

# Automatic Annotation of Heart Rate Sequences

Júlio Castro Lopes  
Research Center for Digitalization  
and Intelligent Robotics,  
Instituto Politécnico de Bragança  
5300-252 Bragança, Portugal  
Email: juliolopes@ipb.pt

João Vieira  
Research Center for Digitalization  
and Intelligent Robotics,  
Instituto Politécnico de Bragança  
5300-252 Bragança, Portugal  
Email: a41701@alunos.ipb.pt

Alexandre Antunes  
Research Center for Digitalization  
and Intelligent Robotics,  
Instituto Politécnico de Bragança  
5300-252 Bragança, Portugal  
Email: alexandrejarosz@ipb.pt

Leonel Deusdado  
Research Center for Digitalization  
and Intelligent Robotics,  
Instituto Politécnico de Bragança  
5300-252 Bragança, Portugal  
Email: leodeus@ipb.pt

Rui Pedro Lopes  
Research Center for Digitalization  
and Intelligent Robotics,  
Instituto Politécnico de Bragança  
5300-252 Bragança, Portugal  
Email: rlopes@ipb.pt

**Abstract**—Heart Rate (HR) measurement is one of the most effective ways to determine whether a person is stressed or not. The analysis of a series of HR measurements can help determine whether the HR decreased, increased dramatically, or remained consistent during that time period. With this in mind, an automatic annotator that can automatically label HR sequences, determining these three possible states, is an ideal solution because it eliminates the need for a human to do it manually. This paper presents a web-based application that, given a .csv file containing Heart Rate successive measurements and their respective time stamps, can label sequences of any size that the user specifies. This opens up the possibility of training Machine Learning models with this data and classifying whether the user is in a stressful situation or not, in real time. Although further refinements will be made, our annotator proved to be robust and consistent in its annotation performance.

**Index Terms**—Heart Rate, Machine Learning, Annotation, Web Application

## I. INTRODUCTION

Data annotation is the process of labeling data to provide context and simplify the training of Machine Learning (ML) models. Labeled examples are required for training supervised models, in order for machines to interpret the input data precisely and unambiguously. It can be used with different formats and data types, helping to provide the context and structure for the model to effectively process and understand the data.

Some of this data is instantaneous, such as the images of the patient's face, and others are time sequences, such as the heart rate and body motion rate. In the latter, it can be applied by indicating the type of event or activity being recorded (e.g. pick a bottle, open a bottle, throw a bottle), assisting the model in understanding the meaning of the data and making more informed predictions [1]. It can also be very useful to annotate speech data with labels indicating the words or phrases being spoken to assist the model in understanding the meaning and

context of the speech [2]. Annotating data is also essential for Natural Language Processing (NLP), which helps ML models absorb and comprehend human language. Sentiment analysis is an example of this, as it requires text data to be tagged with labels reflecting the sentiment expressed in the text (positive, negative, or neutral) [3].

In previous work, facial expressions classification has been used to infer human emotions in a schizophrenia rehabilitation serious game [4]–[6]. This is being complemented with Body Motion Rate (BMR), calculate from the variation of motion in a sequence of video frames of the patient and, finally, with the instant Heart Rate (HR), to infer his stress level. All of this information provides the environment for a dynamic adaptation of the rehabilitation experience [7].

Successive measurements of HR values show the evolution of the heart rhythm but require some understanding, in the form of a label indicating whether these values tended to decrease, increase, or maintain over time. This analysis can be performed in “windows”, or sequences of varying sizes, allowing us to extract portions of e.g. 30 or 45 seconds, and analyze each sequence individually, allowing to classify the succession of HR values into three distinct values (0, 1 and -1).

Labeled examples from different subjects allow building a dataset necessary to train a classification model. This model can then be used to classify HR values in real-time, producing information about the user's emotional state. With this, it will be possible to determine, for example, whether the user is under stress. Expert manual annotation of biosignals is the recognized gold standard in the medical industry. An automated annotating algorithm has largely replaced the manual annotating mode because it saves time and automates the process [8].

This paper describes the development and structure of a web-based automatic annotator that labels sequences of successive human heart rate measurements. It is structured in

five sections, starting with this introduction. Section II performs some considerations regarding the annotation process, followed by the description of the web-based annotation, in section III. The evaluation of the quality of the annotator is performed in section IV and the paper ends with some conclusions, in section V.

