HUMAN ACTIVITY RECOGNITION IMPROVEMENT ON SMARTPHONE ACCELEROMETERS USING CIMA

Aji Gautama Putrada[1], Maman Abdurohman[2], Doan Perdana[3], Hilal Hudan Nuha[4]

[1, 3]Advanced and Creative Networks Research Center, Telkom University
[2, 4]School of Computing, Telkom University
[1]ajigautama@student.telkomuniversity.ac.id, [2]abdurohman@telkomuniversity.ac.id, [3]doanperdana@telkomuniversity.ac.id, [4]hilalnuha@telkomuniversity.ac.id

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Abstrak

***Human activity recognition* (HAR) merupakan bidang penelitian yang berfokus pada pendeteksian aktivitas pengguna serta memiliki aplikasi luas. Namun permasalahan yang dihadapi adalah kendala *real-time* dan dataset yang *imbalance* akibat frekuensi aktivitas yang berbeda. Penelitian kami bertujuan untuk menerapkan *classification integrated moving average* (CIMA) ke HAR dengan mengevaluasi kinerjanya terkait batasan real-time dan kumpulan data yang imbalance. Kami memperoleh kumpulan data akselerometer smartphone dari Kaggle, yang terdiri aktivitas berjalan kaki, joging, memanjat, dan menuruni tangga. Kami mengembangkan algoritma *windowing* CIMA umum dengan *hyperparameter* J dan W. Kami melakukan *benchmarking* CIMA dengan dua metode HAR yang terkini, yaitu *distributed online activity recognition system* (DOLARS) dan *convolutional neural network* (CNN). Kami melakukan analisis ketidakseimbangan dan ukuran model. Hasil pengujian menunjukkan bahwa dengan $J = 10$ dan $W = 240$, kinerja CIMA lebih baik dibandingkan DOLARS dan CIMA dengan recall, *precision*, dan *f1-score* masing-masing sebesar 0,996, 0,993, dan 0,994. Kami juga membuktikan bahwa CIMA dengan bantuan kuantisasi memiliki ukuran model terkecil dibandingkan ukuran model CNN dan DOLARS. Terakhir, kami menunjukkan bahwa CIMA berkinerja baik untuk kumpulan data yang tidak seimbang, dengan perolehan CIMA pada aktivitas di lantai atas dan bawah lebih baik daripada DOLARS dan CNN, dengan nilai masing-masing 1,00 dan 0,98.**

Kata Kunci: ***classification integrated moving average*, *human activity recognition*, smartphone, akselerometer, *imbalanced dataset***

Abstract

Human activity recognition (HAR) is a research field that focuses on detecting user activities and has wide applications. However, the problems that need to be solved are real-time constraints and imbalanced datasets due to different activity frequencies. Our research aims to apply classification integrated moving averages (CIMA) to HAR by evaluating its performance regarding real-time constraints and imbalanced datasets. We achieved the smartphone accelerometer dataset from Kaggle, which consists of several activities: walking, jogging, climbing, and descending stairs. We develop a general CIMA windowing algorithm with hyperparameters J and W. We benchmark CIMA with two state-of-the-art HAR methods: distributed online activity recognition system (DOLARS) and convolutional neural network (CNN). We conducted some imbalance and model size analysis. The test results show that, with $J = 10$ and $W = 240$, CIMA performs better than DOLARS and CIMA with recall, precision, and f1-score of 0.996, 0.993, and 0.994. We also prove that CIMA, assisted by quantization, has the smallest model size compared to the CNN and DOLARS model sizes. Finally, we demonstrate that CIMA performs well for imbalanced datasets, where CIMA's recall on upstairs and downstairs activities is better than DOLARS and CNN, with values of 1.00 and 0.98, respectively.

***Key Words*: classification integrated moving average, human activity recognition, smartphone, accelerometer, imbalanced dataset**

1. Introduction

Human activity recognition (HAR) is a research field that focuses on detecting user activities such as sitting, standing, and walking, which has wide applications such as smart homes and sports [1]. HAR is divided into several types based on the type of sensor used, including environment-based HAR and smartphone [2]. Research such as that conducted by Lupion *et al.* [3] combines these two types of HAR in a HAR method called *distributed online activity recognition system* (DOLARS). The research detected 14 types of activity, where the study was aimed at smart homes, while the actions seen in this research were indoors. This research's superior machine learning method is random forest.

