Missing Data Imputation in Daily Wearable Data for Improved Classification Performance

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Abstract: In the realm of wearable technology, the continuous monitoring of health parameters through smartwatches provides a wealth of daily data for research and analysis. However, this data often encounters missing values, presenting a challenge for interpretation and utilization. Remarkably, there exists a notable gap in the literature concerning the imputation of missing daily data from smartwatches. To address this gap, our study systematically explores a diverse set of imputation methods with Fitbit wearable data, encompassing various scenarios and missing rates. Our primary objectives are: (i) measure the influence of missing values rate and distribution on the proposed imputation methods; (ii) assess the role of data imputation in enhancing the performance of machine learning algorithms. Our results underscore the pivotal role of missing data patterns in imputation method selection. Furthermore, we demonstrate that more advanced data imputation approaches positively contributes to the efficacy of classification algorithms, improving 4,4% and 0,4% in terms of F-measure for the proposed classification tasks. This study not only addresses the challenges associated with missing data in wearable daily monitoring but it also provides practical insights for the optimization of machine learning applications in health monitoring.

1 INTRODUCTION

The wearable market including wrist wearable devices, has being growing in the last decade reaching an industry size of 137.89 billion USD in 2022 and it is expected to continue increasing, reaching 1.300 billion USD by 2035 (Nester, 2023). This technology allows the continuous and remote monitoring of the users 's health parameters.

The utility of wearable devices have turn them into a suitable tool for research in the healthcare domain, enabling the development of data analytics, data visualization and artificial intelligence techniques for the prevention and analysis of upcoming health events (Iqbal et al., 2021; Lu et al., 2016). Data gathered by wearable devices is categorized into two primary classes in this work: sparse health parameters, which encompass raw time series collected from wearable data with frequencies lower than one day, and daily health statistics, which comprise daily summaries of sparse health parameters.

Wearable devices include some limitations such as a finite battery duration, error in the readings of several parameters for not having the wearable well tighten, connectivity problems, deterioration of the hardware components or even the user can forget to wear it (Baek and Shin, 2017). As a result, the data gathered from these devices can present significant time spans without readings, even though removing the registers would be the easiest procedure, this may lead to unfavorable outcomes: less data to analyze, inconsistencies and depending the class of missing values (more precisely: missing not at random) removing them will cause a biased result (Weber et al., 2017).

Consequently, several works have attempted to develop and evaluate automatic tools for missing data imputation, learning the behavioral patterns of the different variables in the data and predicting the missing values (Buczak et al., 2023). However, there are few works that have evaluated the effectiveness of different data imputation techniques on smart watch data, and most of them evaluating large time series such as

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heart rate or breathing, leaving out a wide range of daily health statistics.

To address this issue, the main objective of this paper is to evaluate the effectiveness of a wide range of imputation methods on wearable data in order to improve the classification performance of the proposed models. In our work we address the following research questions:

- **RQ1.** Do existing imputation algorithms obtain better results compared to mean and median methods (baselines) in wearable data?
- **RQ2.** Does considering data from previous days improve the quality of data imputation?
- **RQ3.** Is the performance of the proposed data imputation algorithm better than baselines when the missing value rate increases?
- **RQ4.** Does including imputed data in the training set help to improve the performance of classification models?

The structure of the paper is organized as follows. In section 2, we delve into the previous research conducted by other authors on data imputation techniques for data obtained from wearables. Section 3 provides an explanation of the dataset utilized and the preprocessing steps taken. Section 4 explains the techniques used for data imputation and the different scenarios where the proposed data imputation algorithms will be tested. Section 5 shows the results obtained with the proposed methodology, including a discussion, whereas section 6 concludes the study by summarizing the key findings.

2 PREVIOUS WORK

There are several works that have addressed the imputation of missing values in wearable data. In Lin et al. (2020), the authors present a deep learning approach utilizing LSTM layers (Yu et al., 2019) to impute missing heart rate values in time series data acquired from Fitbit and Garmin wearables. Besides, personal data for each subject is considered separately for imputation. The authors feed the model with a set of time series and make use of the adversarial training (Zhao et al., 2022) to obtain results that improve the performance of baselines, such as linear interpolation (Noor et al., 2015) and moving average. The proposed method is then tested in two smartwatch datasets: in the case of the Garmin dataset (Mattingly et al., 2019) increasing the RMSE (Willmott and Matsuura, 2005) score from 4,1% to 58,5%, whereas in the Fitbit dataset (Faust et al., 2017) the improvement went from 6,9% to 54,3% both of them over the baselines and weighing specific periods of time. In (Feng and Narayanan, 2019) the OMsignal, a wearable that attaches to a shirt, is employed to obtain various physiological metrics. The authors decide to impute the missing values in the heart rate time series, breath and steps time series using a recurrent neural network (Medsker and Jain, 2001) that considers time dependency of the input to fill the gaps. The authors develop a model that enhances the attained scores in comparison to mean imputation and KNN imputations—chosen as baseline methods—particularly as missing rates escalate. The authors of Wu et al. (2020), propose a convolutional autoencoder (Masci et al., 2011) that has the ability to evaluate adjacent values to fill in the missing values, moreover the authors make use of transfer learning (Bozinovski, 2020) to incorporate the knowledge of a model trained on wearable data with different users of Garmin (Mattingly et al., 2019) or Fitbit (Faust et al., 2017) devices to address the lack of data in some subjects. The authors conclude that their model is able to effectively impute data on heart rate time series. The performance of the model substantially improves the results over the baseline methods obtaining a 4,67% reduction of MAPE (De Myttenaere et al., 2016) throughout two different datasets and distinct test scenarios. Other studies as in (Huo et al., 2022), consider accelerometer, gyroscope and magnetometer data collected from smartphones with a frequency of 20 seconds. Following the example of Wu et al. (2020), the authors opted for the implementation of an autoencoder (Bank et al., 2023), which comprises LSTM layers to capture and retain information from previous inputs. This design allows the model to consider the temporal dependency of the input data. The achieved results surpassed those of baseline methods, including mean imputation, KNN, and random forest models. Notably, there was a substantial mean increase in accuracy of 6,25% when the missing rate values exceeded 10%. Additionally, increasing in the rate of missing values does not have a significant impact in the performance of the model as in this work for certain methods.

