VR-Induced Balance Monitoring via Tibialis EMG and Ground Reaction Forces Using Machine Learning

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*Abstract*—VR environments like Hyper Dash require dynamic movements to balance the body's posture. The usage of VR has increased by 30% in the past five years in the domain of rehabilitation and motion sciences. Integrating the VR environments with the modalities like EMG, Ground Reaction forces, and Machine learning creates a framework that has a full potential for applications like rehabilitation of strokes and neuromuscular Disorders, Fall risk assessment, and Performance monitoring of athletes and patients. In this study, the EMG from the Tibialis Anterior muscle is acquired, which plays an important role in postural correction and foot clearance during gait, bilaterally, with the acquisition of Ground reaction forces. This offers close insights into pressure shifts, rate of force development, and other features. Asymmetry Index (AI) is a quantitative approach that we have used in our study to observe the difference of performance between two limbs. So, if the AI is ≥ 15% body will be labeled as imbalanced. Supervised Machine learning was employed using the features from the EMG and GRF, and it achieved an F1 score of 97%, an Accuracy of 96% to detect the balanced/Imbalanced state of the body.

Keywords—Neurorehabilitation, Balanced Prediction, Balance Monitoring, GRF Analysis, Asymmetry index

# Introduction

The tibialis anterior muscle plays a vital role in controlling ankle dorsiflexion and keeping us upright. It’s essential for stabilizing our bodies when we’re standing still and during balance tasks, especially when things get a bit dynamic [4], [5]. Thanks to its quick response to swaying and its part in managing lower limb movements, it’s often the focus of surface electromyography (EMG) studies that look at how our muscles behave during balance [5,6].

We utilized the BIOPAC MP36 system to capture muscle activity from both legs while participants engaged in a VR game. The MP36 is a popular choice in biomedical research because it can record various body signals, including EMG (muscle signals) [12,13,14,15], EHG (uterine contraction signals) [11], and EOG (electrical activity of eyes) [16]. It delivers precise and high-quality data, which is crucial for understanding how muscles function during movement. In our study, it enabled us to gather EMG signals from the tibialis anterior muscles, allowing us to explore balance and muscle coordination during both standing and gameplay. When it comes to Virtual Reality (VR), it brings about some pretty significant changes in our senses and cognitive processes. These shifts can lead to changes in how we maintain our posture as our brains deal with conflicting visual and proprioceptive information [7,8]. This kind of destabilization can trigger quick muscle responses, particularly in muscles like the tibialis anterior, which are quite sensitive to shifts in balance. That is why VR serves as a great environment for studying how we adapt our posture. In our study, we recorded EMG signals from both tibialis anterior muscles while participants played a fast-paced VR game called Hyper Dash. Surface electromyography (EMG) was recorded bilaterally from the tibialis anterior muscles using the BIOPAC MP36 acquisition system, sampled at 1000 Hz. Electrodes were placed over the muscle belly, ensuring optimal signal quality and minimal crosstalk [9]. Simultaneously, ground reaction forces were recorded using the Capstone force plate, also sampled at 1000 Hz. Sensor assignments were grouped such that sensors 1 and 4 corresponded to the left leg, while sensors 2 and 3 represented the right. All signal streams were time-synchronized via a shared acquisition clock to preserve temporal alignment between neuromuscular and kinetic events, all while standing on a Capstone force plate. This setup allowed us to gather both neuromuscular and kinetic data.

We broke the signals into 3-second segments and labeled them using an asymmetry index (AI) based on iEMG values. Our main contributions include a synchronized dataset of tibialis anterior EMG and force data collected during VR gameplay. An explanation of balance asymmetry grounded in muscle activation. A lightweight machine-learning model designed for real-time classification of postural states.