Some progress has been made in smartphone-based HAR. For example, Xu *et al.*'s [4] smartphone-based research uses convolutional neural networks (CNN) to detect several types of activity, including walking, jogging, climbing stairs, and descending stairs. That research shows that CNN has better accuracy than support vector machine (SVM) in detecting these four activities.

Activity detection using the accelerometer on a smartphone is sequential classification. In previous research, we discovered a method called classification integrated moving average (CIMA), which is effective for the intelligent lighting sequential category [5]. This method predicts the presence of movement data produced by the passive infrared (PIR) sensor. Meanwhile, the classification model is k-*nearest neighbor* (KNN). We highlight the research gap, where there is a research opportunity to apply the CIMA method to smartphone-based HAR and compare it with state-of-the-art prediction models.

Our study aims to evaluate the performance of CIMA when applied to HAR using data from smartphone accelerometers. We get the smartphone accelerometer dataset from Kaggle. The dataset consists of several activities: walking, jogging, climbing, and descending stairs. We use three types of classifiers for benchmarking: KNN, which we use at CIMA; random forest, operated in DOLLARS; and CNN. We comprehensively analyzed the results of these three methods, including imbalance and model size.

To our knowledge, a study has never applied CIMA to HAR using smartphone accelerometers. Following are our research contributions:

1. A more optimal CNN model for HAR using time step CIMA windowing analysis results.
2. HAR method that has the optimal model size required for real-time systems.
3. Optimal method for vulnerable *imbalanced dataset* in HAR case study.
4. The DOLARS method uses smartphone accelerometers for jogging, going upstairs, and going downstairs with recall values of 1.00, 0.99, and 0.97.

Next, our paper is organized systematically: Section 2 contains documents highlighting the novelty of our research. Section 3 shows our methodology, which includes our proposed CIMA windowing method. Section 4 presents proof of our theory. Finally, Section 5 reports the achievement of our research objectives.

2. Related Works

In this section, there are several new things about HAR, but we limit it to HAR that uses smartphone accelerometers, CIMA, and windowing algorithms. Several studies have applied several *advance* models to HAR on smartphone accelerometers. Xu *et al.* [4] based smartphones using CNN to detect several types of activity, including walking, jogging, going upstairs, and going downstairs. This research shows that CNN has better accuracy than SVM in detecting these four activities. On the other hand, in a previous study, we found an effective CIMA method for intelligent lighting sequential classification [5]. This method predicts the presence of movement data generated by the PIR sensor. There is a research opportunity to apply the CIMA method to smartphone-based HAR and compare it with state-of-the-art prediction models.

Several windowing algorithms are usually proposed in various signal-processing case studies. Gannouni *et al.* [6] proposed a windowing algorithm for feature extraction in *electroencephalography* (EEG) to perform emotion detection. Lupion *et al.* [3] creates a dynamic sliding window in a HAR method called DOLARS. This active sliding window has a different number of windows for additional sensors and has a different window size for each window. The superior machine learning method in this research is random forest. There were 14 types of activity detected in the study. However, jogging was not carried out because the investigation was aimed at the smart home. The activities seen in this research are indoor activities. There are two-fold research opportunities. First, proposing a new windowing algorithm for CIMA is a research opportunity. Second, to use DOLLARS for outdoor activities such as jogging. Table 1 summarizes our explanation while highlighting our research contributions.

3. Proposed Method

We propose a research methodology to achieve our research objectives. First, we obtained a smartphone accelerometer dataset from Kaggle consisting of several activities, such as walking, jogging, climbing, and descending stairs. We perform three types of pre-processing on the dataset: DOLARS windowing, CIMA windowing, and pre-processing CNN. We use three types of classifiers for benchmarking: KNN, which

