

Information We Can Extract About a User From ‘One Minute Mobile Application Usage’

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Abstract—Understanding human behavior is an important task and has applications in many domains such as targeted advertisement, health analytics, security, and entertainment, etc. For this purpose, designing a system for activity recognition (AR) is important. However, since every human can have different behaviors, understanding and analyzing common patterns become a challenging task. Since smartphones are easily available to every human being in the modern world, using them to track the human activities becomes possible. In this paper, we extracted different human activities using accelerometer, magnetometer, and gyroscope sensors of android smartphones by building an android mobile applications. Using different social media applications, such as Facebook, Instagram, Whatsapp, and Twitter, we extracted the raw sensor values along with the attributes of 29 subjects along with their attributes (class labels) such as age, gender, and left/right/both hands application usage. We extract features from the raw signals and use them to perform classification using different machine learning (ML) algorithms. Using statistical analysis, we show the importance of different features towards the prediction of class labels. In the end, we use the trained ML model on our data to extract unknown features from a well known activity recognition data from UCI repository, which highlights the potential of privacy breach using ML models. This security analysis could help researchers in future to take appropriate steps to preserve the privacy of human subjects.

Index Terms—Activity Recognition; Data Security; t-SNE; Information Gain

I. INTRODUCTION

Nowadays, our mobile phones have evolved into powerful handheld computing devices. Holding a smartphone is now part of our daily activities. This is why many research studies explored smartphone sensors such as an accelerometer and gyroscope to detect human activities [1]. In general, one of the most significant tasks in pervasive computing is to provide precise and timely information about people’s activities and behaviors [2]. In fact, the study of human activities has emerged as one of the most active research areas in computer vision [3].

Authors in [4] discussed the following four challenges that people might face when studying human activities. First, human activities are concurrent; different actions might be happening at the same time. Secondly, human activities are intertwined. Thirdly, similar activities can be perceived in various ways. Finally, there might be more than one user in the studied environment. All of these human factors alongside

technological challenges can contribute to the difficulties of accurately predicting human activities. They also differentiated between ‘Activity Recognition’ and ‘Activity Pattern Discovery’. They defined ‘Activity Recognition’ as the detection of human activities accurately using a predetermined activity model, which means that the model is built first then it gets implemented into a suitable pervasive system. On the other hand, ‘Activity Pattern Discovery’ means that the data is collected first and then models are applied to discover some information and unknown patterns about the activities, which means that the pervasive system is built first and then the sensor data gets analyzed to uncover some patterns.

In this paper, we adopt the ‘Activity Pattern Discovery’ method and collect data from lower level smartphone sensors to reveal some information about the user. First, we want to observe whether we can predict what type of mobile (social media) application the user is currently running. We chose the following four applications for our experiments : (Facebook, Instagram, Whatsapp, Twitter). Then, after getting the sensor patterns (using different built-in sensors in the smart device), we want to analyse them further and identify hidden patterns (if there is any such pattern) to uncover additional information about the experiment subjects like : what is the gender of the subject? Do females have different behavior patterns than males? What age group the person belongs to? Can we predict the age of the subject while using some mobile application? And finally we want to observe whether we can recognize if the user is using his left hand, right hand or both hands while browsing the social media application. All of this information might help in recognizing if different users have different experiences while using any application and whether certain patterns disclose some private information about the smartphone users. In the real-world, such a system could be used to enhance user experience while designing any mobile application, for getting likes/dislikes of people, for targeted advertisement, for fall detection (specifically for older people), and for securing the private information of the users based on the detected patterns from the sensor data.

Using the existing data (of 60 seconds social media application usage), we show that the private information of users can be predicted using simple machine learning models. This behavior shows the vulnerability of the currently available activity data on the internet. Using the analysis we show in

this paper, relevant authorities could take appropriate steps to ensure the privacy of the data of people so that it can be avoided to be misused.

