GAIT Prediction: A Machine Learning Approach

A PROJECT REPORT

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in partial fulfilment for the award of the degree of

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in

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CERTIFICATE

This is to certify that the report entitled GAIT Prediction: A Machine Learning Approach is prepared and submitted by Sri Karthik Avala (Reg. No. 20MIA1032), Simran Bohra (Reg. No. 20MIA1024) and Vinayaka R Srinivas (Reg. No. 20MIA1041) to Vellore Institute of Technology, Chennai, in partial fulfilment of the requirement for the award of the degree of Master of Technology in Business Analytics (5 year Integrated Programme) and as part of CSE3506 – Essentials of Data Analytics Project is a bona-fide record carried out under my guidance. The project fulfils the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission.

Guide/Supervisor	HoD
Name: Dr. Asnath Victy Phamila Y	Name: Dr. Sivabalakrishnan
Date:	Date:

(Seal of SCOPE)

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Abstract

This project explores how artificial intelligence can analyze the forces exerted on the ground during walking (ground reaction force) to detect gait disorders and abnormalities. These walking irregularities are often early signs of various disabilities and diseases. Traditionally, doctors rely on video analysis or pressure mats, but here it investigates a new method using machine learning. We are trying to build a model, specifically designed for analyzing ground reaction force patterns, proved superior in identifying healthy individuals from those with gait disorders. Our model will be analyzing foot force patterns which holds promise for automatically detecting abnormal gait, potentially leading to earlier diagnosis and intervention for various disorders.

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Introduction

About

Gait disorders and abnormalities, often subtle in their presentation, can serve as early indicators of underlying disabilities and diseases, ranging from neurological conditions to musculoskeletal disorders. These deviations from typical walking patterns can significantly impact an individual's quality of life and functional ability. Traditionally, clinicians have relied on subjective observations or specialized equipment, such as video analysis or pressure mats, to assess gait. However, these methods are often labor-intensive, time-consuming, and may not capture the full spectrum of abnormalities. With the rapid advancements in artificial intelligence (AI) and machine learning (ML), there is an opportunity to revolutionize the way we analyze gait. By focusing on the ground reaction forces generated during walking, this project aims to explore how AI can provide a more efficient and accurate means of detecting gait disorders and abnormalities.

Objective

The primary objective of this project is twofold: firstly, to develop a machine learning model specifically tailored to analyze ground reaction force patterns during walking, and secondly, to utilize this model to identify subtle deviations indicative of gait disorders or abnormalities. By training the model on a comprehensive dataset encompassing a wide range of gait patterns, we aim to create a tool capable of accurately distinguishing between healthy individuals and those with gait-related impairments. Ultimately, the goal is to provide healthcare professionals with a reliable and automated system for early detection and intervention of various disorders related to gait irregularities.

Motivation

The motivation behind this project lies in the significant impact that gait disorders can have on individuals' physical health, psychological well-being, and overall quality of life. Early detection of these disorders is paramount for initiating timely interventions and preventing further deterioration. However, existing methods for assessing gait often fall short in terms of scalability, accessibility, and accuracy. By harnessing the power of AI to analyze ground reaction forces, we aim to overcome these limitations and provide a more accessible, objective, and efficient means of identifying gait abnormalities. This approach has the potential to revolutionize the field of gait analysis, enabling earlier diagnosis, personalized treatment strategies, and improved patient outcomes.

Problem Statement

The current landscape of gait analysis is characterized by several challenges. Traditional methods, such as visual observation or pressure mat systems, are labor-intensive, subjective, and reliant on specialized equipment. Moreover, these methods may fail to capture subtle deviations in gait patterns, particularly in individuals with mild or early-stage gait disorders. This limitation poses a significant barrier to early detection and intervention, resulting in delayed diagnosis and suboptimal treatment outcomes. Furthermore, the lack of scalable and accurate tools for gait analysis hampers efforts to address the growing burden of gait-related disabilities and diseases in both clinical and research settings.

