Proceedings of the 2023 International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/27/20230164

An AI-based ambulatory ankle brace with wearable sensor used for preventing ankle sprains

Gao Zimu[1,3] and Zheng Xu[2,4,5]

[1]Wuhan San New School, Wuhan, China
[2]Johns Hopkins University, Baltimore, America

[3]ericgaostyau@sina.com
[4]zxu67@jhu.edu

[5]corresponding author

Abstract. Ankle sprain is one of the most common injuries in the game of basketball. The ankle sprain may bring tremendous time and cost loss, and patients with a history of ankle sprain are susceptible to further ankle injuries. This paper proposes an AI-based ambulatory ankle brace with wearable sensors that can be used for ankle-sprain prevention. The equipment consists a sensor, a microcomputer, a Bluetooth module, and a muscle stimulator. Ten volunteers performed twelve basketball moves with the ankle brace on, and the twelve basketball moves were labeled as high-risk and low-risk. The sensor on the ankle brace measured the 3-dimensional angular velocity and angular displacement of the subject's ankle in real-time, and the data were then fed to different machine learning algorithms to create models to predict future ankle motions. The model with the best performance created by the Random Forest algorithm was imported into the microcomputer. Once the model predicts a high-risk move, the microcomputer sends a Bluetooth signal to the muscle stimulator. The one end of the stimulator is a pair of electrodes attached to the peroneal muscles to restrict ankle motion. When the stimulator receives the "high-risk" signal, it's activated and the spraining motion would be alleviated. In this way, the ankle brace doesn't restrict normal ankle movement while providing adequate protection for potential ankle sprain cases.

Keywords: Ankle-Sprain Prevention, Machine Learning, Wearable Sensor, Muscle Stimulator.

1. Introduction

Ankle sprain increases the risk of further ankle injuries. It's been reported that most patients who experienced ankle sprain are vulnerable to further ankle injuries [1], which can be described as "chronic ankle instability" (CAI). A previous study indicated that 28% of ankle sprain cases sustained during basketball were recurrent and 60 % of participants reporting an ankle sprain had sprained ankles more than once [2], which can be described as the symptoms of CAI. What's more, the CAI is related to the instability of peroneal muscles [3] that control the ankle motion.

Besides harming patients' physical health, ankle sprains may bring tremendous cost loss. Although more validated and comprehensive estimations on ankle sprain's societal cost have to be made, previous studies showed that the social cost of ankle sprains in a population of British emergency department patients is £940 per case [4]. In the Netherlands, the costs of ankle sprain presenting at an ED are calculated to be €823 from when the ankle sprain occurs to the moment it recovers [5].

Ankle sprains have various effects on sporting populations as well. The ankle sprain is one of the most common injuries in indoor and court sports [6]. Even in the professional context, ankle sprains affect approximately 26% of NBA players on average each season and account for a large number of missed NBA games in aggregate. In some cases of high ankle sprain, players even missed 16 NBA games and took up to 37 days to recover from the injuries [7]. The games missed become especially crucial concerning the "playoffs" in NBA, where 16 teams strive for the final championship. If the most skillful player suffers a severe ankle sprain in the playoffs, his team is likely to miss the championship. Therefore, minimizing the risk of ankle sprains increases the chance for teams to win the championship.

From direct (lateral ankle sprain) to indirect damage (chronic ankle instability), and from short-term (medical spending) to long-term cost (the loss of working time), ankle sprain has significant effect. To prevent these negative effects, researchers have found many ways to detect or protect people from such injuries. The identification and detection of ankle sprains have been explored much, and multifunctional sensors are used as a tool. Pressure sensors have been used on three crucial positions of the sole to detect the ankle sprain [8]. Some other researchers have used eight motion sensors with a tri-axial accelerometer and gyroscope to collect angle data to train a support vector machine for the identification of ankle sprains, and the angle sensor on the ankle that produces the highest signal strength is the one on the medial calcaneus [9].

To prevent ankle sprains, prophylactic equipment is recommended, because participants with a history of an ankle sprain are less likely to suffer ankle sprain again with such protection [10]. From the research, extra protection can make up for the instability (such as CAI) caused by previous injuries, and these protections include ankle braces, fibular re-position tape, and ankle taping. Other than passive protections, active corrections are also explored. A semi-rigid brace can turn rigid immediately when it’s stimulated, and thus reducing the angular velocity and controlling the angle of the ankle [11]. Another study utilized myoelectric stimulation for peroneal muscles to react to protect the ankle [12]. However, in previous ankle sprain prevention devices, models and thresholds for predicting sprains were largely empirically established, which made sprain predictions occasionally misjudged. This study established a threshold to identify ankle sprains, and its method of using myoelectric stimulation for peroneal muscle is eligible because the muscle can be stimulated to react faster (about 25ms) to prevent ankle sprain (usually occurs in 50ms). Most methods of muscle stimulation take about 60ms.