In this paper, our contributions are the following:

- 1) We collect human activity data using three sensors of the android smartphones namely accelerometer, magnetometer, and gyroscope by building an android application.
- 2) By using our application (for data collection) for just 60 seconds, we were able to classify different attributes related to human activities with high accuracy.
- 3) Using statistical analysis (information gain), we show that some features are important for the classification of certain classes.
- 4) We show that privacy of the existing data could be exploited very easily, which requires relevant authorities to take appropriate steps to avoid the misuse of activity information.

The rest of the paper is organised as follows: Section II contains the related work for the human activity recognition problem. Our main methodology is introduced in Section III. Details related to the experiments and dataset statistics are given in Section IV. Our results are reported in Section V. Finally, we conclude the paper in Section VI

II. RELATED WORK

Human activity recognition (HAR) is a well studied problem in the literature [5], [6], [7], [8]. Authors in [5] use K-nearest neighbor algorithm for HAR. Using machine learning based algorithms for HAR is done in [7]. Authors in [9] used accelerometer data from wrist watches to detect different behaviors of humans. Similarly, authors in [10] use data from wrist watches to classify different human exercises using the ML models.

Converting the unstructured data into a fixed-length numerical representation is an interesting and ongoing research problem. It has been studied in many fields such as graphs [11], [12], nodes in graphs [13], and electricity consumption [14], [15], texts analytics [16], [17], [18], electroencephalography and electromyography sequences [19], Networks [20], and biological sequences [21], [22], [23], [24], [25], [26]. For time series data, several authors proposed machine learning and deep learning based methods for time series classification [27], [28], [29], [30]. However, since deep learning based models are “data hungry”, they cannot be applied when we have limited data [31].

III. PROPOSED METHOD

In this section, we discuss the proposed approach in detail, which includes data collection and generating fixed-length numerical representation from the raw sensor data.

A. Mobile Application Usage

In the first step, we designed an android mobile application that takes some basic information (we use this information as class labels later on) from the user such as the type of social

media application they want to use, their gender, age, and the hand in which they hold the smart phone while browsing the social media applications (this information is going to help us in training our classification algorithms). When they click on the start button, the application starts collecting the information from three different sensors namely accelerometer, magnetometer, and gyroscope in the background. The user minimizer our application and start using the required social media application for 60 seconds. The social media application, which user can use are Facebook, Instagram, Whatsapp, Twitter. After 60 seconds, the application stops collecting the data and sends a message to the user that the data collection process is stopped. The final data for each sensor is added to separate excel sheets located at the download folder of the mobile. The user then sends the data to us for further analysis.

B. Data Processing and Feature Extraction

Once the data are received, we then start extracting the features. Because the raw sensor data can be of varying lengths, and the machine learning (ML) algorithms require a fixed-length vector as input, we did not use the raw data in the analysis and chose specific features only to get a fixed-length feature vector. Although there are methods that could be used to make the (raw) signal of a fixed-length (such as data padding). However, this approach will only increase the dimensionality of the data (will cause a curse of dimensionality) and hence the classifiers’ runtime. Furthermore, from the information gain analysis (explained in the later section), we discovered that only a few features are important to predict different labels from our data. This means that analysing the raw signal would not help much in improving the classifier’s performance and would have only added a huge computational cost. The features selected are Mean, Median, Mode, Quantiles (Divide data into 3 intervals with equal probability), Population Standard Deviation, Sample Standard Deviation, and Variance (total 9 features). Several ways has been proposed in the literature to use combination of different statistical features to get the fixed-length representation from the raw signals [19]. However, there is no standard way defined to select a specific types of features. Therefore, we selected the standard features used for statistical analysis. In this way, we got 9 features for x, y, and z-axis each from different sensors. Therefore, there will be a total $9 + 9 + 9 = 27$ features for each sensor data. In total we had 81 Features that include 27 Magnetometer, 27 Accelerometer, and 27 Gyroscope features. The total entries (data samples) that we collected from all 29 users are 112, which contains samples for different user using different social media applications (with each sample having 81 features).

