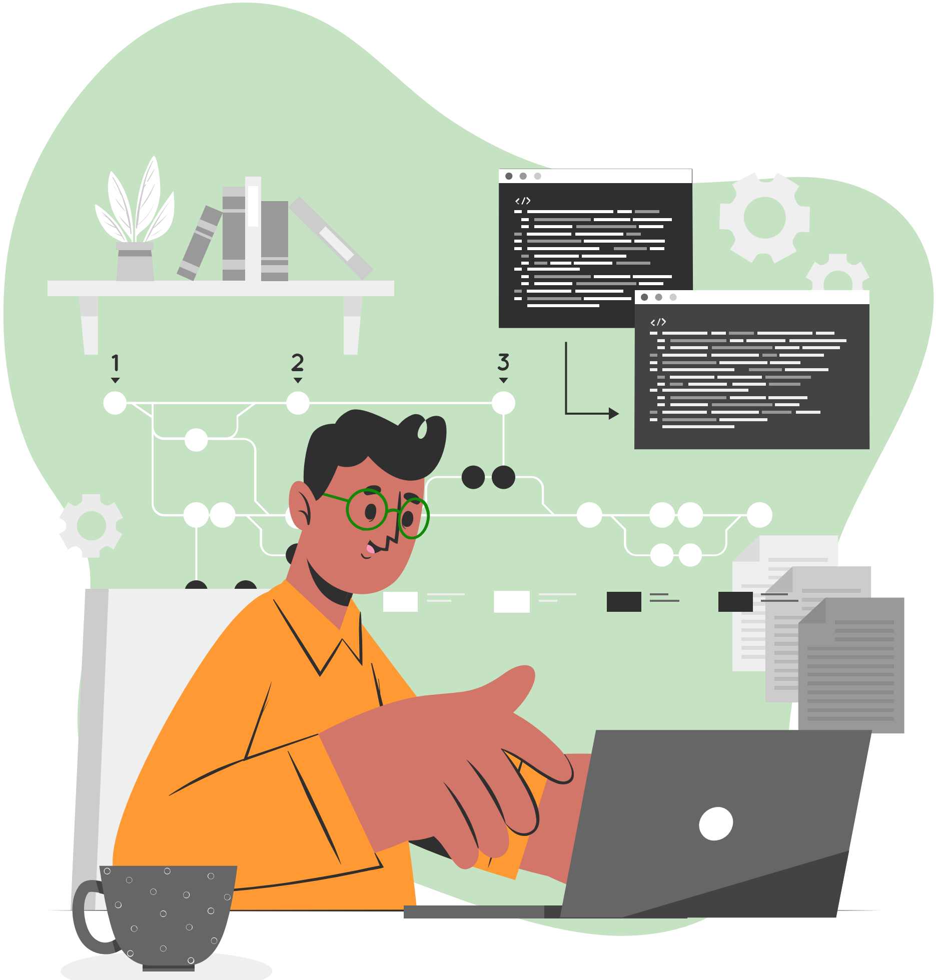

Single IMU-Based Multi Segment Motion Analysis and Prediction

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Achievements

1. [ICDATE2023] Lower Limb Gait Estimation Using Foot Motion and Neural Network (Published)

01

Introduction

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Background

- Human Gait and Accurately Estimating Joint Motion is crucial in the field of rehabilitation and motion analysis.
- Traditional methods of gait analysis include motion tracking systems that capture joint angles and provide insights to movement disorders - prove to be complex, expensive and require extensive setup [1]
- Abnormal Gait is the result of injuries that affect joints in the body that further affect the cyclic patterns that emerges [6].

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Literature Review

Author	Methodology	Input	Output	Results
Mundt et al. [2]	IMU data fed to FNN	IMU Acceleration	Joint Angles and Moments	Joint Angle $\rho = 0.85$ RMSE < 4.8 Joint Moment $\rho = 0.95$ nRMSE < 13%
Mundt et al. [3]	IMU data fed to ANN (MLP, LSTM, CNN)	IMU Acceleration	Joint Angles and Moments	Joint Angle $\rho = 0.832$ Joint Moment $\rho = 0.96$
Senanayake et al. [4]	IMU data fed into DNN (GAN)	IMU Inverse Kinematics	Joint Angles	IK $\rho < 0.05$ IMU $\rho < 0.001$
Komaris et al. [5]	IMU data fed to ANN	Acceleration	Running Speeds and GRFs	Running Speed $\rho = 0.23$ RMSE vertical = 0.146
Chin-Hsien et al. [6]	IMU data fed into DNN	IMU Inverse Kinematics	Parkinson's Stage Condition	Advanced Stage Detection accuracy: 92.72% Early Stage Detection accuracy: 99.67%

Hypothesis

- In Human Gait there is an evident relationship between the shank and the thigh segment in terms of biomechanics and the cyclic patterns of gait [6].
- This relationship between the kinematic chain of shank and thigh will be investigated and used to estimate values of thigh angular velocities from data collected from shank

- Research Gap - Minimal approaches that can provide accurate joint motion estimation while being minimally invasive and cost-effective
- Novelty - Collect subject data estimating thigh angular velocities from shank angular velocity data to see progression of injury

