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# Longitudinal Evaluation of Hemiplegic Ankle Rehabilitation Efficacy by Wearable Inertial Sensor Systems with an Assortment of Machine Learning Algorithms

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## ABSTRACT

**With the amalgamation of wearable systems equipped with inertial sensors, such as a gyroscope, and machine learning a therapy regimen can be objectively quantified, and then the initial phase and final phase of a one year therapy regimen can be distinguished through machine learning. In the context of rehabilitation of a hemiplegic ankle, a longitudinal therapy regimen incorporating stretching and then a series of repetitions for raising and lowering the foot of the hemiplegic ankle can be applied over the course of a year. Using a smartphone equipped with an application to function as a wearable and wireless gyroscope platform mounted to the dorsum of the foot by an armband, the initial phase and final phase of a one year longitudinally applied therapy regimen can be objectively quantified and recorded for subsequent machine learning. Considerable classification accuracy is attained to distinguish between the initial phase and final phase by a support vector machine for a one year longitudinally applied hemiplegic ankle therapy regimen based on the gyroscope signal data obtained by a smartphone functioning as a wearable and wireless inertial sensor system.**

## 1. INTRODUCTION

Wearable and wireless systems equipped with internal sensors, such as the gyroscope, are uniquely suited for discerning the efficacy of a therapy regimen for rehabilitation [1-3]. For example, the smartphone with its gyroscope sensor has been demonstrated to objectively quantify the characteristics of a hemiplegic affected ankle relative to the associated unaffected ankle [4]. The dorsiflexion of the ankle can be quantified through the gyroscope internal to the smartphone through an appropriate software application with the smartphone mounted about the dorsum of the ankle by an elastic band. The associated software application can convey the gyroscope signal data as an attachment to an email representing a provisional Cloud computing resource [4-6].

Furthermore, the gyroscope signal data can be post-processed into a feature set for machine learning to distinguish between the hemiplegic affected ankle and unaffected ankle [4, 7]. The application of the smartphone as a wearable and wireless inertial sensor platform in conjunction with machine learning has also been demonstrated to differentiate various knee joint orientations that influence the ability to dorsiflex the ankle and the influence of ankle stretching duration [5, 6]. The implications of these preliminary research achievements suggest that the amalgamation of wearable and wireless inertial sensor systems, such as enabled by the smartphone, and machine learning classification can determine the efficacy of a long-term hemiplegic ankle rehabilitation regimen over a longitudinal span, such as one year.

An advantage of the gyroscope signal acquired through an inertial sensor is the ability to record the quantified data in a manner suitable for historic retention [1-7]. The ramification is the ability to contrast gyroscope signal data regarding ankle dorsiflexion while engaging in a therapy regimen for rehabilitation of the hemiplegic ankle. The gyroscope signal data can then be post-processed to a feature set for machine learning for distinguishing between the initial state of the rehabilitation endeavor and resultant effect in an longitudinal context, such as after one year of conducting the therapy regimen. Also, an assortment of machine learning algorithms are recommended for consideration, in order to determine the machine learning algorithm that provides the best performance, such as in terms of classification accuracy and time to compose the machine learning model. Therefore, the research objective is to ascertain the ability of an assortment of machine learning algorithms to distinguish between the initial phase and final phase after one year of a hemiplegic ankle rehabilitation therapy regimen using the quantified gyroscope signal data acquired through a smartphone functioning as a wearable and wireless inertial sensor system platform.

## 2. BACKGROUND

### 2.1. Significance of Dorsiflexion during Gait

The ability to dorsiflex the ankle serves as an influential role for the quality of gait. The musculature that enables dorsiflexion is the tibialis anterior, and antagonist musculature are the gastrocnemius and soleus. Ankle dorsiflexion facilitates the smooth procedure of gait swing phase while mitigating adverse contact with the ground. Transition to initiating stance phase of gait through preliminary contact of the heel requires sufficient dorsiflexion. Additionally, during a subphase of stance the dorsiflexion musculature undergoes eccentric contraction in order to mitigate foot-slap, which from a long term perspective, can induce morbidities associated with gait [8, 9].