# Methodology

## Particpants

In this study, eight healthy adult volunteers, aged between 22 and 30 (including five males and two females), took part after giving their written informed consent. All participants had either normal vision or corrected vision, no known issues with neuromuscular function or balance, and they had previous experience with virtual reality (VR) to help minimize any adaptation bias

## Experimental setup

Surface electromyography (EMG) was recorded bilaterally from the tibialis anterior muscles using the BIOPAC MP36 acquisition system, sampled at 1000 Hz. Electrodes were placed over the muscle belly. Simultaneously, ground reaction forces were recorded using the Capstone force plate, also sampled at 1000 Hz. Sensor assignments were grouped such that sensors 1 and 4 corresponded to the left leg, while sensors 2 and 3 represented the right. All signal streams were time-synchronized via a shared acquisition clock to preserve temporal alignment between neuromuscular and kinetic events. Each volunteer stood on a Capstone force plate while engaging in a continuous 3-minute VR gameplay session of Hyper Dash, a fast-paced, movement-oriented combat game played through the Oculus Quest 2 headset. This game was chosen for its quick and reactive movements, which are known to put the sensory and motor systems that help regulate balance to the test. Below is the Block Diagram of the experimental setup for better understanding:

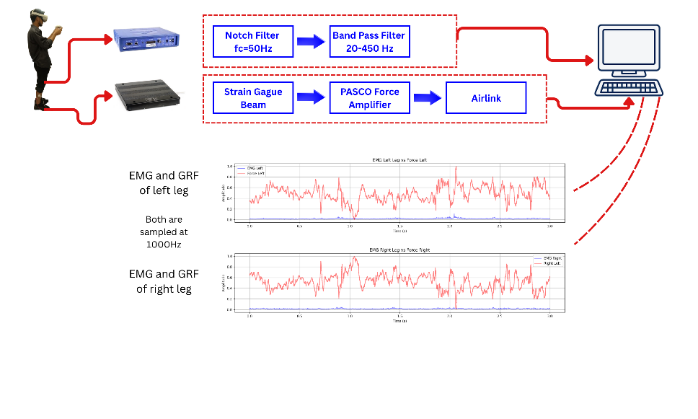


Figure 1:Experimental Setup

## Features

For every 3-second segment, we pulled out a range of physiologically relevant features from both EMG and force plate data to get a clear picture of balance-related neuromuscular and kinetic behavior. These features were carefully selected because of their known importance in controlling posture, detecting asymmetry, and monitoring dynamic stability. The Asymmetry Index (AI) served as our main labeling metric. It shows the percentage difference in iEMG values between the left and right tibialis anterior muscles, calculated like using the equation 1

This metric is commonly used in both clinical and performance environments to identify muscle imbalances during dynamic movements [7], [8]. A threshold of 15% was chosen based on existing literature to differentiate between normal and imbalanced activation patterns [9], [10].

We calculated the Integrated EMG (iEMG) using Equation 2 for both the left and right muscles as the area under the rectified EMG envelope:

This feature reflects the total muscle effort over time and has been linked to fatigue, workload, and compensatory muscle recruitment. Peak Activation, which is the highest rectified EMG amplitude recorded in each time window, was also analyzed. This measurement indicates quick bursts of muscle activation and has been shown to reflect how responsive the neuromuscular system is during balance challenges. The Mathematical Representation of the Peak Activation is given below as equation 3.

We also looked at the Rate of Force Development (RFD) to measure how fast vertical force is produced. RFD is a well-known indicator of explosive force generation and postural responsiveness, which is particularly crucial in situations that require quick motor adjustments, and its formula is given below as equation 4.

