Person Recognition using Smartphones’ Accelerometer Data

Abstract—Smartphones have become quite pervasive in various aspects of our daily lives. They have become important links to a host of important data and applications, which if compromised, can lead to disastrous results. Due to this, today’s smartphones are equipped with multiple layers of authentication modules. However, there still lies the need for a viable and unobtrusive layer of security which can perform the task of user authentication using resources which are cost-efficient and widely available on smartphones. In this work, we propose a method to recognize users using data from a phone’s embedded accelerometer sensors. Features encapsulating information from both time and frequency domains are extracted from walking data samples, and are used to build a Random Forest ensemble classification model. Based on the experimental results, the resultant model delivers an accuracy of 0.9679 and Area under Curve (AUC) of 0.9822.

I. INTRODUCTION

User authentication and security of smartphones have become issues of paramount importance as smartphones have become ubiquitous devices. With smartphones being one of the most important agents for the push towards digitization across the globe, there has been an ever increasing number of applications dealing with financial transactions, health, contacts information, etc. These applications generate an increasing amount of critical information, the security of which is very much essential and is also of great concern among users today [10]. As a result, various methods of user authentication in smartphones have surfaced over the past few years, starting from the usual password based authentication to pattern lock, fingerprint biometric authentication to even face recognition [11]. However, all of these require active user participation at the beginning and there is no way to continuously authenticate the user at fixed intervals without causing discomfort to the user. In the past, certain methodologies and designs have been proposed which attempt to use gait features from sensors embedded into the smartphones to recognize user activity, used for tasks such as activity monitoring, fall detection, and so on. However, data from embedded sensors can also be used to detect inherent patterns in the activities performed by a particular user, which can be subsequently used to recognize the person given the sensor data for activities carried out by them [13]. In this work, a system to identify the user based on accelerometer data is presented. The system works ubiquitously in the background, without needing the user to perform additional actions for authentication purposes. For the task of user recognition, we train a Random Forest ensemble classifier on a 31-features dataset extracted from accelerometer data recorded during walking.

The presented work is organized as follows. Section II introduces existing literature in gait analysis and use of embedded sensors for activity and person recognition. The methodology of the proposed work is described in section III. The subsections describe the feature extraction process, the Random Forest model and the validation method. This is followed by section IV which presents the results achieved by the model, followed by conclusion and future work in section V.

II. PREVIOUS WORK

While delving into the sphere of person recognition using activity data recorded using smartphones’ accelerometers, an important aspect is identifying the activity. In the past, significant work has been done in this sphere, where activities are identified using various supervised learning methods with a great deal of accuracy. Any user authentication system would require activity identification as one of the initial layers. Once the activity has been identified, we can proceed with the task of user recognition. Some of the directly related works are of Johnston et al. [13], Lee et al. [10] and Haong et al. [14], where works of similar nature have been attempted. In [13], a strawman model using accelerometer data from smartphones has been proposed for user identification. The strawman model is then iterated over continuous 10-seconds samples over a longer duration, following which the most voted person, as identified by the model, is returned as the output. Time domain features are used to generate a feature vector for an identification window of 10 seconds. The dataset generated with the corresponding feature vectors is used to train WEKAs J48 and Neural Network models. For the activity of walking, an accuracy of 90.9% was achieved by the Neural Network, while the J48 model produced an accuracy of 84.0%. On the other hand, [10] uses data from both smartwatches and smartphones. In [10], the feature vector is composed of both time domain (magnitude, mean, min, max, variance) and frequency domain (amplitude of first peak, frequency and amplitude of second peak of Discrete Fourier Transform) features with a focus on the integration of smartphone and smartwatch, while considering identification from a number.
of activities. The model used for classification/identification is Kernel Ridge Regression. In a similar work [14], SVM is used as the classifier. SVM and KRR are similar classifiers based on the kernel method. Kernel Ridge Regression (KRR) [22] is a kernel method classifier model which uses the kernel trick. Instead of learning a fixed set of parameters for the input features, kernel classifiers instead learn a weight for each training example. The class prediction for the new inputs is carried out using a similarity function k, which is called the kernel, between the learned examples and the new input [23]. Kernel based classifiers use a 1 vs others approach for multi-class classification problems, wherein the model is trained separately for each class separately [22][24]. The basic premise of activity recognition and user identification being that users perform activities differently, or in other words they have a markedly different signature for each activity. The work proposed in this paper combines established powerful features used in activity recognition such as magnitude, correlation, etc. with time domain features used in past work on person recognition [10][13][14] to selectively build a feature vector suitable for person the recognition task, while eliminating any redundant features, and at the same time keeping the identification window minimal, i.e., just two seconds. A Random Forest ensemble classifier is used which delivers a robust non-parametric model [1][2].

