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Smote and OVO Multiclass Method for Multiple Handheld Placement Gait Identification on Smartphone's Accelerometer

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Abstract: Gait identification has been a well-known type of biometric recognition for many purposes. However, the usage and its application are still limited due to uncertainty factors that lead to its lack of use. One of the factors is the position of the smartphone. Current research uses pouch, pocket and other parts of the body but not handheld. The second factor is the nonstationary data that resemble the person which contains only a few meaningful dataset for learning purposes. The third factor is the ability of the classifier itself whether is it efficient enough in tackling the multiclass problem. In this research, investigation on the handheld smartphone position is proposed. Besides that SMOTE is applied to the dataset to increase its sample data before the training procedure. For classification, OVO multiclass structure is proposed instead of using a single classifier algorithm. From the result, it shows that handheld placement of the smartphone is viable for gait recognition. At the same time, using SMOTE and OVO methods do increase the accuracy of the gait identification.

Key words: SMOTE, OVO, handheld placement, gait identification, smartphone position

INTRODUCTION

Gait recognition has been widely used in many research and application. The field that widely uses this type of biometric recognition is the security. In security application, gait recognition is used for authentication and identification.

Gait is a term that comes from the manner of walking (moving on foot) which consist of two steps. A normal walk may consist of many gaits (Nickel, 2012). Every person may have their own walking style or gait which make it as a unique identifier.

In gait recognition, generally there are 3 ways in capturing the gait signal. The methods are machine vision, floor sensor and wearable sensor (Gafurov *et al*., 2006). The advantage of the machine vision is the ability to capture from a distance. For the floor sensor and wearable sensor, the advantage is the ability by providing unobtrusive gait authentication and identification.

With the rapid development of Micro Electro Mechanical System (MEMS) technology, gait signal of a person can be recorded easily without the need of the expensive devices. Now a days, the smart phone is part of it and most of the smartphone do equip with accelerometer and gyroscope which are part of Inertial Measurement Unit (IMU). In the current gait research and application using the smartphone most of the time the smartphone is placed in the pocket or in the pouch. However, in the real situation, it is hard to get the gait signal if the particular person does not have a pocket or pouch to be used as a placement for the smartphone. The best solution is to be placed on the hand. However, this poses a question whether the captured signal from the smartphone on hand is viable for the identification process. Generally, there are few complicated steps that need to be taken in performing gait recognition using machine learning methods. The steps involved are data acquisition, pre-processing, segmentation, feature extraction and recognition (Sprager and Juric, 2015).

In wearable sensor using a smartphone, the placement positions vary among the part researchers. Most common positions are in pocket (Derawi and Bours, 2013; Sun *et al*., 2014; Hoang *et al*., 2015), pouch (Sun *et al*., 2014; Ngo *et al*., 2014; Nickel and Busch, 2013) clipped to the waistband of the clothes (Frank *et al*., 2013) and multiple body positions (Ren *et al*., 2015). None of them tried placing the smartphone on the hand. However, according to Derawi and Bours (2013), Gafurov *et al*. (2006) and Das *et al*. (2010) there is a method to overcome the sensor variation from multiple

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placements which is by calculating the magnitude from the acceleration signal. However, according to the research experiment, somehow by doing this in this work does decrease the classification accuracy due to the low informative dataset. In this experiment, another problem that can be seen is the type of data which is non-stationary added with the low number of samples obtained for training which influence the class distribution (Mouchaweh and Lughofer, 2012; Sugiyama and Kawanabe, 2012). In-order to get an optimum result, data collection need to be in a long distance. However, it would be difficult if the area is small. Before training can be done to any machine learning algorithm, the amount of data should be sufficient in producing good accuracy. If the dataset is small, the dataset needs to be oversample or if the dataset is too huge, it needs to be undersampled.

In dataset situation, the characteristics of the dataset do influence the classification accuracy. According to Sugiyama and Kawanabe (2012), most people assume that low classification accuracy gained because of the bad features selection but instead, it is because of the dataset itself which is imbalanced. Non-stationary data also do cause bad classification accuracy. The main cause of this problem is due to the density of the dataset which is not well distributed among all classes. However, according to Jain *et al.* (2014) there are 2 approaches that can be taken which is at the data level or at the algorithm level. At the data level, re-sampling is the option such as oversampling and undersampling. At the algorithm level the methods include adjusting the cost of various classes, probabilistic estimation and decision threshold.

In classification, multiclass classification has been well known in many researches. One of the well-known methods is One-Vs-One (OVO) classification. The rationale of using this method is to disseminate the overlapped classes boundaries (Fernandez *et al.*, 2010) which can be seen in Fig. 1. The idea of using this method is to transform the original multiclass problem into binary subsets using binarization method. In multiclass classification, overlapped class boundary has posed an issue especially in dealing with many classes in a dataset.

To solve the problem, methods such as One-vs-Rest (OvR) and One-vs-One (OvO/pairwise) has been widely used in general classification that involve more that binary class. The rationale of binarization of classes is to separate the class boundary which is easier for the classifier to distinguish binary classes instead of multiclass in a dataset (Hullermeier *et al.*, 2008).