The objective of this study is to invent an AI-based ambulatory ankle brace for ankle sprain prevention. A sensor with an accelerometer and gyroscope is used on the medial calcaneus of the foot to monitor the user’s ankle movement. The data collected by the sensor is sent to cellphones through Bluetooth and is recorded. Then the data sets are fed to machine learning algorithms to create predictive models that can identify the risk level of different basketball moves with respect to ankle sprain injuries. The best-performed model is integrated to the micro-controller program. If the model identifies high-risk cases, it sends a message through the Bluetooth module to activate TenS (Transcutaneous Electrical Nerve Stimulator) stimulator. The TenS stimulator attached on the peroneal muscle emits neuro-muscular electrical stimulation that stimulates the muscles to contract to resist the sprain. Altogether, an ankle brace with both detective and protective functions is developed. Models predicted by machine learning methods have many advantages over ones derived from empirical modeling. For example, the prediction model is more accurate with the support of a large amount of data. The data is continuously recorded and imported, and the model will be optimized to be more accurate. The accuracy of the model will make the prediction of ankle sprain more accurate and prevent misjudgement.

DOI: 10.54254/2755-2721/27/20230164

2. Method

2.1. Characteristics of Hardware

The ankle brace consists of five essential parts (as Figure 1. shown): A Micro- Electro- Mechanic System (MEMS) sensor, Bluetooth modules, a single-chip microcomputer, a power source, and a muscle stimulator.

1) The sensor is a JY-61 sensor with a 3-axial gyroscope and 3-axial accelerometer that was developed based on Micro-Electro-Mechanic System (Wit-Motion, Shenzhen, China).

2) Bluetooth modules are HC-06 with a working frequency of 2.4GHZ.

3) For the single-chip microcomputer, Nano V3.0 ATMEGA168P is used. ATMEGA168P is a low-power CMOS8 - bit microcontroller based on AVR. It has an enhanced RISC architecture. By executing powerful instructions in a single clock cycle, throughput close to MHz1MIPS is achieved, allowing system designers to optimize power consumption and processing speed. The AVR kernel combines a rich instruction set with 32 general-purpose working registers. All 32 registers are directly connected to the Arithmetic Logic Unit (ALU), allowing access to two independent registers in a single instruction executed in a clock cycle. The resulting architecture achieves throughput up to ten times faster than traditional CISC microcontrollers while achieving higher code efficiency. The AI algorithm requires high computational power, and this MCU supports the operational computational power requirements of the AI algorithm.

4) The power of the device is provided by Philips battery with a voltage of 9V.

5) The muscle stimulator is the TenS, a neuro-muscular electrical stimulation that stimulates a group of muscles to make them contract using the current at the frequency of 20-50Hz.

2.2. Arrangement of Hardware

The JY-61 sensor and the Bluetooth module are connected to the microcomputer with a movable power source. The sensor collects and sends the data at a frequency of 15 Hz, then the data are sent through the Bluetooth to experimenter's mobile phone.

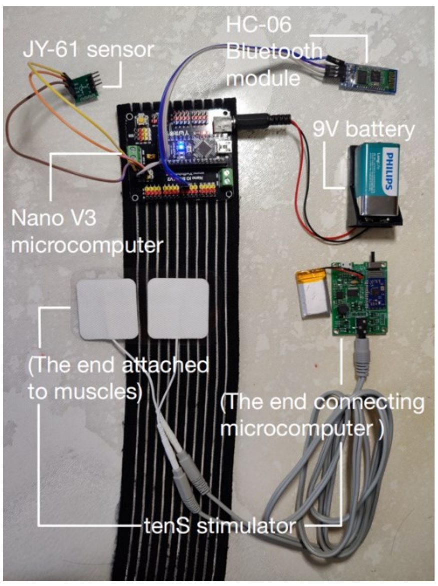


Figure 1. The components of the device

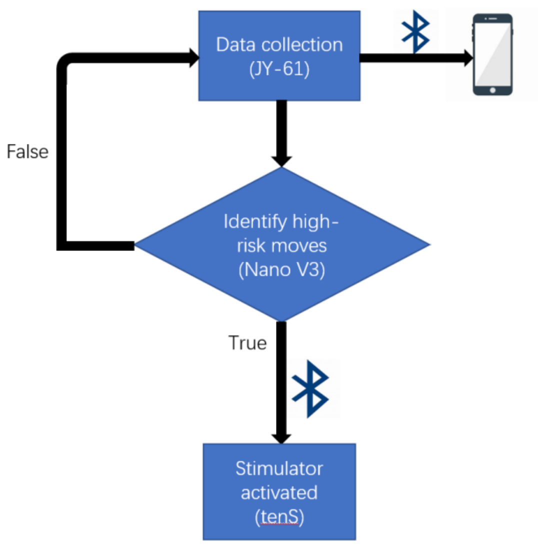


Figure 2. The flow chart of the device

The JY-61 sensor is located on the medial calcaneus of the foot. According to previous research on the signal strength of the sensors on different locations of the foot, the sensor on medial calcaneus had the highest signal strength [9]. The one end of the TenS stimulator is attached to the peroneal muscles for effective muscle stimulation [7].