### 2.2. Influence of Hemiparesis on Dorsiflexion and Gait

With respect to hemiparesis the affected ankle displays impairment to the ankle's ability to dorsiflex with the antagonist plantar flexors predominating and even adversely impacting range of motion. Hemiplegic gait characteristically associates with foot drop, which can adversely impact swing phase, the initiation of stance, and the sub-phases of stance [8, 10-15]. The predominance of the plantar flexors can be attenuated through the prescription of an ankle stretching intervention, such as through a wedge board to stretch the plantar flexor musculature [5, 16, 17].

### 2.3. Rehabilitation of the Hemiplegic Affected Ankle

In addition to stretching of the plantar flexor musculature, the strengthening of the dorsiflexion musculature can potentially further benefit the rehabilitation process of the hemiplegic affected ankle. The application of numerous dorsiflexion cycles of the hemiplegic affected ankle promotes a means of strengthening the ankle dorsiflexion musculature [18]. The ability to dorsiflex the ankle, especially with regards to a hemiplegic ankle, is dependent on multiple factors, such as knee joint angle and associated ankle stretching duration [5, 6, 16, 17, 19].

The gastrocnemius, which contributes to plantar flexion, has an origin at the lateral and medial condyles of the femur [9]. The implication is the knee joint angle influences the characteristics of the gastrocnemius, such as the amount of stretch, which impacts the ability to dorsiflex the associated ankle [6, 9, 19]. With respect to the evaluation of hemiplegic ankle rehabilitation in terms of the ability to dorsiflex the hemiplegic affected ankle, a recommendation would be to evaluate the quality of dorsiflexion with the constraint of applying the relatively same knee joint angle. For example, an angle between the femur and tibia, such as 120 degrees, could be applied during the evaluation of the hemiplegic affected ankle dorsiflexion for a longitudinal evaluation of the efficacy of a hemiplegic ankle rehabilitation therapy regimen.

Another variable that influences the ability to dorsiflex the ankle is the duration of stretching the plantar flexor musculature through a wedge board prior to dorsiflexing the ankle [5, 16, 17]. The duration of stretching the ankle has been demonstrated to influence the ability of a hemiplegic ankle to dorsiflex [5]. For example, consistently first stretching the ankle through a wedge board, such as for a 15 minute duration at a 30 degree angle, would likely provide a benefit to rehabilitation of a hemiplegic affected ankle through a series of dorsiflexion cycles as a prescribed therapy regimen.

### 2.4. Wearable and Wireless Systems for Movement Quantification

LeMoyne and Mastroianni have implemented numerous applications for wearable and wireless systems for the domain of healthcare from a proof of concept perspective [1-7, 13, 20, 21]. In particular, many of these applications have featured the smartphone as a wearable and wireless system for the quantification of health status. The smartphone is equipped with an inertial sensor package that consists of an accelerometer and gyroscope. The gyroscope signal data has been deemed as highly representative for clinical purposes, since the gyroscope signal provides a quantified perspective of a joint's rotational attributes [1-7, 20, 21].

Preliminarily, LeMoyne et al. developed an ankle rehabilitation system that relied upon a 3D printed foot plate with a rotational joint connected to 3D printed brackets. A smartphone was mounted to the foot plate to quantify the ability to dorsiflex the ankle. The smartphone was equipped with a software application that enabled the recording of the gyroscope signal. The signal data was then transmitted wirelessly as an email attachment with the email account serving as a provisional Cloud computing resource. The signal data was post-processed for machine learning classification using the Waikato Environment for Knowledge Analysis (WEKA), and considerable classification accuracy was attained [20].

