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# Using a long short-term memory model to predict force values of Taekwon-do turning based on spatio-temporal parameters

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*Purpose*: The aim of this study was to investigate the feasibility of using Long Short-Term Memory (LSTM) neural networks to predict Taekwondo kick force from data obtained by inertial measurement unit (IMU) sensors, providing a cost-effective alternative to traditional force plates in sports biomechanics. *Methods*: IMU (Noraxon Ultium) data from 13 International Taekwon-do Federation (ITF) athletes (9 training, 4 validation) across genders and skill levels (expert in training, expert/advanced in validation) were collected. Sensors were attached to a foot, shank and tight of kicking leg. Athletes performed turning kicks in diverse stances towards a padded force plate (2000 Hz) attached to a wall. LSTM models were trained to predict kick force value, and trained on capturing the IMU data from sensors placed on the lower limb. *Results*: The trained LSTM models showed accuracy on the training data ($R^2$ values in the range of 0.972–0.978). Feature validity analysis highlighted the importance of ankle dorsiflexion in shaping the model score. Model performance on the validation dataset was less consistent, ranging from good accuracy (RMSE 6.91) to poor accuracy (RMSE over 30), depending on the participant tested. *Conclusions*: This study demonstrated the potential of LSTM models combined with IMU data to predict Taekwondo kick forces. Although the validation performance indicated the need for further model refinement or the inclusion of additional input variables, the results highlighted the feasibility of predicting force values without relying on a force plate. This approach could enhance the accessibility of field studies conducted outside laboratory settings.

*Key words*: *Taekwon-do, inertial measurement units, machine learning, force analysis*

## 1. Introduction

Taekwon-do is a dynamic martial art that relies heavily on complex biomechanical movements [5], [27]. Taekwon-do techniques involve the sequential energy transfer from larger body segments (hips, torso) to smaller segments (arms, legs) [3]. Among these techniques, rotational kicks are particularly challenging because they require precise coordination of spatio-temporal parameters such as speed, acceleration and joint alignment to generate maximum force [11], [23]. Accurate measurement of the force produced during such kicks is crucial for performance analysis, injury prevention, and training optimization [25]. Traditionally, this force is measured using force plates, which, although highly accurate, are expensive, cumbersome and limited to laboratory environments. Consequently, there is growing interest in alternative solutions that can measure or predict kick force in real-world settings [29].

In recent years, statistical computing based on Machine Learning (ML) has become more accessible due to the availability of many ready-made libraries. In martial arts, ML applications mainly focus on two key areas: (1) using models to detect or predict movement and combat performance [4], [35], and (2) performing advanced analysis to discover complex relationships in sensor signals (treated as time-series data) or to prevent

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injuries [6], [20]–[22]. To support such studies, inertial measurement units (IMUs) [14] have emerged as a promising solution for capturing spatiotemporal parameters of athletic movements. IMUs are lightweight, portable devices that can record acceleration, angular velocity and orientation data, making them particularly well--suited for biomechanical research conducted outside controlled laboratory environments.

Two primary approaches can be used to predict desired kinematic variables in martial arts biomechanics. The first approach utilizes standard descriptive statistics to extract specific features from the acquired data, followed by predictive modeling using techniques such as regression analysis, *K*-Nearest Neighbors (KNN), or Support Vector Machines (SVM) [13], [14]. The second approach analyzes the entire time-series data, treating captured motion and associated variables as signals over a defined period to predict the target variable. Long Short-Term Memory (LSTM) models, in particular, show significant potential for analyzing complete motion sequences, such as full kick executions, without the need to manually extract key features [14]. While LSTMs demand substantial computational resources and larger datasets for optimal performance, they offer great promise for applications like kinetic analysis, injury prediction, and performance optimization. By capturing temporal dependencies within sequences, LSTMs provide deeper insights into complex biomechanical movements [1], [34], [36]. Furthermore, inspecting feature importance within machine learning models is an established method for gaining a better understanding of the data and its underlying patterns [28]. Together, these approaches highlight the potential of machine learning to advance biomechanical research and enhance martial arts training methodologies. This study aims to evaluate the feasibility of using an LSTM model to predict the force values of Taekwon-do turning kicks based on spatiotemporal parameters collected from IMU sensors. Specifically, it seeks to: (1) investigate the determinants of force generation by analyzing the importance of features within the LSTM models, and (2) evaluate the model's predictive performance on data outside the training set, thereby assessing its potential for practical applications.

# 2. Materials and methods

## 2.1. Participants

The study involved 13 athletes: 9 participants (5 females, 4 males) provided training data for the model, while 4 participants (3 males, 1 female) were used for testing its accuracy on new data (Table 1). All participants were master-level athletes with over 5 years of experience, except for two underage testers (16 years old, blue belts, advanced level). All participant declared that they preferred kicking leg is right. Informed consent was obtained from participants (or their parents in the case of minors). The study was approved by the Human Subjects Research Committee of Jan Długosz University (KE-O/4/2022), meeting ethical research standards.