There are numerous works that have studied the utility of daily health statistics reported by wearable devices. In Sathyanarayana et al. (2016), the ActiGraph GT3X+ (Aadland and Ylvisåker, 2015) wearable is used to monitor the sleep of different subjects. The objective of this study is to predict the sleep efficiency of the user, differentiating between good (SE > 85%) and bad sleep (SE < 85%). For that, recorded physical activity of the same day obtained from accelerometers is considered. They proposed various deep learning methods reaching a 89% accuracy for their best one, a LSTM based neural network. The research conducted in Conroy et al. (2022) with Garmin smartwatches, Oura rings and Empatica E4 wristbands aimed to detect Covid-19 with the recorded physiological metrics. First of all, they standardize the metrics from different wearables, getting a time series with a sampling frequency of 10 minutes (this allows to merge breath and heart parameter from different devices). Once the data is standardized, cleaning is done according to the adequateness of sleep data. Using machine learning models an AUC of 0,82 and an F-score of 0,44 is achieved for the prediction of Covid-19. In the work of Kanokoda et al. (2019), a glove is made in order to collect data from strain sensors located in three fingers to predict hand gestures via a TDNN (Längkvist et al., 2014) deep learning model. Attaining a model capable of real-time result prediction, achieving a mean accuracy of 84,6% when forecasting the next 10 steps, decreasing to 61.1% when considering 30 steps ahead. In the study conducted in Zhu et al. (2020), daily data from various smartwatches, including Fitbit and Apple Watch, was collected from a substantial cohort of 30.529 participants over a two-month period. The primary goal of this study was to monitor the outbreak of Covid-19 and predict potential infections. Lastly, both Ghandeharioun et al. (2017) aim to predict depression based on wearable data. According to Ghandeharioun et al. (2017), the authors employ E4 wristbands and the smartphone usage data that then is aggregated in both, intervals of 6 hours and days. They introduce the data on an ensemble machine learning method to predict the Hamilton Depression Rating Scale (Williams, 2001). Achieving an RMSE of 4,5 on the test exercise. The results suggest that the information provided by health metrics gathered from wearable devices can monitorize wearers with the recorded data.

This study aims at assessing the impact of a diverse range of imputation methods on daily health statistics derived from wearable devices. Notably, existing research predominantly focuses on the influence of various data imputation algorithms on time series data obtained from wearables. However, there is a significant gap in understanding how these algorithms perform when applied to daily health statistics obtained from wearable devices. Moreover, while daily health statistics from wearables have been utilized in various artificial intelligence tasks, the investigation into the effects of imputation algorithms on commonplace tasks, such as classification, remains largely unexplored.

3 MATERIALS

The popularity of wearable devices has increased to such an extent that using their data is becoming more frequent (Lu et al., 2016). This has led to several datasets employed by previous works: Faust et al. (2017), Tesserae project (Mattingly et al., 2019), WISDM (Weiss, 2019), Bent et al. (2021), harAGE presented in (Mallol-Ragolta et al., 2021), Vaizman et al. (2017) and PMData (Thambawita et al., 2020).

As for private datasets, in Faust et al. (2017), a smartphone and Fitbit dataset is introduced, where the Fitbit smartwatch is given to approximately 700 students for two different periods of time. The Tesserae project (Mattingly et al., 2019) collects data from 757 workers over a year using Garmin smartwatches collecting capturing heart rate, sleep and calories data. As for public datasets, in Weiss (2019), the WISDM is introduced, consisting of accelerometer and gyroscope data obtained from the LG G Watch and smartphones of 51 people while performing certain actions. The dataset discussed in Bent et al. (2021), focuses on data collected using the Empatica 4 wristband, which gathers information such as heart rate (HR), blood volume pulse (BVP), and interbeat interval (IBI). Additionally, data from glucose sensors is included, involving a total of 16 subjects observed over a period ranging from eight to ten days. The harAGE dataset (Mallol-Ragolta et al., 2021) records data of Garmin smartwatches of 30 people performing various physical activities. Lastly, a public dataset is introduced in Vaizman et al. (2017) where the authors collect data from both, pebble smartwatches and smartphones from a group of 60 people reaching a total of 300k minutes of data focusing on accelerometer and gyroscope sensors, although location and audio data is collected as well.

Our work is focused on the PMData (Thambawita et al., 2020) database. The dataset consists of data collected from 16 individuals throughout a period of five months (November 2019 to end of march 2020) and using the Fitbit Versa 2 smartwatch. This smartwatch is capable of detecting different states of physical activity such as time exercising or being sedentary as well as heart rate, kcal burnt, steps and sleep data, each being collected in different time frequencies. For instance, a heart rate value is stored each five seconds while the time stayed active is accumulated for each day. The availability of the data given by the original authors can be seen in table 1. Aside from the smartwatch data, additional information from each subject is gathered as well: age, weight, coronary prone behaviour (Johnston, 1993), sex etc. However, due to the scope of this work subject data will be only con-

Table 1: Categorization of the variables recorded and computed from the Fitbit smartwatch into two separate groups: daily health statistics and sparse health parameters. For each variable the sample frequency of the wearable device is provided.

