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M.Sc. Eng. Justyna Skibińska

MACHINE LEARNING-AIDED MONITORING AND PREDICTION OF RESPIRATORY AND NEURODEGENERATIVE DISEASES USING WEARABLES

SHORTENED VERSION OF PH.D. THESIS

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Supervisors:	Assoc. Prof. Jiri Hosek, Ph.D. Assoc. Prof. Radim Burget, Ph.D. Prof. Evgeny Kucheryavy, Ph.D.
Pre-Examiners:	Prof. Marcos Faúndez Zanuy Prof. Anna Esposito
Opponent:	Prof. dr. Peter Peer
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1 INTRODUCTION

The COVID-19 pandemic and the aging society are considered the biggest issues which Europe faces [1]. They are emergency problems on a large scale that need fast taking care of them - developing methodologies destinated for diagnosis diseases such as COVID-19 and Parkinson's disease (PD). The COVID-19 pandemic has caused a plethora of deaths and this disease has a high contagiousness rate [2]. Screening tests of society are highly desirable and they should be easily approachable and destinated to be used in the early stage to limit the spreading of the disease. The screening tests are defined as the procedure used to get to know if the examined person has a disease before it will manifest visible symptoms. Moreover, the aging society carries neurodegenerative diseases and PD belongs to this group of diseases [1]. The most accurate test is the positron emission tomography (PET), magnetic resonance imaging (MRI) and computer tomography (CT), however, those methods are used in the advanced stage of the disease and are expensive [3]. The usage of wearables and solutions based on mobile health (mHealth) and Electronic Health (eHealth) concepts seems to be justified for PD detection, but also for COVID-19 recognition. Wearables are electronic devices which are relatively inexpensive and accessible [4]. Furthermore, the utility of machine learning (ML) allows for creating the support system methodologies which could predict the occurrence of the illness [5]. Additionally, the usage of novel explainable artificial intelligence (XAI) can provide the clinical interpretability of the created models [6].

1.1 Research Motivation

The wearable devices are electronic devices which could sense, gather and upload the data [7]. The wearables can be classified as on-body (e.g., smartwatches), in-body (implants [8]), and also around-body wearables (mobile phones, smartcards) [9]. It is expected that the wearable market will be growing increasingly. The interesting niche is the wearable health technology (WHT) global market. The WHT global market achieved 16 billion $ in 2021 [10]. Nevertheless, the WHT is an atypical market because it characterises the conditions of two markets, not just one, i.e., the healthcare and technology market. This multidisciplinarity is generating an unique opportunity for the implementation of new approaches. Moreover, the existing neurodegenerative and chronic diseases occurring among the elderly people are creating the need for solutions from WHT market [11]. Additionally, WHT offers a big potential in fighting with many diseases including COVID-19 disease. The support system methodologies trained with the usage of ML and data gathered by the wearables could serve as an extra diagnostic/monitoring tool to determine the occurrence of the diseases or their progress [12]. Additionally, the low-cost and easy accessibility for the population makes wearables a potentially valuable screening tool [8].

The data acquired by wearable devices are predominantly of the time series type [13]. This kind of data requires appropriate architectures to extract information from them. Based on the data, there could be created support decision methodologies that serve in classification, forecasting, or anomaly detection problems [14, 15]. For this purpose, ML algorithms are commonly utilised [16]. Depending on the data type - structured or unstructured, the approaches of ML methodologies could be appropriately selected [17]. To use some groups of the ML algorithms for the detection (for instance disease) purpose such as Support Vector Machines (SVM), XGBoost, k-Nearest Neighbour (k-NN), Random Forest, Decision Tree [18], the data for the input should be provided in the structured form. Moreover, the usage of neural networks is appropriate for the raw time series, i.e., unstructured data. The examples of the neural networks which are commonly used for the time series are one dimensional (1-D) convolutional neural network (CNN), Long-Short Term Memory Network (LSTM), Gated Recurrent Units (GRU), Bidirectional Long Short-Term Memory (BLSTM). Additionally, the utility of transfer learning allows for achieving the state-of-the-art-results [19]. With the usage of the aforementioned solutions, it is feasible to create support system methodologies, including those for healthcare, that are even highly accurate. However, that is not all.

Official confirmation of Coronavirus has been announced on 29 December 2019 by the World Health Organization (WHO) in China. The relatively high death rate is the reason why the disease has become one of the most deadly pandemics in history [2]. Thereby, screening and testing of COVID-19-positive people are nowadays considered to be one of the most effective ways how to stop or limit the further spreading of the infection likewise eliminate the danger of renovating the high passed so far state of emergency. Wearables open doors to completely new ways of how the health status can be monitored and possibly how to recognise the disease in its early stage. In the case of COVID-19, the early detection of this illness is of high importance, since the disease is communicable approximately two days before the first symptoms. The development of the disease is illustrated in Fig. 1.1.

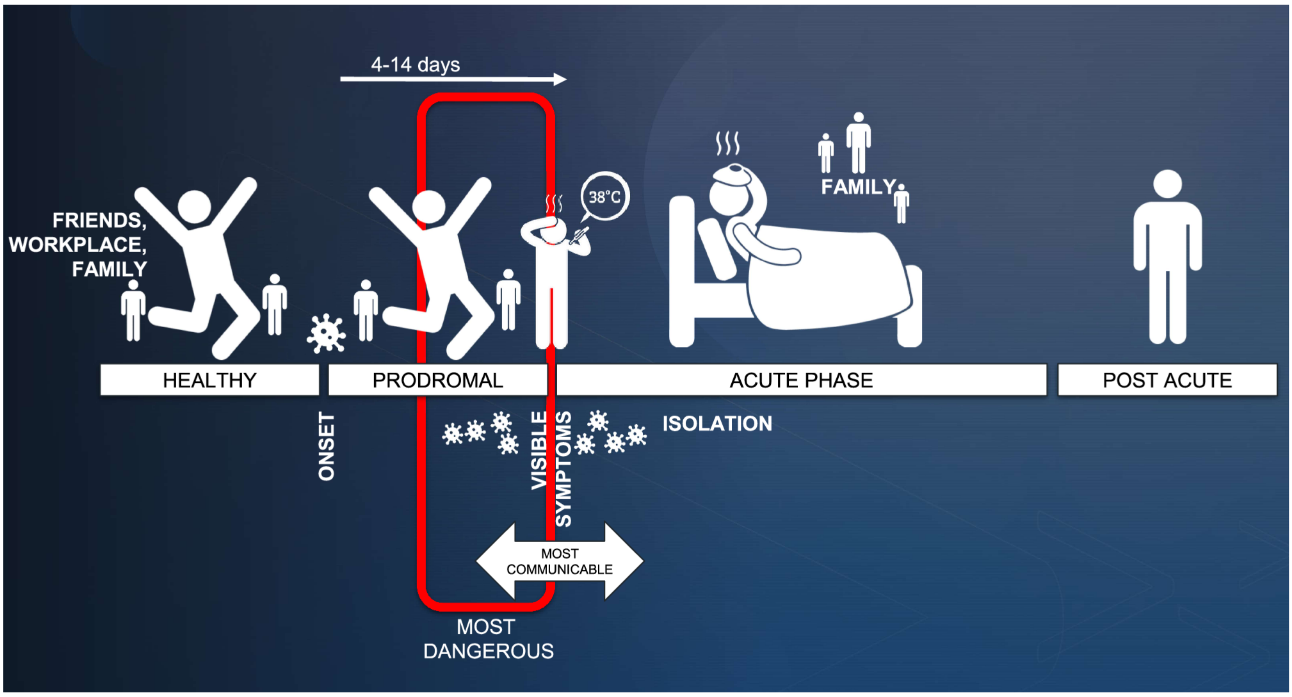

Fig. 1.1: The COVID-19 development [20].

The question is where else the wearable together with ML could find broader and needed applications. One of the concepts deserves extra attention. Ambient Assisted Living (AAL) is defined as the usage of Internet of Things (IoT) and Information and Communication Technology (ICT) for home healthcare. The idea is of high importance in the view of the aging society. The standard medical practice is creating a big burden for the economy of the healthcare system. By the same token, less expensive and more approachable technologies need to be introduced. The usage of wearables and digital technologies could support ‘enabling aging in place’. The elders could live in their domestic environments, with the community to which they are accustomed. This approach is supported by society and has a positive influence on the elders. Additionally, the maintenance costs of the wearables-aided healthcare systems are decreased [21]. . Those aforementioned cases are regarded as highly demanded especially in the still-developing countries because of the limited number of institutions to care for the elders and lacking financial resources [22]. The special target of this thesis will be PD. This illness is the second most common neurodegenerative disorder with a prevalence of 2 % for people over the age of 65 years[23].

This thesis is focused on the usage of ML techniques together with the wearables for COVID-19 detection, and creating methods of AAL dedicated to recognise PD. These techniques represent a big promise for new innovative solutions in the mHealth and eHealth areas and have the potential to form the future of health care. To develop ML models and train them, three datasets are utilised for creating support system methodologies, mHealth and eHealth solutions. Two of them represent the records of COVID-19 cases, Influenza and healthy control (HC) group. HC is regarded in clinical studies as a person who does not have the illness or disorder being studied, however, this person could suffer from other diseases [24]. Those data were collected thanks to the Fitbit device and contains records of the heart rate and activity of the person - the number of steps taken. The third dataset represents the records of PD patients and HC. The dataset contains video and audio records. The symptoms of PD - hypomimia and hypokinetic dysarthria (HD) are computationally analysed.

The conducted COVID-19 detections consider the character of the disease, i.e., the contagiousness of the disease and incubation period. Taking into account those parameters allows for the detection of the disease in the early stage. In addition, the distinction between the diseases, i.e., COVID-19 and Influensa, is possible thanks to the existing representation of the Influensa cases in the dataset. The target of the practical part of the thesis is also not only to design the support system methodologies but also to present the clinical interpretability of the models. They are provided for COVID-19 and PD detection thanks to the statistical analysis and usage of SHapley Additive exPlanations (SHAP) values. In addition, the creation of several models is the scope of the thesis to identify the most accurate of them and to determine the parameters of predictions inter alia such as accuracy, sensitivity, and specificity.

Moreover, the aim of this work is to analyse the possibility to detect PD detection based on hypomimia and HD motor symptoms. The aforementioned dataset contains video and audio records. 43 unique clinical speech exercises are used to detect PD. The utility of the whole spectrum of speech exercises allows for the identification of the most suitable task for automatic PD detection in clinical practice. Furthermore, the multimodality approach of PD detection is explored, i.e., the combination of audio and video modality. Additionally, the prediction models generated thanks to the single modality are compared to those created for the multimodal approach to identify if the combinations of selected modalities could achieve better results. Moreover, the possibility of PD detection is evaluated for emotion recognition tasks between the groups. It is justified by the fact that PD patients manifest impairments in expressing emotions. Furthermore, the thesis provides the theoretical basements of the conducted experiments, likewise describes the transferable methodologies used for a spectrum of diseases, and which are suitable for PD recognition based on sleep disorders symptoms. Moreover, the characteristic of EEG signals and the application of EEG in diagnosis were presented. There are illustrated approaches with the usage of deep learning methods likewise the novelty: neural ordinary differential equation (ODE). ODEs are regarded as neural networks having big potential and they could be applied to wearable-related data.

1.2 Research objectives and methodology

The subject of this thesis is correlated to the usage of machine learning and wearables for the detection and monitoring diseases thanks to the usage of machine learning and wearables. The particularly considered topics are COVID-19 detection and neurodegenerative diseases like PD likewise electroencephalography (EEG) analysis. Thereby, the following seven main Research Objectives (ROx) in this thesis have been identified.

RO1. Classification of COVID-19 cases thanks to the wearable-related data: heart rate and number of steps taken

RO2. Differentiation COVID-19 patients from Influensa cases based on wearable data

RO3. The distinction of COVID-19 patients from Influensa cases and HC thanks to the wearable data and two datasets

RO4. Recognition of PD hinged on facial expression impairments and classification of emotions

RO5. Recognition of PD thanks to the multimodality – audio and video

RO6. The review of the transferable methodologies of detection of sleep disorders thanks to the actigraphy device for Parkinson's disease detection

RO7. The review of the application of deep learning techniques in the EEG analysis

1.3 Dissertation Outline

This doctoral thesis is the descriptive outcome of the study funded from European Union's Horizon 2020 Research and Innovation programme under the Marie Skłodowska Curie grant agreement No. 813278 (A-WEAR: A network for dynamic wearable applications with privacy constraints, http://www.a-wear.eu/). The described research was conducted between 2019 and 2022. The most important part of the research is included in the chapters 2 - 5 based on the published conference and journal papers.

The structure of the thesis is starting from the introduction and acknowledgements (Chapter 1), the theoretical background of the research (Section 2), likewise the instances of the conducted research about COVID-19 (Chapter 3) and PD (Chapter 3) with the usage of ML and wearables. The thesis ends with a summary in Chapter 5.

1.4 Acknowledgements

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2 BACKGROUND

This chapter contains the theoretical background described in this thesis. The topics relate to diseases such as COVID-19, PD likewise their detections. Firstly, the nature of COVID-19 and the symptoms of this illness are mentioned likewise a few approaches to recognise this disease. Additionally, the methods dedicated to its recognition including wearable devices are briefly depicted. Furthermore, the PD is similarly described, i.e., the character of this disease together with the signs of this illness are listed. Some symptoms of PD: hypomimia, HD, and sleep disorders in PD are broadly illustrated. The instances of detection PD based on those symptoms are described.

2.1 COVID-19 Pandemic and Possibility for Detecting Disease

The pandemic of COVID-19 began in December 2019 [25]. On 11 March 2020, the WHO officially announced the outbreak of the pandemic [4]. The world faces up to a pandemic, which causes a state of emergency, numerous infections, and deaths likewise the occurring obstacles in everyday life. The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is the reason for this illness [26].

There is a wide range of symptoms associated with COVID-19. The symptoms range from coughing, fever, hoarseness, shortness of breath, chest pain, or abdominal pain [27], as well as the rare loss of smell and taste [28]. Additionally, examining the wearable records revealed that there were changes in heart rate (HR) around the time of onset of symptoms [29]. According to [30], the authors have identified the three stages of COVID-19: the early stage (stage I), the pulmonary phase (stage II), and the hyperinflammation phase (stage III). If the disease is detected at the prodromal stage (stage I), it will have the greatest impact since it represents a time when a person feels healthy but is already infectious, which is resulting in social contact and the spread of the disease to others. As mentioned by the authors [30], this phase is characterized by fever, dry cough, and mild constitutional symptoms. Detection in the stage I prevents further complications, and the duration of the illness is reduced [30]. If COVID-19 is detected early, the reproduction rate can be significantly reduced and the infection can be prevented from spreading.