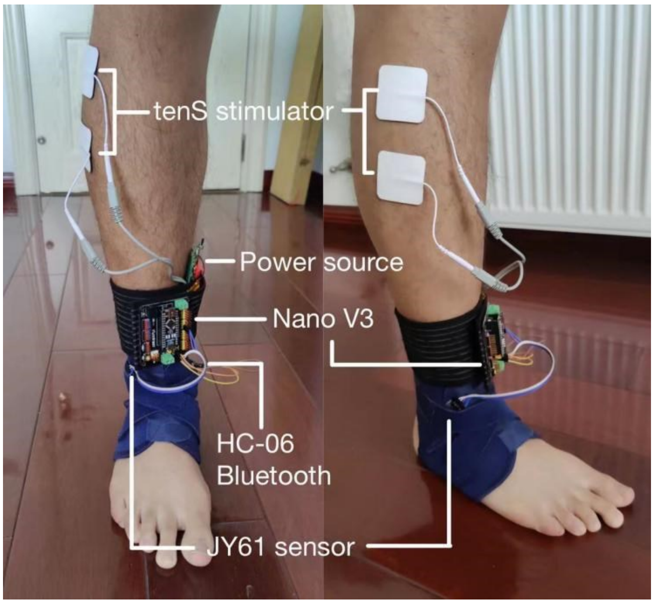


Figure 3. The arrangement of the hardware

2.3. Subjects

Ten male high school students (age = 16yrs, height = 178.8cm, body mass = 74.96kg) were recruited. All of them have some experience of basketball playing. All the subjects were provided with project protocols before the experiment, and the experimenter received all of their consent.

2.4. Experiment design

Ten volunteers were assigned to perform twelve basketball movements in total, each for ten times. The basketball moves were separated based on the categories of "finishing" (6 moves) and "dribbling" (6 moves), and each move has been previously labeled with "high risk" or "low risk".

2.4.1. List of basketball moves

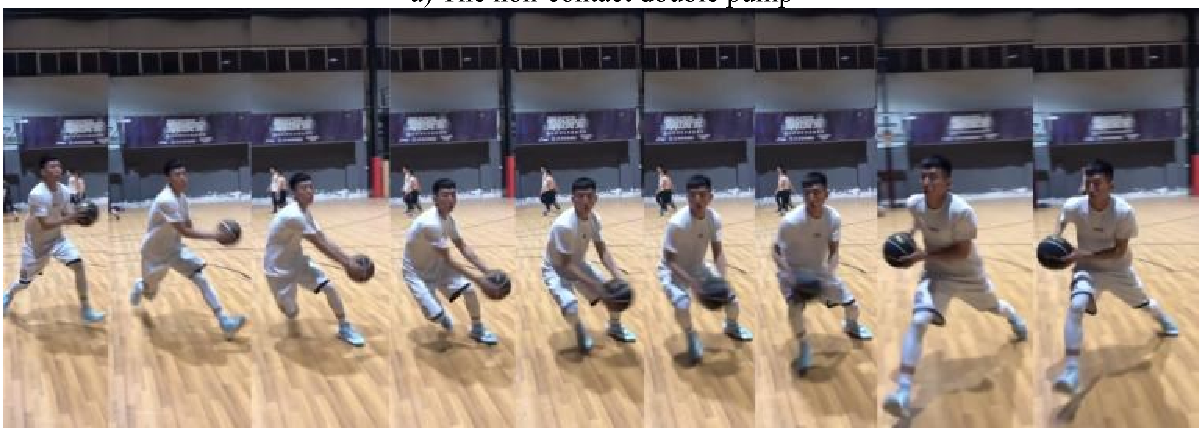
The list and risk level of the basketball moves was concluded based on the empirical evidence given by my varsity team basketball coach and teammates.

Table 1. The list of basketball moves

	High-risk	**Low-risk**
Finishing	Non-contact double pump	Floater
	Euro step	Finger roll
	Fade-away shot	Reverse Layup
Dribbling	Shot fake and drop pivot	Drag Step
	Hang leg and go	Post Spin
	Drop and go	Under drag