III. METHODOLOGY

A. Data Preprocessing

1) Data Collection:
Walking data is collected for 10 users using a smartphone which records tri-axial accelerometer readings at a frequency of 50Hz. For this, we use a Samsung Galaxy J-1 phone, which is kept in the side pocket of the users’ trousers during data recording. The data is collected using OARS, a data collector application for Android smartphones.

2) Feature Extraction:
The raw data is divided into identification intervals of 100 samples width with 50% overlap. The feature extraction is achieved by leveraging the methodologies of different activity recognition projects as discussed earlier. We picked up a basket of statistical features and added to it features like spectral centroid, widely used in audio recognition experiments [18][19]. As done in many activity recognition problems [20][21], both time and frequency domain features are extracted. The Fast Fourier Transform (FFT) of the axial data of the identification windows for each of the axes is evaluated, which forms the base for all frequency domain features. The parameters extracted from the identification windows, which serve as the features for the classification problem are defined as follows:

(i) Mean: The mean values of the triaxial accelerometer data within each window are calculated for both the raw data and the FFT data for each of the three axes, which gives us a set of six mean values, abstracting data in both time and frequency domains.

(ii) Median: The median is calculated in a similar way as the mean. The median values are calculated for each of the axes taken in a similar way for both time and frequency domains for each of the three axes.

(iii) Magnitude: The magnitude is defined as the average of the root mean square of the tri-axial data (both time and frequency domain), and is calculated as follows:

\[ \text{Magnitude} = \left( \sum_{k=1}^{l} \sqrt{x_k^2 + y_k^2 + z_k^2} \right) / l \]  

where:\n\[ x_k, y_k, z_k = \text{Instantaneous acceleration values} \]
\[ l = \text{Length of window} \]

The magnitude for frequency domain is calculated by putting instantaneous values of fourier transformed data in place of acceleration.

(iv) Cross-correlation: The cross-correlation is defined as the ratio of mean of x axis and z axis data and that of y axis and z axis data. The z axis is selected as the frame of reference as it remains constant for almost all possible orientations of the smartphone, and the ratios are taken with respect to z axis. The cross correlation of z axis with x axis and y axis are mathematically defined as follows:

\[ \text{Corr}_{xz} = x_{mean} / z_{mean} \]
\[ \text{Corr}_{yz} = y_{mean} / z_{mean} \]

where:
\[ \text{Corr}_{xz} = \text{Cross-correlation of x axis& z-axis} \]
\[ \text{Corr}_{yz} = \text{Cross-correlation of y axis& z-axis} \]
\[ x_{mean} = \text{Mean of acceleration values in x-axis} \]

(v) Peak Count: Peak count for each axis refers to the number of local maxima for the axial data in the identification window. The average of the peak count over the three axes for the time domain data is selected as a feature.

(vi) Distance between Peaks: Distance between peaks refers to the average time interval between two successive peaks in a window.

(vii) Spectral Centroid: Spectral centroid is a measure used to characterise a spectrum. In this case, spectrum refers to the identification window of acceleration values. It indicates where the center of mass of the spectrum is[17]. The spectral centroid of each window for the three axes using the FFT values as weights is given by:

\[ \text{Centroid} = \sum_{k=1}^{l} \frac{x_{tk} * f_{tk}}{l} \]  

where:
\[ x_{tk} = \text{Instantaneous acceleration} \]
\[ f_{tk} = \text{Instantaneous value of FFT} \]
\[ l = \text{length of window} \]

(viii) Average Difference from Mean: The absolute difference from mean of the window for each axis (time domain) is calculated as follows:

\[ \text{Diff}_{x} = \text{Avg}(|x_t - x_{mean}|) \]  

where:
\[ \text{Diff}_{x} = \text{Difference from mean} \]
\[ x_t = \text{Instantaneous acceleration} \]
\[ x_{mean} = \text{Mean as defined in eq. } 1 \]

The plots of comparison of two of the users for magnitude, cross-correlation(xz) in frequency domain, and cross-correlation(yz) in frequency domain are shown in figures.
The features were extracted using numpy library and the resultant feature vectors were then labeled with the respective users.