As for choosing the sensors for the data collection, authors in [1] state that in the field of activity recognition, the accelerometer sensor has acquired the greatest attention in research. They also stated that when aiming to enhance and boost the performance of activity recognition tasks, the gyroscope and magnetometer have been integrated alongside the accelerometer sensor. In addition, most of the old android

devices only had these three sensors. Therefore, we decided to use these basic sensors in order to reach a larger audience for the data collecting.

C. Classification Step

After the feature extraction step, we run different machine learning (ML) algorithms to help us correctly identify the user’s behaviour during the mobile application usage. We ran seven classification algorithms: Support vector machines(SVM) with a linear kernel, Naive Bayes (NB), Multi-layer perceptron (MLP) where we had 10 hidden layers, K-nearest neighbors (KNN) where K=5, Random Forest (RF) with 100 as the number of trees, Logistic regression (LR) with a ‘liblinear’ solver because it is the best choice for small datasets, and Decision tree (DT). We aimed to compare and contrast the performance of each algorithm in hope that we find one that will outperform the others. In Figure 1, we provide an overview of our system components working together to achieve the goal of predicting different class labels.

IV. EXPERIMENTAL SETUP

In this section, we describe the implementation detail and dataset statistics used for the experimentation. For mobile application development in android studio (using the java code), we simply used the built-in sensor libraries for Accelerometer, Gyroscope, and Magnetometer. For the ML classification models, we use the python language. Our Java and python code along with the raw and pre-processed data is available online for reproducibility .

We use the standard 5 fold cross validation approach for the experiments and report the average results of 5 runs. We use different evaluation Metrics to measure the performance of classifiers. The metrics used are : Average Accuracy, Precision, Recall, F1 (weighted), F1 (Macro),F1 (Micro), and ROC AUC (one-vs-rest). For computing the information gain (statistical analysis), we use Weka software.

A. Dataset Statistics

We collected the data from 29 subjects; 17 of which were males and the other 12 were females. Also, 12 of the 29 subjects under the study used right handed, 10 preferred using left handed, while 7 preferred using mobile applications from both hands. To better illustrate a summary of the collected labels we provide the pie charts in Figure 2. Similarly, the signal patterns for different sensors and axis are shown in Figure 3.

To compute the importance of different features, we use a statistical method, called Information Gain (IG). The IG computes the importance of each feature with respect to the class label. More formally: $IG(Class, position) = H(Class) - H(Class|position)$, where $H = \sum_{i \in Class} -p_i \log p_i$ is the entropy, and p_i is the probability of the class i .

⁰Available in the published version

V. RESULTS AND DISCUSSION

In this section, we first show the classification results for different class labels. After that, we show the procedure for data prediction for unknown data using our trained models.

A. Gender Prediction

Table I shows a summary of the ML algorithms for gender prediction (best values are shown in bold). SVM performed the best on this task. Figure 4 illustrates the information gain values for different features. A feature having higher information gain value means that it is contributing more towards the prediction of the class label (gender). We can observe that large number of features are contributing towards the prediction of gender because of which, we are getting the classification accuracy of 98.2% (for SVM).

TABLE I: Performance of the ML algorithms on gender prediction. Best values are shown in bold.

ML Algo.	Acc.	Prec.	Recall	F1 weigh.	F1 Macro	ROC-AUC	Train. runtime (sec.)
SVM	0.982	0.984	0.982	0.982	0.981	0.980	0.011
NB	0.791	0.814	0.791	0.778	0.754	0.749	0.014
MLP	0.979	0.981	0.979	0.979	0.977	0.976	0.248
KNN	0.905	0.917	0.905	0.902	0.893	0.886	0.014
RF	0.941	0.949	0.941	0.940	0.935	0.932	0.132
LR	0.976	0.979	0.976	0.976	0.974	0.972	0.013
DT	0.851	0.862	0.851	0.850	0.838	0.842	0.008

1) *Hand Prediction:* It was really difficult to accurately predict the hand used by the subjects as shown in Table II (best values are shown in bold). To help us understand why that happens, we used information gain to reveal if there is a correlation between the class label (hand) and the data features. Generally, when information gain value for more features is higher, it implies that those features are (positively) related to the class label, and hence they will contribute more towards increasing the predictive accuracy of the classifiers. However, as shown in Figure 5, there are only a few attributes/features with larger information gain. As a result, just a few features actually aid the classifiers in distinguishing between distinct hands.

