Feature-based Method for Nurse Care Complex Activity Recognition from Accelerometer Sensor

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ABSTRACT

As the number of patients in hospitals is increasing day by day, proper monitoring and hospital care towards patients must be ensured. In this regard, Nurse care activity recognition can play a significant role in improving the existing healthcare system. Research in this domain is very challenging because nursing activities are very complex and troublesome than other normal activities. Nursing activities are dependent not only on nurses but also on the patients' various states of illness. As a result, each activity has a high intra-class variation. We have participated in '3rd Nurse Care Activity Recognition Challenge 2021' and proposed a simple machine learning approach to recognize nursing activities. After data pre-processing and feature engineering, we have used several machine learning algorithms. Among them, we have achieved our best results in the Random Forest model. Using this model, We have obtained 72 percent validation accuracy classifying several challenging activities.

CCS CONCEPTS

• **Computing Methodologies → Machine Learning** ; • **Data Preprocessing →** *Low-Pass Filter, Re-sampling*; • **Algorithm →** Random Forest.

KEYWORDS

Nurse care activity Recognition; Smartphone; Accelerometer Data; Class imbalance; Machine learning; Random Forest

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1 INTRODUCTION

Recent advances and improvements in different sensors are playing a significant part in human action analysis, which is becoming increasingly popular in numerous sectors such as elderly person monitoring [3, 4], locomotion and transportation [5, 6], context-aware [7], security-homes [8], human-robot interaction [9], and so on. Sensor-based human activity recognition deals with motion sensor data such as accelerometer, magnetometer, gyroscope, gravity, Bluetooth sensors, and so on. These types of data provide the most important features which are proficient to recognize a broad range of activities such as walking, running, riding a bicycle, sleeping, jumping, lifting weights, and so on. Aside from thriving developments and booming growth in low-cost and easily worn body sensors, sensor-based HAR requires lower hardware requirements and processing time than video-based HAR. Nowadays there is a lot of interest in healthcare research but it is not developed yet. There are just a few publicly available datasets due to the tiny number of patients willing to contribute data. Because therapists prescribe various wearable sensors to be placed on patients' bodies, it raises concerns about patients' comfort and privacy.

Researchers have made a lot of progress and explored various machine learning and deep learning frameworks in the HAR domain. C. Dewi et al. [15] used the Random Forest model to classify different human actions. They also used SVM, KNN, and LDA models with a different feature set to get the best performance. Akram Bayat et al. [13] extracted various important statistical features from accelerometer data to recognize human activities. They used 5 different classical machine learning algorithms and performed fusion mechanism and achieved an overall 91.15% accuracy. Researchers in [14] proposed a CNN model for robust action recognition given data from different body sensors. F. Rustam et al. [16] provided a Deep Stacked Multilayered Perceptron (DS-MLP) model to recognize different human actions and achieved highly accurate results. In their proposed method, they have used a meta-learner and also five different MLP models. Mekruksavanich et al. [17] used a 4-layer CNN-LSTM hybrid model to improve action recognition performance. They implemented their model on the UCI-HAR dataset and increased 2.2 percent accuracy compared to the previous state-of-the-art approaches. A. Das Antar et al. [18] represented an in-depth analysis of various machine learning approaches used in some benchmark datasets.

Due to the rising number of patients in hospitals, adequate monitoring, proper treatment, and thorough records of medical care towards patients must be ensured. Human action analysis and recognition can be performed via visualization of video recordings. But in reality, it takes a lot of time and effort. In this context, automated action analysis of caregivers or nurses in hospitals can help patients' health, optimize the process of hospital care towards patients and improve overall healthcare systems. Sozo Inoue et al. [11] provided a big nursing dataset for mobile activity recognition. Nursing activity recognition is a difficult and challenging task unlike normal activities like, jogging, walking, running, standing, sitting etc [12]. Because, nurses carry out actions on patients. For example, instead of getting up from bed, nurses help the patients to get up. There is a large intra-class variation in nursing activities because traits of an action depend on both patients and nurses. This type of research is very challenging as it has not been studied yet in other activity recognition domains.