DOI: 10.54254/2755-2721/27/20230164

a) The non-contact double pump



b) The euro step

c) The fade-away shot

d) The floater

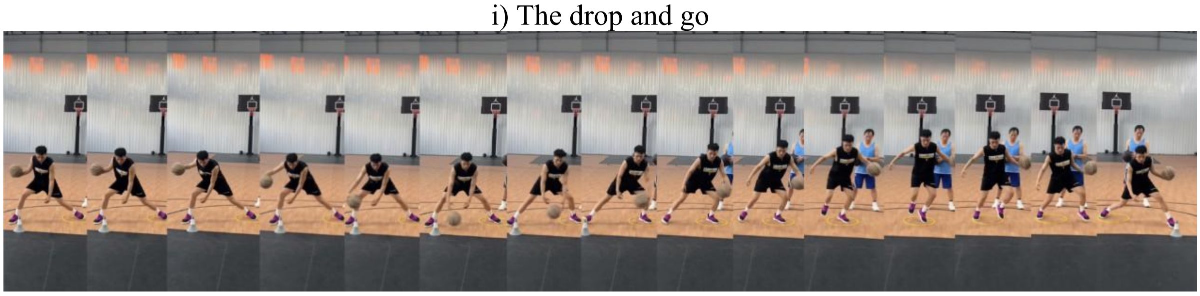
e) The finger roll


f) The reverse layup

g) The shot fake and drop pivot

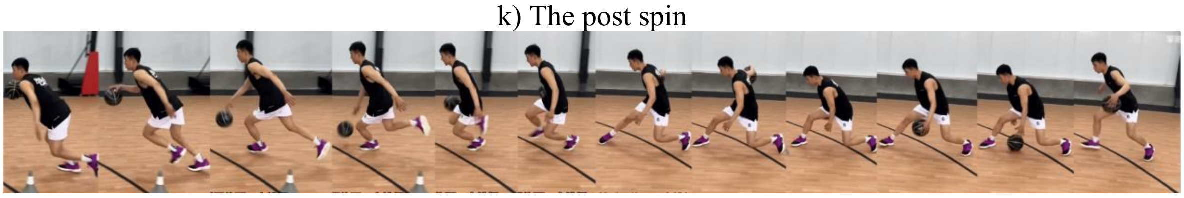
h) The hang leg and go

i) The drop and go



j) The drag step

k) The post spin



l) The under drag

Figure 4. The basketball move

2.4.2. Experimental Procedure

Participants were instructed to review certain moves from the instructive videos I selected on Bilibili video website. After 5 minutes of learning time, they put on the ambulatory ankle brace. Before they

DOI: 10.54254/2755-2721/27/20230164

started performing, a research staff with knowledge of the motion sensor checked the stability of the equipment and the accuracy of the sensor while the participant kept still. Then each volunteer followed the instructions to start performing. Each move needed to be performed 10 times, and there were 10 seconds for static poses between each move in order to distinguish the trials. Between each move (10 trials for each), the participant was allowed to take 3-minute rest to have better performance.

2.5. Data Processing

2.5.1. Data Extraction

HC-06 Bluetooth module sent data continuously without any pause, so I extracted the data representing the volunteer's moving status from those representing static pose based on the dynamic changes in x-axis gyroscope. According to the examination, a change that exceeds a value of 20 in x-axis gyroscope (unitless) represents the start of one move.

2.5.2. Data Feature

The three-dimension angular velocity and angular displacement are converted into one-dimensional vectors using the two equations below.

$$\|\theta\| = \sqrt{\theta_x^2 + \theta_y^2 + \theta_z^2} \tag{1}$$

$$a_{total} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{2}$$

Then I calculated the minimum, median, mean, standard deviation, and maximum of each angular velocity and displacement vector. The skewness and kurtosis are also represented by unitless values. Skewness is a statistical term used to estimate the shape of the data distribution: if the value > 0, then there's more weight in the left tail of the distribution; if the value < 0, then there's more weight in the right tail of the distribution. Kurtosis is a statistical term used to estimate the shape of the data distribution, for distribution with kurtosis value < 3, it is platykurtic; for distribution with kurtosis value > 3, it is leptokurtic.

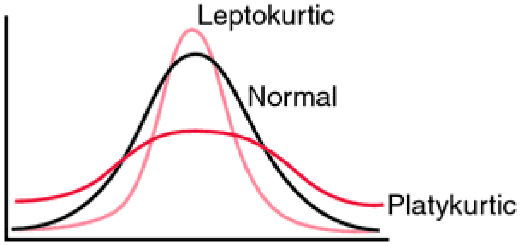


Figure 5. The kurtosis of a distribution.
(The Free Dictionary, https://medical-dictionary.thefreedictionary.com/Platykurtic+distribution)

2.5.3. Data Importing

Two lists were imported to the training model: X is the list of data features, and Y is a list of the risk level. The dimension of X is 1200*64, where 1200 means that 12 volunteers are performing 10 moves, each for 10 times (12*10*10 moves); where 64 means that for each time of the move, there are 64 features in total, including mean, standard deviation, minimum, median, maximum, skewness, kurtosis, and interval (8 features) under 8 categories: angular velocity in , , dimensions; net angular velocity; angular displacement in , , dimensions; and net angular displacement (8*8 features).

In the list Y, high-risk basketball moves were labeled with 1, and low-risk moves were labeled with 0.

Then, the "train_test_split" function was used to randomly split the whole data sets into training and testing sets. The testing size was set as 0.2.

DOI: 10.54254/2755-2721/27/20230164

2.5.4. Data Standardization

Data standardization is a common requirement for many machine learning estimators, and it can unify different data into a standard format. It requires removing the mean and scaling to unit variance by using the following equation:

$$z = (x - u)/s \tag{3}$$

The z, x, u, and s represent: standard score (-score), one feature in the sample, the mean of the sample, and the standard deviation of the sample. Initially, the training set was assigned as the object of the function StandardScaler(), and then I used fit_transform() to transform and standardize both the training and testing set.