Table 1. Characteristics of the participants (mean ± standard deviation, minimum and maximum values)

| Parameter | Age [years] | Body mass [kg] | Body height [cm] | Age [years] | Body weight [kg] | Body height [cm] |
|---|---|---|---|---|---|---|
| Female | Model ($N = 5$) | | | Outside ($N = 1$) | | |
| Mean ± SD | 28 ± 5.34 | 64.2 ± 6.5 | 163 ± 7.21 | 16 | 63 | 169 |
| (Min, Max) | (24, 37) | (57, 72) | (152, 170) | | | |
| Male | Model ($N = 4$) | | | Outside ($N = 3$) | | |
| Mean ± SD | 29.3 ± 9.18 | 77 ± 8.12 | 180.3 ± 1.71 | 17.3 ± 2.31 | 70 ± 4.36 | 176.7 ± 4.51 |
| (Min, Max) | (24, 43) | (72, 89) | (178, 182) | (16, 20) | (67, 75) | (172, 181) |

## 2.2. Techniques description

The turning kick is a dynamic Taekwon-do technique relying on angular momentum initialized by core rotation driven by the hip muscles, transferring torque through the body to the kicking leg. The knee flexes to reduce the moment of inertia, allowing for greater angular velocity, before extending rapidly to maximize foot velocity. Two variations were analysed:

1. The sports stance – a flexible stance used in sparring, prioritizes mobility and adaptability with no formal restrictions, enabling practitioners to adjust their positioning based on situational demands. The dorsal

foot (instep) is typically used as the striking surface for the turning kick [30];

2. The traditional stance (L-Stance or Niunja Sogi in ITF Taekwon-Do) – an "L"-shaped stance used for power-breaking. The front foot points forward, the rear foot is perpendicular, and the back heel aligns with the front instep. This stance allows for greater torso rotation, critical for generating power in strikes and kicks. Typically used in board-breaking demonstrations, it prioritizes maximum force, with the plantar foot (sole) as the striking surface [30].

## 2.3. Setup and protocol

A combined method was used to measure impact forces and segment kinematics during kicks. A padded force plate (AMTI, model MC12-2K, 2000 series, Watertown, MA, USA) served as the target, measuring ground reaction forces in three dimensions synchronized with a motion capture system (Noraxon, MR 3.18, Scottsdale, AZ, USA) for precise timing.

## 2.4. Data collection

For each participant, five strikes per kicking technique were recorded. Data from the Noraxon MR 3.18 system (with MyoMotion module) was exported to Excel in *.slk format, then converted to *.xlsx for analysis. Using Python libraries (pandas, numpy, matplotlib, scipy), acceleration data was processed, converting units from milli-g to m/s². Force peaks were detected (threshold: 300 N), and filtering isolated the kicks. Each peak was segmented within a 200 ms window before and after the maximum force value. Data were visualized, summarizing event times, peak forces, and resultant accelerations, with individual events saved for further analysis (Fig. 1).

Excel (.xlsx) files containing acceleration and time data were processed to calculate velocity for each sensor axis using a custom compute_velocity function. The updated files, including velocity columns, were saved and used for model input or testing. Strike events were identified using a 12 m/s$^2$ acceleration threshold, and key

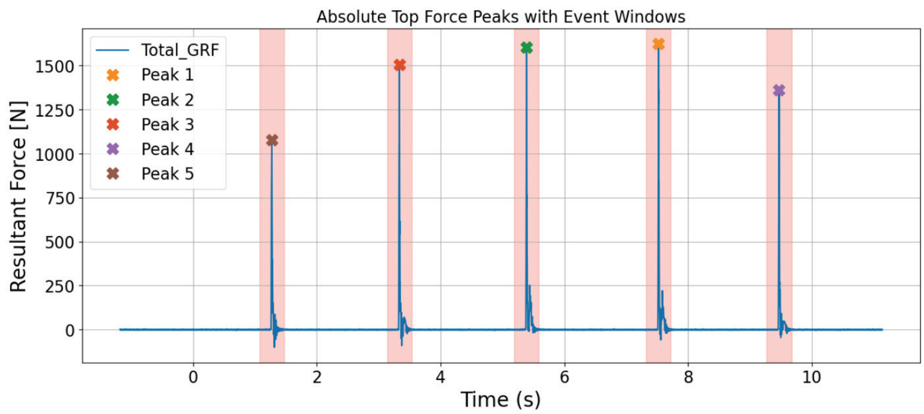


Fig. 1. Visualization of peak detection using a sliding window for event segmentation

For kinematic analysis, three wireless Inertial Measurement Units (IMUs) – Noraxon Ultium (2000 Hz, 400 g) were placed on the kicking foot (the lateral malleolus), shank, and thigh. Both devices data transfer was synchronized using add-on MyoSync, responsible for data synchronization and integrity of signals over time.

After a 10-minute warm-up of dynamic stretches and shadow kicks (kicks performed without a target), sensors were attached, and participants performed five maximal kicks per condition with one-minute rest intervals and alternating legs. Each participant completed 40 kicks (5 reps × 4 conditions × 2 legs). Thus, the data set included 90 strikes per technique (9 participants × 2 legs × 5 strikes). Validation involved predicting 40 strikes for the sports kick and 30 for the traditional version, ensuring minimal fatigue or learning effects.

parameters (strike duration, peak force, accelerations, velocities) were extracted if conditions were met. Results were compiled into a DataFrame for analysis, descriptive statistics and model validation. The code is available on GitHub (https://github.com/Dareczin/tkd_data_preparation_slicing_for_events).

## 2.5. Model architecture

This study used an LSTM network to predict the maximum ground reaction force (GRF) from sequential sensor data. Inputs included standard accelerometer features, along with derived metrics like resultant acceleration and velocity. The model featured three stacked bidirectional LSTM layers with 50 hidden units, capturing complex temporal patterns. Dropout regularization (0.3) was applied to reduce overfitting.

