.037829305	0.001431056	0.987849661
DT	0.105234785	0.124333483	0.015458815	0.868747418
DNN	0.102590499	0.124651268	0.015537939	0.868075622
CNN	0.280946102	0.295305788	0.087205508	0.259584381
LSTM	0.10345793	0.118895511	0.014136143	0.879977527

Table 5. Performance evaluation for 6 inputs and 1 output (Triceps Force)

Algorithm	MAE	RMSE	MSE	R
RF	0.072064116	0.09664418	0.009340098	0.920698196
SVM	0.16945695	0.183090749	0.033522222	0.715380627
LR	0.385029399	0.4564842	0.208377825	0.769225355
DT	0.103210367	0.124440722	0.015485493	0.868520908
DNN	0.1389857	0.146625999	0.021499183	0.817461861
CNN	0.288013156	0.356984343	0.127437821	0.082006805
LSTM	0.15376997	0.163219724	0.026640678	0.773808161

Despite the promising results from EMG based predictions, several challenges remain [60]. Proper electrode insertion, individual variations in muscle structure, accurate calibration, and noise reduction are significant hurdles. Traditional motion analysis methods, involving expensive equipment and intricate marker placements, further complicate the process. Software like AnyBody and OpenSim facilitate joint moment computation, but they still require substantial input data and complex setups. Our study focuses on predicting elbow moments and triceps force during the RPTK exercise, treating the shoulder and wrist joints as "weld joints" with zero DOF and the elbow joint as a "revolute joint" with one DOF. This setup simplifies the dynamic analysis, allowing for precise calculation of the elbow joint moment using inverse dynamics. By combining joint moment data with the moment arm distance of the TB muscle, we accurately calculated the muscle force. The findings offer a robust approach for measuring joint moments and muscle forces during specific exercises, which can be instrumental in developing improved rehabilitation regimens for individuals with joint injuries or conditions. The high accuracy of the LSTM algorithm suggests its potential for broader applications in biomechanics research and practical rehabilitation settings.

The current study marks a significant breakthrough in a number of motion analysis-related areas. One important addition is the utilization of a new dataset, which greatly improved the applicability of the suggested methods and produced positive results. Joint moments were determined using MATLAB multibody tools and a descending dynamics method, as opposed to methods that call for specialist software and knowledge. This method lessened the requirement for intricate and time-consuming muscle measurements by enabling joint moment calculation without the need of EMG data. With just a few markers and a single ordinary camera, motion analysis was accomplished successfully. Furthermore, by employing just seven input variables, the study produced data appropriate for machine learning algorithms, allowing for the effective assessment of common events. These results have important ramifications for creating algorithms in motion analysis research that are more successful and efficient. The study enables a less complicated and intrusive motion analysis procedure by doing away with the requirement for EMG data and using MATLAB multibody capabilities. Motion analysis may become more affordable and accessible with the capacity to forecast joint moments with a simple setup consisting of just a few markers and a single traditional camera. In the end, the study emphasizes how crucial it is to use contemporary motion analysis techniques to enhance the planning of rehabilitation programs for those with joint illnesses or accidents.

Regarding the selection of features (elbow angle, upper arm mass, forearm mass, height, forearm mass, and triceps muscle moment arm) plays a crucial role in accurately estimating elbow joint moments and triceps force during the RPTK exercise. Each feature was chosen based on its significant influence on the biomechanics of the upper limb. The elbow angle is particularly important, as it directly affects mechanical leverage and muscle activation patterns, which are vital for understanding how forces are transmitted across the joint. Additionally, the masses of the upper arm and forearm contribute to the gravitational load experienced at the elbow joint, thereby impacting joint dynamics. Height serves as an essential anthropometric measure that can modify leverage during movement, while the moment arm of the triceps provides valuable insight into the internal forces exerted during the exercise. The integration of these features not only enhances the predictive capability of our machine learning models but also supports the broader understanding of upper limb biomechanics, with potential implications for clinical applications and athletic training programs. By elucidating the relationship between these features and joint mechanics, our study offers a framework for future research in biomechanical modeling and rehabilitation strategies.

The 6-input LSTM model was shown to be the most effective technique for calculating triceps force and elbow joint moments, with the highest R value of 0.98375. This study used a relatively small number of inputs in comparison to other studies in the literature, which often require more inputs to obtain equivalent prediction accuracy. The efficacy of the six-input LSTM model suggests that it can be applied in a range of research contexts, particularly when data collection is limited or when it is more practical or cost-effective to employ fewer input variables. This method may be especially helpful for researchers in fields like sports science and rehabilitation, where accurate joint moment estimation across a range of activities is required.

