Investigating the impact of combining handwritten signature and keyboard keystroke dynamics for gender prediction

CAVALCANTE BANDEIRA, D.R., DE PAULA CANUTO, A.M., DA COSTA ABREU, Marjory <http://orcid.org/0000-0001-7461-7570>, FAIRHURST, M., LI, C. and NASCIMENTO, D.S.C.

Published version

CAVALCANTE BANDEIRA, D.R., DE PAULA CANUTO, A.M., DA COSTA ABREU, Marjory, FAIRHURST, M., LI, C. and NASCIMENTO, D.S.C. (2019). Investigating the impact of combining handwritten signature and keyboard keystroke dynamics for gender prediction. In: 2019 8th Brazilian Conference on Intelligent Systems (BRACIS). IEEE, 126-131.

Copyright and re-use policy

Investigating the impact of combining handwritten signature and keyboard keystroke dynamics for gender prediction

Danilo R. C. Bandeira, Anne M. P. Canuto and Márjory Da Costa-Abreu
Dept. of Informatics and Applied Mathematics - DIMAp
Federal University of Rio Grande do Norte - UFRN
Natal, Brazil
danilorodrigo@ppgsc.ufrn.br, {anne,marjory}@dimap.ufrn.br

Michael Fairhurst and Cheng Li
School of Engineering and Digital Arts
University of Kent
Canterbury, England
m.fairhurst@kent.ac.uk, durrrivey@outlook.com

Diego S. C. Nascimento
Department of Informatics
Federal Institute of Education, Science and Technology of Rio Grande do Norte - IFRN
Natal, Brazil
diego.nascimento@ifrn.edu.br

***Abstract*—The use of soft biometrics as an auxiliary tool on user identification is already well known. It is not, however, the only use possible for biometric data, as such data can be adequate to get low level information from the user that are not only related to his identity. Gender, hand-orientation and emotional state are some examples, which it can be called soft-biometrics. It is very common to find work using physiologic modalities for soft-biometric prediction, but the behavioural data is often neglected. Two possible behavioural modalities that are not often found in the literature are keystroke dynamics and handwriting signature, which can be seen used alone to predict the users gender, but not in any kind of combination scenario. In order to fill this space, this study aims to investigate whether the combination of those two different biometric modalities can impact the gender prediction accuracy, and how this combination should be done.**

I. INTRODUCTION

The use of convectional biometrics, as fingerprints and iris scanner recognition, to uniquely identify a specific person is widely known. Those characteristics containing information that are exclusive to a specific person are called hard biometrics [6]. There are two kinds of hard biometrics: physiological and behavioural. The first is related to everything a user has, such as fingerprint, face or iris. The other is related to everything a user produces, such as handwriting, gait or voice [5]. More recently, researchers started to study characteristics that belongs to a person but are not unique to them. Those characteristics are called soft-biometrics, some example are: handedness, gender or age [4].

Due to hardware noise or failure on physiological biometric acquisition and, thus, lack of data, for example, on behavioural biometric the necessity for using additional data on user identification tasks emerged. Many researchers started to incorporate soft-biometric data together with hard-biometrics in order to overcome hardware problems and improve identification accuracy [10] or even to identify a false identity use [21]. This combination between soft and hard biometrics has shown positive results, and, because of that, soft-biometrics had its main use during the years as an auxiliary tool for hard biometrics in identification tasks.

Over the time, behavioural biometrics started to be used to predict soft biometrics, instead of just use them. Some studies investigated the capability of different behavioural biometrics in identifying such features. [3] showed in his study that keystroke and handwriting biometrics can predict gender with a good precision. In order to get these results, three different machine learning classifiers were trained on keystroke and handwriting data separately. However, some techniques can be applied aiming the enhancement of this accuracy, some of those techniques are related with the Machine Learning algorithms themselves and others are related to dataset manipulation [7].

One well explored dataset enhancing technique is the combination of different kinds of biometrics [8]. [7] discuss whether data collected over the same conditions, it implies that that combination results in an enhancement of the accuracy by predicting user identity on an online game match. The combination described on the research consists of concatenate the data side by side, using only dataset manipulation.

This paper will present the details of an investigation on how combining different biometric data can enhance the gender prediction accuracy on the data collected on [1]–[3]. However, not only dataset manipulation or Machine Learning enhancement techniques were tested, but also the combination of both following a rigorous protocol.

Identify applicable funding agency here. If none, delete this.