2.6. Machine Learning

To distinguish between high-risk and low-risk basketball moves, three different machine learning algorithms were used to create models. After I created models with the training set, the testing set was used to evaluate the performance of the models for later comparison. Therefore, the relatively most effective model for my classification problem was found. The workflow is as presented:

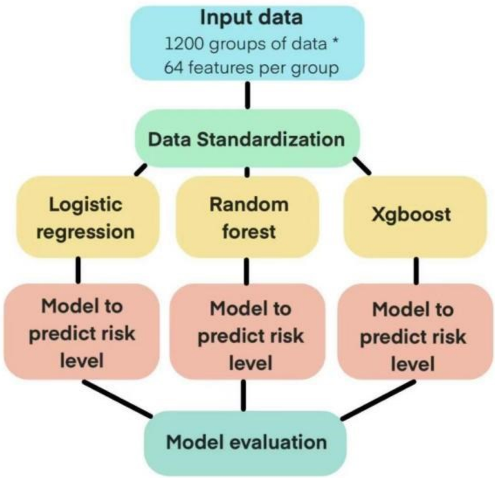


Figure 6. The workflow of machine learning

2.6.1. Algorithm 1: Logistic Regression

Logistic regression is a supervised machine learning algorithm, and it's also a discriminative model that can be used for classification problems. It allows the analysis of "dichotomous or binary outcomes with 2 mutually exclusive levels" [13], such as the "low-risk" and "high-risk" in my case.

I imported Logistic Regression from Scikit-learn in python and created a model using the training set.

2.6.2. Algorithm 2: Random Forest

Random forest is a supervised machine learning algorithm, which means that my final model is created by a training dataset with certain labels. The model would learn from the training set and its label in order to predict future data [14]. Random forest is an ensemble composed of multiple decision trees, and the tree resembles a flow chart with multiple conditions and two pathways ("yes" or "no"), working based on the if-then-else rule. The decision trees in random forest are trained with the "bagging" method, which reduces the variance (an error that makes the model too sensitive to noise) in high variance algorithms like decision tree.

Each tree would generate one result, and finally, the algorithm would identify the most frequent classification result of the decision tree as the final result.

DOI: 10.54254/2755-2721/27/20230164

2.6.3. Algorithm 3: Xgboost

Xgboost is a scalable extreme gradient boosting method that's widely used by data scientists to provide state-of-the-art data [15]. Similar to random forest, Xgboost is also a decision tree ensemble algorithm, but the difference is how trees are built and combined.

2.7. Reporting the Risk Level

The best performed model is integrated into our programs using python and arduino software.

The python program is run on our laptop computer. After the model is integrated, two sets of demo data from high-risk and low-risk movements are imported to python program.

```
import pickle
import arduino as ad

class InferModel:
    def _init__ (self, modelpath) -> None:
        with open (modelpath,'rb') as f:
            self.model = pickle.load(f)

    def _call__(self, x): # input feature vec (64 dim)
        return self.model.predict([x])[0]

model = InferModel('xgboost.pickle')

ft= [...]

pred = model(ft)
print ("Example Inference Result", pred)
if pred == 1:
    ad.send ()
    print ("Send Successful")
```

Code 1. The python program to predict risk level

Then, the feedback is given by the model (either 1--high risk or 0--low risk). The feedback then is sent to the program in microcomputer through a serial port on our laptop computer. For example, we imported a set of high-risk data to the program, and the feedback is 1.

```
ft = [
-4.21183964e-01, -2.92254596e-01, -3.61373781e-01, -7.14758151e-01,
-2.95741776e-01, 2.10886238e-01,-2.94568382e-02, -2.95098118e-01,
-2.06365545e-01, -2.74776626e-01, -3.06229614e-01, -6.63539259e-01,
-2.85071745e-01, -4.53816739e-01,-5.17750683e-01,-2.84379986e-01,
-8.64288705e-01, -7.79292175e-01, -6.58738635e-01, -6.68080604e-01,
-7.86009976e-01, -1.44810241e+00, -1.21554917e+00, -7.84892463e-01,
-6.86568877e-01, -5.56898237e-01, -6.52132233e-01, - 7.60023046e-01,
-5.28906452e-01, 5.04208689e-02, -1.10762002e-01, -5.26353400e-01,
1.21780330e-01, 6.32385322e-01, -2.60825450e-01, 1.17822401e-01,
1.14078319e+00, 7.94703630e-01, 9.46204842e-01, 1.18644610e+00,
2.59940082e-01, 7.65598918e-01, 3.50757930e-01, 3.02984285e-03,
4.04547735e+00, 2.17411034e+00, 1.81705281e+00, 1.68965612e+00,
8.87488527e-01, 8.90971179e-01, -4.61055725e-01, 8.78987883e-01,
1.02977772e+00, -1.96255930e+00, 2.36158581e+00, 1.73683620e+00,
8.83706733e-01, 1.41991653e-01, 9.71442675e-01, 7.00592183e-01,
1.81439895e+00, 1.78045792e+00, 2.54400535e+00, 6.73957938e-01,]
```

Code 2. The imported high-risk dataset

DOI: 10.54254/2755-2721/27/20230164

C: \Users \86188\anaconda3\python.exe "D: \ERIC GAO\Sports Rehab\semi-final\Code\inference.py"
Example Inference Result 1

Code 3. Successful program output: 1 for high-risk case

Then, an arduino program is uploaded to Nano V3 microcomputer, where the LED lights on the microcomputer is turned on if it receives the signal of 1, staying off when it receives the signal of 0 or no signal. Ideally, the signal is sent to activate TenS stimulator. In our sutdy, we used the LED light as an indicator of whether the TenS stimulator can receive the message reporting high risk level and activates to work.