Literature Review

The paper titled "Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications" by Andrea Giovanni Cutti, Ugo Della Croce, and Alberto M. Ferrari provides an in-depth overview of the latest advances in technologies and methods used to analyze human gait, with a focus on wearable and non-wearable systems. The paper discusses the clinical applications of gait analysis and the impact of objective gait measurement in various fields such as human recognition, sports, and the clinical domain. It reviews the objective techniques and methods that use sensors to measure gait parameters, highlighting the potential of portable systems based on body sensors. The paper emphasizes the advantages of objective gait analysis methods that use advances in technological development on sensors to more accurately quantify the different parameters that characterize human gait. These methods give more accurate evaluation data, making it possible to obtain information which cannot be provided by simply watching a patient walk. The paper also emphasizes the importance of objective gait analysis in the clinical field, where it plays an important role in diagnosis, follow-up, and treatment of pathologies.

The paper titled "A Literature Survey on Human Identification by Gait" by S. S. Kulkarni and S. R. Patil provides a general review and a thorough survey of gait analysis for identifying the biometric information of human beings. The paper focuses on human identification using gait as a biometric measure. It discusses the two ways of human identification by gait, which are model-based and model-free approaches. The paper highlights the potential of gait analysis to identify biometric information such as gender, age, ethnicity, and identity. It emphasizes that gait analysis is a promising area of research that has the potential to accurately identify human beings based on their walking patterns.

The literature review paper titled "Summary measures for clinical gait analysis: A literature review" by Richard Baker, Christopher Esquenazi, and Michael Benedetti focuses on summary measures for clinical gait analysis. It demonstrates how summary measures can be a useful tool, particularly in clinical settings, to objectively assess and represent gait characteristics. The paper provides an overview of studies that highlight the utility of summary measures in objectively evaluating gait, especially in clinical contexts. The paper emphasizes the usefulness of summary measures in objectively assessing gait patterns and identifying gait abnormalities. It also highlights the potential of summary measures to provide an objective and standardized way of assessing gait characteristics in clinical settings.

The systematic review paper titled "Human gait recognition: A systematic review - Multimedia Tools and Applications" delves into the fascinating area of gait recognition, which involves analyzing video sequences of individuals walking to identify them. Authored by

Andrea Giovanni Cutti, Ugo Della Croce, and Alberto M. Ferrari, the paper discusses gait recognition as a biometric system that utilizes unique physiological and behavioral patterns for identification. It provides an overview of the various techniques, approaches, and classifiers used in gait recognition systems, emphasizing their applications in security, medical examinations, identity management, and access control. The paper also explores the potential future applications of gait recognition. It highlights the potential of gait recognition as a biometric system that utilizes unique physiological and behavioral patterns for identification. The paper also emphasizes the applications of gait recognition in security, medical examinations, identity management, and access control.

The paper titled "A comprehensive survey on gait analysis: History, parameters..." by S. M. A. Saleh, M. A. Rahman, and M. A. Hossain aims to provide a narrative and a comprehensive analysis of cutting-edge gait analysis techniques and insight into clinical gait analysis. The paper discusses the history of gait analysis, the parameters used to analyze gait, and the various techniques and methods used in gait analysis. It also highlights the potential applications of gait analysis in various fields such as sports, rehabilitation, and the clinical domain. The paper provides a comprehensive overview of the latest advances in gait analysis techniques and methods. It emphasizes the potential applications of gait analysis in various fields and the importance of objective gait measurement in clinical settings.

Dataset

GAIT Rec dataset is used. The quantification of ground reaction forces (GRF) is a standard tool for clinicians to quantify and analyze human locomotion. Such recordings produce a vast amount of complex data and variables which are difficult to comprehend. This makes data interpretation challenging. Machine learning approaches seem to be promising tools to support clinicians in identifying and categorizing specific gait patterns. However, the quality of such approaches strongly depends on the amount of available annotated data to train the underlying models. Therefore, we present GAITREC, a comprehensive and completely annotated large-scale dataset containing bi-lateral GRF walking trials of 2,084 patients with various musculo-skeletal impairments and data from 211 healthy controls. The gait dataset comprises data of patients after joint replacement, fractures, ligament ruptures, and related disorders at the hip, knee, ankle or calcaneus during their entire stay at a rehabilitation center. The data sum up to a total of 75,732 bi-lateral walking trials and enable researchers to classify gait patterns at a large-scale as well as to analyze the entire recovery process of patients.