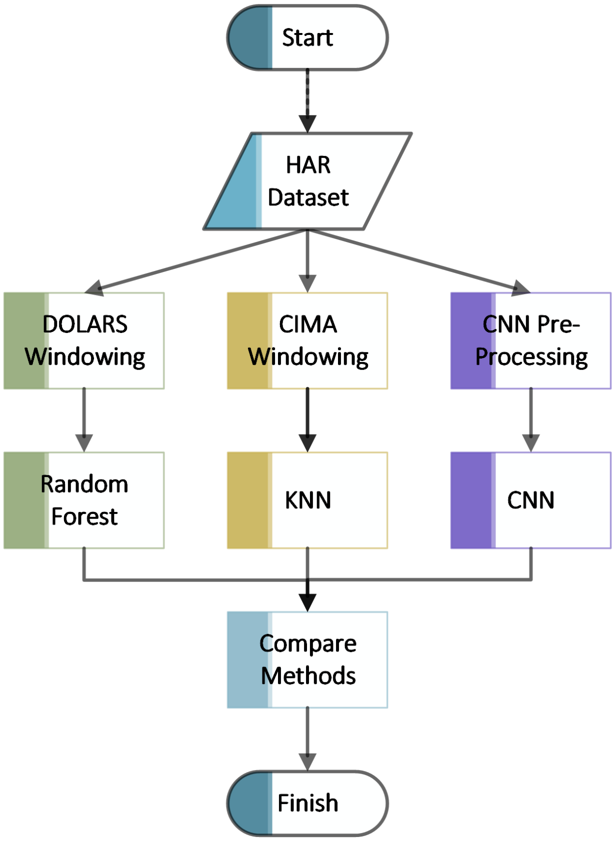

Figure 1. Our proposed methodology.

we operate at CIMA; random forest, which is used in DOLARS; and CNN. We comprehensively analyzed the results of these three methods, including in terms of imbalance and *model size*. Figure 1 shows our practice in a flowchart.

3.1 HAR with Smartphone Accelerometer

HAR is the process of identifying a person's activities through a combination of sensors and machine learning [7]. HAR has a taxonomy based on the type of sensor used, where the first group of HAR is video-based and the second is sensor-based [8]. Then, sensor-based HAR is divided into environment-based, wearable-based, and smartphone-based. HAR using smartphone-based sensors becomes interesting because much information can be obtained from smartphones at low prices [9].

Table 1. Literature study on HAR research using smartphone accelerometers

Cite	HAR	*Smart-phone*	CIMA	Windowing
[3]	✓	✗	✗	✓
[4]	✓	✓	✗	✗
[5]	✗	✗	✓	✗
[6]	✗	✗	✗	✓
Proposed Method	✓	✓	✓	✓

Many sensors can be found on smartphones and have been used in several studies. Sampaio *et al.* [10] used a smartphone with a gyroscope, accelerometer, and magnetometer sensors. Al-Turjman *et al.* [11] utilized the global positioning system (GPS), radio frequency identifier (RFID), camera, and microphone systems on smartphones. An accelerometer is a sensor that can detect acceleration or changes in speed in three axes, x, y, and z [12].

Using a smartphone accelerometer, the HAR process consists of four stages: Sensing, pre-processing, model training, and [13] classification. In the sensing process, the accelerometer collects human movement data, producing three features: the x-axis, y-axis, and z-axis. These three features plus a movement label for each data: walking, jogging, going upstairs, or going downstairs. In the pre-processing stage, there is usually a feature extraction step; time series data is processed into better-understood data with a classification model at the next sub-process. The data that has been processed becomes training data, where a classification model is formed based on the training data through the model training process. This study compares three models: KNN, random forest, and CNN. Finally, if the classification model has been tested and performs well, it can classify the four activities based on the mentioned labels. Figure 2 summarizes the explanation of the HAR process flow with a smartphone accelerometer in an image.

We use a dataset from Kaggle uploaded by the Wireless Sensor Data Mining (WSDM) Lab. For User 1, the dataset size is 29,978 lines, with a sampling rate of 20 Hz. There are four labels in the dataset, namely 'Walking,' 'Jogging,' 'Upstairs,' and 'Downstairs,' with the number of datasets for each label being 12,861, 11,056, 3,120, and 2,941, respectively. Each label represents one activity we apply label encoding in the pre-processing stage. Label encoding converts labels in text form to numbers. This step is important because some models and analyses cannot process text.