Training used the Adam optimizer (learning rate: 0.001) with Mean Squared Error (MSE) as the loss function. An 80/20 train–test split was applied, and the model was trained for 20 epochs with a batch size of 8 to optimize memory usage (32 GB RAM). The trained model and feature scaler were serialized for future predictions. Feature codes, detailed in Table 2, follow naming conventions established by the lab, starting at 2.

After training, the model's performance on the test set was evaluated using the $R^2$ metric. The model was set to evaluation mode, predictions were generated, and the $R^2$ score was calculated. Four models were created for separate kick-stance pairs using the same code, each run in Jupyter Lab v. 4.11. In Figure 2, the process and algorithm are illustrated.

Feature importance analysis was performed on the baseline model by shuffling feature values and running 100 iterations to compare average importance weights across techniques. The baseline $R^2$ was calculated on the original test set. Then, each feature was permuted individually, while others remained unchanged. The drop in $R^2$ after each permutation indicated feature importance, with averages computed similarly.

Model verification used external data from participants excluded from training. Predictions involved loading the model, selecting the same features, and excluding Total_GRF (force). Each event was processed separately, and predictions were compared to actual force

Table 2. Overview of the 24 selected features and their descriptions, where $x$ denote anteroposterior direction, $y$ denote mediolateral direction, $z$ – longitudinal direction

| Feature name | Description |
|---|---|
| 2$x$, 2$y$, 2$z$ | acceleration along each axis of the foot sensor |
| 3$x$, 3$y$, 3$z$ | acceleration along each axis of the shank sensor |
| 4$x$, 4$y$, 4$z$ | acceleration along each axis of the thigh sensor |
| resultant_acceleration_1 | resultant acceleration from 2$x$, 2$y$, 2$z$ foot sensor |
| resultant_acceleration_2 | resultant acceleration from 3$x$, 3$y$, 3$z$ shank sensor |
| resultant_acceleration_3 | resultant acceleration from 4$x$, 4$y$, 4$z$ thigh sensor |
| velocity_2$x$, 2$y$, 2$z$ | velocity computed from 2$x$, 2$y$, 2$z$ foot sensor for each axis |
| velocity_3$x$, 3$y$, 3$z$ | velocity computed from 3$x$, 3$y$, 3$z$ shank sensor for each axis |
| velocity_4$x$, 4$y$, 4$z$ | velocity computed from 4$x$, 4$y$, 4$z$ thigh sensor for each axis |
| resultant_velocity_1 | resultant velocity computed from velocity_2 axes |
| resultant_velocity_2 | resultant velocity computed from velocity_3 axes |
| resultant_velocity_3 | resultant velocity computed from velocity_4 axes |

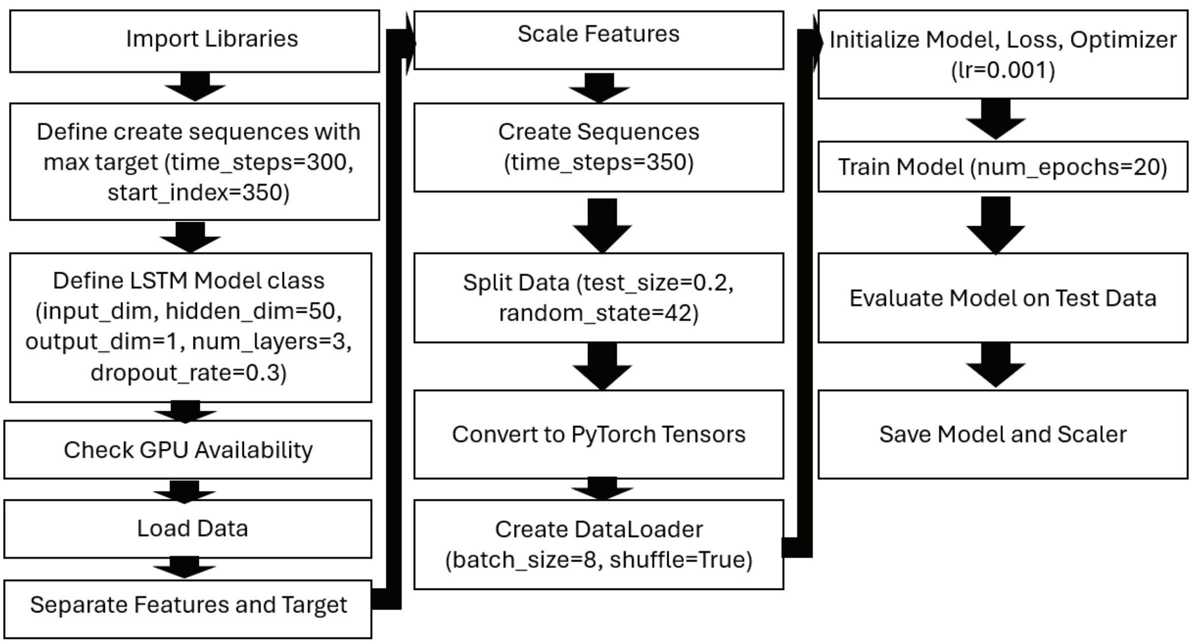


Fig. 2. Flowchart of the model development process with parameter configuration

values for specific kicks. Accuracy was evaluated using RMSE for individual participants and the overall dataset. All models and the corresponding dataset are available on the Zenodo open repository at https://doi.org/10.5281/zenodo.10895668.