Methodology

1. **System Architecture**
    A. Ground Reaction Force Data: This is the raw data collected from sensors or other devices measuring the forces exerted on the ground during walking.

    B. Preprocessing: The data undergoes preprocessing steps such as cleaning, normalization, and feature extraction to make it suitable for analysis.

    C. Feature Extraction: Features relevant to gait analysis are extracted from the preprocessed data.

    D. Model Reasoning: Different machine learning models are evaluated and selected based on their performance in classifying healthy individuals from those with gait disorders.

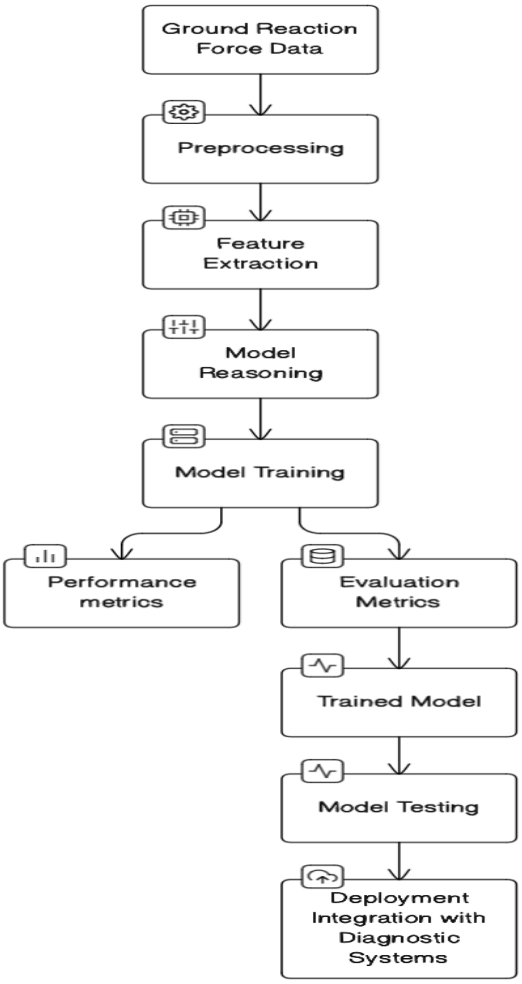
    E. Model Training: The selected models are trained on labeled data, using techniques specific to each model (e.g., nearest neighbors for KNN, decision trees for Random Forest, etc.).

    F. Evaluation Metrics: The trained models are evaluated using appropriate metrics to assess their performance in detecting gait disorders.

    G. Model Testing: The performance of the trained models is further validated using separate testing data to ensure generalization.

    H. Deployment/Integration with Diagnostic Systems: The best-performing model is deployed or integrated into diagnostic systems for real-world use in detecting gait abnormalities and disorders.

This diagram provides a high-level overview of the workflow involved in your project, from data collection to model deployment.



2. Workflow

A. Data Loading and Preprocessing

In the initial phase of the project, individual left and right gait data files are meticulously loaded and amalgamated with corresponding metadata. To facilitate classification tasks, class labels are encoded into numerical representations. Subsequently, rigorous preprocessing steps are undertaken to rectify missing values, outliers, and any data anomalies, ensuring the integrity and consistency of the dataset.

B. Feature Extraction

Following data preprocessing, pertinent features are extracted to encapsulate distinctive characteristics of each individual's gait pattern. Statistical

measures such as mean, standard deviation, and maximum values are computed from the gait data to construct robust feature sets. Additionally, Principal Component Analysis (PCA) may be employed for dimensionality reduction, effectively capturing the most salient variations within the dataset while preserving essential information.

