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Research Article

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A Leap Forward in Biomechanics: Predicting Ground Reaction Forces with Dual-Branch GRNN

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Abstract

Background: *Accurate vertical ground reaction force (VGRF) analysis is essential for understanding biomechanics, balance, and injury prevention. However, many current predictive models face limitations in accuracy, simplicity, and applicability outside laboratory settings.*

Objective: *This study aims to develop a predictive model for VGRF using anthropometric data to enhance the precision and applicability of biomechanical analysis.*

Methods: *A dual-branch General Regression Neural Network (GRNN) was designed to predict VGRF at ten key points on the sole, total force, and ground contact time. The dataset included 14 selected participants. Key input variables included height, weight, BMI, navicular drop, foot size, and age. Separate branches analyzed right and left feet to improve prediction accuracy.*

Results: *The model achieved a mean squared error (MSE) of 0.545% for total force. Compared to CNN and LSTM architectures, the accuracy of the GRNN model was significantly better while also maintaining computational efficiency. Its simple structure and fast processing capabilities make it suitable for real-time applications.*

Conclusion: *The proposed model significantly improves VGRF prediction and is valuable for clinical diagnostics and sports science applications. Future efforts will aim to validate the model with larger datasets and integrate hybrid architectures to enhance spatiotemporal analysis.*

Keywords: Vertical Ground Reaction Force (VGRF), Dual-Branch GRNN Neural Network, Anthropometric Data, Force Prediction, Estimation, Biomechanical Analysis, Real-Time Applications

1. Introduction

Human Movement Biomechanics is one field of scientific research concerning the interaction of the musculoskeletal system with the environment. Vertical ground reaction force constitutes a critical component in biomechanical studies since this force will indicate the interaction between the human body and the ground surface. Knowledge of VGRF eases information on the distribution of force and its influences on health and performance [1-3]. Understanding force distribution and maintaining balance during movement requires analyzing VGRF at the Toe 1, Toes 2 through 5, Metatarsals 1 through 5, Midfoot, Heel Medial, and Heel Lateral.

These points transfer forces in a range of ways during the gait cycle, for example, Toe 1's key function at the end of the gait cycle and medial and lateral heels' capture of initial impact energy to avoid injury [4,5]. Analysis of these forces is sufficiently accurate and robust to be used in identifying movement abnormalities as well as developing treatment [6,7].

2. Literature Review

A range of high-tech sensors (wearable sensors, accelerometers, gyroscopes, pressure sensors, force plates, and laboratory-scale devices) are used to acquire gait-related data [8-10]. While these tools are precise, they are often expensive and confined to medical and biomechanical applications that are inconvenient for routine medical or biomechanical work [11,12]. In parallel, automated analytical methods using artificial intelligence (AI) algorithms, including convolutional neural networks (CNNs), long short-term memory (LSTM) networks, support vector machines (SVMs), and generalized regression neural networks (GRNNs), have emerged as powerful tools in gait analysis [13-15]. These approaches transform basic motion data into sophisticated models that estimate ground reaction forces. In particular, foot pressure data has been used by Pataky et al. to get an accuracy of 99.6% in individual identification [13]. Likewise, Khokhlova et al. applied a hybrid LSTM-based model for the gait classification using the Kinect v.2 sensors that extracted features, like foot joint movements, to discover abnormal gait patterns.s. [16,17]. These models are great at processing images and sequential data, but running them requires large datasets, complicated configurations, and many computational resources [18].

2.1. Problem Statement

Despite prospering AI-based gait analysis, these complex models have significant barriers to general application in scenarios with sparse data or real-time constraints. While CNNs and LSTMs are powerful, they also have limitations on cost, computational complexity, and operational feasibility [18]. GRNNs are a more compact solution based on simpler architectures, fewer data demands, and the opportunity to learn nonlinear relationships [19]. These attributes make GRNNs a promising alternative for real-time and cost-efficient VGRF analysis [3,20]. Current research has not fully utilized GRNNs for complete VGRF prediction at all key foot-ground contact points; a model incorporating extra biomechanical features is needed for improved accuracy.

2.2. Research Objective

This study aims to develop and implement a dual-branch neural network-based prediction model consisting of GRNNs. This model provides predictions for ten important foot ground contact points and the total VGRF It will then be integrated with the height, weight, foot size, BMI, age, and foot ground contact time for enhanced accuracy. The model will independently predict the left and right feet' time in contact with the ground to further the model's capability to account for the biomechanical differences between the feet.

2.3. Significance and Contribution

This study proposes a novel approach to VGRF estimation using a dual-branch neural network architecture for left-right foot data separation to handle individual biomechanical variability. In addition, foot contact time has been used as an input in the model for further improvement in the prediction capability of the model. Though the disadvantages exist in the previous approaches, this study uses the efficiency and accuracy of GRNNs to overcome these disadvantages and result in a low-cost and real-time solution for biomechanical research and clinical applications. The result of this study will contribute to enhancing personalized treatment plans, sports injury prevention plans, and overall performance for motor tasks.

3. Methodology

3.1. Study Design

This study employed a General Regression Neural Network (GRNN) to predict the Vertical Ground Reaction Force (VGRF) for both the right and left feet. The participants' anthropometric data, including height, weight, foot size, navicular drop, age, and Body Mass Index (BMI), were collected as inputs for the GRNN model to estimate ground contact time and VGRF. The study aimed to model the relationship between these variables and VGRF under controlled conditions.