3.2 The CIMA Windowing Algorithm

CIMA is a classification of time series data case studies that utilize moving averages to increase the correlation of time series data with predicted labels [5]. The process involves several simultaneous moving average windows and Pearson correlation coefficient (PCC) analysis. The number of moving average windows can vary and be selected via several feature selection methods.

CIMA windowing is a pre-processing method,

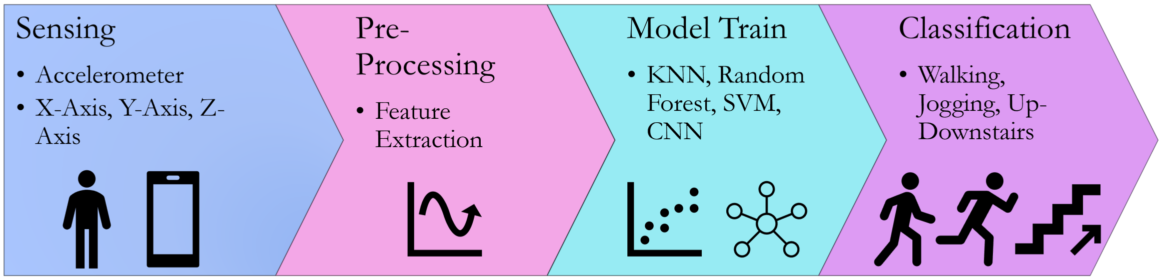

Figure 2. The HAR with smartphone accelerometer process flow.

specifically, a feature extraction that extracts features by simultaneously applying several moving average windows to a signal-like feature. Our hypothesis is when applied to smartphone accelerometer data, then it will increase the PCC of the feature and enhance the classification ability in defining human activities.

Algorithm 1 shows our CIMA windowing algorithm. There are four inputs, where x is the feature in the dataset, y is the label, N is the amount of data, and J is the desired number of windows. The output is MA, *double pointer* to a two-dimensional data structure in the form of a new feature of MA with several windows and the original data. The variable V is a multiplier that differentiates the window size of each MA. Lastly, do a PCC analysis of each new feature. If the new PCC is better than the original PCC, then end the CIMA windowing process, but if not, continue one more iteration using a different W size. To optimize features in the classification process, we run the *mean decrease in impurity* (MDI) algorithm [14].

We benchmark our CIMA windowing with other windowing methods also implemented for HAR. Lupion *et al.* [3] created a HAR called DOLARS, which also has its windowing approach. The DOLARS window uses four different windows for the accelerometer, each with a different sampling rate and window size. The feature extraction from each window is carried out in the maximum, minimum, and average values. With four windows, three features for each window, and three extracted features for each original feature, the total features for DOLARS windowing is 36.

We compared three classification methods: KNN, which was the superior model in our previous study [5], random forest, which was the definitive model in Lupion *et al.*'s study [3], and then CNN which was superior in Xu *et al.*'s [4] research. KNN is a method that classifies new data based on the distance to existing data in the feature space. The latest data class is determined based on majority voting based on k nearest neighbors [15].

HAR can be classified as a real-time [16] system. Meanwhile, Duggal *et al.* [17] stated that model size is important in real-time systems because they have a harsh environment (for example, small memory size). Model compression is a method for reducing model size and is motivated by real-time constraints. Quantization is a model compression method that reduces the size of a machine learning model by changing its data type to make it more compact without reducing its performance [18]. We apply quantization so that the CIMA model we produce is more compact. Before changing the data type, quantization goes through one important stage: scaling. The function of scaling is to save important values when fractional values are lost due to data type changes.

Random forest is an ensemble learning method of the bootstrap-aggregating (bagging) type. Random forest utilizes several weak learners in the form of a decision