TABLE II: Performance of the ML algorithms on hand prediction. Best values are shown in bold.

ML Algo.	Acc.	Prec.	Recall	F1 weigh.	F1 Macro	ROC-AUC	Train. runtime (sec.)
SVM	0.404	0.452	0.404	0.408	0.378	0.548	0.015
NB	0.404	0.504	0.404	0.412	0.393	0.562	0.016
MLP	0.416	0.450	0.416	0.416	0.390	0.555	0.210
KNN	0.330	0.415	0.330	0.332	0.321	0.518	0.017
RF	0.410	0.440	0.410	0.405	0.374	0.547	0.140
LR	0.423	0.441	0.423	0.413	0.380	0.556	0.019
DT	0.434	0.461	0.434	0.433	0.399	0.563	0.010

2) *Application Prediction:* Table III shows a summary of the results computed using different ML algorithms for social media mobile application prediction (best values are shown in bold). MLP performed the best on this task. We realized that the mobile applications used in our study (Facebook, Twitter,

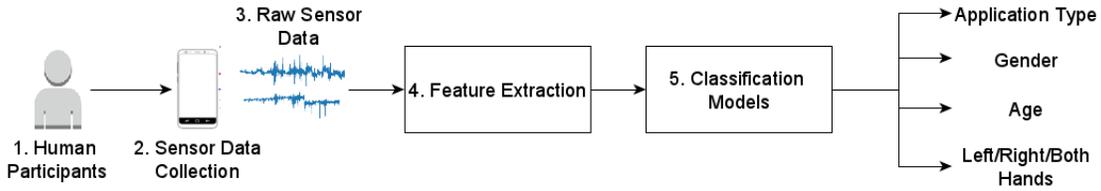


Fig. 1: Overview of the system components.

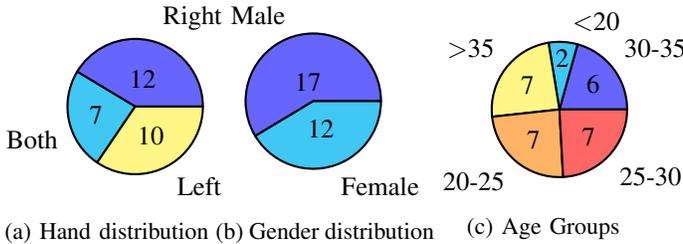


Fig. 2: Gender, hand, and age distribution. Figure is best seen in color.

and Instagram) produce similar clicking patterns. As a result, there are small differences in information gain values for these applications (see Figure 6). Hence, it is difficult for classifiers to distinguish between applications.

TABLE III: Performance of the ML algorithms on application prediction. Best values are shown in bold.

ML Algo.	Acc.	Prec.	Recall	F1 weigh.	F1 Macro	ROC-AUC	Train. runtime (sec.)
SVM	0.365	0.402	0.365	0.363	0.358	0.583	0.010
NB	0.221	0.267	0.221	0.218	0.209	0.480	0.011
MLP	0.521	0.574	0.521	0.520	0.515	0.688	0.192
KNN	0.206	0.249	0.206	0.197	0.196	0.479	0.021
RF	0.477	0.542	0.477	0.478	0.473	0.660	0.132
LR	0.379	0.430	0.379	0.378	0.369	0.591	0.023
DT	0.421	0.460	0.421	0.417	0.411	0.620	0.014

3) *Age Prediction*: Table IV shows summary of results computed using different ML algorithms for age prediction (best values are shown in bold). MLP performed the best on this task. Figure 7 illustrates different features contribution towards the prediction of age. We can see that since more features have high IG values, therefore, we are getting a higher predictive accuracy as shown in Table IV. It means that there is a correlation between the number of features having higher IG value and the classification performance for different ML classifiers.