3. Results

3.1. The Performance of Models

Statistically, we test the performance of our device by running the performance test to different models. In this way we can tell which model is best at predicting the risk level of ankle sprain and to what extent it can give correct feedback.

Table 2. Performance evaluation values

	AUC	Accuracy	Recall	Precision	F1-Score
Random Forest	0.828	0.723	0.689	0.739	0.713
Logistic Regression	0.727	0.668	0.664	0.669	0.667
Xgboost	0.818	0.718	0.714	0.720	0.717

The testing set of ankle data was applied to performance evaluation, and five performance evaluation values shown in Table 2 were given. The label of data is either positive (high-risk) or negative (low-risk). All values below were calculated using the elements from the confusion matrix.

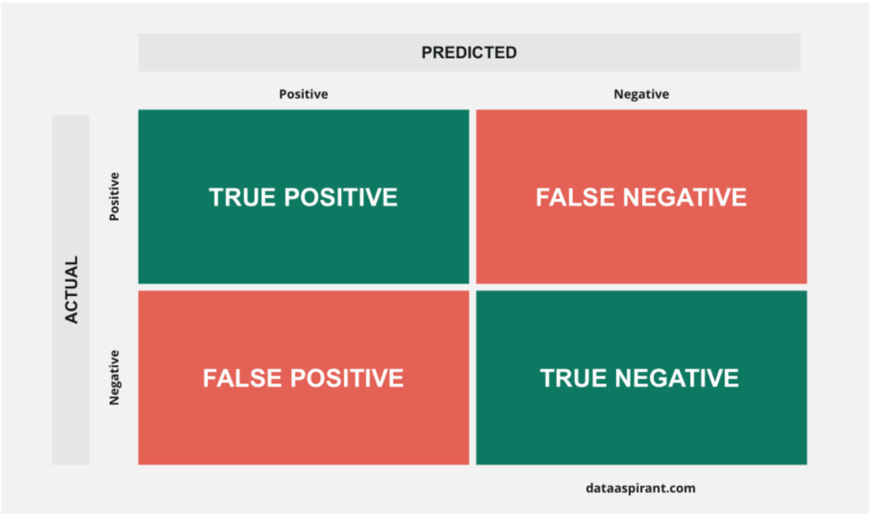


Figure 7. Confusion matrix. (Confusion matrix, https://dataaspirant.com/3_confusion_matrix/)

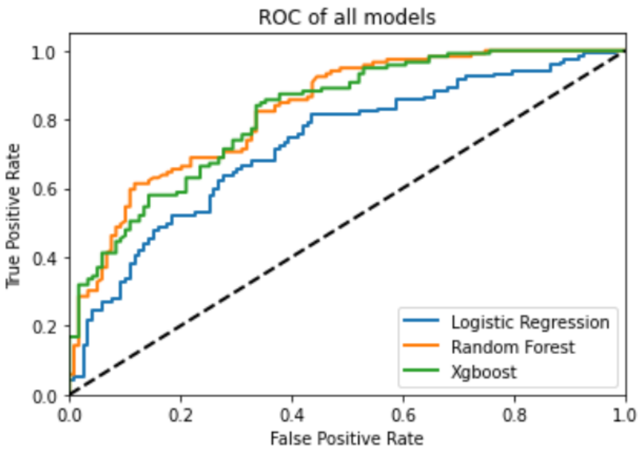


Figure 8. ROC curves for three models

Accuracy: accuracy shows the model's performance in making correct predictions, and it's calculated using the equation below:

$$Accuracy = Correct\ predictions/All\ predictions \quad (4)$$

Recall: recall, also known as "sensitivity", is a performance metric that shows the correctly identified positive among all data supposed to be positive. The equation is:

$$Recall = TP\ (true\ positive)/[TP\ (true\ positive) + FP\ (false\ positive)] \quad (5)$$

The false negative belongs to the positive class because it's falsely identified as the opposite.

Precision: precision is the proportion of correct positive data out of all positive data (including false positive). It can be calculated by:

$$Precision = TP\ (true\ positive)/TP\ (true\ positive) + FP\ (false\ positive) \quad (6)$$

F1-Score: f1-score gives the combined information of accuracy and precision, or it can be interpreted as the weighted average. It ranges from 0 to 1, and the higher the value is the better performance the model has.

As Table 2. shown, the model of random forest algorithm performs the best relatively, since it has the highest value of AUC (0.828), accuracy (0.723), and precision (0.739). However, the model of Xgboost algorithm has the highest recall value (0.714), and the recall value affects its f1-score, resulting in the highest f1-score (0.717) as well.