II. BACKGROUND AND RELATED WORK

Since our aim in this paper is to investigate the gender predictability of combining handwritten signature with keystroke dynamics, it is important to understand what has been done in this sense. Thus, this section will present the main works that in some way focus on this topic.

The first research to study the capabilities of the behavioural biometrics was [21] and its application consisted in work together with physiological biometrics and others information for reducing duplication and impersonation when sampling hidden population for respondents. For a long time many others studies investigated the use of the soft biometrics as an auxiliary tool for user identification [22]–[24]. However, as it was said before, the potential of soft biometrics goes beyond its conventional use over the years.

Next, we will present what can be found in the literature about the two biometric modalities used on this paper together with the different uses for the soft biometrics and manipulation aiming for accuracy improvement.

The first behavioural biometric used on this paper is keystroke dynamics, which consists on using information about the typing, like latency between keys, error rate and others for user identification/authentication. We can find several studies that present this modality, such as in [11] which presents different methods used to capture this data along with a review of its background. Many other researchers reported the use of keystroke in a variety of applications, as example for example: [12] presented a review on its use for user identification, [13] used keystroke to identify the device used during the typing and [14] used keystroke together with the password to make the authentication more secure.

The second behavioural biometric data used on this paper is handwritten signature, which consists in using information about the writing of the user for identification/authentication and can be divided in two types: static and dynamic []. Static information is related to the data that can be retrieved from the image of the writing. On the other hand, dynamic information is related to data that can be collected by the hardware with which the writing is performed and it is not always available. As example of relevant works that used handwritten signature, [18] presented a result towards proving the handwriting capable of identifying its author based on the style generated by the writing. Following that idea, the use of handwriting for writer recognition was widely explored, as [20] detailed. In addition, [19] presented a review of handwriting using for user identification and authentication.

We can also find relevant works that use keystroke and handwriting to predict soft biometrics, instead of the conventional use as a helper on identification tasks. Thus, [15]–[17] used handwriting-based data to predict gender and [2] used keystroke and handwriting to predict emotional state. On all those cases, it was possible to predict soft-biometrics from behavioral hard biometrics.

In [3], the author also studied the gender prediction capability of combining keystroke and handwriting signature on a newly collected bimodal dataset. On the evaluation, the biometric data was tested separately and for the handwriting dataset only the static and dynamic features were tested individually as well. However, according to [7], the combination of different modalities imply in an enhancement on the prediction accuracy. where the study improved the accuracy of about 17%, in some cases, for user identification using keystroke, mouse dynamics and handwritten signature. Another example can be found in [9], where the combination of face and iris biometrics was investigated.

Analyzing the points presented on this section is possible to notice the evolution of the soft-biometrics role and how it have been gaining more importance over the time. Starting as a auxiliary tool for hard-biometrics, and after being used as object of Machine Learning algorithms prediction, using behavioral hard-biometrics as training data. The next step is naturally the enhancement of this prediction accuracy, what is a very important point, one time that most systems where this kind of precision are mandatory are commonly classified as critical. Having this growing need for security as objective, this paper uses the technique investigated by [7] applied to the dataset built by [3] aiming the enhancement of gender prediction accuracy.

III. BEHAVIOURAL BIMODAL DATASET: KEYSTROKE DYNAMICS AND HANDWRITING

The database used oh this work was collected and first studied in [1]–[3]. This database is divided in two parts: the keystroke and the handwriting data. For its creation, a total of 100 participants were interviewed and had their typing and handwriting collected following a rigorous protocol described in [3]. For each modality, four tasks were performed, resulting in 400 instances for each base. The dataset contained information about the gender, hand-orientation and emotion for each participant.

Since this work will only focus on the gender prediction, Figure 1 presents the gender distribution of the participants.

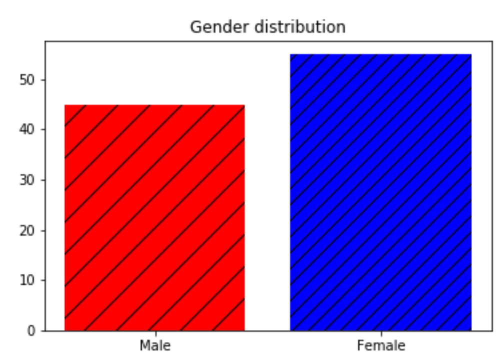

Fig. 1. Gender distribution

The protocol was performed at once to avoid differences between sessions for each user. Each task was designed aiming at specific emotions.

