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Multi-Model Gait-Based KAM Prediction System Using LSTM-RNN and Wearable Devices

Doyun Jung, Cheolwon Lee and Heung Seok Jeon *

Department of Computer Engineering, Konkuk University, 268 Chungwon-daero, Chungju-si 27478, Chungcheongbuk-do, Republic of Korea; dayever@kku.ac.kr (D.J.); cheolwonlee@kku.ac.kr (C.L.)
* Correspondence: hsjeon@kku.ac.kr

Abstract: The purpose of this study is to develop an optimized system for predicting Knee Adduction Moment (KAM) using wearable Inertial Measurement Unit (IMU) sensors and Long Short-Term Memory (LSTM) RNN. Traditional KAM measurement methods are limited by the need for complex laboratory equipment and significant time and cost investments. This study proposes two systems for predicting Knee Adduction Moment based on wearable IMU sensor data and gait patterns: the Multi-model Gait-based KAM Prediction System and the Single-model KAM Prediction System. The Multi-model system pre-classifies different gait patterns and uses specific prediction models tailored for each pattern, while the Single-model system handles all gait patterns with one unified model. Both systems were evaluated using IMU sensor data and GRF data collected from participants in a controlled laboratory environment. The overall performance of the Multi-model Gait-based KAM Prediction System showed an approximately 20% improvement over the Single-model KAM Prediction System. Specifically, the RMSE for the Multi-model system was 6.84 N · m, which is lower than the 8.82 N · m of the Single-model system, indicating a better predictive accuracy. The Multi-model system also achieved a MAPE of 8.47%, compared with 12.95% for the Single-model system, further demonstrating its superior performance.

Keywords: deep learning; long short-term memory (LSTM); knee adduction moment (KAM); gait pattern; inertial measurement unit (IMU)

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1. Introduction

The prevalence of knee osteoarthritis (OA) is on the rise as modern society ages. According to the HIRA Big Data Open Portal, the prevalence of knee osteoarthritis among patients aged 50 years and older is continuously increasing [1]. Osteoarthritis of the knee is a chronic disease that continues to be costly to treat and manage, and various studies are being conducted to reduce this cost. Among these studies, the Knee Adduction Moment (KAM) is widely used as an important indicator of knee osteoarthritis development. KAM is a mathematical model that calculates the load on the medial knee joint during walking, and the lower the KAM, the slower the progression of knee osteoarthritis and the less severe the symptoms [2]. KAM is measured in Newton-meters (N · m), which represents the rotational force applied at a distance from the knee joint. One N · m is defined as the torque produced by a one Newton force applied at a one meter distance.

Therefore, accurately and cost-effectively measuring KAM is an important challenge in the management of knee osteoarthritis. Recently, there have been several studies that utilize wearable sensors and machine learning algorithms to predict KAM values [3–19].

In this work [3], Inertial Measurement Unit (IMU) sensors and machine learning algorithms were used to measure KAM in everyday walking and to try reduce its cost. Wang proposed a KAM prediction solution for three different gait patterns using a fully connected artificial neural network (FCNN) and extreme gradient boosting (XGBOOST) [20], and the model was built by training all of the data together. However, this study mainly focused on mild and moderate OA patients, and there were limited data on severe OA patients. This limits the accuracy of KAM prediction for OA patients and may limit the prediction for patients with a wider range of KAM values due to the application of fewer gait patterns.

The following work [4] combined wearable sensors and machine learning techniques to develop an assistive device for OA patients. The study aimed to develop an artificial neural network (ANN) to estimate the Knee Flexion Moment (KFM) and KAM during different walking tasks using two wearable sensors. IMU signals were collected from seven participants performing six different gait tasks, which were used to train an ANN to estimate the KFM and KAM time series. However, while the KFM estimation showed a high accuracy, the KAM estimation showed a relatively low accuracy. This highlights the limitations of using only two IMUs to consistently estimate KAM.

Other studies have explored various machine learning methods to enhance KAM prediction accuracy. For example, Kwon et al. [5] developed a diagnostic model associated with OA severity using the random forest regression method, while Boswell et al. [6] used 3D fully connected neural networks to predict KAM based on anatomical landmarks extracted from 2D video analysis. Brisson et al. [7] focused on correlating knee contact force with cartilage loss over time using random forest regression models, and Akiba et al. [8] employed a deep learning algorithm using convolutional layers to estimate KAM from a single IMU sensor. Additionally, Snyder et al. [13] combined deep learning models, including feed-forward, convolutional, and recurrent neural networks, with instrumented insoles for real-time KAM prediction, while Giarmatzis et al. [16] applied a feed forward network to predict joint forces based on motion capture data. Each study demonstrates unique approaches, but they often lack the ability to account for the full diversity of gait patterns in daily life, which is a significant factor in enhancing the robustness and accuracy of gait analysis systems.

The problem with existing studies is that they do not fully reflect the variety of walking patterns, and they often suffer from an insufficient number of IMU sensors, limiting the ability to capture comprehensive gait features. People have different walking patterns in daily life, and the lack of adequate sensor data hinders the accuracy of gait analysis. Therefore, using multiple IMU sensors to capture rich feature data and dividing the process into classification and regression steps could lead to improved results and more accurate predictions.

In comparison with previous studies, our approach introduces a Multi-model Gait-based KAM Prediction System that utilizes a two-step method. First, it classifies gait patterns based on IMU sensor data, and then applies a specific regression model tailored to each classified gait pattern. Unlike the single-model approach employed in studies such as Wang et al. [3], our method improves prediction accuracy by integrating classification and regression processes, which allow the system to adapt its prediction model based on specific gait characteristics. By capturing these gait-specific nuances, our model achieves superior accuracy in KAM prediction, particularly when compared with a single-model system that does not account for gait pattern variation.

In this study, we used a Long Short-Term Memory (LSTM) RNN model to predict KAM. LSTM-RNN is a type of Recurrent Neural Network (RNN) that has the advantage of effectively learning long-term dependencies from long sequence data. Previous studies have mainly used artificial neural networks or XGBoost for KAM prediction [3], but LSTM-RNN has been shown to have a higher prediction accuracy for temporally continuous data [21]. For this reason, this study proposes a KAM prediction model utilizing LSTM-RNN.