In light of the implications of the preliminary ankle rehabilitation system equipped with a smartphone functioning as a wireless inertial sensor signal platform, notable opportunity for improvement was apparent. The primary issue was 3D printed aspects of the system, which were susceptible to damage. Additionally, the securing of the foot to the 3D printed foot plate was an awkward process, especially in consideration of the risk of breaking the 3D printed foot plate and brackets.

Generally, the smartphone functioning as a wearable and wireless system for the quantification of human movement, such as gait and reflex response, involved mounting the smartphone through an elastic band, such as through a sock [1, 2]. During 2016 LeMoyne and Mastroianni utilized an armband intended for securing the smartphone to the arm for mounting the smartphone as a wearable and wireless inertial sensor system near the wrist for quantifying reduced arm swing for hemiplegic gait [21]. The strategy of using the equivalence of the elastic band for mounting a smartphone through an armband also was demonstrated for the quantification of various dorsiflexion activities regarding the characteristics of ankle dorsiflexion, such as for conditions influencing hemiplegic ankle dorsiflexion and contrast to the associated unaffected ankle [4-6].

### 2.5. Machine Learning in Conjunction with Wearable and Wireless Systems

Machine learning has been demonstrated for the distinction of hemiplegic ankle dorsiflexion relative to the unaffected ankle and also for an assortment of conditions that influence the ability to dorsiflex the hemiplegic affected ankle, such as based on knee joint orientation and ankle stretch duration. These machine learning endeavors featured the smartphone as a functional wearable and wireless inertial sensor platform for quantifying ankle dorsiflexion through the available gyroscope signal [4-6, 20]. The Waikato Environment for Knowledge Analysis (WEKA) provides an assortment of machine learning algorithms:

- K-nearest neighbors
- Random forest
- Support vector machine
- Logistic regression
- Naïve Bayes
- Multilayer perceptron neural network [22-24]

The evaluation of multiple machine learning algorithms is recommended in order to ascertain the performance characteristics of each algorithm. Machine learning algorithm performance can be established in terms of both classification accuracy and time to develop the machine learning model.

## 3. MATERIALS AND METHODS

The research objective was realized through a single subject with chronic hemiparesis from the perspective of engineering proof of concept. The Waikato Environment for Knowledge Analysis (WEKA) served as the machine learning platform to enable the respective machine learning algorithms, and tenfold cross validation was incorporated [22-24]. A long term therapy regimen was applied in a longitudinal one year context. Additionally, an experimental protocol was conducted upon the initial phase and final phase after one year of the longitudinal therapy regimen.

### 3.1. Longitudinal Ankle Rehabilitation Therapy Regimen

A therapy regimen was applied with the desire of improving the functionality of the hemiplegic ankle. The role of first stretching the hemiplegic ankle for an extended duration constitutes a benefit to the kinematic properties of the hemiplegic ankle [5, 16, 17]. Lifting and lowering the ankle multiple times represents a viable therapy strategy [18]. Therefore, the therapy regimen incorporated an extended stretch using a wedge board followed by numerous repetitions of raising and lowering the foot of the hemiplegic ankle, based on the following procedure:

1) Stretch the hemiplegic ankle on a wedge board set to approximately 30 degrees for a duration on the order of a minimum of 15 minutes.

2) From a sitting position raise and lower the foot of the hemiplegic ankle on the order of 1000 times.

### 3.2. Experimental Protocol for Acquiring the Longitudinal Phases of the Therapy Regimen

The experimental protocol obtained gyroscope signal data from the initial phase and final phase after one year of the therapy regimen. The gyroscope signal data was recorded by means of an application for a smartphone equipped with a gyroscope sensor. The gyroscope signal has been demonstrated as highly robust for the acquisition of clinically representative kinematic data for measuring human movement [1-7, 20, 21]. The application recorded the gyroscope signal data at a sampling rate of 100 Hz. The recorded gyroscope signal data was wirelessly transmitted as an email attachment to an email account that represented a provisional Cloud computing resource.