The keystroke dataset is composed by a total of 29 features extracted from each of the four tasks. In addition, the key press and release events were saved in the ASCII code for the hit key on the keyboard along with the timestamp.

The handwriting dataset is composed by a total of 49 features extracted from each of the four tasks. 24 features are dynamic and 25 are static. In addition, the timestamp, X and Y coordinate, normal and tangential pressure, status, cursor, context, azimuth, altitude, twist, pitch, roll and yaw informations were also saved. The Table I present a description of each task for keystroke and handwriting.

TABLE I
TASKS DESCRIPTION

Task	Description
Task 1 of Keystroke	Type pre-determined text
Task 2 of Keystroke	Free typing text
Task 3 of Keystroke	Free typing text leading to positive state
Task 4 of Keystroke	Free typing text leading to less positive state
Task 1 of Handwriting	Copy pre-determined words
Task 2 of Handwriting	Free writing leading to positive state
Task 3 of Handwriting	Free writing leading to less positive state
Task 4 of Handwriting	Copy pre-determined words with contdown time

IV. METHODOLOGY

The main goal of this paper is to investigate whether the combination of keystroke and handwriting biometrics will result in an enhancement for the gender prediction accuracy. In order to achieve that, two different approaches will be performed. The first, consists in combining both datasets, side by side, creating only one database to train the classifiers. On the second approach, the classifiers will be trained separately for keystroke and handwriting and the result of each classifier will be combined in order to predict gender.

However, just combining the datasets may imply that all the features on handwriting (static and dynamic) are appropriate, which not necessarily is true. In order to guarantee the best results, a new step was included which aims on testing several different combinations of the features. With the addition of this step, for each approach, three sets of tests will be performed, the first using the whole handwriting dataset, the second using only the static features and the third using only the dynamic features. In addition, the second approach will also use a random feature selection on some of its tests.

A. Pre-processing

The original datasets contained a wide range between features values which may cause slowness and imprecision on the classifiers, thus, we have decided to perform some pre-processing techniques. The first technique applied on the database was the normalisation, which brings all the features on the database to the same scale. For simplicity, the implementation chosen was the offered by Scikit-learn [33]. After this step, the full keystroke and handwriting datasets were set up and ready for the training process.

We have also created several sub-sets of databases in order to investigate the impact of using only dynamic handwriting features or only static handwriting features. They will be refered in the text as: static and dynamic datasets.

B. Classification algorithms

In order to test whether the datasets will be able to predict gender, four different classifiers were selected from a range of well known classical supervised set. They can be seen listed below and the parameters for each one can be found on the Appendix VI-B. Those classifiers used the exact same configuration over all tests reported here. Next the classifiers, each approaches will be explained in details.

- K-Nearest Neighbours (KNN) [25];
- Multi-Layer Perceptron (MLP) [26];
- Decision Tree (DT) [27]; and
- Support Vector Machine (SVM) [28].

The first approach, consists in combining both keystroke and handwriting datasets side by side, creating only a single dataset, and training the classifiers. The class column, also called target, on each biometrics dataset was sorted in a way to make each line of the keystroke base matches the correspondent line on handwriting base. After the sorting, the target column on each dataset set was removed and kept separated, because those columns would be equal and only one will be used. Once, we have both datasets without the target columns, they were put together following the order keystroke and handwriting, respectively. Lastly, the target column was incorporated back at the end.

The second approach, consists in training two instances of each classifier, one using the keystroke dataset and the other using the handwriting dataset. In order to combine the results of each classifier into one, the given probabilities for each class were added, being the biggest the final prediction. In addition, this approach was divided in two different parts. On the first, only one instance of each classifiers was used with the full current dataset for keystroke and handwriting, as described above. On the other hand, the second part uses ensembles containing five, ten and 20 instances for each classifiers, being the features of the datasets chosen randomly and differently on each classifier keeping the percentage between 70% and 90% of the original, aiming an improvement [29].

C. Training and testing

After having the datasets ready and the approaches chosen, a reliable strategy to test the classifiers accuracy was necessary. In order to guarantee that the results are as correct as possible, a decision to execute each test 30 times and using the mean was made. A total of 75% of the dataset was used for training and 25% for testing, that split used a stratified strategy to keep the men and women proportion. However, the used Scikit-learn split method shuffle the instances on the dataset before the separation and for reproducibility purpose that shuffle was performed using a fixed and different seed for each one of the 30 execution. Next, will be detailed the used procedure on each approach.