3.2. Participants and Ethical Considerations

Fourteen healthy, right-handed male participants took part in this study. These individuals were free from any skeletal, muscular, or neurological disorders and had not experienced any injuries in the past six months. Their anthropometric data are presented in Table 1. Participants were selected using convenience sampling, as they volunteered for the study. The Bu-Ali Sina University Ethics Committee (IR.BASU.REC.1402.083) approved the research and complied with the ethical principles outlined in the Helsinki Declaration. All participants provided informed consent after being informed about the study's purpose, methodology, and potential risks.

Feature	Unit	Mean ± Standard Deviation
Age	years	22.15 ± 5
Height	centimetres	178 ± 11
Mass	kilograms	72.30 ± 14
Body Mass Index (BMI)	kg/m²	22.86 ± 4
Sagittal Plane	millimeters	7 ± 2
Dominant Hand	-	Right

Table 1: Anthropometric Data

3.3. Equipment and Materials

The VGRF data were captured using an RSSCAN-9 foot scanner, manufactured in Belgium, with a sampling rate of 300 Hz. Participants were asked to walk barefoot during the data collection process. The device was calibrated by having the subjects stand on a platform in their natural, uncorrected posture. The subjects then walked a 10-meter path five times, with a Stabil platform placed in the middle. VGRF measurements were taken at ten anatomical points on each foot. Figure 1 shows the anatomical points, while Figure 2 illustrates the summed VGRF forces at these points.

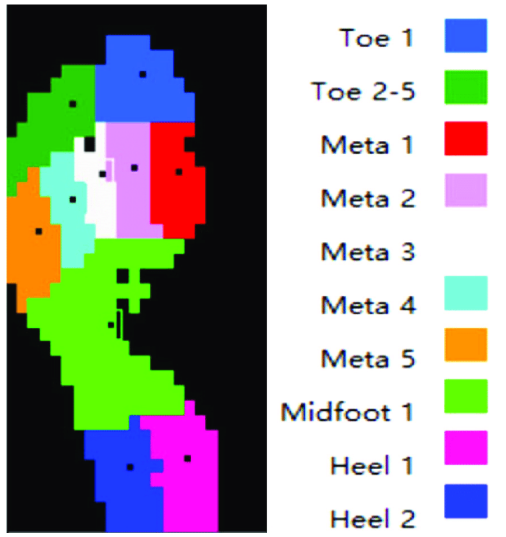

Figure 1: The Footscan® system divides the sole into ten areas: the big toe (T1), toes 2–5 (T2–T5), the 1st to 5th metatarsal (M1, M2, M3, M4, and M5), midfoot (MF), medial heel (H1, MH), and lateral heel (H2, LH) [21]

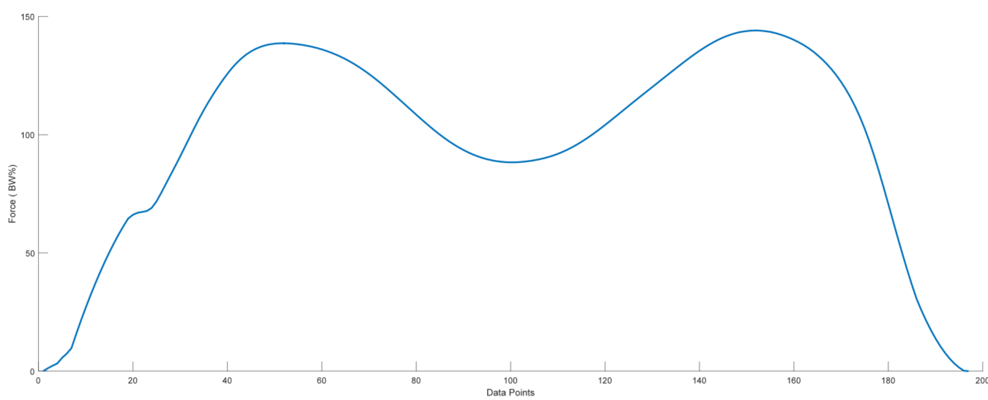

Figure 2: Vertical Ground Reaction Forces

3.4. Experimental Procedure

Participants were required to walk barefoot along a 10-meter path five times to familiarize themselves with the procedure. Ten anatomical points on the foot were recorded as foot contact points, and the total force at these points was summed for each individual. The ground contact time for each participant was calculated from the sequences collected at 300 Hz.

3.5. Data Preparation and Processing

This study carefully carried out the data preparation process to ensure uniformity and consistency across all input sequences. The sequences were initially padded to match each batch's most extended sequence length, standardizing the input dimensions. This step was critical to avoid dimension mismatches during model training and prediction.

The collected data were divided into a sequence, and the number of data points in the sequence was multiplied by the sampling interval (3ms) to get the ground contact time (in milliseconds) for each subject, as the data were collected at 300 Hz. As a result, an exact calculation of the contact duration for each patient could be performed. Preprocessing steps included:

- Removal of Outliers: To maintain the integrity of the dataset, extreme data points that could potentially skew the results were identified and removed.

- Data Normalization: All input features, including height, weight, and ground contact time, were normalized. Normalization ensured the features were comparable, preventing any feature from disproportionately influencing the neural network's training process.