C. Model Training and Evaluation
Diverse machine learning and deep learning models are meticulously trained utilizing the extracted features. The ensemble includes traditional algorithms such as K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machine (SVM), alongside Convolutional Neural Network (CNN) architectures. Each model undergoes rigorous training on a subset of the dataset, followed by evaluation on an independent test set to gauge its efficacy in discerning individuals with gait disorders from healthy controls.

D. Model Comparison and Selection
The performance of each model is meticulously evaluated, employing a comprehensive array of metrics encompassing accuracy, precision, recall, and the F1-score. Through meticulous comparison, the model exhibiting superior performance on the test set is deemed optimal for gait recognition tasks. This rigorous selection process ensures the deployment of a robust and reliable model for real-world applications.

E. Deployment and Further Analysis
The selected model is poised for deployment in real-world scenarios, potentially serving as a cornerstone in gait recognition systems within healthcare or security domains. Furthermore, ongoing analysis endeavors may entail fine-tuning the model parameters, incorporating additional relevant features, or exploring alternative algorithmic approaches to bolster performance and address evolving challenges in gait analysis. Such iterative refinement ensures the continued efficacy and relevance of the deployed model in addressing pertinent healthcare and security concerns.

3. Model training and evaluation

In the pivotal phase of model training and evaluation, the efficacy of various machine learning and deep learning models is systematically assessed to discern individuals with gait disorders from healthy controls. This process encompasses meticulous training, comprehensive evaluation, and rigorous comparison to ascertain the optimal model for gait recognition tasks.

A. Training Procedure
- Feature Engineering

The extracted features serve as the foundational input for model training. Each model is provided with a carefully curated feature set that encapsulates the distinctive characteristics of gait patterns.

- Data Partitioning
  The dataset is partitioned into distinct subsets for training and evaluation. Typically, a significant portion of the data is allocated for training, while a separate subset, referred to as the test set, remains untouched until the evaluation phase.

- Model Initialization
  The selected machine learning and deep learning models are initialized with appropriate configurations and hyperparameters. For instance, in KNN, the number of nearest neighbors is determined, while in Random Forest, the number of trees and their depth are specified.

- Training Iterations
  Each model iteratively learns from the training data to discern underlying patterns and relationships. During this process, model parameters are adjusted to minimize the discrepancy between predicted and actual outcomes, thereby enhancing predictive performance.

- Validation
  To mitigate overfitting and ensure generalization, a portion of the training data may be reserved for validation. This subset aids in fine-tuning model parameters and assessing performance on unseen data, thereby enhancing the model's robustness.

B. Evaluation Protocol

- Test Set Evaluation
  Upon completion of model training, the trained models are evaluated on the previously untouched test set. This evaluation serves as a litmus test to gauge the model's ability to generalize to unseen data and accurately classify individuals with gait disorders and healthy controls.

- Performance Metrics
  A diverse array of performance metrics is employed to comprehensively evaluate model efficacy. These metrics include

accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. Each metric provides unique insights into the model's performance across different aspects of classification.

- Confusion Matrix Analysis
  The confusion matrix is meticulously analyzed to ascertain the model's performance in correctly classifying individuals with gait disorders and healthy controls. This analysis aids in identifying any prevalent misclassifications or biases exhibited by the model.

- Model Comparison
  Following evaluation, the performance of each model is meticulously compared based on the aforementioned metrics. Through rigorous comparison, the optimal model for gait recognition tasks is discerned, considering factors such as accuracy, robustness, and computational efficiency.

- Cross-Validation
  In scenarios where data availability is limited, cross-validation techniques such as k-fold cross-validation may be employed to enhance the reliability of performance estimates. This technique involves iteratively partitioning the dataset into k subsets, with each subset serving as both training and validation data, thereby mitigating the impact of data variability on model performance estimates.