The main contributions of this study are as follows: First, we developed a Multi-model Gait-based KAM Prediction System that classifies gait patterns before KAM prediction, resulting in significantly improved prediction accuracy across varied gait types. Next, we integrated IMU sensors with an LSTM-RNN model to create a cost-effective and efficient KAM prediction system, enabling non-invasive and continuous monitoring of knee joint load in real-world settings. Finally, by combining classification and regression processes, we demonstrated that accurate gait pattern classification can enhance regression performance, leading to a higher accuracy in KAM predictions.

2. Materials and Methods

First, in the simultaneous measurement phase and the data acquisition and processing phase, the reference KAM data and data from the IMU sensor required for training are collected simultaneously and integrated into a single trainable dataset through the RAW dataset construction phase. After that, the RAW data are pre-processed to make it favorable for learning, and then the LSTM-RNN model is used for learning and prediction. This process is illustrated in Figure 1, which shows the overall flowchart of the system.

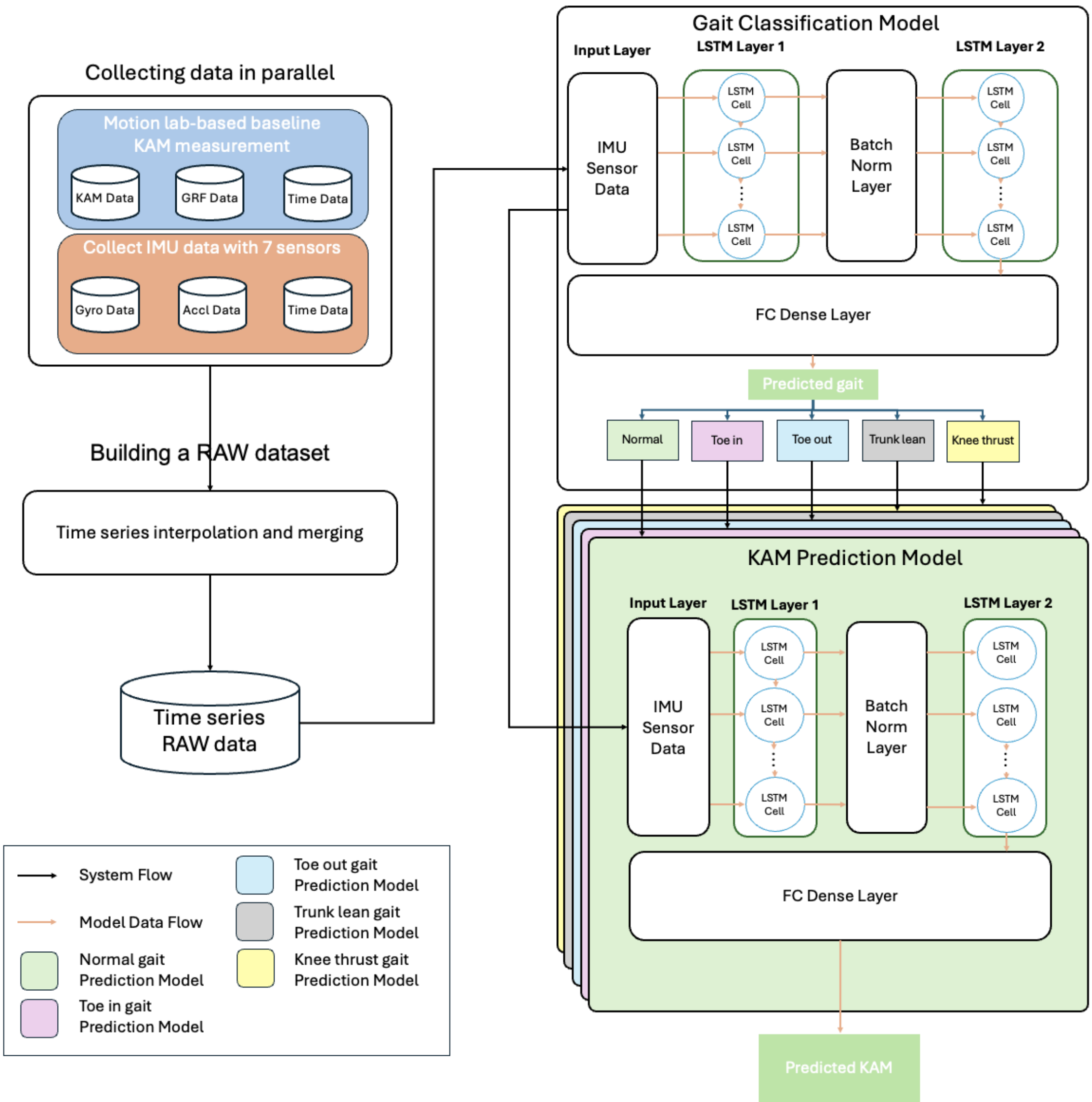


Figure 1. Overview of Multi-model Gait-based KAM Prediction System.

2.1. Collecting Data in Parallel

To predict KAM, accurate and reliable baseline data are required. Baseline KAM data are data that accurately reflect the loads on the knee joint and their distribution, which is essential to ensure the accuracy and reliability of model training. Without accurate ground truth, the model may learn incorrect patterns, which can lead to inaccurate predictions. Reliable ground truth data are essential for machine learning models to accurately reflect real-world situations. To obtain this data, baseline KAM data are collected through systematic measurements using motion and pressure sensors.

Figure 2 shows a lab environment for collecting baseline KAM data. The lab is equipped with a camera (A) to track motion and a force plate (B) to measure Ground Reaction Forces (GRFs). The study involves participants wearing sensors to collect data. The participants attache 29 spherical markers to fixed locations on the body and perform a linear reciprocating motion at regular intervals in the lab. The pressure data after the participant steps on the force plate and the data obtained from the motion camera are synthesized to measure the reference standard value of the KAM acting on the knee joint. The data obtained through this process serve as an accurate and reliable reference for the machine learning model to predict the knee load moment.