Algorithm 1: The CIMA Windowing Algorithm

Data: x, y, N, J
Result: x'
while $|PCC_F| \geq |PCC_M|$ **do**
    Adjust W;
    MA $\leftarrow [J][N-W]$;
    for $i \in \{W, \ldots, N\}$ **do**
        for $j \in J$ **do**
            $V \leftarrow 1 - j \times \frac{1}{J}$;
            Assign a moving average value to MA$[j][i]$ with the following equation:

$$\mathrm{MA} = \frac{1}{V \times W} \sum_{n=i-V\times W}^{i} x_n \quad (1)$$

        end
    end
    Calculate the $\mathrm{PCC_F}$ and $\mathrm{PCC_M}$ with the following equation:

$$\mathrm{PCC} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \quad (2)$$

end
$x' \leftarrow MDI([x, MA])$;

tree. Then, the final result of the model is a majority vote from all weak learners [19]. Finally, CNN is a type of deep learning where one type of sublayer is the convolutional layer, namely a kernel that carries out the convolution process on the input data [20]. Here, we use 1D-CNN because our data is in the form of a time series signal. Our model has five hidden layers: one 1D convolutional layer, one dropout layer, one max pooling layer, one flatten layer, and one fully connected dense layer. The output is a fully connected dense layer with size four and a softmax activation function.

In a dataset, an imbalance can occur when the number of one label is much greater than the other labels [21]. The impact of imbalance is twofold [22]. First, imbalance can affect the performance of the classification model. Second, imbalances can affect performance measurement; Some metrics become ineffective in measuring model performance due to imbalanced data. In an imbalanced dataset, the label with the most *data item* is called the majority label. Meanwhile, apart from the majority label, it is called the minority label. The degree of imbalance is calculated using a metric called *imbalance ratio* (IR), with the following formula:

$$\mathrm{IR} = \frac{N_m}{N_i} \tag{3}$$

where N_m is the number of data items labeled as the majority, then N_i is the number of data items labeled as the minority i.

Singh *et al.* [23] said that accuracy cannot measure the performance of a model with an imbalanced dataset because if the results are good, there is a possibility that the results are only a representation of the majority label. In other words, accuracy may hide the poor performance of minority labels. On the other hand, recall is a good metric in imbalanced datasets because it does not involve values from other classes [24].

4. Results dan Discussion

4.1 Results

After downloading the HAR data from Kaggle and going through pre-processing, we applied CIMA windowing. We set $J = 10$, where, through an optimization process in Algorithm 1, we find that the optimal W is 240. Our CIMA windowing process produces 33 features, whereas, through MDI, that number is reduced to 16. Apart from reducing the number of features, the MDI process also improves the performance of the CIMA classification carried out by KNN. Initially, the accuracy was 0.979; after MDI, the HAR performance became 0.999. The next target is to simplify the CIMA model without reducing its performance. We reduced the model size from 2,035 kB to 479 kB through quantization. On explaining the implication of our findings, CIMA windowing can produce higher performance than DOLARS windowing, albeit having less used features. On the other hand, unexpectedly, DOLARS, the superior HAR method in previous research, under-performs the CIMA method.

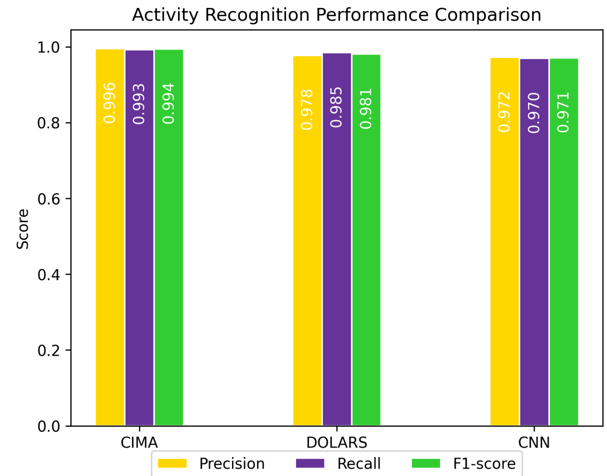

Figure 3. Comparison of the performance of three classification methods with CIMA windowing.

We then compare the performance of CIMA with DOLARS and CNN, where the comparison metrics are *precision*, recall, and *f1-score*. We apply the W values from the CIMA analysis results to the CNN windowing process. Figure 3 shows the results, where CIMA is better than the other two methods on all three metrics measured. The values are 0.996, 0.993, and 0.994, respectively. DOLARS is the second-best method, where the nominal of the three metrics are 0.978, 0.985, and 0.981. The final CNN performance values are 0.971, 0970, and 0.971.