For the first approach, three sets of the five classifiers were tested, being the first with the keystroke data, the second with the handwriting data, and the third with the combined data. The result used was the provided by the score method performed on the test dataset. No ensemble was used in any of the 30 executions.

For the first part of the second approach, two sets of the four classifiers were tested. As mentioned before, one set was trained with the keystroke data and the other set with the handwriting data. For the evaluation, each sample on the test dataset was predicted by each classifiers on both sets and had the probabilities for each class added, forming a combined result.

The second and last part of the second approach was made with no combined database and for each biometrics dataset, three different ensembles containing five, ten and 20 was trained. In addition, for the training and testing, the features on each set were randomly selected, keeping a percentage between 75% to 90% of the total. For the evaluation process, each sample of the tested data was predicted by each instances of each set and had the probabilities of each class added, forming a combined result, as the previous test.

The Table II present the approaches just detailed along with the abbreviations used over the entire paper. The first line refers to the first approach, the second line refers to the first part of the second approach and line tree, four and five refer to the last part of the second approach.

TABLE II
TESTED APPROACHES

Abbreviation	Description
COMB	Datasets combined side by side
SEP	Separated classifiers for each dataset with summed probabilities
ENS5	Separated 5 classifiers for each dataset using 75% to 90% of features with summed probabilities
ENS10	Separated 10 classifiers for each dataset using 75% to 90% of features with summed probabilities
ENS20	Separated 20 classifiers for each dataset using 75% to 90% of features with summed probabilities

V. RESULTS

In order to facilitate our experimental reproducibility, all the classification tests and plots were performed using the following Python's libraries: Numpy, Scipy, Sci-kit learn, Matplotlib and Pandas [31]–[35], and all the statistical tests were performed using the following R's libraries: PMCMR and NSM3 [36]–[38]. In order to compare all algorithms in each dataset, the results will be displayed by a dataset showing the correspondent classifiers grouped.

Tables III, IV, V and VI present the complete results using the modalities isolated, the whole dataset, only the statics features of handwriting and only the dynamic features of handwriting, respectively. The data on the tables used, as the format, the accuracy followed by the standard deviation multiplied by two, in parenthesis, both with four decimal precision float points.

To guarantee the consistency of the statistical test, we have used the Friedman-Nemenyi post-hoc test [30] for each set (full, static and dynamic) using the 30 execution results. By analysing only the isolated modalities on Table III, the handwriting archived better scores than keystroke. While the highest accuracy using only keystroke was 64.00% with SVM classifiers, handwriting signature got 68.03% of accuracy with MLP using all features. When we observe the handwriting results, most algorithms presented better performance on the full database, with only KNN and one test of DT increasing the accuracy after the splitting. Next, each algorithm will have its performance analyzed separately.

KNN algorithm obtained the second lowest result with 63.80% using 10 component ensembles with only dynamic features (Table VI). According to Figure 2, full, static and dynamics sets of result follow a similar behaviour with dynamic features presetting more significance to a better result. Making a comparison between isolated modalities and the tested combination approaches, those last showed better overall results.

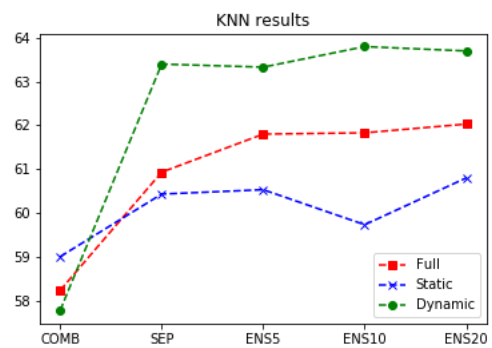

Fig. 2. KNN results for full, static and dynamic datasets

MLP algorithm obtained the best overall result reaching 71.03% of accuracy using the full features dataset (Table IV). By analysing its performance on the handwriting derivations, it is possible observe that a clear improvement using the complete features, with the dynamic showing more influence on the results than the statics as presented on Figure 3. Comparing isolated modalities with the approaches tested, it is possible affirm that the combination generates a clear enhancement on the accuracy.

In terms of overall accuracy, Decision Tree had the lowest result obtaining 65.60% using 10 components ensembles with only dynamic features (Table VI). In addition, like the KNN, the dynamic handwriting features were more significant than the statics for the prediction. Figure 4 also shows that the three datasets had a similar behaviour over all tested approaches. In comparison with the isolated modalities, the combining approaches showed better results.

