Effects of Class Imbalance in Unsupervised Human Activity Recognition for Office Work Task Characterization

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Abstract: Office workers spend most of their time sitting, often with rigid postures, for prolonged periods of time. This has been recognized by the European Union as a risk factor for work-related musculoskeletal disorders. To study work activities and their distribution over time, Human Activity Recognition (HAR) techniques need to be implemented. Since supervised learning techniques require labeled data and large datasets for training, unsupervised learning is a viable alternative for HAR. However, these models may be affected by the highly imbalanced distribution of activities typically observed in office workers. Considering this, this work studied the impact of data imbalance on clustering performance when the dataset is comprised of 33 %, 50 %, 70 %, and 90 % of sitting activity. Office activities were collected from 19 subjects and three traditional clustering models were employed. KMeans and Gaussian Mixture Model were more affected than Agglomerative Clustering, which seems to be more robust to data imbalance. With 90 % of sitting time, all three models performed poorly, which emphasizes the need for clustering models that can handle highly imbalanced data.

1 INTRODUCTION

Since the early 2000s, the number of people employed in computer-based office work has been steadily increasing across the European Union (EU). Specifically, from 2000 to 2015, the percentage of workers who spent at least a quarter of their workday doing computer work increased from 47 % to 58 % (European Agency for Safety and Health at Work et al., 2019). Office work predominantly consists of low variance activities such as sitting for long periods of time, often with rigid postures (Zerguine et al., 2023), (European Agency for Safety and Health at Work et al., 2017), (Srinivasan and Mathiassen, 2012). This has been linked to musculoskeletal pain, particularly in the lower back, neck, shoulders, and knees (Owen et al., 2020). Additionally, office workers are often confronted with high job demands, while being limited by low job resources (Bakker and de Vries, 2021). A combination of these factors contributes to the development of work-related musculoskeletal disorders (WRMDs), stress, depression, and anxiety-related problems, which are a significant health concern for 7.4 % of European workers (European Agency for Safety and Health at Work et al., 2017). WRMDs are associated with loss of productivity and increased absenteeism, resulting in medical burden and increased economic costs for organizations (European Agency for Safety and Health at Work et al., 2019), (Punnett and Wegman, 2004). This problem has been recognized by the EU, which is actively funding initiatives under the 2021-2024 Horizon Europe program, particularly within Cluster 1, to promote healthier living and working environments (European Commission and Directorate-General for Research and Innovation, 2021). Implementing more active work practices that reduce sitting time and encourage more walking and standing, is crucial for occupational health and has shown positive health outcomes (Owen et al., 2020), (Park et al., 2020).

To address some of the above-mentioned issues, the PrevOccupAI (Prevention of Occupational Disorders in Public Administrations based on Artificial Intelligence) was carried out with the objective of evaluating occupational risk factors for WRMDs in office workers (Oliosi et al., 2023). Biosignals were acquired with the purpose of studying workers' postures during their workday. As subjects were not observed during work, the resulting dataset is unlabeled.

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While PrevOccupAI focused on postural information, the dataset also allows for the study of human activities and their distribution over time, using Human Activity Recognition (HAR) techniques. Supervised learning is often preferred for HAR, since classification techniques usually produce state-of-the-art results. However, unsupervised learning has been increasingly explored as an alternative, since training supervised learning models requires large amounts of data and label annotation, which is costly and time-consuming (Ige and Mohd Noor, 2022).

As mentioned above, office work is highly imbalanced with regards to the activities performed. Although sitting, standing, and walking, are commonly studied activities in the literature (Ige and Mohd Noor, 2022), the datasets used for model training are usually balanced, since supervised learning requires it. However, if dealing with completely unlabeled data, it can not be assumed that classes are balanced, as there is no information about them. This data imbalance must be taken into consideration when employing unsupervised learning models for HAR. Therefore, the impact of data imbalance on clustering performance should be studied.