# 3. Results

## 3.1. Descriptive statistics of kicks

Descriptive statistics for two techniques in both styles, based on data from nine participants included in the model is provided in Table 3. Since gender was not a factor in the analysis, no division by gender was necessary. The table presents indices recorded at the moment of peak force, which is the model's target prediction value. This data offered a reference for analysing feature importance and understanding how specific variables influence the model, including the impact of performance variability on training.

The lowest force values were recorded for the turning kick from a traditional stance, with a mean of 1427.89 N. Interestingly, in this variation, the IMU data from the thigh exceeded that from the shank, a distinctive observation. In comparison, the traditional stance generally showed lower statistical values than the sports stance, which had a mean force of 2004.71 N. Although the mean force difference between the two styles was notable, the range of minimum to maximum values was considerably smaller.

## 3.2. Model evaluation with permutated feature importance

### 3.2.1. Turning kick in sport version

Each model was evaluated independently, beginning with the turning kick in the sports version. The LSTM model for force prediction achieved a strong baseline $R^2$ score of 0.972. Permutation importance analysis identified key velocity-related features, such as the vertical and rotational components of thigh velocity ("velocity_4$y$" with a drop to 0.773 and "velocity_4$z$" with a drop to 0.837) and the resultant velocity of the shank ("resultant_velocity_2" with a drop to 0.763), as critical for accurate force predictions. These features caused substantial declines in the $R^2$ score when permuted, highlighting their significance. Additionally, acceleration features such as "3$x$" (drop to 0.860) played a notable role. Whereas features such as "2$z$" (0.962), "3$z$" (0.914), and "4$z$" (0.918), representing accelerations along the $z$-axis, exhibited minimal impact on $R^2$ scores when permuted (Fig. 3).

### 3.2.2. Turning kick in traditional version

The next model focused on the turning kick in the traditional version, achieving a high baseline $R^2$ score

Table 3. Descriptive statistics for the model participants across all kick variations performed at maximal force (Max Force), including mean ± standard deviation, as well as minimum and maximum values.

| 2 | Mean ± SD | (Min, Max) |
|---|---|---|
| Turning kick in sport stance version | | |
| Max Force [N] | 2005 ± 820 | (625, 4228) |
| Foot acceleration [m/s$^2$] | 142.06 ± 60.56 | (30.01, 295.52) |
| Shank acceleration [m/s$^2$] | 52.93 ± 22.31 | (16.26, 136.50) |
| Thigh acceleration [m/s$^2$] | 60.95 ± 35.78 | (12.24, 196.32) |
| Foot velocity [m/s] | 12.53 ± 3.84 | (5.40, 21.00) |
| Shank velocity [m/s] | 8.42 ± 2.16 | (4.18, 14.80) |
| Tight velocity [m/s] | 8.03 ± 2.75 | (1.47, 14.57) |
| Turning kick in traditional stance version | | |
| Max Force [N] | 1428 ± 566 | (513, 3942) |
| Foot acceleration [m/s$^2$] | 134.15 ± 65.54 | (37.54, 305.44) |
| Shank acceleration [m/s$^2$] | 42.77 ± 13.65 | (11.00, 69.59) |
| Thigh acceleration [m/s$^2$] | 61.39 ± 36.81 | (17.77, 177.33) |
| Foot velocity [m/s] | 10.91 ± 4.12 | (2.49, 19.03) |
| Shank velocity [m/s] | 7.45 ± 1.70 | (4.20, 10.64) |
| Tight velocity [m/s] | 7.60 ± 2.50 | (2.89, 15.40) |

of 0.978. Permutation importance analysis identified several key features, with "resultant_acceleration_1" showing the largest drop in $R^2$ score (to 0.711) when permuted, emphasizing its critical role in accurate force predictions. Additionally, "resultant_velocity_1", which was linked to acceleration data, also displayed a noticeable drop (to 0.827). Another important feature was the rotational axis of the shank sensor's acceleration data "3*x*", which dropped to 0.854. Compared to the sports version, this model exhibited fewer features with significant drops in $R^2$ scores (Fig. 4).

### 3.3. Descriptive statistics for outside model participants

The available data for testing involved 4 participants, with data from only 3 participants being usable for the

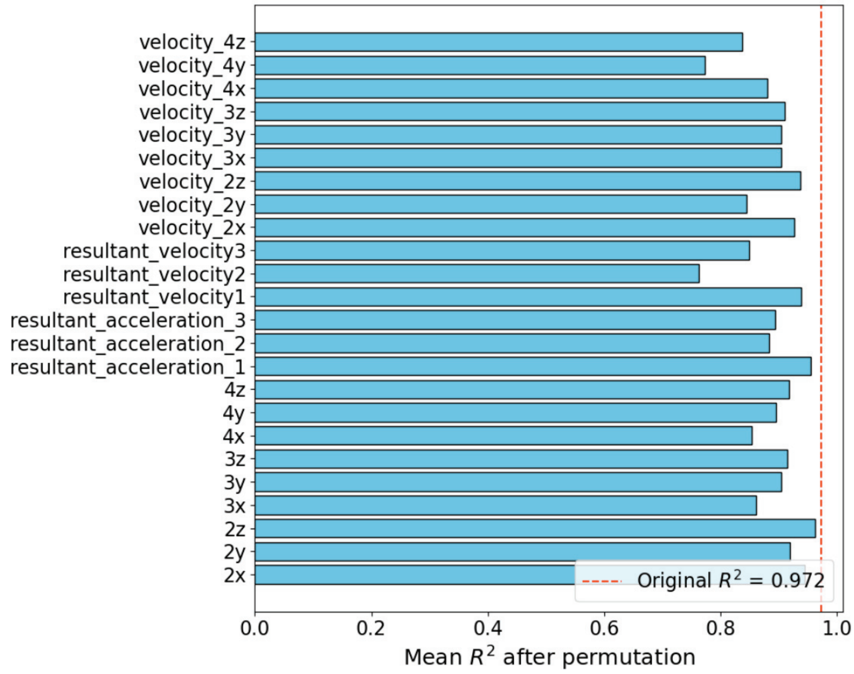


Fig. 3. $R^2$ scores for each feature after 100 permutation runs in the kick model (sport version)