B. UCI Repository Data Analysis

To further analyse our results, we use our trained ML models on the UCI Repository data (for testing purpose) [32] to discover how similar their activity signals (Walking, Walking Upstairs, Walking Downstairs, Sitting, Standing, Laying) are to our collected data. Their dataset had a total of 30 Subjects. They used the Accelerometer, and Gyroscope sensors to collect

TABLE IV: Performance of the ML algorithms on age prediction. Best values are shown in bold.

ML Algo.	Acc.	Prec.	Recall	F1 weigh.	F1 Macro	ROC-AUC	Train. runtime (sec.)
SVM	0.917	0.931	0.917	0.916	0.893	0.940	0.014
NB	0.736	0.779	0.736	0.730	0.722	0.827	0.015
MLP	0.925	0.938	0.925	0.923	0.905	0.948	0.227
KNN	0.843	0.836	0.843	0.825	0.752	0.867	0.016
RF	0.915	0.924	0.915	0.911	0.884	0.934	0.139
LR	0.911	0.923	0.911	0.907	0.882	0.933	0.020
DT	0.837	0.856	0.837	0.833	0.810	0.891	0.009

the data. They had a Total of 2947 Entries. Despite the fact that the labeled 'activities' collected in their experiment varied from those collected in ours, it is still possible that the users were walking, laying, sitting, etc. when they were using our mobile application to collect the data. In this case, the collected signals from UCI data and our data should have some correlations. Therefore, we used all of our data, 112 samples, for training the ML models and all of their data, 2947 samples of UCI repository data, for testing. Because their labels are different from the ones used in our experiment, the classifiers we trained will predict the labels that it already detected during the training phase (the labels that we have in our data). Due to the label differences, we cannot compute accuracy, precision, etc. for this experiment. Instead, we analyzed the patterns using a contingency table as shown in Table V. Table VI, Table VII, and Table VIII for social media applications, gender, age, and hands (using the best performing classifiers only). We then used the information gain to see the contribution of features towards the prediction of class labels. As previously stated, if more features have high information gain values, the predicted labels are more likely to be correct (because accuracies will be higher as can be seen from Table I to Table IV). Since we can see the higher information gain values in some cases, this indeed means that there is some undiscovered correlation between their data and our data as shown in Figure 8 for Age, Application, and Hand labels, respectively (for only the best classifiers from Table II, Table III, and Table IV).

C. *t*-distributed stochastic neighborhood embedding (*t*-SNE)

The *t*-SNE [33] is an approach used to get a 2-dimensional representation of the data while preserving the pairwise distance between the data points. This method is ideal for visual data analysis because it allows us to visually see if the data has any natural clustering. We use *t*-SNE to get 2-D representation

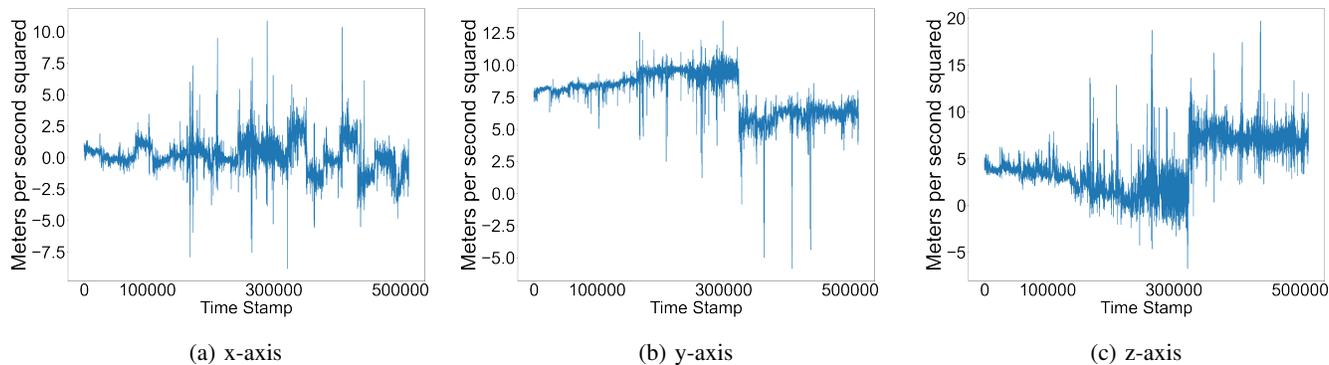


Fig. 3: Time series signals for Accelerometer sensor.