2 RELATED WORK

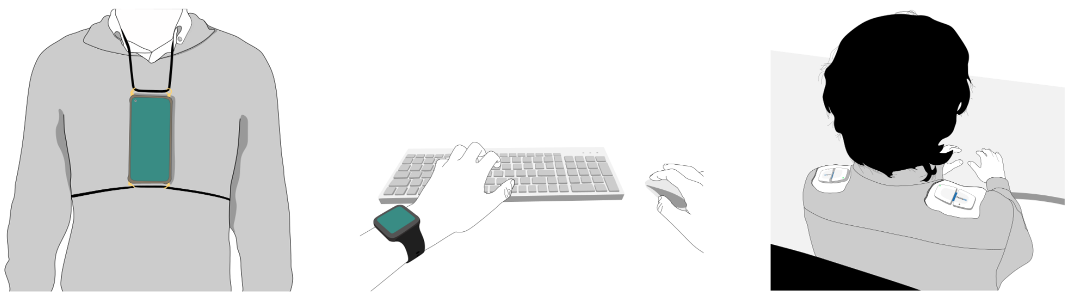
HAR is a prominent research area, due to advances in sensor technology and increased computational power (Jobanputra et al., 2019). Basic activities are the most common activities studied, which typically involve low-variability movements with clear and repetitive patterns (Dentamaro et al., 2024). The studies by Machado et al. (Machado. et al., 2014) and Kwon et al. (Kwon et al., 2014) focus on lab-collected basic activities like standing, sitting, walking, running, and lying down. Machado et al. used data from eight subjects collected via a waist-mounted tri-axial accelerometer (ACC), while Kwon et al. collected tri-axial ACC and gyroscope (GYR) data from a single subject using a smartphone in a trouser front pocket. Publicly available datasets such as UCI-HAR (Anguita et al., 2013a), HHAR (Stisen et al., 2015), and MHEALTH (Banos et al., 2014) also focus on basic activities. UCI-HAR includes data from 30 subjects performing six activities (standing, sitting, lying down, walking, and climbing stairs) using a waist-mounted smartphone with ACC and GYR sensors. HHAR features the same activities as UCI-HAR, with addition of biking and running, performed by nine subjects, using ACC and GYR sensors from eight smartphones placed on the waist and four smartwatches on the wrists. MHEALTH includes similar activities with additional movements like waist bending, crouching, and arm raises, performed by ten subjects, using ACC, GYR, and magnetometer (MAG) sensors on the chest, wrist, and ankle (Banos et al., 2014).

The above-mentioned datasets were utilized for unsupervised HAR. In (Machado. et al., 2014), multiple statistical, temporal, and spectral features were extracted from the sensor data and used for clustering. KMeans was applied, achieving 99.3 % Adjusted Rand Index (ARI) in a subject-specific approach, and 88.6 % in a subject-independent approach. In (Kwon et al., 2014), the mean and standard deviation (SD) were extracted from the time and frequency domains of the sensor data for clustering. When the number of clusters (k) is known, KMeans, Gaussian Mixture Model (GMM), and Agglomerative Clustering (AGG), achieving ARIs of 72.0 %, 100 %, and 80.0 %, respectively. To simulate an unknown k, values between two and 50 were tested. The highest accuracy obtained with KMeans and AGG was close to 80.0 %, while GMM maintained 100 %. DBSCAN was also employed in this scenario, reaching a 90.0 % ARI. Similar experimental setups were used in (Mejia-Ricart et al., 2017) an additional smartwatch and pedometer readings were incorporated. The clustering models used included KMeans, Spectral Clustering, AGG (average and Ward linkage), DBSCAN, and Mean Shift. KMeans was the best-performing model, followed by AGG with Ward's method and Spectral Clustering. No clustering metrics were provided in this study.

The works mentioned above achieve high performance in clustering basic activities using traditional models. However, the data used, whether lab-collected or publicly available, is balanced, meaning all activities have the same duration. Since this balanced scenario doesn't reflect real-world office environments, traditional clustering models should be tested on data where some activities have longer durations than others.

3 METHODS

The following sections present the proposed framework for studying the effects of data imbalance in unsupervised HAR within office environments. It begins with the description of the labeled dataset, which consists of office tasks performed by 19 subjects. Next, the signal pre-processing and feature extraction methods are outlined, followed by the explanation of the selected unsupervised models and feature selection approach. Finally, the imbalanced datasets are cre-



(a) Smartphone (b) Smartwatch (c) MuscleBANs

Figure 1: Sensor placement adapted from (Oliosi et al., 2023).

ated, with the sitting activity comprising 33 % (balanced), 50 %, 70 %, and 90 % of the dataset, to assess the impact of data imbalance on clustering performance[1].

