Is It Possible to Distinguish COVID-19 Cases and Influenza with Wearable Devices? Analysis with Machine Learning

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***Abstract*—The COVID-19 situation is enforcing the creation of the diagnosis and supporting methods for early detection, which could serve as screening tools. In this paper, we introduced the methodologies based on wearable devices and machine learning, which distinguishes between COVID-19 disease and two types of Influenza. We checked the results of binary classification for various scenarios and multiclass classification. The results were evaluated separately for the cases before the pandemic and in the middle of the pandemic. In the middle of the pandemic, the best classification accuracy was achieved when distinguishing between COVID-19 and Influenza cases with *k*-NN (the balanced accuracy was equal to 73%). The highest sensitivity was achieved for Logistic Regression - 61%. The successful distinction between Influenza types was achieved in 80 % for XGBoost and Decision Tree. Additionally, the balanced accuracy for multiclass classification was equal to 69 % for *k*-NN.**

***Index Terms*—COVID-19, artificial intelligence, signal processing, machine learning, wearables**

I. Introduction

The world nowadays is struggling with the COVID-19 pandemic. This pandemic was caused by the coronavirus SARS-CoV-2 [1]. According to John Hopkins University, the COVID-19 pandemic caused more than 3.86 mln deaths worldwide [2]. The spectrum of symptoms is various. The most common symptoms belong to cough, fever, shortness of breath, pain in the chest, and voice changes [3], [4]. Additionally, changes in resting heart rate were observable around symptoms onset confirmed by the analysis of the wearable records [5]. Moreover, there could also occur more rare symptoms like loss of smell and taste [6].

This situation implies the usage of diagnostic techniques. The most frequently and regarded gold standard used nowadays is the Reverse Transcription-Polymerase Chain Reaction (RT-PCR) [7]. Computer Tomography (CT) is also used for the detection of COVID-19 disease. The accuracy of these methods could reach results near 100 % [8]. However, the drawback of this method is that it is applied later than in the early stage of the disease [7].

The ideal solution is to detect the disease before the highest contagiousness period to limit spreading the disease, which is regarded as manifesting 2 days before the onset of the disease till 1 day after the onset [9]. It is also not the only problem that is occurring. The diagnosis methods which are commonly used as CT and RT-PCR tests are performed mostly after the onset of the disease and are quite expensive. For this reason, there is a need to apply more approachable solutions. To them belong wearable devices, which are cheaper, commonly available, and possible to use as screening tests [10]. So far, a few works have been reported which are describing the usage of wearable devices for monitoring COVID-19 disease [11]-[14].

In this paper, we have reused the dataset which contained COVID-19 disease samples. two types of Influenza samples were gathered before and in the middle of the pandemic. This paper is trying to distinguish between the cohort before the onset of the visible symptoms. It uses data gathered by wearable devices and machine learning techniques for this purpose. We carried out binary classification for various scenarios and multiclass classification preceded by pre-processing and feature extraction. The algorithms which were applied were: XGBoost, *k*-NN, Logistic Regression, Support Vector Machine (SVM), Decision Tree, and Random Forest.

The main contribution of this paper is providing a methodology for the distinction between the COVID-19 disease and Influenza, not carried out earlier in the research. What is unusual, two types of Influenza are taken into consideration occurring before the main pandemic and in the middle. The obtained methodology considering COVID-19 disease and Influenza cases in the middle of pandemic achieved 73 % of balanced accuracy. 61 % of sensitivity and 75 % specificity were obtained for Logistic Regression. Moreover, the distinction between the Influenza types was succeeded in 80 % for XGBoost and Decision Tree.

Additionally, multiclass classification (COVID-19, Influenza before the pandemic, and Influenza during the pandemic) was performed for those data. The discussion

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was carried out for the obtained results and compared with the conclusion stated in the original paper.