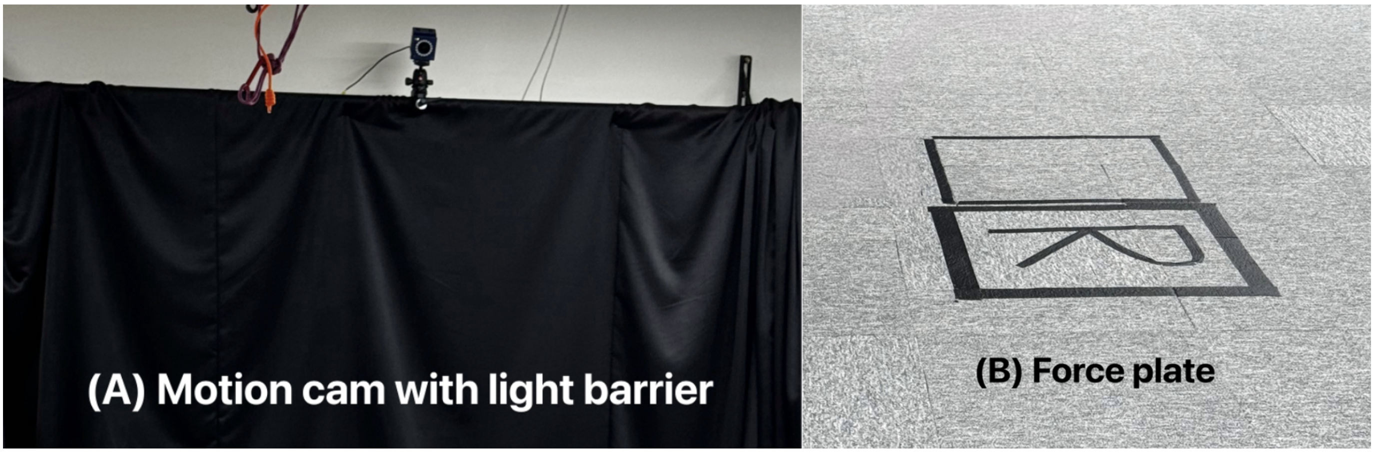


Figure 2. Laboratory environment with motion camera (**A**) and force plate (**B**) installed.

At the same time as measuring KAM, the participant wears the IMU sensors at the prescribed attachment points to collect data from the IMU sensors. A total of nine IMU sensors are used, all from Delsys' Trigno Avanti Sensor. Four of the sensors include acceleration and angular velocity for the X, Y, and Z axes, and the remaining five sensors include only acceleration for the X, Y, and Z axes.

Figure 3 shows the IMU sensor attachment locations for the participant. Sensors 1, 2, 3, and 4 are 6-axis sensors, attached to the knee, collecting data from the knee. Sensors numbered 5, 6, 7, 8, and 9 are 3-axis sensors and collect ankle and thigh data.

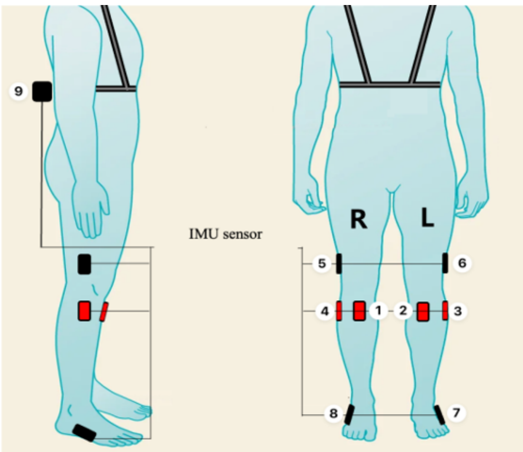


Figure 3. Detailed sensor attachment locations for the participants.

As shown in Figure 4, the experimenter steps on the two pressure plates with the right foot and then the left foot to collect sensor data, and then turn around and does the same thing to generate and collect KAM data.

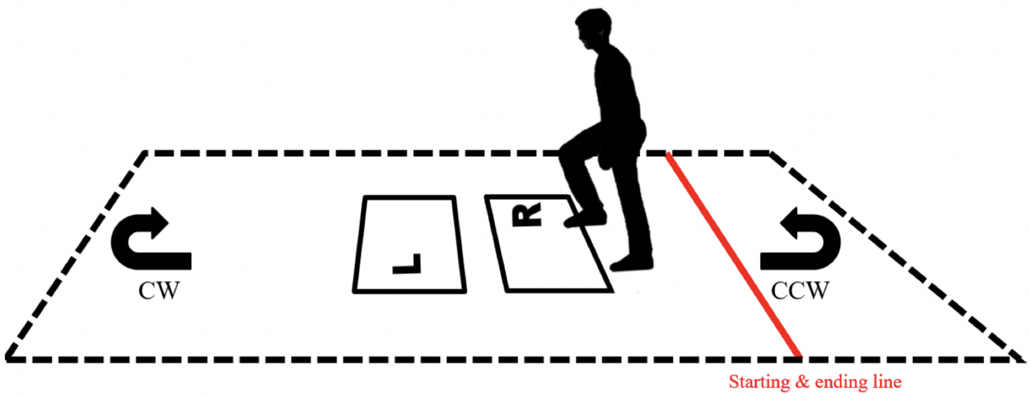


Figure 4. Collecting datasets with IMU and GRF sensors.

2.2. Building a RAW Dataset

IMU sensor data required inter-sensor calibration due to the use of different types of IMU sensors: 3-axis and 6-axis. As the 3-axis sensor had a measurement frequency of 180 Hz, and the 6-axis sensor had a frequency of 380 Hz, the data were converted to 450 Hz. This conversion involved interpolation to ensure temporal alignment, and the processed data were included in the RAW dataset. Additionally, for the KAM measurement, motion lab data were incorporated into the RAW Dataset, including both motion sensor and pressure plate data. The RAW dataset was structured to predict KAM as the target variable, using IMU sensor data as the input. Furthermore, the interpolated data were merged and synchronized with the KAM measurement data to align with the time series accurately. The structure of the dataset used for the final training and learning is shown in Table 1.

Table 1. Structure of the RAW dataset.