Group	Category	Data	Frequency
Daily health statistics	Sleep data	Waso sleep, sleep latency, rem latency, total sleep time, time rem, time light, time deep, time awake and SRI	Daily
	Activity	Kcal and steps	Daily
	Heart rate	Maximum, minimum, standard deviation and mean values	Daily
Sparse health parameter	Heart rate	Beats per minute	Per 5 seconds
	Exercise/activity	Distance, steps and kcal	Per minute
	Sleep data	Sleep phases and sleep score	When happens

sidered as label in the classification problem in order to characterize users given solely the data collected from smartwatch.

Given the circumstances described previously in section 2, the PMData dataset is the only one, to the best of our knowledge, that collects a wide range of physiological parameters: heart, sleep data and sports data among others, reaching a total of 16 daily health statistics, and does not focus on HAR (Human Activity Recognition). This number of variables is prominent for this study and the volume of data is public and large enough to test a wide range of imputation methods.

As stated, values collected from wearables are stored as a time series and converted to tabular data, where each row represents the temporal component and each column the different daily health statistics. Then, the data is aggregated by day, reducing significantly the number of rows. In addition, the data obtained from the wearable lets us compute other variables such as SRI (i.e. Sleep Regularity Index, averaged over 7 days) (see eq. (1)) where N is the number of days and M is the number of epochs per day. The function $\delta(s_{i,j}, s_{i+1,j})$ is equal to one, when the sleep–wake state is the same 24 hours apart. Other example is WASO (Wakefulness After Sleep Onset) sleep (see eq. (2)), which is computed taking into account TST (Total Sleep Time) and the sleep period. Note that this variables are related to sleep but sleep efficiency depicts a more complete assessment of the sleep quality.

$$SRI = 100 - \frac{200}{M(N-1))} \sum_{j=1}^{M} \sum_{i=1}^{N} \delta(s_{i,j}, s_{i+1,j}) \quad (1)$$

$$WASO = Sleep\ period - TST \quad (2)$$

Once the data is sorted and aggregated by day, missing values are found in the recorded data. In table 3, a small sample of the dataset is shown for a given user. Every row of the table corresponds to a day of a specific user, whereas each of the columns corresponds to each of the daily health statistics that have been either collected or calculated from the Fitbit smartwatch.

After the preprocessing, the data contains 2.397 days from which 603 have at least one missing value. However, the subject referred as "p12" by Thambawita et al. (2020) has only sleep registers for 3 days from the 152 days that lasted the study. For this reason, the data of the subject is not representative enough and the subject is removed from the study. A brief analysis of the data is shown in table 2 for the train and test subsets in both classification tasks: sleep efficiency and personality. The difference between these two tasks is how the data has been divided. For sleep efficiency, data has been randomly selected for training, whereas the remaining data without missing values has been used for testing the imputation methods. Leaving test data without missing values let us evaluate classification algorithms with and without imputation methods in the training subset, under the same conditions. The same happens with personality, but this label does not vary per user, thus, data has been split by user, leaving 10 users for training and the rest for testing.

4 METHODOLOGY

This section presents the methodological approach employed on the study. In subsection 4.1 the algorithms employed for data imputation are presented, whereas 4.2 presents the two evaluation approaches. Finally, subsection 4.3 explains the classification tasks after data have been imputed.

4.1 Data Imputation Methods

This section presents the selected imputation methods, grouping them in baseline, column-based and

Table 2: Description of the dataset gathered from Fitbit wearable devices and employed in this study. The dataset has been split into train and test subsets in order to evaluate different classification algorithms in each of the proposed classification tasks: personality and sleep efficiency.

	Personality				Sleep efficiency			
	Train		Test		Train		Test	
	Total	**%**	**Total**	**%**	**Total**	**%**	**Total**	**%**
Users	10	66%	5	34%	15	100%	15	100%
Instances	1.600	71,2%	645	28.7%	1.648	73,4%	597	26,5%
Missing values at random	1.575	8,7%	0	0%	1.600	8%	0	0%
Missing values at random per user	157,5	9,4%	0	0%	106,6	7,7%	0	0%
Missing values at lines	159	10,6%	0	0%	191	11,5%	0	0%
Missing values at lines per user	15,9	10,5%	0	0%	12,7	10,6%	0	0%
Consecutive missing values	2.878	72,6%	0	0%	2.941	74,7%	0	0%
Consecutive missing values per user	14,4	8,4%	0	0%	9,33	16,6%	0	0%
Personality label								
A	989	44%	361	16,1%	–	–	–	–
B	611	27,2%	284	12,6%	–	–	–	–
Sleep efficiency label								
< 85 (Normal / Bad)	–	–	–	–	171	7,6%	65	2,8%
≤ 90 (good)	–	–	–	–	825	36,7%	286	12,7%
≤ 95 (Very good)	–	–	–	–	602	26,8%	246	10,9%

Table 3: Sample of the dataset for a given user and for different daily health statistics, including TST (i.e. Total Sleep Time), mean_hr (i.e. mean heart rate) and std_hr (i.e. standard deviation of heart rate).

