Comparative Analysis of Neural Network Architectures for Ankle Joint Moment Prediction Using Varied Input Combinations

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Abstract—This paper investigates the accuracy of ankle joint moment prediction using neural network models, considering different subsets of input data. The dataset comprises six columns: time, vertical ground reaction force, hip joint angle, knee joint angle, ankle joint angle and ankle joint moment. The primary goal is to understand the predictive capabilities of neural networks better when trained on varying amounts of data to determine the minimal sensor requirements for accurate ankle joint estimation. Two different neural network architectures were used: a convolutional neural network (CNN) and a recurrent neural network (RNN). The RNN uses a short time history of the input data to capture temporal dependencies as the CNN focuses on predicting ankle joint moment using only the information available at a given time point. To address the temporal dependence of the data, it was carefully divided into training and testing sets. The results indicate that the predictive accuracy varies across different input combinations. The results provide insight into the potential for reducing the number of sensors required for ankle joint moment prediction.

I. Introduction

The biomechanical complexities of the human body have long been a subject of research and interest. The ankle joint has played an important role in this exploration and has been Integral to human balance, movement and athletic prowess. By understanding the ankle's dynamics, we can better understand the broader intricacies of human locomotion. Traditional methodologies such as biomechanical models and gait analysis have provided helpful insights into human movement. However, with the advancement in computational technology, using computational power for further understanding is the only logical step.

Machine learning has changed how we look at things, especially since neural networks have become powerful. Neural networks are a subset of machine learning, which is known for its capabilities in data processing and pattern recognition. CNNs are particularly good with image recognition thanks to their spatial processing capabilities, whereas RNNs are good at handling time series data. Long Short-Term Memory (LSTM) cells are used to handle time series data. Given the temporal nature of our data, using neural networks was the best approach.

The paper aims to use CNNs and RNNs to predict ankle joint moments and employ varying combinations of biomechanical data. The objective has two parts; the first is to find the optimal neural network architecture for such predictions and to find the most relevant data combinations to make those predictions.

II. Methods

The study aims to compare the predictive power of Convolutional Neural Networks and Recurrent Neural Networks in the field of ankle biomechanics. To compare each neural network, the networks were given different input data. There are five features in the given dataset and one target. The input data given to the first neural network is only ankle angle. For the second neural network, two features were given as input, namely ankle angle and vertical ground reaction force. The third neural network was trained on ankle angle, knee angle and hip angle. In contrast, the last neural network was trained on the entire dataset. In total, we trained eight neural networks, four of which were convolutional neural networks, and the other four were recurrent neural networks.

After checking the shape and content of the data, the next step is to visualize the data using histograms to understand the distribution of each feature and identify any outliers or anomalies. The correlation heatmap provides much-needed insight into the relationship between different features and helps us understand which features are more important. Lastly, we created time series plots due to the temporal nature of the data.

Since neural networks generally perform much better when the input features are on a similar scale, we normalized the data using a standard scaler so that each feature has a mean of 0 and a standard deviation of 1. This step is crucial as it ensures that no feature disproportionately influences the model due to its scale.

Neural networks need the data to have a specific shape. For the convolutional neural networks, the date was reshaped so that it has an additional dimension to represent the channels. As for the recurrent neural networks, the data was reshaped to represent sequences. The last step before we began training the networks was to split the data into train and test sets. Due to the temporal nature of the data, the main focus during the split was to ensure that the data points remained in the same sequence and preserve the temporal sequence.

A. Study-Design

The study's primary objective was to identify the most efficient neural network for the given dataset. An intrinsic part of the process was understanding the difference in the predictive accuracy based on the type and amount of data fed into the model.

B. Data Collection

The dataset used in this study comprised 48,000 time points and six columns. Each time point consists of the ankle angle, hip angle, knee angle, vertical ground reaction force and ankle moment, which was also the target.

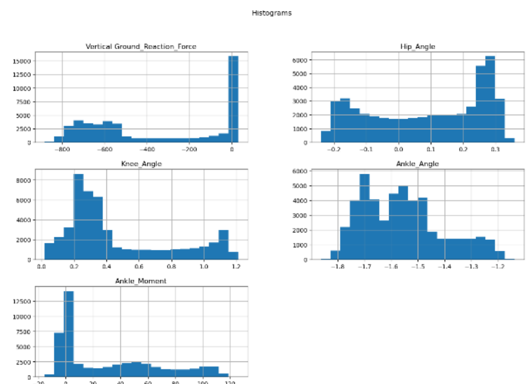

Fig. 1. The figure describes the histograms for all columns in the dataset against the target.