Motion Lab Data	IMU Sensor Data
Motion sensor data	Accelerometer data
GRF data	Gyro sensor data
Baseline KAM data	

2.3. Learning and Prediction

The LSTM-RNN model was trained and implemented for KAM prediction under OS Ubuntu 20.04.5 LTS, CPU Intel Xeon W-2245, GPU NVIDIA Quadro RTX 5000, RAM 128 GB, Python 3.8.8, and PyTorch 2.0.1 [22]. Although Recurrent Neural Networks are used to identify patterns or meanings in sequential data, we chose LSTM layers to overcome the limitations of RNNs in effectively learning long-term dependencies in long sequence data, which can improve the prediction accuracy for temporally continuous data, such as KAM values that change with the gait cycle.

As LSTM-RNNs operate on sequential data, a sliding window function is used to convert consecutive data points into overlapping sequences by shifting the window over the data one step at a time. This method allows the model to capture continuous patterns effectively and improve generalization. The transformed data are then converted to PyTorch tensors and utilized for model training via PyTorch's DataLoader, which handles batching and shuffling of the data to optimize the training process [22]. To facilitate training, the data are scaled using StandardScaler from scikit-learn [23], which normalizes the features based on the training data, adjusting all features to have a mean of 0 and a standard deviation of 1.

To compare the predictive accuracy of the models, we evaluated two systems: a multi-model system that includes both a classification model and a regression model, and a single-model system that includes only a regression model. The multi-model system first classifies the input IMU sensor data into one of five gait pattern types: normal gait, toe-in gait, toe-out gait, trunk lean, and knee thrust. Once the pattern is classified into one of these five types, the IMU sensor data are then passed as the input to a KAM regression model that is specifically trained for that gait pattern to make the final prediction. A detailed description of each gait type, along with the encoding methods used for the gait types, can be found in Table 3.

2.4. Multi-Model Gait-Based KAM Prediction System

Figure 5 illustrates the Multi-model Gait-based KAM Prediction System. Initially, the system receives IMU sensor data as the input to the gait pattern prediction model. After predicting the gait pattern from the input data, the system selects a prediction model tailored to the identified gait pattern. Finally, it predicts the KAM using this specific model. The classification model and regression model both use LSTM-RNN and have the same number of layers.

$$\mathcal{L}_{\text{classification}} = -\frac{1}{B}\sum_{i=1}^{B}\sum_{c=1}^{C} y_i^{(c)} \log(p(\hat{y}_i^{(c)})) \quad (1)$$

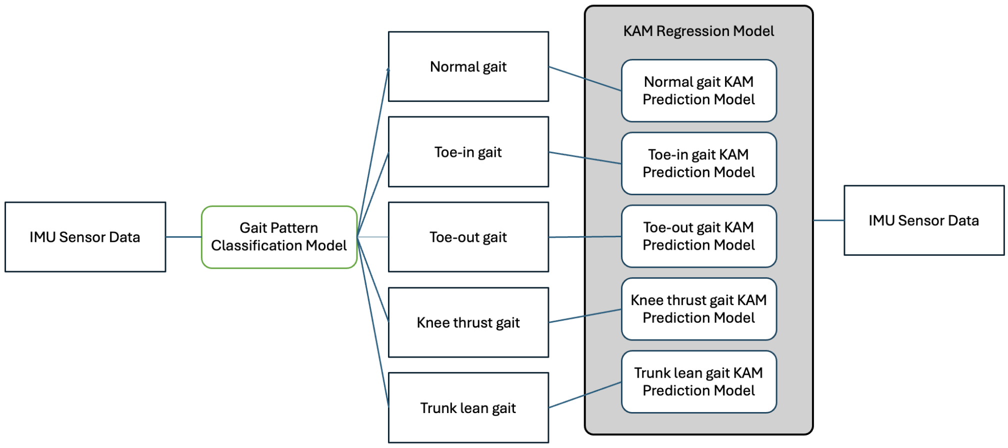


Figure 5. Organization of models in Multi-model Gait-based KAM Prediction System.

The first step in the system is the classification model. By classifying a particular gait pattern based on the input gait data, the model predicts what kind of gait pattern it belongs to. The model is trained using the Cross-Entropy Loss function, which is commonly used in classification tasks to measure the difference between the predicted class probabilities and the actual class labels by penalizing inaccurate predictions. The loss function is described by Equation (1), where B is the batch size, C is the number of classes, $y_i^{(c)}$ is the actual class label for sample i, and $p(\hat{y}_i^{(c)})$ represents the predicted probability of class C for sample i.

The structure of the gait pattern prediction model of the Multi-model Gait-based KAM Prediction System is shown in Table 2. First, the Input Layer receives 39 features, which is the number of IMU sensors, along with the batch size and timestep, and passes through two LSTM layers. Each layer has 32 nodes, and the final output is the gait data. The gait data values are numerically encoded and represented and used as shown in Table 3.

Table 2. Gait Ccassification model dtructure for the Multi-model Gait-based KAM Prediction System.

Layer	Value
Input Layer	feature = 39
LSTM Layer 1	32 Node
LSTM Layer 2	32 Node
Output Layer	1 Node = gait

Table 3. Set label values by gait pattern.

Label (Value)	Description
Knee thrust (0)	exaggerated forward movement of the knee
Normal (1)	normal walking
Toe in (2)	inward pointing of the toes
Toe out (3)	outward pointing of the toes
Trunk lean (4)	tilting of the upper body to one side

The second step in the system is the regression model. By combining the output of the classification model with the original input data, the regression model predicts the KAM value. The regression model takes both the classified gait pattern and the gait data as the inputs, enabling a more accurate prediction of the KAM value. This model minimizes the error between the predicted KAM value and the actual KAM value using the Mean Squared Error (MSE) loss function. The loss function is described by Equation (2), where B is the batch size, y_i is the actual KAM value for sample i, and $\hat{y}_i$ is the KAM value predicted by the model for sample i.

$$\mathcal{L}_{\text{regression}} = \frac{1}{B}\sum_{i=1}^{B}(y_i - \hat{y}_i)^2 \tag{2}$$

The hyperparameter settings for the KAM prediction model of the Multi-model Gait-based KAM Prediction System are shown in Table 4.