3.1 Experimental Setup and Placement

A labeled dataset comprised of office work activities was collected to study the impact of data imbalance on clustering models. The acquisitions were conducted in an office environment with a group of 19 healthy volunteers, comprising 14 women and 6 men, aged between 19 and 54 years (age: 26.0 ± 8.3 years). The purpose of the study and the acquisition protocol were thoroughly explained to the participants, and each were provided with an informed consent form. The same setup as the PrevOccupAI project was utilized which was approved by the Universidade Nova de Lisboa Ethics Committee and conducted in accordance with the Declaration of Helsinki (Oliosi et al., 2023).

The sensors used and correspondent placement, as shown in Figure 1, include a Xiaomi Redmi Note 9 smartphone on the subject's chest, an OPPO 41 mm smartwatch on the non-dominant wrist, and two muscleBANs (PLUX Wireless Biosignals) on the left and right Trapezius. The smartphone and the smartwatch run the Android operating system and were used to acquire tri-axial ACC, GYR, and MAG data. ACC and GYR were acquired at 100 Hz and MAG at 50 Hz (restricted by the operating system). The muscleBAN contains an EMG sensor and a tri-axial ACC and MAG, acquiring at 1000 Hz. The muscleBAN was placed in accordance with the SENIAM guidelines (Hermens et al., 2000).

[1]The presented work is available on GitHub: https://github.com/SaraLMS/Unsupervised-HAR-Models-for-Characterizing-Office-Tasks.

3.2 Acquisition Protocol

At the start of each acquisition, subjects stood straight with arms parallel to the body, followed by ten short, vertical jumps, to allow for synchronising the signals from the different devices. A total of 15, 20, and 30 minutes were acquired for sub-activities that can be associated with sitting, walking, and standing, respectively. To facilitate the data acquisitions, sub-activities more similar in nature were performed within the same recording with ten-second stop sequences (with a jump in the middle for standing activities) in between, except for the sitting acquisition, which was done continuously. Thus, five acquisition sessions were devised. The first session involved subjects walking at their slow, medium, and fast speeds, with five minutes per speed (15 minutes total). The second session included stair climbing, alternating between going up and down for four segments of one minute and 15 seconds each (five minutes total). The third session involved two tasks with a duration of seven minutes and 30 seconds each (totaling 15 minutes) using a tall cabinet: preparing and drinking tea or coffee and organizing items within the cabinet. The fourth session consisted of standing still and standing while conversing for seven minutes and 30 seconds each (15 minutes total). The fifth session involved sitting at a desk and working on a computer for 15 minutes.

3.3 Signal Pre-Processing

Given that the focus of this work is on the impact of data imbalance on the clustering, only the simplest scenario, comprising only smartphone sensors and three sub-activities, will be used. The selected sub-activities are standing still, walking at a medium speed, and sitting, as they represent the most basic forms of standing, walking, and sitting. The pre-processing steps for the ACC, GYR, and MAG signals from the smartphone are as follows: resampling and alignment of the signals, task segmentation, and filtering.

3.3.1 Alignment and Resampling

The Android operating system is not optimized for continuous data acquisition, leading to issues like variable sampling rates and sensors not starting or stopping simultaneously. To address this, signals were cropped based on the timestamp of the last sensor to start and the first to stop acquiring data. Additionally, to ensure uniform sampling for the smartphone and smartwatch sensors (ACC, GYR, and MAG), signals were up-sampled to 100 Hz using quadratic interpolation, ensuring consistent data across all sensors within the same device.

3.3.2 Task Segmentation

An onset-based segmentation approach was employed to extract the walking at a medium speed from the recording containing the walking patterns. First, the absolute value of the signal was computed, followed by the application of a root-mean-square filter with a window length of 100 samples to obtain the signal's envelope. The signal was then binarized, setting values above 0.01 m/s^2 to one and values below to zero. The first order discrete difference was calculated to identify the start points (where the difference is one) and stop points (where the difference is minus one). These values were subsequently validated to remove any incorrect detections, primarily caused by the synchronisation jumps.