Additionally, long-term complications have been identified such as cardiovascular, respiratory, as well as neurological problems, in addition to many others that have not yet been fully described [31]. In order to limit the spread of the disease, it is ideal to detect the disease before the highest contagious period, which is considered to manifest 2 days prior to the visible onset of the symptoms until 1 day after the onset[32].

It is especially notable that variations in HR are present in COVID-19 cases, and that they persist for a longer period than common influensa. The resting HR is elevated nearly the time when symptoms have started [29]. Moreover, COVID-19[33] also showed variations from norms during sleep [33].

The virus is primarily transmitted through social contact, namely face-to-face contact, coughing, talking, or sneezing [34]. The possible solution for controlling social contact to limit the spreading of the virus is the usage of tracing apps, mobile phones and wearables [4]. There are several ways in which the screening test data can be collected. Imaging technologies offer the most accurate diagnostics, even approaching 100 percent in some cases [35]. Furthermore, reverse transcription-polymerase chain reaction (RT-PCR) is the most widespread diagnostic, despite being relatively accurate, these methods are typically used after the onset of disease in order to confirm the diagnosis. Nevertheless, wearable devices [4] appear to be the most inexpensive and fastest method of screening a large population. They appear in the population quite widely which makes them a good candidate to be used as a screening test. Wearable sensors can be used to analyse a variety of physiological parameters, including activity levels, temperature, cardiovascular strain, blood pressure, sleep parameters, respirations variable, sound monitoring, coughing, SpO_2 level, humidity sensors [4]. Analysing the data is the final step in creating the support methodology - assisting technology for clinical purposes. ML holds great promise for the analysis of COVID-19-related data [20].

A review of the methodology of COVID-19 recognition and pandemic evolution with ML and wearable devices is presented in Table 2.1.

The authors in [36] made an analysis of changes in heart rhythm and daily activity of COVID-19 cases based on records of HR and the number of steps taken during the day. The sampling rates were one per minute and one per day, respectively. The records of the devices come from the Fitbit smartwatch. The target of the experiment was to detect anomalies in the prodromal stage of the disease. The authors obtained 32 COVID-19 cases, 15 Influensa, and 73 HC among 5300 participants. Three algorithms were developed: Resting Heart Rate (RHR) Difference anomaly detection, the heart rate over steps anomaly detection (HROS-AD), and cumulative sum (CuSum) [36]. Thanks to the CuSum algorithm, 63 % of COVID-19 cases were recognised positively. Nevertheless, the authors did not consider specificity [36]. RHR Difference (RHR-Diff) offline anomaly detection tried to find anomaly detection in HR thanks to the residuals standardization of RHR. 1 hour signal of RHR was standardised on the RHR average of 28 days. The time window - interval is considered to be an anomalous if the window is under the relevance of 0.05. The HROS-AD is an unsupervised learning anomaly detection algorithm [36]. The metric the ratio of heart rate to the number of steps taken (HROS) and Gaussian distribution analysis were used. The moving average, undersampling to one hour, and Z-score transformation were utilised for HROS-AD algorithm. The anomalies found by the Gaussian distribution analysis were recognised as outliers. The algorithm which was working in real time was CuSum. The deviations of residuals of RHR were summed and 28 days of records were taken into account during performing CuSum.

In another work [29], the Fitbit - wearable device was also utilised for COVID-19 analysis. COVID-19 cases and two types of Influensa were taken into consideration. The authors enrolled 7000 participants and gathered data for 41 COVID-19 cases, 85 Influensa during the pandemic, and 1265 Influensa before the main pandemic. The number of steps taken by human was collected together with RHR records. A longer median duration of COVID-19 cases (12 days) was observed than the spanning of Influensa before the main pandemic (7 days, Pre-COVID-19 Flue) and during the pandemic (9 days, Non-COVID-19 Flue). The self-reported illness duration is illustrated in Fig. 2.1. Thanks to the statistical analysis, it was proved that raised RHR manifests often nearly the onset of the disease. The authors also compared the RHR between COVID-19 and Influensa cases, and COVID-19 records characterise higher values of RHR.

Tab. 2.1: An overview of the methods of COVID-19 detection and pandemic development with the wearables and AI.[20].

Citation	Main aim	Device	Kind of data gathered	Size of the dataset	Accuracy, efficiancy	Machine learning method	Comments
[37]	Predicting the epidemic trend including anomaly detection with COVID-19 infection rate	Huami (ACC, photoplethysmography (PPG))	HR, sleep data	1.3 mln participants	The highest Pearson correlation for Chinease cities: Foshan 0.81, average 0.68	CDNet (CatNN, DenNN)	The simulation provided for North, Central, South China, and South-Central Europe.
[38]	Statistical analysis of daily temperature for COVID-19 disease and creating digital biomarkers	Oura ring	temperature	50 COVID-19 cases	38/50 patients exhibited some temperature anomalies before the onset of the disease	Threshold based on min/max temperature record after z-score, Statistical evaluation: nonparametric Kruskal Wallace test, with Tukey-Kramer post hoc comparison	More wearables should include temperature sensors.
[36]	Anomaly detection of COVID-19 disease	limited to Fitbit	HR, sleep disorders, number of steps	73 HC, 32 COVID-19 cases, 15 Influensa	63 % anomaly detection in COVID-19 cases	Developed algorithms: RHR-Diff, HROS-AD, CuSum	Anomaly detection evaluated on COVID-19 disease cases without considering classification problem.
[39]	Correlation of wearables related data with gender and IoT factors	Lack of detailed informations	respiration rate (RR), oxygen saturation	208 COVID-19 cases	no significant differences between IoT factors and gender	Chi-Square distribution and independent measures t-Test	There should be a difference of future created support system methodologies between the population according to the analysed factors.
[40]	Evaluation of COVID-19 disease based on Empatica device	Empatica E4	galvanic skin response (GSR), inter-beat interval (IBI), skin temperature, pulse oximeter, blood pressure questionnaire	30 HC, 57 COVID-19 cases (27 asymptomatic, 30 symptomatic)	98.1 % accuracy	CovidDeep	The data contains self-assement done by patients, the pre-processing step is not clear. The results are obtained with the medical device – Empatica.
[41]	Detection of COVID-19 disease	WHOOP Strap	Respiration rate	81 COVID-19 cases, 190 HC	20 % COVID-19 subjects recognised before the onset, 80 % cases 3 days after onset	Gradient Boosting	80 % is well results of accuracy, however, the target is to detect disease before the clear onset.
[33]	Prediction of the COVID-19 disease based on RR, HR, Heart Rate Variability (HRV) and also age, gender, Body Mass Index (BMI)	Fitbit	RR, HR, HRV	2754 COVID-19 cases	0.77 +/- 0.03 Area Under the Curve (AUC), sensitivity 47 %, specificity 95 %	Computed parameters: Shannon entropy of the noctural RR series, the mean noctural HR during deep sleep, pre-processing: transformation into z-score, algorithm: CNN	Some extra parameters were provided during training – among others:age, gender, BMI. HR together with RR is increasing during illness, HRV is decreasing.
[29]	Comparision of COVID-19 disease in the early outbreak, later outbreak and also with Influezna	Fitbit	self-report data, RHR, step counts, nightly sleep hours	41 COVID-19 cases, 42685 self-reported flu, 1265 pre-pandemic COVID-19	statistical differences in tests	Statistical evaluations	The authors demonstrate the higher intensity and variety in symptoms for COVID-19 cases than for normal flu.
[42]	Anomaly detection of COVID-19 disease in the early stage	Fitbit	HR, number of step taken	25 COVID-19 cases, 10 Influensa, 67 HC	0.946 precision, 0.234 recall, F-beta 0.918	PCovNet	F-beta is an unreliable metric.
[43]	Anomaly detection of COVID-19 disease	Fitbit	HR, number of step taken	32 COVID-19 cases, 74 HC	Anomalies were detected 23.5%-40 % earlier in comparison to [36] 21/29 found anomalies for RHR-OCSM 24/29 found anomalies for HROS-OC-SVM	One Class-Support Vector Machine (OC-SVM)	There is no consideration of classification problem.
[44]	Checking the influence of temperature on the classification task	Oura Ring	temperature, HR HRV, RR metabolic equivalents (MET)	73 COVID-19 cases, approximately 63000 HC	AUC = 0.819 for all modalities, AUC = 0.770 for all modalities without temperature	Random Forest	The temperature was confirmed to be valuable for COVID-19 detection.
[45]	Determination of the need of hospitalization	VitalConnect VitalPatch, Proactive, Protekt® Finger Pulse Oximeter 20110	raw 125 Hz electrocardiography (ECG), 50 Hz triaxial accelerometer, 0.25 Hz skin temperature, SpO_2	22 positive cases (required hospitalization), 308 negative cases	AUC = 0.84	Gradient Boosting	The determination of the need for hospitalization was decided based on decompensation index (CDI).

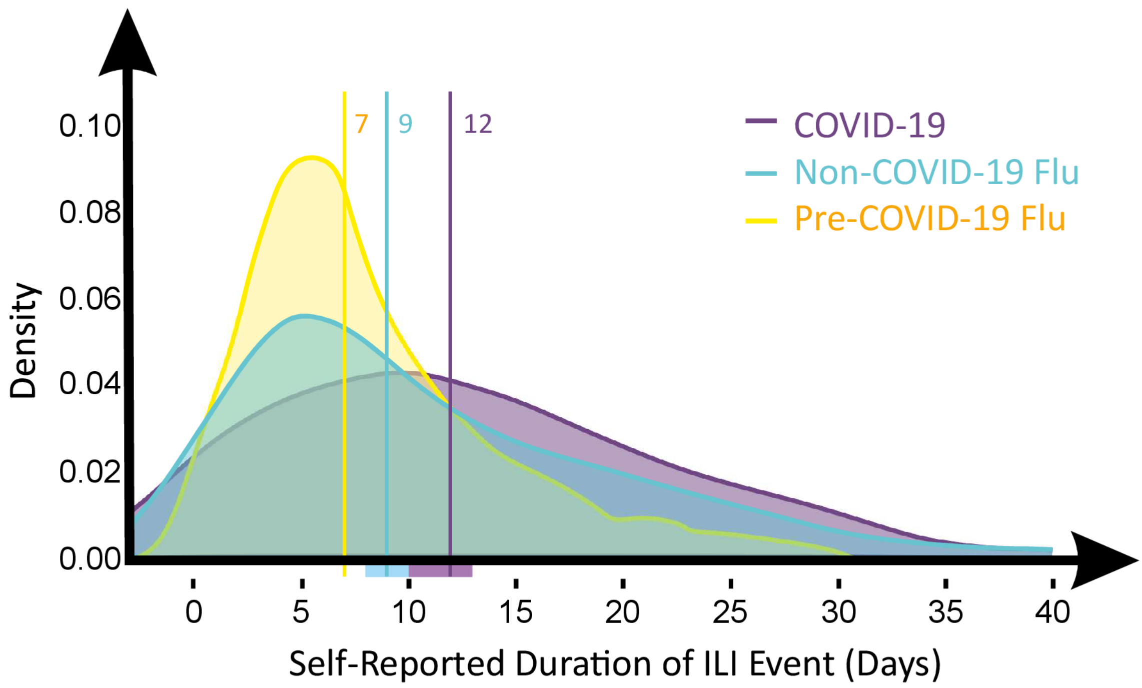

Fig. 2.1: The illness duration for COVID-19, Influensa before the main pandemic and during the pandemic [29].

2.2 Parkinson's Disease and the Methods of its Detection

PD is one of the most prevalent neurodegenerative diseases in society. This disease occurs in 2-3 % of society in the European Union (EU) beyond 65 years old [23]. A major challenge that the EU will have to deal with within the next 30 years is the aging of society. This issue is associated with neurodegenerative diseases, and one of them is PD [1]. A distinction can be made between the motor and non-motor symptoms of PD. Among the motor symptoms could be distinguished the following signs: hypomimia, HD, the Freezing of Gait (FOG), bradykinesia, tremor, PD dysgraphia, dyskinesia, dysphagia [46]. Sleep disorders, hallucinations, depression, anxiety, constipation, cognitive deficits, urinary symptoms, etc. belong to the non-motor symptoms [47].

If the disease is detected in the early stage, the deterioration of the health is minor because the treatment is implemented. Because of this fact, early detection is especially desirable [48]. The aging of society forces the demand of creating new technologies for detecting neurodegenerative diseases in their early stage. Recently, the novelty in technology allows for utilising them for purpose of PD detection [49].

Nevertheless, the serious issue is that the early symptoms of the disease are lowly apparent. The methods which are the most accurate, however, are thereby expensive including MRI, CT, and PET. Those methods are rather used in more advanced stages and the hospital environment. The limitation is also the price of the examination. Because of those factors, there is a need for relatively cheaper and more approachable solutions for patients [3].

This disease cannot be cured, however, the process of development could be inhibited. There are applied methodologies such as neurostimulation or pharmacotherapy [50]. The patients visit the hospital several times per year to maintain relatively good health, nevertheless, they could meet the Hawthorne effect or this amount of appointments per year is not sufficient [51]. Patients with PD can experience sudden neurodegeneration, side effects such as levodopa-induced dyskinesia, or numerous fluctuations in motor function. To prevent the deterioration of health quality, such incidents require immediate intervention. Telemedicine solutions, which are capable of addressing those issues, are in the research interest of many scientists. The application of mobile phone usage for PD detection and monitoring of the progress of the disease seem to be especially interesting [52].

PD management is challenging despite the achievements in treatment approaches [53]. One of the most desirable targets is PD detection, especially in the early stage. The used tools for this purpose are based on artificial intelligence.

One of the symptoms which could be utilised for PD detection is hypomimia. The hypomimia manifests in an expressionless face with no or little sense of animation, the reduction of facial expression [54], the slowness and limitation of facial motion (facial bradykinesia) [55]. Moreover, there is observed a stiffness of muscles, the issue with orofacial movements, i.e., the slower speed of the jaw lips [56], decreased blinking rate [57], unconsciously opened mouth [58], flattened nasolabial folds [58], occurring asymmetry in the face [59], decreased ability to raise eyebrows [60], etc. It is considered that PD patients recollect a so-called 'poker face'. Furthermore, expressing emotions by them is a challenging task [60].

There are a few techniques that were applied for hypomimia analysis, i.e., the affectograms, facial action coding system (FACS), the automatic maximally discriminative facial movement coding systems (MAX), facial electromyography (fEMG), the Action Units (AUs), automatic facial expression recognition (FER), and techniques with the usage of artificial intelligence (AI) for emotion recognition [49, 61]. There could be distinguished two main groups of techniques utilizing video, or image, and ML. The methods belong to the first group are detecting pixels or facial landmarks on a face. The second group represents the solutions that utilize neural networks to extract features from images or videos [61].