Table 4. Hyperparameters of gait classification models in Multi-model Gait-based KAM Prediction Systems.

Parameter	Value
Batch Size	64
Learning Rate	0.001
Epochs	500
LSTM Nodes	32
LSTM Layers	2

The final loss function used in the Multi-model Gait-based KAM Prediction System is defined by combining the loss functions of the classification model and the regression model. Training is conducted in the direction of minimizing the losses of both models, which allows us to simultaneously optimize the performance of the gait pattern classification and KAM prediction. The final loss function is shown in Equation (3).

$$\mathcal{L}_{\text{MKGP}} = \mathcal{L}_{\text{classification}} + \mathcal{L}_{\text{regression}} \tag{3}$$

3. Performance Evaluations

To evaluate the performance of the Multi-model Gait-based KAM Prediction System, we use the Single-model KAM Prediction System as a comparison. The Single-model KAM Prediction System is a simple structure that trains all patterns into a single model and outputs KAM with data from IMU sensors as the input, regardless of the gait pattern. This model is composed of the same structure as the regression model of the Multi-model Gait-based KAM Prediction System.

3.1. Performance Evaluation Metrics

Before evaluating the performance of our models, we defined key metrics to assess their accuracy and robustness. We chose Accuracy and F1 Score as the primary performance metrics for evaluating the LSTM-RNN model in the Multi-model Gait-based KAM

Prediction System. This choice aligns with our goal of improving KAM prediction accuracy by accurately classifying individual gait patterns.

Accuracy is defined as the percentage of correct predictions made by the model over the entire dataset, providing a broad measure of the model's general predictive capability. It is calculated by Equation (4), where TP_{kt}, TP_{n}, TP_{ti}, TP_{to}, and TP_{tl} represent the true positives for each gait pattern: knee thrust, normal, toe-in, toe-out, and trunk lean, respectively, and N is the total number of samples. Here, TP_{kt} is defined as the cases where the actual gait pattern A_{kt} matches the predicted gait pattern P_{kt}. A high Accuracy score indicates that the model is effective in generalizing across diverse gait patterns, minimizing misclassifications.

$$\text{Accuracy} = \frac{TP_{\text{kt}} + TP_{\text{n}} + TP_{\text{ti}} + TP_{\text{to}} + TP_{\text{tl}}}{N} \tag{4}$$

F1 Score, the harmonic mean of Precision and Recall, is useful for unbalanced class distributions, as it balances the trade-off between Precision (the correctness of positive predictions) and Recall (the completeness of capturing actual positives). It is calculated by Equation (5), with Precision and Recall defined in Equations (6) and (7). Here, FP represents the number of false positives, where the model incorrectly predicts a positive class, and FN represents the number of false negatives, where the model fails to detect an actual positive class. F1 Score highlights the model's ability to handle both frequent and infrequent gait patterns accurately, which is crucial in our study where certain gait patterns may appear more frequently than others.

$$\text{F1 Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

For KAM prediction, we use the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) to evaluate regression accuracy. MAPE measures the error between predicted and actual values as a percentage, providing an intuitive sense of the model's accuracy relative to the actual data scale. MAPE is calculated by Equation (8), where $A.K_t$ is the actual KAM value and $P.K_t$ is the predicted KAM value for each index t in the dataset of size n. MAPE is particularly useful in this study as it allows for comparing error rates across different KAM values, facilitating a normalized understanding of prediction performance.

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A.K_t - P.K_t}{A.K_t}\right| \tag{8}$$

RMSE, shown in Equation (9), calculates the square root of the mean squared differences between the actual and predicted KAM values, making it sensitive to larger errors. In RMSE, $A.K_t$ represents the actual KAM value, while $P.K_t$ denotes the predicted KAM value. RMSE is particularly valuable in this context as it captures the model's robustness against large deviations, reflecting the overall predictive accuracy of the KAM prediction model.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A.K_t - P.K_t)^2} \tag{9}$$

By combining these metrics, we achieve a comprehensive view of the model's performance: Accuracy and F1 Score evaluate classification reliability, while MAPE and RMSE assess regression accuracy for KAM prediction. Additionally, a Confusion Matrix visualizes classification accuracy across the five gait patterns, enabling intuitive interpretation of the per-pattern model performance.

3.2. Evaluating the Performance of Multi-Model and Single-Model Gait-Based KAM Prediction Systems

The Multi-model and Single-model Gait-based KAM Prediction Systems were evaluated to compare their classification performance and predictive accuracy across multiple gait patterns. Figure 6 shows the Confusion Matrix for the Multi-model Gait-based KAM Prediction System. This matrix visualizes how the model predicted each actual gait pattern and highlights the classification accuracy for each specific pattern. As shown in the graph, the normal (94.03%), toe in (92.59%), and toe out (89.77%) patterns, which have clear and consistent characteristics, are predicted accurately. However, the trunk lean pattern, which exhibits irregular and complex characteristics, is predicted with a lower accuracy (82.23%) compared to the other patterns. This suggests that while the model effectively captures the stable features of certain gait types, it has more difficulty with variable patterns like trunk lean. Based on these results, we calculated the overall Accuracy and F1 Score, as shown in Table 5, both of which are around 0.9 or higher.

Table 5. Classification accuracy of the Multi-model Gait-based KAM Prediction System.