user_id	waso_sleep	sleep_efficiency	TST	kcal	steps	...	mean_hr	std_hr
P01	20	94,88	391	3.912,61	16.450	...	64,78	14,57
P01	10	97,63	422,5	4.014,13	17.843	...	64,82	17,05
P01	6	98,31	356	3.614,06	12.519	...	68,15	22,08
P01	16	96,21	423	3.386,19	10.392	...	63,91	13,30
P01	24	93,35	361	3.312,92	11.185	...	62,41	12,58

row-based algorithms. The proposed approaches have been widely used by previous works, excluding those methods that require large amounts of data like recurrent neural networks (Medsker and Jain, 2001), LSTM based networks (Yu et al., 2019) and transformers (Vaswani et al., 2017), which are not feasible as daily health statistics are recorded on a daily basis. The imputation methods used are the following:

- **Baselines.** Baseline methods are considered the easiest approach for data imputation (Engels and Diehr, 2003). More complex approaches are expected to significantly increase the performance compared to these methods. In this way, other approaches can be compared and considered sufficient in order to be applied as input for a classification task.
  - **Mean.** Sets the mean for each feature respectively on all the missing values of the same feature.
  - **Median.** In this case, the median of each parameter is set respectively in the missing values.
- **Column-Based.** Includes methods that use as input the historical data recorded for each health parameter. For that, a model is trained for each daily health statistics and the missing values are predicted using as input of the algorithm the previous w values of previous days. Thus, w is a key hyperparameter that is tuned in order to maximize the performance of the column-based methods. The optimal w value will depend on the rationale behind each of the proposed methods.
  - **Moving Average.** Each missing value found on the recorded daily health statistics will be replaced by the mean of the last known values of each parameter (Hyndman, 2011).
  - **LOCF (Last Observation Carried Forward).** This method takes the last observation before a missing value and drags it to the missing value. Note that if there are several missing values together, the same value will be imputed for all of them (Twumasi-Ankrah et al., 2019).

  - **Linear Interpolation.** The linear interpolation fits a line between the last known value and the next known value. With this, missing values distributed together are imputed depending on the amount of missing values. If only one is missing the midpoint is used. In the case of 3 missing values the quartiles are used (Noor et al., 2015).
  - **SVM.** A support vector machine regressor algorithm that predicts the missing value depending on the previous values of the same feature (Boser et al., 1992).
  - **RF.** A random forest regressor algorithm that imputes the missing value taking into account the last values of the same feature (Breiman, 2001).
  - **ARIMA.** Auto Regressive (AR) Integrated (I) Moving Average (MA) models, are statistic models used for time series were given a set of values the next one can be predicted. This model consists of 3 parameters: p, d and q each one refers to each of the acronyms respectively (Box, 2013).
  - **KNN.** This is a variation of KNN, where the values taken to estimate the neighbours are the previous values of the feature. Besides, this method evaluates the amount of missing values placed together and if there are more than one, the first missing value will be imputed and then, the last one evaluating the next values to the missing value. Lastly, a linear gradient is applied to the values this way the method has the ability to weight the feature values with the time.
- **Row-Based.** Methods that use as input other daily health statistics recorded in the same day. Thus, in this case, data imputation consists in a regression task and every time a value is imputed, a model is trained considering the daily health statistics with known value in the day corresponding to the missing value. For example, if for a given day the total sleep time must be imputed and the other daily health statistics with known value are burnt calories and steps, a model is trained considering just those two features to predict total sleep time, including the data available of all the users.
  - **RF.** A random forest algorithm that imputes the missing values depending on the values of other features gathered the same day, as for KNN, if all the day is missing the mean of each daily health statistics is imputed (Breiman, 2001).
  - **KNN.** K-nearest neighbour takes the values of other known variables on the same day and computes the distance (uniform weights so all points in each neighborhood are weighted equally) between other days. Once the distances are computed, the K-nearest neighbours are considered to fill the value. This method is obtained using the KNN imputer from (Pedregosa et al., 2011).

Some of the selected methods are also considered as baselines for many studies that tackle wearable time series imputation. For example, mean imputation is used in Feng and Narayanan (2019); Huo et al. (2022), other studies as Lin et al. (2020) consider Linear interpolation, moving average and LOCF. KNN is widely used as baseline method as can be seen in Feng and Narayanan (2019); Huo et al. (2022); Lin et al. (2020). Lastly, Huo et al. (2022) considers random forest approaches as well.

Before data imputation is carried out with the aforementioned algorithms, a "MinMaxscaler" (Pedregosa et al., 2011) is applied to standardize data as the daily health statistics are in different magnitudes. This method turns the maximum value of each feature to one and the minimum value to zero, being the rest of the values converted proportionally. This is done in order to compare the selected imputation methods, making all metrics weigh the daily health statistics equally.

4.2 Missing Data Scenarios

The distribution of the missing values may impact the performance of the proposed approaches for data imputation. For this reason, the proposed methodology aims at evaluating the methods for data imputation in different scenarios and with an increasing number of missing values in order to address the first and second research questions. In this work, two scenarios have been considered: missing values at random and missing values at lines. These scenarios are depicted in Fig. 1, where first, days without missing values are selected and second, missing values are added for evaluation of the proposed methods.