Joint Estimation using Machine Learning

1

Data Collection

INITIAL STAGE
Data collected from wearable sensors

2

Preprocessing and Feature Extraction

Required relevant features extracted from sensors to represent joint

3

Machine Learning Model Training

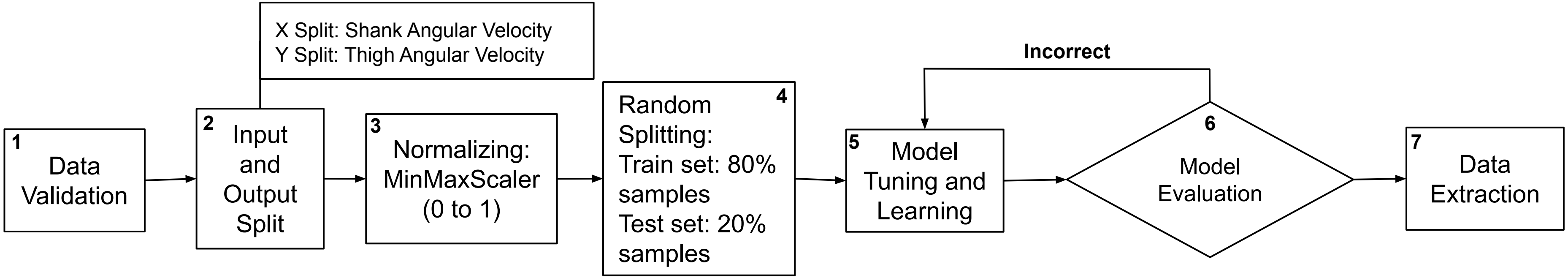
Use suitable algorithms to train model

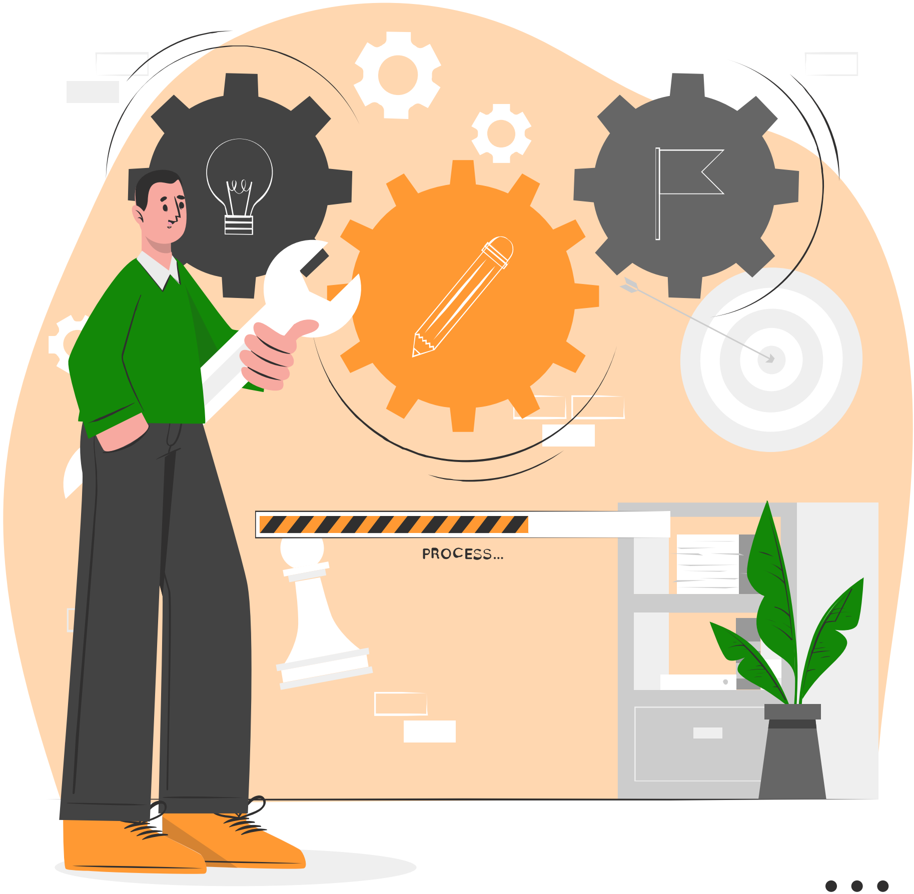
4

Joint Estimation

Provide quantitative estimations of thigh angular velocities for analysis

Gait Angular Velocity Estimation Flow Diagram





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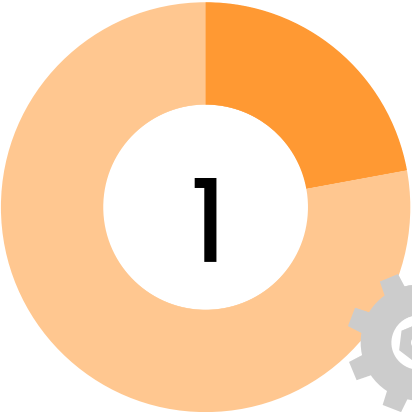
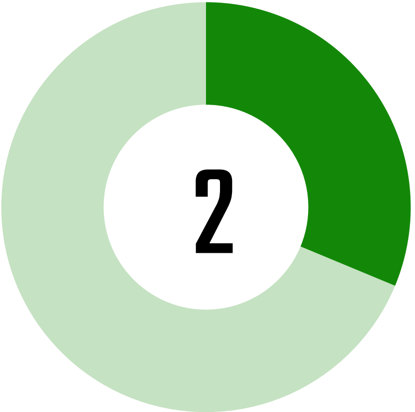
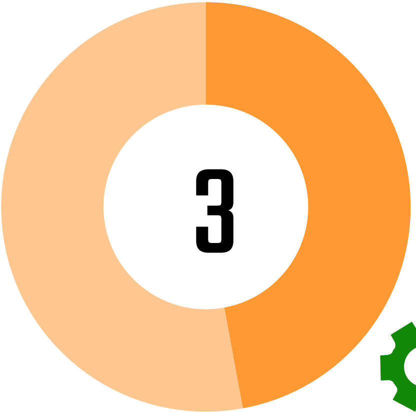
Objectives