For all computations and processing steps, MATLAB 2024a was utilized, leveraging its advanced toolboxes and computational capabilities to streamline the data preparation workflow. This ensured precision and efficiency in preparing the dataset for subsequent analysis and model development.

3.6. GRNN Model Description

The General Regression Neural Network (GRNN) model predicted the right and left foot's Vertical Ground Reaction Force (VGRF). This model is powerful for regression problems and thus would be a good fit for regression problems predicting continuous variables (VGRF). The GRNN was trained on discriminative input features, such as height, weight, foot size, navicular drop, age, and body mass index. Following the ground contact time estimation, this information was entered into a dual-branch neural network to more accurately estimate the VGRF at each of the ten anatomical sites of the foot. The dual-branch design allowed a whole estimation by using the combined input features and the contact time, thus accurate force predictions of VGRF. Figure 3 shows one proposed example architecture for VGRF prediction and contact time estimation. This figure provides a comprehensive schematic of the neural network, showing the model's GRNN and bilateral-branch architecture.

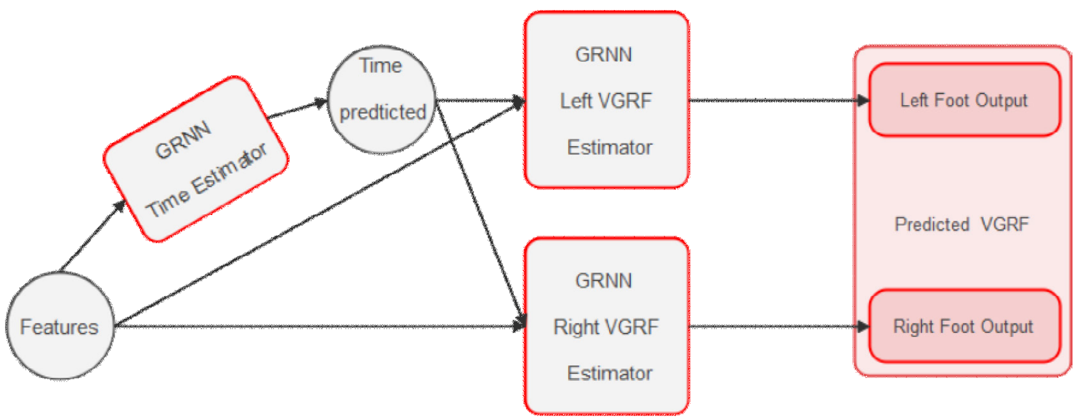

Figure 3: Proposed Neural Network Architecture for Predicting Vertical Ground Reaction Force (VGRF) and Estimating Contact Time

3.7. GRNN Structure

- **Input Layer:** The number of neurons equals the number of input features, such as height, weight, contact time, and BMI. Values are passed as input to the network.
- **Pattern Layer:** This layer contains neurons connected to the training samples. Each neuron is a radial basis function and compares input features to training data.
- **Kernel Density Function:** The neurons in the pattern layer use the Gaussian kernel density function to assess the proximity of input features to the training data points. The kernel function weights the input data based on its closeness to the training data.
- **Output Layer:** The output layer consists of a single neuron that produces the estimated value of the ground contact time, which is subsequently used to predict the VGRF forces for both feet.
- The Gaussian kernel function was employed in the pattern layer, and the training was done to optimize kernel parameter sigma to fit the best data. Model parameters were also trained by incorporating cross-validation during training.

3.8. Evaluation Metrics

The performance of the GRNN model was calculated through MSE, which is for each participant's right and left foot; this indicates the model's accuracy in mapping inputs and outputs. MSE is given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (1)$$

Where:

- $\hat{y}_i$ is the predicted VGRF for the i-th data point.
- y_i Is the true VGRF for the i-th data point.
- n Is the total number of data points.

3.9. Error Calculation and Result Storage

The output of the GRNN model was stored and compared for all the subjects' feet (right and left). Thus, the MSE of each person's prediction was computed to determine the model's accuracy. The GRNN parameters were then tuned so that the final VGRF prediction decreased the model's mean absolute error.

4. Result

For the present study, a General Regression Neural Network (GRNN) model was developed and subjected to evaluation to predict the vertical ground reaction forces (VGRF) and estimate the ground contact time of regular walking. It used the variables of height, weight, navicular drop, foot size, age, and BMI. Here, the primary purpose of this analysis was to check the performance of the model in predicting the forces on the right and left foot at a total of ten contact points (big toe (toe 1), toe 2-5, Meta 1-5 (first metatarsal to fifth metatarsal), and midfoot arch and medial heel, lateral heel), as well as for both feet and the time of contact on the ground for each.

4.1. Prediction of Ground Contact Time

The GRNN network was trained separately for each of the 14 individuals using input variables such as height, weight, navicular drop, foot size, age, and BMI. Initially, the ground contact time was estimated using this network. Table 2 shows the predicted mean squared percentage error (MSE) for the contact times of the right and left feet.