## II. DATASET ANNOTATION

Annotating a dataset can be done either automatically or manually. For the manual way, it requires the human to be consistently annotating large amounts of data, based on a set of consistent parameters [9]. The most efficient and time-saving method is to use ML algorithms to find patterns in data and label it automatically [10]. Data annotation is necessary for many different domains of knowledge, such as Healthcare [11], Text and Document analysis [12], Human Pose estimation [13], Human Activity Recognition [14], etc.

Nabizadeh et al. [15] developed an annotator, using instructional text in electronics repair manuals (MyFixit). MyFixit is a library of repair manuals. These manuals were broken down into several steps by the instructors, and at each step, the user should typically take a specific piece of the device under repair apart. Part of the dataset was manually annotated but the authors have also proposed an unsupervised method for the automatic annotation of tools from each step description. Their method uses the Jaccard similarity between the bags of n-grams in the text description of steps and each tool name, to return the tool with the highest similarity as the required tool of the step. In addition to the sequential model trained on human-annotated data, they also evaluated the models trained on automatically annotated tools but tested on human annotations. They were then able to access the impact of hierarchy-aware prediction in the presence of annotation errors.

Chudacek et al. [16] presented an annotation software that was developed in order to obtain new expert annotations of the recordings in their newly established database. Since preliminary tests revealed that sole post-delivery pH measurement does not provide a complete picture of the clinical evaluation of ongoing delivery, they created a tool to allow expert obstetricians to annotate the signal in the way suggested by the guidelines. This new expert annotation tool may be useful for improving our knowledge of inter-observer and intra-observer differences when evaluating fetal heart rate data.

Sodmann et al. [17] proposed an approach that combines supervised deep learning for the annotation of raw electrocardiograph (ECG) data with XGBoost [18] for classifying annotated ECGs into various heart rhythms. Their work's main achievement is in the CNN's capacity to annotate P, T, and R waves, which may then be further converted into features for rhythm classification.

Xie et al. [8] used a probabilistic model to synthesize the HR annotations from various annotators for ECG signals and deduced the underlying actual annotations and the precision of each annotator when the ground truth was not accessible. They used the idea of selective ensemble [19] to search for the best outcome in each experiment.

Further Di et al. [20] compared their model with commonly mean, median method, and existing fusion model for HR labels (Xie et al. [8]). They suggested an unsupervised Bayesian framework to aggregate various HR annotations from the ECG signal and infer the underlying accuracy and precision of annotators, when the ground truth is unavailable.

## III. WEB-BASED ANNOTATOR

The work described in this paper focuses on the development of an automatic annotator for sequences of HR, to assess whether the heart is beating faster, slower, or keeping a steady rhythm. For that, a heuristic based on a statistic model is used, namely, based on trying to fit linear regression parameters in each sequence.

### A. Raw data

The annotator receives, as input, raw HR data, retrieved with smart bands or smartwatches, registering periodically the heart rate and timestamp (Table I).

Timestamp	BPM
2022-03-05 15:05:06 +0000	72
2022-03-05 15:05:11 +0000	69
2022-03-05 15:05:16 +0000	68
2022-03-05 15:05:20 +0000	68
2022-03-05 15:05:26 +0000	68
2022-03-05 15:05:27 +0000	68
2022-03-05 15:05:34 +0000	69
2022-03-05 15:05:40 +0000	70
2022-03-05 15:05:42 +0000	70
2022-03-05 15:05:48 +0000	65
2022-03-05 15:05:56 +0000	64
2022-03-05 15:06:00 +0000	65
2022-03-05 15:06:04 +0000	65
2022-03-05 15:06:07 +0000	66
2022-03-05 15:06:13 +0000	70
...	...

TABLE I: Sample of raw heart rate data

The timestamp contains information about the date and instant of each sample. The sample represents the instant beats-per-minute (BPM) of the subject's heart. This data is sent to the annotator so that sequences can be made and tendency annotation added to each of the sequences.

### B. Web-based Interface

The HR Annotator was built as a Web application, composed of two main parts (Figure 1).

The backend is developed in Java, with the SpringBoot libraries and SMILE (Statistical Machine Intelligence and Learning Engine) library (<https://haifengl.github.io>), accelerated with the OpenBLAS library for the Linear Algebra calculations. A RAM (volatile) database based on the H2 database engine (<http://www.h2database.com/>) is also used to assist in the construction and visualization of the intermediate graphs and annotations (see below).