SVM algorithm obtained the second best overall result using the combined approach with the full handwriting features, reaching 67.13% of accuracy (Table IV). According to Figure 5, three sets follow a very similar behaviour. However, the static features presented a more significant result than the

TABLE III
TEST RESULTS FOR ALL ALGORITHMS USING THE ISOLATED DATASETS

Dataset	KNN	MLP	DT	SVM
Keystroke	0.6007 (+/- 0.0835)	0.6257 (+/- 0.0718)	0.5920 (+/- 0.0856)	0.6400 (+/- 0.0880)
Handwriting Full	0.5520 (+/- 0.1043)	0.6803 (+/- 0.0665)	0.6027 (+/- 0.0865)	0. 6427 (+/- 0.0639)
Handwriting Static	0.5863 (+/- 0.0717)	0.6153 (+/- 0.0838)	0.5287 (+/- 0.0978)	0.6047 (+/- 0.1015)
Handwriting Dynamic	0.5797 (+/- 0.1048)	0.6367 (+/- 0.0754)	0.6113 (+/- 0.0838)	0.5857 (+/- 0.0686)

TABLE IV
TEST RESULTS FOR ALL ALGORITHMS USING THE WHOLE HANDWRITING DATASET

Dataset	KNN	MLP	DT	SVM
Combined	0.5823 (+/- 0.0872)	0.6723 (+/- 0.1027)	0.6253 (+/- 0.1114)	0.6713 (+/- 0.0905)
Separated	0.6093 (+/- 0.0829)	0.6910 (+/- 0.0963)	0.6103 (+/- 0.0841)	0.6663 (+/- 0.0700)
Ensemble (5 classifiers)	0.6180 (+/- 0.0937)	0.7027 (+/- 0.0858)	0.6467 (+/- 0.0819)	0.6473 (+/- 0.0756)
Ensemble (10 classifiers)	0.6183 (+/- 0.0844)	0.6980 (+/- 0.0776)	0.6507 (+/- 0.0777)	0.6350 (+/- 0.0700)
Ensemble (20 classifiers)	0.6203 (+/- 0.0816)	0.7103 (+/- 0.0787)	0.6543 (+/- 0.0775)	0.6447 (+/- 0.0718)

TABLE V
TEST RESULTS FOR ALL ALGORITHMS USING THE STATIC FEATURES OF THE HANDWRITING DATASET

Dataset	KNN	MLP	DT	SVM
Combined	0.5900 (+/- 0.0664)	0.6263 (+/- 0.0823)	0.5733 (+/- 0.0907)	0.6350 (+/- 0.0801)
Separated	0.6043 (+/- 0.0670)	0.6530 (+/- 0.0761)	0.5827 (+/- 0.0807)	0.6293 (+/- 0.0703)
Ensemble (5 classifiers)	0.6053 (+/- 0.0808)	0.6493 (+/- 0.0672)	0.5997 (+/- 0.0771)	0.5993 (+/- 0.0464)
Ensemble (10 classifiers)	0.5973 (+/- 0.0695)	0.6500 (+/- 0.0759)	0.6090 (+/- 0.0924)	0.6013 (+/- 0.0563)
Ensemble (20 classifiers)	0.6080 (+/- 0.0686)	0.6520 (+/- 0.0872)	0.6180 (+/- 0.0707)	0.5950 (+/- 0.0525)

TABLE VI
TEST RESULTS FOR ALL ALGORITHMS USING THE DYNAMIC FEATURES OF THE HANDWRITING DATASET

Dataset	KNN	MLP	DT	SVM
Combined	0.5777 (+/- 0.1011)	0.6653 (+/- 0.0900)	0.6260 (+/- 0.0920)	0.6237 (+/- 0.0894)
Separated	0.6340 (+/- 0.0811)	0.6537 (+/- 0.1026)	0.6257 (+/- 0.0664)	0.6273 (+/- 0.0621)
Ensemble (5 classifiers)	0.6333 (+/- 0.0987)	0.6587 (+/- 0.0853)	0.6487 (+/- 0.0664)	0.5803 (+/- 0.0526)
Ensemble (10 classifiers)	0.6380 (+/- 0.0836)	0.6560 (+/- 0.0959)	0.6560 (+/- 0.0733)	0.5820 (+/- 0.0547)
Ensemble (20 classifiers)	0.6370 (+/- 0.0814)	0.6603 (+/- 0.0969)	0.6550 (+/- 0.0786)	0.5800 (+/- 0.0490)