Person	Left	Right
1	7.6E-22	2.4E-21
2	1.0E-04	1.3E-04
3	6.3E-11	1.2E-10
4	7.9E-06	1.2E-05
5	5.2E-26	1.2E-25
6	7.9E-06	1.2E-05
7	5.5E-08	9.3E-08
8	6.2E-11	1.2E-10
9	9.5E-05	1.2E-04
10	9.7E-17	5.2E-26
11	7.7E-17	5.7E-26
12	8.9E-17	2.3E-16
13	5.2E-12	9.8E-12
14	1.2E-10	2.3E-10

Table 2: MSE of Predicting Contact Time

Based on the obtained results, all participants' mean squared percentage error (MSE) indicated very high accuracy in estimating the ground contact time (Table 2). The final MSE of the model was 1.75E-05, and for both feet, it was less than 1.3E-04, indicating a good match between the model output and actual ground contact time data. This high accuracy in estimating the contact time, particularly when considering the complexities of human movement during normal walking, indicates the model's high ability to process data and make accurate predictions.

4.2. Prediction of VGRF at Individual Contact Points

Once the ground contact time was estimated, a General Regression Neural Network (GRNN) model was trained to predict the vertical ground reaction forces (VGRF) of ten different contact points on the foot. Individual input variables included left and right ground contact time (estimation performed via the GRNN network), height, weight, navicular drop, foot size, age, and BMI. Table 3 provides the mean squared error (MSE) or predicting the right limb vertical ground reaction force (VGRF) at each contact point, and the total averaged over the 14 individuals.

Connect point	Left MSE	Right MSE
Toe 1	0.095	0.099
Toe 2-5	0.021	0.021
Meta 1	0.072	0.076
Meta 2	0.137	0.143
Meta 3	0.024	0.025
Meta 4	0.033	0.035
Meta 5	0.021	0.022
Midfoot	0.103	0.107
Heel Medial	**0.188**	**0.196**
Heel Lateral	0.120	0.125
Sum	**0.545**	**0.568**

Table 3: Average of MSE for Predicting VGRF

For the prediction of the VGRF forces at these points, the MSE values were lower than 0.196%, which indicates the high accuracy of the model in estimating these forces. The most significant prediction error was found at the heel point (Heel Medial), with an MSE of 0.196% on the right and 0.188% on the left foot. The results perfectly matched the model and actual VGRF data at the different foot contact points. (Figure 4 shows an example of the estimation at all points for individual number 1 on the right foot.)

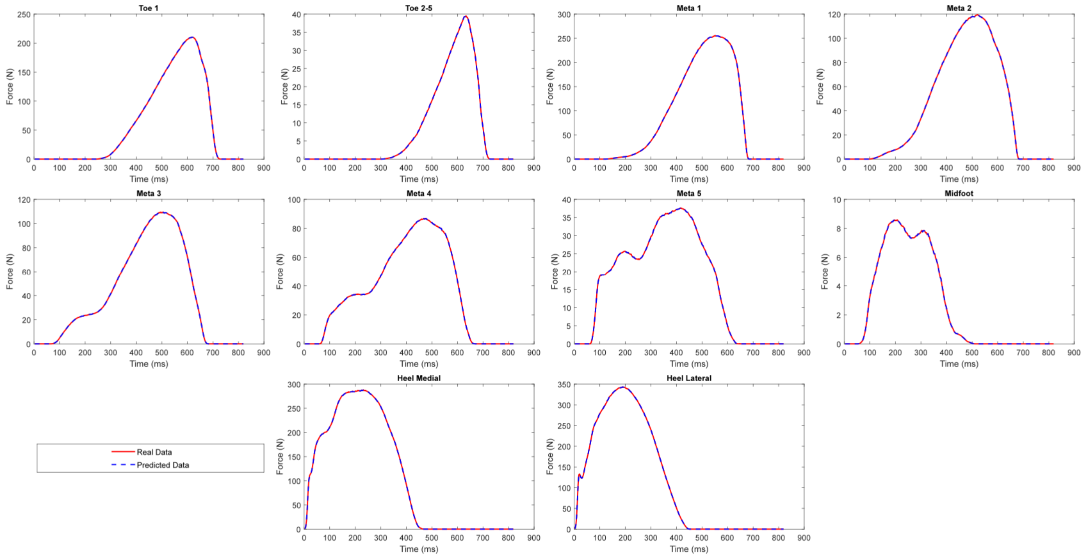

Figure 4: Estimation at All Points for Individual Number 1 On the Right Foot

4.3. Prediction of Total VGRF

The model encountered increased errors when estimating the total VGRF for both the right and left feet (Table 3). The MSE values for the sum of the ground reaction forces were 0.545% and 0.568% for the left and right feet, respectively. This increase in the error in estimating the total forces was due to the complexities of the combined forces at the different contact points. However, these errors remained within acceptable and desirable ranges. This indicates the ability of the model to predict the overall ground reaction forces, although the error was higher for the total forces than for specific points. (Figures 5 and 6 show the total ground reaction forces for the left and right feet, respectively.)