3.2. The Actualization of Signal Reporting

After statistically achieving a high performance in predicting the risk level of ankle sprain, we used two computer programs to report the result from our model to the microcomputer. First, a python program sends the prediction by the model to serial port on laptop computer.

```
import serial
import serial.tools.list_ports

def send ():
    #get serialport list
    port_list = list(serial.tools.list_ports.comports())
    #print (port_list)
    if len(port_ list) == 0:
        print ('none')

    try:#set serialport parameters
```

DOI: 10.54254/2755-2721/27/20230164

```
        portName="COM6"
        baudRate=115200
        timeOut=3
        ser=serial.Serial (portName baudRate_timeout=timeOut)

        #write in serialport
        if ser.isOpen():
            ser-write('1' .encode("utf-8"))
            ser .close ()

    except Exception as e:
        print ("enros accured: ",e)
```

Code 4. The python program that sends model feedback to serial port

Then the arduino program is uploaded to microcomputer to use the LED light as an indicator of whether model feedback is successfully sent.

```
void setup () {
    // put your setup code here, to run once:
Serial.begin (115200);
Serial.println ("hello arduino!");
pinMode (LED BUILTIN, LOW);
}

void loop() {
    //put your main code here, to run repeatedly:
    int n = Serial.available ();
    if (n > 0)
    {
    //Serial.print ("Read ");
    //Serial.print (n);
    //Serial.print ("chars. in Rev:");

    char c = serial .read ();
    Serial.print (c);
    if (c == '1')
    {
        for (int i=0; i<3; i++) {
        digitalWrite (LED_BUILTIN, HIGH);
        delay (300);
        digitalWrite (LED_BUILTIN, LON);
        delay (300);
        }
    }
}
}
```

Code 5. The arduino program that activates the LED light on microcomputer

If the LED light is turned on, it means that the model feedback is successfully reported to the microcomputer, which also indicates that the feedback can activate TenS stimulator.

DOI: 10.54254/2755-2721/27/20230164

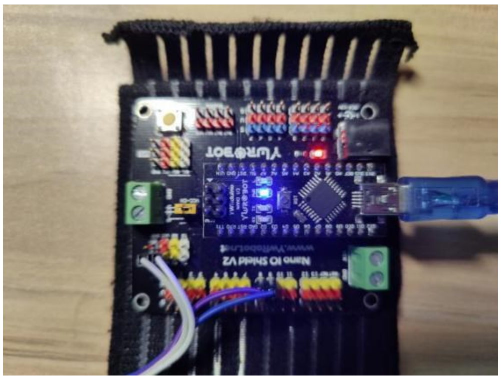


Figure 9. Low-risk dataset, result 0, no green LED indicator

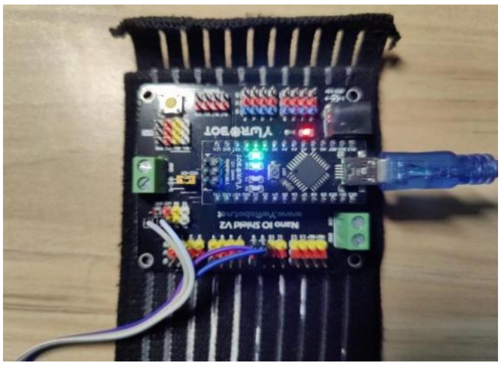


Figure 10. High-risk dataset, result 1, green LED light turned on

4. Discussion

Among various AI algorithms, the above three algorithms are chosen because each of them has some unique advantages, and there are also trade-offs in the use of these three methods in this study:

1) Logistic regression. Using logistic regression, I can know that under certain conditions, how possible the move can be high-risk. However, the algorithm is prone to overfitting, particularly when there are many variables from the data.

2) Random Forest. The identification of risk level is a classification problem, and random forest performs well in classification. Its bagging method works to decrease the bias. The feature of imported data is also high-dimensional (with 64 values for each), and this algorithm doesn't need dimension reduction when facing data with the high-dimensional features. Furthermore, when I was collecting the data, there wasn't an ideal laboratory environment, so there was more or less noise in the data, but random forest algorithm is not easily overfitted. However, the training time and storage can be disadvantages as the number of trees increases.

3) Xgboost. Xgboost sets a targeted outcome for next model, and the targeted outcome comes from the difference (gradient) between the error and the predicted value, so the algorithm usually generates high accuracy. But because it's constantly decreasing the gradient with the next model, the algorithm is sensitive to outliers.

As my result shown, random forest and Xgboost algorithms are relatively ideal for our classification problem. For the most evaluations, random forest generates a more precise result, so it can be still used in further experiments; at the same time, Xgboost has a higher value of recall, which is of great significance in my project. Higher recall means a higher chance for high-risk cases to be identified. My project aims at preventing the ankle from spraining, so high recall is crucial for the model used in my project.

The project creates an ankle brace device that can actively prevent ankle sprains. The identification of high risk is reliable because three different machine learning models trained with 1200 data sets were compared and filtered. The advantages of the device are apparent: 1) the cost of each component is low compared to other ankle protective equipment; 2) with large amount of training, the machine learning can effectively find the pattern of high-risk moves that cause ankle sprain; 3) more intense protection can only be activated when there's potentially an ankle sprain case, so it exerts no restriction for the user's normal movement.