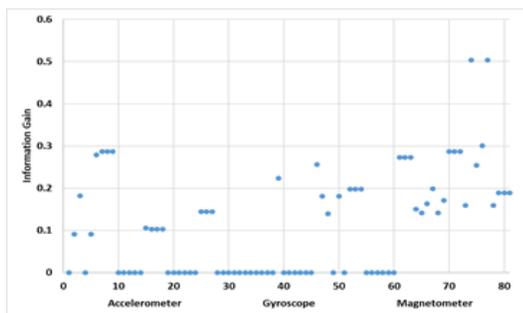


Fig. 4: Importance of the features (accelerometer, gyroscope, and magnetometer) for Gender label.

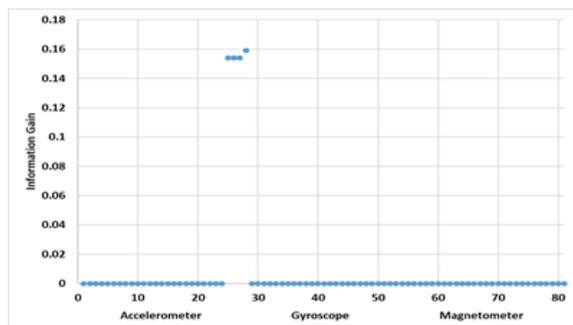


Fig. 6: Importance of the features (accelerometer, gyroscope, and magnetometer) for Application label.

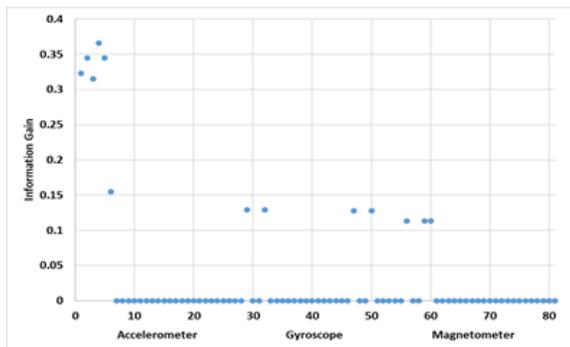


Fig. 5: Importance of the features (accelerometer, gyroscope, and magnetometer) for Hand label.

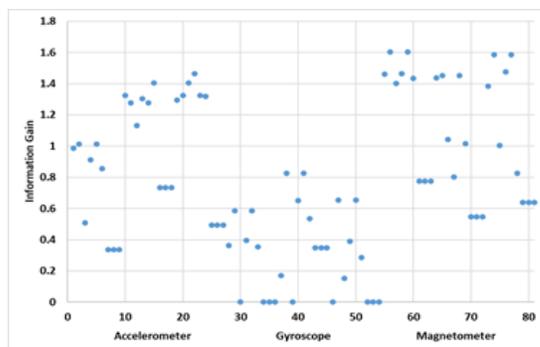


Fig. 7: Importance of the features (accelerometer, gyroscope, and magnetometer) for Age label.

TABLE V: Contingency table for MLP classifier for Application label.

Position	Twitter	Facebook	Instagram	Whatsapp	Total
Laying	53	348	32	104	537
Sitting	36	326	36	93	491
Standing	54	321	19	138	532
Walking	21	169	15	291	496
Walking Downstairs	26	144	11	239	420
Walking Upstairs	26	218	16	211	471
Total	216	1526	129	1076	2947

TABLE VI: Contingency table for SVM classifier for Gender label.