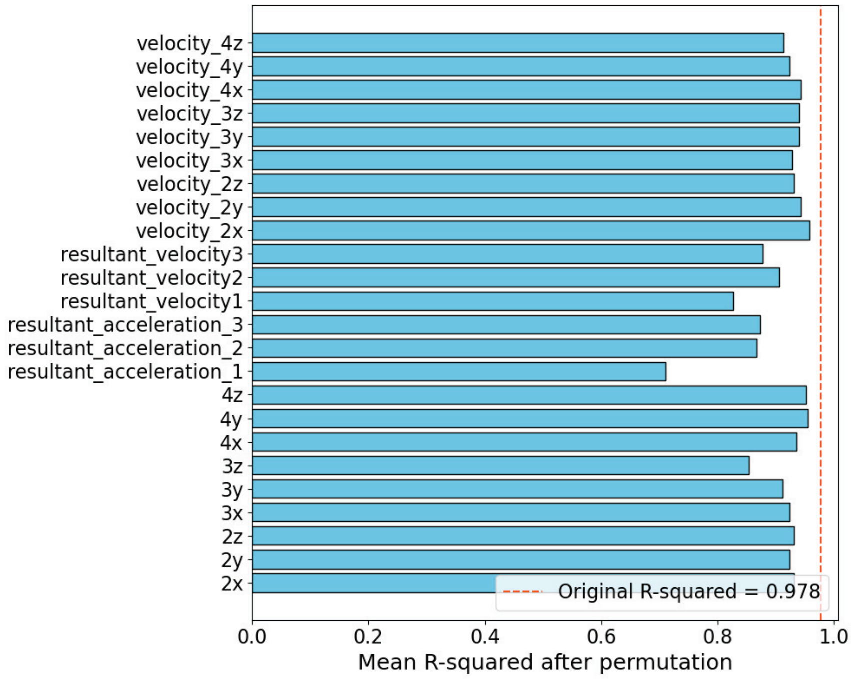


Fig. 4. $R^2$ scores for each feature after 100 permutation runs in the kick model (traditional version)

turning kick in the traditional version. Descriptive statistics revealed similar trends in the switching of acceleration/velocity order for the traditional version of the turning kick, compared to other conditions, which aligned with the data from the model set (Table 4).

Table 4. Descriptive statistics of kicks for outside model participants across all kick variations performed at maximal force (Max Force), including mean ± standard deviation, as well as minimum and maximum values

| Variable | Mean ± SD | (Min, Max) |
|---|---|---|
| Turning kick in sport stance version | | |
| Max Force [N] | 1548 ± 573 | (656, 3179) |
| Foot acceleration [m/s$^2$] | 107.72 ± 41.03 | (48.60, 189.18) |
| Shank acceleration [m/s$^2$] | 62.45 ± 5.91 | (27.03, 201.85) |
| Thigh acceleration [m/s$^2$] | 74.40 ± 57.51 | (26.94, 228.02) |
| Foot velocity [m/s] | 11.35 ± 3.07 | (6.61, 16.15) |
| Shank velocity [m/s] | 9.56 ± 2.08 | (6.47, 15.35) |
| Tight velocity [m/s] | 8.59 ± 3.72 | (4.41, 18.82) |
| Turning kick in traditional stance version | | |
| Max Force [N] | 1631 ± 1182 | (545, 5503) |
| Foot acceleration [m/s$^2$] | 62.51 ± 14.31 | (27.49, 82.35) |
| Shank acceleration [m/s$^2$] | 77.29 ± 32.19 | (36.71, 135.72) |
| Thigh acceleration [m/s$^2$] | 91.32 ± 58.34 | (27.76, 197.33) |
| Foot velocity [m/s] | 8.82 ± 1.24 | (6.75, 11.64) |
| Shank velocity [m/s] | 9.83 ± 2.21 | (6.98, 14.08) |
| Tight velocity [m/s] | 10.57 ± 4.14 | (5.89, 17.55) |

## 3.4. Model performance for outside model participants

The comparison between observed Max Force values and model predictions showed varying accuracy across participants and trials (Table 5). Participant 1 exhibited strong performance, with RMSE values below 50 N, indicating minimal errors. In contrast, Participant 2 had larger errors, with RMSEs exceeding 100 N in some trials. Dynamic tasks, like Participant 3's trial with a Max Force of 3031 N, led to significant prediction errors of nearly 2000 N (RMSE = 38.3). Participant 4 showed RMSE values over 20, highlighting the need for model improvement. In the traditional stance, turning kicks varied in RMSE, reflecting fluctuations in model accuracy. For Participant 1, dynamic scenarios like the right-leg kick showed large prediction errors, with a true Max Force of 5502 N predicted as 1582 N (RMSE > 41). Participant 2 had moderate errors (RMSE between 30.9 and 31.8). Participant 3 displayed smaller RMSE values in low-force trials but significant overestimations in high-force cases, such as a true Max Force of 931 N overestimated by over 700 N (RMSE = 27.2).