Evaluation for the imputation methods was carried out creating missing values. For that, clean data is obtained removing days with at least one missing value and thus, only days with complete readings for all the daily health statistics are considered. Then, missing values are generated by removing known values randomly for each of the missing data scenarios. Finally, each of the proposed methods is applied to estimate the missing values and compare it with the actual value, where the method that assigns the closest value to the actual is considered to have the best performance. In the case of missing values at lines,

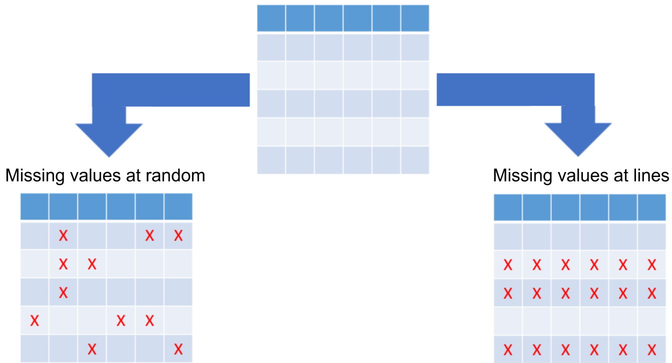


Figure 1: The proposed two missing value scenarios from clean data to evaluate the selected data imputation methods: missing values at random and missing values at lines.

the range of applicable methods is reduced, as there are no other daily health statistics in the same day to be used for these methods. Thus, only baseline and column-based methods are used in this scenario.

The rationale behind the proposed methods may lead to significantly different results, depending on the missing values scenario and rate. For that reason, both data imputation scenarios have been simulated increasing the rate of missing values at random in the first scenario and the number of days without any recording in the second scenario. Note that missing values at lines (days) comes closer to the reality of the wearables as explained in Chakrabarti et al. (2023).

Each scenario is executed ten times to enhance reliability. This repetition is essential because, in every iteration, the missing values are placed in different segments of the dataset. Running the various algorithms only once may lead to biased or unrealistic results, as they could adapt too easily to those specific missing values in a single run.

4.3 Classification

In order to answer the fourth research question proposed in section 1, several machine learning algorithms are proposed to be trained and then, to assess the effect of the imputed data in different classification problems. In this case, all the data is considered including days with missing values for both the train subset.

Classification models have been tested splitting the data into train and test subsets and assuring that there is not imputed data on the test subset. Thus, days without any missing values have been considered for test and the rest for training the classification algorithms. Then, the missing values in the train set are imputed with the best algorithm for the specific scenario and rate of missing values. Finally, several algorithms are trained with the imputed train set and evaluated in the test set, using the F-score and the accuracy metrics. Beside this, various feature selection methods are used to improve the representation of the input and increase overall performance of the classification algorithms: lasso penalty (Kim and Kim, 2004), fisher test (Gu et al., 2012) and decision tree feature importance (Grabczewski and Jankowski, 2005). The overall data distribution for both the train and the test subsets for the classification exercise can be seen in table 2.

The proposed classification models are the following: SVM (Support Vector Machine)(Boser et al., 1992), KNN (K-Nearest Neighbour)(Peterson, 2009), Linear regression (Montgomery et al., 2021), decision tree (Quinlan, 1986), Random forest (Breiman, 2001), feed forward neural network (Sazli, 2006) and a gradient boosting trees method (Friedman et al., 2000), in each of them various models are created changing different hyper parameters.

5 RESULTS

In this section, the results obtained after applying the proposed algorithms in section 4 are discussed. In subsection 5.1 the evaluation metrics for both the data imputation and classification tasks are explained. In subsection 5.2 the results for the missing values at random scenario are shown whereas in subsection 5.3, the results of the missing values at lines scenario are discussed. In subsection 5.4, classification models are trained to asses the effect of the imputed data and lastly, in subsection 5.5 the results obtained are further discussed.

5.1 Evaluation

Evaluation of the methods has been carried out computing various metrics. The metrics considered for data imputation are the Mean Absolute Error (see eq. 3) and Mean Square Error (see eq. 4) which measure the difference between the imputed and the actual value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

In both eq. (3) and (4) y_i stands for the actual value and $\hat{y}_i$ stands for the predicted value by the data imputation algorithm. A MAE or MSE close to 0 indicates a good performance with a prediction close to the actual value.

Finally, the evaluation of the classification task is made by means of F-score (see eq. 5) and the accuracy (see eq. 6)(Vujović et al., 2021). Both metrics give a value between 0 and 1, being 1 a perfect classification score.

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{5}$$

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

5.2 Missing Values at Random

The objective of these experiments, is to evaluate the performance of different data imputation algorithms when the distribution of missing values is random and with an increased rate of missing values. For that, as explained in section 4, three types of data imputation algorithms are employed: baselines, row-based and column-based methods. The results of these methods can be seen in Fig. 2a with a missing values rate ranging from 5% to 70%.

Preliminary experiments were carried out for each of the proposed algorithms, testing the identical model with various parameters and assessing which configuration yielded the best performance. The detailed results can be found in table 4.

Comparing all the method types, when the ratio of missing values changes from 5 to 70%, the mean relative performance in terms of MAE curiously increases 1% for baselines and decreases 5,65% for column-based methods and 42,3% for row-based methods. These results suggest that row-based methods have a significant decrement when the number of missing values increases.

In addition, the results indicate that row-based methods obtain the best performance when missing value rates are lower than 35%. When missing rates are lower than 30%, RF achieved better results than KNN scoring an average MAE enhancement of 0,011 while KNN outperforms RF in higher missing (40 to 70%) rates averaging a 0,004 improvement. However, both methods showed a relative improvement respect to the best column-based method, the KNN, of 25% and 11% (averaged for 5% to 30%), respectively.