Evaluation Metrics	Value
Accuracy	0.9288
F1 Score	0.9077

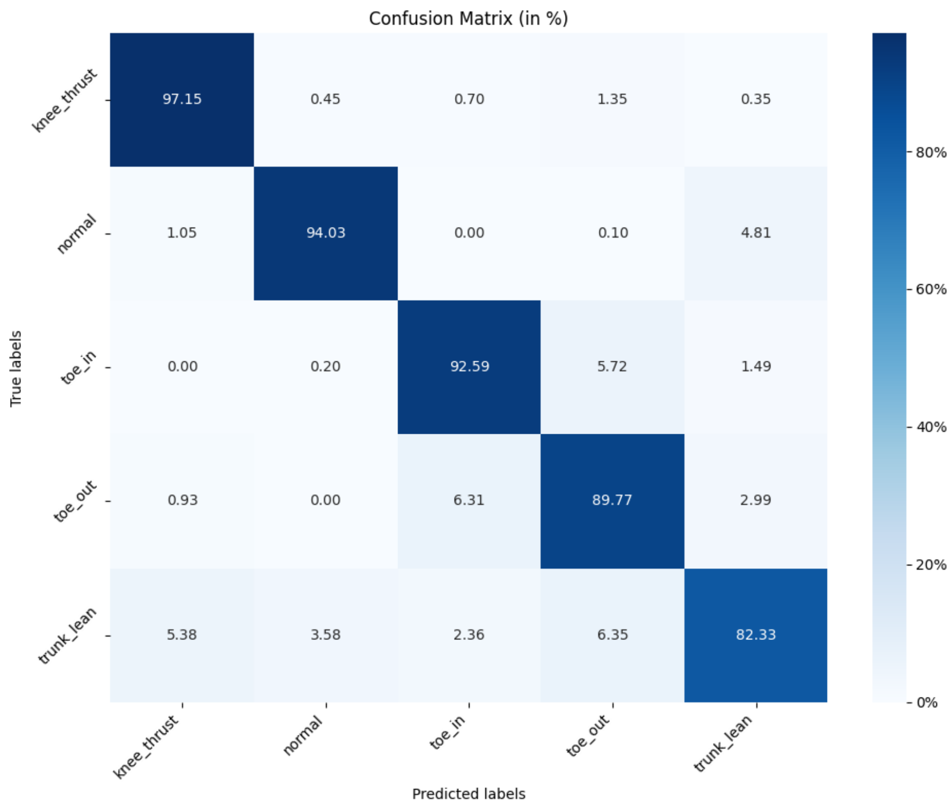
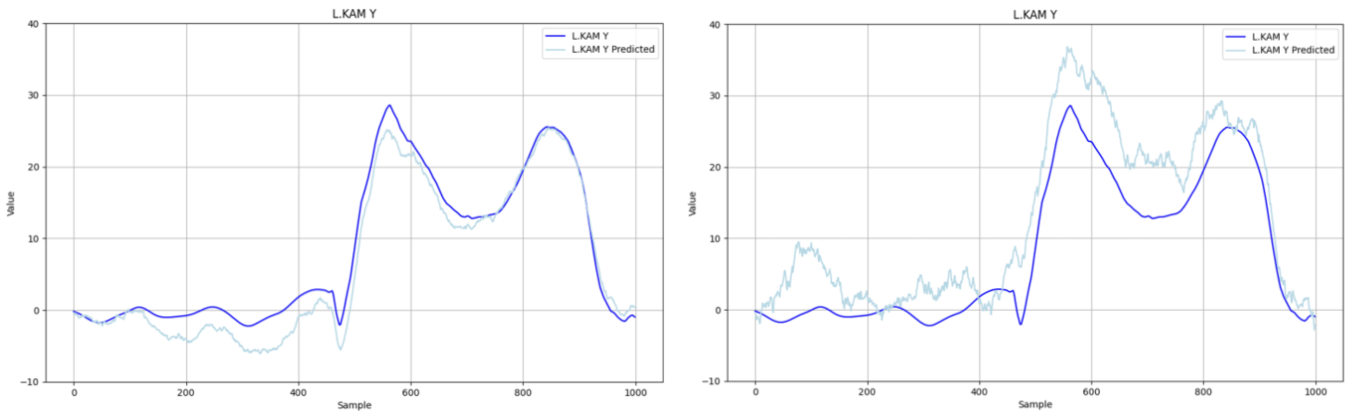


Figure 6. Confusion matrix of Multi-model Gait-based KAM Prediction System (Knee Thrust 97.15%, Normal 94.03%, Toe in 92.59%, Toe out 89.77%, Trunk lean 82.23%).

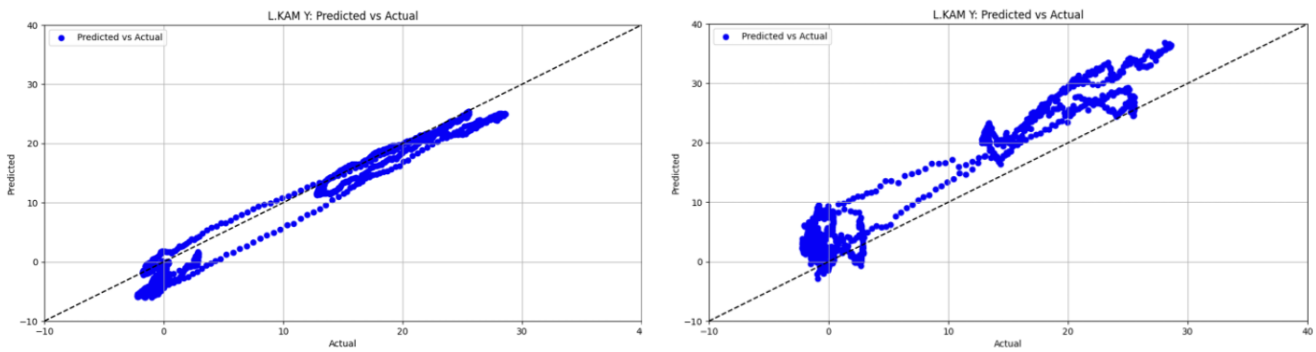
Figure 7 shows a comparison of the actual versus predicted KAM values for both systems, demonstrating that the Multi-model system's predictions more closely align with the actual measurements than the Single-model system. This alignment signifies the Multi-model system's robustness in predicting KAM values across diverse gait patterns, as it leverages gait classification to adjust predictions according to specific gait patterns. In contrast, the Single-model system, which does not incorporate prior gait pattern classification, exhibits a larger prediction error and less alignment with the actual values.



(A) Graph of actual vs. predicted values for MGKP System. (B) Graph of actual vs. predicted values for Single Model System.

Figure 7. comparison of the actual vs. predicted KAM values for the Multi-model and Single-model Gait-based KAM Prediction Systems. The close alignment of actual and predicted values in the Multi-model system demonstrates a higher prediction accuracy, especially across varying gait patterns.

