WeedGait: Unobtrusive Smartphone Sensing of Marijuana-Induced Gait impairment By Fusing Gait Cycle Segmentation and Neural Networks

Ruojun Li, Emmanuel Agu, Ganesh Balakrishnan, Debra Herman, Ana Abrantes, Michael Stein and Jane Metrik

***Abstract*— The use of marijuana is now legal for medical purposes in 39 of the 50 United States. Eleven of these 39 states have also legalized marijuana for non-medical usage. Marijuana impairs the motor skills of users, making Driving Under the Influence of Marijuana (DUIM) a growing public health concern. There are currently few accessible and accurate methods to assess the impairment levels of drivers who have used marijuana. Current assessment methods include self-reports and testing urine, oral fluid, and blood. However, self-reports are often biased and biological tests are cumbersome to perform in situ. In this paper, we investigate whether dose-dependent changes in participants gait (walk) can be detected using data gathered from their smartphone motion sensors (accelerometer and gyroscope). We envision WeedGait, a smartphone sensing system that will assess the gait of marijuana users passively and warn them when they are too impaired to drive safely. To the best of our knowledge, this is the first study on using smartphones to assess marijuana-induced gait impairment. Gait data was collected from 10 subjects and pre-processing steps included low pass filtering, step cycle detection and segmentation, and normalization. We present a novel gait analysis approach that analyzes normalized, single-step segments to achieve higher accuracy than prior approaches. We compared the classification results of various machine and deep learning models, and found that Long Short Time Memory (LSTM) and Support Vector Machines performed best, discriminating the gait of subjects after smoking either marijuana with 3% or 7.2% THC versus smoking a placebo marijuana cigarette with an accuracy of 92.1%. These results suggest that smartphone-based marijuana testing is more accurate than urine-based tests but slightly less accurate than oral fluid based testing. Moreover, smartphone sensing of marijuana is completely passive and hence more convenient, which facilitates pervasive testing in natural settings and could have massive impact due to the near-ubiquity of smartphones.**

Keywords: Marijuana, Gait analysis, Step Detection, Step Segmentation, Deep Learning

I. INTRODUCTION

The use of marijuana is now legal for medical purposes (decriminalized) in 39 of the 50 United States. Eleven of these 39 states have fully legalized marijuana for non-medical recreational usage [1]. Controlled experimental research examining dose-dependent effects of smoked marijuana has demonstrated a direct relationship between blood Δ^9-tetrahydrocannabinol (THC) concentration and impaired driving ability. Marijuana acutely impairs psychomotor functioning relevant to driving ability, and has dose-dependent effects on all eight areas of executive functioning deemed critical to driving behavior by the International Council on Alcohol, Drugs, and Traffic Safety: attention and information processing, cognition and judgment, divided attention, motor performance and maneuvers, perception, risk-taking and impulsivity, sustained attention, and tracking and steering. Acute marijuana intoxication has been related to several indices of driving impairment in laboratory simulated driving studies and during actual driving in normal traffic conditions.Thus, the risk of motor vehicle crashes, has been found to almost double after marijuana use. The percentage of fatally injured drivers that tested positive for drugs was 44% in 2011, increasing to 53% in 2016.[2]

Consequently, methods to detect acute psychomotor impairment in marijuana users and notify them in order to prevent driving under the influence of marijuana, are important. However, there are currently few accessible and accurate methods to assess the impairment levels of drivers who have used marijuana. Current assessment methods include self-reports and testing urine, oral fluid, and blood. However, self-reports are often biased and biological tests are cumbersome to perform in situ.

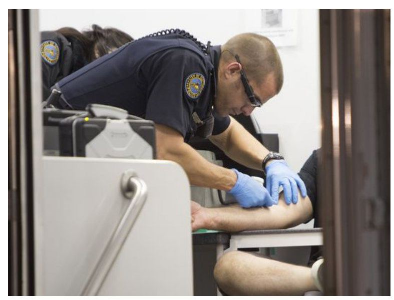

Fig. 1: DUI Suspect gives blood sample for drug test

In this study, we investigated whether changes in participants gait after smoking either marijuana with 3% and 7.2% THC could be discriminated from gait changes after smoking a marijuana placebo cigarette by using machine and deep learning analysis on gait (walk) data gathered from their smartphone motion sensors (accelerometer and gyroscope). We envision WeedGait, a smartphone sensing system that will passively assess the gait of marijuana users and warn them when they are too impaired to drive safely. We believe the analysis of smartphone gait data could benefit from current advances in neural networks, which has significantly improved results in related fields such as Human Activity Recognition. Gait analysis using data from smartphone sensors or wearable sensors placed in shoes, backs or calves has become increasingly popular [3].