To extract the standing still activity from the recording that also contains standing while conversing, and to isolate the sitting activity, a peak-based segmentation approach was developed. The *findpeaks* function from SciPy was applied with a peak height of 7 m/s^2 and a minimum distance of 15 000 samples for standing still, conversing, and sitting, and 40 000 samples for the other standing sub-activities. Due to subject-to-subject differences in jumping velocity, the above-mentioned threshold were slightly adapted for some subjects. This function detected the peaks from the synchronization jumps and the jumps in the middle of the stop segments. Since these peaks are roughly centered within the ten-second stop segments, the start and stop points were set five seconds before and after each peak. For the first peak, which pertains to the synchronisation jumps, the start was set to 15 seconds after the peak. For the sitting activity, where there were no separation segments, this method was used solely to remove synchronisation jumps.

3.3.3 Filtering

After extracting sitting, walking medium, and standing still from the remaining activities, these signals were filtered to prepare it for feature extraction. The filtering pipeline designed by (Anguita et al., 2013b) was used for the smartphone's ACC, GYR, and MAG signals. Since human activities are mostly of low frequency, a median filter with a window length of eleven samples was applied, followed by a Butterworth low-pass filter with a cutoff frequency of 20 Hz. To isolate the gravitational component, another Butterworth low-pass filter with a 0.3 Hz cutoff frequency was applied. This component was then subtracted from the signal.

3.4 Unsupervised Models

To study the impact of class imbalance on the ARI, three traditional clustering models were selected: KMeans, AGG Ward's linkage, and GMM. These models are commonly used for HAR and allow for the specification of the number of clusters, which was set to three, as the objective is to cluster the three different activities.

KMeans is the most widely used clustering model. The KMeans algorithm works in two steps: first, data points are assigned to the closest cluster center based on a distance metric, usually euclidean distance. Next, the cluster centers are updated by computing the mean of the data points within each cluster, shifting the centers to the new average position (Badillo et al., 2020). The GMM algorithm assumes that all data points are generated by a mixture of a finite number of Gaussian distributions, each with its own mean and covariance matrix (Biernacki et al., 2000). This model allows for oval-shaped clusters that may be more robust than KMeans, which assumes only spherical clusters. The AGG algorithm starts by treating each data point as its own cluster (Aghabozorgi et al., 2015) and with each iteration, pairs of close clusters are merged (Kaufman and Rousseeuw, 1990), based on the chosen linkage criterion. AGG may handle imbalanced data to some extent, as it is not constrained by specific cluster shapes or centroids.

3.5 Feature Engineering

In a completely unsupervised scenario, it is not possible to optimize a feature set for each subject. Therefore, a common feature set for all subjects must be obtained to cluster the three activities. For this, a two-stage feature selection method was implemented. The first stage involved finding the best feature sets for each subject. The second stage comprised of identifying the most common features across all subjects to obtain the final feature set. These feature sets were then used to cluster each subject individually.

The TSFEL package (version 0.1.7) (Barandas et al., 2020) was used for feature extraction. Different window sizes were tested, but it was experimentally found that 1.5 seconds, approximately one walking cycle, with 50 % overlap performed the best. In the time domain, the following statistical features were extracted: maximum, minimum, mean, median, variance, SD, and Interquartile range. From the frequency domain, the median frequency, spectral centroid, and spectral entropy were also obtained.

The initial step in this feature selection process involves normalization (between zero and one) and elimination of features with low variance and high correlation. The variance and correlation thresholds were set to 5 % and 99 %, respectively. The remaining features underwent a forward feature selection approach. Features were initially shuffled and then added iteratively to a sub-dataset that was then passed to the model for clustering. If the addition of a feature did not improve the ARI, it was removed. This procedure was repeated ten times to account for the randomness introduced by the shuffling, thereby ensuring that various combinations of features were tested. From the subject-specific feature sets, the n most common features across all subjects were selected to form a final feature set. Figure 2 illustrates the two-stage feature selection process for finding the three most common features (orange, yellow, and green) across all subjects. To determine the most suitable number of features for the final feature set, values of $n = 4, 5, 6, 7, 8$ were tested. For the particular scenario of the three basic sub-activities with only smartphone sensors, the best feature sets obtained were as follows: for KMeans — xMAG maximum, yACC interquartile range, zMAG maximum, xACC minimum, yACC minimum; for AGG — yACC maximum, zACC interquartile range, zMAG maximum, yMAG maximum; and for GMM — xMAG maximum, yACC maximum, zMAG maximum, yACC minimum, and yGYR standard deviation.