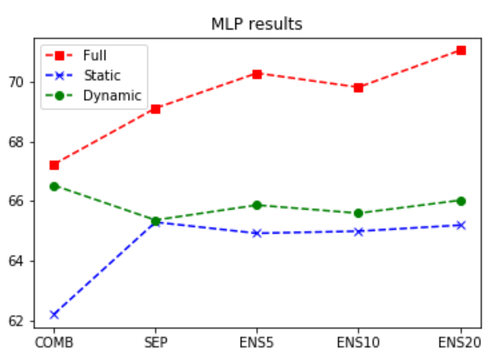

Fig. 3. MLP results for full, static and dynamic datasets

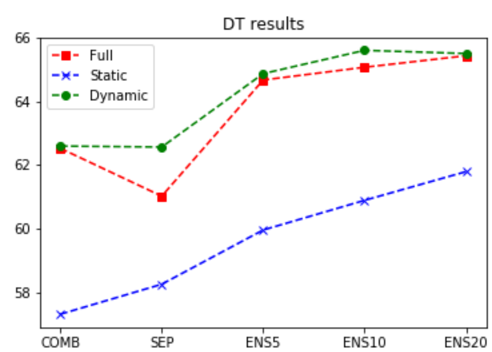

Fig. 4. DT results for full, static and dynamic datasets

dynamics. Comparing the isolated modalities with the tested approaches, this last one presented better results most of the time on all situations (full, static and dynamic features).

By analysing the performance of all algorithms on all sets and approaches, a pattern emerged, pointing at an improvement of combined biometrics modalities over isolated modalities in terms of accuracy. Figure 6 shows the best result of each algorithm over all the dataset combination. Any one of those result came from the isolated modalities, showing that, in this context, combining different biometrics has generated an enhancement on its gender prediction capabilities.

Figure 7 shows the lowers results of each algorithm over all the dataset combination. With the exception of the SVM, all results came from isolated modalities. Those scores go in

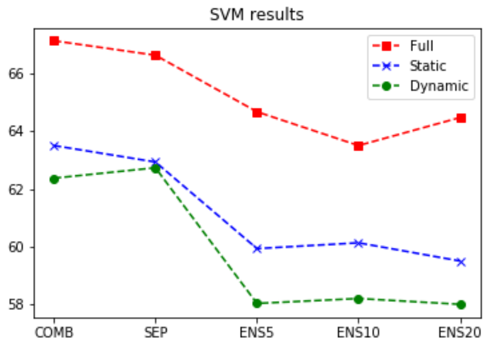

Fig. 5. SVM results for full, static and dynamic datasets

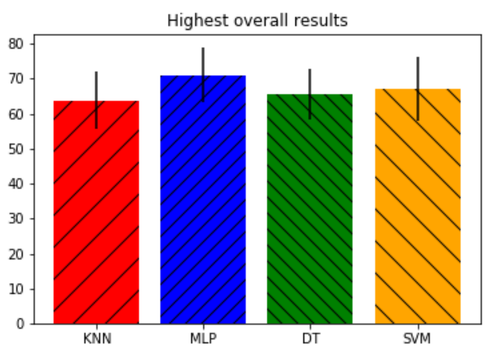

Fig. 6. Overall best results for each algorithm

accord with the analysis made with Figure 6 and reinforces the statement made on the last paragraph.

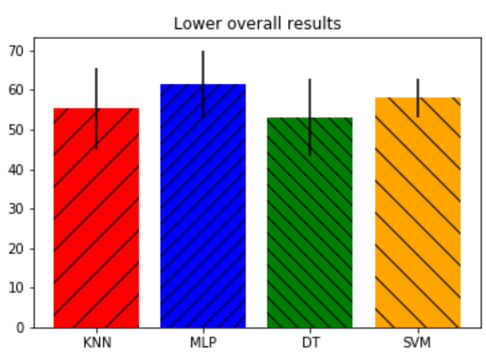

Fig. 7. Overall best results for each algorithm

In summary, the results presented in this section, show that, in our context, combining these two different biometrics modalities implies on a higher accuracy for gender prediction. The presented overall best and lower scores corroborates with this idea. However, the influence of the handwriting static and dynamic features on the behaviour of the different classifier differs between each other and deserve a deeper analysis.