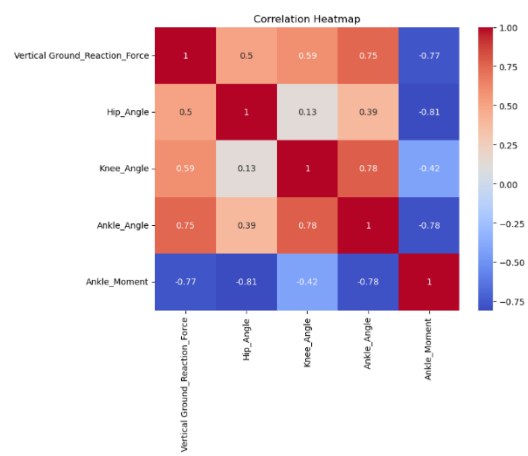

Fig. 2. The correlation heatmap shows the correlation coefficients between the different features in the dataset.

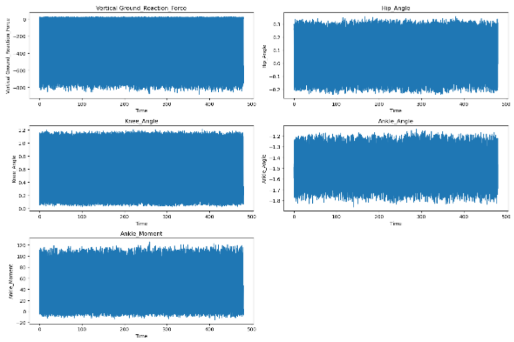

Fig. 3 Time series visualization of all features in the dataset's duration.

C. Analysis

The exploration into predicting ankle joint moments using neural networks heralded a series of enlightening findings, underscoring the synthesis of biomechanics and advanced computational techniques. As we delved into the extensive dataset comprising 48,000-time points across six distinct categories, the richness and diversity of the biomechanical data became evident. Visualizations, such as histograms and time series plots, painted a vivid picture of the data distributions and temporal patterns. Notably, the correlation heatmap highlighted the interplay between different biomechanical factors, revealing some intrinsic relationships that could potentially influence joint moments.

The heart of our investigation revolved around two neural architectures: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). While both exhibited promising results, subtle nuances emerged upon a deeper dive. CNNs, with their spatial processing capabilities, were adept at capturing the immediate biomechanical intricacies. RNNs, on the other hand, excelled in recognizing and leveraging the temporal sequences within the data, a testament to their prowess in handling time series datasets.

A salient aspect of our analysis was the exploration of varying data combinations, ranging from individual data points to comprehensive amalgamations. This approach illuminated the relative importance of different biomechanical factors. For instance, while individual factors like the ankle angle offered a level of predictive accuracy, combinations that included the ground reaction force or multiple joint angles often enhanced the model's precision.

Our rigorous evaluation, anchored by the training and validation loss metrics, provided a granular view of each model's performance. Patterns emerged, hinting at potential overfitting in specific scenarios and emphasizing the importance of a balanced dataset. In summation, this analysis not only spotlighted the potential of neural networks in biomechanical research but also underscored the need for a judicious blend of data and architecture to achieve optimal results.

D. Evaluation

To evaluate the research, we rigorously assessed all the neural network models employed during the project. All of this helped provide a comprehensive understanding of the applicability and performance of the networks. The central part of the evaluation was comparing the convolutional neural networks and the recurrent neural networks.

Upon examination of the training and validation loss curves, a few critical insights became apparent. The behavior of the loss metrics allowed us to learn more about the learning trajectories of the models. While some models showed a smooth convergence and stable learning, others showed signs of volatility, especially during the initial epochs. The training and validation loss curves served as an early indicator of the responsiveness and effectiveness of the models.

One of the main focuses of the evaluation was assessing the models based on the different data combinations given as input. The results were ground-breaking. While competent, models trained on individual data points, such as the ankle angle, frequently performed less well than those trained on more comprehensive data sets. This highlighted the beneficial effects of several multiple biomechanical parameters.

Additionally, the models' capacity for generalization was examined. The test dataset clearly evaluated each model's capacity to predict outcomes from new data. This was essential to comprehending how applicable our models were in the real world. While some models demonstrated admirable generalization, others showed potential for development and may have overfitted.