In the final stage, the model by random forest algorithm was imported to use and the microcomputer was programmed to detect high-risk moves, and the LED light on it shows successful activation of TenS stimulator. Because of potential harm done by the stimulator on human body, we didn't actually use actual TenS stimulator to send electric shock to muscles, and none of our subjects were treated with muscle stimulation. Instead, we used the LED light on the microcomputer to indicate a successful activation.

5. Future Work

1) Larger sample size. Due to nowadays COVID condition, we were not able to recruit a large number of volunteers from a more representative population. For later studies, larger data sets can be fed, because the large sample size significantly lowers the error rates [14], and it's likely to improve the recall.

2) More machine learning algorithms. More types of data (such as acceleration) can be collected using more sophisticated and expensive sensors; Other randomness can be injected to random forest and xgboost algorithms; More machine learning algorithms can be employed to create models and the performance may even be further improved.

3) More powerful microcomputer. Arduino Nano V3 microcomputer is compatible with arduino programme, which is more accessible and easier to learn. However, arduino is not yet able to process all the programme we used. Therefore, we use laptop computer as a more powerful tool to run the programme and directly sent the results to Nano V3. At present Nano V3 can only process real-time data and indicate results with laptop computer. For further studies, more powerful ARM Cortex-M microcomputer, STM32, is able to process all information on its own, and it can receive real-time data and give feedback independently. The fast process of STM32, combined with the conduction time (within 25ms from stimulator to muscle), can ensure that the final effect is within the general reaction time of ankle sprain (50ms).

6. Conclusion

This project develops a protective ankle brace that can be used to lower the rate of ankle sprain given the consequence of this injury. The application of AI method improved the effectiveness and accuracy of detection for high-risk moves. The activation mechanism of TenS stimulator lowers the restriction for normal ankle movement, since TenS only provides protection in high-risk cases.

References

[1] Sze Anandacoomarasamy A, Barnsley L., (2005), Long term outcomes of inversion ankle injuries, British Journal of Sports Medicine 2005;39:e14.

[2] Attenborough, A.S., Hiller, C.E., Smith, R.M. et al., (2014), Chronic Ankle Instability in Sporting Populations. Sports Med 44, 1545–1556 (2014).

[3] Daniel Tik-Pui Fong, Vikki Wing-Shan Chu, Kai-Ming Chan, Myoelectric stimulation on peroneal muscles resists simulated ankle sprain motion, Journal of Biomechanics Volume 45, Issue 11, 26 July 2012, Pages 2055-2057.

[4] Cooke MW, Marsh JL, Clark M, et al. Treatment of severe ankle sprain: a pragmatic randomised controlled trial comparing the clinical effectiveness and cost-effectiveness of three types of mechanical ankle support with tubular bandage. The CAST trial. Health Technology Assessment (Winchester, England). 2009 Feb;13(13): iii, ix-x, 1-121.

[5] De Boer, A.S., Schepers, T., Panneman, M.J. et al.,2014, Health care consumption and costs due to foot and ankle injuries in the Netherlands, 1986–2010. BMC Musculoskelet Disord 15, 128

(2014).
[6] Doherty, Cailbhe, et al., (2014), The Incidence and Prevalence of Ankle Sprain Injury: A Systematic Review and Meta-Analysis of Prospective Epidemiological Studies: ankle sprain in prevalent broadly, Sports Medicine, 44 (1): 123-140.
[7] Mackenzie M. Herzog, et al., (2019), Ankle Sprains in the National Basketball Association, 2013-2014 Through 2016-2017, The American Journal of Sports Medicine 1–8.
[8] Daniel Tik-PuiFong, et al., (2008), "A three-pressure-sensor (3PS) system for monitoring ankle supination torque during sport motions", Journal of Biomechanics Volume 41, Issue 11, 7 August 2008, Pages 2562-2566.
[9] Yue-Yan Chan, et al., (2010)"Identification of ankle sprain motion from common sporting activities by dorsal foot kinematics data", Journal of Biomechanics Volume 43, Issue 10, 20 July 2010, Pages 1965-1969.
[10] Handoll HHG, Rowe BH, Quinn KM, de Bie R., (2001), Interventions for preventing ankle ligament injuries. Cochrane Database of Systematic Reviews 2001, Issue 3. Art. No.: CD000018.
[11] Y. M. Tang, Z. H. Wu, et al., (2010), A study of semi-rigid support on ankle supination sprain kinematics, Scand J Med Sci Sports 2010: 20: 822–826.
[12] Daniel Tik-Pui Fong, (2013), "Investigating and preventing sport-related ankle sprain injury", 31 International Conference on Biomechanics in Sports (2013).
[13] Michael P. LaValley, (2008), Logistic Regression, Circulation. 2008;117:2395–2399.
[14] Leo Breiman, (2001), Random Forests, Machine Learning, 45, 5–32, 2001.
[15] Tianqi Chen, (2016), XGBoost: A Scalable Tree Boosting System, KDD '16: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.