Our Contributions:

- While prior work has explored smartphone sensing of gait impairments caused by alcohol [4] [5], to the best of our knowledge, our study is the first to detect marijuana-induced gait impairment using smartphone sensors.
- In our methodology, we adapted the Cycle-Pro step detection approach [6] in order to detect step cycles, segment and normalize the gait data, improving the accuracy of gait analysis.
- We compared the accuracy of various machine and deep learning classification models, finding SVM and LSTM to perform the best, discriminating the gait of participants after smoking either 3% or 7.2% THC doses from gait after smoking a placebo dose with 92.1% accuracy.

II. Methodology

A. Subjects and Data Collection:

Study Design: As part of the larger parent study at Brown University (RO1 AA024091, PI Metrik), participants (N = 10) completed three double-blind experimental laboratory sessions following 15-hour abstinence from marijuana, in which they smoked a marijuana cigarette with 3% THC, 7.2% THC, and placebo (0% THC), with order of administration counter-balanced across subjects. Participants completed a brief walking task before they smoked and then approximately 15, 40, and 60 minutes after they smoked the assigned dose, while a smartphone app gathered their gait data. Visits to the smoking lab were separated by at least 5 business days. Immediately after smoking, participants completed the brief walking task.

Walking Task: A 50-foot tape line was placed in a straight line on the floor. Participants started their walk in the middle of the line, walked at their normal pace to the end of the line, turned, walked to the other end, turned, and returned to their starting point. Each walk lasted 45-60 seconds.

Study hardware: The Google Pixel XL was used for data collection. Using a Velcro belt around the participants waist, the phone was holstered over their left-back pocket with the face accessible.

B. Data Preprocessing

Filter: Gait signals contain two types of information frequently utilized in recognition or biometric tasks: gait shape and gait dynamics.[7]. Gait dynamics is the rate of transition between gait phases. Shape refers to the shape of the people (computer vision approaches) or shape of the gait cycle (accelerometry approaches) as they perform different gait phases. Recognition based on gait shape is generally more robust. Since the smartphone sampling frequency is 400 Hz, which is far higher than the static gait signal frequency ($> 1Hz$) and the Gait Dynamic signal frequency ($< 50Hz$), the smartphone gait data were first passed through a low-pass filter to remove higher frequencies and noise [8]. After filtering, subjects'(N=10) data were processed into 120 walking scenario sequences (Sensor/scenario=2).

Step Cycle Segmentation: Segmentation of gait into individual steps that are then analyzed facilitates more accurate gait recognition and analysis. Current gait analysis methods primarily include Hidden Markov Model(HMM) [9], Principle Component Analysis(PCA) [10] and Machine Learning approaches [11]. However, these studies did not segment gait into individual steps or normalize gait shape in order to extract a stable gait shape, prior to analysis [7].

CyclePro *et al* is a reliable, parameterless, step detection algorithm with an accuracy higher than 95-percent. This algorithm learns the gait cycle without the need for setting platform-specific parameters or thresholds and is invariant to changes in sampling frequency, signal dynamic range and sensor orientation [6]. The main CyclePro steps include 1) Calculating the Signal Vector Magnitude (SVM) 2) Generating templates of a single gait cycle (stride) using the SVM 3) Capturing repetitive patterns in the signal using a normalized cross-correlation approach and 4) Optimal stride detection. Using the CyclePro approach, we segmented 120 subject walks into 17039 steps.

Normalization: of the gait shape improves gait recognition [7][12]. While different subjects may have different gait lengths and magnitudes, we normalized the magnitudes of the three-axial accelerometer and gyroscope data using the signal magnitude cross-correlation (equation.1)[13], and rescaled the time-series to yield segments (single steps) of equal magnitude and duration.

$$\hat{data_i} = \sqrt{\frac{data_i - \mu_{SignalVectorMagnitude_i}}{\rho_{SignalVectorMagnitude_i}}} \tag{1}$$

where i is accX, accY, accZ, gyroX, gyroY, gyroZ, ρ is standard deviation,μ is average.

Features Extraction: Intoxication classification is another application of continuous gait assessment using wearable sensors. For intoxication classification, Aiello and Agu [4] found that the Random Forest classifier outperformed other machine learning algorithms using time and frequency domain features including sway area, sway volume, kurtosis and skew extracted from smartphone accelerometer and gyroscope data. We utlize similar features in this work.