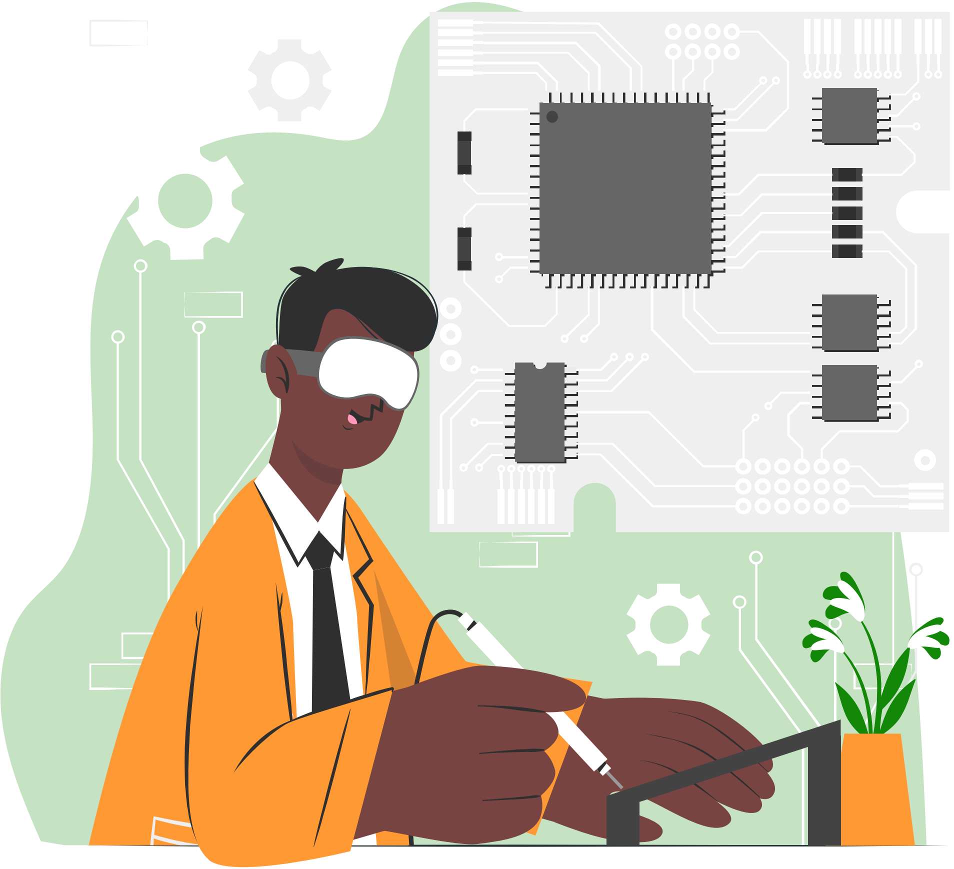
Develop dataset using IMU sensors to capture angular velocity data during gait



Create machine learning model with at least 80% pearson correlation for estimation of thigh angular velocity using data obtained from a single IMU sensor attached to the shank



Develop IMU sensor system for the collection of angular velocity data from shank and thigh segments



03

Methodology

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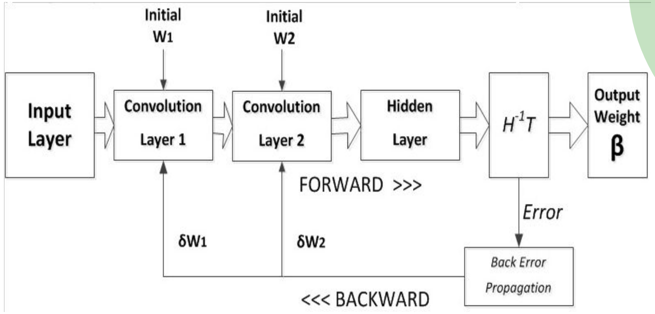
Using Deep Learning -CNN

Introduction

- Creates a linear stack of layers in deep learning models
- Easily learn dynamics of joint movements through *feature selection [3]*



$$y(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$$

Convolutional Neural Network

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Training

- Feeding integrated sensor data (80%) + optimize model parameters
- Integrated data divided into training and validation sets
- Use of backpropagation

Evaluation/Validation

- Training on evaluation set consisting of data the model has not seen (20%)
- CNN generates predicted values

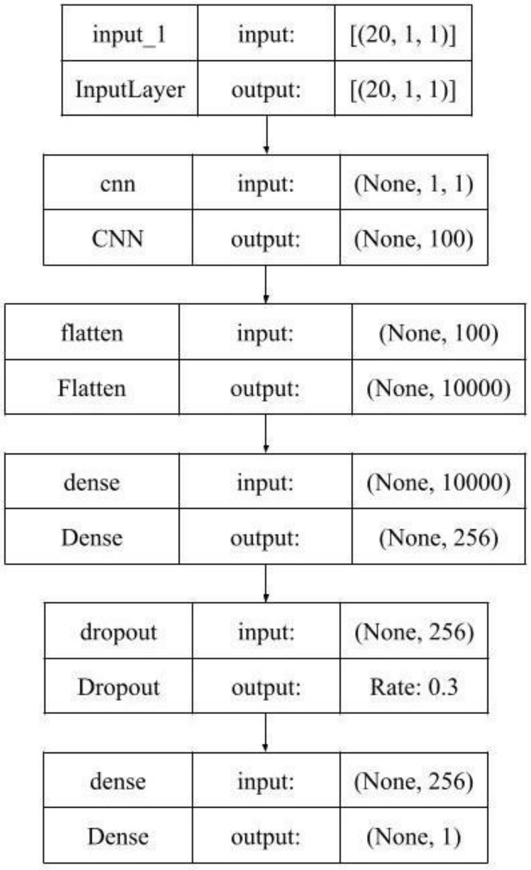
The CNN Model - Layers

1. **Input Layer** has a shape of [20, 1, 1]. This shape indicates model is designed to handle time-series data with 20 time steps and one feature.