In essence, the evaluation stage helped to distinguish the grain from the chaff. It sheds light on each neural network model's advantages and disadvantages and sets the stage for potential improvements and new lines of inquiry. The main conclusion was unmistakable: while neural networks show enormous promise in biomechanical research, their effectiveness is closely correlated with the calibre of data and the careful choice of architecture.

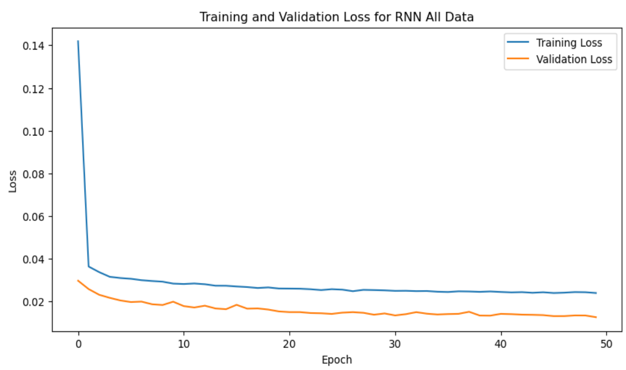

Fig. 4. Training and validation loss of RNN on the entire dataset.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50)                11000

 dropout (Dropout)           (None, 50)                0

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 11,051
Trainable params: 11,051
Non-trainable params: 0
_________________________________________________________________
```

Fig. 5. Model performance metrics when trained exclusively on the entire dataset.

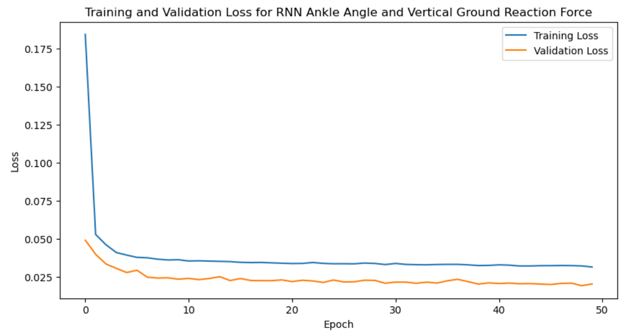

Fig. 6. Loss metrics for the RNN model using ankle angle and vertical ground reaction force data.

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_1 (LSTM)               (None, 50)                10600

 dropout_1 (Dropout)         (None, 50)                0

 dense_5 (Dense)             (None, 1)                 51

=================================================================
Total params: 10,651
Trainable params: 10,651
Non-trainable params: 0
_________________________________________________________________
```

Fig. 7. Model performance metrics when trained exclusively on ankle angle and vertical ground reaction force data.

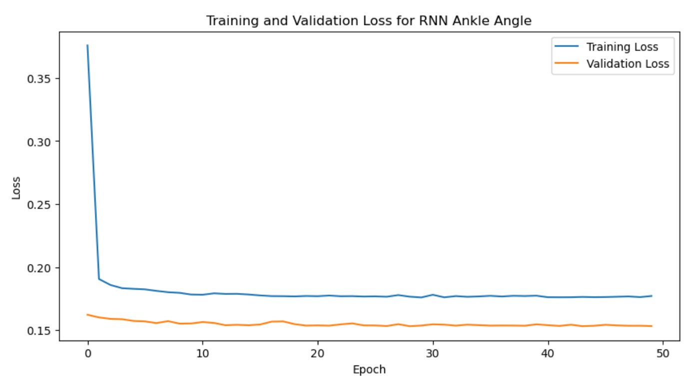

Fig. 8. Training and validation loss of the RNN trained exclusively on ankle angle.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50)                10400

 dropout (Dropout)           (None, 50)                0

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 10,451
Trainable params: 10,451
Non-trainable params: 0
_________________________________________________________________
```

Fig. 9. Model performance metrics when trained exclusively on ankle angle data.

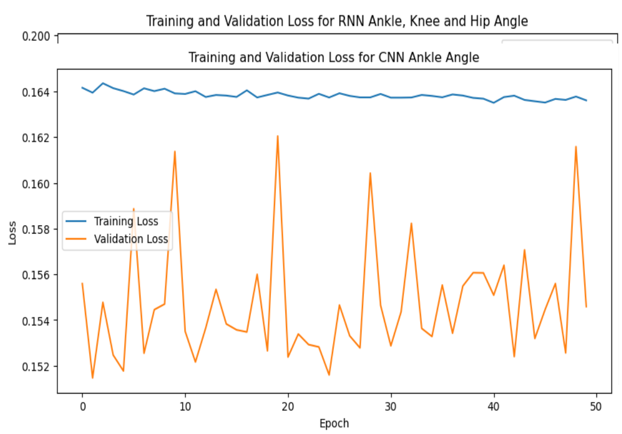

Fig. 10. Performance metrics for the RNN model using combined data from ankle, knee, and hip angles