The gyroscope signal data was post-processed to an Attribute-Relation File Format (ARFF) suitable for WEKA by automation software enabled by Python. The Python automation software consolidated the gyroscope signal data to numeric attributes. These five numeric attributes that have been previously applied for machine learning classification of ankle kinematic properties based on inertial sensor data:

- Maximum of the gyroscope signal data
- Minimum of the gyroscope signal data
- Mean of the gyroscope signal data
- Standard deviation of the gyroscope signal data
- Coefficient of variation of the gyroscope signal data [1-7, 20]

A combined total of 60 instances were obtained that encompassed both the initial phase and final phase after one year of the longitudinally applied therapy regimen. The initial phase of the longitudinal study consisted of three days of recording in conjunction with a 10 second window. Likewise, the final phase after one year of the longitudinal study was comprised of three days of recording in conjunction with a 10 second window.

The following experimental protocol was applied for obtaining the kinematic characteristics of the hemiplegic ankle, respective of the initial phase and one year phase of the prescribed therapy regimen:

1) Enclose the smartphone within an armband and secure the armband about the hemiplegic foot in a manner such that the smartphone is positioned about the dorsum of the foot and representative of **Figure 1**.

2) Align the knee joint in a manner such that the angle between the femur and tibia is approximately 120 degrees.

3) Activate the smartphone application in order to record the gyroscope signal.

4) Continually raise and lower the foot of the hemiplegic ankle until the completion of the gyroscope signal recording from the smartphone application.

5) Using the smartphone's wireless connectivity to the Internet, email the gyroscope signal data as an attachment to an email account functioning as a provisional Cloud computing resource.

## 4. RESULTS AND DISCUSSION

The smartphone equipped with an application to serve as a functional wearable and wireless gyroscope platform provides a uniquely suitable system for ascertaining the efficacy of a therapy regimen, such as for the improvement of kinematic characteristics of a hemiplegic ankle [4-6, 20]. Other systems for quantifying the kinematic properties through gyroscope sensor measurement exist, such as a conformal wearable capable of acquiring FDA certified medical grade data. However, the more sophisticated conformal wearable requires a relatively more advanced level of expertise for operation [7]. By contrast, the smartphone application is equipped with a user friendly graphic user interface, which is intuitively logical to operate and readily accessible [1-6, 20, 21].

The post-processing of the gyroscope signal data reveals a notable increase in kinematic range for the hemiplegic ankle with regards to the initial phase compared to the one year phase, for which the rehabilitation

**Figure 1. Illustration of the mounting procedure for the smartphone representing a wearable and wireless gyroscope platform about the dorsum of the foot and supported by an armband.**

therapy regimen has been prescribed. **Figure 2** presents the kinematic conditions of the hemiplegic ankle in the context of the initial phase. After one year of persistent implementation of the prescribed rehabilitation therapy regimen considerable improvement of the kinematic attributes of the hemiplegic ankle are illustrated in **Figure 3**. **Figure 2** and **Figure 3** are perceptibly distinguishable. With the consolidation of the gyroscope signal data to five numeric attributes for an ARFF file, the perceptible distinction of the visualization inferred by **Figure 2** and **Figure 3** can be distilled to machine learning classification accuracy established by numerous instances of the initial phase and one year final phase.

In addition to machine learning classification accuracy, which represents the quantity of correctly classified instances relative to the total number of instances, the time to compose the machine learning model constitutes another significant performance parameter. Machine learning classification accuracy represents the primary performance parameter, and the time to develop the machine learning model serves as the performance parameter of secondary significance. Through WEKA six machine learning algorithms are evaluated in terms of the performance parameters:

- K-nearest neighbors
- Random forest
- Support vector machine
- Logistic regression
- Naïve Bayes
- Multilayer perceptron neural network [22-24]

Prior to full consideration of the machine learning algorithms' performance capability, the multilayer perceptron neural network presents a visualized machine learning algorithm. The multilayer perceptron neural network for this machine learning classification endeavor is featured in **Figure 4**. This multilayer perceptron neural network consists of five input layer nodes based on the five numeric attributes, three hidden layer nodes, and two output layer nodes based on the two respective classes (initial phase and final phase after one year) for the longitudinal study.