When the number of missing values rate reaches 50%, column-based KNN algorithm achieves a relative improvement of nearly 7,5% compared to row-based RF method in terms of MAE. In addition, the mean performance of column-based methods improves the mean performance of row-based methods in a 13%, indicating that it is more convenient a column-based approach over the 50% of missing values.

Comparing baseline methods with the best row-based method, the RF, and the best column-based method, the KNN, the results show a improvement of 23% and 18% respectively. In this scenario, baseline methods do not improve the results achieved by other methods.

All the proposed methods significantly improve the baselines except for LOCF, which achieves the worst performance in all the missing rates. Although the LOCF method performs reasonably well in time series data due to short intervals between samples, it is less effective in this context, where each parameter is registered on a daily basis.

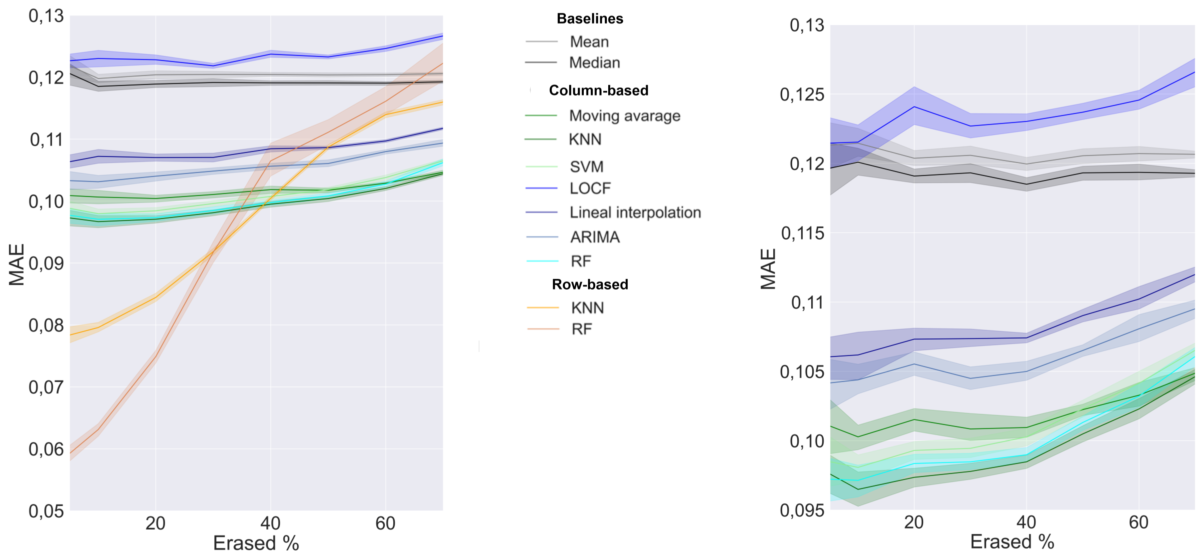
Among the column-based methods, the KNN and the RF scored very similar results, but the KNN achieved an average of 6% MAE improvement compared to the RF.

As a conclusion, row-based methods achieve the best data imputation performance with a low missing values ratio. Having a ratio of missing values higher than the 35% the column-based methods would be the best suited for imputation. Although the difference in performance between some of the column-based methods is small, KNN method averaged the best results. Lastly, the baselines showed robustness to the missing rate and only scored consistently better than LOCF which, as stated, is not suitable for this task.

5.3 Missing Values at Lines

Similarly, in this set of experiments the proposed algorithms are evaluated with an increasing rate of missing values. In this case, missing values are present in the whole day, consequently, row-based methods cannot be used. The objective of these experiments is to evaluate the proposed methods in a missing values distribution closer to the reality of wearable devices, including the limitation of not being able to use other daily health statistics from the same day for data imputation.

The same missing rates as in the first scenarios



(a) Missing values at random.

(b) Missing values at lines.

Figure 2: Normalized MAE (y axis) for various imputation methods with an increasing rate of artificially generated missing values (x axis). Shaded areas show both the maximum and minimum MAE for each method across multiple runs for each percentage of missing values. Scale over y axis is different in the second image to stand out the trend of column-based methods.

have been tested for this scenario, the performances of the methods is shown in Fig. 2b. Following the same proceeding, the hyperparameters have been tuned for this experiment as well. The detailed results are shown in table 5.

In the column-based approaches, the MAE scores are similar in both the first and last rate of missing values. Methods showed a 6% decrease in performance when these points are compared. Once more, the baseline methods demonstrate notable resilience to missing data by scoring 4% better at 70% of missing rate, surpassing LOCF in performance.The rationale of the poor performance has is the same as mentioned in section 5.2.

Once more, the KNN proved to be the the top-performing method, achieving overall a 18% improvement over the baseline methods and 1% over the second best method the RF, making it the best option for data imputation using information from previous days.

In both scenarios, the SVM was the column-based method that most suffered from the missing rate increase, with an 8% worsening over the missing rate making it unreliable when the missing values rate is high.

In conclusion, both baseline methods and column-based methods exhibit no significant variation based on the distribution of the missing values, averaging similar scores in both scenarios. Regardless of the missing value pattern, KNN consistently demonstrated superior performance as the top-performing column-based method.