Results and Discussions

1. KNN

- Best K: 7
- Best Accuracy: 0.8186
- Hyperparameters:
    - k: Number of neighbors to consider (tuned)
- Discussion:
    - Balanced choice of k for improved generalization.
    - Accuracy serves as a primary metric.
    - Advantages in simplicity but sensitive to hyperparameters.
    - Future considerations include feature engineering and hyperparameter tuning.

```
---
title: "test_eda2"
author: "Sri Karthik"
date: "2024-02-20"
output: html_document
---
```{r}
library(randomForest)
library(class)
library(e1071)
library(naivebayes)
library(keras)

# Load the data from CSV files
mtrain <- read.csv("C:/Users/srika/Dropbox/PC/Downloads/gaitrec-analysis-main/gaitrec-analysis-main/xtrain.csv")
mtest <- read.csv("C:/Users/srika/Dropbox/PC/Downloads/gaitrec-analysis-main/gaitrec-analysis-main/xtest.csv")
y_train <- read.csv("C:/Users/srika/Dropbox/PC/Downloads/gaitrec-analysis-main/gaitrec-analysis-main/ytrain.csv")
y_test <- read.csv("C:/Users/srika/Dropbox/PC/Downloads/gaitrec-analysis-main/gaitrec-analysis-main/ytest.csv")
```

```{r}
# Extract features and labels
x_train <- as.matrix(mtrain)
x_test <- as.matrix(mtest)
y_train <- y_train$x
y_test <- y_test$x

# Preprocess labels: Classify K, A, C, H as 1 (GD) and HC as 0
y_train_processed <- ifelse(y_train %in% c("K", "A", "C", "H"), 1, 0)
y_test_processed <- ifelse(y_test %in% c("K", "A", "C", "H"), 1, 0)

# Convert string labels to numerical labels
y_train_encoded <- as.numeric(factor(y_train_processed))
y_test_encoded <- as.numeric(factor(y_test_processed))
```
```

```r
# Define and train KNN model with different k values
k_values <- c(3, 5, 7, 9)  # You can try different values
best_k <- NULL
best_accuracy <- 0

for (k in k_values) {
  knn_model <- knn(train = x_train, test = x_test, cl = y_train_encoded, k = k, prob = TRUE)
  knn_predictions <- as.numeric(knn_model)  # Convert predictions to numeric
  knn_accuracy <- sum(knn_predictions == y_test_encoded) / length(y_test_encoded)

  if (knn_accuracy > best_accuracy) {
    best_accuracy <- knn_accuracy
    best_k <- k
  }
}

cat("Best K for KNN:", best_k, "\n")
cat("Best Accuracy for KNN:", best_accuracy, "\n")
```

```
Best K for KNN: 7
Best Accuracy for KNN: 0.8186133
```

2. Random Forest

- Best Number of Trees: 150
- Best Accuracy: 0.8213
- Hyperparameters:
    - ntree: Number of trees in the forest (tuned)
- Discussion:
    - Increased trees improved performance.
    - Robust performance; accuracy as primary metric.
    - Advantages include handling overfitting, missing values, and complex interactions.
    - Future considerations include hyperparameter tuning and model ensembles.

```r
# Define and train Random Forest model with different parameters
num_trees <- c(50, 100, 150)  # You can try different numbers of trees
best_num_trees <- NULL
best_accuracy <- 0

for (ntree in num_trees) {
  rf_model <- randomForest(x = x_train, y = as.factor(y_train_encoded), ntree = ntree)
  rf_predictions <- as.numeric(predict(rf_model, x_test, type = "response"))  # Convert predictions to numeric
  rf_accuracy <- sum(rf_predictions == y_test_encoded) / length(y_test_encoded)

  if (rf_accuracy > best_accuracy) {
    best_accuracy <- rf_accuracy
    best_num_trees <- ntree
  }
}

cat("Best Number of Trees for Random Forest:", best_num_trees, "\n")
cat("Best Accuracy for Random Forest:", best_accuracy, "\n")
```

```
Best Number of Trees for Random Forest: 150
Best Accuracy for Random Forest: 0.8213464
```