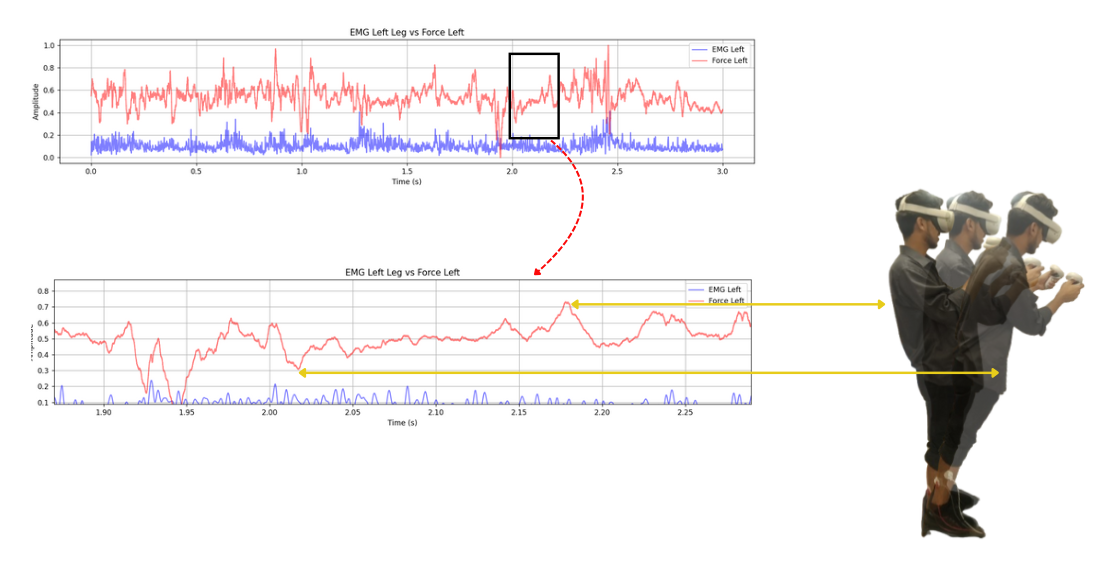


Figure 2: Feature Extraction from the EMG and GRF

## ML Classification

After we pulled features from each 3-second segment, we set up a machine learning pipeline to determine if the subject was in a balanced or imbalanced state. We based the classification label on the Asymmetry Index (AI), which we calculated using the iEMG values from the left and right tibialis anterior muscles. If the AI was under 15%, we labeled the segment as balanced; if it was 15% or higher, it was considered imbalanced. This threshold aligns with previous studies that highlight its significance in identifying postural asymmetry [10]. To create a meaningful input feature vector for each window, we combined both EMG-based features (like iEMG and peak activation) and kinetic features (such as the rate of force development and peak vertical force). This blended approach was chosen to minimize overfitting and enhance the model's generalizability, as research suggests that merging neuromuscular and force-based signals boosts classification robustness. We trained and evaluated several classification models using 10-fold cross-validation. The models we tested included logistic regression, k-nearest neighbors (KNN), support vector machines (SVM), Gaussian Navie Bayes and Linear Discriminant Analysis. In figure 3 the whole architecture of the Machine learning pipeline is illustrated

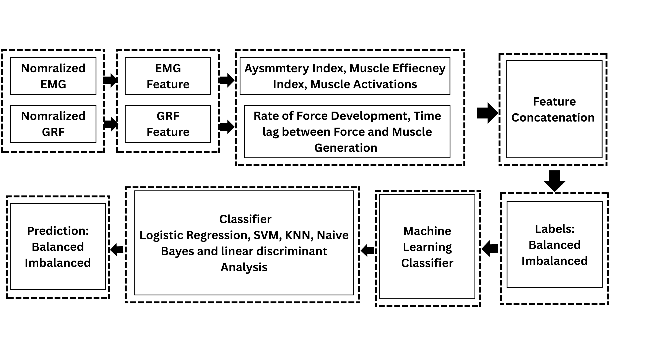


Figure 3: Feature Extraction and Machine Learning Classification

# Results

## Power spectral Analysis of EMG

The analysis of the Power Spectral Density (PSD) for tibialis anterior EMG signals from all seven participants showed a clear and consistent spectral profile across different trials. From figure 4 and Figure 5 we can clearly observe that In every instance, most of the signal power was found in the 30–100 Hz frequency range, with a gradual drop-off beyond 150 Hz.

This pattern is typical of motor unit firing frequencies that occur during postural control and maintaining balance. There was minimal variation in spectral distribution among subjects, which suggests a stable pattern of muscle recruitment while navigating the dynamic balance challenges induced by VR.

The presence of strong low-frequency components across all participants indicates sustained muscle activation during an upright stance, while occasional spikes in high-frequency energy hint at brief reactive activations in response to the challenges presented by VR gameplay. These spectral similarities among participants enhance the reliability of the recorded EMG responses and reinforce the strength of the experimental protocol in capturing consistent neuromuscular signatures during immersive VR-based balance tasks.