3) Dataset Creation:
Using features extracted from the raw accelerometer data as described in the previous section, a dataset is generated where each row corresponds to an interval of 100 continuous samples, with the output label being the person the samples are from. Evaluation of any learning model involves splitting of the dataset into a training set and a testing set to check how the model performs on a dataset it hasn’t seen. However, this method is susceptible to high variance. The evaluation may depend heavily on which data points end up in the training set and which end up in the test set, and hence, the performance of the model may significantly vary depending on the division into training and testing datasets. This is overcome by k-fold cross-validation in which the original dataset is split into k equally sized subsets. Of these k subsets, k-1 subsets are used for training while the remaining one subset is used for testing the model. This process is repeated k times so that each observation is used for validation only once. The average of the k results is calculated to arrive at a single estimation for the model [8] [9]. In this work, we use a stratified 10-fold classification model so that each fold (subset) is representative of the whole dataset.

B. Model
We use a Random Forest Classifier as our classification model, which is an ensemble of 64 decision trees generated from a set of 30 features. Random Forest (RF) Classifier is a learning-based classification algorithm which relies on an ensemble of multiple decision tree classifiers. Taking advantage of two powerful machine-learning techniques in bagging and random feature selection, the RF classifier combines the output of individual decision trees which are generated by selecting a random subset of the features.

1) Decision Tree Classifier:
The model used in this work is implemented with scikit-learn's Random Forest Classifier which uses an optimized version of Classification and Regression Trees (CART) classification algorithm, proposed by Breiman et al. [1], for building the decision trees. CART is a non-parametric learning algorithm which generates a classification or regression tree. Each decision node of the tree splits the data into groups, with the attribute being chosen such that the resultant groups are increasingly homogenous as we move down the tree [2].

In classification problems, CART uses the Gini impurity measure for producing homogenous groups.
The Gini impurity measure at a node for a category k is defined as:

\[ G(p_k) = p_k \times (1 - p_k) \]  

where: \( p_k = \text{Proportion of observations in class } k \)

Impurity at a node n is defined as the sum of impurities for all categories [3], and is given by:

\[ I_n = \sum_{k=1}^{K} G(p_k) \]  

\[ G(p_k) = p_k \times (1 - p_k) \]
where: $I_n = \text{Impurity at node } n$

$G(p_k) = \text{Gini impurity for class } k$

The CART algorithm considers all possible splits across the input features and selects the feature which maximizes the drop in impurity [3], defined as:

$$
\Delta I = p(n_0)I(n_0) - (p(n_1)I(n_1) + p(n_2)I(n_2)) \quad (8)
$$

where: $\Delta I = \text{Change in impurity}$

$n_0 = \text{Parent node}$

$n_1, n_2 = \text{Children nodes}$

$p(n) = \text{Ratio of observations at the node } n$

2) Random Forest Ensemble:

Since Decision Trees are non-parametric classifiers, they are suitable for datasets which are not linearly separable. They are also robust to classifiers due to the splitting during the tree generation. However, Decision Trees are often associated with high variance since the branches made by the splits are enforced at all lower levels of the tree. As a result, a slight error in the data could result in a considerably different sequence of splits, resulting in a different classification rule [5]. A bootstrap is a random sub-sample of the dataset. In Random Forests, multiple Decision Trees are generated using bootstrap samples and the result is determined by aggregating the output of the individual trees. While selecting the feature for splitting at a node, the RF algorithm only uses a random subset of features. This reduces the correlation between the individual trees. The architecture of the RF Classifier is shown in figure 4 [4].

![Fig. 4. Architecture of Random Forest Classifier](image)

IV. RESULTS AND ANALYSIS

The dataset for our model was prepared by collecting raw accelerometer data and then extracting features from this time-series data using the process described in section III A. The resultant dataset of 31 input features consisted of 3600 examples.

A. Metrics

In this section, we define the metrics used to measure the performance of the classifier.

For a binary classification problem, its performance can be determined by computing the number of correctly labeled positive observations (true positives), the number of correctly labeled negative observations (true negatives), the number of negative observations incorrectly labeled as positive (false positives) and the number of positive observations incorrectly labeled as negative (false negatives) [6]. These four values constitute a confusion matrix as shown in Table 1.

| As Classified by Model | Positive' | Negative' |
|------------------------|-----------|-----------|
| Positive               | True Positive | False Negative |
| Negative               | False Positive | True Negative |

TABLE 1: Confusion Matrix

Recall, Specificity and Area under Curve (AUC) are metrics originally used for binary classification problems. However, in our case, we have multiple classes (equivalent to the number of users in dataset). Due to this, for each class, a ”1 vs others” approach is used [6].