Experimental Datasets: By applying different sequences of operations to the gait data, six experimental datasets were generated: Dataset A contains Signal Vector Magnitudes of accelerometer and gyroscope segments generated by the CyclePro algorithm; Dataset B contains three-axial accelerometer and gyroscope data segments, re-scaled on the time axis; Dataset C contains Dataset B normalized; Dataset A', B', C' contain features extracted from the corresponding datasets respectively. [6]

C. Machine and Deep Learning Classification:

Long Short Time Memory(LSTM): LSTM networks can learn long term dependencies in data and have recurring LSTM cells that pass information through time and have a memory about previous states. LSTM has gates that can control the amount of information that each cell adds (input

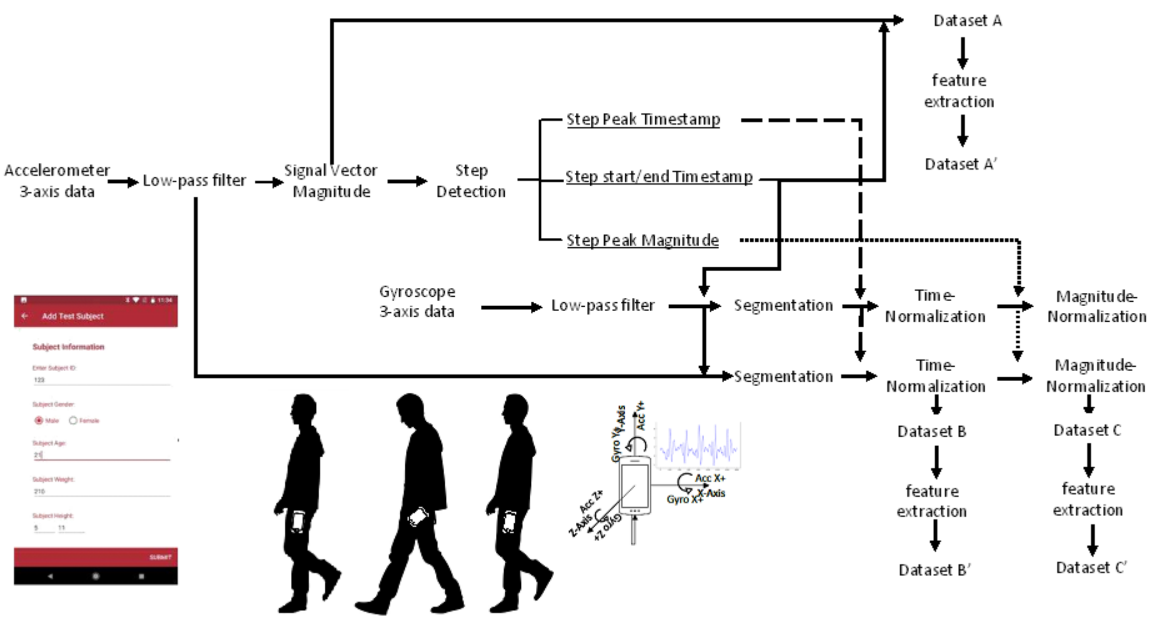

Fig. 2: Flow Chart of Experiments

TABLE I: Binary Classification Accuray

Bi-Classification Accuracy	Dataset A'	Dataset B'	Dataset A	Dataset B	Dataset C	Dataset C'
Decision Tree	72.3%	71.5%	72.0%	76.3%	76.8%	82.0%
Discriminant Analysis	68.4%	72.0%	55.9%	57.8%	68.6%	71.5%
SVM	77.6%	84.3%	82.6%	**92.2%**	83.1%	83.3%
KNN	76.8%	82.5%	83.8%	90.7%	83.6%	86.3%
Ensemble Classifier	76.6% (BT*)	84.0%(S-K)	83.1%(S-K*)	89.3%(S-K*)	80.8%(S-K*)	86.6%(BT*)
LSTM	/	/	87.1%	90.1%	88.7%	/