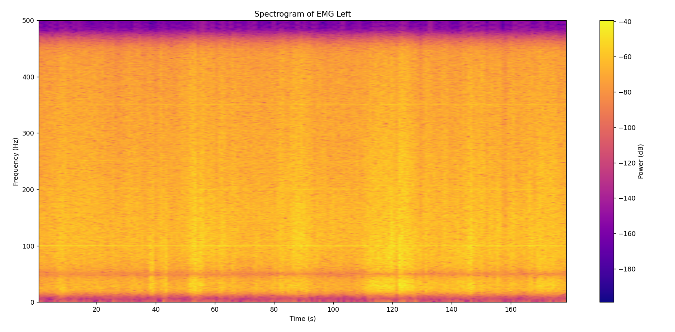


Figure 4:PSD of EMG Left

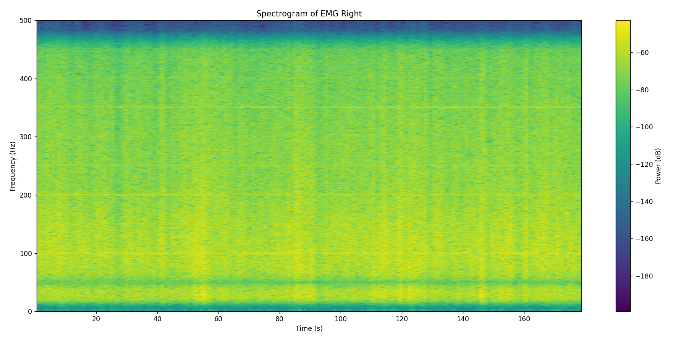


Figure 5: PSD of EMG Right

## Confusion Metrices

Confusion matrix helps us assess how well a classifier is performing by summarizing the comparison between predicted labels and actual labels. In this study, the labels are Balanced and Imbalanced. The diagonal value of the confusion metric indicated the true positives for each class while on the other instance of diagonal are the false negatives in the below figure 6 confusion metrices of multiple Machine learning classifier are illustrated:

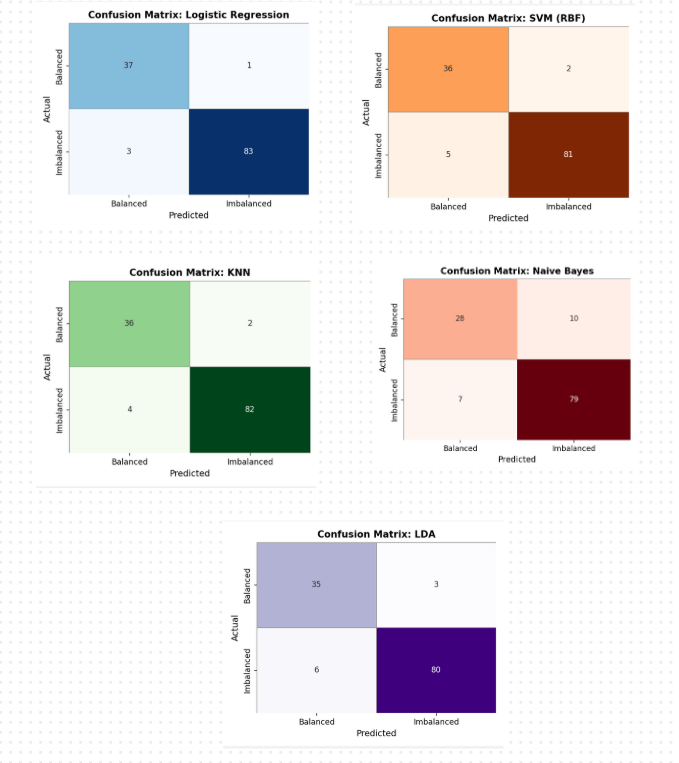


Figure 6: Confusion Metrices

## Performance Metrices

In this analysis, we calculated various evaluation metrics such as accuracy, precision, recall, and the F1 score using the confusion matrices displayed in Figure 7