The frontend was developed with Angular and Angular Material components, running on a web browser. The user interface allows the user to upload raw data files, in CSV format, and download annotated data, also in CSV format.

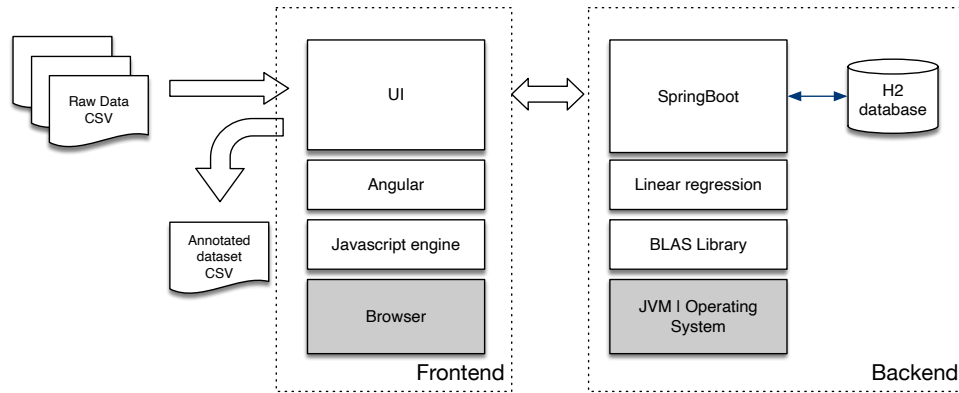


Fig. 1: General architecture

The user connects to a web server to access the initial screen of the annotator (Figure 2). In this, the user can select an existing file from the annotator’s database or upload a new one.

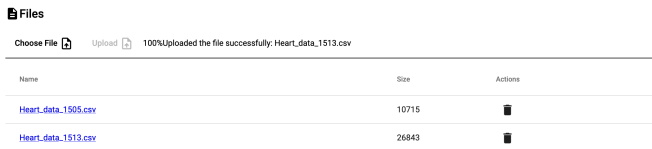


Fig. 2: File upload tool

Then, the user can proceed to the next screen where three tools are available (“stats”, “preview” and “annotate”). Selecting the “stats” tab, some basic metrics such as the mean, minimum, and maximum HR values in a given CSV file are displayed (Figure 3).

The screenshot shows the file statistics interface. It includes a table with the following data:

Name	Rows	Mean	Max	Min
f6d4e910-fc9f-4e18-bfd3-2c8e477f6426	369	69.33604336043359	89	58
16c71800-f57f-44f2-b45c-2466cfd06484	921	89.78393051031489	152	75

Fig. 3: File statistics

By clicking in the “preview” tab the user is then able to select a dataset from the annotator’s database and choose the interval of seconds for preview (Figure 4). For proof of concept, a dataset was recorded for approximately 60 minutes, by two subjects, while performing daily activities (driving, walking, chatting, etc.).

The displayed graphics feature three distinct colors: red, blue, and black, for the corresponding suggested classes (-1 - decreasing, 1 - increasing, 0 - maintaining). These classes represent three possible labels of the dataset, which determines whether the successive HR values are decreasing, increasing, or maintaining some stability.

Finally, in the “annotator” tab the user can choose the window time interval that he/she wants to annotate and proceed to download the annotated sequences (Figure 5).

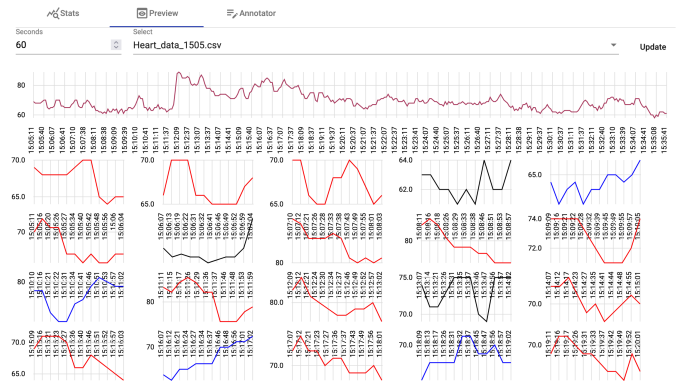


Fig. 4: Preview of suggested annotation in 60s sequences



Fig. 5: Downloading annotated file

### C. Annotated data

The data is annotated based on a simple heuristic. For this, a linear regression model is calculated for each sequence of points (Ordinary Least Squares - OLS [21]). A threshold of 20 in the inclination parameter of the linear regression defines the class within three possibilities:

- if the inclination is below the threshold, it can be assumed that the user’s HR tends to decrease during that time
- if the inclination is higher than the threshold, it can be assumed that the user’s HR increased during that time
- if the threshold is not exceeded, it can be assumed that the HR was consistent and that no abrupt changes were made.

Table II and III, show the produced final file properly annotated. As can be seen in both tables, the length of each sequence is not required to be the same. Table II does not include any sample with less than 4 samples and in Table III, there are no sequences with less than 10 samples.

Label	v0	v1	v2	v3	v4	v5
0	69.0	68.0	68.0	68.0	68.0	69.0
1	70.0	70.0	65.0	64.0	65.0	65.0
0	66.0	70.0	70.0	70.0	66.0	66.0
-1	65.0	65.0	65.0	65.0	67.0	68.0
1	70.0	70.0	66.0	65.0	65.0	68.0
1	68.0	70.0	69.0	67.0	65.0	66.0
1	63.0	63.0	62.0	62.0	61.0	62.0
-1	61.0	64.0	62.0	62.0	64.0	
0	64.0	61.0	63.0	64.0	61.0	63.0
-1	63.0	65.0	65.0	64.0	65.0	67.0
1	70.0	73.0	71.0	71.0	65.0	65.0
-1	63.0	65.0	63.0	63.0	65.0	65.0
1	67.0	64.0	65.0	64.0	64.0	

TABLE II: Annotated dataset in sequences of 30s

#### IV. EVALUATION

The manual annotation of potentially huge collections of data is a boring and repetitive task, prone to error and misinterpretations. Automatic annotation relieves the user from this burden, although it is not exempt of error. As this annotator is based on a simple heuristic, it is important to assess the quality of the annotation.

For this, a statistical method was used. Since the heuristic is based on linear regression, the adjusted  $R^2$  was chosen to explain the degree to which input variables (predictor variables) and explain the variation of output variables (predicted variables) [22]. The  $R^2$  of a linear model describes the amount of variation in the response that is explained by the least squares line. This allows to evaluate the strength of the linear relationship between two variables. The linear relationship is stronger for values near one and weaker for values below one. For example, if the R-squared is 0.9, it means that the input variables explain 90% of the variation in the output variables.

The adjusted  $R^2$  was calculated for 30s and 45s sequences of HR data, in a total of 170 and 114 examples respectively, annotated previously. In relation to the 30s window, it was necessary to remove the examples with less than 3 samples, resulting in a total of 155 examples.

Each sequence was annotated with one of three classes: -1 (decreasing), 0 (maintaining) and 1 (increasing). The  $R^2$  was calculated for each of the sequences (155 for the 30s and 114 for the 45s) and the density was represented in the figures 6 and 7.

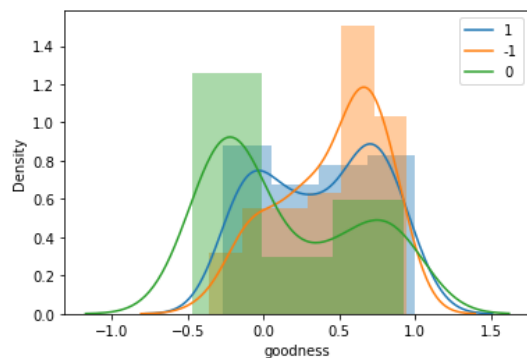


Fig. 6: Adjusted  $R^2$  for 30s sequences

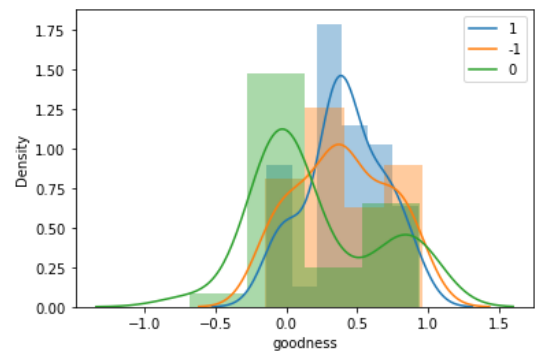


Fig. 7: Adjusted  $R^2$  for 45s sequences

The adjusted  $R^2$  is represented separately for each of the three classes. Class '0' (maintaining) obtained lowest values, peaking near 0.0  $R^2$ . This is explained by the fact that many of these sequences provide high variance in the relation between variables, which causes higher linear regression error (Figure 8). It is also worth noting that the curves for class '0' are nearly identical for both 30s and 45s sequences.