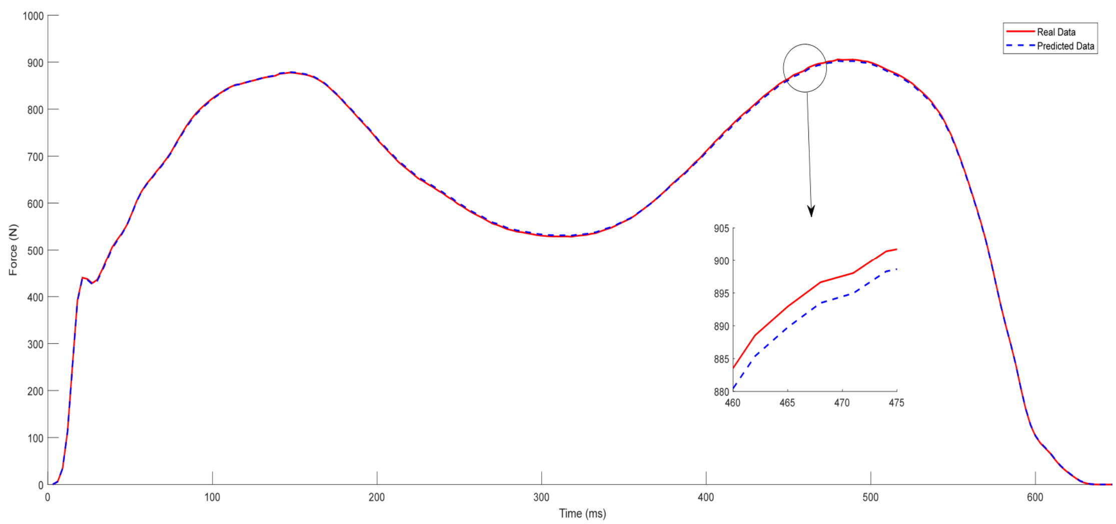

Figure 5: This Compares Actual and Predicted Vertical Ground Reaction Force (VGRF) Data for The Left Foot of Person 2, With A Zoomed-In Region Highlighting the Model's Accuracy in Capturing Subtle Variations

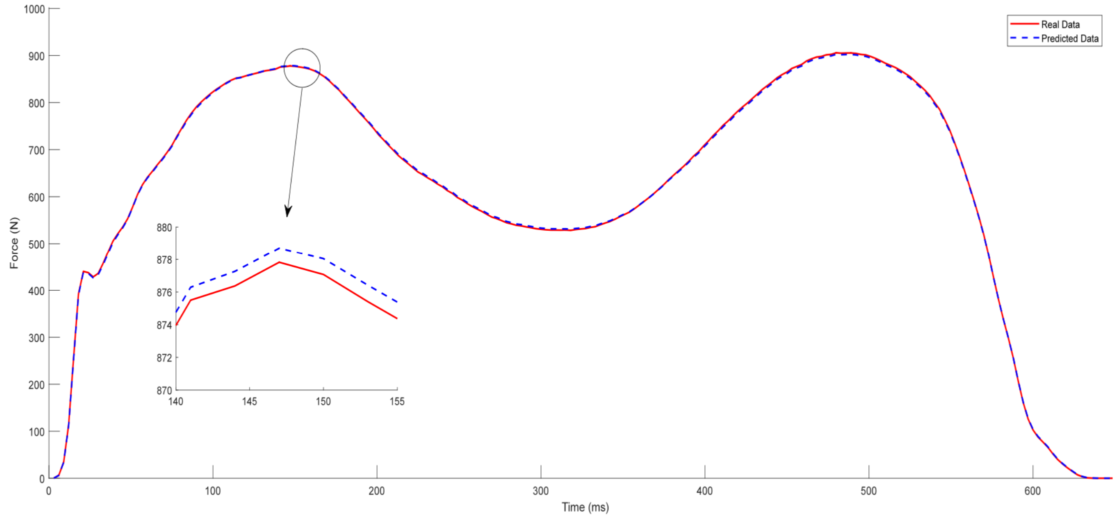

Figure 6: This Compares Actual and Predicted Vertical Ground Reaction Force (VGRF) Data for The Right Foot of Person 2, With A Zoomed-In Region Highlighting the Model's Accuracy in Capturing Subtle Variations

4.4. Performance Comparison between Left and Right Feet

The dual-branch neural network of this model was designed to predict the VGRF forces on the right and left feet (Figure 3 in the Methods section). The results showed that the model could create a similar pattern for predicting forces on both the left and right feet. This dual-branch structure allows the model to predict the forces for each foot separately and fit the data well. (Figure 7 shows the MSE at 10 points and the sum of VGRF.)