There have been very few studies on nursing activity recognition. The nurse care activity recognition challenge was organized in 2019 [19, 20] and 2020 [21], where several teams participated and provide satisfying results. Researchers can use their expertise and experiences to improve nurse care activity detection tasks by participating in these challenges. In 2019, four teams participated in the challenge. Among them, Team 'IITDU' [22] was ranked first in the competition. They extracted some hand-crafted features from motion capture and meditag sensor data and used an ensemble of KNN classifiers and achieved 87 percent accuracy in 10-fold cross-validation. First runners-up team TDU-DSML [23] proposed a spatial-temporal graph convolutional network (ST-GCN) to process 3D motion capture data to recognize nursing activities. In the 2020 challenge, the top 3 teams proposed a machine learning approach to solve the nursing activity challenge. The Winner team 'MoonShotBD' [24] achieved their highest score using the KNN algorithm. The 2nd team 'Team Apophis' [25] used the random forest algorithm after feature engineering and obtained a satisfying score of 65 percent accuracy.

In this paper, we will propose a machine learning approach that will correctly classify highly correlated and imbalanced nursing activities of 3rd Nurse care activity challenge. Our method is very simple and can be trained with low computational costs. The rest of the paper is organized as follows. Section 2 gives a short review of the dataset in this challenge. Section 3 focuses on our proposed method which mainly consists of feature engineering and model training. The last two sections describe the results our method and few future works regarding this challenge.

2 DATASET DESCRIPTION

The dataset [1] consists of the activities of the nurses helping patients to perform their daily life activities. The dataset contains only tri-axial accelerometer sensor data acquired from a smartphone located in the pocket of a nurse performing their daily works at a healthcare facility. Twelve professional nurses took part in the data collection process. In the dataset, we found different Teatime formats in the train and label file. In this challenge, the dataset is more imbalanced and troublesome than the previous challenges. Because in the previous two challenges, the dataset consists of only 6 and 12 activities respectively. There are a total of 28 activities which are categorized into 4 groups. These activities along with 4 groups are shown in Figure 1.

In both train and test dataset, there were lots of duplicate values.

Group Activity Name	Number of Activities	Label in the Dataset	Activity Name
Direct Care	18	1	Vital
		7	Morning gathering/ exercises
		13	Family/guest response
		2	Meal/medication
		8	Rehabilitation / recreation
		14	Outing response
		3	Oral care
		9	Morning care
		19	Get up Assistance
		4	Get up Assistance
		10	Daytime user response
		20	Change dressing assistance
		5	Bathing/wiping
		11	Night care
		21	Washing assistance
		7	Treatment
		12	Nighttime user response
		28	Emergency response such as accident
Residence Cleaning	4	15	Linen exchange
		23	Preparation and checking of goods
		24	Organization of medications
		16	Cleaning
Documentation/ Communication Activities	4	17	Handwriting recording
		22	Doctor visit correspondence
		25	Family/doctor contact
		18	Delegating/meeting
Other	2	26	Break
		28	Special remarks/notes

Figure 1: List of Activities Performed by Nurses

Majority of the samples in train dataset had no label. Therefore, we had to drop these samples before feature extraction method. In the dataset, the samples were collected at a varying sampling rate. The dataset was very noisy and no prepossessing method was applied in it. In the training dataset, the imbalance ratio was extremely high. For some activities, the imbalance ratio exceeded 5000. This type of research and dataset is very rare in HAR domain. In the test dataset, we found samples from only nine user files instead of twelve.