2. **Convolutional Layer** is the first hidden layer. It is 1D convolutional layer with 128 filters [for time series data where data proximity matters]. Scans input data to identify important patterns, with each filter looking for different patterns. The ReLU activation function is used to introduce non-linearity into the model.

3. **Flatten Layer** takes output of convolutional layer and transforms it into a 1D tensor. Necessary as subsequent Dense layers require a 1D input and not the multidimensional output of the convolutional layer.

4. **Dense Layers**
   - First Dense layer with 256 units as an output layer. Processes the flattened data to make predictions.
   - Dropout layer with a rate of 0.3 is added to prevent overfitting by randomly disabling a portion of neurons during training.
   - Final Dense layer with 1 unit provides the model's output, the estimated thigh angular velocity.



Layer Architecture of CNN

The CNN Model - Parameters

1. **Optimizer**

    - *Adam Optimizer* used is a optimization algorithm in deep learning. Adapts learning rates for each parameter individually - leads to faster convergence + better performance.

    - A learning rate of 0.001 indicates the step size at which the model's weights are updated during training.

    - Smaller learning rate can result in slower training but helps model converge more effectively
    - Larger learning rate may speed up training but could lead to overshooting optimal weights.

1. **Hyperparameters**

    - *Batch Size:* Determines how many data samples processed in each forward/backward pass during training. Smaller batch (32-128) size-more stable training but slower. Larger batch (>256) size-speed up training but less stable.

    - *Number of Epochs:* An epoch is one complete pass through the entire training dataset. Total number specifies how many times model sees entire dataset - depends on dataset and convergence of model. Early stopping also implemented where training stops when performance on validation set no longer improves.

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The CNN Model - Parameters

3. **Loss Function and Metrics**

- *Mean Squared Error (MSE)* is a loss function for regression tasks. Calculates average of squared differences between model's predictions and actual target values. *Lower MSE values indicate better performance*.

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

- *Mean Absolute Error (MAE)* is a metric that calculates the average of the absolute differences between predictions and actual values. Less sensitive to outliers compared to MSE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

- *Root Mean Squared Error (RMSE)* takes into account relative error and provide insights into the model's ability to estimate thigh angular velocity.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

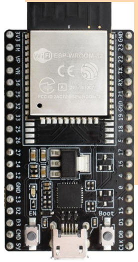
- Correlation Coefficient *(ρ)* measures linear relationship between predicted and actual values. Ranges from -1 to 1: 1 indicating perfect positive linear relationship, -1 indicating perfect negative linear relationship. 0 means no linear relationship.

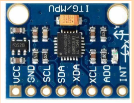
$$\rho = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

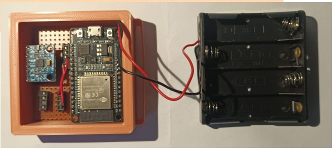
Obtaining the Dataset

Hardware

- ESP32 Microcontroller serves as central processing units for data collection
- MPU6050 Module employed to measure and record angular velocity values of shank and thigh







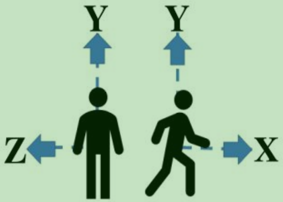
Data Collection + Recording

- 10 subjects selected (5M/5F):

Age (years)	21.6±0.92
Weight (kg)	63.2±11.79
Height (cm)	164.8±7.57

- Subjects wear sensor equipped devices on shank and thigh
- Angular Velocity Collected: Gait motion and apparent analysis
- Z-Axis for Shank and Y-Axis for Thigh [7]

- Normal Gait Data Collected
- 1 kg Sandbag simulate knee injury-Abnormal Gait Data Collected
- Data stored in time series datasets



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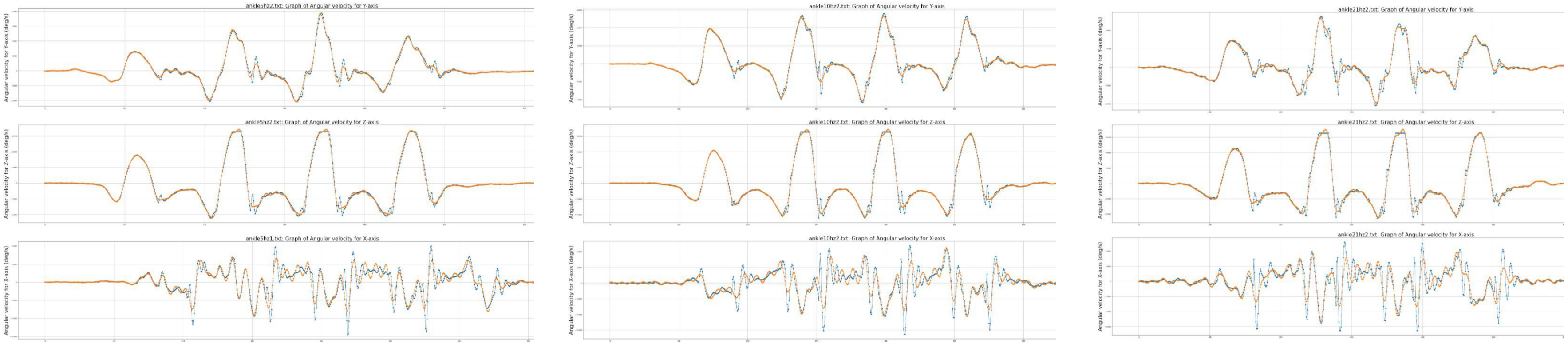
Software

- To facilitate data transmission and recording
- Bluetooth technology to establish wireless connection between hardware and device
- Python Script to generate appropriate data format
- Received data is processed / stored as .CSV file

Data Preprocessing and Training

Filter Selection

- Filters are essential for noise reduction and ensuring relevant information is captured.
- Experimented with multiple filter frequencies: 5Hz, 10Hz, and 21Hz. These frequencies were applied to raw data collection to preprocess for subsequent modeling.
- Data filtered at 10Hz emerged as best choice, delivering best results for model.