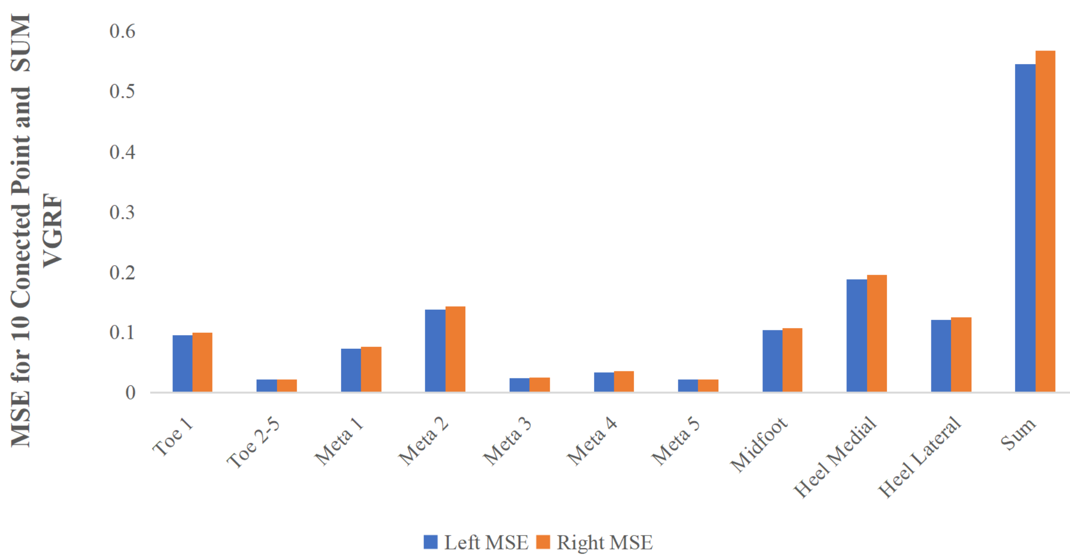

Figure 7: Average of MSE for Predicting VGRF

Despite the model's high accuracy, minor differences in the MSE were observed between the estimated VGRF forces at the ten contact points and the total VGRF forces (Figure 7). These differences were more pronounced for the total forces than individual contact points. However, considering the model's high predictive accuracy, these differences were negligible and within the acceptable range. Figure 8 shows the difference in the MSE between the left and right feet.

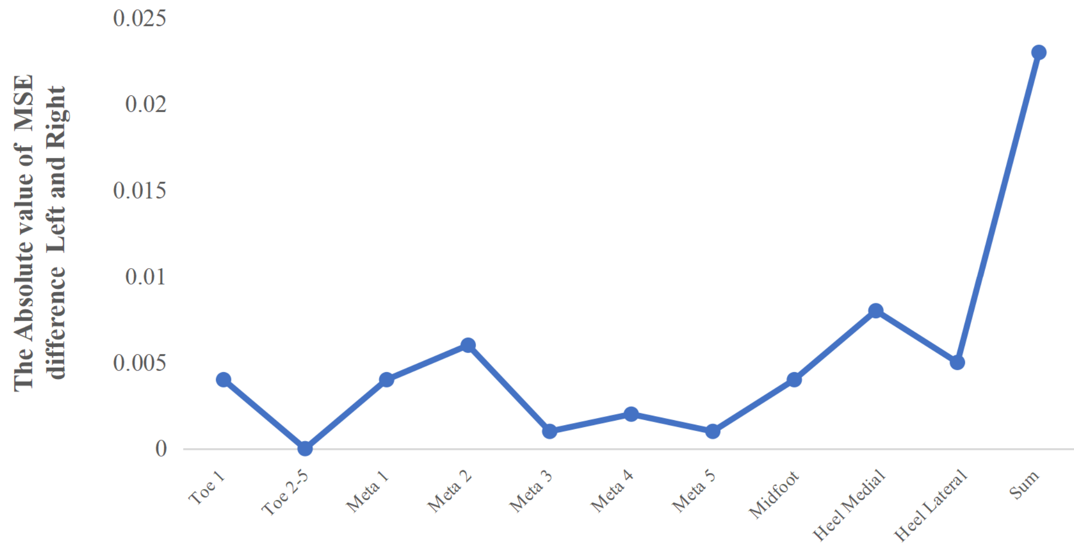

Figure 8: MSE Difference Between the Left and Right feet

4.5. Summary of Findings

Under normal walking conditions, the VGRF forces and the ground contact time were accurately predicted by the GRNN model. The model can predict peak and average forces at multiple points of foot-ground contact, including foot-ground contact time, based on a person's height, weight, navicular drop, foot size, age, and BMI. Results showed that the model could predict the time and estimated VGRF forces were under control in all contact points with acceptable errors. In addition, the model could perform analogous patterns on both the left and right feet and accuracy differences in prediction between the two feet were not significantly different. VGRF forces and ground contact time were predicted efficiently with an overall mean squared error (MSE) of 0.126. Overall, the results suggest this model is reasonably accurate in estimating the GRFs under normal walking conditions.

5. Discussion

The results of this study indicate that the GRNN model produced reasonable estimates when predicting VGRF at ten important time points of foot contact along with the total forces. 0.129% MSE per point and 0.545% for total force suggest that the model can control the internal complexity of biomechanical interactions. This is above average in typical biomechanics and machine learning standards. This is especially critical in applications where accurate calculation of force distribution is necessary, namely rehabilitation, sports science, and injury prevention.

One of the main advantages of the GRNN model is its dual-branch architecture, which accounts for biomechanical asymmetries between the left and right legs. Additionally, variables such as body mass index (BMI), height, weight, and foot size in the model inputs provide personalized and multipurpose predictions, which strengthens their use in clinical and sports environments [22,23].

This model can also be helpful in other fields, not just scientific focus. An accurate prediction of the force applied to the foot's key points would have a significant impact on the design of prostheses [24]. For example, accurately estimating pressure at the foot can help mitigate the risk of pressure ulcers in such patients as diabetics and others with prostheses [25]. Numerous studies have shown that an accurate estimation of the force applied to the key points of the foot can have many applications in rehabilitation after orthopedic surgeries and body condition monitoring, particularly in assessing walking or running performance [26,27]. Similar models could be used for home health monitoring and rehabilitation control using wearable devices [27]. Furthermore, similar models can play a significant role in the design of sports shoes and help companies design shoes with optimal pressure distributions to prevent sports injuries [28,29].