The facial landmarks were detected and 12 features were obtained based on them in [62]. Areas and distances were extracted features. The performed exercise was a one-minute monologue of native speakers in the Czech language. In this exercise, 79 HC and 91 de-novo (in the early stage) and drug-naive (untreated) patients participated, excluding those suffering from depression. The classification task was performed thanks to the 5 features, the leave-one-subject-out cross-validation with binary Logistic Regression as a classifier. The metrics which were calculated were as follows: AUC = 0.87, accuracy = 78.3 %.

Another early motor symptom of PD is HD [63]. This mark occurs parallelly with hypomimia [46]. HD manifests in 90 % of PD patients [64] and this speech disorder occurs because of a basal ganglia control circuit pathology [46]. HD occurs in the field of phonation, prosody, articulation, and respiration. The exact difficulties are apparent in irregular pitch fluctuations, breathy and harsh voice quality, monoloudness, reduced loudness, airflow insufficiency, unnatural speech rate, imprecise articulation, monopitch, improper pausing, etc. The detailed description of HD is attached in [65, 66].

Furthermore, dysarthria affects articulators and their debility may manifest particularly during the performance of exercises such as the tongue twister - validated speech exercise [67]. Pronunciation in this speech exercise is challenging and could reveal the PD level because of difficulty in the appropriate usage of tongue and mouth.

In [68], the basic features recommendation was utilised for the detection of PD. Three groups were taken into account, namely: HC (30), PD patients (30), and 50 individuals suffering from idiopathic rapid eye movement sleep behavior disorder (iRBD). The data were gathered by smartphone for speech exercises. They were the monologue, the diadochokinetic exercise – repeating of pa-ta-ka, and the sustained phonation of vowel [a]. PD vs. HC, and PD vs. iRBD were classified based on collected records. The outcome of the detection of PD was equal to 0.85 AUC for Logistic Regression. Moreover, the benefit was the usage of smartphone technology for the prodromal detection of the disease. Furthermore, the most profitable biomarkers occurred to be decreased rate of follow-up intervals, inappropriate silences, and the monopitch. Further, the classification of the second scenario, PD vs. iRBD, had an AUC of 0.78.

The methods for determining the progress of the PD were presented in [69]. In this approach, the Mel-frequency cepstral coefficients (MFCC) and AU were extracted from audio and video modalities, respectively. The regression method classifies PD patients into four categories for the development of the disease. The collected 772 records were gathered from 117 PD patients. The aim of the exercise was to talk about their positive and negative experiences by them. A Hierarchical Bayesian neural network (HBNN-C) was used as a ML method. The scheme of the performed experiment is presented in Fig. 2.2. The multiclass classification was equal to 0.55 F1-score. Unfortunately, the experiment is not repeatable because the dataset is private.

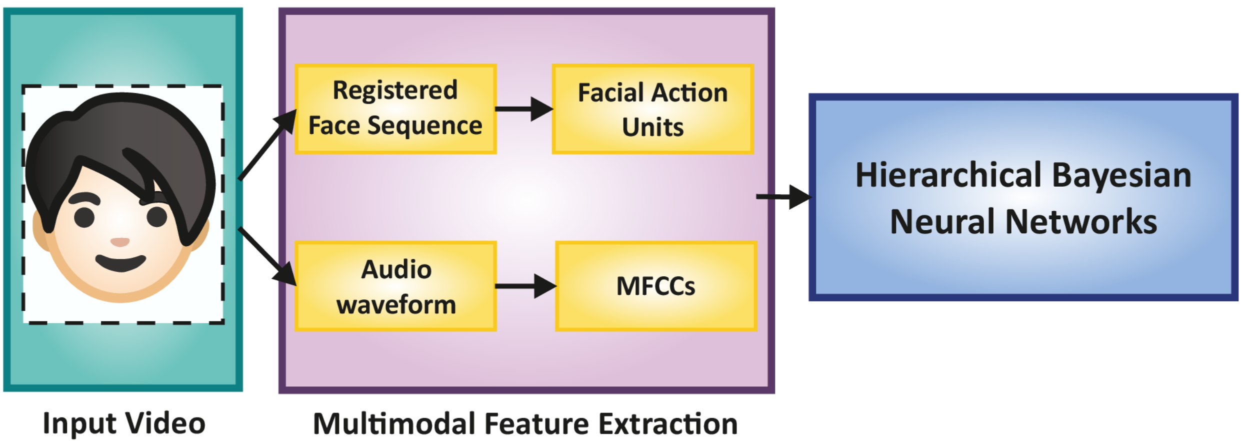

Fig. 2.2: The flow of the experiment from [69].

Tab. 2.2: Potential methodologies for detecting PD based on sleep disorders [70].

Main Aim	Features/Architectures	Results	Disease/Case	Comments
Evaluation of temporal and spatial augmentation [71]	Deep CNN	0.87 AUC	The gait of PD patients	Data augmentation improved the prediction
Testing XGBoost and SMOTE for sleep/awake stages detection [72]	XGBoost	80 % accuracy, 84 % with SMOTE	Sleep/awake stages	Using SMOTE improved accuracy, XGBoost was a good choice of algorithm
Evaluation of the performance of personalised factors, Testing various algorithms [73]	**Features:** 10th, 20th, 50th, 75th, and 90th percentiles, mean, sum of values, coefficient of variation, peak-to-peak amplitude, skewness, kurtosis, signal power, peak intensity, zero crossings, standard deviation (std) time above threshold, and maximum value, interquartile range (IQR) **Algorithms:** XGBoost, Naive Bayes, Regularized logistic regression (RLR) with L2 regularizer, Stochastic gradient descent (SGD), AdaBoost	86 % accuracy, 95 % specificity, 45 % sensitivity	Sleep/awake stages	Personalised sleep/awake prediction is better, the best observable results are for XGBoost
Detection of attention-deficit hyperactivity (ADHD) [74]	Features extracted from accelerometer and gyroscope records, SVM	95 % accuracy	ADHD in children	It is possible to recognise ADHD in children. It is needed extension of the database
Usage of CNN and spectrograms for detection of ADHD based on 1-day record [75]	CNN + spectograms	97.62% sensitivity, 99.52% specificity, AUC values over 99%	ADHD	Deep learning together with actimetry records allows for the detection of the ADHD
Converting triaxial accelerometer signals into spectrograms [76]	Unsupervised pre-training step, supervised discriminative step, deep belief networks (DBNs), hybrid approach of deep learning and Hidden Markov Models	91,5 % accuracy	Freezing of Parkinson's gait	Pre-training with feature extractions allows achieving better prediction
Detection of Alzheimer disease in the early stage with time-aware NN [77]	Time-aware Toeplitz Inverse Covariance-based Clustering (TICC) Clustering TICC and CNN (TATC)	86.2 AUC	Alzheimer disease	The great potential of using TICC for predicting Alzheimer disease
Comparison of the proposed method with different solutions [78]	Deep-ACTINet (1-D CNN and LSTM)	89.65 % accuracy	Sleep/awake	Achieved detection of sleep/awake stages with the end-to-end deep learning model
Testing bidirectional version of LSTM for sleep/awake stages [79]	Bidirectional LSTM	96.5 % accuracy	Sleep/awake	The solution adequate for real-time application obtained good results
Comparing algorithms according to the detection of bradykinesia [80]	CNN	90,9 % accuracy	Bradykinesia	CNN outperformed other algorithms about 4.6 %
Checking if it possible to automatically detect periodic limb movements and actigraphy analysis could give results as polysomnography (PSG) [81]	Time-based, frequency-based and signal morphology-based features, Linear Discriminant Analysis (LDA)	74,2 % accuracy	Periodic limb movements	Actigraphy records with support system methodology could serve as a method for recognising periodic limb movements
Personalised detection of sleep/awake stages [73]	10th, 20th, 50th, 75th, and 90th percentiles, mean, sum of values, std, coefficient of variation, peak-to-peak amplitude, IQR, skewness, kurtosis, signal power, peak intensity, zero crossings, time above threshold, and max value with normalized actigraphy records, Naive Bayes, RLR, SGD, Random Forest, AdaBoost, XGBoost	Up to 91% accuracy	Sleep/awake	The differences in sleep patterns were confirmed between the groups, the highest results were registered for AdaBoost and XGBoost

Moreover, sleep problems are considered signs of PD. Among them could be distinguished following symptoms: insomnia, Excessive Daytime Sleepiness (EDS), Rapid Eye Movement Behavioral Disorder (RBD), Restless Leg Syndrome (RLS), and breathing difficulties. Those symptoms manifest in the early stage of illness [82].

The quality and quantity of sleep influence people's health. The measurements describing sleep could be indicators of illnesses. Wearable devices (including smartwatches) can be used to evaluate sleep disorders as well as sleep diaries, WiFi-based, bed sensors, PSG, videosomnography (VSG), radiofrequency (RF), and EEG [83]. However, the PSG is considered to be the gold standard [84, 85]. Unfortunately, this procedure is carried out in the hospital environment [83]. The drawback of the PSG is that it is often executed in the later stage, not in the highly demanded early stage, and it is performed in hospitals.

The Table 2.2 summarises the potential techniques which could be used for the recognition of PD based on sleep disturbances. They were used as different applications in various diseases and disorders such as ADHD, Alzheimer, and bradykinesia. The analysis of sleep/awake stages was also taken into consideration. The records which were analysed were gathered by wearable - actigraph. The suitable ML algorithms were identified. They were: SVM, Naive Bayesian, k-NN, XGBoost, or Random Forest, Logistic Regression, GRU, LSTM, and CNN, neural ODE, 1-D CNN, Deep-ACTINet, AdaBoost, TICC and CNN (TATC).

3 WEARABLES FOR COVID-19 DETECTION - PRACTICAL SOLUTIONS

The purpose of this chapter is to investigate the use of wearable devices for the detection of COVID-19. Furthermore, the ML methodology was utilized for this aim. Chapter 2 presents the state-of-the-art methods and related works, whereas this Chapter 3 presents my research, experiments, and obtained results. The introduced in the thesis ML approaches are built upon two papers [36] and [29] that sought to identify COVID-19 among analysed cohorts. In the first them, 4642 volunteers were involved in the experiment by Stanford University, whereas 114 of them were diagnosed with COVID-19 disease. Additionally, the cohorts had HC group and Influensa. The dataset had records of the heart rate and the number of steps. The sampling rate was 1 per minute. The personal activity was expressed as the heart rate value divided by the number of steps. The research idea in this thesis is the extension of this paper [36]. Nevertheless, the novelty in this thesis is focusing on the data classification problem, not just anomaly detection like in the original paper. The two scenarios were considered. The first of them distinguished COVID-19 cases from HC, while the second scenario focused on the classification of ill cases from HC. The physiological base of the assumption of the thesis was taken inter alia from [29]. The resting time of the heart rate is higher for an ill person than in the case of HC group. Moreover, there are differences in heart rate rhythm between COVID-19 and Influensa cases, they last longer and begin earlier. Furthermore, the highest contagiousness period is regarded as -2 to 1 day after the onset of COVID-19, which determines the necessity of early COVID-19 detection. This issue was likewise considered in this thesis. The second dataset from [29] contains the heart rate record and the number of steps but at a different sampling rate. Three groups can be distinguished: COVID-19, Influensa prior to the main pandemic, and Influensa during the main pandemic. The thesis also focuses thanks to the combination of the two mentioned reused datasets on more diverse datasets in terms of demographic. The experiments provided the statistical analysis of the datasets likewise creation of support methodologies suitable for COVID-19 diagnosis in the early stage.

3.1 COVID-19 Diagnosis at Early Stage Based on Smartwatches and Machine Learning Techniques

The primary objective of this study was to develop a support system methodology for the early detection of COVID-19 [20, 36]. Furthermore, the criteria were to focus on wearable measurements. This was accomplished by reusing the publicly available dataset prepared by Stanford University with cases of COVID-19, Influensa, and HC [36]. Data from smartwatches - heart rate, number of steps were collected by Fitbit device. The selected dataset contains the records of steps per minute and heart rate per second. COVID-19 disease was diagnosed in 114 of the participants. The full records of 34 HC, 27 COVID-19 patients were taken under analysis. HC and COVID-19 cases were balanced in this study, along with 7 Influensa cases. Additionally, this work focused on developing a ML model suitable for use as a screening test. Taking into consideration the contagiousness and incubation periods of the analysing sample, the model should be able to identify which of the analysing sample is ill or healthy during the prodromal stage. The two scenarios were investigated, i.e., COVID-19 detection and Illness recognition when COVID-19 and Influensa were treated as one group and the second was regarded as HC. Experiments were conducted in the following manner. First, the ratio of heart rate to steps was calculated. Next, the time windows - selected interval taken under analysis, for two scenarios were defined, i.e., COVID-19, Influensa, and HC likewise for COVID-19 and HC. There are three types of windows: five-day, seven-day, and ten-day. For each window, a set of features was computed. The difference in the windows between the later and earlier set of features was then calculated. Maximum Relevance Minimum Redundancy (mRMR) was used for feature pre-selection with 50 features. Lastly, stratified cross-validation was performed. The following classifiers were used: Random Forest, Decision Tree, Logistic Regression, SVM, k-NN, XGBoost, and Generalised Learning Vector Quantisation (GLVQ).

The inspiration for analysing physiological signal features was taken from the following articles: [86–89]. Three types of features were extracted, i.e., temporal, statistical, and spectral. A Python package called tsfel [90] was used to extract the features. A diagram illustrating how features are extracted is shown in Fig. 3.1.

Two windows of features were computed for the HC cohort in order to extract the HC samples (p_{HC1} - earlier window and p_{HC2} - later window). Windows were fixed in size and separated by a specified spacing. The difference between a set of features for each window was calculated. Where:

- Based on the earlier healthy state, the vector of features is expressed as follows: $\overrightarrow{f_{HC1}}$
- In the later healthy state, the vector of features is expressed as follows: $\overrightarrow{f_{HC2}}$
- For HC, the final vector is as follows:: $\overrightarrow{f} = \overrightarrow{f_{HC2}}$ - $\overrightarrow{f_{HC1}}$
- There is an end point to the earlier healthy state window described as follows: t_{HC1}
- In order to indicate when the later healthy state window begins, it was used the following variable: t_{HC2}

Similarly, COVID-19 cases were extracted using the same procedure. To detect disease in the prodromal stage, shifts in the computation of windows were defined. Due to the contagious nature of this disease, the highest contagious peak occurs two days before the disease begins. Following the same steps as when extracting HC samples, the next step was the extraction of COVID-19. As shown in Fig. 3.1, the steps are described in a systematic manner.