Based on the results obtained and acknowledging the linear pattern of missing values in the dataset, the KNN is employed as the optimal imputation method for conducting the classification experiment. Results of applying the model to the dataset can be seen in Fig. 3. In this instance, the variables TST (Total Sleep Time) and steps for the user 'p15' are displayed, where the column-based KNN effectively replicates the variations in the original data. However, there are cases where imputation may deviate from reality, as observed in the steps imputation towards the concluding dates, where the KNN placed a noticeable peak.

5.4 Classification

In this set of experiments, two classifications problems have been proposed in order to asses the effectiveness of data imputation when training machine learning models. The goal of data imputation in this work is to extend the data that can be used to train the classification models, if imputation is carried out correctly and information is restored from the missing values, we hypothesize that overall performance of the predictive models should be increased.

More specifically, the first classification task consists in the prediction of the sleep efficiency of each day considering the rest of the daily health statistics (Johnston, 1993). In this case, the data is split ran-

Table 4: Mean MAE and MSE for 5 to 70% of artificially generated missing values at random scenario.

	5%		20%		50%		70%	
Method	**MAE**	**MSE**	**MAE**	**MSE**	**MAE**	**MSE**	**MAE**	**MSE**
Baselines								
Mean	0,1218	0,0241	0,1203	0,0236	0,1203	0,0237	0,1205	0,0237
Median	0,1205	0,0248	0,1189	0,0242	0,1190	0,0243	0,1192	0,0243
Column-based								
Moving average	0,1008	0,0186	0,1004	0,0184	0,1028	0,0189	0,1046	0,0198
KNN	0,0972	0,0172	0,0970	0,0169	**0,1004**	**0,0180**	**0,1044**	**0,0194**
LOCF	0,1226	0,0285	0,1228	0,0285	0,1246	0,0286	0,1266	0,0300
Linear interpolation	0,1064	0,0212	0,1070	0,0214	0,1086	0,0219	0,1117	0,0231
ARIMA	0,1032	0,0194	0,1040	0,0198	0,1060	0,0204	0,1093	0,0202
SVM	0,0988	0,0174	0,0984	0,0173	0,1018	0,0183	0,1065	0,0196
RF	0,0977	0,0171	0,0973	0,0169	0,1008	0,0181	0,1062	0,0199
Row-based								
KNN	0,0783	0,0117	0,0844	0,0133	0,1087	0,0203	0,1159	0,0255
RF	**0,0592**	**0,0085**	**0,0748**	**0,0118**	0,1111	0,0216	0,1222	0,0253

Table 5: Mean MAE and MSE for 5 to 70% of artificially generated missing values at lines scenario.

	5%		20%		50%		70%	
Method	**MAE**	**MSE**	MAE	**MSE**	MAE	**MSE**	**MAE**	**MSE**
Baselines								
Mean	0,1213	0,0240	0,1203	0,0236	0,1205	0,0238	0,1206	0,0237
Median	0,1196	0,0246	0,1190	0,0243	0,1193	0,0245	0,1192	0,0243
Column-based								
Moving Average	0,1010	0,0188	0,1015	0,0190	0,1022	0,0191	0,1048	0,0195
KNN	0,0976	**0,0171**	**0,0973**	**0,0172**	**0,1004**	**0,0181**	**0,1046**	**0,0194**
LOCF	0,1214	0,0281	0,1240	0,0293	0,1236	0,0289	0,1265	0,0301
Linear interpolation	0,1060	0,0210	0,1073	0,0216	0,1092	0,0221	0,1119	0,0234
ARIMA	0,1041	0,0200	0,1055	0,0205	0,1065	0,0206	0,1095	0,0215
SVM	0,0984	0,0174	0,0993	0,0178	0,1023	0,0185	0,1065	0,0196
RF	**0,0972**	**0,0171**	0,0983	0,0174	0,1013	0,0184	0,1060	0,0198

domly regardless the user. The second classification task is to predict the behaviour of the user based on the daily health statistics. In this case, a user has the same behaviour regardless the day and the data is split into train and test subsets by user. That is, the same user does not appear in both the train and test subset as only one subset is considered for a user. A more detailed description of the data and labels used for each classification tasks can be found in table 2. In table 6 the results for the classification tasks are shown with and without data imputation for the best method in each case, for simplicity.

For personality classification, the model that reached the best results was the logistic regression with Lasso's penalty (Ranstam and Cook, 2018) regardless of the imputation that is applied. For the prediction of the sleep efficiency, the best model was the neural network when missing values are filled. Without imputation, however, the support vector machine classifier achieved the best performance.

In the case of personality the F-score improved by 4,4% while the accuracy scored 2,9% higher. In the case of sleep efficiency, although the enhancements were not as pronounced as those seen in personality, both the F-score and the accuracy went up by 0,3%. Thus, it is made clear that both classification task are benefited when data is imputed and added to the training set.

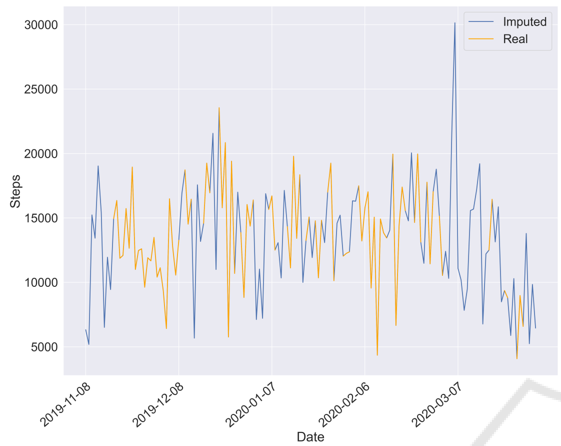
As previously noted, there is considerable variation in the improvement of the models between the classification tasks. This variability could be attributed to the fact that in sleep efficiency, the value itself is imputed, underscoring the critical importance of ensuring accurate imputation for the feature.