5.1 Comparison with Previous Studies

This study has contributed to the literature by forecasting the VGRF at ten key points and the total forces simultaneously with one single model. While neural networks have been reported as practical estimators for VGRF in past literature [30], which typically analyze single-point or total forces separately [31,32], this research, by integrating the analysis of total force, has enhanced biomechanical insights and enabled its use in assessing gait and designing sports shoes [28,29,33].

For example, while GRNN models have advantages, other biomechanical methods, such as force plates, IMU sensors, and pressure-sensitive insoles, have also been used to measure VGRF. However, each of these ways has drawbacks. The main disadvantages of IMU sensors are that they require accurate calibration and that force plates are expensive and must be expressly set up when used under open-loop conditions [34,35]. The GRNN model, proposed as a good alternative using simple and measurable features like height, weight, age, BMI, and foot size to predict ground reaction forces, does not require complex equipment. This feature makes the GRNN model more cost-effective and efficient under complex operational conditions.

Force plates are still considered the gold standard for measuring VGRF. However, their limited applicability in laboratory environments has restricted their use under real-world conditions [36]. The GRNN models have superior portability and scalability, and their accuracy is comparable to laboratory-level measurements. For example, Sharma and Dehzangi et al. (2021, 2017) used IMU sensors to estimate the VGRF indirectly, but their error rate (up to 15%) was higher than that of the GRNN model. This indicates the GRNN model's superiority in prediction accuracy and usability under real-world conditions.

The insoles in highly flexible pressure-sensitive insoles have other drawbacks, such as sensor wear and noise, which also tend to decrease prediction accuracy [37,38]. The GRNN model overcomes such limitations with comprehensive inputs like age, weight, and foot size and higher prediction accuracy in various populations. This feature will primarily enable the model to better approximate biomechanical variability between individuals of different physical structures. For example, the size of the feet can influence force distribution while walking [39], whereas BMI may directly affect pressure patterns and ground reactions [40,41]. These inputs enable the model to make accurate predictions, even for subjects with different physical characteristics. The GRNN model can thus be adopted as an alternative to the methods in existence to date, both from the point of view of accuracy and the capability to model different conditions.

Unlike others, the GRNN model has a dual-branch structure processing each foot separately. For the first time in gait analysis, such a great novelty is essential for individuals with gait problems, such as hemiplegia or unilateral joint replacement. Zhou et al. (2022) Indeed, the asymmetry between legs cannot be ignored when predicting forces, or one will fall prey to an incorrect diagnosis [42]. GRNN captured this variation well and provided valuable clinical and sports application information. The dual-branch architecture presents superior accuracy for predicting VGRF forces compared to single-branch models that conventionally neglect biomechanical asymmetry. Compared to recurrent neural networks (RNNs) and long short-term memory (LSTM), which effectively analyze time-series data, the GRNN model has similar or higher accuracy but with reduced computational complexity. Although RNNs and LSTMs often face problems with vanishing gradients and computational complexity [43,44]Due to their lower computational cost and similar or even higher prediction accuracy, the GRNN model is a better model than the GRNN model for real-time applications [45]. Mundt et al. (2021) reported that the correlation between the predicted and actual VGRF values in RNNs varied between 0.87 and 0.96. However, with a reduced computational load and much higher prediction accuracy, the results of this study showed that the GRNN model was a better choice for practical applications.

The GRNN and CNN models have applications in biomechanical analysis, but they also have advantages. Studies have shown that CNNs can predict the ground reaction force (VGRF) through image inputs, such as video imaging data, and are accurate in these cases [46]. However, there are also limitations reported in using CNNs to analyze time series data like VGRF without further processing; this will make the model very hard to give an accurate prediction without specific inputs, such as in thermal imaging [47]. In contrast, the GRNN model can directly process biomechanical variables and achieve high accuracy without complex preprocessing, making it a more suitable option for analyzing biomechanical data [48].

In particular, the investigation shows that a GRNN model with dual branches could correctly forecast VGRF variation under various conditions using comprehensive biomechanical inputs; this model should work well in real-world applications for estimating forces and be suitable for clinical and sports force measurement tasks. This model has a higher prediction accuracy than traditional methods and is useful in practical and applied fields owing to its reduced computational complexity and real-time usability.

5.2 Practical Applications and Policy Implications

Recent research has mentioned the theoretical viewpoints of thermal imaging integrated with deep learning to detect an injury. For example, a particular work by Trejo-Chavez et al. (2022) identified knee injuries using CNNs and thermal imaging data as high as 98.7% accuracy. This demonstrated that neural networks could be used for sports injury diagnosis in addition to how deep learning works on top of thermal imaging for injury detection [49]. Along this line, the hybrid models proposed by Xiong et al. Some promising outcomes reported have been using CNNs and recurrent layers for gait pattern recognition and injury type classification.