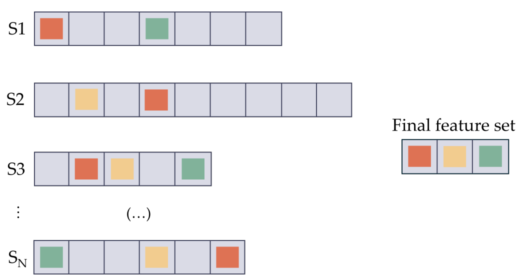


Figure 2: Second step of the two-stage feature selection scheme.

3.6 Creation of Imbalanced Datasets

For the data imbalance experiment, four scenarios were tested, with sitting comprising 33 % (balanced dataset), 50 %, 70 %, and 90 % of the dataset. Figure 3 illustrates the process of creating the imbalanced datasets. In the balanced case, all instances of sitting, standing still, and walking medium speed are included, resulting in a single dataset. For imbalanced scenarios, all available sitting instances were used, with standing and walking instances added to achieve final sitting proportions of 50 %, 70 %, and 90 %. The standing and walking classes then represented 25 %, 15 %, and 5 % of the imbalanced dataset, respectively. Since only a portion of the total instances is included, multiple chunks of the original standing and walking instances were selected, in order to test all available data. The size of each chunk (CS) and the step size between consecutive chunks (SS) is defined as follows:

$$CS = \frac{\frac{a}{b} - a}{2} \quad (1) \qquad SS = \frac{a - CS}{n - 1} \quad (2)$$

Where a is the number of sitting instances, b is the sitting proportion (0.5, 0.7 or 0.9), and n is the number of chunks. The number of chunks was determined based on the percentage of the sitting class and the chunk size, ensuring overlap between the chunks. At 50 % of sitting, four chunks were used, therefore covering the entire walking and standing instances with overlap. As the sitting proportion increased, the required number of chunks also increased, with seven chunks at 70 % and 20 chunks at 90 %. For each imbalanced scenario, the clustering results for each subject is the mean ARI over all chunks. The final results correspond to the mean ARI over all subjects.

4 RESULTS

The influence of data imbalance on the ARI for the three clustering models is shown in Figure 4. In this plot, the points were slightly displaced horizontally to facilitate the analysis of the error bars of each model. Both KMeans and GMM show lower performance on imbalanced datasets. With a balanced dataset, these models reach 92.5 % and 89.9 % mean ARI, respectively. Compared to the balanced scenario, at 50 % of sitting activity, KMeans and GMM dropped 39.6 % and 39.0 %, and at 70 % dropped 25.4 % and 25.1 %, respectively. At 90 % of sitting, KMeans achieved 63.8 % and GMM reached 62.9 %. AGG behaved