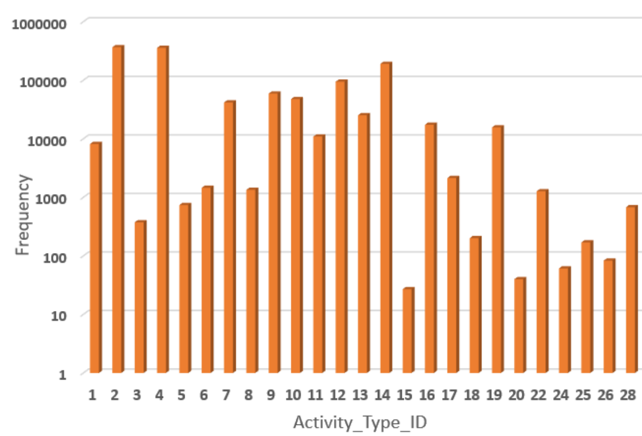

Figure 2: Distribution of activities in train dataset

3 METHODOLOGY

In this Section, we will describe our workflow for recognizing the nurses activities on dataset [1]. We have applied feature-engineering

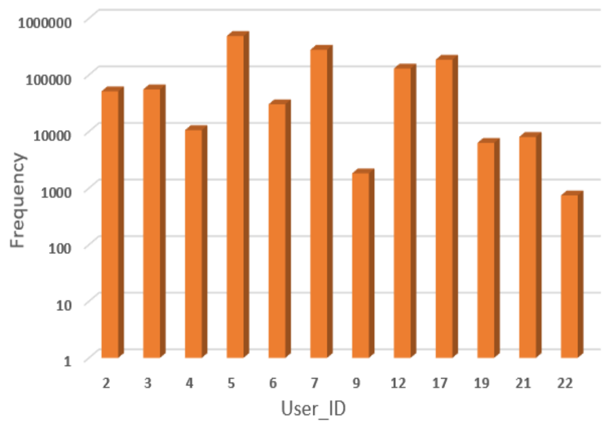

Figure 3: Distribution of Nurses performing activities in train dataset

based classical machine learning technique for this challenging task. Our whole workflow is divided into three steps: Data pre-processing, Features extraction, Classification. Figure 4 depicts the overall workflow scenario.

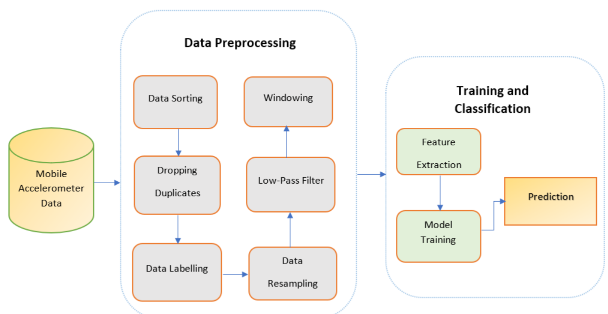

Figure 4: Workflow diagram of our proposed methodology

3.1 Pre-processing

Pre-processing is the most key component of any technique, especially when dealing with sensor-based data. Because, the majority of the time, raw sensor data is unclean, noisy, and unstructured, which can lead to misclassification of several classes. The raw data of the competition consist of three axial (X, Y, and Z axis) accelerometer data, as well as a timestamp gathered from accelerometer sensors. The unlabeled data are in one file, while the labels are in another file are merged together to label the data. Because the timestamps of the raw and label data are in different time zones, they are all converted to UTC format. All of the data that are duplicated or unlabeled was discarded. Several activities are too short in period (less than 1 second) to be labeled also discarded since they have a little impact on the overall classification. After confirming these procedures, the raw data is cleaned and formatted so that it can be segmented and windowed in the next stage. Since machine learning models typically require fixed-size input and time series data are not well sampled, we may turn a time series problem into a machine learning problem using the windowing approach. By changing the settings of the windowing technique like window size, and step size, we can fine-tune our models. We have divided a label into numerous segments depending on the time difference (threshold 2 second) between two consecutive data points before performing the windowing approach. If there is a significant time difference between two consecutive data points, the re-sampling technique will generate data with similar characteristics, which may result in the model being under-fitted. As a result, label segmentation is a pretty effective step. The sliding windowing approach is then used with different window sizes as well as different step sizes. The data is then normalized for each window, with the statistics of the segment where the data is being sampled. Sensors are used to capture raw data at a sampling rate of 20 Hz. However, due to sensor failure or other factors, the training data sampling rate is between 5 and 10 Hz. That is why, we have re-sampled the original data at a rate of 20 Hz. We have selected linear interpolation for the re-sampling method over the other interpolation methods because it best fits the data points. We have used a $2nd$ order Butterworth low-pass filter with a cut-off frequency of 3 Hz to remove noise from re-sampled data. The data is also smoothed using the median filter.