Table 5. Model performance for each participant and condition, presented separately

| Participant | Side | Mean true values [N] | Mean predictions [N] | RMSE |
|---|---|---|---|---|
| Turning kick in sport stance version | | | | |
| 1 | left | 1573 | 1620 | 6.91 |
| | right | 2703 | 1465 | 38.27 |
| 2 | left | 867 | 1915 | 32.37 |
| | right | 1780 | 2094 | 17.71 |
| 3 | left | 1399 | 2028 | 25.08 |
| | right | 1535 | 1320 | 14.64 |
| 4 | left | 1125 | 2008 | 29.72 |
| | right | 1475 | 2098 | 25.62 |
| Turning kick in traditional stance version | | | | |
| 1 | left | 1553 | 1502 | 7.18 |
| | right | 3321 | 1603 | 41.45 |
| 2 | left | 1172 | 1013 | 31.83 |
| | right | 1030 | 1986 | 30.92 |
| 3 | left | 759 | 584 | 13.23 |
| | right | 888 | 1630 | 27.23 |

# 4. Discussion

This study aimed to evaluate the feasibility of using an LSTM model to predict the force values of Taekwon-do turning kicks based on spatiotemporal parameters collected from IMU sensors. Specifically, it sought to: (1) investigate the determinants of force generation by analyzing the importance of features within the LSTM models, and (2) evaluate the model's predictive performance on data outside the training set, thereby assessing its potential for practical applications.

LSTM models are currently used for predicting different variables related to martial arts for movement prediction [12] or health-related properties of a wider spectrum [19]. As this type of analysis is quite new, there are not any papers that directly reflect this work. Existing models aim to recognize specific techniques based on kinematic data. The paper of Barbosa, et al. [2], reveals high accuracy of movement recognition in Taekwondo techniques with the value of accuracy 0.991 [2]. This value corresponds to the accuracy of the model obtained in this study in values ranging from 0.972 to 0.984. This is outside justification of method correctness, at least at the starting point of this model.

The analysis of external model data often proved inaccurate. The turning kick in the sports version showed the best performance, with the lowest RMSE values. However, predictions missing over 1000 N in a range of 600–4300 N fail to meet the goal of practical training applications, aside from the force plate's immobility issue. Despite limited comparable studies, we discuss potential reasons for this lack of accuracy. Only one participant demonstrated that predicting force without a force plate might be feasible, suggesting this approach holds future potential.

Participants in the new dataset differed in age and experience from those in the trained sample, which, in traditional research, would be unacceptable due to the importance of homogeneity for comparison. However, for the model's practical application, it must adapt to all training participants, not just those resembling the trained sample. Participant 1, a master-level athlete, initially aligned well with the model but displayed unexpected variability. His exceptionally powerful right-leg strikes altered the time-series data patterns, leading to poor predictions. This outcome was unforeseen, as initial indicators suggested compatibility. From previous studies, Taekwon-do martial arts did not exhibit specific lateralization between lower limbs in their strikes [31].

Other participants were less experienced and younger, which could have led to differences in kick kinematics. If their coordination differed, the LSTM model might have been sensitive to these variations. Since the bidirectional LSTM model relies on both forward and backward relationships between features processed as signals in windows, any irregular fluctuations compared to the trained data could result in prediction errors. This hypothesis is supported by previous studies that have explored differences in the kinematics of the turning (roundhouse) kick between novices and experts. These differences were not only observed in muscle activation but also overall kinematic metrics, including the generated force [23].

Participants had the freedom to adjust their distance from the target independently, particularly in the sports stance. Numerous studies have highlighted the importance of distance in turning (roundhouse) kicks [7], [9], [10], [15]. Variations in distance are related to the concept of effective mass, which refers to the utilization of one's body mass in generating force. Insufficient distance or poor timing at the moment of contact with the target can lead to a decrease in the generated force values [17], [18], [32].

The first model explored was the turning kick in the sports version. None of the individual axis accelerations showed a significant drop in $R^2$ scores; however, the most important determinants, according to the permutation feature analysis, were the resultant acceleration of the shank (resultant_acceleration_2) and the acceleration of the thigh (resultant_acceleration_3). Since this is a circular motion, the non-linearity of the kick may explain the lack of dominance of a single axis, with the overall acceleration of these segments being crucial. Therefore, developing strong flexion strength in the hip and knee joints is recommended for this kick, which aligns with findings from Moreira et al. [26], where isokinetic strength in these areas was also shown to be important. In contrast to previous studies on the effects of target kinematics [16], [33], maximum foot velocity was not a critical factor for overall performance based on its resultant values. However, when analyzing the data for each axis separately, the vertical component of foot velocity emerged as important. This highlights the significance of foot dorsiflexion speed in generating kick force. It is recommended that athletes focus on strengthening the tibialis anterior muscles to enhance dorsiflexion speed as a key factor in improving kick power.