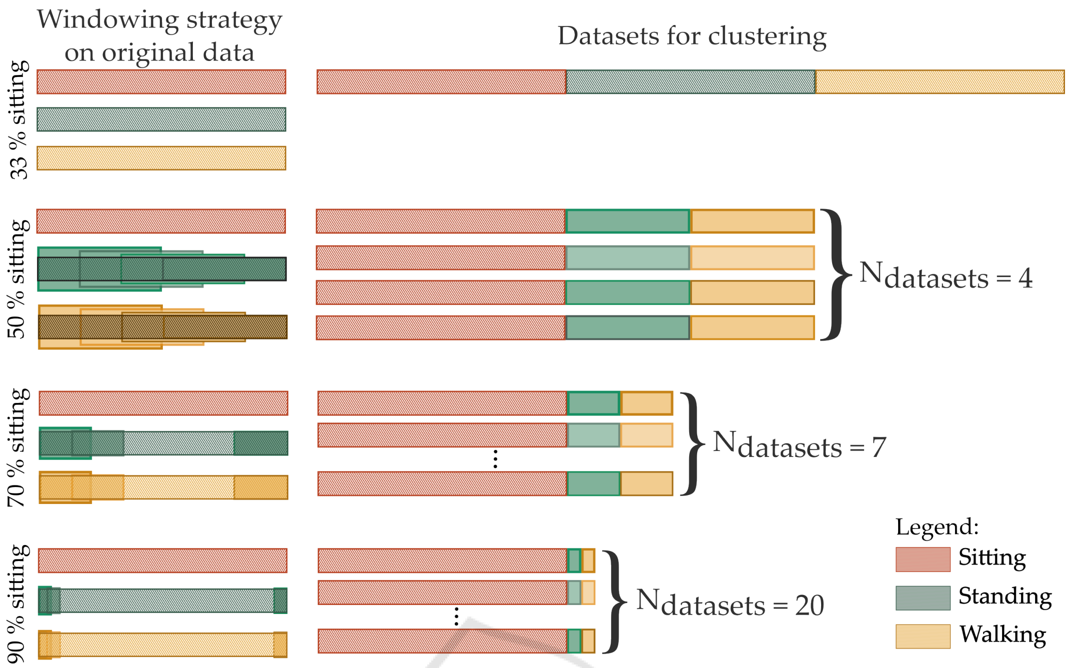


Figure 3: Representation of the imbalanced datasets. For balanced classes, only one dataset is needed to include all available instances. When the sitting class comprises 50 % of the dataset, four different chunks of standing and walking were used. At 70 % sitting, seven chunks were used, and at 90 %, 20 chunks.

differently, starting with 78.3 % mean ARI with a balanced dataset and increasing 5.1 % and 3.6 % at 50 % and 70 % of sitting class, respectively. Similar to the previous two models, at 90 %, AGG obtained 65.9 % mean ARI. The SDs for each clustering model are generally high, with the highest being 29.8 % for AGG at 90 % sitting class and the lowest at 11.4 % for KMeans at 50 % sitting class. When the sitting class reaches 90 %, SDs are particularly high, with values of 24.3 %, 29.8 %, and 24.1 % for KMeans, AGG, and GMM, respectively. Overall, the SD tends to increase with a higher class imbalance.

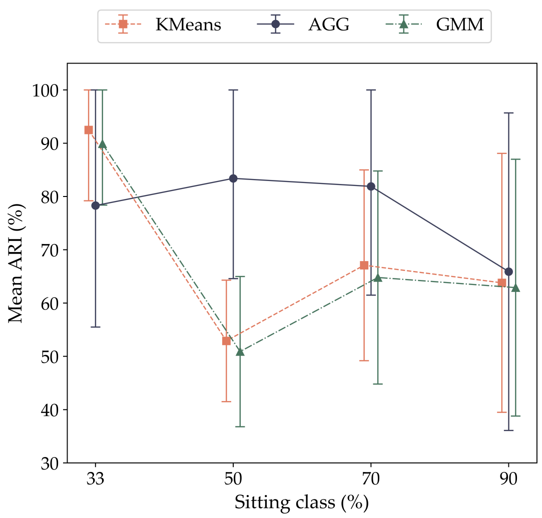


Figure 4: Influence of data imbalance on the performance of KMeans, AGG, and GMM.

5 DISCUSSION

As seen from the results in Figure 4, overall, the datasets with imbalanced classes perform worse than the balanced datasets, with performance decreasing as the imbalance increases. However, there are notable exceptions. AGG shows an improvement in ARI when the dataset consists of 50 % sitting class, while KMeans and GMM improve from 50 % to 70 % sitting class. This can be attributed to the fact that, to achieve the remaining proportions for the standing still and walking medium, majority of these instances are removed. As described previously, this was done in subsets, meaning that different portions of the standing still and walking medium clusters were tested. If some of these instances were originally (with a balanced dataset) overlapping in the feature space, by removing them, it can actually enhance clustering results. Nevertheless, this improvement is limited. With increasing imbalance, the sitting cluster becomes dominant in terms of size and amount of data points. When imbalance reaches 90 % sitting class, some underrepresented instances, if close to it, may be incorrectly assigned to the larger sitting cluster.

AGG tends to be more robust to data imbalance than KMeans and GMM. This robustness probably arises since AGG does not assume specific cluster shapes or rely on centroids, making it more flexible in identifying smaller, irregularly shaped clusters that can appear when samples are removed to create the imbalanced datasets. However, at 90 % imbalance, the three clustering models obtain a similar ARI, showing that, with higher imbalance, the advantages of linkage diminish.

The results also show high SDs for the three clustering models. This happens not only on the imbalanced datasets, but also in the balanced scenario. This could be due to subjects showing different behaviours even when performing basic activities such as sitting, standing still, and walking at a medium speed. More static subjects are probably easier to cluster than more active ones. Active subjects have more variability in their movements, which can result in a more spread out feature space and, therefore, overlapping clusters. For these subjects, the imbalanced scenarios can further emphasize this overlap, resulting in an even poorer performance. Static subjects with completely separated clusters can still cluster well with imbalanced datasets, as seen from the high SDs despite the low mean ARI.