Where:

- An analysis of the healthy state yields the following vector of features: $\overrightarrow{f_H}$
- COVID-19 early state features are expressed as a vector as follows: $\overrightarrow{f_C}$
- COVID-19's final vector can be expressed as follows: $\overrightarrow{f} = \overrightarrow{f_C}$ - $\overrightarrow{f_H}$
- A healthy state window ends as follows: t_H
- COVID-19 begins at the following time: t_C
- Symptoms begin to appear at the following time: t_0
- COVID-19 is diagnosed as follows: t_D
- In terms of the Onset, it is: $Onset = t_C + p_C$
- The shift between the diagnosis time and the Onset of the disease is expressed as: $SHIFT = t_D$ - t_0

The incubation and contagiousness period were considered and a 7 day interval between windows and a 2 day SHIFT is used (please, check the designation in Fig. 3.1). The extracted features were

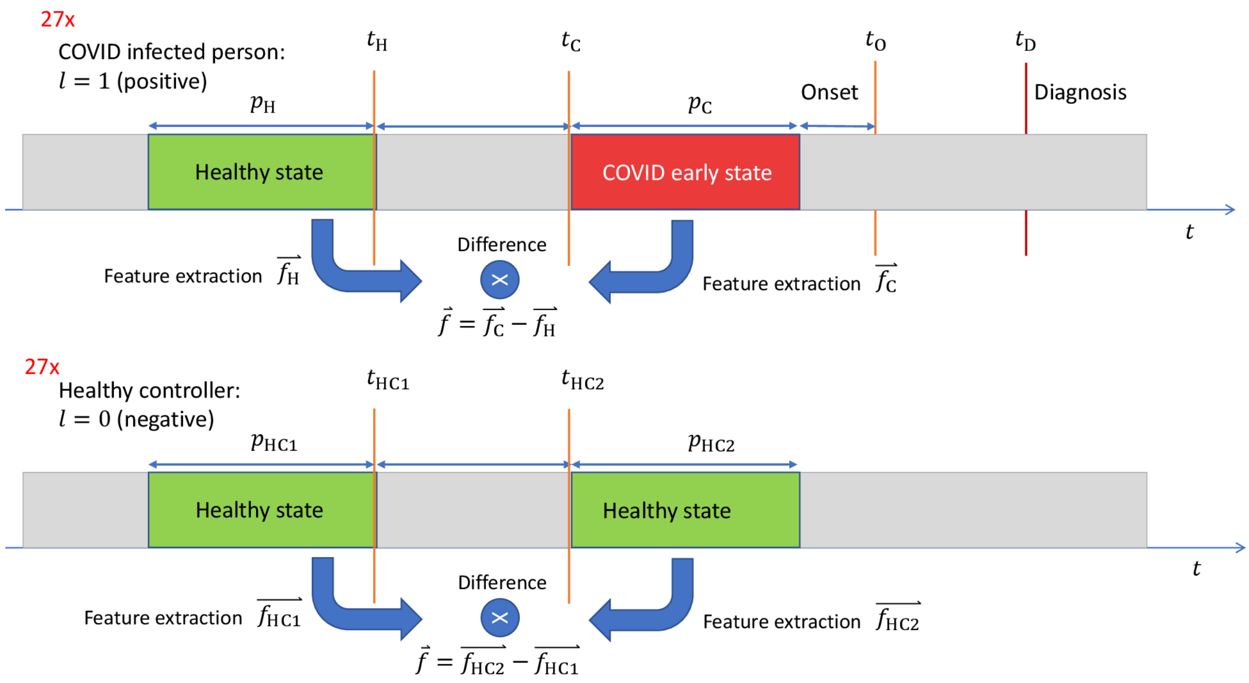

Fig. 3.1: An outline of the feature extraction process for cases of HC and COVID-19.

statistically evaluated using the Mann–Whitney U test with false discovery rate (FDR) correction. It was found that MFCC, Fast Fourier Transform (FFT), histogram, spectral-based, and linear prediction cepstral coefficients (LPCC) could be used to distinguish between HC and COVID-19. The most important features for the scenarios COVID-19 and Influensa vs. HC were spectral-based, FFT, and MFCC. Nevertheless, after applying stronger criteria, i.e., FDR correction, none of the features fulfilled the requirements with significance level alfa = 0.05. However, for the cohort with Influensa, the p-value after FDR correction was lower.

There is a presentation of the best results of the classifications for the cohort that contains COVID-19 cases and HC in Table 3.1. The most accurate (0.78) with specificity 0.77, sensitivity 0.80, and Matthews correlation coefficient (MCC) 0.60, were registered for k-NN during the 5-days window (see Table 3.1). The best sensitivity was registered for GLVQ: 0.81.

Tab. 3.1: COVID-19 disease detection results for 5-day windows (cohorts: 27 HC, 27 COV).

Classifier	**Accuracy**	**Sensitivity**	**Specificity**	MCC
XGBoost	0.71	0.72	0.71	0.46
k-NN	**0.78**	0.77	**0.80**	**0.60**
SVM	0.65	0.66	0.65	0.33
Logistic Regression	0.69	0.69	0.69	0.41
Decision Tree	0.50	0.52	0.49	0.01
Random Forest	0.62	0.59	0.66	0.27
GLVQ	0.76	**0.81**	0.71	0.55

There is created second sub-dataset that includes 27 COVID-19 disease cases and 7 Influensa patients (ill cases), and 34 HC. As a result of the case for a 5-day window, the best accuracy (0.73) and the best specificity (0.76) were recorded for k-NN, as well as the best MCC (0.49). With Logistic Regression, the sensitivity was the highest (0.76). GLVQ obtained also the accuracy equal to 0.73.

The obtained values of classification for 7-day and 10-day windows were aggravated in comparison to the 5-day window.

To summarize, the methodology was developed to aid the detection of COVID-19 disease at the prodromal stage. Moreover, the advantage of the presented methodology is taking into consideration the character of the disease, i.e., incubation and contagiousness period. A model based on five-day windows enables an accuracy of 78 percent in prediction. Realistically, the solution based on 5-day windows is likely to be the most useful and practical. This research focuses on creating a more powerful classification algorithm than the originally proposed model to detect anomalies in [36]. Based on the technology used in this experiment, it may be possible to perform a screening test utilising smartwatches. The study revealed the statistical importance of the majority of features from the statistical and spectral domain based on the Mann-Whitney U test. Moreover, the advantage of this research is that the model results were learned for two different cohorts.

3.2 The Distinction between COVID-19 Cases and Two Types of Influensa with Wearable Devices and Machine Learning

The major objective of this study was to distinguish COVID-19 cases from Influensa cases using ML and wearable technology. The two types of Influensa cases from various periods (before and during the pandemic) were examined. The data were retrieved from [29]. 37 cases of non-COVID-19 flu (in the middle of the pandemic), 37 cases of pre-COVID-19 flu (before the main pandemic), and 21 cases of COVID-19 were included in the recalculated and filled dataset. There are records of heart rate and the number of steps gathered by Fitbit device. The presented in the thesis support methodologies were developed to confirm the conclusions and assumptions from the original paper regarding the differences in heart rate between the types of viruses tested. Moreover, the incubation and contagiousness periods were taken into consideration to create a solution suitable for early COVID-19 detection. As a first step, the time window was selected to extract features concerning the contagious period and the incubation period. The features were also extracted from a 5-day window covering 7 to 2 days prior to the visibility of the onset. Several features were calculated for the isolated time window, including std, skew, variance (var), range, minimum (min), maximum (max), mean, kurtosis, slope, and approximate entropy. A feature pre-selection method was then applied to select the most valuable features. Next, a 10-fold cross-validation method was used. The applied classifiers were Logistic Regressions, Random Forests, k-NNs, XGBoosts, SVMs, Decision Trees, and GLVQs. Using cross-validation, the classification results were determined.

The most successful algorithm in balanced accuracy, specificity, and MCC for the distinction between COVID-19 cases and Influensa cases during the pandemic was k-NN. The balanced accuracy was equal to 0.73, specificity achieved 0.87 and MCC was 0.49. The sensitivity was the highest for Logistic Regression and was equal to 0.61.

Tab. 3.2: Identifying Influensa cases during the middle of the pandemic and cases of COVID-19.

Classifier	ACC Bal	Accuracy	Sensitivity	Specificity	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
GLVQ	0.70 ± 0.19	0.74 ± 0.17	0.57 ± 0.34	0.83 ± 0.21	0.43 ± 0.40

In the second experiment, Influensa cases were classified before and during a pandemic. GLVQ achieved the best results. This classifier obtained achieved the highest balanced accuracy, i.e., 0.82. sensitivity (0.96), MCC (0.68), while XGBoost achieved the highest specificity (0.74).

To summarize, the research aimed to distinguish between each type of case, i.e.: COVID-19 cases, Influensa before the main pandemic, and during the pandemic. The most important of four performed classifications show that COVID-19 cases and Influensa in the middle of the pandemic can be distinguished with a 0.73 balanced accuracy via k-NN. Moreover, the contribution of this study is the introduction of models differentiating two types of influensa likewise COVID-19 cases vs. Influensa cases before the main pandemic. The achieved balanced accuracies for GLVQ were equal to 0.82 and 0.84, respectively.

3.3 Wearable Analytics and Early Diagnostic of COVID-19 Based on Two Cohorts

The purpose of this study was to combine two datasets previously explored in chapters 3.1 and 3.2. Both datasets considered COVID-19 disease. First of them with a higher sampling rate contains COVID-19 cases, Influensa, and HC (referred to as dataset A). The second dataset does not have HC cases, however, it has the representatives of two types of Influensa – before the main pandemic and during the pandemic, and COVID-19 cases (referred to as dataset B). From the first dataset were chosen 27 COVID-19 cases, 15 Influensa, and 73 HC. 21 COVID-19 cases, 37 Non-COVID-19 Flu, and 675 Pre-COVID-19 Flu were in dataset B. Both datasets (A and B) contain heart rate records and steps taken. They were collected by the wearable – Fitbit device.

Tab. 3.3: The combinations of datasets and classes for each experiment.

Types of data	Experiment 1a	Experiment 1b	Experiment 2	Experiment 3	Experiment 4	Experiment 5
COVID-19 A	1	1	1	1	1	2
COVID-19 B	1	1		1	1	2
Influensa A			1	0	1	1
Non-Covid-19 Flu				0	1	1
Pre-Covid-19 Flu				0	1	1
HC	0	0	0		0	0

In the beginning, dataset A was undersampled in order to unify both datasets. Two modalities were sampled at a rate of one sample per day. The next step was to merge the datasets. The 5-day time window for each time series was then provided. According to the contagiousness of the disease and the incubation period, the time window was extracted from -7 to -2 days before the onset of the disease. Next, the features were calculated. Then, the ratios of the heart rate-related features to the number of step-related were computed. mRMR was used to select the features. Twenty features were chosen from a total of 36. Additionally, 10-fold stratified cross-validation was conducted. Classifiers used in this study included k-NN, SVM, Random Forest, Decision Tree, Logistic Regression, XGBoost, and GLVQ. Experiments were conducted according to Table 3.3. The confidence level alfa = 0.05.

The features were extracted according to the receipt from [91]. Fig. 3.2 illustrates the scheme for calculating the time window with respect to the onset disease.

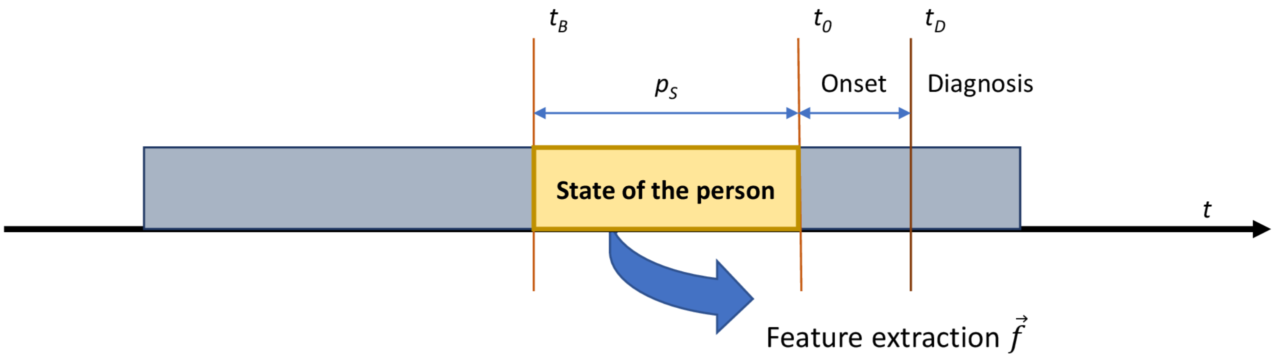

Fig. 3.2: Feature extraction.

The following time points are computed:

- t_D is the detection of the disease $t_D = t_0 + 2$
- t_0 is the visible Onset of the illness $t_0 = p_S + t_B$
- p_S is the duration of the time window
- t_B is the beginning of the disease

Subsequently, a few parameters were calculated for the time windows of heart rate and the number of steps for the datasets A and B. These were: max, min, mean, std, relative standard deviation (rsd), range, Shannon entropy, approximate entropy, skewness, kurtosis, variance, and slope. Furthermore, the ratios between the parameters of heart rate and the number of steps were calculated.

Having analysed COVID-19 cases vs. HC, the 13 features were statistically significant according U-Mann Whitney test after FDR correction. The most valuable features occurred to be those indicated on personal activity. Furthermore, heart rate-related parameters have statistical significance. The statistical analysis of ill cases vs. HC revealed the importance of changes in the heart, as well as variations in personal activity. The Shannon entropy of the steps taken is also important.

The distinction of COVID-19 (27 and 21 cases from datasets A and B, respectively) from 48 HC was conducted using 20 features out of 36. XGBoost obtained 0.73 accuracy, 0.71 sensitivity, and 0.48 MCC (see Table 3.4. While GLVQ achieved a specificity of 0.91.

The outcome of the distinction of 48 cases COVID-19 (A and B dataset) vs. 48 Influensa (for all analysed cases, from A and B dataset) showed the best accuracy (0.67) and MCC (0.36) for XGBoost. The highest sensitivity: 0.66 was obtained for Random Forest and GLVQ, whereas the best specificity: 0.73 was achieved for SVM. The results of the classification of 48 COVID-19 cases (A and B dataset),

Tab. 3.4: The outcome of distinction COVID-19 (A and B dataset) from HC (for selected 20 features).

Classifier	**Accuracy**	**Sensitivity**	**Specificity**	MCC
XGBoost	**0.73 ± 0.14**	**0.71 ± 0.22**	0.75 ± 0.19	**0.48 ± 0.29**
k-NN	0.72 ± 0.15	0.58 ± 0.24	0.86 ± 0.16	0.47 ± 0.30
SVM	0.67 ± 0.14	0.60 ± 0.22	0.73 ± 0.19	0.35 ± 0.29
Logistic Regression	0.65 ± 0.15	0.59 ± 0.23	0.70 ± 0.20	0.31 ± 0.31
Decision Tree	0.68 ± 0.15	0.64 ± 0.23	0.71 ± 0.18	0.37 ± 0.30
Random Forest	0.70 ± 0.16	0.64 ± 0.24	0.76 ± 0.20	0.42 ± 0.33
GLVQ	0.66 ± 0.12	0.40 ± 0.21	**0.91 ± 0.12**	0.36 ± 0.26

26 Influensa (for all three cases, from A and B dataset) vs. 74 HC cases indicated that SVM and GLVQ obtained the highest accuracy of 0.72. Logistic Regression had a sensitivity equal to 0.66, and it was the highest, whereas the best specificity (0.90) and MCC (0.47) were observed for the Decision Tree.