The six selected machine learning algorithms are contrasted in terms of their classification accuracy as represented in **Figure 5**. Additionally, the time to compose the machine learning models for the six selected machine learning algorithms are presented in **Figure 6**. Based on consideration of **Figure 5** and **Figure 6** the support vector machine achieves the optimal machine learning classification accuracy with a classification accuracy of 96.7%, and the support vector machine requires 0.04 seconds to be composed. The naïve Bayes is developed in less than 0.01 seconds with a 95% classification accuracy.

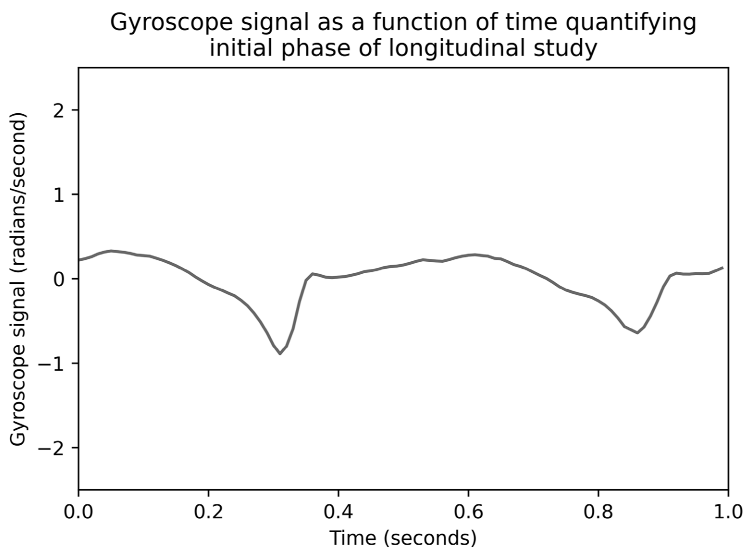


**Figure 2. Initial phase assessment of the kinematic characteristics of the hemiplegic ankle quantified by a smartphone functioning as a wearable and wireless gyroscope platform.**

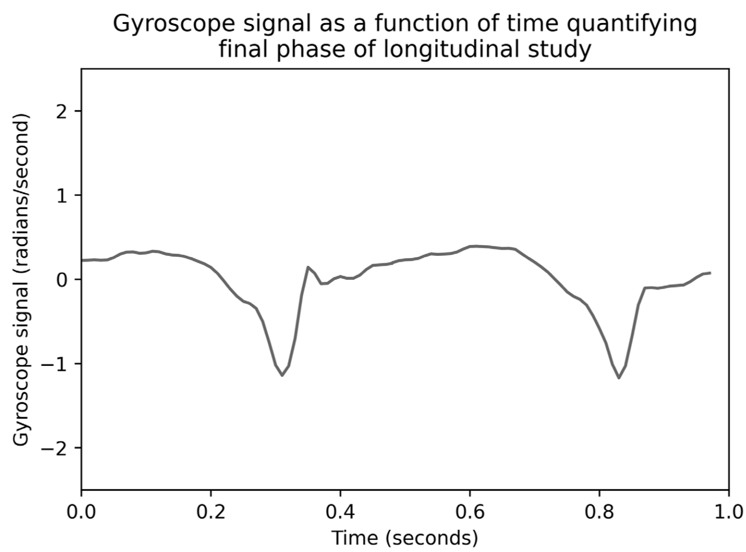


**Figure 3.** One year final phase assessment of the kinematic characteristics of the hemiplegic ankle after a prescribed rehabilitation therapy regimen. The gyroscope signal data is acquired through a smartphone serving as a wearable and wireless gyroscope platform. Note the considerable amplification of gyroscope signal kinematic characteristics subsequent to the one year adherence to the prescribed rehabilitation therapy regimen.