The rest of the paper is structured as follows: Section II contains the summary of the related works, whereas Section III describes the performed experiment. It contains the experiment description (Subsection III.A), data description (Subsection III.B), feature extraction (Subsection III.C), and used metrics for this research (Subsection III.D). The results are presented in Section IV. The discussion is provided in Section V and the conclusions are described in Section VI.

II. Related Works

The spectrum of COVID-19 disease symptoms is broad. According to [4], the development of the disease could be distinguished into 3 stages: early infection, pulmonary involvement without or with hypoxia, and inflammation phase. The most important will be to recognise the disease in its early stage. The symptoms which could be pointed out are fever, dry cough, lymphopenia [4], changing the resting heart rate nearly the onset of the disease [5].

The target is to recognise the disease in the early stage because it will potentially limit and decrease the ratio of contagiousness cases. Additionally, techniques that would be used, should serve as a screening test. For this purpose, the usage of wearables seems to be justified. It could be explained by the fact that they are commonly available and relatively cheap [10]. Moreover, there were published a few works which considered the usage of wearables likewise machine learning methodologies for COVID-19 disease analysis [11]-[14].

In [5], the authors collected and analysed the COVID-19 cases (41 wearable data), Influenza before the main pandemic (1226 wearable data), and in the middle of the pandemic (85 wearable data). They were analysing the steps records, sleep records, and also heart rate rhythm. It occurs that during nearly the onset of the disease, in patients' records, were visible deviations from the resting heart rate. The assumptions were evaluated thanks to the statistical tests. They have also reported the differences between the COVID-19 cohorts and Influenza cohorts, with manifesting higher intensity for the COVID-19 cases.

In another work [13], anomaly signal detection was performed in 32 COVID-19 cases. The considered data were gathered by Fitbit - a wearable device. The features which were used for algorithms were: abnormal resting heart rate (RHR) and heart-rate-to-steps ratio. The authors introduced algorithms: the abnormal Resting Heart Rate (RHR-Diff), the Heart Rate-to-Steps (HROS-AD algorithm), CuSum. Based on resting heart rate, it was possible to detect anomalies for COVID-19 cases in 63 % before the onset of the disease. However, the method was not performed for Healthy Control (HC). Additionally, the authors checked 15 Influenza cases and confirmed the changes for 9 of them.

Moreover, the usage of medical devices - Empatica was evaluated for COVID-19 detection. Thanks to it, there could be gathered many types of physiological signals, i.e.: skin temperature, pulse oximeter, blood pressure, heart rate, Galvanic Skin Temperature (GSR). In this paper, they were also provided the answers to questionnaires by patients, such as the occurrence of the symptoms, age, gender, habits, addiction to smoking and drinking, weight, height. 57 COVID-19 patients and 30 HC took part in the research. The author introduced CovidDeep - a four-layer Neural Network (NN) and also used augmentation techniques. This NN contains such steps: data pre-processing, grow-and-prune synthesis likewise output generation through softmax. The highest achieved accuracy was equal to 98.1%. Nevertheless, such a result was obtained for a combination of the modalities (GSR, oxygen saturation, blood pressure, and questionnaire), and also it has to be emphasized that Empatica is a medical device and it is not widespread so commonly, this same it cannot serve as a screening test.

Some works used other wearables than smartwatches for analysing COVID-19 data. In [11], it was checked if there are some temperature anomalies of disease by the Ourora ring. They were observed for 38 of 50 patients before occurring other symptoms. The statistical evaluation was performed thanks to the nonparametric Kruskal Wallace test, with Tukey-Kramer post hoc comparison.

III. Experiment

A. Experiment Description

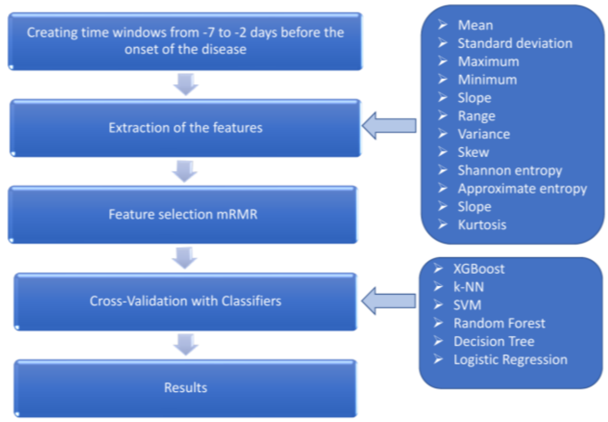

Figure 1. Scheme of the experiment.