To summarize, the support methodology of COVID-19 detection based on two cohorts was proposed. The combined dataset is one of the largest presented in the literature (see Subsection 2.1). The valuable features from the point of view of distinguishing COVID-19 cases from HC cases were identified by statistical analysis. They were derived from the heart rate and the number of steps taken records. The proposed models are one of a kind. Among the six performed classifications, XGBoost was found to be the most powerful algorithm. The distinction of COVID-19 cases from HC from both datasets was possible in 0.73 balanced accuracy, whereas differentiation of ill cases achieved 0.72 balanced accuracy for k-NN and GLVQ.

4 MHEALTH DEDICATED SOLUTIONS FOR PARKINSON'S DETECTION

This chapter is targeting the detection of PD and is dedicated to mHealth and eHealth solutions for AAL. The undoubted advantage of mobile phones is their broad ownership in society. Moreover, the monitoring and detection of Parkinson's motor and non-motor symptoms are becoming approachable for the elders and their families. The additional clear advantage of this is the reduction of the cost of the healthcare system. This chapter presents the automatic analysis of changes in emotions to recognise PD likewise the multimodal detection of PD based on hypomimia and HD symptoms with the usage of audio and video records. Furthermore, the chapter discusses the used material and methods, the collected dataset, and the feature extraction methodology. Moreover, the used ML approaches with the solutions for the interpretability of the model, the used features, and the discussion of the key findings are provided. Those kinds of techniques allowed the creation of support system methodologies for the detection of PD together with their interpretability.

4.1 Parkinson's Disease Detection based on Changes of Emotions during Speech

This research aims to develop a methodology which is detecting PD. Symptoms of hypomimia manifested in the difficulty of expressing emotions were the basis of the study. For the purpose of this research, 45 HC and 70 PD patients were involved. Using a numerical analysis of the changes in emotions over time, the set of features was determined. Face expression recognition (FEC) based on neural networks was used as the first step to detect differences frame by frame. Initially, the face was detected by using Multitask Cascaded Convolutional Networks (MTCNN) [92]. The neural network architecture was used in the second step to determine the intensity of seven analysed emotions. Aside from surprise and neutral emotions, disgust, sadness, happiness, fear, and anger are considered. For the evaluation of the disease, a tongue twister and reading aloud long texts were tested. A Czech sentence (Celý večer se učí sčítat)[1] was pronounced by the participants. The sentence means "He's been learning to count all night", however, the difficulty in pronouncing sentence matters in the case of this experiment. Next, scalars for each emotion were calculated based on the time series. The following features were determined: approximate entropy, Shannon entropy, skewness, kurtosis, std, rsd, range, max, and min. Using the mRMR, the feature pre-selection process was then performed. A stratified cross-validation with standardization and classification was conducted. k-NN, SVM, Random Forest, Decision Tree, Logistic Regression, and XGBoost were used as classifiers. Ethical approval was granted by the Masaryk University Ethical Committee.

Based on the detection of seven emotions in each video frame and statistical analysis thank to a Mann-Whitney U test with FDR correction, it occurs that fear is the most meaningful emotion. The results indicated that the most informative variables were mean, std, variance, maximum, mean and range of fear, mean, std, variance, min of anger, and approximate entropy of sadness.

The outcomes of the tongue twister classification showed that the prediction of PD classification

[1]Link for the pronunciation of the sentence: https://bit.ly/2DVPJ5M

with XGBoost achieved the highest balanced accuracy 0.69. MCC for this classifier was 0.39. Logistic Regression had the highest sensitivity of 0.73, while the best specificity was observed for the Decision Tree.

The SHAP values provided for the XGBoost classifier the interpretability of the model. SHAP values confirmed the importance of fear emotion (std, var, range, max, and mean) for the classification. This may be explained by the fear of difficulty in correctly pronouncing the speech exercise by PD patients and laboratory conditions. The changes in entropy for surprise and sadness were negatively correlated with PD, which could be explained by impairment to express emotions generally by PD patients. A tongue twister speech exercise proved to be more predictive and robust for detecting PD than reading a lengthy text. For this task, the XGBoost achieved a balanced accuracy of 0.69 (see Table 4.1).

Tab. 4.1: XGBoost predictions for tongue twister and reading text exercise.

Speech exercise	**ACC Bal**	**Sensitivity**	**Specificity**	MCC
Tongue twister	0.69 ± 0.14	0.71 ± 0.17	0.67 ± 0.22	0.39 ± 0.29
Long text	0.60 ± 0.16	0.66 ± 0.21	0.54 ± 0.27	0.20 ± 0.34

As a conclusion, this study was designed to provide support methods for the detection of PD in order to assist clinicians in their diagnosis of this disease. This research is exploring the potential of rarely analysed - hypomimia symptom for PD detection. The contribution of this study is the identification of fear as the most statistically significant emotion based on SHAP values for the XGBoost model. XGBoost delivered the 0.69 balanced accuracy for a tongue twister, indicating that it is the most important speech task that has been evaluated and clinically valuable.

4.2 Multimodal Detection of Parkinson Disease

The PD methodology detection based on a multimodality approach (combination of video and audio) was set up as the goal. The 43 characteristic speech exercises were used to evaluate the PD thanks to the video and audio analysis. A total of 73 people with PD were included in the analysis and HC. Individuals participated in a variety of speech exercises during the experiment. The Czech language was considered. A variety of exercises were examined, including tongue twisters, poems, free speech, diadochokinesis tasks, reading texts, sentences, words, vowels, and others. The feature extraction was designed to capture the hypomimia symptoms and changes in HD dimension between HC and illness cases. Especially, the facial features were created based on facial landmarks, which are valuable anthropometrically. In the first step, a previously introduced dataset in Subsection 4.1 was prepared for extracting features for each speech exercise. The exact feature extraction for video and audio modality was then provided separately. The regression out of the confounding factors (age and gender) was performed. Next, the feature preselection method mRMR was also applied. The

Stratified 10-fold Cross-Validation with XGBoost was used. The SHAP values were applied for the clinical interpretation of the model.

The voice features were extracted with respect to [65]. Parameters related to personal impairments, phonation, articulation, and prosody were calculated. Details can be found in Table 4.2.

A feature extraction algorithm was developed. This proposed methodology contains the extraction of facial landmarks and the computations of the differences between them within a specified period. The varieties between distances and angles in time were calculated from the facial measurements. 68 facial landmarks were detected using an open source framework [2]. Fig. 4.1 illustrates the schematic illustration. The algorithm involves two steps: first, it detects faces using the histogram of oriented gradients (HOG) and Haar feature-based cascade classifiers. Detection of facial landmarks was performed using a neural network in the second step. The proposed facial features are presented in Table 4.3. Lastly, the scalars were calculated to determine how the characteristic points on the face differentiated over time. The measurements were the Shannon entropy (se), the approximate entropy (ae), the max, the min, the std, the rsd, the var, the range, the slope, and the mean.

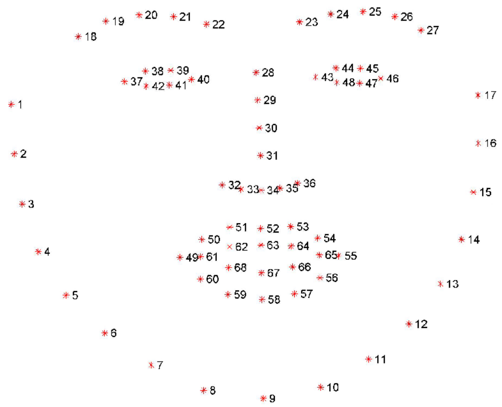

Fig. 4.1: Illustration of facial features [93].

Tab. 4.2: Description of the acoustic features. The details of the features implementation are provided in [94].

Code of Acoustic feature	Description of the features	HD dimension	Specific disorder
DDK rate	DDK rate	articulation	slow alternating motion rate
DDK reg	std of DDK cycle periods	articulation	irregular alternating motion rate
DUV	fraction of locally unvoiced frames	phonation	aperiodicity
MPT	total speech time	phonation	airflow insufficiency
NSR	net speech rate	prosody	unnatural speech rate
SPIR	speech index of rhytmicity	prosody	inappropriate silences
jitter	period perturbation quotient	phonation	microperturbations in frequency
mean HNR	mean of harmonic-to-noise ratio	phonation	increased noise
relF0SD	relative std of fundamental frequency	prosody	monopitch
relF1SD	relative std of 1st formant	articulation	rigidity of tongue and jaw
relF2SD	relative std of 2nd formant	articulation	rigidity of tongue and jaw
relSEOSD	relative std of short-time energy	prosody	monoloudness
shimmer	amplitude perturbation quotient	phonation	microperturbations in amplitude

[2]https://pypi.org/project/face-recognition/

Tab. 4.3: Features extraction explanation [95].

Name feature	Points, angle
D1	37, 49
D2	46, 55
D3	22, 23
D4	52, 58
D5	20, 38
D6	25, 45
D7	39, 41
D8	45, 47
D9	31, 9
D10	1, 17
D11	18, 22
D12	23, 27
D13	34, 52
EYEBROW1	Angle: (22,19) vs. (40, 43)
EYEBROW2	Angle: (22, 19) vs. (23, 26)
EYEBROW3	Angle: (22, 19) vs. (23, 26)
EYEBROW4	Vertical: 19, 37
EYEBROW5	Vertical: 26, 46
EYE1	37, 38
EYE2	37, 39
EYE3	46, 45
EYE4	46, 44
EYE5	40, 39
EYE6	40, 38
EYE7	43, 44
EYE8	43, 45
EYE9	37, 42
EYE10	37, 41
EYE11	43, 48
EYE12	43, 47
EYE13	40, 41
EYE14	40, 42
EYE15	46, 48
EYE16	46, 47
EYE17	38, 42
EYE18	45, 47
EYE19	39, 41
EYE20	44, 48
EYE21	37, 40
EYE22	43, 46
M1	49, 52
M2	49, 58
M3	55, 52
M4	55, 58
M5	49, 55
M6	52, 58
M7	60, 54
M8	50, 56
RATIO_MOUTH	M5/M6
MOUTH_AREA	The area of the inside of the mouth
LEYE_AREA	The area of the left eye
REYE_AREA	The area of the right eye
RATIO_FACE	D1/D2
RATIO_MOUTH _SKEW_UP	M3/M1
RATIO_MOUTH _SKEW_DOWN	M4/M2

Tab. 4.4: Meaning of the part of the exercises in Czech and English.

Code	In Czech	English translation
TSK19	Chcete vidět velký lov? Budu lovit v džungli slov. Osedlám si Pegasa Chytím báseň do lasa.	Would you like to see a big hunt? I will be hunting in a jungle of words. I will saddle the Pegasus, I will catch a poem into a lasso.
TSK20	Prostřete k obědu?	Will you lay the table?
TSK21	Prostřete k obědu!	Lay the table!
TSK22	Prostřete k obědu.	Lay the table.
TSK23	Teď musíš být chvíli trpělivý, než to dokončíme.	Now you have to be patient for a while until we finish.
TSK24	Tak dáš mi už konečně pokoj!	I urge you to leave me alone.
TSK25	Už mě to nebaví, dej mi už konečně pokoj!	I am fed up, I urge you to leave me alone.
TSK26	Tak co, jak to dopadlo?	So, what happened?
TSK27	rychlonožka	lightfoot
TSK28	marnotratný	wasteful
TSK29	horolezectví	mountaineering
TSK30	stříbrotepec	silversmith
TSK31	železobetonový	iron-concrete
TSK32	zákonodárce	legislator
TSK33	horkovzdušný	convection
TSK34	strastiplná	tortuous
TSK35	záviděníhodný	enviable
TSK36	československý	Czechoslovak
TSK37	Do čtvrt hodiny tam byla smršť.	In a quarter of an hour there was a whirlwind.
TSK38	Prohovořte to s ním dopodrobna.	Discuss it with him in detail.
TSK39	Při ústupu pluku duní bubny.	Drums are pounding during the retreat of regiment.
TSK40	Kuchařští učni nejsou jak zlatničtí.	Apprentices of cookery school are not as those from goldsmith one.
TSK41	Celý večer se učí sčítat.	He is learning to add the whole evening.

The results are presented for classification between PD patients and HC with the usage of XGBoost. For the purpose of evaluating the best classification model, the models were trained on the set of all video, audio, and multimodal features. Table 4.6 presents the results of that classification. The multimodality approach achieved the highest scores for balanced accuracy (0.83), specificity (0.78), and MCC (0.68). The sensitivity was equal to 0.88 for the video and multimodality.

The interpretability of the model for the multimodality approach is presented thanks to the SHAP values in Fig. 4.2. The SHAP values for the combination of all features showed the importance of changes in eye blinking during the pronunciation vowel 'a' (aeEYE12 (TSK13)) for multimodality. During the longer activity, i.e., the pronunciation of tongue twister was observed a negative correlation between PD and the irregular pattern of eye behavior (aeEYE16 (TSK37)). The changes in the mouth's ability to pronounce were observed (slopeM7 (TSK41)). Furthermore, there were challenges in moving the jaw during the pronunciation of the vowel 'e' (varD9 (TSK4)). In addition, the multimodality analysis model indicates a negative correlation between rsd of the eyelid (rsdD8 (TSK32)) and hard to pronounce words. For PD, a lower value of skew of the mouth was observed (maxM3 (TSK31)) when persons were speaking a difficult word. It was noted that the open mouth variance was lower for PD when pronouncing 'u' (varM6 (TSK12)). Furthermore, PD displayed a higher harmonic-to-noise ratio during the pronunciation of vowel 'i' (mean HNR (TSK15)).

The results for the multimodality and video have been compiled in Table 4.7 to compare the results of the most powerful speech exercises. Five of the 10 exercises showed an improvement in classification, and two showed no improvement. In the multimodality approach, TSK41 (the tongue twister) demonstrated the best accuracy of 0.74.

To summarize this section, the support methodology for PD detection based on multimodality, i.e., video and audio was presented. The proposed dataset is exceptional and contains 73 PD patients and 46 HC. A total of 43 unique speech exercises were evaluated in order to identify the most reliable ones.

Tab. 4.5: Carried-out vocal tasks.