Recall, Specificity and Area under Curve (AUC) are calculated for each of the classes with the class in consideration being the positive class, while the other classes are interpreted as negative. The final values are generated by calculating a weighted average (micro-averaging) of the respective values for each class, where weight of each class is given by:

$$
W_c = n_c/n \quad (9)
$$

where: $W_c = \text{Weight of class } c$

$n_c = \text{Number of actual observations in class } c$

$n = \text{Total number of observations}$

The metrics used for evaluating the model are defined as follows:

1) Accuracy: Accuracy is the ratio of correctly predicted observations to the total observations and indicates the overall effectiveness of a classifier and is given by:

$$
\text{Accuracy} = \frac{n_{\text{Correct}}}{n} \quad (10)
$$

where: $n_{\text{Correct}} = \text{No. of correctly labeled observations}$

$n = \text{Total number of observations}$

2) Recall (Sensitivity): Recall is the ratio of correctly labeled positive observations to the total number of actual positive observations and indicates the effectiveness of classifier in identifying positive observations [6], and is defined as:

$$
\text{Recall} = W_c \ast R_c \quad (11)
$$

$$
R_c = \frac{tp_c}{(tp_c + fn_c)} \quad (12)
$$
where: \( R_c = \) Recall of class c
\( tp_c = \) True positives in class c
\( fn_c = \) False negatives in class c

3) Specificity: Specificity is the ratio of correctly labeled negative observations to the total number of actual negative observations and indicates the effectiveness of classifier in identifying negative observations [6], and is defined as:

\[
Specificity = W_c \times S_c 
\]

\[
S_c = \frac{tn_c}{(fp_c + tn_c)} 
\]

where: \( S_c = \) Specificity of class c
\( tn_c = \) True negatives in class c
\( fp_c = \) False positives in class c

4) Area under Curve (AUC): Area under Curve (AUC) is the macro-average of Recall and Specificity and indicates the classifier’s ability to avoid false classification [6], and is defined as:

\[
AUC = W_c \times AUC_c 
\]

\[
AUC_c = \frac{(R_c + S_c)}{2} 
\]

where: \( AUC_c = \) Area under Curve for class c

B. Number of Trees in the Forest

The time complexity of a Random Forest is given by:

\[
O(t \times k_{try} \times n\log(n)) 
\]

where: \( t = \) Number of trees in ensemble
\( k_{try} = \) Number of features
\( n = \) Number of records

In general, more the number of trees, better the performance of the model. But beyond a point the performance starts to plateau and the additional time overhead isn’t commensurate with the performance improvement. For our model, the performance, both in terms of accuracy, as well as area under curve, plateaus as the number of trees reaches 64 as shown in figure 5.

C. Person Recognition Results

In this section, the results for Person Recognition using the RF Classifier model are presented. In addition to the RF classifier, we also present the results obtained by using three other popular classification models using the same set of features. The models used in addition to the RF classifier are Logistic Regression (LR), Support Vector Machine (SVM), and Decision Trees (DT) (defined in section III).

| Model/Metric | Accuracy | AUC  | Recall |
|--------------|----------|------|--------|
| RF           | 0.9679   | 0.9823 | 0.9966 |
| DT           | 0.9613   | 0.9784 | 0.9955 |
| LR           | 0.8768   | 0.9314 | 0.9861 |
| SVM          | 0.7158   | 0.8422 | 0.9685 |

TABLE 2: Performance of Classification Models
The Random Forest (RF) classifier outperforms the Decision Tree (DT) classifier due to advantages of bagging and randomized feature selection as described in section III B. The Logistic Regression model is stumped by both RF classifier and the DT classifier. This stems from the limitations of LR classifiers in handling large feature vectors and large number of categorical outputs. The Support Vector Machine (SVM) classifier is also trumped by the RF and DT classifier. This stems from SVMs being originally designed for binary classification problems. Additionally, SVMs also perform poorly for imbalanced classes.

In related work, the model proposed by Johnston et al. [7] produced an accuracy of 90.9% using a Neural Network model and an accuracy of 84.0% using WEKA’s J48 model on a dataset containing 2081 samples. On the other hand, the model proposed by [8] delivered an accuracy of 92.1% using kernel Ridge Regression on a dataset containing 800 samples. It must be noted that for the use case of authentication, an important measure would be the model’s ability to avoid misclassification as it is essential to make sure the right person is identified, i.e., false negatives are minimized to avoid an inconvenient user experience, and false positives are minimized to avoid false authentication. This is well represented by the Area under Curve (AUC) metric as described previously.