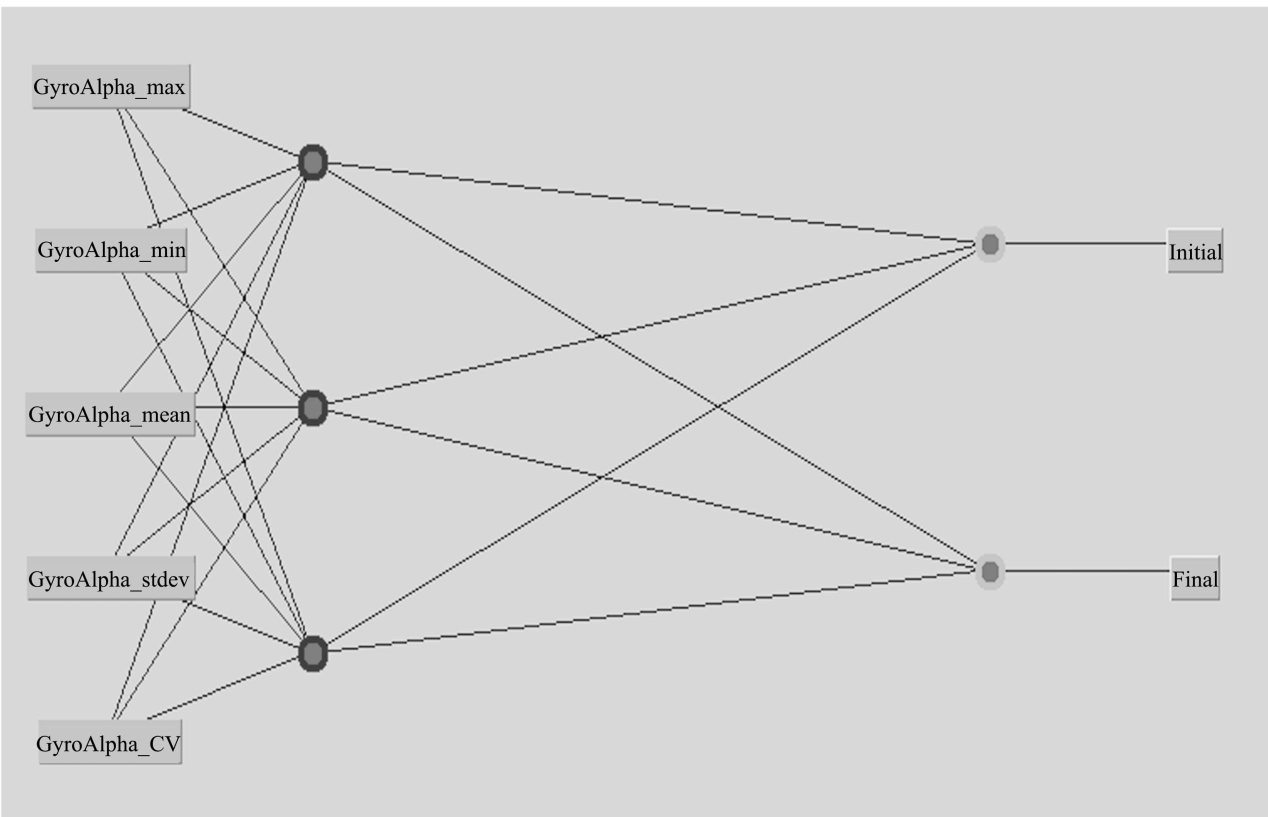


**Figure 4.** Multilayer perceptron neural network for distinguishing between the initial phase and final phase after one year of a longitudinal application of a therapy regimen.