```
X_train_rnn, y_train, X_test_rnn, y_test = extract_data_for_combination(['Ankle_Angle', 'Knee_Angle',
rnn_model = create_rnn_model_for_combination(input_shape=(X_train_rnn.shape[1], X_train_rnn.shape[2]))
rnn_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_1 (LSTM)               (None, 50)                10800

 dropout_1 (Dropout)         (None, 50)                0

 dense_5 (Dense)             (None, 1)                 51

=================================================================
Total params: 10,851
Trainable params: 10,851
Non-trainable params: 0
_________________________________________________________________
```

Fig. 11. Model performance metrics when trained exclusively on ankle, knee and hip angle data.

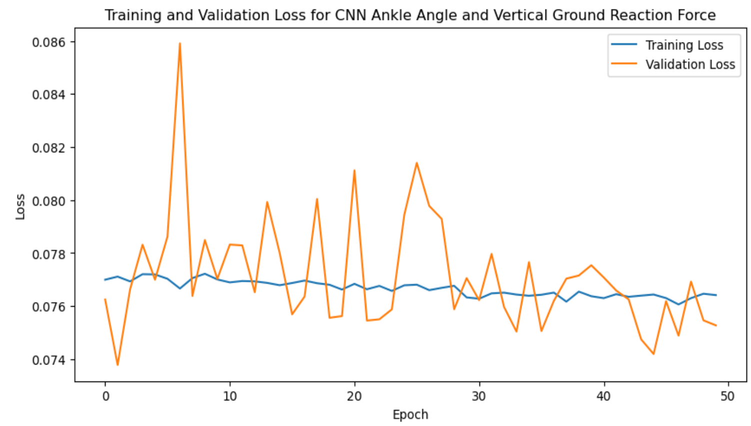

Fig. 12. Loss metrics for the CNN model trained using ankle angle and vertical ground reaction force data.

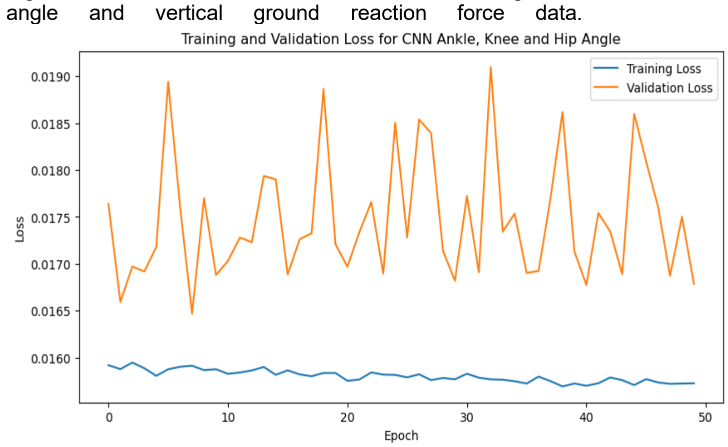

Fig. 13. Training and validation loss progression for the CNN model trained on combined data from ankle, knee, and hip angles

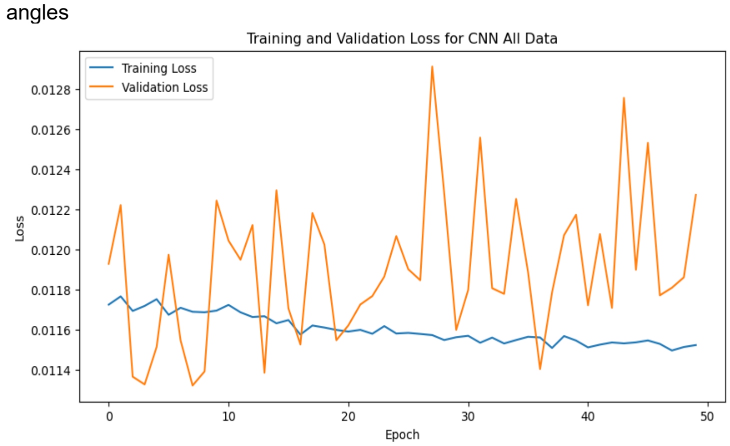

Fig. 14. Training and validation loss progression for the CNN model trained on the entire dataset.

III. Results

The results represented the fruition of our research efforts and offered a precise and measurable evaluation of the neural network models' capability to predict ankle joint moments. The results were informative and instructive, utilizing the complex fusion of biomechanical data and cutting-edge computer approaches. All of the neural networks were trained on 50 epochs, and the training and validation loss was a performance measure for the CNNs and RNNs and described the mean squared error between the ground truth and the predicted values.

Based on the selected data combinations, there were observable differences in performance among the Convolutional Neural Networks (CNNs). Models that only used specific inputs, like the ankle angle, showed a certain level of competency. However, the models developed using merged data sets stood out, particularly those that included ground reaction force and numerous joint angles. These models demonstrated a remarkable ability to capture the nuanced biomechanical details in addition to achieving lower loss metrics.

Results from the Recurrent Neural Networks (RNNs), which naturally analyze time series data, were both encouraging and instructive. The temporal data processing prowess of the RNNs was evident in the time series plots and loss curves produced during the assessments. RNN models demonstrated a discernible advantage in terms of accuracy and predictive power, particularly those incorporating a more comprehensive range of biomechanical data.

The comparison between CNNs and RNNs proved particularly interesting. Although each architecture had its advantages, it was clear that the type and combination of input data significantly impacted the selected model. RNNs frequently outperformed CNNs due to their ability to handle temporal data, especially when time-dependent patterns were important.

In conclusion, the findings highlighted neural networks' enormous potential for biomechanical study. They emphasized the significance of data quality, brain architecture selection, and the beneficial interaction of several biomechanical aspects. The conclusions, which were based on quantitative measures and visual assessments, offered a clear road map for pursuing further research in this interdisciplinary field.

IV. Discussion