### Table 3: Person-wise Accuracy

| Person | RF    | DT    | LR    | SVM   |
|--------|-------|-------|-------|-------|
| 1      | 0.9443| 0.9619| 0.9032| 0.8592|
| 2      | 0.9623| 0.9623| 0.8899| 0.5797|
| 3      | 0.9683| 0.9405| 0.8651| 0.4524|
| 4      | 0.9615| 0.9586| 0.7278| 0.6361|
| 5      | 0.9385| 0.9198| 0.7273| 0.6872|
| 6      | 0.997 | 0.9881| 0.9941| 0.9555|
| 7      | 0.9882| 0.9794| 0.7971| 0.7441|
| 8      | 0.9853| 0.9765| 0.868 | 0.3196|
| 9      | 0.9692| 0.9513| 0.9538| 0.7974|
| 10     | 0.968 | 0.9699| 0.9812| 0.9303|

In future, we aim to further improve the AUC of the model due to the detrimental effects misclassification could have for the proposed authentication use case. We also plan to increase the number of users and incorporate more natural activities and more positions for keeping the smartphone during data collection, such as back pocket, shirt pocket, etc.

### References

[1] L. Breiman Random forests, Springer - Machine learning, 2001.
[2] A. Liaw, M. Wiener Classification and regression by randomForest, R news, 2002.
[3] C. Strobl, A.-L. Boulesteix, and T. Augustin. Unbiased split selection for classification trees based on the gini index, Computational Statistics & Data Analysis, 2007.
[4] Cuong Nguyen, Yong Wang, Ha Nam Nguyen Random forest classifier combined with feature selection for breast cancer diagnosis and prognostic, J. Biomedical Science and Engineering, 2013.
[5] DW Opitz, R Maclin Popular ensemble methods: An empirical study, J. Artif. Intell. Res.(JAIR), 1999.
[6] M Sokolova, G Lapalme A systematic analysis of performance measures for classification tasks Information Processing & Management, Vol. 45, 2009.
[7] http://scikit-learn.org/stable/modules/cross_validation.html.
[8] https://www.cs.cmu.edu/~schneide туф№42.html.
[9] Scott Davidson,Derrick Smith,Chen Yang and Sebastian Cheah. Smartwatch User Identification as a Means of Authentication,2016.
[10] Wei-Han Lee,Ruby Lee,Implicit Sensor-based Authentication of Smartphone Users with Smartwatch, HASP16, 2016.
[11] http://www.expres.co.uk/life-style/science/technology/SMS/2015/Apple-features-buy-specs.
[12] A. Johnston, G. Weiss. Smartphone-based biometric gait recognition. Biometrics Theory, Applications and Systems (BTAS), 2015 IEEE 7th International Conference, 2015.
[13] A. Johnston, G. Weiss. Cellphone based biometric identification. Biometrics Theory, Applications and Systems (BTAS), 2010.
[14] Thang Hoang, Deokja Choi and Thuc Nguyen. On The Instability of Sensor Orientation in Gait Verification on Mobile Phone, 12th International Joint Conference on e-Business and Telecommunications (ICETE), 2015.
[15] Akram Bayat, Marc Pomplun, Duc A. Tran. A Study on Human Activity Recognition Using Accelerometer Data from Smartphones, 11th International Conference on Mobile Systems and Pervasive Computing, 2014.
[16] Zengtao Feng,Lingfei Mo,Meng Li. A Random Forest-based ensemble method for activity recognition, Engineering in Medicine and Biology Society (EMBC), 2015.
[17] https://en.wikipedia.org/wiki/Spectral_centroid.
[18] K.K. Paliwal. Spectral subband centroid features for speech recognition. Acoustics, Speech and Signal Processing, 1998.
[19] Phu Ngoc Le, Eliathambam Ambikarajah, Julien Epps, Vishyasaharan Sethu, Eric H.C. Choi. Investigation of spectral centroid features for cognitive load classification, Speech Comm., 2011.
[20] Yongjin Kwon, Kyuchang Kang, Changsook Baek. Unsupervised learning for human activity recognition using smartphone sensors, Expert Systems with Applications, 2014.
[21] Oscar D Lara and Miguel A LabradaA Survey on Human Activity recognition using wearable sensors, IEEE Communications Surveys and Tutorials, 2013.
[22] N Cristianini, J Shawe-Taylor. An introduction to support vector machines and other kernel-based learning methods, 2000.
[23] B Schlkopf. The kernel trick for distances, Advances in neural information processing systems, 2001.
[24] H Yu, J Yang, J Han. Classifying large data sets using SVMs with hier-archical clusters, Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining, 2003.
[25] Chao-Ying Joanne Peng and Kuk Lida Lee and Gary M. Ingersoll. An Introduction to Logistic Regression Analysis and Reporting, The Journal of Educational Research, 2002.