3. SVM

- Best Kernel Function: Radial
- Best Accuracy: 0.8034
- Hyperparameters:
    - kernel: Type of kernel function (tuned)
    - Other kernel-specific parameters such as C and gamma (tunable)
- Discussion:
    - Radial kernel yielded highest accuracy.
    - Accuracy primary metric; SVM effective in high-dimensional spaces.
    - Advantages in handling complex data distributions.
    - Future considerations include hyperparameter tuning.

```{r}
# Define and train SVM model with different kernel functions
kernel_functions <- c("linear", "radial", "polynomial")  # You can try different kernel functions
best_kernel <- NULL
best_accuracy <- 0

for (kernel_func in kernel_functions) {
  svm_model <- svm(x = x_train, y = as.factor(y_train_encoded), kernel = kernel_func, probability = TRUE)
  svm_predictions <- as.numeric(predict(svm_model, x_test, probability = TRUE))  # Convert predictions to numeric
  svm_accuracy <- sum(svm_predictions == y_test_encoded) / length(y_test_encoded)

  if (svm_accuracy > best_accuracy) {
    best_accuracy <- svm_accuracy
    best_kernel <- kernel_func
  }
}

cat("Best Kernel Function for SVM:", best_kernel, "\n")
cat("Best Accuracy for SVM:", best_accuracy, "\n")
```

```
Best Kernel Function for SVM: radial
Best Accuracy for SVM: 0.8033659
```