The main goal of this research was to validate whether it is possible to use wearable devices and machine learning algorithms for early detection of COVID-19 and Influenza cases, before the highest contagiousness period. Moreover, the distinction between the COVID-19 pandemic before and in the middle of the pandemic was taken into consideration. The data were reused and could be found in [1]. The data were gathered by wearables devices, in particular, it was various models of Fitbit smartwatches. The devices were used to record values about sleep, the number of steps, and heart rate. The overall process of the conducted experiment is visible in Fig. 1. In the first step, the feature extraction was done for each cohort. We used a time window in the range from 7 to 2 days before the reported onset of the disease by the patients. The data were downsampled to one per day. Next, the set of parameters was computed for the chosen window, which is described more in detail in the 3.3 Section. For avoiding the curse of dimensionality, the feature selection was carried out, i.e. minimum redundancy maximum relevance. The number of features was set as 50. Subsequently, the classifiers were used together with 10-fold cross-validation. They were XGBoost, k-NN, Support Vector Machines (SVM), Logistic Regression, Decision Trees, and Random Forest. The scenarios were carried out for binary classification and multiclass classification.

B. Data Description

The data were reused from [1]. The number of gathered, so-called, dense data in the original paper was 41 COVID-19 patients, 85 non-COVID-19 flu patients, and also 1226 pre-COVID-19 flu patients. The obtained dataset was recomputed and raw features were in the respect to 1 per day.

The shared data from the authors were lacking. The subset which was taken into consideration required to have completed all of the sleep, step, and heart rate records. After cleaning the dataset and balancing them: 21 COVID-19 cases, 37 non-COVID-19 flu cases, and Pre-COVID-19 cases were obtained.

The demographic summarization of the data is provided in the original paper by the authors, with the distinction for the cohorts [1].

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C. Data Description

To obtain features for machine learning training, the following steps were performed. First of all, the window contains information before the onset of the disease was extracted for each patient. The window was extracted for the range -7 to -2 days before the onset of the disease. This is justified by the fact the highest contagiousness of the COVID-19 disease is regarded as the -2 days before the onset of the disease. It was handled with missing data, and such obtained data were cleaned. The next step was creating some scalars. For the earlier extracted time series, the following features were computed: some common statistical measurements like mean, standard deviation, maximum, minimum, range, variance, likewise time-series specific parameters: Shannon entropy, approximate entropy, slope, skew, and kurtosis.

D. Metrics

For the evaluation of the algorithms, the following metrics were computed. There were: balanced accuracy, accuracy, sensitivity, specificity, Matthews correlation coefficient, and F1-score. The equations are presented below:

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

$$BalancedAccuracy = \frac{Sensitivity + Specificty}{2}$$

$$MCC = \frac{TN * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

$$F1\ score = 2 * \frac{Precision * Recall}{(Precision + Recall)}$$

E. Results

The results of the carried-out experiment are presented in this section. Table I-IV contain the outcome of the classification. Here, they are described respective scenarios:

- Table I: Influenza in the middle of pandemic and COVID-19 cases distinction
- Table II: Influenza in the middle of the pandemic and COVID-19 cases before the pandemic distinction
- Table III: COVID-19 cases and Influenza cases before the main pandemic distinction
- Table IV: Multiclass Classification for COVID-19, COVID-19 cases before the main pandemic and Influenza distinction

The results of the scenario with Influenza in the middle of pandemic and COVID-19 disease are presented in Table I. The best-balanced accuracy (73%) and MCC (0.49) were achieved for the k-NN algorithm. Nevertheless, the data were imbalanced (37 Influenza cases and 21 COVID-19 cases). 58% of the COVID-19 cases were classified as positive (sensitivity), whereas 87% of the Influenza cases were classified as Influenza. The highest specificity was achieved for Logistic Regression (61%). The outcomes for the three classifiers were the lowest.