Position	Male	Total
Laying	537	537
Sitting	491	491
Standing	532	532
Walking	496	496
Walking Downstairs	420	420
Walking Upstairs	471	471
Total	2947	2947

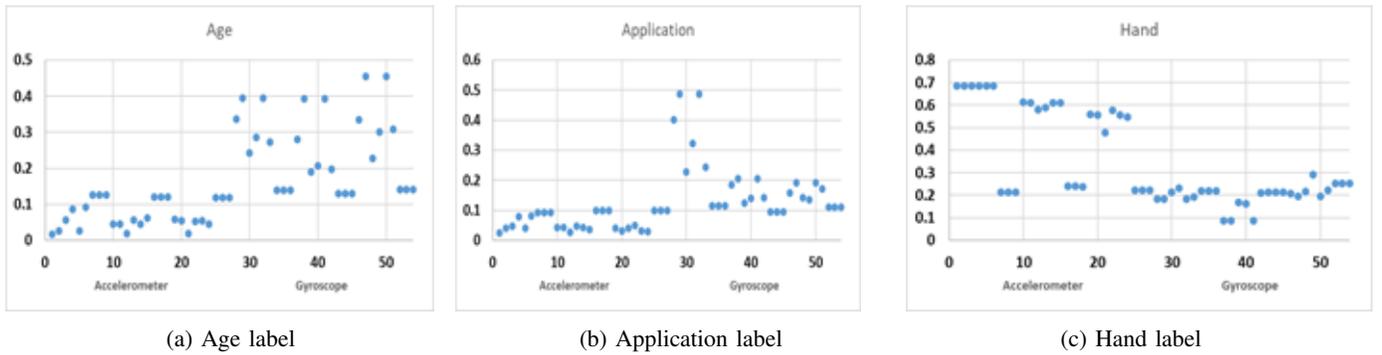


Fig. 8: Importance of the features (accelerometer and gyroscope) for Age, Application, and Hand attributes, respectively (y-axis shows the IG values). We did not show the information gain plot for gender as the best classifier predicted all Males. Since UCI repository data uses only accelerometer and gyroscope sensors, we report the IG values for these two sensors only.

TABLE VII: Contingency table for MLP classifier for Age label.

Position	< 20	20-25	25-30	30-35	> 35	Total
Laying	13	140	200	165	19	537
Sitting	45	119	121	201	5	491
Standing	41	123	186	159	23	532
Walking	1	175	218	31	71	496
Walking Downstairs	2	155	119	71	73	420
Walking Upstairs	3	151	189	80	48	471
Total	105	863	1033	707	239	2947

TABLE VIII: Contingency table for DT classifier for Hand label.

Position	Left Hand	Right Hand	Both Hands	Total
Laying	-	280	257	537
Sitting	491	-	-	491
Standing	532	-	-	532
Walking	496	-	-	496
Walking Downstairs	420	-	-	420
Walking Upstairs	471	-	-	471
Total	2410	280	257	2947

of the UCI data and use the predicted labels (from our trained classifiers) to represent the data points by different colors. We can see that there are some patterns in the data, e.g., in Figure 9d, we can notice that those who prefer to use the phone with their left hand (green dots) form separate clusters and are different from people who prefer to use the phone with their right hand or using both hands. The contingency table (in Table VIII), can also be used to validate this behavior. This behavior shows that most of the subjects involved in collecting the UCI data were left handed, an information which is originally not provided in that data repository.

VI. CONCLUSION

In summary, we show that using statistical features and standard machine learning models, we can predict the patterns of people, which can be used by researchers and relevant authorities to understand their behavior. Moreover, we show that using information gain, we can observe some correlation

between the features in the data and the predictive performance of the ML models. Using this correlation based analysis, we can predict some missing attributes about user, which were not known to the ML models initially. This could be a potential privacy concern because of which, authorities need to take more steps to ensure the privacy of people’s data. In future, we will collect more people’s data to further analyse the robustness of ML models. Collecting data for applications other than social media could also help us to understand some more hidden features about humans. Similarly, using deep learning for human activity recognition could also be a potential future work.