This experiment indicates that class imbalance has a major impact on clustering performance. Thus, when designing unsupervised HAR systems, class imbalance has to be considered and models that robustly handle these imbalances have to be explored. A potential model that could be explored in the future is the recently published Equilibrium KMeans, which was designed to handle imbalanced data (He, 2024). This adaptation of the traditional KMeans model introduces a mechanism that repels centroids, with larger clusters experiencing stronger repulsion. This approach overcomes the ”uniform effect” of traditional KMeans, which tends to form clusters of similar sizes, even when the input data contains groups of varying sizes. This could be useful for highly imbalanced scenarios such as real-world office work.

6 CONCLUSIONS

Computerized office work is often sedentary, with workers exhibiting low levels of activity for extended periods and across consecutive days. This can lead to workers experiencing WRMDs, stress, depression, and anxiety-related issues. Since occupation health is a significant concern for European workers, HAR techniques can be useful in studying workers' activities and their durations. Although HAR is a prominent area of research, studies typically use balanced, lab-collected, or publicly available datasets to train machine learning models. However, this approach does not accurately represent real office environments where workers spend most of their time sitting rather than standing or walking. This leads to data imbalance that can affect clustering performance. To study this, data was collected from 19 subjects performing nine different office tasks. Standing still, walking medium speed, and sitting while working on a computer were chosen for this experiment. Four different scenarios were tested where the dataset was comprised of 33 % (balanced), 50 %, 70 %, and 90 % of sitting activity. Imbalanced datasets were created by including all available sitting instances and adjusting the standing and walking instances to achieve the desired final proportions. To ensure all standing and walking instances were used, different subsets of the available instances were applied. Traditional clustering models, including KMeans, AGG, and GMM, were used to cluster the imbalanced datasets. Results indicate that all three clustering models are affected by data imbalance, with an overall decrease in accuracy as imbalance increases. AGG appears to be more robust to data imbalance, as it does not assume specific cluster shapes, allowing it greater flexibility in identifying smaller, irregular-shaped clusters. With 90 % sitting activity, all three models perform poorly, highlighting the need for clustering models that can effectively handle highly imbalanced datasets.

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REFERENCES

Aghabozorgi, S., Seyed Shirkhorshidi, A., and Ying Wah, T. (2015). Time-series clustering – a decade review. *Information Systems*, 53:16–38.

Anguita, D., Ghio, A., Oneto, L., Parra, X., and Reyes-Ortiz, J. L. (2013a). A public domain dataset for human activity recognition using smartphones. In *The European Symposium on Artificial Neural Networks*.

Anguita, D., Ghio, A., Oneto, L., Parra, X., and Reyes-Ortiz, J. L. (2013b). A public domain dataset for human activity recognition using smartphones.

In *ESANN 2013 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium)*. i6doc.com.

Badillo, S., Banfai, B., Birzele, F., Davydov, I. I., Hutchinson, L., Kam-Thong, T., Siebourg-Polster, J., Steiert, B., and Zhang, J. D. (2020). An introduction to machine learning. *Clinical Pharmacology & Therapeutics*, 107(4):871–885.

Bakker, A. B. and de Vries, J. D. (2021). Job demands–resources theory and self-regulation: new explanations and remedies for job burnout. *Anxiety, Stress, & Coping*, 34(1):1–21.

Banos, O., Garcia, R., Holgado-Terriza, J. A., Damas, M., Pomares, H., Rojas, I., Saez, A., and Villalonga, C. (2014). mhealthdroid: A novel framework for agile development of mobile health applications. In *Ambient Assisted Living and Daily Activities*, pages 91–98. Springer International Publishing.

Barandas, M., Folgado, D., Fernandes, L., Santos, S., Abreu, M., Bota, P., Liu, H., Schultz, T., and Gamboa, H. (2020). Tsfel: Time series feature extraction library. *SoftwareX*, 11.

Biernacki, C., Celeux, G., and Govaert, G. (2000). Assessing a mixture model for clustering with the integrated completed likelihood. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(7):719–725.

Dentamaro, V., Gattulli, V., Impedovo, D., and Manca, F. (2024). Human activity recognition with smartphone-integrated sensors: A survey. *Expert Systems with Applications*, 246.