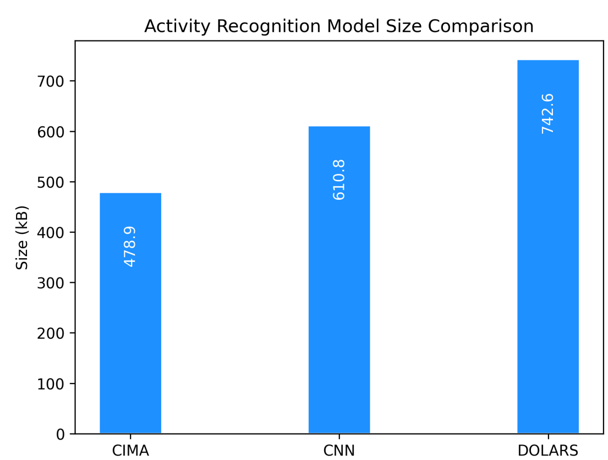

Figure 4. The comparison between CIMA, DOLARS, and CNN model size.

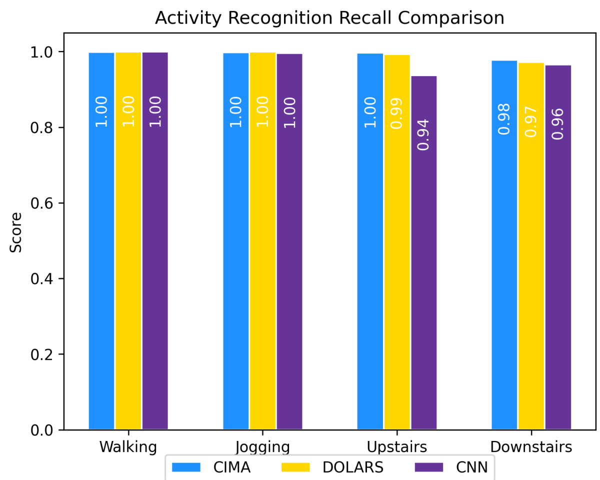

Figure 5. Performance of each method on the classification of each activity.

In addition to prediction performance, we also compare the size of the CIMA model with DOLARS and CNN. This is related to the real-time constraints of our system. Figure 4 shows the size comparison, where CIMA has the smallest model. Although DOLARS performs better than CNN, its model size is the largest. The CNN model size is 610.8 kB, while the DOLARS model size is 742.6 kB.

Dataset imbalance is calculated from the training data. Measuring each data item, 'Walking' becomes the majority label, with 6,309 data items. With 5,493 data items, 'Jogging' is the minority label with the lowest IR, namely 1.14×. The IR value is included in the mild imbalance category. 'Upstairs' and 'Downstairs' are the second and first highest minority labels. With 1,595 and 1,472 data items, the IR values are 3.96× and 4.29×, respectively. Both IR labels are in the moderate imbalance category range. Table 2 summarizes our explanation.

Finally, we compare the performance of each method in detecting each activity with the recall of each label. Figure 5 shows the comparison. Each method predicts 'Walking' and 'Jogging' perfectly. However, only CIMA could get the 'Upstairs' recall with a perfect score. DOLARS predicted 'Upstairs' with a performance of 0.99, while CNN predicted 'Upstairs' with a recall of 0.94. Finally, despite being imperfect, CIMA still shows 'Downstairs' with the highest recall value compared to DOLARS and CNN, namely 0.98 compared to 0.97 and 0.96.

4.2 Discussion

Some papers call KNN a 'lazy learner' because the KNN training process does not build in any computational logic [25]. In effect, KNN feeds all the training data into its model and then classifies the unknown data using the training data. This highlights the importance of reducing the size of the training data to reduce the size of the KNN model in CIMA. Existing research has demonstrated the effectiveness of quantization in reducing model size, as we show in this study [26].

We use the CNN model from paper [4], which uses the model for HAR. The HAR with CNN in the article was reported as 0.94, while the CNN we created had an accuracy of 0.98. The paper writes that it uses a time step with a value of 90 but does not explain the origin of the time step value. Our CNN time step is 240, which we adopt from the W value in CIMA windowing. Our research contributes to a more optimal CNN model for HAR using time step results from CIMA windowing analysis.