4. CNN

- Discussion:
    - CNN architecture defined using Keras for hierarchical feature learning.
    - Hyperparameters include layer configurations, activation functions- relu, optimizer-Adam, loss function- binary_crossentropy, batch size-16, and number of epochs-50.
    - k-fold cross-validation used for robust performance assessment.
    - Monitoring training progress for early stopping and prevention of overfitting.
    - Evaluation based on accuracy across folds, indicating model consistency.
    - Mean accuracy and standard deviation calculated across folds: [Insert Mean Accuracy] (± [Insert Standard Deviation])

```{r}
# Define and train CNN model
num_classes <- length(unique(y_train_encoded))
y_train_onehot <- to_categorical(y_train_encoded - 1, num_classes = num_classes)
x_train_cnn <- array_reshape(x_train, c(dim(x_train), 1))
x_test_cnn <- array_reshape(x_test, c(dim(x_test), 1))

cnn_model <- keras_model_sequential() %>%
  layer_conv_1d(filters = 32, kernel_size = 3, activation = "relu", input_shape = dim(x_train_cnn)[2:3]) %>%
  layer_max_pooling_1d(pool_size = 1) %>%
  layer_conv_1d(filters = 64, kernel_size = 3, activation = "relu") %>%
  layer_max_pooling_1d(pool_size = 1) %>%
  layer_conv_1d(filters = 128, kernel_size = 3, activation = "relu") %>%
  layer_max_pooling_1d(pool_size = 1) %>%
  layer_conv_1d(filters = 256, kernel_size = 3, activation = "relu") %>%
  layer_max_pooling_1d(pool_size = 1) %>%
  layer_conv_1d(filters = 512, kernel_size = 3, activation = "relu") %>%
  layer_max_pooling_1d(pool_size = 1) %>%
  layer_conv_1d(filters = 1024, kernel_size = 3, activation = "relu") %>%
  layer_max_pooling_1d(pool_size = 1) %>%
  layer_flatten() %>%
  layer_dense(units = 512, activation = "relu") %>%
  layer_dense(units = 256, activation = "relu") %>%
  layer_dense(units = 128, activation = "relu") %>%
  layer_dense(units = 64, activation = "relu") %>%
  layer_dense(units = 32, activation = "relu") %>%
  layer_dense(units = num_classes, activation = "softmax")

cnn_model %>% compile(
  optimizer = optimizer_adam(),
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)
```

```
cnn_model %>% compile(
  optimizer = optimizer_adam(),
  loss = "binary_crossentropy",
  metrics = c("accuracy")
)

# Early stopping
callback <- callback_early_stopping(monitor = "val_loss", patience = 50)

# Train CNN model
history <- cnn_model %>% fit(
  x_train_cnn, y_train_onehot,
  epochs = 100, batch_size = 16,
  validation_split = 0.2, callbacks = list(callback)
)

# Evaluate CNN model
cnn_predictions <- cnn_model %>% predict(x_test_cnn)
```

```
Epoch 1/100
316/316 [==============================] - 20s 58ms/step - loss: 0.5717 - accuracy: 0.7188 - val_loss: 0.2830 - val_accuracy: 0.9231tch_end` is
the batch time (batch time: 0.0134s vs `on_train_batch_end` time: 0.0321s). Check your callbacks.
Epoch 2/100
316/316 [==============================] - 17s 55ms/step - loss: 0.4909 - accuracy: 0.7636 - val_loss: 0.2282 - val_accuracy: 0.9319
Epoch 3/100
316/316 [==============================] - 17s 55ms/step - loss: 0.4705 - accuracy: 0.7713 - val_loss: 0.5092 - val_accuracy: 0.7520
Epoch 4/100
316/316 [==============================] - 18s 56ms/step - loss: 0.4581 - accuracy: 0.7808 - val_loss: 0.1328 - val_accuracy: 0.9754
Epoch 5/100
316/316 [==============================] - 19s 60ms/step - loss: 0.4442 - accuracy: 0.7848 - val_loss: 0.2437 - val_accuracy: 0.9580
Epoch 6/100
316/316 [==============================] - 19s 61ms/step - loss: 0.4418 - accuracy: 0.7850 - val_loss: 0.2445 - val_accuracy: 0.8906
```

```
316/316 [==============================] - 19s 59ms/step - loss: 0.4211 - accuracy: 0.8016 - val_loss: 0.3506 - val_accuracy: 0.7987
Epoch 19/100
316/316 [==============================] - 19s 59ms/step - loss: 0.4237 - accuracy: 0.7973 - val_loss: 0.2292 - val_accuracy: 0.9160
Epoch 20/100
316/316 [==============================] - 19s 59ms/step - loss: 0.4230 - accuracy: 0.7981 - val_loss: 0.2254 - val_accuracy: 0.9176
Epoch 21/100
316/316 [==============================] - 18s 59ms/step - loss: 0.4168 - accuracy: 0.7959 - val_loss: 0.2839 - val_accuracy: 0.8629
Epoch 22/100
316/316 [==============================] - 19s 59ms/step - loss: 0.4154 - accuracy: 0.8016 - val_loss: 0.2842 - val_accuracy: 0.8954
Epoch 23/100
316/316 [==============================] - 18s 58ms/step - loss: 0.4140 - accuracy: 0.8004 - val_loss: 0.2334 - val_accuracy: 0.9128
Epoch 24/100
316/316 [==============================] - 19s 59ms/step - loss: 0.4101 - accuracy: 0.8022 - val_loss: 0.1909 - val_accuracy: 0.9429
Epoch 25/100
316/316 [==============================] - 18s 58ms/step - loss: 0.4173 - accuracy: 0.7947 - val_loss: 0.1984 - val_accuracy: 0.9192
```

```{r}