TABLE I. THE RESULTS OF CLASSIFICATION OF INFLUENZA IN THE MIDDLE OF PANDEMIC AND COVID-19 CASES

Classifier	ACC Bal	ACC	SEN	SPEC	MCC
XGBoost	0.67 ± 0.20	0.71 ± 0.19	0.56 ± 0.37	0.81 ± 0.19	0.38 ± 0.42
k-NN	**0.73 ± 0.19**	**0.77 ± 0.16**	0.58 ± 0.33	**0.87 ± 0.16**	**0.49 ± 0.39**
SVM	0.64 ± 0.20	0.66 ± 0.19	0.56 ± 0.34	0.72 ± 0.23	0.29 ± 0.42
Logistic Regression	0.68 ± 0.20	0.70 ± 0.18	**0.61 ± 0.35**	0.75 ± 0.22	0.38 ± 0.42
Decision Tree	0.58 ± 0.20	0.62 ± 0.19	0.44 ± 0.35	0.72 ± 0.25	0.17 ± 0.44
Random Forest	0.58 ± 0.20	0.61 +/ 0.19	0.50 ± 0.36	0.67 ± 0.25	0.18 ± 0.42

The next scenario was considering the distinction between the Influenza types: in the middle of the pandemic and before the pandemic (Table II). The results of the obtained balanced accuracies were on a similar level for each of the classifiers ~ 80%. This could indicate the simplicity of dependencies occurring in the data. XGBoost and Decision Tree had exactly these balanced accuracies. The highest MCC were also obtained for XGBoost (0.63) and Decision Tree (0.64). 95% of cases of Influenza in the middle of the pandemic were classified correctly for Decision Tree, however, the second type of Influenza was only recognised in 66% of cases. The highest percentage of Influenza diagnosed before the pandemic was found by XGBoost - 74% and sensitivity for this classifier was equal 86%.

TABLE II. INFLUENZA IN THE MIDDLE OF PANDEMIC AND INFLUENZA CASES BEFORE THE PANDEMIC DISTINCTION

Classifier	ACC BAL	ACC	SEN	SPE	MCC
XGBoost	**0.80 ± 0.15**	0.80 ± 0.15	0.86 ± 0.18	**0.74 ± 0.24**	0.63 ± 0.29
k-NN	0.79 ± 0.14	0.79 ± 0.14	0.89 ± 0.15	0.69 ± 0.24	0.61 ± 0.27
SVM	0.79 ± 0.15	0.79 ± 0.15	0.91 ± 0.14	0.67 ± 0.25	0.61 ± 0.29
Logistic Regression	0.76 ± 0.16	0.76 ± 0.16	0.81 ± 0.20	0.71 ± 0.24	0.55 ± 0.32
Decision Tree	**0.80 ± 0.14**	**0.80 ± 0.14**	**0.95 ± 0.13**	0.66 ± 0.24	**0.64 ± 0.27**
Random Forest	0.78 ± 0.15	0.78 ± 0.15	0.87 ± 0.18	0.69 ± 0.24	0.59 ± 0.29

The results of the classification between COVID-19 cases and Influenza cases before the main pandemic are presented in Table III. For this case, the highest balanced accuracy was obtained for SVM. Additionally, the highest number of detection Influenza cases before the main pandemic (96%) was achieved for this classifier. The metric MCC, which is taking into consideration the imbalance of the data, was the best for k-NN 69% and similarly for the SVM 68%. 77% of the COVID-19 cases were correctly confirmed by the k-NN algorithm.