Code	Vocal task	Description
TSK1	expiration	maximum phonation of [m] in one breath
TSK2	expiration	maximum phonation of [i] in one breath
TSK3	phonation	vowel [a] (sustained and normal intensity)
TSK4	phonation	vowel [e] (sustained and normal intensity)
TSK5	phonation	vowel [i] (sustained and normal intensity)
TSK6	phonation	vowel [o] (sustained and normal intensity)
TSK7	phonation	vowel [u] (sustained and normal intensity)
TSK8	phonation	vowel [a] (sustained and maximum intensity)
TSK9	phonation	vowel [e] (sustained and maximum intensity)
TSK10	phonation	vowel [i] (sustained and maximum intensity)
TSK11	phonation	vowel [o] (sustained and maximum intensity)
TSK12	phonation	vowel [u] (sustained and maximum intensity)
TSK13	phonation	vowel [a] (sustained and minimum intensity, but not whispering)
TSK14	phonation	vowel [e] (sustained and minimum intensity, but not whispering)
TSK15	phonation	vowel [i] (sustained and minimum intensity, but not whispering)
TSK16	phonation	vowel [o] (sustained and minimum intensity, but not whispering)
TSK17	phonation	vowel [u] (sustained and minimum intensity, but not whispering)
TSK18	diadochokinesis (DDK)	DDK pa-ta-ka
TSK19	rhytmical units	read poem
TSK20	main intonation pattern	same sentence read as interrogative
TSK21	main intonation pattern	same sentence read as imperative
TSK22	main intonation pattern	same sentence read as declarative
TSK23	intonation variability	monitoring prosody (declarative read sentence)
TSK24	intonation variability	monitoring prosody (imperative read sentence)
TSK25	intonation variability	monitoring prosody (imperative read sentence)
TSK26	intonation variability	monitoring prosody (interrogative read sentence)
TSK27	intelligibility of repeated words	repeated word complicated for the articulation
TSK28	intelligibility of repeated words	repeated word complicated for the articulation
TSK29	intelligibility of repeated words	repeated word complicated for the articulation
TSK30	intelligibility of repeated words	repeated word complicated for the articulation
TSK31	intelligibility of repeated words	repeated word complicated for the articulation
TSK32	intelligibility of repeated words	repeated word complicated for the articulation
TSK33	intelligibility of repeated words	repeated word complicated for the articulation
TSK34	intelligibility of repeated words	repeated word complicated for the articulation
TSK35	intelligibility of repeated words	repeated word complicated for the articulation
TSK36	intelligibility of repeated words	repeated word complicated for the articulation
TSK37	intelligibility of repeated sentences	repeated sentence complicated for articulation
TSK38	intelligibility of repeated sentences	repeated sentence complicated for articulation
TSK39	intelligibility of repeated sentences	repeated sentence complicated for articulation
TSK40	intelligibility of repeated sentences	repeated sentence complicated for articulation
TSK41	intelligibility of repeated sentences	repeated sentence complicated for articulation
TSK42	monitoring intelligibility and articulation	long read paragraph
TSK43	interview at the beginning - monitoring prosody, hesitations, time needed for response, etc.	free speech, usually the answer to "What are your hobbies?", "Where do you come from?", etc.

Tab. 4.6: Accuracy of PD detection from different modalities.

Modality	**Accuracy (balanced)**	**Sensitivity**	**Specificity**	MCC
Speech	0.77 (0.11)	0.81 (0.12)	0.73 (0.19)	0.54 (0.21)
Video	0.81 (0.13)	**0.88 (0.12)**	0.74 (0.23)	0.64 (0.24)
Multimodality	**0.83 (0.11)**	0.88 (0.13)	**0.78 (0.20)**	**0.68 (0.22)**

The strength of this research is the identification of the most effective and clinically valuable speech

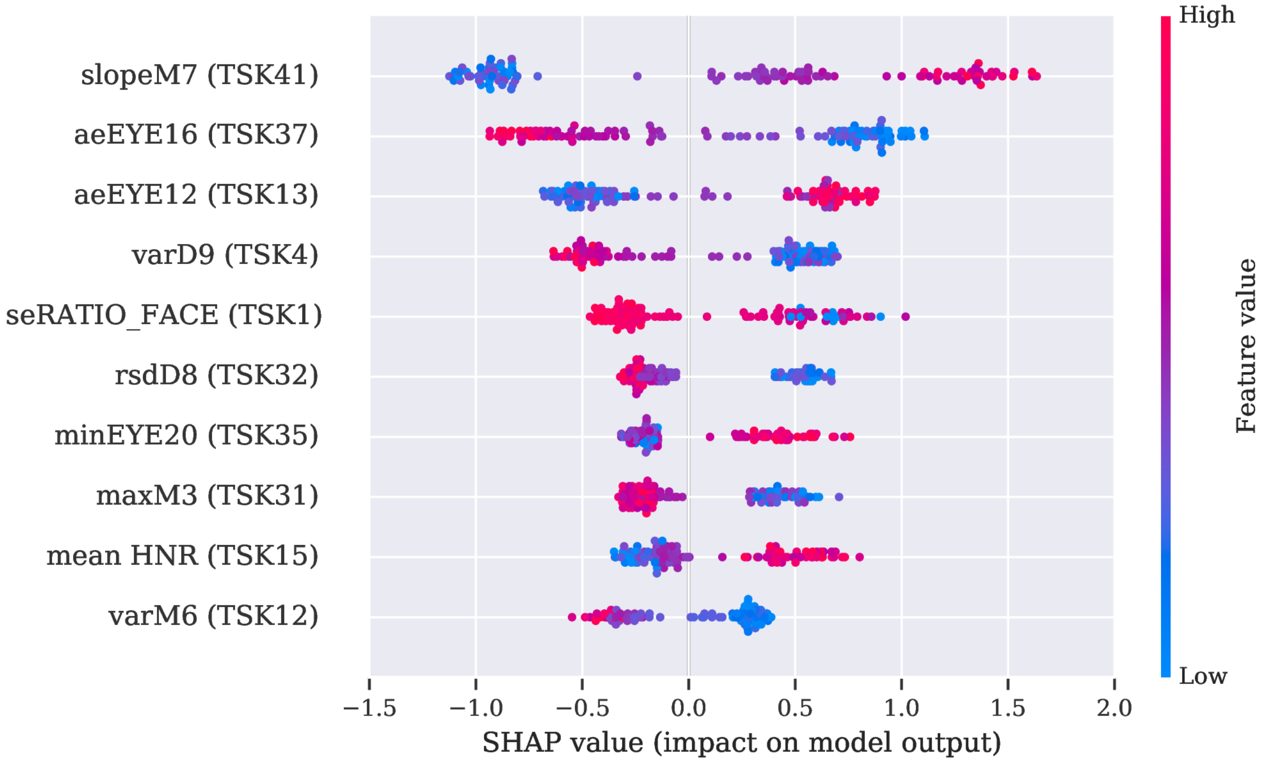

Fig. 4.2: SHAP values for the best 10 features from the multimodality.

Tab. 4.7: An analysis of the results obtained from multimodal and video approaches.

Exercise	**Accuracy (balanced) for multimodality**	**Accuracy (balanced) for video**
TSK41	0.74 (0.13)	0.73 (0.13)
TSK23	0.73 (0.15)	0.71 (0.15)
TSK39	0.73 (0.14)	0.73 (0.14)
TSK18	0.73 (0.13)	0.71 (0.12)
TSK40	0.72 (0.16)	0.72 (0.15)
TSK8	0.72 (0.14)	0.71 (0.14)
TSK22	0.72 (0.14)	0.70 (0.13)
TSK4	0.72 (0.13)	0.72 (0.13)
TSK9	0.72 (0.13)	0.72 (0.13)
TSK1	0.71 (0.13)	0.71 (0.13)

exercise - tongue twister. Moreover, the results obtained by the XGBoost classifier were satisfactory. The multimodal approach showed that it outstands the solutions based on a single modality. With the usage of a multimodal approach, the detection of PD was possible on the level 0.83 balanced accuracy. The desirable clinical interpretability was obtained thanks to the statistical analysing and SHAP values. The SHAP values explain the value of parameters measuring the eye blinking, the openness of the mouth, and asymmetry of the face. The accuracy of PD detection based on the most powerful speech exercise – tongue twister and multimodality achieved 0.74 balanced accuracy.

5 CONCLUSION

First and foremost, the thesis considers developing the application of wearables and ML technologies for healthcare solutions. The WHT is still expanding type of technology on the market and will consume and adapt new solutions based on wearable technology. Because of this reason, the developed technologies in this thesis are appropriate, considering the still progressing field. Additionally, the desirable solutions are those with provided interpretability. The main focus of this thesis is concentrated on used ML methods likewise also the applicability of the presented support system methodologies - i.e., their performance and interpretability.

Two main thematic issues were discussed in this thesis, i.e., the wearable solutions for COVID-19 detection likewise the application of AAL for PD. The introduced research in this thesis is focused on finding solutions to prevent and minimize the effects of those emergency problems. The common denominator in this work is the usage of ML to generate support methodologies.

The section Introduction is guiding the readers into the topic. The background about COVID-19 and its diagnosis likewise PD and its recognition are presented in Chapter 2. The summarisation of the existing approaches for the detection of COVID-19 and pandemic models with the usage of wearable and ML is described. Next, a description of how PD symptoms hypomimia, HD, and sleep disorders can be used to diagnose PD is illustrated. Moreover, the summary of the recognition of other diseases based on actigraphy records and ML. Those methods were identified because of their potential applications for PD detection based on sleep records.

The practical solutions for COVID-19 detection based on ML and wearables for three scenarios are presented in Chapter 3. The thesis tried to find the answer to the emergency need for screening tests in the early stage of the disease. Two datasets are the basement of those presented solutions [29,36]. The kinds of analysing signals were heart rate and the number of steps taken. The data were gathered by the Fitbit device and presented solutions are destinated for this device. Moreover, the biggest contribution of the illustrated approaches is the consideration of the nature of the disease, i.e., the contagiousness of the disease and incubation period. To reduce the increase in the number of sick people, those two parameters were taken into account. Additionally, the amount of presented solutions based on ML and wearables dedicated to COVID-19 detection is limited. By the same token, there is still room for exploring this area. Moreover, as the outcome of the first experiment, the support system methodology for the emergency issue - COVID-19 detection in the early stage of illness, was presented. The best-identified model based on 5-day windows allows obtaining the prediction of 78 % accuracy for differentiating the COVID-19 cases from HC.

The next presented subject in this thesis concerned computerised automatic PD detection. The outcomes of the research were described in Chapter 4. The presented methods in the thesis could be potentially applied as still lacking the mHealth methods for PD recognition. They are more inexpensive and more accessible alternatives to the common tests: PET, MRI, CT, and PSG. Moreover, not only the support methodologies are desirable but also clinical interpretability is well perceived together with recommending valid biomarkers. Furthermore, there are just few papers that treated the multimodal detection of PD, especially with the participation of hypomimia symptom. The choice of the audio and video modality and combined ML methodology allowed for obtaining 0.83 balanced accuracy for the fusion of biomarkers generated for all studied speech exercises in the thesis.

The future directions are targeting the usage of ML methodologies for PD detection based on multimodal approaches and extending databases. Furthermore, there is still space for researching COVID-19 detection thanks to the wearables, increasing databases, and extending the number of types of analysing signals.

To sum up, there were introduced ML-aided monitoring and prediction of respiratory and neurodegenerative diseases using wearables in the thesis. The first topic considered COVID-19 detection. The solutions were destinated for early recognition thanks to taking into account contagiousness and incubation period. It is an incredible asset. There is still a research gap for COVID-19 detection, and the obtained outcomes in this thesis outperformed those already presented in the literature. Thereby, they introduced new solutions for diagnosis of COVID-19. Moreover, a longer discussion together with illustrating the classification between a few types of viruses, including COVID-19 was presented. Such distinctions have not been previously published. The merging of two datasets allows for having the largest such dataset. Moreover, the second topic presented the methods of PD detection. The symptom of hypomimia was the basement of the presented classification problem. The research on this topic filled the existing scientific demand. Furthermore, the HD was also evaluated. The multimodal methodology was proposed and approved as better than the single modality. The tongue twister arose as the best speech exercise which has special clinical value. The extra interpretability of the experiment was provided thanks to the statistical analysis and SHAP values. Furthermore, the computational analysis of emotion demonstrated to have potential in recognition of PD and could replace the other uncomfortable or fair subjective tests. Additionally, the transfer of probable methodology of detection PD based on discrepant sleep disorders was explored and depicted.

BIBLIOGRAPHY

[1] *Global Europe 2050*, 2020 (Accessed 2020-08-18).

[2] E. Sheikhzadeh, S. Eissa, A. Ismail, and M. Zourob, "Diagnostic techniques for covid-19 and new developments," *Talanta*, vol. 220, p. 121392, 2020.

[3] B. R. Bloem, E. J. Henderson, E. R. Dorsey, M. S. Okun, N. Okubadejo, P. Chan, J. Andrejack, S. K. Darweesh, and M. Munneke, "Integrated and patient-centred management of parkinson's disease: a network model for reshaping chronic neurological care," *The Lancet Neurology*, vol. 19, no. 7, p. 623 – 634, 2020.

[4] A. Channa, N. Popescu, **Justyna Skibińska**, and R. Burget, "The rise of wearable devices during the covid-19 pandemic: A systematic review," *Sensors*, vol. 21, no. 17, p. 5787, 2021.

[5] R. J. Oskouei, Z. MousaviLou, Z. Bakhtiari, and K. B. Jalbani, "Iot-based healthcare support system for alzheimer's patients," *Wireless Communications and Mobile Computing*, vol. 2020, pp. 1–15, 2020.

[6] E. Tjoa and C. Guan, "A survey on explainable artificial intelligence (xai): Toward medical xai," *IEEE transactions on neural networks and learning systems*, vol. 32, no. 11, pp. 4793–4813, 2020.

[7] S. Seneviratne, Y. Hu, T. Nguyen, G. Lan, S. Khalifa, K. Thilakarathna, M. Hassan, and A. Seneviratne, "A survey of wearable devices and challenges," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 4, pp. 2573–2620, 2017.

[8] H. Bridgman, M. T. Kwong, and J. H. Bergmann, "Mechanical safety of embedded electronics for in-body wearables: A smart mouthguard study," *Annals of biomedical engineering*, vol. 47, no. 8, pp. 1725–1737, 2019.

[9] A. Ometov, V. Shubina, L. Klus, **Justyna Skibińska**, S. Saafi, P. Pascacio, L. Flueratoru, D. Q. Gaibor, N. Chukhno, O. Chukhno, *et al.*, "A survey on wearable technology: History, state-of-the-art and current challenges," *Computer Networks*, vol. 193, p. 108074, 2021.