The 6-input LSTM model emerged as the most effective approach for calculating triceps force and elbow joint moments, achieving the highest R value of 0.98375. This study utilized a relatively small number of inputs compared to other works in the literature, which typically require more inputs to achieve similar prediction accuracy. The success of the six-input LSTM model suggests its potential for application in various research contexts, particularly in scenarios where data collection is limited or where fewer input variables are more practical or cost-effective. This method could be especially valuable for researchers in fields such as sports science and rehabilitation, where accurate joint moment estimation during diverse activities is required. The results also point to a viable avenue for further motion analysis research, specifically in the creation of joint moment estimating methods that are more effective and understandable. With a lower input density than earlier studies, the 6-input LSTM model has shown itself to be a useful tool for calculating joint moments during walking. Given its effectiveness, this methodology has the potential to be widely applied in a variety of study fields, providing a useful tool for investigators looking to improve their work.

The findings of this study demonstrate that the research objectives were successfully achieved. A key aspect of this research is the utilization of a more extensive dataset of mass and inertia parameters, which forms the foundation of the analysis. The proposed machine learning models are adaptable to individuals with varying physical characteristics, which is believed to contribute to a more efficient training process for the machine learning algorithms. Furthermore, compared to other research that use commercial motion capture equipment, the motion analysis carried out in this study is rather simple. Nevertheless, a reasonable degree of accuracy was achieved in determining the joints' angular displacement. Joint moments were computed using MATLAB Multibody tools, a widely recognized software platform employed by researchers across diverse fields. The performance of the proposed machine learning models surpasses that of previous studies, even though the current analysis is less complex, uses fewer input variables, and computes joint moments without relying on EMG data.

To consider the ethical concerns regarding this study revolve around the risks that could arise if the model makes incorrect predictions, especially in critical areas like rehabilitation or assistive devices. If the model misjudges joint moments or muscle forces, it could result in poor device support, increasing the chance of injury or slowing down recovery. Since the model was developed using a small and diverse group of participants, it might not work as well for everyone, potentially leading to biased outcomes. To address these risks, it's important to rigorously test the model, keep human experts involved, and continuously improve the system to ensure that AI enhances, rather than replaces, professional decision-making in healthcare.

5. CONCLUSIONS

Thorough study sought to precisely quantify the elbow joint moment and triceps force during the RPTK exercise using a variety of ML techniques. Motion analysis was performed on a diverse group of 14 volunteers, and the resulting dynamic analysis aided in the creation of a thorough biomechanical model. The elbow joint moment was highly accurately estimated by the study using DT, LR, SVM, RF, and three DL algorithms: CNN, LSTM, and DNN. With an outstanding correlation value R of 0.98374 for six input parameters, the study's findings showed that the LSTM algorithm did a remarkable job of forecasting triceps force and elbow joint moment. R-values of 0.92793, 0.92106, 0.88812, 0.75769, 0.70011, and 0.44690, respectively, showed that the LSTM method performed better than RF, CNN, DT, DNN, SVM, and LR. The exceptional accuracy and reliability of the LSTM model were validated through a comprehensive assessment of these algorithms, using statistical metrics such as MSR, RMSE, R, and MAE.

The effective prediction of elbow joint moment and triceps force with LSTM has important implications for the design and development of biomechanical systems. It enables the design of systems with the precise mechanical qualities required for real-time applications, such as active orthosis controllers. These findings not only increase our understanding of the RPTK exercise, but also contribute to the larger area of biomechanics by providing a reliable dataset of upper limb joint moments. This dataset has significant promise for future research and validation investigations, enabling advances in real-time biomechanical analysis and applications.

This study is regarded as a pioneering article in the application of ML techniques to predict elbow joint moments and triceps force during the RPTK exercise. Considering the lack of existing research that combines these methodologies with EMG data in this specific context, one of the future studies aims to expand our findings by exploring the integration of EMG signals with machine learning algorithms. This approach may increase the accuracy and reliability of joint moment estimates, providing useful data for both clinical and athletic performance.

The proposed machine learning models, especially the LSTM algorithm, show promise for real-time biomechanical analysis applications due to their ability to make highly accurate predictions with a small amount of input data. This approach can be integrated into low-cost wearable devices or motion tracking systems used in rehabilitation. Such systems, which provide real-time feedback, can support clinical decision-making processes or optimize individual training programs. However, in future studies, additional parameters such as EMG signals and IMU data could be included to further improve the model's prediction accuracy. The integration of such multi-data sources could enhance the model's prediction accuracy.