TABLE III. THE RESULTS OF COVID-19 CASES AND INFLUENZA CASES BEFORE THE MAIN PANDEMIC

Classifier	ACC BAL	ACC	SEN	SPE	MCC
XGBoost	0.80 ± 0.19	0.84 ± 0.16	0.93 ± 0.14	0.68 ± 0.35	0.64 ± 0.37
k-NN	0.83 ± 0.15	0.85 ± 0.13	0.89 ± 0.15	**0.77 ± 0.27**	**0.69 ± 0.28**
SVM	**0.82 ± 0.17**	**0.86 ± 0.14**	**0.96 ± 0.10**	0.68 ± 0.33	0.68 ± 0.33
Logistic Regression	0.78 ± 0.17	0.79 ± 0.16	0.82 ± 0.19	0.74 ± 0.31	0.57 ± 0.34
Decision Tree	0.75 ± 0.19	0.79 ± 0.17	0.89 ± 0.21	0.61 ± 0.34	0.54 ± 0.38
Random Forest	0.74 ± 0.18	0.73 ± 0.18	0.70 ± 0.25	0.79 ± 0.31	0.50 ± 0.36

TABLE IV. THE RESULTS OF MULTICLASS CLASSIFICATION FOR COVID-19, INFLUENZA CASES BEFORE THE MAIN PANDEMIC AND INFLUENZA IN THE MIDDLE OF PANDEMIC

Classifier	F1 SCORE	ACC BAL	ACC	MCC
XGBoost	0.61 ± 0.17	0.63 ± 0.15	**0.67 ± 0.14**	0.50 ± 0.22
k-NN	**0.64 ± 0.17**	**0.69 ± 0.13**	0.66 ± 0.15	**0.54 ± 0.22**
SVM	0.62 ± 0.16	0.64 ± 0.15	**0.67 ± 0.14**	0.51 ± 0.21
Logistic Regression	0.56 ± 0.16	0.58 ± 0.16	0.59 ± 0.15	0.39 ± 0.24
Decision Tree	0.46 ± 0.09	0.53 ± 0.09	0.62 ± 0.10	0.42 ± 0.18
Random Forest	0.48 ± 0.15	0.52 ± 0.14	0.57 ± 0.14	0.35 ± 0.22

Moreover, we carried out the multiclass classification for the recognition between COVID-19 cases, Influenza before and in the middle of a pandemic (Table IV). For this purpose, we evaluated the performance of the classifiers with the usage of F1-score, balanced accuracy, accuracy, and MCC, whereas F1-score is regarded as harmonic means of precision and recall. The highest results for F1-score were registered for k-NN (64%), this same situation was observed for balanced accuracy (69%) and MCC (0.54). The highest accuracy was achieved for XGBoost and SVM (67%).

IV. DISCUSSION

This work aims to analyse and compare if COVID-19 symptoms differ between Influenza cases and are possible to be distinguished based on usage of commonly available wearables and recent machine learning techniques. First of all, it should be mentioned that the obtained results for respective scenarios differ from each other. It is caused by the imbalance of the data likewise differences between the cohorts and types of the diseases.

The best results expressed by balanced accuracy for those scenarios were achieved for the distinction between COVID-19 cases and the Influenza cases before the main pandemic. The possible reason is that the people's lifestyle and daily customs changed during the pandemic and some people were self-quarantined during carried-out measurements. For this reason, the classification for this scenario should be considered as highly probable to be distinguished, nevertheless, those factors should be emphasized as a possible reason for the outcome. Regarding the classifiers, the SVM outperformed other evaluated algorithms. However, the Influenza cases were detected almost fully, COVID-19 cases were recognised in 68% of cases.

Regarding the distinction between Influenza cases, the results are promising. Nevertheless, the differences for Influenza cases could be explained by the fact that there were various waves of influenza types for those cases, as the original paper states [1]. Additionally, the highest possible factor is changing the lifestyle of the people. The best results were achieved for the XGBoost classifier for this case. The sensitivity and specificity for this algorithm do not differ too much.