5.5 Discussion

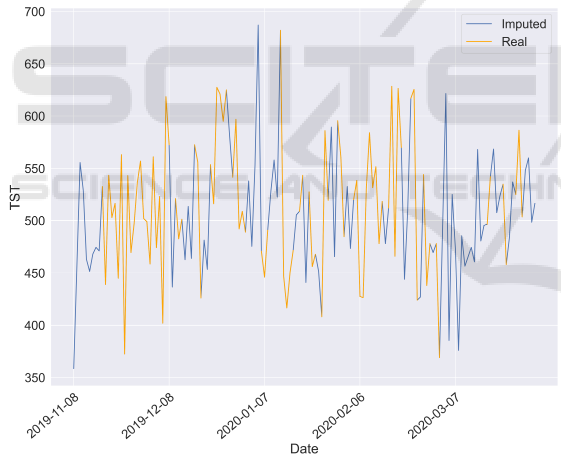
The results of the experiments showed that imputation of data is beneficial for the proposed classification methods. Addressing the research questions, the im-

Table 6: Results of the best classification algorithm in each of the classification tasks when using only data without missing values (i.e. Original) and when adding imputed values to Original data (i.e. Imputed).

	Personality		**Sleep efficiency**	
Data	**F-score**	**accuracy**	**F-score**	**accuracy**
Original	67,3%	53,0%	80,2%	79,5%
Imputed	71,7%	55,9%	80,5%	79.8%



(a) Steps.



(b) Total sleep time (TST).

Figure 3: Example of data imputation in two different daily health statistics.

putation employing various algorithms obtained significantly better results in some cases than using the baseline methods. As seen in both scenarios, baseline methods (i.e. mean and median imputation) are outperformed by all methods except for LOCF and these methods should only be considered when computational time has to be reduced as much as possible or the number of samples is very limited. Notably, the results showed that using features of the same day (i.e., row-based methods) is the best option whenever feasible and if the missing values rate does not reach 35-40% for a dataset of a similar size and variables, being RF the best algorithm. Nevertheless, when the missing rates are higher or it is not possible to impute missing values using other daily health statistics, the column-based methods should be used rather than mean or median imputation.

The experiments comparing data imputation between two different scenarios revealed that there is not much difference in the effectiveness of algorithms when applied to both cases, although the results for random missing values scenario are slightly better. However, understanding the distribution of missing values is crucial for determining the most suitable algorithm for the dataset. Among the proposed methods, we note that LOCF, which was the worst preforming method, is suitable for situations where the time elapsed between samples or records is sufficiently low (Twumasi-Ankrah et al., 2019). If this does not fulfil, results may be poor as in this case, as lineal interpolation is relevant when the feature being imputed is dependent strictly on the last known value and the next known value. However, in a more general scenario where data doesn't strictly depend on the surrounding known value, and the time between samples is moderate, other column-based methods outperforms these approaches. Among them, is worth remarking KNN and RF algorithms, which obtained the best results.

The classification results show that data imputation has enhanced the performance of the models on unseen data. However, the increase reported in the performance may be dependent on the classification task to be carried out and each use case requires experimentation to test if data imputation is still beneficial.

It is necessary to take into consideration some of the limitations of this work. First of all is the lack of data, as more data would lead to an increase in the performance of the algorithms and more accurate imputations. However, as the main focus of this work are daily health statistics, it would be required to have a longitudinal study combined with data augmentation techniques to acquire enough data for deep learning models. In addition, the results obtained are specific for the dataset employed and may vary depending the subjects of the study and the daily health statistics considered. For that reason, this study is also understood as a evaluation framework of data imputation methods for improved classification performance, where a methodological approach is proposed to evaluate different data imputation algorithms considering the nature of wearable devices and popular smartwatches such as Fitbit.

6 CONCLUSIONS

In this study, we have designed an evaluation framework of different data imputation algorithms under two missing values scenarios: missing values at random and at lines (days). The best algorithm for missing values at lines scenario is then used due to resemblance of the data to this scenario for two specific classification tasks. Being able to consider more data and improve the performance of the classification algorithms.

More specifically, in the first two experiments, for the evaluation of methods imputing missing values, gaps were intentionally introduced in the dataset. This is done with two different patterns to test the methods in diverse scenarios. One scenario focused on missing values occurring randomly, whereas in the other, missing values were situated in lines, resulting in the deletion of an entire day of data. Additionally, each scenario was executed 10 times to ensure that the results are not dependent on specific missing values.

In the third experiment, machine learning and deep learning methods were developed to evaluate the effectiveness of adding or not imputed data to clean data. Two distinct classification problems were undertaken: in the first, personality prediction was performed, with the dataset divided by subjects as classes repeated every day for each subject; in the second exercise, sleep efficiency was stratified into three levels and the dataset was randomly divided as sleep efficiency changes every day.

In our study, we reached the conclusion that imputing missing values proves beneficial for classification, enabling us to sidestep the challenges associated with working with smaller datasets that can not be representative enough of the data distributions behind. Nevertheless, it is crucial to evaluate the proposed imputation methods for each dataset to ensure that the imputed values significantly improve the baselines and to select the best algorithm depending the missing values distribution in the dataset. This precaution helps prevent biased outcomes stemming from inappropriate imputation methods or data deletion.

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