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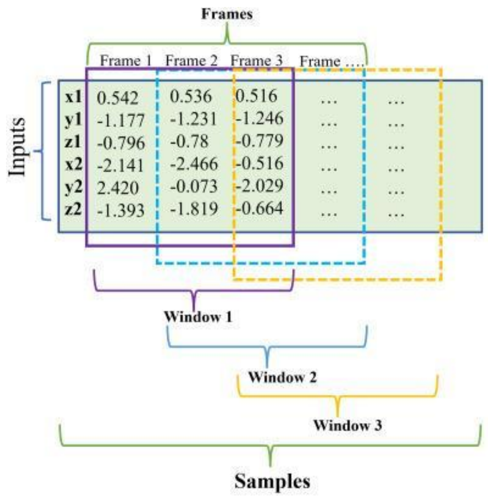
Data Preprocessing and Training

Windowing

- Windowing involves dividing time-series data into small segments. Each segment, or "window," captures local patterns within the data, allowing the model to analyze sequences effectively [8].

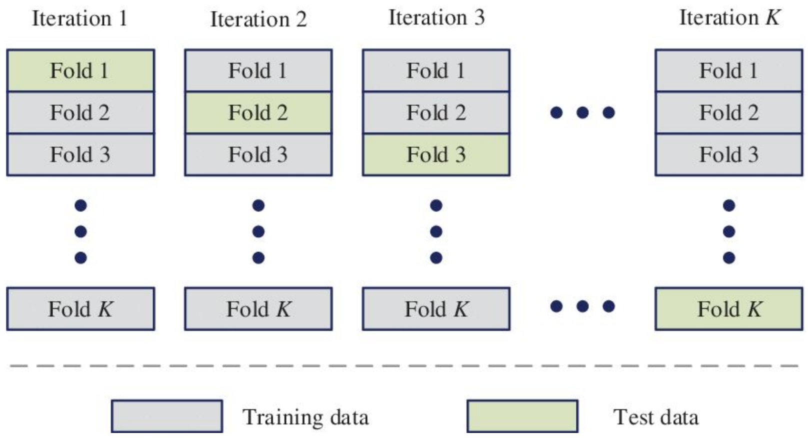
- Model considers last 20 time steps to predict next value, creating input-output pairs for neural network.
- Improves understandability and complex time-series data by enabling model to focus on relevant local patterns.

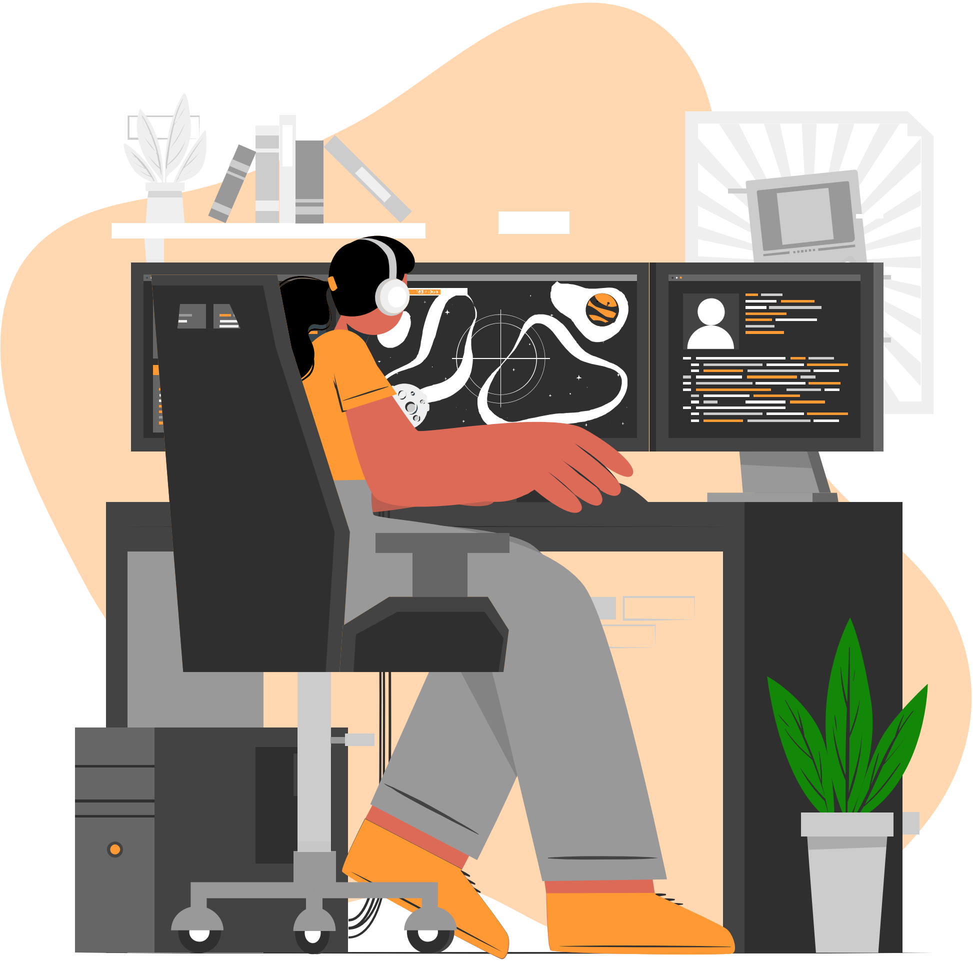


Data Preprocessing and Training

K-Fold Validation

- Robust technique used to assess performance of machine learning models. Partitions dataset into "k" subsets, trains the model on "k-1" subsets, and tests on remaining subset [9].
- Implemented 5-fold cross-validation using scikit-learn. Each fold trained on different portion of data.
- Helps detect overfitting, where model performs well on training data but poorly on new data. By assessing performance on multiple subsets, it provides insights into model's ability to generalize to unseen data.