VI. CONCLUSIONS

This paper presented the results of the investigation on how keystroke and handwriting biometrics modalities combination can impact gender prediction accuracy. The results analysis has shown that combining different modalities using the correct approach generates a real enhancement on gender prediction. In addition, it was possible to note a dissonance on how different Machine Learning algorithms behave when using handwriting static features, dynamic features or a combination of both.

In future studies, we plan explore more the pattern of the different handwriting signature features on different algorithms in the same way we intent to deepen feature selection method for single and ensemble classifiers and even investigate dimensionality reduction can impact the prediction. More algorithms and different settings can be tested together with new ways to combine the biometrics modalities, as different percentages of each one as an example.

APPENDIX

A. Environment

The Table VII presents all the programming languages and its libraries version used during the research.

TABLE VII
DEVELOPMENT ENVIRONMENT USED ON THE TESTS

Language/Lib	Version
Python	3.5.4
Matplotlib	2.2.2
Numpy	1.14.3
Pandas	0.23.4
Scipy	1.1.0
Scikit-learn	0.19.1
R	3.4.2
PMCMR	4.3
NSM3	1.12

B. Classifiers parameters

For the classifiers was used the following parameters, if the not specified on the below list the value chosen was the default set by the scikit-learn.

- KNeighborsClassifier(n_neighbors=3);
- MLPClassifier(hidden_layer_sizes=(58,), max_iter=20000);
- DecisionTreeClassifier(); and
- SVC(C=2.0, kernel='linear').

ACKNOWLEDGMENT

This work has been financially supported by CNPq/Brazil, under process numbers 305876/2015-5

REFERENCES

[1] Erbilek, M., Fairhurst, M., & Li, C. (2016, May). Exploring gender prediction from digital handwriting. In Signal Processing and Communication Application Conference (SIU), 2016 24th (pp. 789-792). IEEE.

[2] Fairhurst, M., Li, C., & Erbilek, M. (2014, October). Exploiting biometric measurements for prediction of emotional state: A preliminary study for healthcare applications using keystroke analysis. In Biometric Measurements and Systems for Security and Medical Applications (BIOMS) Proceedings, 2014 IEEE Workshop on (pp. 74-79). IEEE.

[3] Li, C. (2016). Extending the predictive capabilities of hand-oriented behavioural biometric systems (Doctoral dissertation, University of Kent).

[4] Dantcheva, A., Velardo, C., Dangelo, A., & Dugelay, J. L. (2011). Bag of soft biometrics for person identification. Multimedia Tools and Applications, 51(2), 739-777.

[5] Jain, A. K., Ross, A. A., & Nandakumar, K. (2011). Introduction to biometrics. Springer Science & Business Media.

[6] Niinuma, K., Park, U., & Jain, A. K. (2010). Soft biometric traits for continuous user authentication. IEEE Transactions on information forensics and security, 5(4), 771-780.

[7] Da Silva, V. Ribeiro, JCG De Arajo Silva, and Mrjory Da Costa-Abreu. "A new Brazilian hand-based behavioural biometrics database: Data collection and analysis." (2016): 17-6.

[8] Ross, A., & Jain, A. (2003). Information fusion in biometrics. Pattern recognition letters, 24(13), 2115-2125.

[9] Wang, Y., Tan, T., & Jain, A. K. (2003, June). Combining face and iris biometrics for identity verification. In International Conference on Audio-and Video-Based Biometric Person Authentication (pp. 805-813). Springer, Berlin, Heidelberg.

[10] Zewail, R., Elsafi, A., Saeb, M., & Hamdy, N. (2004, July). Soft and hard biometrics fusion for improved identity verification. In Circuits and Systems, 2004. MWSCAS'04. The 2004 47th Midwest Symposium on (Vol. 1, pp. I-225). IEEE.

[11] Banerjee, S. P., & Woodard, D. L. (2012). Biometric authentication and identification using keystroke dynamics: A survey. Journal of Pattern Recognition Research, 7(1), 116-139.

[12] Pisani, P. H., & Lorena, A. C. (2013). A systematic review on keystroke dynamics. Journal of the Brazilian Computer Society, 19(4), 573.

[13] Tsimperidis, I., & Katos, V. (2013, September). Keystroke forensics: are you typing on a desktop or a laptop?. In Proceedings of the 6th Balkan Conference in Informatics (pp. 89-94). ACM.

[14] Modi, S., & Elliott, S. J. (2006, October). Keystroke dynamics verification using a spontaneously generated password. In Carnahan Conferences Security Technology, Proceedings 2006 40th Annual IEEE International (pp. 116-121). IEEE.