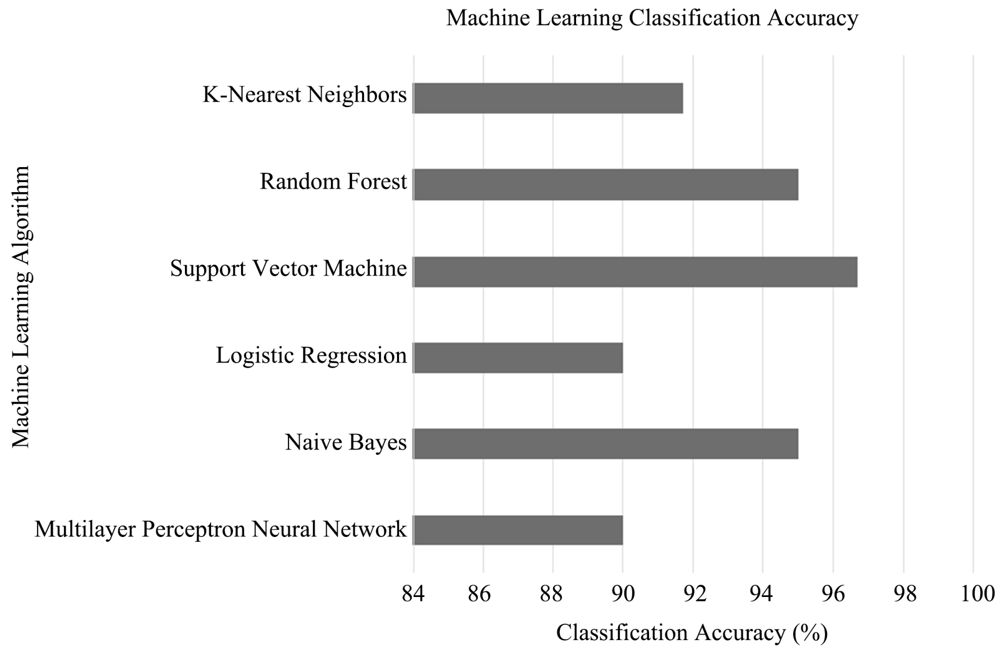


**Figure 5.** **The classification accuracy respective of the six selected machine learning algorithms (K-nearest neighbors, random forest, support vector machine, logistic regression, naïve Bayes, and multilayer perceptron neural network) for the differentiation of the preliminary initial phase and final phase after one year of the longitudinally applied therapy regimen.**