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AUTHORS' CONTRIBUTIONS

Mohammed MANSOUR: contributed to the conceptualization, data curation, formal analysis, investigation, methodology, project administration, software development, validation, visualization, and writing of the original draft and review/editing of the manuscript

Kasim SERBEST: contributed to the formal analysis, funding acquisition, supervision, and writing/editing of the manuscript.

Mustafa KUTLU: contributed to the formal analysis, funding acquisition, supervision, and writing/editing of the manuscript.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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APPENDIX

A. FIGURE RESULTS

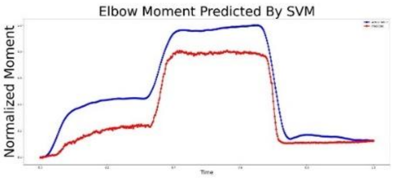

Figure A1. SVM

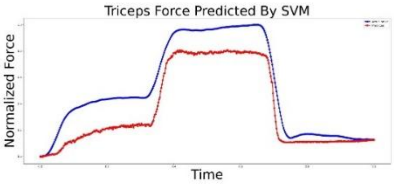

Figure A2. SVM

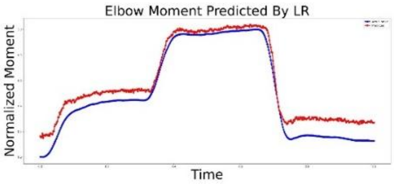

Figure A3. LR

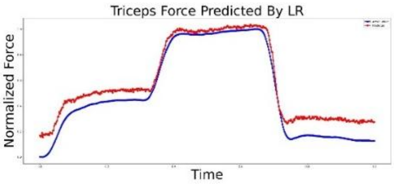

Figure A4. LR

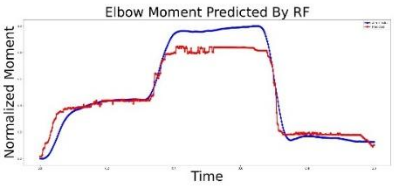

Figure A5. RF

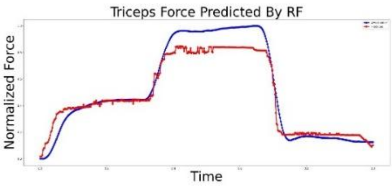

Figure A6. RF

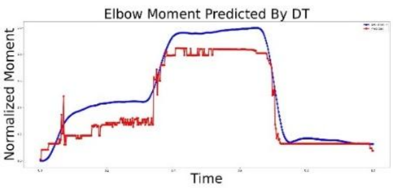

Figure A7. DT

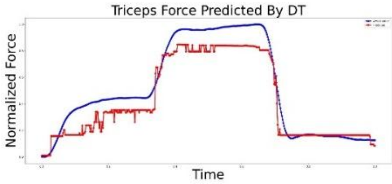

Figure A8. DT

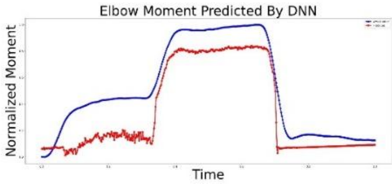

Figure A9. DNN

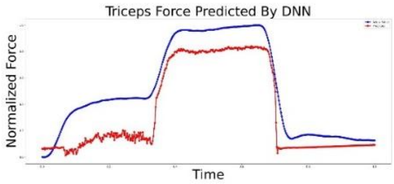

Figure A10. DNN

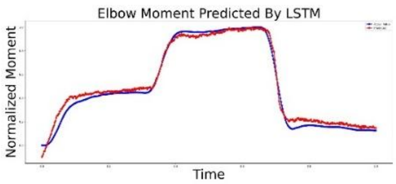

Figure A11. LSTM

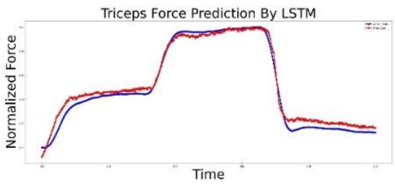

Figure A12. LSTM

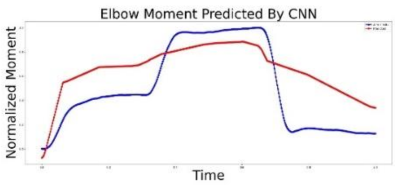

Figure A13. CNN

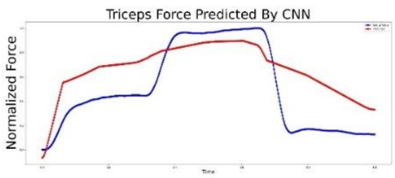

Figure A14. CNN