This paper has demonstrated that combination methods enhance the joint angle predictions and showed a notable decrease in root mean square error (RMSE) by up to 3.8°. Thus, it suggests that integration between GRNN models and CNN architectures may lead to even better spatiotemporal predictions [50]. Ye et al. (2023) extended image-based modeling with DCAE, which can be used to estimate injury risk with AUC values above 0.89. These findings validate that the combination of image-based models with GRNN performs well in these areas for minimizing the prediction errors and also enhances the processing speed in comparison with other models [51]. In particular, owing to its high accuracy, the dual-branch GRNN model can be effectively generalized to detect and monitor gait-related injuries in diseases such as Parkinson's, diabetes, and post-surgical conditions. In addition to providing an accurate diagnosis, owing to its high portability, it enables applications in home care settings and non-laboratory environments [32].

These models have significant advantages for their use in a clinical setting to study movement patterns or the prediction of forces in patients, has significant advantages. Different studies have evidenced that using a GRNN model predicts most joint forces without real-time usage of precise ground reaction force [52].

The basic idea of such models is to evaluate fall risk and balance analysis in home care settings for older adults. For instance, a GRNN will forecast the possibility of a fall with high precision using pressure sensors placed in soles, which might be most important in handling such subjects' safety [53]. Besides, such models help simulate movement conditions, such as when older adults get out of chairs, to suggest more appropriate movement patterns [54]. These capabilities make GRNN an effective tool for therapeutic and preventive applications.

However, its implementation in realistic scenarios is challenging. Some difficulties include needing more quality data to perform excellently under various scenarios. Some of the technical challenges are sensor accuracy and requirements for exact calibration [55]. This, too, may affect it. Moreover, real-time data processing is required under actual conditions, while there can be complications under variable environmental conditions [56,57]Therefore, analyzing the existing challenges and finding appropriate solutions to improve the model's application in practical environments is necessary.

Besides its clinical applications, the GRNN model can be utilized in designing sports shoes and controlling personalized training programs. This model helps identify overuse patterns in athletes and can reduce the risk of stress fractures [33]. Finally, the GRNN model can be integrated into prostheses and exoskeletons to improve users' gait patterns through dynamic adaptation [42].

5.3 Limitations of the Study

- **Sample size and diversity:** Using data from only 14 participants limits the generalizability of the results. Therefore, expanding the dataset to include individuals of different ages, genders, and conditions is essential.
- **Real-world validation:** The model's performance in uncontrolled environments, such as uneven terrain or running, has yet to be tested. Future studies should investigate its validation in these environments.

Although this research demonstrates the GRNN model's high potential for various applications, further studies are required to address its limitations and improve its capabilities.

5.4 Suggestions for Future Research

- **Expanding the dataset:** Future research should include larger datasets comprising diverse populations, including patients with specific gait abnormalities.
- **Multimodal integration:** Advanced imaging techniques, such as infrared thermography and motion capture systems, can improve diagnostic accuracy.
- **Real-time applications:** The GRNN model should be embedded into wearable devices for real-time gait monitoring and analysis.
- **Hybrid model development:** Combining GRNN with CNN or RNN architectures to leverage spatial and temporal data can improve predictive capabilities.
- **Dynamic validation:** The model should be tested under various real-world conditions, such as outdoor walking, running, or uneven surfaces.

In summary, this study highlighted the potential of GRNN models in biomechanics, but there is still room for improvement. Future research should address the limitations identified in this study and explore new applications for this technology.

6. Conclusion

This study proposes a new dual-branch General Regression Neural Network model, a fresh step in this domain. It provides the most precise estimation of the VGRF at ten anatomical points of the foot and the total VGRF, which has been a very encouraging tool for biomechanical analysis. By combining anthropometric data (such as height, weight, body mass index, and foot size) with biomechanical features such as ground contact time, the model achieved a mean squared error (MSE) as low as 0.021% for specific contact points (such as toes and metatarsals) and 0.545% for predicting the total force across the foot. This high accuracy demonstrates the model's strength in understanding the complexities of human movement dynamics. The model features a dual-branch architecture that considers the differences between the right and left feet, an aspect often ignored in traditional methods.

This resulted in shallow MSE differences between the two feet, such as 0.196% for the right foot and 0.188% for the left foot at the Heel Medial, reassuring the model's ability to handle biomechanical variations without compromising accuracy. The strong correlation between the predicted and actual forces, along with an overall mean Mean Squared Error (MSE) of just 0.126% for the entire model, demonstrates its superiority over traditional methods like force plates and other machine learning techniques, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Besides its technical accuracy, the General Regression Neural Network (GRNN) model provides substantial practical advantages.

- **Efficiency:** Computational simplicity reduces processing time, making it suitable for real-time applications.
- **Scalability:** Unlike laboratory-dependent methods, this model relies on easily measurable features, increasing its applicability in practical settings.
- **Versatility:** Its predictive power extends to clinical diagnoses (such as gait abnormalities and prosthesis design) and sports science (including injury prevention and footwear design).

A limitation is that only 14 participants could be considered, limiting generalizability. Increasing this dataset to a more representative sample and testing under dynamic conditions, such as uneven terrain or changing walking speeds, would increase the model's validity. Hybrid models, such as GRNN with CNN or RNN, for enhancement in the handling of spatiotemporal data and providing accurate, adaptive applications, are potential further avenues of research. In summary, the GRNN model bridges the gap between high-precision laboratory tools and practical and cost-effective solutions for biomechanical analyses. With consistently low MSE values below 1% across all predictions, this study sets a new standard in VGRF modeling. It provides a scalable, accurate, versatile framework with transformative potential in clinical, sports, and rehabilitation domains.

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