3.2 Extraction of Features

Rather than dealing with raw data, feature extraction is a powerful tool for dealing with sensor data. Finding hidden patterns in raw data is extremely difficult for machine learning or deep learning models. The primary goal of feature extraction is to extract features from multidimensional sensor data in order to achieve the optimal recognition result possible. Various signal statistics, filter response, and the co-efficient of various transformations are among the features. We have analyzed the data in both the time and frequency domains for this competition. The low-pass filter mentioned before is used to create a time domain noiseless signal. The frequency response of the time domain signal is then obtained using the Fast Fourier Transform (FFT) using the equation:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{i \cdot 2\pi kn}{N}} \tag{1}$$

where, x_n and X_k are the time domain and frequency domain signal (complex form) respectively. We have only considered the magnitude response rather than phasor response of the frequency domain signal.

On both the time and frequency domain signals, the jerk signal is then computed using the gradient operation on three axes. Following that, using the equation 2, the magnitude of each time and frequency domain signal, as well as its jerk, is calculated.

$$A = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{2}$$

where, A represent the magnitude of the signal whereas A_x, A_y, and A_z are the three components of the signal. Finally, both time domain and frequency domain signals are analyzed for statistical

features.
Mean: It is defined as the sum of all data divided by the total number of observation.

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} \quad (3)$$

where, x_i is the i_{th} data and N is the total number of observations.
Standard Deviation: It is the measure of variability of the data from mean usually defined as σ can be defined as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N-1}} \quad (4)$$

Median Absolute Deviation (*MAD*): It is the average absolute distance from the data points to the mean is expressed as:

$$MAD = \frac{\sum_{i=1}^{N} \mid x_i - \bar{x} \mid)}{N} \quad (5)$$

Entropy: It is a metric for a system's randomness, indicating the average amount of uncertainty in the possible outcomes. Entropy of just Shannon entropy can be expressed as:

$$H(X) = -\sum_{i=1}^{N} P(x_i) \cdot \log P(x_i) \quad (6)$$

where $P(x)$ is the probability distribution function.
Inter Quartile Range (*IQR*): It is the range in which the middle half of the data is found is simply defined as:

$$IQR = Q_3 - Q_1 \quad (7)$$

where Q_1 and Q_3 are the 1^{st} quartile and 3^{rd} quartile, respectively.
Skewness: It is the measure of the asymmetry from the mean of the data.

$$g = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^3}{(N-1) \cdot \sigma^3} \quad (8)$$

Kurtosis: It is a statistical measure of how much a distribution's tails diverge from the tails of a normal distribution.

$$k = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^4}{(N-1) \cdot \sigma^4} - 3 \quad (9)$$

Pearson's Correlation Coefficient: It is a test statistic for determining the statistical relationship (or association) between two continuous variables. If x and y are the two variables then it can be expressed as:

$$r_{xy} = \frac{n \cdot \sum xy - \sum x \sum y}{\sqrt{(n \cdot \sum x^2 - (\sum x)^2) \cdot (n \cdot \sum y^2 - (\sum y)^2)}} \quad (10)$$

In Appendix, there are a collection of temporal and frequency domain features and its descriptions.

3.3 Classification

The most crucial aspect of a technique is this section. The overall classification performance is improved by selecting a suitable model and adjusting its hyper-parameter. There are 176 features set whereas the number of samples in training are varied due to the variable length of window size and step size. We have trained several models and are attempting to figure out the optimal model and its hyper-parameters. Because we utilize classical machine learning models, we do not normalize the features before training. The training and validation data are randomly separated using the stratified as its time before windowing at the ratio of 80% to 20%. The total time of training and validation data is about 1 day 12 hours and 10 hours respectively. We have used several machine learning models such as Random Forest Classifier (RFC), XGBoost classifier (XGB), K-Nearest Neighbors (KNN) and Support Vector Classifier (SVC). Based on validation accuracy, we have pseudo-trained the models and configured the best model and its hyper-parameters. Finally, the best model is trained on the entire dataset (train and validation). Using the fine-tuned model, we have predicted the activities on test data. Among these models, RFC performs the best.