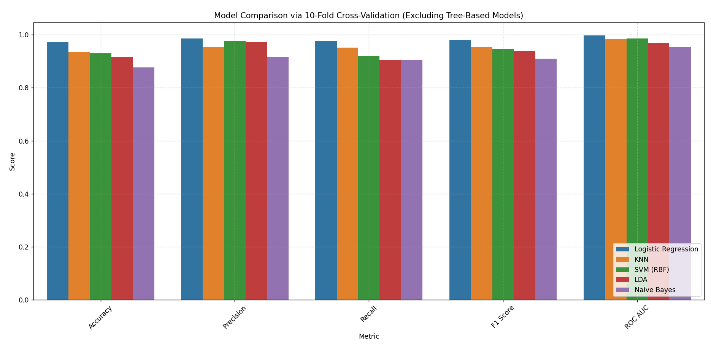


Figure 7:Performance metrices

The top performer of the them is the logistic regressions with an approximately AUC of 0.99 and precision and recall 0.99 and 0.97 respectively. Then comes SVM because it has a slight dip in recall and recall. KNN also perform well but its data driven and its results depend upon the better standard scalar if it is done correctly At the end Navie Bayes and LDA perform similar.

## ROC Curve

All five models showed impressive classification performance, with Logistic Regression taking the lead in terms of accuracy, precision, recall, F1 score, and ROC AUC. SVM (RBF) and LDA also delivered strong results, demonstrating their ability to effectively capture the patterns in the data. KNN maintained consistent performance, while Naive Bayes lagged a bit behind, likely because of its assumption that features are independent. In summary, the models are well-optimized, with Logistic Regression proving to be the best fit for this dataset. Below is the ROC Illustrated in the Figure 8:

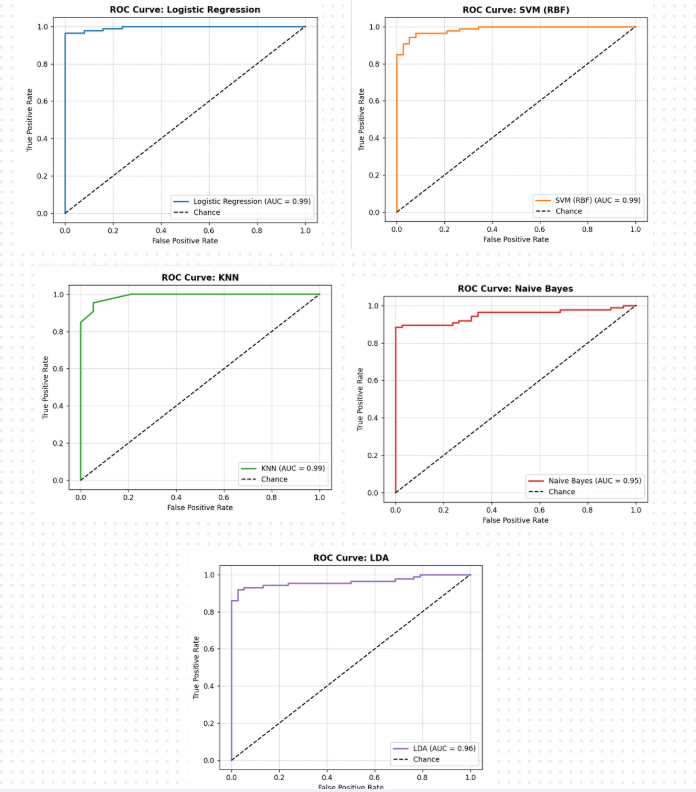


Figure 8: ROC Curves of Models

# Conclusion

In this study, we took a closer look at how muscle activity (EMG) and ground force data work together to help us understand balance during movement, particularly when playing a VR game. By pulling out key features like iEMG, peak activation, and the asymmetry index, we categorized each 3-second segment as either “balanced” or “imbalanced.” We put several machine learning models to the test to see how well they could classify these states, and guess what? Logistic Regression came out on top, hitting an impressive 97% accuracy in 10-fold cross-validation. Not only was it spot-on, but it was also straightforward and dependable, leaving more complex models like decision trees in the dust, which struggled with overfitting. All in all, this research highlights that with clean signal processing and relevant features, we can harness lightweight machine learning to spot balance issues in real time. This opens up exciting possibilities for smarter rehabilitation tools and VR-based motor training.

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