TABLE II: Triple Classification Accuray

Tri-Classification Accuracy	Dataset A'	Dataset B'	Dataset A	Dataset B	Dataset C	Dataset C'
Decision Tree	47.4%	54.8%	50.4%	58.6%	52.6%	62.4%
Discriminant Analysis	48.7%	62.4%	35.1%	50.1%	49.2%	60.8
SVM	55.6%	67.9%	68.9%	**79.1%**	70.3%	69.4%
KNN	54.1%	68.1%	68.4%	79.1%	68.9%	70.6%
Ensemble Classifier	53.8% (BT*)	64.8%(S-K*)	69.8%(S-K*)	77.5%(S-K*)	69.3%(S-K*)	69.4%(BT*)
LSTM	/	/	70.0%	73.2%	72.0%	/

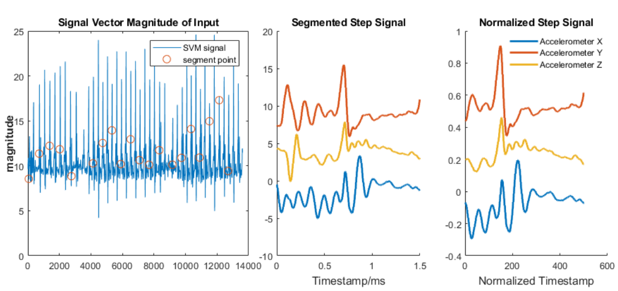

Fig. 3: Signal Preprocessing

gate) to the memory (cell state) and the amount of information each cell's outputs (output gate). Our LSTM model is a simple 2-layer-cell structure followed by a drop out layer.

Signal Support Vector Machines (SVM): Support vector machines are supervised learning models that can be used for classification and regression analysis. Data instances are represented as points in space in SVMs, divided by a gap.

K-Nearest Neighbor(KNN): K-nearest neighbor is a non-parametric learning algorithm. The K closest instances in feature space are taken as the input and the corresponding property value or category of other data points are determined by their distance from the K closest examples.

We used 10-fold cross-validation to ensure consistency.

III. Results

The classification performance was evaluated using accuracy and F1-score metrics (equations 2 and 2).

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total number of Predictions}} \tag{2}$$

$$F1\_score = \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

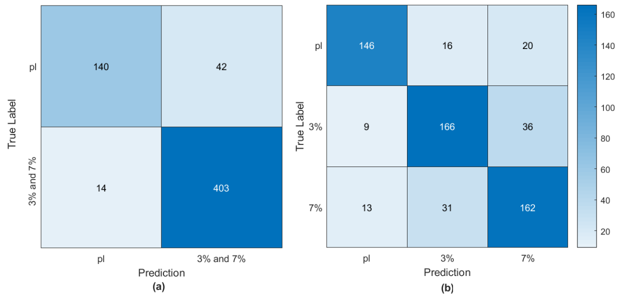

Fig. 4: Classification Confusion Matrix of Smartphone Sensors:(a)Binary Classification ;(b)Triple Classification. pl denotes placebo dose

The accuracy of 2-bin and 3-bin Classification are presented in Table I and Table II. In the two tables, BT* denotes Bagged Trees; S-K* denotes Subspace KNN. Two-bin classification investigates the classifier's ability to discriminate participants' gait changes after smoking either of the two doses of marijuana with 3% THC and 7.2% THC (positive label) versus after smoking the placebo dose (negative label). Three-bin classification investigates the classifier's ability to discriminate gait changes after smoking the placebo dose vs 3% THC vs 7% THC.

Figure 4 shows the confusion matrix of SVM on the 2-bin and 3-bin classification tasks. We note that the f1-score of the 2-bin classification is 0.935 and an accuracy of 92.2%. Next we compared our smartphone sensing results with the accuracy and f1 scores (equation 2) and f1-score (equation 3) of oral and urine drug tests, which we calculated based on results published by Niedbala *et al* [14] (Table III). Biosensors are sometimes also used, but we could not find their accuracy for comparison. ([14] [15]).

TABLE III: Evalution Comparison

Drug Test	Accuracy	F1-score
Smartphone Sensors	92.2%	0.935
Oral Fluid	93.22%	0.9418
Urine	77.92%	0.7571

IV. Discussion

Table III demonstrates that smartphone sensors could be utilized for accurate marijuana testing. Table I demonstrates that SVM and LSTM outperform other binary classifiers. Meanwhile, the superior accuracy achieved using Dataset-B (table I) demonstrates that step detection improves the accuracy of gait analysis.

Our work is novel in two main ways. First, prior gait analyses did not utilize step detection and segmentation to extract gait shape, which made data normalization complicated. Secondly, prior marijuana testing using gait analysis on smartphone sensor data has not been explored previously. We classified marijuana-induced gait changes using data gathered from subjects who walked before and after smoking a placebo, 3% THC dose, and 7.2% THC dose. We also compared the impairment classification accuracy and f1 scores of several machine and deep learning models.