It is important to go into more detail in this debate since the junction of biomechanics and neural networks, as demonstrated in our research, offers many opportunities and difficulties. One of the most striking findings was how adept neural networks are at understanding complex biomechanical patterns. The adaptive and dynamic nature of neural networks, especially RNNs, demonstrated a degree of sophistication that may very well change how we understand joint dynamics. Traditional biomechanical models have provided fundamental insights. It was especially impressive how well they processed time series data, picking up on temporal details that other models could have missed.

However, difficulties accompanied these developments. The differences in performance based on data combinations highlighted the importance of choosing your data carefully. It brought up important issues, such as how to choose the best combination of biomechanical characteristics. Is there a saturation limit after which more data does not really improve model performance? As we proceed to optimize neural network models for biomechanical applications, these issues are crucial.

The performance of CNNs and RNNs in comparison is a further aspect that merits discussion. Both architectures showed promise, but only in specific situations. Although RNNs genuinely shone in scenarios with a significant temporal component, CNNs, which are famous for their image-processing abilities, also showed promise in biomechanical applications. This finding might drive future studies in the direction of structures that are most appropriate for time series biomechanical data.

Furthermore, the models' performance on the test dataset demonstrated their capacity to generalize, which highlighted crucial questions regarding their applicability in the real world. The delicate balancing act between model complexity and generalization was brought to light by our findings, which also called attention to potential overfitting areas.

The findings of our study are encouraging, but they also open the door for more research.

Discussions like these will be crucial in guiding our course and ensuring that we fully realize the promise of these interdisciplinary synergies in the developing subject of the intersection of biomechanics and neural networks.

V. Summary and Outlook

This research aimed to predict ankle joint moments with unmatched precision using neural networks as we explored the complex biomechanics of the ankle joint. The study examined a dataset with 48,000 time points across several biomechanical characteristics via the lenses of convolutional neural networks (CNNs) and recurrent neural networks (RNNs).

Key findings showed how performance varied subtly depending on the selected data combinations, with combined data sets frequently outperforming individual factors. RNNs, which excel at processing temporal data, have emerged as particularly strong models, frequently outperforming CNNs in situations with a lot of time-dependent patterns.

The journey, however, comes with difficulties. With some models indicating potential overfitting, the balance between model complexity and real-world generalization emerged as a crucial factor. The selection of the best data combinations, as well as the probable data input saturation point, opened up fascinating new directions for investigation.

In essence, this research provided a road map for future initiatives in addition to illuminating the enormous potential of neural networks in biomechanical applications. The results from this work serve as a beacon, pointing the way towards greater understanding and ground-breaking discoveries in the area of human movement and physiology as we stand at the nexus of biomechanics and modern computational approaches.

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