Finally, the most interesting carried-out binary classification, i.e. classification of the COVID-19 cases and Influenza in the middle of the pandemic shows that it is much easier to correctly recognised Influenza from COVID-19 cases (the differences between the specificity and sensitivity were significant). The COVID-19 cases were regarded as ‘positive’ for this classification. The Logistic Regression outperformed other classifiers in the context of sensitivity, however, the results still were not so impressive - 61%. This indicates slightly the simplicity and linearity of the data.

According to the used classifier and their performance for the binary classification, none of them was preferable. The tree’s classifiers seem to perform worse than the rest. The Influenza cases were much easier to classify correctly in comparison to the COVID-19 cases. It should be noted also that the imbalance of the data influences the differences in specificity and sensitivity.

The multiclass classification shows that it is possible to somehow distinguish between the COVID-19 cases and Influenza types. The best results expressed by the balanced accuracy were achieved for *k*-NN (69%). The possible explanation of the outcome is that the data were gathered during the pandemic and without, and possibly with people's self-quarantine period. An additional reason is that the types of influenza were taken into consideration for this research. However, the lacking of healthy control definitely is limiting the possibility of the usage of the created methods as screening tools.

Moreover, the results and conclusions are also compared with the original work. The original paper states that between cohorts, they observed significant statistical differences for age and race. The data were collected in the USA and could be biased in comparison to the rest of the population. Additionally, as the authors refer, the patients with recent flu were more frequently hospitalised than at the time before the pandemic [1]. It could be explained by the fact that social awareness of taking care of health increased during this difficult time. This could be also a possible reason why the performed classifications allow distinguishing between analysing here cohorts. Moreover, the original paper emphasised that, as expected, the intensity of the COVID-19 symptoms versus Influenza symptoms was much higher. They were not only confirmed with the usage of the wearable but also others like cough, etc. It should be noted again that the cohort was collected only in the USA, because of this, the conclusion and analysis of those data are suitable for this cohort. An additional explanation of the obtained successful results is that the duration of the illness was varied between cohorts [1]. Moreover, what is important for this research is that the resting Heart Rate (RHR) was reported in the original work as different for COVID-19 cases and Influenza, and the data were collected by the wearable devices. Another factor that should be considered is that people, according to the article, were self-quarantined and this same number of activities could be different and depend on the restriction provided in the USA [1].

V. Conclusion

This work is considering using wearable devices and machine learning to distinguish between COVID-19 cases and two types of Influenza - in the middle of pandemic and before the pandemic. For this purpose, we used a public dataset of wearable sensor records [5]. The various scenarios of classification between cohorts were checked. We have achieved distinction in 73% of balanced accuracy thanks to the *k*-NN for COVID-19 disease and Influenza between the pandemic. The highest sensitivity was achieved with Logistic Regression (61%). Moreover, the separation of different Influenza cases was successful in 80% thanks to the XGBoost and Decision Tree algorithms. The balanced accuracy for the distinction between COVID-19 cases and Influenza before the middle of the pandemic was equal to 89% and was the easiest to obtain. Moreover, the balanced accuracy for the multiclass classification was equal to 69%. The possible reasons standing behind the obtained results for those classifications were existing various types of Influenza, lifestyle changes, and people self-quarantine, which was also reported in the original paper [5]. It has to be also highlighted that the original data were imbalanced, it was much more difficult to gathered COVID-19 cases than Influenza. Additionally, the raw features have a sampling rate of 1 per day (they were computed from raw records), which definitely limits the possibility and quality of the predictions.

Nevertheless, it has to be emphasised that for this research, it was not taken into consideration the healthy control group. The methodologies which were created could serve as an interesting analysing tool. Nevertheless, they are not enough to be considered as a screening tool, because of the lack of inclusion of healthy control.

Conflict of Interest

The article states no conflict of interest.

Author Contributions

Justyna Skibinska conducted the research, analyzed the data, wrote the paper; Radim Burget analyzed the data, wrote the paper.

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