European Agency for Safety and Health at Work, Kok, J., Vroonhof, P., Snijders, J., Roullis, G., Clarke, M., Peereboom, K., Dorst, P., and Isusi, I. (2019). *Work-related musculoskeletal disorders – Prevalence, costs and demographics in the EU*. Publications Office.

European Agency for Safety and Health at Work, Zwaan, L., Oldenburg, C., Emmerik, M., Eekhout, I., Heuvel, S., Janowsk, P., Dam, L., Oude-Hengel, K., Brück, C., and Wilhelm, C. (2017). *Estimating the cost of work-related accidents and ill-health – An analysis of European data sources*. Publications Office.

European Commission and Directorate-General for Research and Innovation (2021). *Horizon Europe strategic plan 2021-2024*. Publications Office of the European Union.

He, Y. (2024). Imbalanced data clustering using equilibrium k-means. *arXiv preprint arXiv:2402.14490*.

Hermens, H. J., Freriks, B., Disselhorst-Klug, C., and Rau, G. (2000). Development of recommendations for semg sensors and sensor placement procedures. *Journal of Electromyography and Kinesiology*, 10(5):361–374.

Ige, A. O. and Mohd Noor, M. H. (2022). A survey on unsupervised learning for wearable sensor-based activity recognition. *Applied Soft Computing*, 127.

Jobanputra, C., Bavishi, J., and Doshi, N. (2019). Human activity recognition: A survey. *Procedia Computer Science*, 155:698–703.

Kaufman, L. and Rousseeuw, P. (1990). *Finding Groups in Data: An Introduction To Cluster Analysis*.

Kwon, Y., Kang, K., and Bae, C. (2014). Unsupervised learning for human activity recognition using smartphone sensors. *Expert Systems with Applications*, 41(14):6067–6074.

Machado., I., Gomes., R., Gamboa., H., and Paixão., V. (2014). Human activity recognition from triaxial accelerometer data - feature extraction and selection methods for clustering of physical activities. In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing (BIOSTEC 2014) - BIOSIGNALS*, pages 155–162. INSTICC, SciTePress.

Mejia-Ricart, L. F., Helling, P., and Olmsted, A. (2017). Evaluate action primitives for human activity recognition using unsupervised learning approach. In *2017 12th International Conference for Internet Technology and Secured Transactions (ICITST)*, pages 186–188.

Oliosi, E., Probst, P., Rodrigues, J., Silva, L., Zagalo, D., Cepeda, C., and Gamboa, H. (2023). Week-long multimodal data acquisition of occupational risk factors in public administration workers. In *2023 19th International Conference on Intelligent Environments, IE 2023 - Proceedings*. IEEE.

Owen, N., Healy, G. N., Dempsey, P. C., Salmon, J., Timperio, A., Clark, B. K., Goode, A. D., Koorts, H., Ridgers, N. D., Hadgraft, N. T., Lambert, G., Eakin, E. G., Kingwell, B. A., and Dunstan, D. W. (2020). Sedentary behavior and public health: Integrating the evidence and identifying potential solutions. *Annual Review of Public Health*, 41:265–287.

Park, J., Moon, J., Kim, H., Kong, M., and Oh, Y. (2020). Sedentary lifestyle: Overview of updated evidence of potential health risks. *Korean Journal of Family Medicine*, 41:365–373.

Punnett, L. and Wegman, D. H. (2004). Work-related musculoskeletal disorders: the epidemiologic evidence and the debate. *Journal of Electromyography and Kinesiology*, 14(1):13–23.

Srinivasan, D. and Mathiassen, S. E. (2012). Motor variability - an important issue in occupational life. In *Work*, volume 41, pages 2527–2534.

Stisen, A., Blunck, H., Bhattacharya, S., Prentow, T. S., Kjærgaard, M. B., Dey, A., Sonne, T., and Jensen, M. M. (2015). Smart devices are different: Assessing and mitigatingmobile sensing heterogeneities for activity recognition. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems*, page 127–140. Association for Computing Machinery.

Zerguine, H., Healy, G. N., Goode, A. D., Zischke, J., Abbott, A., Gunning, L., and Johnston, V. (2023). Online office ergonomics training programs: A scoping review examining design and user-related outcomes. *Safety Science*, 158.