HAR can be classified as a real-time system [16]. Meanwhile, Duggal *et al.* [17], in their research, especially on advanced driving assistance systems (ADAS), said that real-time systems are related to the size of the machine learning model because real-time systems have a harsh environment (for example, small memory size). This research proves that CIMA supported by quantization has a smaller model than CNN and DOLARS for HAR. Our research contribution is the HAR method with the optimal model size required for real-time systems.

Hu *et al.* [27], in their research, said that the HAR dataset is prone to imbalance due to varying activity frequencies. This is also seen in our dataset, where 'Upstairs' and 'Downstairs' fall into the moderate imbalance category. DOLARS and CNN seem to be affected by this imbalance condition because the recall of these two labels is much lower than the others. On the other hand, CIMA's performance on both labels is better than that of both methods. Our research contribution is an optimal method for the vulnerable imbalanced dataset in the HAR case study.

Additionally, DOLARS is a HAR method created for smart homes. Lupion *et al.* [3] classifies 14 types of activities, but among them, there is no jogging, going upstairs, and going downstairs. Our contribution is the DOLARS method using smartphone accelerometers for jogging, going upstairs, and going downstairs with recalls of 1.00, 0.99, and 0.97, respectively.

Some limitations still come across our research regarding the funding and time we have to conduct our research. Related to that matter, a broad possibility of future work is foreseen. Our work is limited to only one dataset collection. There is an opportunity to explore the potential of the CIMA algorithm across diverse datasets and varied conditions. Then, toward applying our research for commercial use, there is an opportunity to investigate the scalability aspects of the CIMA algorithm

Table 2. The imbalance condition of the HAR training data.

Label	'Walking'	'Jogging'	'Upstairs'	'Downstairs'
Data Items	6,309	5,493	1,595	1,472
Status	*Majority*	*Minority*	*Minority*	*Minority*
IR	–	1.14×	3.96×	4.29×
Level	–	*Mild*	*Moderate*	*Moderate*

concerning larger user groups or a more extensive range of activities.

Furthermore, our research is limited to only four activities. In the future, extending the scope of activity recognition beyond the specific activities studied (e.g., walking, jogging) is possible. Then, only two imbalance conditions are found in our research. In further research, we can conduct comprehensive experiments to assess the proposed method's performance under various imbalances within datasets. Subsequently, our research is limited to only two state-of-the-art methods. It is possible to consider an expanded benchmarking approach encompassing a wider array of existing methods and including the latest advancements in the field. Lastly, here, the case study is only a smartphone accelerometer. Further, we can investigate the adaptability and generalizability of the proposed method beyond smartphone accelerometers, exploring its feasibility and effectiveness when applied to diverse sensor types or configurations.

5. Conclusion

We developed The CIMA method in previous research to improve the performance of smart lighting. However, in this study, we intuitively use it for HAR and evaluate its performance. We use DOLARS and CNN as benchmarks for our method. We also evolved DOLARS from HAR for smart homes to HAR for jogging, going upstairs, and going downstairs. The test results show that with $J = 10$ and $W = 240$, CIMA's performance is better than DOLARS and CIMA with recall, precision, and f1-score of 0.996, 0.993, and 0.994, respectively. With the help of quantization, we also prove that CIMA has the smallest model size compared to the CNN and DOLARS model sizes. Finally, our key findings are that CIMA performs well for the imbalanced dataset, with CIMA's results for going upstairs and going downstairs better than DOLARS and CNN, with values of 1.00 and 0.98, respectively. The significance of our research lies in its advancement of human activity recognition, by demonstrating superior performance over existing state-of-the-art methods, particularly in handling imbalanced datasets, contributing to more accurate and reliable real-world applications. The novelty of our research stems from pioneering a robust and effective approach in human activity recognition, showcasing a notable leap forward in addressing the challenges posed by imbalanced data, potentially impacting various domains reliant on accurate activity recognition systems.

There are many possibilities to expand our work in future research, for example expanding our research to a broader option of dataset collections, other sensors, and various activities. Then, we can compare our study with more state-of-the-art HAR methods. We can also observe our method with a wider set of imbalance conditions. Lastly, in commercializing our research, we can test the scalability of our method by expanding the devices in use and observing the consequences.

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