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Results and Discussion

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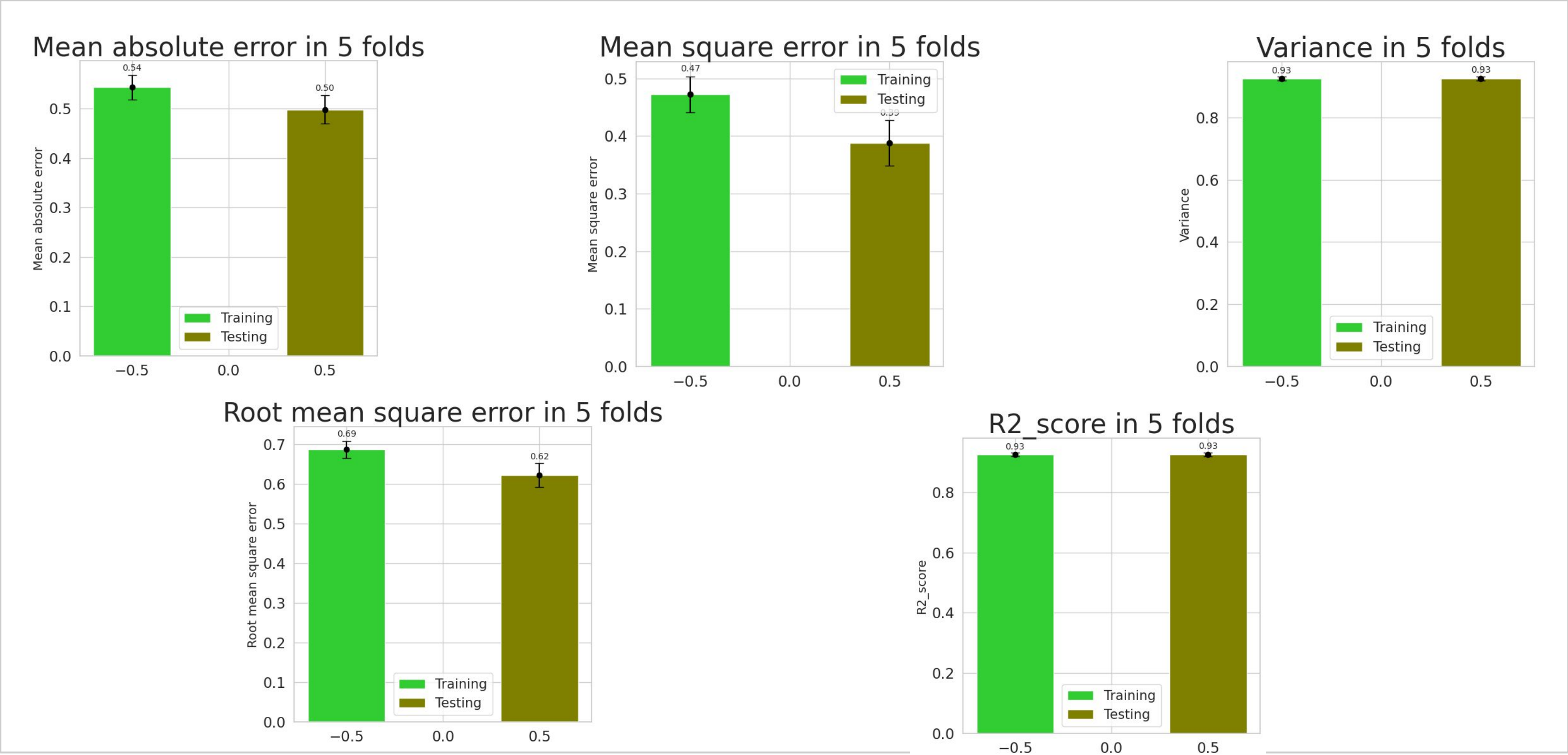
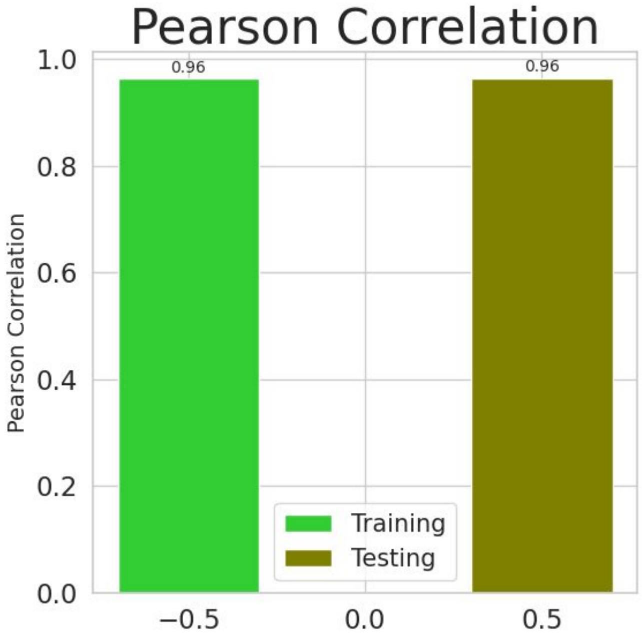
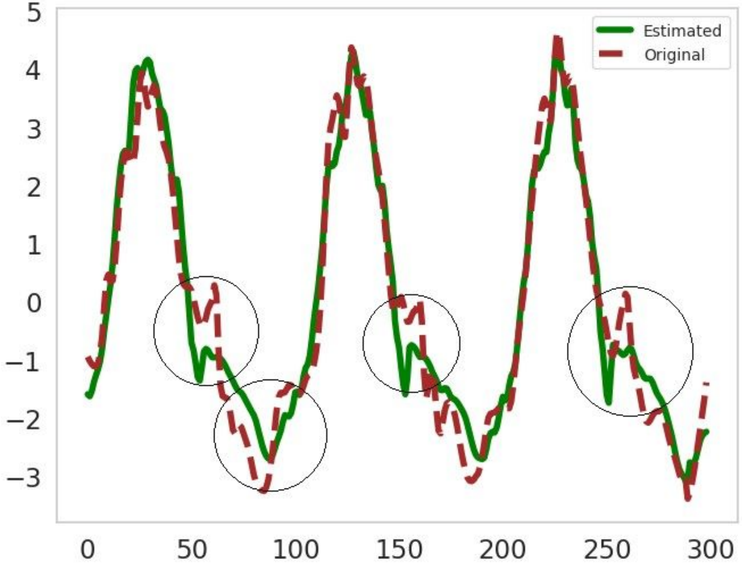
Results - Normal Thigh Angular Velocity Estimation