The permutation feature analysis of the second model reveals noticeable differences in the $R^2$ scores of selected features, supporting the need for separate analyses of the two stances. The primary difference in the traditional version lies in the contact area with the target. Since the plantar side of the foot in the metatarsal joint region strikes the shield, the foot must be fixed in position before contact, leading to different kinematics at the end of the technique execution. In this model, the most important determinant was the resultant acceleration of the foot (resultant_acceleration_1), suggesting that the timing of foot position fixation is crucial for predicting the force of the kick. As a practical application, trainers could use high-speed cameras (e.g., 100 frames per second or higher) to assess the timing of ankle movements during this technique. Feature importance analysis does not equate to correlation, so we cannot directly conclude that later fixation leads to a stronger impact. In this model, shank velocity and acceleration were less important, but the kinematics of the segments remained significant. This challenges the assumption of a proximal-to-distal pattern being crucial for the turning kick in ITF Taekwondo athletes [8], [24].

### *Limitations of the study*

The permutation feature analysis highlights important technical nuances that trainers should consider during motor learning. While it identifies key components influencing force predictions, it also reveals the model's limitations with the current sample, which orders us to be cautious about strength of those evidence.

Testing on new data suggests that the model is not suitable for general use, possibly due to the small sample size of nine participants or the need for refinement based on permutation analysis insights. Higher sample size of testing data outside the model would also help to better understand which group is suitable for using this models, as single successful assessments indicate that there might be a profile of athletes that could utilize this solution. Expanding the feature set, using sliding windows, or adjusting model parameters could improve performance, but computational constraints, such as a 32 GB memory limit of device used for training models, restrict batch sizes and cause system errors. These limitations emphasize the need for further optimization and larger datasets. Additionally, using more number of sensors could fill the gap in prediction ability of proposed models.

The key takeaway from this paper is that it is indeed possible to train an effective model to predict the force of a kick without the need for a force plate. The main objective of this study has been achieved, and we aim to promote the idea of eliminating stationary equipment for sports analysis conducted outside of laboratory settings.

# 5. Conclusions

This study rigorously evaluated the capability of Long Short-Term Memory (LSTM) models to predict the force of Taekwon-do kicks using inertial measurement unit (IMU) data. The LSTM models demonstrated impressive predictive performance, with $R^2$ values ranging from 0.972 to 0.978 across different kick stances. This suggests a high level of accuracy in capturing the nuanced dynamics of Taekwon-do techniques.

Feature importance analysis pinpointed specific kinematic variables – particularly the velocity of the thigh and the rotational velocity of the shank – as key determinants of kick force. These insights offer actionable guidance for technique optimization, highlighting the importance of both segmental velocities and acceleration patterns of the ankle joint motion in generating powerful kicks.

While these findings are encouraging, the model's predictive accuracy was less consistent when tested with data from new participants. Differences between predicted and actual force values, highlighted by RMSE values, indicate limitations in generalization across a broader athlete spectrum.

Future research should focus on addressing these limitations by expanding the training dataset, refining model architecture, and incorporating a wider array of kinematic and kinetic variables. These advancements hold the potential to significantly enhance the predictive power and broaden the applicability of the model across various sports biomechanics applications.

# References


[1] Barbosa P., Cunha P., Carvalho V., Soares F., *Classification of Taekwondo Techniques using Deep Learning Methods: First Insights*, 2021, 201–208.

[2] Barbosa P., Cunha P., Carvalho V., Soares F., *Deep Learning in Taekwondo Techniques Recognition System: A Preliminary Approach*, 2022, 280–291.

[3] Campos F., Bertuzzi R., Dourado A., Ferreira Santos V., Franchini E., *Energy demands in Taekwondo athletes during combat simulation*, European Journal of Applied Physiology, 2011, 1121221-1228.

[4] Cenanovic N., Kevric J., *Mixed Martial Arts Bout Prediction Using Artificial Intelligence*, 2022, 452–468.

[5] Cherifi N., Johnson J., Chin S.-T., *Expertise development of elite Taekwondo coaches*, Physical Activity Review, 2023, 11131–11145.

[6] Duki M., Shapiee M., Abdullah M.A., Mohd Khairuddin I., Razman A., P P Abdul Majeed A., *The Classification of Taekwondo Kicks Via Machine Learning: A feature selection investigation*, Mekatronika, 2021, 361–367.

[7] Estevan I., Falco C., *Mechanical analysis of the roundhouse kick according to height and distance in taekwondo*, Biology of Sport, 2013, 30 (4), 275–279.

[8] Estevan I., Falco C., Silvernail J.F., Jandacka D., *Comparison of Lower Limb Segments Kinematics in a Taekwondo Kick. An Approach to the Proximal to Distal Motion*, J. Hum. Kinet., 2015, 4741–4749.

[9] Falco C., Alvarez O., Castillo I., Estevan I., Martos J., Mugarra F., Iradi A., *Influence of the distance in a roundhouse kick's execution time and impact force in Taekwondo*, J. Biomech., 2009, 42 (3), 242–248.

[10] Falco C., Molina-García J., Alvarez O., Estevan I., *Effects of target distance on select biomechanical parameters in taekwondo roundhouse kick*, Sports Biomechanics, 2013, 12 (4), 381–388.

[11] Góra T., Mosler D., Ortenburger D., Wąsik J., *Sex differences in utilizing effective mass among taekwon-do athletes performing turning and side kick*, Physical Activity Review, 2024.

[12] Hui B., *Visualization system of martial arts training action based on artificial intelligence algorithm*, 2023.

[13] Jaya I.G.P., Dharmmesta R.A., Rizal A., ISTIQOMAH. Application Foot Kick Classification in Taekwondo with Inertia Sensor and Machine Learning, in 2022 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob). 2022.

[14] Juneau P., Baddour N., Burger H., Bavec A., Lemaire E.D., *Comparison of Decision Tree and Long Short-Term Memory Approaches for Automated Foot Strike Detection in Lower Extremity Amputee Populations*, Sensors (Basel, Switzerland), 2021, 21 (21).