Fig. 8: Class '0' examples

Classes '1' (increasing) and '-1' (decreasing) show good indicators in the 30 seconds sequences annotation (Figure 6), being able to achieve high goodness values, with class '-1' being the most accurate, as class '1' has a significant portion of goodness values, near 0.

Also in Figure 7, the class '-1' was able to produce higher goodness values despite having a significant portion of low goodness values. Class '1' in this annotated sequences has the most uniform curve, despite the fact that the majority of the classified sequences did not exceed 0.5.

For comparison, the '-1' and '1' classes are closer to a linear representation, which explains better results than for class '0' (Figure 9).

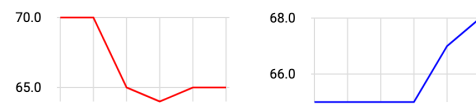


Fig. 9: Class '-1' and '1' examples

As expected, the quality of these annotations improved as the sequences are bigger. More values improve the linear regression indicators, although require more time to make a decision (45s or more).

#### V. CONCLUSIONS

This paper proposes a web-based annotator to automatically label sequences of HR values for training machine learning

Label	v0	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11
-1	69.0	68.0	68.0	68.0	68.0	69.0	70.0	70.0	65.0	64.0	65.0	65.0
-1	66.0	70.0	70.0	70.0	66.0	66.0	65.0	65.0	65.0	65.0	67.0	68.0
-1	70.0	70.0	66.0	65.0	65.0	68.0	68.0	70.0	69.0	67.0	65.0	66.0
0	63.0	63.0	62.0	62.0	61.0	62.0	61.0	64.0	62.0	62.0	64.0	
1	64.0	61.0	63.0	64.0	61.0	63.0	63.0	65.0	65.0	64.0	65.0	67.0
-1	70.0	73.0	71.0	71.0	65.0	65.0	63.0	65.0	63.0	63.0	65.0	65.0
0	67.0	64.0	65.0	64.0	64.0	62.0	63.0	64.0	64.0	67.0	77.0	
-1	89.0	88.0	85.0	85.0	85.0	86.0	85.0	81.0	80.0	81.0	80.0	81.0
-1	85.0	87.0	85.0	81.0	78.0	78.0	78.0	76.0	76.0	73.0	73.0	73.0
-1	74.0	74.0	74.0	74.0	73.0	72.0	71.0	71.0	71.0	72.0	74.0	
1	78.0	78.0	73.0	71.0	71.0	75.0	76.0	79.0	81.0	80.0	79.0	79.0

TABLE III: Annotated dataset in sequences of 60s

classifiers. These are important for several applications, such as serious games for rehabilitation or dynamic adaptation of goals in games, just to mention a couple. The annotator is composed of two main parts: the backend, developed in Java and with OpenBLAS as a Linear Algebra engine; and the web-based user interface, built in Angular. The annotator allows the user to upload several sessions of HR measurements, usually acquired with generic wearables, such as smart bands or watches, and stored as CSV files. The application is easy to use and allows the user to preview the annotation before producing a file with labeled sequences. The resulting annotation can then be adjusted by the user, in case of faulty or wrong labels. This relieves the burden of building sequences of samples and annotating each one of them manually.

#### ACKNOWLEDGMENT

This work is funded by the European Regional Development Fund (ERDF) through the Regional Operational Program North 2020, within the scope of Project GreenHealth - Digital strategies in biological assets to improve well-being and promote green health, Norte-01-0145-FEDER-000042. This work has been supported by FCT - Fundação para a Ciência e Tecnologia within the Project Scope: UIDB/05757/2020.