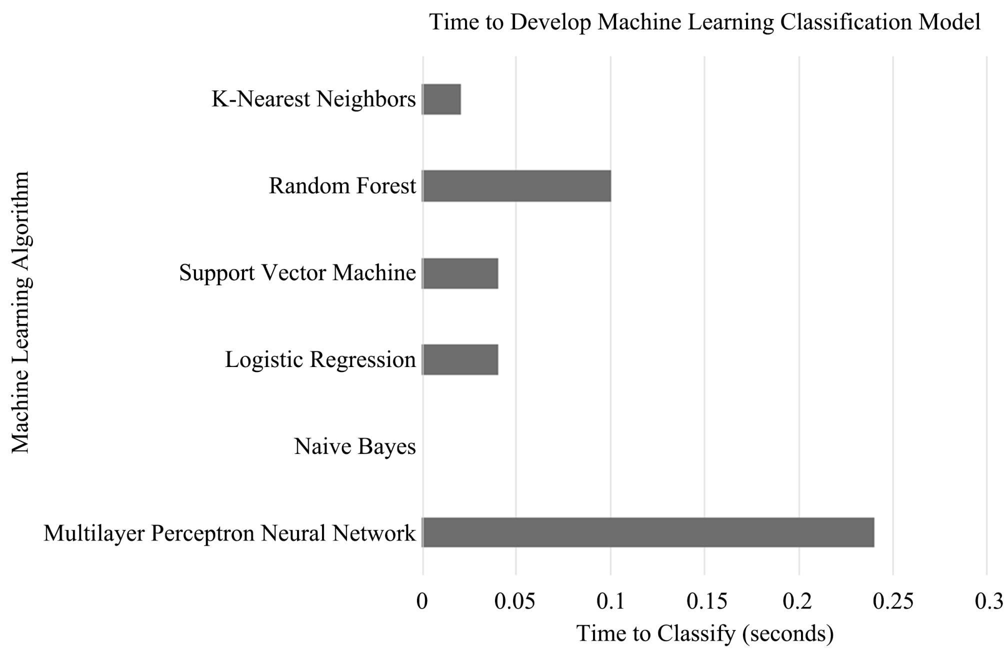


**Figure 6.** **The time to develop the machine learning models respective of the six selected machine learning algorithms (K-nearest neighbors, random forest, support vector machine, logistic regression, naïve Bayes, and multilayer perceptron neural network) for the distinction of the preliminary initial phase and final phase after one year of the longitudinally applied therapy regimen. The naïve Bayes machine learning model is developed within less than 0.01 seconds.**

Based on the prioritization of the performance parameters the support vector machine achieves the optimal overall performance. Depending on whether the machine learning classification is conducted at a Cloud computing environment or in proximity to the sensor level, the significance of the machine learning algorithms time to develop the model and classification accuracy may vary according to system level requirements. For example, with respect to an architecture that features machine learning classification utilizing Cloud computing resources with considerable processing capabilities, classification accuracy predominates the time to develop the machine learning model, for which the support vector machine provides the most preferable machine learning algorithm.

However, there are scenarios that imply restricted processing power requirements. In consideration of limited processing resources proximal to the sensor level, the time to develop the machine learning model constitutes a parameter of increasing significance. In the event of highly limited processing capability the naïve Bayes machine learning algorithm may prove to be more desirable if the associated classification accuracy is deemed sufficient.

Based on the present findings this application of a smartphone as a functional gyroscope platform and machine learning algorithms to ascertain the distinguishable efficacy of a therapy regimen, there are multiple observations for improvement. The application that enables the gyroscope signal recording through the smartphone is a subject of continuous improvement for accommodating the user. Additionally, remote activation of the respective smartphone application, such as through a locally situated tablet, may serve to facilitate the ability of the subject to minimize movement prior to the activation of the respective smartphone application.

Other machine learning algorithms should be considered. For example, deep learning by means of the convolutional neural network, is representative of the visual cortex from a conceptual perspective [25]. Rather than relying on a prescribed feature set consisting of numeric attributes, deep learning utilizes the original signal data, which has been successfully demonstrated for classifying movement disorder status using inertial sensor signal data [25, 26].

## 5. CONCLUSION

In summary, the research achievement advocates the benefit of utilizing wearable and wireless systems, such as enabled by a smartphone, for visualizing inertial sensor signal data in conjunction with machine learning classification. Considerable classification accuracy is attained for distinguishing the initial phase and final phase of a therapy regimen through an assortment of machine learning algorithms. The therapy regimen incorporated a minimum of 15 minutes of stretching the hemiplegic ankle followed by a series of approximately 1000 repetitions of raising and lowering the foot of the hemiplegic ankle. During the initial phase and final phase after a one year longitudinal application of the therapy regimen a smartphone functioning as a wearable and wireless gyroscope platform recorded the ability of the hemiplegic ankle to raise and lower the foot of the hemiplegic ankle for a 10 second window for three days of each phase. The gyroscope signal data was consolidated to a series of numeric attributes for machine learning evaluation. The primary performance parameter was established as the classification accuracy, and the time to develop the machine learning model constituted the secondary performance parameter. The support vector machine was determined to provide the greatest classification accuracy while developing the model within a brisk timeframe. However, naïve Bayes machine learning algorithm displayed the fastest time to compose the machine learning model while achieving sufficient classification accuracy. Additional machine algorithms are warranted for consideration, such as deep learning. These achievements establish a pathway toward the development of patient-specific and optimized rehabilitation.

## CONFLICTS OF INTEREST

The authors declare no conflicts of interest regarding the publication of this paper.

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