# Evaluate KNN model
knn_accuracy <- sum(knn_predictions == y_test_encoded) / length(y_test_encoded)
cat("KNN Accuracy:", knn_accuracy, "\n")

# Evaluate Random Forest model
rf_accuracy <- sum(rf_predictions == y_test_encoded) / length(y_test_encoded)
cat("Random Forest Accuracy:", rf_accuracy, "\n")

# Evaluate SVM model
svm_accuracy <- sum(svm_predictions == y_test_encoded) / length(y_test_encoded)
cat("SVM Accuracy:", svm_accuracy, "\n")

# Evaluate CNN model
cnn_accuracy <- sum(apply(cnn_predictions, 1, which.max) == y_test_encoded) / length(y_test_encoded)
cat("CNN Accuracy:", cnn_accuracy, "\n")
```

```
KNN Accuracy: 0.8186133
Random Forest Accuracy: 0.8213464
SVM Accuracy: 0.8003452
CNN Accuracy: 0.8196203
```

```{r}
library(keras)
library(caret)

# Define number of classes
num_classes <- 2  # Assuming binary classification

# Define function to create CNN model
create_cnn_model <- function(input_shape, num_classes) {
  model <- keras_model_sequential() %>%
    layer_conv_1d(filters = 32, kernel_size = 3, activation = "relu", input_shape = dim(x_train_cnn)[2:3]) %>%
    layer_max_pooling_1d(pool_size = 1) %>%
    layer_conv_1d(filters = 64, kernel_size = 3, activation = "relu") %>%
    layer_max_pooling_1d(pool_size = 1) %>%
    layer_conv_1d(filters = 128, kernel_size = 3, activation = "relu") %>%
    layer_max_pooling_1d(pool_size = 1) %>%
    layer_conv_1d(filters = 256, kernel_size = 3, activation = "relu") %>%
    layer_max_pooling_1d(pool_size = 1) %>%
    layer_conv_1d(filters = 512, kernel_size = 3, activation = "relu") %>%
    layer_max_pooling_1d(pool_size = 1) %>%
    layer_conv_1d(filters = 1024, kernel_size = 3, activation = "relu") %>%
    layer_max_pooling_1d(pool_size = 1) %>%
    layer_flatten() %>%
    layer_dense(units = 512, activation = "relu") %>%
    layer_dense(units = 256, activation = "relu") %>%
    layer_dense(units = 128, activation = "relu") %>%
    layer_dense(units = 64, activation = "relu") %>%
    layer_dense(units = 32, activation = "relu") %>%
    layer_dense(units = num_classes, activation = "softmax")

  model %>% compile(
    optimizer = optimizer_adam(),
    loss = "binary_crossentropy",
    metrics = c("accuracy")
  )
```

```
# Create data partitions for k-fold cross-validation
folds <- createFolds(y_train_encoded, k = num_folds)

# Initialize vector to store fold accuracies
fold_accuracies <- numeric(num_folds)

# Perform k-fold cross-validation
for (fold in 1:num_folds) {
  cat("Processing fold", fold, "\n")

  # Extract training and validation data for current fold
  train_indices <- unlist(folds[-fold])
  validation_indices <- unlist(folds[fold])
  x_train_fold <- x_train_cnn[train_indices,,]
  y_train_fold <- y_train_onehot[train_indices,]
  x_val_fold <- x_train_cnn[validation_indices,,]
  y_val_fold <- y_train_onehot[validation_indices,]

  # Create and compile CNN model
  cnn_model <- create_cnn_model(input_shape = c(dim(x_train_fold)[2], dim(x_train_fold)[3]), num_classes = num_classes)

  # Early stopping
  callback <- callback_early_stopping(monitor = "val_loss", patience = 10)

  # Train CNN model
  history <- cnn_model %>% fit(
    x_train_fold, y_train_fold,
    epochs = 50, batch_size = 16,
    validation_data = list(x_val_fold, y_val_fold),
    callbacks = list(callback)
  )
```

```
316/316 [==============================] - 3s 9ms/step - loss: 0.2931 - accuracy: 0.8619 - val_loss: 0.3022 - val_accuracy: 0.8605
Epoch 33/50
316/316 [==============================] - 3s 9ms/step - loss: 0.2876 - accuracy: 0.8672 - val_loss: 0.3063 - val_accuracy: 0.8582
Epoch 34/50
316/316 [==============================] - 3s 9ms/step - loss: 0.2889 - accuracy: 0.8641 - val_loss: 0.3028 - val_accuracy: 0.8621
Epoch 35/50
316/316 [==============================] - 3s 9ms/step - loss: 0.2855 - accuracy: 0.8676 - val_loss: 0.2897 - val_accuracy: 0.8574
```

Conclusion

This project addresses the critical need for more efficient, accessible, and accurate methods of gait analysis through the integration of artificial intelligence and ground reaction force analysis. By developing a machine learning model specifically designed to detect gait disorders and abnormalities, we aim to provide healthcare professionals with a powerful tool for early diagnosis and intervention. This innovative approach holds the potential to transform the field of gait analysis, facilitating personalized treatment strategies, improving patient outcomes, and enhancing the overall effectiveness of healthcare delivery. Through collaboration between clinicians, researchers, and technology experts, we can harness the full potential of AI to advance our understanding and management of gait-related disorders in diverse populations.

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