We found impairment detection more accurate with time-series normalization. We also found that LSTM and SVM outperformed other models in 2-bin classification of marijuana-induced impairment (marijuana positive (3% THC and 7% THC) vs negative (placebo)). A comparison with results in [14] showed that while smartphone-based detection is slightly less accurate than oral fluid testing, it is more accurate than urine testing. Moreover, smartphone testing of marijuana-induced gait impairments is unobtrusive, more convenient and enables continuous, pervasive monitoring

Future work: Given that our findings are based on data from only 10 subjects, we would like to gather more data to confirm our results. As more data is gathered, we believe that deep neural networks will outperform SVM, yielding even higher accuracy.

References

[1] (2019) State marijuana laws in 2019 map. [Online]. Available: https://www.governing.com/gov-data/safety-justice/state-marijuana-laws-map-medical-recreational.html

[2] R. Sewell, J. Poling, and M. Sofuoglu, "The effect of cannabis compared with alcohol on driving," *Am J Addict.*, 2009.

[3] A. Muro-de-la Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications," *Sensors*, vol. 14, no. 2, pp. 3362–3394, 2014.

[4] C. Aiello and E. Agu, "Investigating postural sway features, normalization and personalization in detecting blood alcohol levels of smartphone users," in *In Proc Wireless Health*, 2016, pp. 1–8.

[5] B. Nassi, L. Rokach, and Y. Elovici, "Virtual breathalyzer," *CoRR*, vol. abs/1612.05083, 12 2016.

[6] Y. Ma, Z. Esna Ashari, M. Pedram, N. Amini, D. Tarquinio, K. Nouri-Mahdavi, M. Pourhomayoun, R. D. Catena, and H. Ghasemzadeh, "Cyclepro: A robust framework for domain-agnostic gait cycle detection," *IEEE Sensors Journal*, vol. 19, no. 10, pp. 3751–3762, 2019.

[7] S. S. Zongyi Liu, "Improved gait recognition by gait dynamics normalization," *IEEE Transactions on Pattern Analysis Machine Intelligence*, pp. 863–876, sep 2006.

[8] J. M. Hausdorff, S. L. Mitchell, R. Firtion, C. K. Peng, M. E. Cudkowicz, J. Y. Wei, and A. L. Goldberger, "Altered fractal dynamics of gait: reduced stride-interval correlations with aging and huntingtons disease," *J. Applied Physiology*, vol. 82, no. 1, pp. 262–269, 1997.

[9] S. Qiu, L. Liu, Z. Wang, S. Li, H. Zhao, J. Wang, J. Li, and K. Tang, "Body sensor network-based gait quality assessment for clinical decision-support via multi-sensor fusion," *IEEE Access*, vol. 7, pp. 59 884–59 894, 2019.

[10] J. Bernstein, A. DeVito, D. Weitzner, R. MacAulay, M. Calamia, R. Brouillette, H. Foil, O. Carmichael, and J. Keller, "Examining relationships between multiple self-reported sleep measures and gait domains in cognitively healthy older adults. gerontology," 2019.

[11] S. J. Banks, E. Bayram, G. Shan, D. R. LaBelle, and B. Bluett, "Non-motor predictors of freezing of gait in parkinsons disease," *Gait Posture*, vol. 68, pp. 311 – 316, 2019.

[12] A. Nandy, "Statistical methods for analysis of parkinson's disease gait pattern and classification," *Multimedia Tools & Appl*, Feb 2019.

[13] J. Yang and D. Winter, "Electromyographic amplitude normalization methods: improving their sensitivity as diagnostic tools in gait analysis," *Archives of phys. med. & rehab.*, vol. 65, no. 9, p. 517521, September 1984.

[14] R. S. Niedbala, K. W. Kardos, D. F. Fritch, S. Kardos, T. Fries, J. Waga, J. Robb, and E. J. Cone, "Detection of Marijuana Use by Oral Fluid and Urine Analysis Following Single-Dose Administration of Smoked and Oral Marijuana," *J. Anal. Toxicology*, vol. 25, no. 5, pp. 289–303, 07 2001.

[15] S. Carreiro, H. Fang, J. Zhang, and et al, "iMStrong: Deployment of a Biosensor System to Detect Cocaine Use," *J. Medical Sys.*, 11 2014.