Further analysis of the predictive accuracy is shown in Figure 8, which plots the actual KAM values against the predicted values for both systems. In this comparison, the closer clustering of data points along the $y = x$ line in the Multi-model system demonstrates its ability to handle diverse gait patterns more accurately, whereas the Single-model system shows greater deviation from the ideal line. This comparison underscores the advantage of the Multi-model approach, which incorporates pattern-specific classification steps before KAM prediction, allowing for more precise KAM estimation across the varied gait types.



(A) Predictive accuracy visualization for MGKP System. (B) Predictive accuracy visualization Single Model System.

Figure 8. Predictive accuracy visualization for the Multi-model and Single-model KAM Prediction Systems. Data points in the Multi-model system cluster more closely along the $y = x$ line, highlighting its enhanced accuracy and robustness compared with the Single-model system, particularly in managing diverse gait patterns.

3.3. Results of Performance Evaluations

The Single-model KAM Prediction System, which directly inputs the data into the KAM prediction model without prior gait pattern classification, achieves an average prediction error of 8.82 $\mathrm{N} \cdot \mathrm{m}$ and a MAPE of 12.95%. In comparison, the Multi-model Gait-based KAM Prediction System, which first classifies input data by gait pattern before predicting KAM, achieves a significantly lower average prediction error of 6.84 $\mathrm{N} \cdot \mathrm{m}$ and a MAPE of

8.47%. These results represent the best performance achieved by each system and can be seen in Table 6.

Table 6. KAM Prediction System Performance Evaluation Results.

Model	Value
Single-model Avg. prediction error (N · m)	8.82
Single-model MAPE (%)	12.95
Multi-model Avg. prediction error (N · m)	6.84
Multi-model MAPE (%)	8.47

These results indicate that the Multi-model system offers more than a 25% improvement in prediction accuracy compared with the Single-model system. By classifying gait patterns prior to KAM prediction, the Multi-model system can better capture the pattern-specific characteristics, leading to more precise predictions. Specifically, the 4.48% reduction in MAPE reflects the Multi-model system's advantage in minimizing percentage-based prediction errors, which is critical for accurately assessing KAM levels across different gait patterns.

The improvement in average prediction error and MAPE demonstrates that the Multi-model approach effectively addresses the limitations of a one-size-fits-all model by providing tailored predictions based on distinct gait patterns. This capability is particularly important in applications involving diverse movement patterns, as the system can adapt to specific variations in gait, such as the biomechanical differences between toe-in, toe-out, and trunk lean patterns. Such adaptability enhances the model's utility in real-world applications, where capturing subtle variations in KAM across varied gait types is essential for accurate and actionable predictions.

In summary, the Multi-model Gait-based KAM Prediction System demonstrates a robust improvement over the Single-model system by leveraging gait pattern classification to enhance predictive accuracy. This distinction in performance metrics underscores the value of integrating pattern-specific processing steps for models aimed at predicting biomechanical measures like KAM.

4. Discussion

The results of this study demonstrate that pre-classifying gait patterns and integrating them with LSTM-RNN models significantly enhances the predictive power for temporally continuous data, such as the KAM. Specifically, the Multi-model Gait-based KAM Prediction System showed a marked improvement over the Single-model KAM Prediction System, achieving an average prediction error of 6.84 N · m and a Mean Absolute Percentage Error of 8.47%, compared with the Single-model system's average prediction error of 8.82 N · m and MAPE of 12.95%.

The approach of pre-classifying gait patterns using IMU sensor data before predicting KAM proved effective in enhancing prediction accuracy. These findings underscore the potential of combining wearable technology with advanced machine learning techniques to develop cost-effective, efficient, and accurate monitoring systems for knee joint health. This method offers a practical alternative to traditional KAM measurement techniques, which require complex laboratory equipment and significant time and cost investments.

However, this study has certain limitations that warrant attention. First, the sample size was relatively small, and the gait patterns were limited to five types, which may affect the generalizability of the findings. Future research should focus on expanding the dataset to include a broader range of participants and gait patterns, such as stair climbing and inclined walking, to improve the robustness and applicability of the models. Future research will also incorporate a broader range of gait patterns and environmental conditions to enhance model applicability. Additionally, further model architecture improvements will aim to reduce computational complexity and enable real-time KAM prediction, enhancing the system's practicality for real-world applications.

Advancements in this area are expected to contribute significantly to the prevention and treatment of knee osteoarthritis. By providing an accessible and cost-effective method for continuous monitoring of the knee joint load, this system has the potential to improve patient outcomes and reduce healthcare costs associated with osteoarthritis management.

5. Conclusions

This study highlights that integrating wearable IMU sensors with LSTM-RNN models in a multi-model framework significantly enhance the accuracy of KAM prediction. The Multi-model Gait-based KAM Prediction System, which classifies gait patterns and applies tailored regression models, demonstrated a superior performance, achieving an average prediction error of 6.84 $N \cdot m$ and a MAPE of 8.47%. This represents an improvement over the Single-model system's 8.82 $N \cdot m$ average error and 12.95% MAPE. The approach leverages LSTM-RNN's capability to capture long-term dependencies in sequential data, underscoring its effectiveness in diverse gait types.

This methodology extends beyond KAM prediction, offering the potential for other applications requiring precise regression based on unique data patterns. The approach may benefit fields where customized pattern classification can improve the predictive accuracy, broadening the impact of multi-model regression techniques.

Future research will expand the dataset to include more diverse gait patterns and conditions, improve the model architecture for real-time KAM prediction, and enhance system practicality. These efforts will boost predictive accuracy and support cost-effective, continuous knee osteoarthritis monitoring, benefiting clinicians and patients.