#### REFERENCES

- [1] H. Avsar, E. Altermann, C. Reining, F. M. Rueda, G. A. Fink, and M. ten Hompel, "Benchmarking Annotation Procedures for Multi-channel Time Series HAR Dataset," in *2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops)*, Mar. 2021, pp. 453–458. DOI: 10.1109/PerComWorkshops51409.2021.9431062.
- [2] S. Cassidy and J. Harrington, "Multi-level annotation in the Emu speech database management system," en, *Speech Communication*, Speech Annotation and Corpus Tools, vol. 33, no. 1, pp. 61–77, Jan. 2001, ISSN: 0167-6393. DOI: 10.1016/S0167-6393(00)00069-8. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0167639300000698> (visited on 01/07/2023).
- [3] I. Guellil, A. Adeel, F. Azouaou, and A. Hussain, "SentiALG: Automated Corpus Annotation for Algerian Sentiment Analysis," en, in *Advances in Brain Inspired Cognitive Systems*, J. Ren, A. Hussain, J. Zheng, *et al.*, Eds., ser. Lecture Notes in Computer Science, Cham: Springer International Publishing, 2018, pp. 557–567, ISBN: 978-3-030-00563-4. DOI: 10.1007/978-3-030-00563-4\_54.
- [4] A. S. F. Rodrigues, J. C. Lopes, R. P. Lopes, and L. F. Teixeira, "Classification of Facial Expressions Under Partial Occlusion for VR Games," en, in *Optimization, Learning Algorithms and Applications*, A. I. Pereira, A. Koir, F. P. Fernandes, M. F. Pacheco, J. P. Teixeira, and R. P. Lopes, Eds., vol. 1754, Series Title: Communications in Computer and Information Science, Cham: Springer International Publishing, 2022, pp. 804–819, ISBN: 978-3-031-23235-0 978-3-031-23236-7. DOI: 10.1007/978-3-031-23236-7\_55. [Online]. Available: [https://link.springer.com/10.1007/978-3-031-23236-7\\_55](https://link.springer.com/10.1007/978-3-031-23236-7_55) (visited on 01/08/2023).
- [5] R. P. Lopes, B. Barroso, L. Deusdado, *et al.*, "Digital Technologies for Innovative Mental Health Rehabilitation," en, *Electronics*, vol. 10, no. 18, p. 2260, Sep. 2021, IF (2021): 2.69 - Q2, ISSN: 2079-9292. DOI: 10.3390/electronics10182260. [Online]. Available: <https://www.mdpi.com/2079-9292/10/18/2260> (visited on 09/28/2021).
- [6] A. Novo, J. Fonsêca, B. Barroso, *et al.*, "Virtual Reality Rehabilitations Impact on Negative Symptoms and Psychosocial Rehabilitation in Schizophrenia Spectrum Disorder: A Systematic Review," en, *Healthcare*, vol. 9, no. 11, p. 1429, Oct. 2021, ISSN: 2227-9032. DOI: 10.3390/healthcare9111429. [Online]. Available: <https://www.mdpi.com/2227-9032/9/11/1429> (visited on 11/13/2021).
- [7] J. C. Lopes and R. P. Lopes, "A Review of Dynamic Difficulty Adjustment Methods for Serious Games," en, in *Optimization, Learning Algorithms and Applications*, A. I. Pereira, A. Koir, F. P. Fernandes, M. F. Pacheco, J. P. Teixeira, and R. P. Lopes, Eds., vol. 1754, Series Title: Communications in Computer and Information Science, Cham: Springer International Publishing, 2022, pp. 144–159, ISBN: 978-3-031-23235-0 978-3-031-23236-7. DOI: 10.1007/978-3-031-23236-7\_11.