[10] M. R. Reports, "Wearable healthcare devices market." `https://www.futuremarketinsights.com/reports/wearable-healthcare-devices-market`, 2022. Accessed: 2023-02-28.

[11] H. Li, J. Wu, Y. Gao, and Y. Shi, "Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective," *International journal of medical informatics*, vol. 88, pp. 8–17, 2016.

[12] A. Channa, N. Popescu, *et al.*, "Managing covid-19 global pandemic with high-tech consumer wearables: A comprehensive review," in *2020 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*, vol. 2020-October, pp. 222–228, IEEE, IEEE Computer Society, October 2020.

[13] M. Terzi, A. Cenedese, and G. Susto, "A Multivariate Symbolic Approach to Activity Recognition for Wearable Applications," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 15865–15870, 2017.

[14] R. E. Stirling, M. J. Cook, D. B. Grayden, and P. J. Karoly, “Seizure forecasting and cyclic control of seizures,” *Epilepsia*, vol. 62, no. S1, p. S2 – S14, 2021.

[15] D. Bzdok, M. Krzywinski, and N. Altman, “Machine learning: supervised methods,” *Nature methods*, vol. 15, no. 1, p. 5, 2018.

[16] M. M. Baig, H. GholamHosseini, A. A. Moqeem, F. Mirza, and M. Lindén, “A systematic review of wearable patient monitoring systems–current challenges and opportunities for clinical adoption,” *Journal of medical systems*, vol. 41, no. 7, p. 115, 2017.

[17] S. Yaram, “Machine learning algorithms for document clustering and fraud detection,” in *2016 International Conference on Data Science and Engineering (ICDSE)*, (Cochin), pp. 1–6, IEEE, August 2016.

[18] J. Wang, B. Hu, X. Li, and Z. Yang, “Gtc forest: An ensemble method for network structured data classification,” in *2018 14th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN)*, (Shenyang), pp. 81–85, IEEE, December 2018.

[19] Z. Hussain, Q. Z. Sheng, and W. E. Zhang, “A Review and Categorization of Techniques on Device-Free Human Activity Recognition,” *Journal of Network and Computer Applications*, vol. 167, p. 102738, 2020.

[20] **Justyna Skibińska**, R. Burget, A. Channa, N. Popescu, and Y. Koucheryavy, “Covid-19 diagnosis at early stage based on smartwatches and machine learning techniques,” *IEEE Access*, vol. 9, pp. 119476–119491, 2021.

[21] A. Godfrey, “Wearables for independent living in older adults: Gait and falls,” *Maturitas*, vol. 100, pp. 16–26, 2017.

[22] D. Choi, H. Choi, and D. Shon, “Future changes to smart home based on aal healthcare service,” *Journal of Asian Architecture and Building Engineering*, vol. 18, no. 3, pp. 190–199, 2019.

[23] S. Heinzel, D. Berg, T. Gasser, H. Chen, C. Yao, R. B. Postuma, and M. T. F. on the Definition of Parkinson’s Disease, “Update of the MDS research criteria for prodromal parkinson’s disease,” *Movement Disorders*, vol. 34, no. 10, pp. 1464–1470, 2019.

[24] G. Marchesini, F. Marchignoli, and S. Petta, “Evidence-based medicine and the problem of healthy volunteers,” *Annals of hepatology*, vol. 16, no. 6, pp. 832–834, 2017.

[25] **Justyna Skibińska**, J. Hosek, and A. Channa, “Wearable analytics and early diagnostic of covid-19 based on two cohorts,” in *2022 14th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*, vol. 2022-October, (Valencia), pp. 56–63, IEEE, October 2022.

[26] T. P. Velavan and C. G. Meyer, “The covid-19 epidemic,” *Tropical medicine & international health*, vol. 25, no. 3, p. 278, 2020.

[27] C. Menni, A. M. Valdes, M. B. Freidin, C. H. Sudre, L. H. Nguyen, D. A. Drew, S. Ganesh, T. Varsavsky, M. J. Cardoso, J. S. E.-S. Moustafa, *et al.*, "Real-time tracking of self-reported symptoms to predict potential covid-19," *Nature medicine*, vol. 26, no. 7, pp. 1037–1040, 2020.

[28] T. Struyf, J. J. Deeks, J. Dinnes, Y. Takwoingi, C. Davenport, M. M. Leeflang, R. Spijker, L. Hooft, D. Emperador, S. Dittrich, *et al.*, "Signs and symptoms to determine if a patient presenting in primary care or hospital outpatient settings has covid-19 disease," *Cochrane Database of Systematic Reviews*, vol. 2020, no. 7, 2020.

[29] A. Shapiro, N. Marinsek, I. Clay, B. Bradshaw, E. Ramirez, J. Min, A. Trister, Y. Wang, T. Althoff, and L. Foschini, "Characterizing covid-19 and influenza illnesses in the real world via person-generated health data," *Patterns*, vol. 2, no. 1, 2021.

[30] H. K. Siddiqi and M. R. Mehra, "Covid-19 illness in native and immunosuppressed states: a clinical–therapeutic staging proposal," *The Journal of Heart and Lung Transplantation*, vol. 39, no. 5, p. 405, 2020.

[31] A. Pryce-Roberts, M. Talaei, and N. Robertson, "Neurological complications of covid-19: a preliminary review," *Journal of Neurology*, vol. 267, pp. 1870–1873, 2020.

[32] X. He, E. H. Lau, P. Wu, X. Deng, J. Wang, X. Hao, Y. C. Lau, J. Y. Wong, Y. Guan, X. Tan, *et al.*, "Temporal dynamics in viral shedding and transmissibility of covid-19," *Nature medicine*, vol. 26, no. 5, pp. 672–675, 2020.

[33] A. Natarajan, H.-W. Su, and C. Heneghan, "Assessment of physiological signs associated with covid-19 measured using wearable devices," *NPJ digital medicine*, vol. 3, no. 1, pp. 1–8, 2020.

[34] W. J. Wiersinga, A. Rhodes, A. C. Cheng, S. J. Peacock, and H. C. Prescott, "Pathophysiology, transmission, diagnosis, and treatment of coronavirus disease 2019 (covid-19): a review," *Jama*, vol. 324, no. 8, pp. 782–793, 2020.

[35] R. C. Joshi, S. Yadav, V. K. Pathak, H. S. Malhotra, H. V. S. Khokhar, A. Parihar, N. Kohli, D. Himanshu, R. K. Garg, M. L. B. Bhatt, *et al.*, "A deep learning-based covid-19 automatic diagnostic framework using chest x-ray images," *Biocybernetics and Biomedical Engineering*, vol. 41, no. 1, pp. 239 – 254, 2021.

[36] T. Mishra, M. Wang, A. A. Metwally, G. K. Bogu, A. W. Brooks, A. Bahmani, A. Alavi, A. Celli, E. Higgs, O. Dagan-Rosenfeld, *et al.*, "Pre-symptomatic detection of covid-19 from smartwatch data," *Nature Biomedical Engineering*, vol. 4, no. 12, pp. 1208–1220, 2020.

[37] G. Zhu, J. Li, Z. Meng, Y. Yu, Y. Li, X. Tang, Y. Dong, G. Sun, R. Zhou, H. Wang, *et al.*, "Learning from large-scale wearable device data for predicting epidemics trend of covid-19," *Discrete Dynamics in Nature and Society*, vol. 2020, 2020.

[38] B. L. Smarr, K. Aschbacher, S. M. Fisher, A. Chowdhary, S. Dilchert, K. Puldon, A. Rao, F. M. Hecht, and A. E. Mason, "Feasibility of continuous fever monitoring using wearable devices," *Scientific reports*, vol. 10, no. 1, pp. 1–11, 2020.

[39] R. Karthickraja, R. Kumar, S. Kirubakaran, R. Manikandan, *et al.*, "Covid-19 prediction and symptom analysis using wearable sensors and iot," *International Journal of Pervasive Computing and Communications*, vol. 18, no. 5, pp. 499 – 507, 2020.

[40] S. Hassantabar, N. Stefano, V. Ghanakota, A. Ferrari, G. N. Nicola, R. Bruno, I. R. Marino, K. Hamidouche, and N. K. Jha, "Coviddeep: Sars-cov-2/covid-19 test based on wearable medical sensors and efficient neural networks," *IEEE Transactions on Consumer Electronics*, vol. 67, no. 4, pp. 244–256, 2021.

[41] D. J. Miller, J. V. Capodilupo, M. Lastella, C. Sargent, G. D. Roach, V. H. Lee, and E. R. Capodilupo, "Analyzing changes in respiratory rate to predict the risk of covid-19 infection," *PloS one*, vol. 15, no. 12, p. e0243693, 2020.

[42] F. F. Abir, K. Alyafei, M. E. Chowdhury, A. Khandakar, R. Ahmed, M. M. Hossain, S. Mahmud, A. Rahman, T. O. Abbas, S. M. Zughaier, *et al.*, "Pcovnet: A presymptomatic covid-19 detection framework using deep learning model using wearables data," *Computers in biology and medicine*, vol. 147, p. 105682, 2022.

[43] H. R. Cho, J. H. Kim, H. R. Yoon, Y. S. Han, T. S. Kang, H. Choi, and S. Lee, "Machine learning-based optimization of pre-symptomatic covid-19 detection through smartwatch," *Scientific Reports*, vol. 12, no. 1, pp. 1–15, 2022.

[44] A. E. Mason, F. M. Hecht, S. K. Davis, J. L. Natale, W. Hartogensis, N. Damaso, K. T. Claypool, S. Dilchert, S. Dasgupta, S. Purawat, *et al.*, "Detection of covid-19 using multimodal data from a wearable device: results from the first tempredict study," *Scientific reports*, vol. 12, no. 1, pp. 1–15, 2022.

[45] D. M. Richards, M. J. Tweardy, S. R. Steinhubl, D. W. Chestek, T. L. V. Hoek, K. A. Larimer, and S. W. Wegerich, "Wearable sensor derived decompensation index for continuous remote monitoring of covid-19 diagnosed patients," *NPJ digital medicine*, vol. 4, no. 1, pp. 1–11, 2021.

[46] J. R. Duffy, *Motor Speech Disorders E-Book: Substrates, Differential Diagnosis, and Management.* Elsevier Health Sciences, 2019.

[47] W. Poewe, K. Seppi, C. M. Tanner, G. M. Halliday, P. Brundin, J. Volkmann, A.-E. Schrag, and A. E. Lang, "Parkinson disease," *Nature reviews Disease primers*, vol. 3, no. 1, pp. 1–21, 2017.

[48] R. Prashanth and S. D. Roy, "Early detection of parkinson's disease through patient questionnaire and predictive modelling," *International journal of medical informatics*, vol. 119, pp. 75–87, 2018.

[49] **Justyna Skibińska** and R. Burget, "Parkinson's disease detection based on changes of emotions during speech," in *2020 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*, vol. 2020-October, (Brno), pp. 124–130, IEEE, IEEE Computer Society, October 2020.

[50] B. S. Connolly and A. E. Lang, "Pharmacological treatment of parkinson disease: a review," *Jama*, vol. 311, no. 16, pp. 1670–1683, 2014.

[51] B. M. Morberg, A. S. Malling, B. R. Jensen, O. Gredal, L. Wermuth, and P. Bech, "The hawthorne effect as a pre-placebo expectation in Parkinsons disease patients participating in a randomized placebo-controlled clinical study," *Nordic journal of psychiatry*, vol. 72, no. 6, pp. 442–446, 2018.

[52] A. H. Poorjam, M. S. Kavalekalam, L. Shi, J. P. Raykov, J. R. Jensen, M. A. Little, and M. G. Christensen, "Automatic quality control and enhancement for voice-based remote Parkinson's disease detection," *Speech Communication*, vol. 127, pp. 1–16, 2021.

[53] R. Gupta, S. Kumari, A. Senapati, R. K. Ambasta, and P. Kumar, "New era of artificial intelligence and machine learning-based detection, diagnosis, and therapeutics in parkinson's disease," *Ageing Research Reviews*, p. 102013, 2023.

[54] J. Jankovic, "Parkinson's disease: clinical features and diagnosis," *Journal of neurology, neurosurgery & psychiatry*, vol. 79, no. 4, pp. 368–376, 2008.

[55] M. Rajnoha, J. Mekyska, R. Burget, I. Eliasova, M. Kostalova, and I. Rektorova, "Towards identification of hypomimia in parkinson's disease based on face recognition methods," in *2018 10th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*, vol. 2018-November, (Moscow), pp. 1–4, IEEE, November 2018.

[56] P. Gómez-Vilda, J. Mekyska, J. M. Ferrández, D. Palacios-Alonso, A. Gómez-Rodellar, V. Rodellar-Biarge, Z. Galaz, Z. Smekal, I. Eliasova, M. Kostalova, *et al.*, "Parkinson disease detection from speech articulation neuromechanics," *Frontiers in neuroinformatics*, vol. 11, p. 56, 2017.

[57] A. Shinde, R. Atre, A. S. Guleria, R. Nibandhe, and R. Shriram, "Facial features based prediction of parkinson's disease," in *2018 3rd International Conference for Convergence in Technology (I2CT)*, (Pune), pp. 1–5, IEEE, Pune 2018.

[58] A. Grammatikopoulou, N. Grammalidis, S. Bostantjopoulou, and Z. Katsarou, "Detecting hypomimia symptoms by selfie photo analysis: for early parkinson disease detection," in *Proceedings of the 12th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, (Rhodes), pp. 517–522, Association for Computing Machinery, June 2019.

[59] D. Bowers, K. Miller, W. Bosch, D. Gokcay, O. Pedraza, U. Springer, and M. Okun, "Faces of emotion in parkinsons disease: micro-expressivity and bradykinesia during voluntary facial expressions," *Journal of the International Neuropsychological Society: JINS*, vol. 12, no. 6, p. 765, 2006.

[60] A. Bandini, S. Orlandi, H. J. Escalante, F. Giovannelli, M. Cincotta, C. A. Reyes-Garcia, P. Vanni, G. Zaccara, and C. Manfredi, "Analysis of facial expressions in parkinson's disease through video-based automatic methods," *Journal of neuroscience methods*, vol. 281, pp. 7–20, 2017.

[61] B. Sonawane and P. Sharma, "Review of automated emotion-based quantification of facial expression in parkinson's patients," *environment*, vol. 37, no. 5, pp. 1151 – 1167.

[62] M. Novotny, T. Tykalova, H. Ruzickova, E. Ruzicka, P. Dusek, and J. Rusz, "Automated video-based assessment of facial bradykinesia in de-novo parkinson's disease," *NPJ digital medicine*, vol. 5, no. 1, pp. 1–8, 2022.

[63] J. Hlavnička, R. Čmejla, T. Tykalová, K. Šonka, E. Ržička, and J. Rusz, "Automated analysis of connected speech reveals early biomarkers of Parkinson's disease in patients with rapid eye movement sleep behaviour disorder," *Scientific reports*, vol. 7, no. 1, pp. 1–13, 2017.