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Abbreviations

The following abbreviations are used in this manuscript:

KOA	Knee Osteoarthritis (OA)
KAM	Knee Adduction Moment
IMU	Inertial Measurement Unit
GRF	Ground Reaction Force
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error

References

1. Health Insurance Review & Assessment Service. Big Data Open Portal. Available online: https://opendata.hira.or.kr/ (accessed on 17 January 2023).
2. Shin, H.S.; Lee, J.Y.; Cho, Y.J.; Kim, M.J.; Eom, G.M. Mechanism of knee adduction moment reduction through contralateral cane use in healthy subjects. *Int. J. Precis. Eng. Manuf.* **2023**, *24*, 2349–2360. [CrossRef]

3. Wang, C.; Chan, P.P.K.; Lam, B.M.F.; Wang, S.; Zhang, J.H.; Chan, Z.Y.S.; Chan, R.H.M.; Ho, K.K.W.; Cheung, R.T.H. Real-time estimation of knee adduction moment for gait retraining in patients with knee osteoarthritis. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2020**, *28*, 888–894. [CrossRef] [PubMed]
4. Stetter, B.J.; Krafft, F.C.; Ringhof, S.; Stein, T.; Sell, S. A machine learning and wearable sensor based approach to estimate external knee flexion and adduction moments during various locomotion tasks. *Front. Bioeng. Biotechnol.* **2020**, *8*, 9. [CrossRef] [PubMed]
5. Kwon, S.B.; Ku, Y.; Han, H.-S.; Lee, M.C.; Kim, H.C.; Ro, D.H. A machine learning-based diagnostic model associated with knee osteoarthritis severity. *Sci. Rep.* **2020**, *10*, 15743. [CrossRef] [PubMed]
6. Boswell, M.A.; Uhlrich, S.D.; Kidziński, Ł.; Thomas, K.; Kolesar, J.A.; Gold, G.E.; Beaupre, G.S.; Delp, S.L. A neural network to predict the knee adduction moment in patients with osteoarthritis using anatomical landmarks obtainable from 2D video analysis. *Osteoarthr. Cartil.* **2021**, *29*, 387–394. [CrossRef] [PubMed]
7. Brisson, N.M.; Gatti, A.A.; Damm, P.; Duda, G.N.; Maly, M.R. Association of machine learning–based predictions of medial knee contact force with cartilage loss over 2.5 years in knee osteoarthritis. *Arthritis Rheumatol.* **2021**, *73*, 1638–1645. [CrossRef] [PubMed]
8. Akiba, A.; Harato, K.; Yoshihara, H.; Iwama, Y.; Nishizawa, K.; Nagura, T.; Nakamura, M. Development of a deep learning algorithm to estimate knee adduction moment during gait using a single inertial measurement unit. *Res. Sq.* **2023**. [CrossRef]
9. Iwama, Y.; Harato, K.; Kobayashi, S.; Niki, Y.; Ogihara, N.; Matsumoto, M.; Nakamura, M.; Nagura, T. Estimation of the external knee adduction moment during gait using an inertial measurement unit in patients with knee osteoarthritis. *Sensors* **2021**, *21*, 1418. [CrossRef] [PubMed]
10. Telfer, S.; Lange, M.J.; Sudduth, A.S.M. Factors influencing knee adduction moment measurement: A systematic review and meta-regression analysis. *Gait Posture* **2017**, *58*, 333–339. [CrossRef] [PubMed]
11. Kutzner, I.; Trepczynski, A.; Heller, M.O.; Bergmann, G. Knee adduction moment and medial contact force—Facts about their correlation during gait. *PLoS ONE* **2013**, *8*, e81036. [CrossRef] [PubMed]
12. Rokhmanova, N.; Kuchenbecker, K.J.; Shull, P.B.; Ferber, R.; Halilaj, E. Predicting knee adduction moment response to gait retraining with minimal clinical data. *PLoS Comput. Biol.* **2022**, *18*, e1009500. [CrossRef] [PubMed]
13. Snyder, S.J.; Chu, E.; Um, J.; Heo, Y.J.; Miller, R.H.; Shim, J.K. Prediction of knee adduction moment using innovative instrumented insole and deep learning neural networks in healthy female individuals. *Knee* **2023**, *41*, 115–123. [CrossRef] [PubMed]
14. Alexios, A.; Kokkotis, C.; Moustakidis, S.; Papageorgiou, E.; Tsaopoulos, D. Prediction of pain in knee osteoarthritis patients using machine learning: Data from Osteoarthritis Initiative. In Proceedings of the 2020 11th International Conference on Information, Intelligence, Systems and Applications (IISA), Piraeus, Greece, 15–17 July 2020; pp. 1–7. [CrossRef]
15. Wheeler, J.W.; Shull, P.B.; Besier, T.F. Real-time knee adduction moment feedback for gait retraining through visual and tactile displays. *J. Biomech. Eng.* **2011**, *133*, 041007. [CrossRef] [PubMed]
16. Giarmatzis, G.; Zacharaki, E.I.; Moustakas, K. Real-time prediction of joint forces by motion capture and machine learning. *Sensors* **2020**, *20*, 6933. [CrossRef] [PubMed]
17. Foroughi, N.; Smith, R.; Vanwanseele, B. The association of external knee adduction moment with biomechanical variables in osteoarthritis: A systematic review. *Knee* **2009**, *16*, 303–309. [CrossRef] [PubMed]
18. Hashizume, T.; Ishii, Y.; Ishikawa, M.; Nakashima, Y.; Kamei, G.; Iwamoto, Y.; Okamoto, S.; Okada, K.; Takagi, K.; Takahashi, M.; et al. Toe-out gait inhibits medial meniscus extrusion associated with the second peak of knee adduction moment during gait in patients with knee osteoarthritis. *Asia Pac. J. Sports Med. Arthrosc. Rehabil. Technol.* **2023**, *33*, 13–19. [CrossRef] [PubMed]
19. Schmitz, A.; Noehren, B. What predicts the first peak of the knee adduction moment? *Knee* **2014**, *21*, 1077–1083. [CrossRef] [PubMed]
20. Chen, T.; Guestrin, C. XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 785–794. [CrossRef]
21. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. . [CrossRef] [PubMed]
22. Paszke, A.; Gross, S.; Massa, F.; Lerer, A.; Bradbury, J.; Chanan, G.; Killeen, T.; Lin, Z.; Gimelshein, N.; Antiga, L.; et al. PyTorch: An Imperative Style, High-Performance Deep Learning Library. *Adv. Neural Inf. Process. Syst. NeurIPS* **2019**, *32*, 8024–8035.
23. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V.; et al. Scikit-learn: Machine Learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.