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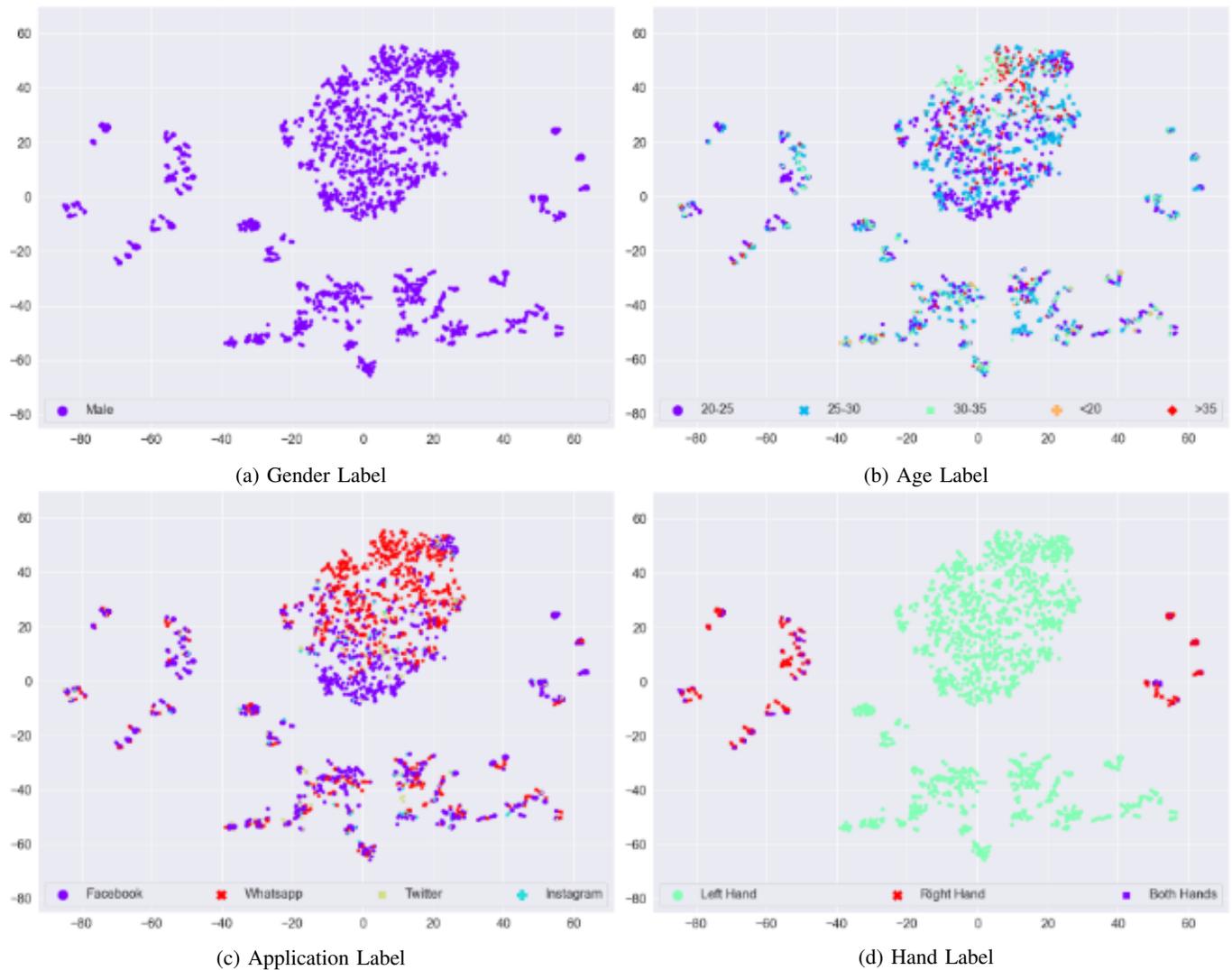


Fig. 9: t-SNE plot for UCI data. The colored dots in the plots show the predicted labels from the best ML classifiers (MLP for application and age, SVM for gender, and DT for hand).

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