4 RESULT AND ANALYSIS

We have analyzed the overall performance of several models in this Section, as well as various strategies for improving the models' accuracy. The above-mentioned segmentation method comes in handy because it prevents the windowing method from producing steady signals with similar characteristics. Data normalization is an important step in any methodology since it enhances the model's performance and reduces overall training time. The statistics (mean and variance) of each segment have been transferred to the each samples discussed in [10]. A simple linear normalization is conducted through the equation,

$$x_t^* = \frac{(x_t - \mu_1) \cdot \sigma_2}{\sigma_1} + \mu_2 \quad (11)$$

where, x_t^* and x_t are normalized and original data whereas μ_1, μ_2 and σ_1, σ_2 are the mean and variance of a particular segment and its samples respectively.
To determine the best fit of the data points, several interpolation methods are employed, including linear, spline of degree 2, 3, and higher order. The linear interpolation approach is one of them that works well on the dataset. The low-pass filter's cut-off frequency may also be adjusted, although a very low cut-off frequency (i.e. 1 Hz or less) distorts the original signal.
The settings (window size, step size) of windowing method are configured before tuning the models' hyper-parameter based on validation accuracy. We set three pre-defined settings for window sizes (2, 5, 10 second) and step size (0.5, 1, 2 second) respectively. On the majority of the models, 10 second window size with 2 second step size (80% overlapping window) performs well because small window size may not be suitable for extracting the hidden patterns from the data. The performance of different models with different settings are shown in Figure 5. Rest of the training processes are performed using this optimal setting.
The hyper-parameters of the model can be tweaked to increase overall recognition performance. However, determining the optimal parameters for any specific model is challenging. We have used a novel grid search technique that applies brute-force on a pre-specified parameters dictionary to determine the best parameters for a model. The search method also employs a five-fold cross-validation technique. After hyper-parameters tuning, the validation accuracy of each models are shown in Figure 6. The accuracy of the RFC outperforms all the time.
Another novel paradigm, sample weight, is described in this section. It automatically assigns a weight to each sample based on the

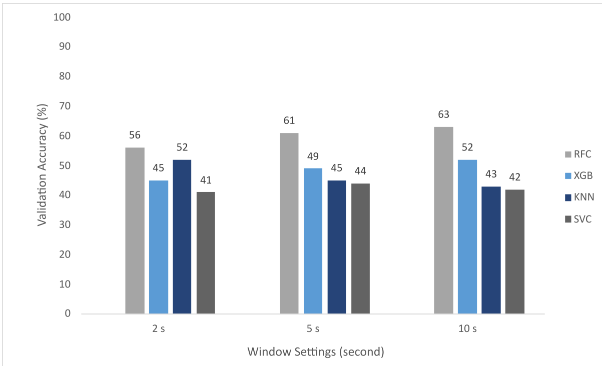

Figure 5: Performance of different models with window settings

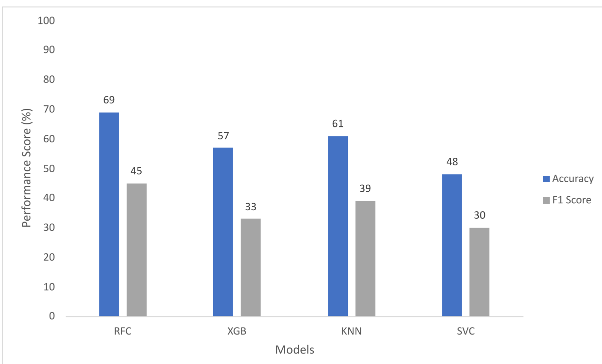

Figure 6: Performance score of different models after hyperparameters tuning

sample's quality. The quality of the samples are calculated according to the sampling theorem using Z-score. Z-score of a sample is determined using the following equation:

$$Z = \left| \frac{\mu_2 - \mu_1}{\sqrt{\frac{\sigma_1^2}{N_1} + \frac{\sigma_2^2}{N_2}}} \right| \tag{12}$$

where, μ_1, μ_2 and σ_1, σ_2 are the mean and variance of a particular segment and it's samples as well as N_1, N_2 are the number of samples respectively. The Z-score is a measurement of how extreme a sample is. The higher the Z-score, the more extreme the samples. Therefore, the weight of a sample is inversely proportional to the Z-score. Thus, geometric mean is suitable for the estimation of the mean. So, mean Z-score can be obtained from three axial Z-score using the following equation:

$$\bar{Z} = \frac{3}{\sum_{i=1}^{3} \frac{1}{Z_i}} \tag{13}$$

where, Z_i denotes the Z-score of a particular axis. Finally, the weight of a sample can be assigned as follow:

$$w_i = \frac{\frac{1}{\bar{Z}_i}}{\sum_{i=1}^{N} \frac{1}{\bar{Z}_i}} \tag{14}$$

where, w_i is the weight of a particular sample and N is the total number of samples. The accuracy comparison of RFC with and without assigning the samples weight is shown in Figure 7. A summary of the methods and environments are presented in Figure 8.

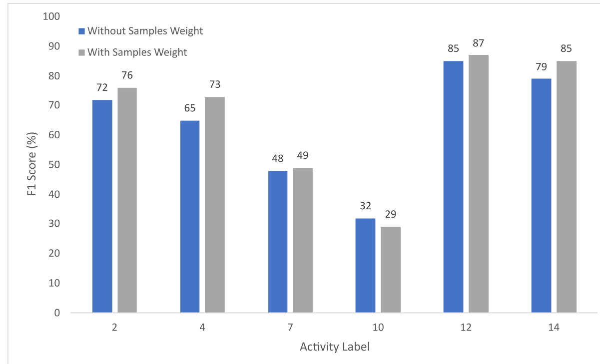

Figure 7: Performance comparison using samples weight on RFC

Used sensor modalities	Accelerometer
Features used	Mean, standard deviation, median absolute deviation, maximum, minimum, energy, entropy, inter quartile range, signal magnitude area, skewness, kurtosis, Pearson correlation co-efficient.
Programming language and libraries used	Language: Python and MATLAB. Libraries: panda, NumPy, matplotlib, Sci-kit learn, SciPy.
Window Settings	Window size: 10 second. Step size: 2 second. Window type: overlapping (80%). Data points per window: 200. Sampling rate: 20 Hz.
Training and Testing time	Training time: approximately 15 minutes. Testing time: 2 second.
Machine specification (RAM, CPU, GPU)	PC specification: RAM: 8 GB. CPU: AMD RYZEN 4000 @ 3 GHz. Google Colab: Free web version with CPU: 2 Intel® Xenon® @2.30 GHz. RAM: 12 GB.

Figure 8: Appendix: Summary of the methods and environments

5 CONCLUSION

This article exhibits the ability of machine learning algorithms to recognize challenging nursing activities and obtain promising results. We discovered that the majority of the activities in our dataset have a small amount of data. The advantage of machine learning is that when the data amount is small, conventional machine learning outperforms deep learning models employing smart hand-crafted features. In this nurse care activity challenge, we have used several machine learning algorithms such as XGBoost, Random Forest, Support Vector Machines (SVM) and achieved promising results. Among them, we have obtained our best results in the Random Forest algorithm. Furthermore, we have discovered that using fixed-width 10s windowing rather than 5s or 2s yields better results. In the future, we will add some complex statistical features to improve the results. The imbalance ratio is very high for some classes, and existing machine learning models perform poorly in distinguishing these actions. To solve this problem, semi-supervised learning like Generative Adversarial Network [2] can be used to create samples of imbalance classes in the future.

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