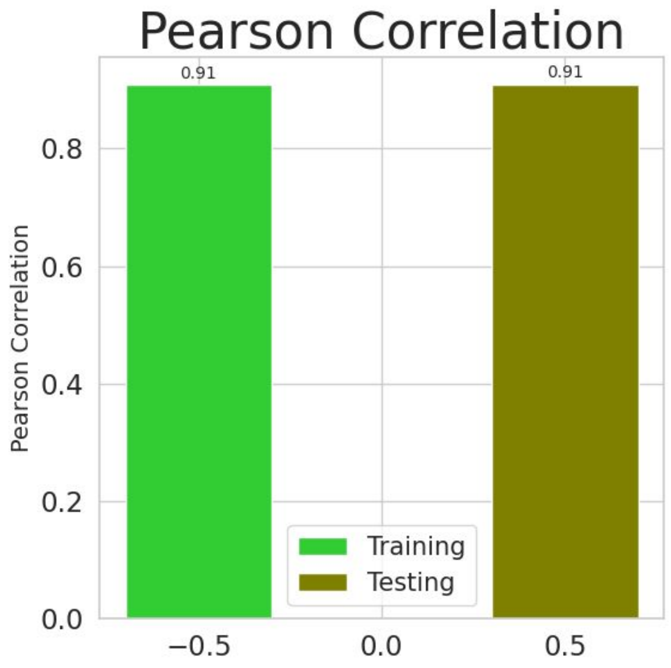
Results - Normal Thigh Angular Velocity Estimation (cont.)