[64] A. K. Ho, R. Iansek, C. Marigliani, J. L. Bradshaw, and S. Gates, "Speech impairment in a large sample of patients with Parkinson's disease," *Behavioural neurology*, vol. 11, no. 3, pp. 131–137, 1998.

[65] L. Brabenec, J. Mekyska, Z. Galaz, and I. Rektorova, "Speech disorders in Parkinson's disease: early diagnostics and effects of medication and brain stimulation," *Journal of neural transmission*, vol. 124, no. 3, pp. 303–334, 2017.

[66] L. Moro-Velazquez, J. A. Gomez-Garcia, J. D. Arias-Londoño, N. Dehak, and J. I. Godino-Llorente, "Advances in Parkinson's disease detection and assessment using voice and speech: A review of the articulatory and phonatory aspects," *Biomedical Signal Processing and Control*, vol. 66, p. 102418, 2021.

[67] P. G. Vilda, J. Mekyska, A. G. Rodellar, D. P. Alonso, V. R. Biarge, and A. A. Marquina, "Monitoring parkinson disease from speech articulation kinematics," *Loquens: revista española de ciencias del habla*, no. 4, p. 2, 2017.

[68] J. Rusz, J. Hlavnička, T. Tykalová, M. Novotnỳ, P. Dušek, K. Šonka, and E. Ržička, "Smartphone allows capture of speech abnormalities associated with high risk of developing parkinson's disease," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 26, no. 8, pp. 1495–1507, 2018.

[69] A. Joshi, S. Ghosh, S. Gunnery, L. Tickle-Degnen, S. Sclaroff, and M. Betke, "Context-sensitive prediction of facial expressivity using multimodal hierarchical bayesian neural networks," in *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, (Xi'an), pp. 278–285, IEEE, June 2018.

[70] **Justyna Skibińska** and R. Burget, "The transferable methodologies of detection sleep disorders thanks to the actigraphy device for parkinson's disease detection," vol. 2880, (Tampere), CEUR Workshop Proceedings, CEUR-WS, June 2021.

[71] H. Zhang, K. Deng, H. Li, R. L. Albin, and Y. Guan, "Deep learning identifies digital biomarkers for self-reported parkinson's disease," *Patterns*, vol. 1, no. 3, 2020.

[72] M. Mikulec, "SYSTÉM ZABEZPEČENÉHO PŘENOSU A ZPRACOVÁNÍ DAT Z AKTIGRAFU," Master's thesis, Brno University of Technology, the Czech Republic, 2020.

[73] A. Khademi, Y. El-Manzalawy, O. M. Buxton, and V. Honavar, "Toward personalized sleep-wake prediction from actigraphy," in *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)*, (Las Vegas), pp. 414–417, IEEE, March 2018.

[74] N. O'Mahony, B. Florentino-Liano, J. J. Carballo, E. Baca-García, and A. A. Rodríguez, "Objective diagnosis of adhd using imus," *Medical engineering & physics*, vol. 36, no. 7, pp. 922–926, 2014.

[75] P. Amado-Caballero, P. Casaseca-de-la Higuera, S. Alberola-Lopez, J. M. Andres-de Llano, J. A. Lopez-Villalobos, J. R. Garmendia-Leiza, and C. Alberola-Lopez, "Objective adhd diagnosis using convolutional neural networks over daily-life activity records," *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 9, pp. 2690 – 2700, 2020.

[76] M. A. Alsheikh, A. Selim, D. Niyato, L. Doyle, S. Lin, and H.-P. Tan, "Deep activity recognition models with triaxial accelerometers," *arXiv preprint arXiv:1511.04664*, 2015.

[77] J. Li, Y. Rong, H. Meng, Z. Lu, T. Kwok, and H. Cheng, "Tatc: Predicting alzheimer's disease with actigraphy data," in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, (London), pp. 509–518, Association for Computing Machinery, August 2018.

[78] T. Cho, U. Sunarya, M. Yeo, B. Hwang, Y. S. Koo, and C. Park, "Deep-actinet: End-to-end deep learning architecture for automatic sleep-wake detection using wrist actigraphy," *Electronics*, vol. 8, no. 12, p. 1461, 2019.

[79] A. Sano, W. Chen, D. Lopez-Martinez, S. Taylor, and R. W. Picard, "Multimodal ambulatory sleep detection using lstm recurrent neural networks," *IEEE journal of biomedical and health informatics*, vol. 23, no. 4, pp. 1607–1617, 2018.

[80] B. M. Eskofier, S. I. Lee, J.-F. Daneault, F. N. Golabchi, G. Ferreira-Carvalho, G. Vergara-Diaz, S. Sapienza, G. Costante, J. Klucken, T. Kautz, *et al.*, "Recent Machine Learning Advancements in Sensor-Based Mobility Analysis: Deep Learning for Parkinson's Disease Assessment," in *Proc. of 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, (Orlando), pp. 655–658, IEEE, August 2016.

[81] A. Zaretskiy, K. Mityagin, V. Tarasov, and D. Moroz, "Periodic limb movements detection through actigraphy signal analysis," in *2019 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*, (Vladivostok), pp. 1–5, IEEE, October 2019.

[82] V. Prasad and C. A. Brown, "A pilot study to determine the consistency of simultaneous sleep actigraphy measurements comparing all four limbs of patients with parkinson disease," *Geriatrics*, vol. 3, no. 1, p. 1, 2018.

[83] I. Perez-Pozuelo, B. Zhai, J. Palotti, R. Mall, M. Aupetit, J. M. Garcia-Gomez, S. Taheri, Y. Guan, and L. Fernandez-Luque, "The future of sleep health: a data-driven revolution in sleep science and medicine," *NPJ digital medicine*, vol. 3, no. 1, pp. 1–15, 2020.

[84] M. A. Grandner and M. E. Rosenberger, "Actigraphic sleep tracking and wearables: Historical context, scientific applications and guidelines, limitations, and considerations for commercial sleep devices," in *Sleep and health*, pp. 147–157, Elsevier, 2019.

[85] J. V. Rundo and R. Downey III, "Polysomnography," *Handbook of clinical neurology*, vol. 160, pp. 381–392, 2019.

[86] H. Banaee, M. U. Ahmed, and A. Loutfi, "Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges," *Sensors*, vol. 13, no. 12, pp. 17472–17500, 2013.

[87] P. Schmidt, A. Reiss, R. Dürichen, and K. V. Laerhoven, "Wearable-based affect recognition—a review," *Sensors*, vol. 19, no. 19, p. 4079, 2019.

[88] F. Li, K. Shirahama, M. A. Nisar, L. Köping, and M. Grzegorzek, "Comparison of feature learning methods for human activity recognition using wearable sensors," *Sensors*, vol. 18, no. 2, p. 679, 2018.

[89] D. J. Cook and N. C. Krishnan, *Activity learning: discovering, recognizing, and predicting human behavior from sensor data.* John Wiley & Sons, 2015.

[90] M. Barandas, D. Folgado, L. Fernandes, S. Santos, M. Abreu, P. Bota, H. Liu, T. Schultz, and H. Gamboa, "Tsfel: Time series feature extraction library," *SoftwareX*, vol. 11, p. 100456, 2020.

[91] **Justyna Skibińska** and R. Burget, "Is it possible to distinguish covid-19 cases and influenza with wearable devices? analysis with machine learning," *Journal of Advances in Information Technology*, vol. 13, no. 3, pp. 265–270, 2022.

[92] I. de Paz Centeno, *Face detection*, 2020 (Accessed August 11, 2020).

[93] "Facial landmark extraction." `https://pypi.org/project/face-recognition/`. Accessed: 2020-11-23.

[94] J. Mekyska, Z. Galaz, T. Kiska, V. Zvoncak, J. Mucha, Z. Smekal, I. Eliasova, M. Kostalova, M. Mrackova, D. Fiedorova, *et al.*, "Quantitative analysis of relationship between hypokinetic dysarthria and the freezing of gait in parkinson's disease," *Cognitive computation*, vol. 10, no. 6, pp. 1006–1018, 2018.

[95] **Justyna Skibińska** and J. Hosek, "Computerized analysis of hypomimia and hypokinetic dysarthria for improved diagnosis of parkinson's disease," *Heliyon*, vol. 9, no. 11, p. e21175, 2023.

Curriculum Vitæ

M.Sc. Eng. Justyna Skibińska

Affiliation

Date of birth:	11. 11. 1991
Place of Birth:	Rzeszów Poland
E-mail:	ski.justyna@gmail.com
WWW:	https://www.linkedin.com/in/justyna-skibi%C5%84ska-3b434715a/ https://orcid.org/my-orcid?orcid=0000-0002-8531-3393

QUALIFICATION AND PROFESSIONAL CAREER

Education

2019–2023	Double degree Ph.D. in Electronics and Information Technologies under the A-WEAR project, Brno University of Technology, Faculty of Electrical Engineering and Communication, Czech Republic; Tampere University, Faculty of Information Technology and Communication Sciences, Finland, Doctoral thesis: *Machine Learning-Aided Monitoring and Prediction of Respiratory and Neurodegenerative Diseases Using Wearables*
2014–2016	MSc. in Biomedical Engineering with the Major in Computer Science and Electronics in Medicine, AGH University of Science and Technology, Faculty of Electrical Engineering, Automatics, Computer Science, and Biomedical Engineering, Diploma thesis: *The use of advanced machine learning methods for the detection of pancreatic cancer based on infrared (IR) imaging*
2012–2017	Eng. in Biomedical Engineering, AGH University of Science and Technology, Faculty of Electrical Engineering, Automatics, Computer Science, and Biomedical Engineering, Engineering thesis: *Detection and classification of neoplastic lesions in the images of lung lobes of mice*

Professional career

2019–2022	Early Stage Researcher under the A-WEAR project, Marie Curie-Skłodowska Fellow, Brno University of Technology, Czech Republic
2018-2019	Data Analytics Engineer, DiCELLa, Poland
2017-2018	Postgraduate, Institute of Nuclear Physics in Krakow, Department of Experimental Physics of Complex Systems, Poland

07.2014-08.2014	Intern, Institute of Nuclear Physics in Krakow, Department of Magnetic Resonance Tomography, Poland

PROFESSIONAL ACTIVITIES

Specialisation	Research and development in the areas of machine learning, wearables, signal processing, Parkinson's disease, COVID-19, pancreatic cancer, image analysis, infrared spectroscopy, histopathological images.
Scientific internships	Tampere University, Tampere, Finland, Ph.D. online secondment; (11/2021–01/2022, 09/2020-12/2020)
Designated reviewer	IEEE Access, Discover Internet of Things, Telecommunications and Radio Engineering
Teaching activities	
2020–2021	Co-supervision of Erasmus master students
2019	Preparation of the educational material for the subject Theoretical Informatics

OTHER QUALIFICATIONS AND KNOWLEDGE

Language knowledge	Polish language (native speaker) English language (advanced level) German language (intermediate level)
Certifications	Cambridge Certificate in Advanced English (CAE) (August 2019) Test of English as a Foreign Language (level C1) (August 2019) Cambridge First Certificate in English (FCE) (August 2017) Deutsch für Naturwissenschaft und Technik – Sommer Universität (Freiburg im Breisgau) (level C1) (September 2015)
Awards	I place in the national competition for the best master's and doctoral thesis in the field of statistics, the master's thesis category (2019) III place at University Contest of Foreign Languages Knowledge (German language) in AGH University of Science and Technology in Cracow (2016)

SUMMARY OF PUBLICATION ACTIVITIES

- Scientific journals with impact factor according to Web of Science or Scopus: 7
- International conferences: 5
- Total number of citations according to GoogleScholar: 482
- H-index according to GoogleScholar: 7
- H-index according to Scopus: 6

ABSTRACT

This thesis focuses on wearables for health status monitoring, covering applications aimed at emergency solutions to the COVID-19 pandemic and aging society. The methods of ambient assisted living (AAL) are presented for the neurodegenerative disease Parkinson's disease (PD), facilitating 'aging in place' thanks to machine learning and around wearables - solutions of mHealth. Furthermore, the approaches using machine learning and wearables are discussed for early-stage COVID-19 detection, with encouraging accuracy.

Firstly, a publicly available dataset containing COVID-19, influenza, and healthy control data was reused for research purposes. The solution presented in this thesis is considering the classification problem and outperformed the state-of-the-art methods, whereas the original paper introduced just anomaly detection. The proposed model in the thesis for early detection of COVID-19 achieved 78 % for the k-NN classifier. Moreover, a second dataset available on request was utilised for recognition between COVID-19 cases and two types of influenza. The classification between the COVID-19 and Influensa groups is proposed as the extension to the research presented in the original paper [29] illustrating the foundation for this study - statistical analysis of the dataset. Differences between the COVID-19 and Influenza cases in duration and intensity of the disease occur likewise manifest in heart rhythm. The accuracy of the distinction between COVID-19 cases and influenza in the middle of the pandemic (data were gathered from 03.2020 to 05.2020) was equal to 73 % thanks to the k-NN. Furthermore, the contribution as the classification model of two aforementioned combined datasets was provided, and COVID-19 cases were able to be distinguished from healthy controls with 73 % accuracy thanks to XGBoost algorithm. The advantage of the illustrated approaches is taking into account the incubation period and contagiousness of the disease likewise presenting the methodologies dedicated to data gathered by the Fitbit device. Furthermore, the parallel analysis of various types of Influensa, COVID-19, and healthy control is novel and has not been thoroughly investigated yet.

In addition, some solutions for the detection of the aforementioned aging society phenomenon are presented. This study explores the possibility of fusing computerised analysis of hypomimia and hypokinetic dysarthria for the spectrum of Czech speech exercises. The introduced dataset is unique in this field because of its diversity and myriad of speech exercises. The aim is to introduce a new techniques of PD diagnosis that could be easily integrated into mHealth systems. A classifier based on XGBoost was used, and SHAP values were used to ensure interpretability. The presented interpretability allows for the identification of clinically valuable biomarkers. Moreover, the fusion of video and audio modalities increased the balanced accuracy to 83 %. This methodology pointed out the most indicative speech exercise – tongue twister from the clinical point of view. Furthermore, this work belongs to just a few studies which tackle the subject of utilising multimodality for PD and this approach was profitable in contrast with a single modality.

Another study, presented in this thesis, investigated the possibility of detecting Parkinson's disease by observing changes in emotion expression during difficult-to-pronounce speech exercises. The obtained model with XGBoost achieved 69 % accuracy for a tongue twister. The usage of facial features, emotion recognition, and computational analysis of tongue twister was proved to be successful in PD detection, which is the key novelty and contribution of this study. Additionally, the unique overview of potential methodologies suitable for the detection of PD based on sleep disorders was depicted.