- [Online]. Available: [https://link.springer.com/10.1007/978-3-031-23236-7\\_11](https://link.springer.com/10.1007/978-3-031-23236-7_11) (visited on 01/08/2023).
- [8] Y. Xie, J. Li, T. Zhu, and C. Liu, “Continuous-Valued Annotations Aggregation for Heart Rate Detection,” *IEEE Access*, vol. 7, pp. 37664–37671, 2019, Conference Name: IEEE Access, ISSN: 2169-3536. DOI: 10.1109/ACCESS.2019.2902619.
- [9] A. Chadha and B. Kaushik, “Machine learning based dataset for finding suicidal ideation on twitter,” English, 2021, pp. 823–828, ISBN: 978-0-7381-1183-4. DOI: 10.1109/ICICV50876.2021.9388638.
- [10] H. Ulrich, A.-K. Kock-Schoppenhauer, B. Andersen, and J. Ingenerf, “Analysis of Annotated Data Models for Improving Data Quality,” eng, *Studies in Health Technology and Informatics*, vol. 243, pp. 190–194, 2017, ISSN: 1879-8365.
- [11] J. A. Lossio-Ventura, S. Boussard, J. Morzan, and T. Hernandez-Boussard, “Clinical named-entity recognition: A short comparison,” in *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Nov. 2019, pp. 1548–1550. DOI: 10.1109/BIBM47256.2019.8983406.
- [12] E. Valveny, “Datasets and annotations for document analysis and recognition,” in *Handbook of Document Image Processing and Recognition*, Jan. 2014, pp. 983–1009, ISBN: 978-0-85729-859-1. DOI: 10.1007/978-0-85729-859-1\_32.
- [13] M. Cormier, F. Röpke, T. Golda, and J. Beyerer, “Interactive Labeling for Human Pose Estimation in Surveillance Videos,” in *2021 IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, ISSN: 2473-9944, Oct. 2021, pp. 1649–1658. DOI: 10.1109/ICCVW54120.2021.00190.
- [14] P. Bota, J. Silva, D. Folgado, and H. Gamboa, “A Semi-Automatic Annotation Approach for Human Activity Recognition,” en, *Sensors*, vol. 19, no. 3, p. 501, Jan. 2019, Number: 3 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1424-8220. DOI: 10.3390/s19030501. [Online]. Available: <https://www.mdpi.com/1424-8220/19/3/501> (visited on 01/03/2023).
- [15] N. Nabizadeh, D. Kolossa, and M. Heckmann, “My-Fixit: An Annotated Dataset, Annotation Tool, and Baseline Methods for Information Extraction from Repair Manuals,” English, in *Proceedings of the Twelfth Language Resources and Evaluation Conference*, Marseille, France: European Language Resources Association, May 2020, pp. 2120–2128, ISBN: 979-10-95546-34-4. [Online]. Available: <https://aclanthology.org/2020.lrec-1.260> (visited on 12/23/2022).
- [16] V. Chudáček, M. Huptych, M. Koucký, J. Spilka, L. Bauer, and L. Lhotská, “Fetal heart rate data pre-processing and annotation,” in *2009 9th International Conference on Information Technology and Applications in Biomedicine*, ISSN: 2168-2208, Nov. 2009, pp. 1–4. DOI: 10.1109/ITAB.2009.5394441.
- [17] P. Sodmann, M. Vollmer, N. Nath, and L. Kaderali, “A convolutional neural network for ECG annotation as the basis for classification of cardiac rhythms,” en, *Physiological Measurement*, vol. 39, no. 10, p. 104005, Oct. 2018, Publisher: IOP Publishing, ISSN: 0967-3334. DOI: 10.1088/1361-6579/aae304. [Online]. Available: <https://dx.doi.org/10.1088/1361-6579/aae304> (visited on 12/22/2022).
- [18] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, arXiv:1603.02754 [cs], Aug. 2016, pp. 785–794. DOI: 10.1145/2939672.2939785. [Online]. Available: <http://arxiv.org/abs/1603.02754> (visited on 01/02/2023).
- [19] Z.-H. Zhou and W. Tang, “Clusterer ensemble,” en, *Knowledge-Based Systems*, vol. 19, no. 1, pp. 77–83, Mar. 2006, ISSN: 0950-7051. DOI: 10.1016/j.knsys.2005.11.003. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0950705105000985> (visited on 01/03/2023).
- [20] J. Di, J. Li, and C. Liu, “A Bayesian Fusion Model for Heart Rate Annotations,” in *2020 International Conference on Sensing, Measurement & Data Analytics in the era of Artificial Intelligence (ICSMD)*, Oct. 2020, pp. 307–312. DOI: 10.1109/ICSMD50554.2020.9261732.
- [21] C. Dismuke and R. Lindrooth, “Ordinary least squares,” *Methods and Designs for Outcomes Research*, Jan. 2006.
- [22] D. Diez, M. Çetinkaya-Rundel, and C. Barr, *OpenIntro Statistics: Fourth Edition*, English. Place of publication not identified: OpenIntro, Inc., May 2019, ISBN: 978-1-943450-07-7.