[15] Kim J.W., Kwon M.S., Yenuga S.S., Kwon Y.H., *The effects of target distance on pivot hip, trunk, pelvis, and kicking leg kinematics in Taekwondo roundhouse kicks*, Sports Biomechanics, 2010, 9 (2), 98–114.

[16] LANDEO R.A., MCINTOSH A.S., *Kinetic and kinematic differences between target and free kicking in taekwondo*, 2008.

[17] LAPKOVÁ D., ADAMEK M., *Using information technologies in self-defense education*, 2016, 1–5.

[18] LENETSKY S., NATES R.J., BRUGHELLI M., HARRIS N.K., *Is effective mass in combat sports punching above its weight?*, Human Movement Science, 2015, 4089–4097.

[19] LI C., ZHAO M., ZHAO X., *Status Quo and Influence of Martial Arts Fitness in Pursuit of Health Using LSTM Recurrent Neural Network Algorithm*, International Journal of Computational Intelligence Systems, 2023, 16 (1), 61.

[20] LI S., LIU C., YUAN G., *Martial Arts Training Prediction Model Based on Big Data and MEMS Sensors*, Scientific Programming, 2021, 2021 (1), 9993916.

[21] LIU Y., KONG J., WANG X., SHAN G., *Biomechanical analysis of Yang's spear turning-stab technique in Chinese martial arts*, Physical Activity Review, 2020, 816–822.

[22] MONTILLA J.A., LATORRE ROMÁN P., SERRANO-HUETE V., LINARES J.C., LOZANO E., JIMÉNEZ P., *Differences in the Force-Velocity profile between Judoist and freestyle wrestlers*, Physical Activity Review, 2022, 102022.

[23] MOREIRA P.V., FRANCHINI E., ERVILHA U., GOETHEL M., CARDOZO A., GONÇALVES M., *Relationships of the expertise level of taekwondo athletes with electromyographic, kinematic and ground reaction force performance indicators during the dolho chagui kick*, Archives of Budo., 2018, 14.

[24] MOREIRA P.V., PAULA L., VELOSO A., *Segmental kick velocity is correlated with kick specific and nonspecific strength performance in a proximodistal sequence*, Archives of Budo., 2015, 11271–11283.

[25] MOREIRA P.V.S., FALCO C., MENEGALDO L.L., GOETHEL M.F., DE PAULA L.V., GONÇALVES M., *Are isokinetic leg torques and kick velocity reliable predictors for competitive success in taekwondo athletes?*, bioRxiv, 20202020.2006.2019.161158.

[26] MOREIRA P.V.S., FALCO C., MENEGALDO L.L., GOETHEL M.F., DE PAULA L.V., GONÇALVES M., *Are isokinetic leg torques and kick velocity reliable predictors of competitive level in taekwondo athletes?*, PLoS One, 2021, 16 (6), e0235582.

[27] OH Y., CHO Y.-J., *Relationship Between Autonomy Support Coaching Perceived by Taekwondo Athletes and Interruption Intention: Mediating Role of Emotional Intelligence*, Physical Activity Review, 2023, 1160–1168.

[28] PAVLOVA I., ZIKRACH D., MOSLER D., ORTENBURGER D., GÓRA T., WĄSIK J., *Determinants of anxiety levels among young males in a threat of experiencing military conflict – Applying a machine-learning algorithm in a psychosociological study*, PLoS One, 2020, 15 (10), e0239749.

[29] WAGNER J., SZYMAŃSKI M., BŁAŻKIEWICZ M., KACZMARCZYK K., *Methods for Spatiotemporal Analysis of Human Gait Based on Data from Depth Sensors*, Sensors, 2023, 23 (3), 1218.

[30] WĄSIK J., *Kinematic analysis of the side kick in Taekwon-do*, Acta Bioeng. Biomech., 13 (4), 71–75.

[31] WĄSIK J., MOSLER D., GÓRA T., ORTENBURGER D., CHALIMONIUK M., LANGFORT J., *Kinematic Differences between Traditional and Sport Version of Roundhouse Kick Executed by Male Taekwon-do Masters*, Journal of Men's Health, 2022, 18 (6), 1–7.

[32] WĄSIK J., MOSLER D., GÓRA T., SCUREK R., *Conception of effective mass and effect of force – measurement of taekwondo master*, Physical Activity Review, 2023, 1111–1116.

[33] WĄSIK J., MOSLER D., ORTENBURGER D., GÓRA T., CHOLEWA J., *Kinematic Effects of the Target on the Velocity of Taekwon-Do Roundhouse Kicks*, J. Hum. Kinet., 2021, 8061–8069.

[34] XIANG L., GU Y., GAO Z., YU P., SHIM V., WANG A., FERNANDEZ J., *Integrating an LSTM framework for predicting ankle joint biomechanics during gait using inertial sensors*, Computers in Biology and Medicine, 2024, 170108016.

[35] YAMANAKA S., SHIMA K., MUTOH A., MORIYAMA K., MATSUI T., INUZUKA N., *Evaluation System for Martial Arts Demonstration from Smartphone Sensor Data Using Deep Neural Networks on Noisy Labels*, 2023, 1–5.

[36] ZHOU S., *Biomechanical analysis of the danger of the whip-leg striking maneuver in martial arts sparring bouts*, Applied Mathematics and Nonlinear Sciences, 2024, 9.