[15] Bouadjenek, N., Nemmour, H., & Chibani, Y. (2014, August). Local descriptors to improve off-line handwriting-based gender prediction. In Soft Computing and Pattern Recognition (SoCPaR), 2014 6th International Conference of (pp. 43-47). IEEE.

[16] Bouadjenek, N., Nemmour, H., & Chibani, Y. (2015, August). Age, gender and handedness prediction from handwriting using gradient features. In Document Analysis and Recognition (ICDAR), 2015 13th International Conference on (pp. 1116-1120). IEEE.

[17] Bouadjenek, N., Nemmour, H., & Chibani, Y. (2015, September). Histogram of oriented gradients for writer's gender, handedness and age prediction. In Innovations in Intelligent Systems and Applications (INISTA), 2015 International Symposium on (pp. 1-5). IEEE.

[18] Srihari, S. N., Cha, S. H., Arora, H., & Lee, S. (2002). Individuality of handwriting. Journal of forensic science, 47(4), 1-17.

[19] Vinciarelli, A. (2002). Online and offline handwriting recognition: a comprehensive survey. Pattern Recognit, 35(7), 1433-1446.

[20] Yu, K., Wang, Y., & Tan, T. (2004). Writer identification using dynamic features. In Biometric Authentication (pp. 512-518). Springer, Berlin, Heidelberg.

[21] Heckathorn, D. D., Broadhead, R. S., & Sergeyev, B. (2001). A methodology for reducing respondent duplication and impersonation in samples of hidden populations. Journal of Drug Issues, 31(2), 543-564.

[22] A. K. Jain, S. C. Dass, and K. Nandakumar, Can soft biometric traits assist user recognition? Proc. SPIE, vol. 5404, pp. 561572, Aug. 2004.

[23] A. K. Jain, S. C. Dass, and K. Nandakumar, Soft biometric traits for personal recognition systems, in Proc. 1st Int. Conf. Biometric Authentication, 2004, pp. 731738.

[24] Jain, A. K., Nandakumar, K., Lu, X., & Park, U. (2004, May). Integrating faces, fingerprints, and soft biometric traits for user recognition. In International Workshop on Biometric Authentication (pp. 259-269). Springer, Berlin, Heidelberg.

[25] Cover, T., & Hart, P. (1967). Nearest neighbor pattern classification. IEEE transactions on information theory, 13(1), 21-27.

[26] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1985). Learning internal representations by error propagation (No. ICS-8506). California Univ San Diego La Jolla Inst for Cognitive Science.

[27] Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). Classification and Regression Trees. CRC Press.

[28] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20(3), 273-297.

[29] Dietterich, T. G. (2000, June). Ensemble methods in machine learning. In International workshop on multiple classifier systems (pp. 1-15). Springer, Berlin, Heidelberg.

[30] Nemenyi, P. (1962, January). Distribution-free multiple comparisons. In Biometrics (Vol. 18, No. 2, p. 263). 1441 I ST, NW, SUITE 700, WASHINGTON, DC 20005-2210: INTERNATIONAL BIOMETRIC SOC.

[31] Oliphant, T. E. (2006). A guide to NumPy (Vol. 1, p. 85). USA: Trelgol Publishing.

[32] Jones, E., Oliphant, T., & Peterson, P. (2014). SciPy: open source scientific tools for Python.

[33] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. Journal of machine learning research, 12(Oct), 2825-2830.

[34] Hunter John, D. (2007). Matplotlib: a 2D graphics environment Comput. Sci. Eng, 9, 90-5.

[35] McKinney, W. (2010, June). Data structures for statistical computing in python. In Proceedings of the 9th Python in Science Conference (Vol. 445, pp. 51-56).

[36] R Core Team. R: A Language and Environment for Statistical Computing. Vienna, Austria, 2017. Available in: ¡https://www.R-project.org/¿.

[37] POHLERT, T. The Pairwise Multiple Comparison of Mean Ranks Package (PMCMR). [S.l.], 2014. R package. Available in: ¡https://CRAN.R-project.org/package=PMCMR¿

[38] SCHNEIDER, G.; CHICKEN, E.; BECVARIK, R. NSM3: Functions and Datasets to Accompany Hollander, Wolfe, and Chicken - Nonparametric Statistical Methods, Third Edition. [S.l.], 2018. R package version 1.12. Available in: ¡https://CRAN.R-project.org/package=NSM3¿.