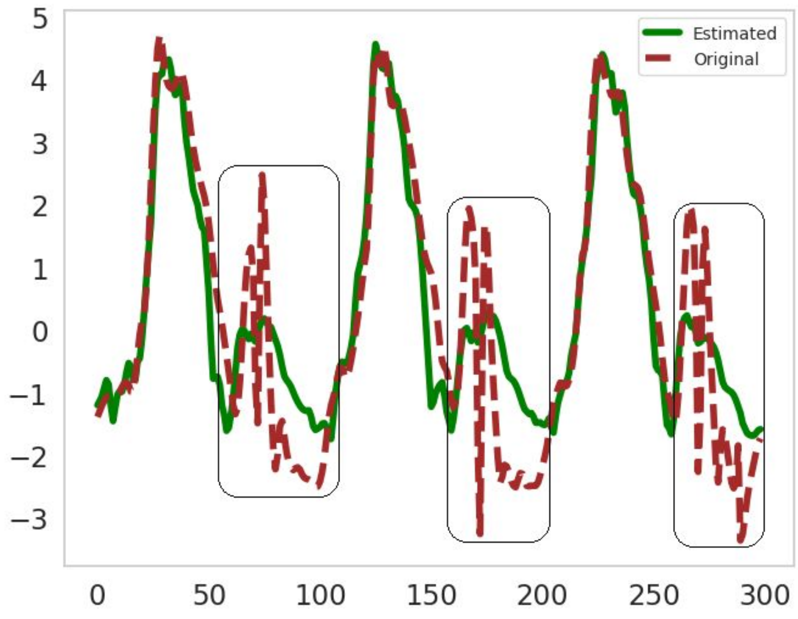


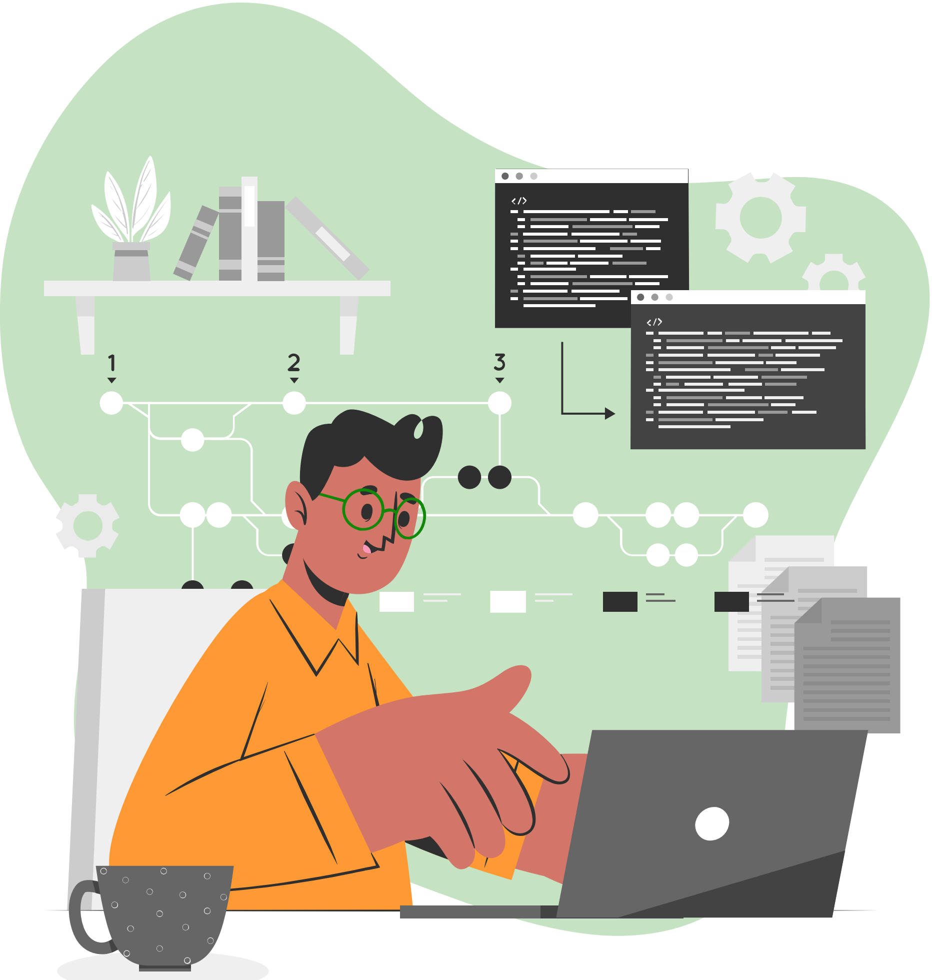


Results - Abnormal Thigh Angular Velocity Estimation

Results - Abnormal Thigh Angular Velocity Estimation (cont.)







05

Conclusion and Future Works

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Conclusion

PROJECT CONCLUSIONS

01	Novelty lies in the unique approach of estimating thigh velocities solely from shank angular velocity data collected using a single IMU sensor
02	Valuable insights into gait injury assessment and rehabilitation by analyzing progression of gait abnormalities and injuries
03	Developed methodology and finding have potential practical applications in various fields

Future Works

01	Further optimization of CNN Model: Fine tune model architecture, exploring different hyperparameters
02	Integration of Additional Sensor Data: Expanding the data set and leveraging multi-sensor techniques to improve reliability and accuracy of joint estimations
03	Real-Time Implementation: This would allow real-time feedback and insights that can be provided to users, facilitating injury prevention

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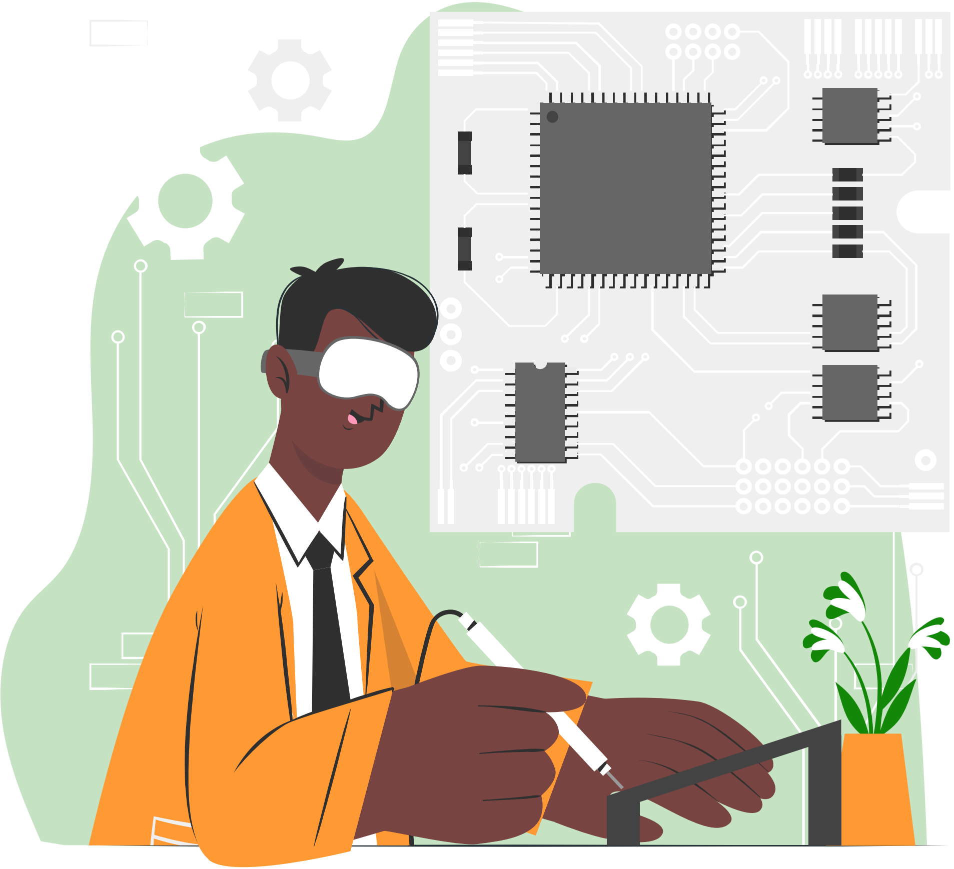

THANKS!

DO YOU HAVE ANY QUESTIONS?

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