One research has been done by Anthony *et al.* (2007) in comparing the OVR and OVO by using a dataset from satellite images in classifying the built up area, vegetation and water. According to the researcher judgment, OvR and OvO produce vary accuracy result based on the uniqueness of the dataset. In other researchs by Hullermeier *et al.* (2008) applied on a various dataset from many domains, OvO method yield better accuracy result compared to OvR. The purpose of this study is to investigate the accuracy performance on gait signal classification on handheld placement whether using handheld placement is viable or not.

Besides that, the application of SMOTE will also be evaluated in increasing the number of the dataset and whether it can increase the classification accuracy or not. Thirdly, the application of OvO classification mapping will be evaluated whether is it viable for increasing the accuracy. Finally, few machine learning methods such as k-NN, MLP, SVM and J48 will be tested with OvO classification mapping to see its performance.

MATERIALS AND METHODS

Handheld placement of smartphone: In this study, the handheld based placement smartphone is examined in determining the viability and reliability in the real world gait recognition application. Since, it is hard to have any pouch or pockets or any sorts of holder that can act as a placement, using hand is the best way to hold the phone. There are 3 different handheld placements that will be evaluated which are touching the abdomen (Dataset 1), hold horizontally in front of the chest (Dataset 2) and on hand swing (Dataset 3) as can be seen in Fig. 1-3, respectively. The walking signal of all the placement types can be seen in Fig. 4. The proposed positions are measured at the final classification which is based on accuracy metric.

One-vs-One (OVO) multiclass mapping: The reduction of classes dimensionality can be seen in Fig. 5. The dataset in Fig. 5a consist many classes in one dataset. The class boundary seems to be overlapped with other classes hence reducing the accuracy rate. By binarizing the dataset, Fig. 5b-d the possibility of overlapped class boundary may be reduced or prevented and will increase the classification accuracy rate. Before classification process is performed, the extracted data for training need to be broken into pair for all classes. The number of paired datasets are driven from Eq. 1:

$$\text{Generated\_learned\_model}_n = \frac{n\times(n-1)}{2} \quad (1)$$

Fig. 1: Placement of smartphone which is on handheld touching the upper abdomen (Dataset 1)

Fig. 2: Placement of smartphone which is on handheld horizontally (Dataset 2)

Fig. 3: Placement of smartphone which is on hand swing (Dataset 3)

Based on the Eq. 1, the number of generated paired dataset depends on the number of total classes in a dataset. So, if a dataset consist of 5 classes, using Eq. 1 the number of generated paired dataset will be 10. The sample of the mapping can be seen in Fig. 6 in which the total of classifiers will be 10 in-order to satisfy the OvO rules.

Pairing of classes starts from the training dataset. The original dataset that contains all the classes need to be sorted based on class, then will be divided into paired dataset based on classes. For example, if the wanted class pair is 1 and 2, only dataset with class Label 1 and 2 will be chosen whereas the remaining classes will be discarded as shown in Algorithm 1. If there are 5 classes in a dataset, the total of 10 binary dataset will be generated which pairing with each other.

Algorithm 1: Converting multiclass data into binary data

```
Data: X
Result: New binary dataset generated from X+
while i < N do
  while j <= N do
    while k < N do
      if label = i and label = j
        add to array X+
      end if
    end while
    generate X+
  end while
end while
```

During training, machine learning algorithm will be applied for each of the generated paired training dataset. When the training phase is completed, the generated learned models will be categorized based in the paired train dataset.

For the testing phase, the test dataset would be used to measure and validate the learned models. As resembling the real world application, the test dataset are not paired and assigned individually on its own class. The prediction of decision is made by aggregating the decisions from the learned binary model by using simple majority voting where each binary classifier votes for the predicted class (Galar *et al*., 2011; Friedman, 1997). The class with the maximum number of votes is predicted as an aggregated result of the classification from the multiple generated confusion matrix from the motivation of:

$$f(x) = \text{argmax}_i \left(\sum_j f_{ij}(x) \right) \quad (2)$$

where, f_{ij} is the classifier where class i are positive examples and class j are negative examples.

Synthetic Minority Over Sampling Technique (SMOTE): SMOTE is a process of generating new dataset from the minority class. It is done only on the training set which the number of instances for a minority class

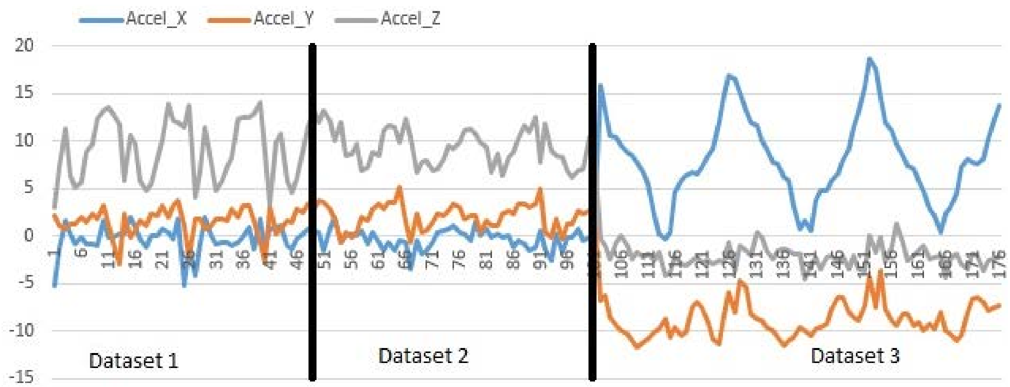

Fig. 4: The signal of a person while walking for Database 1-3

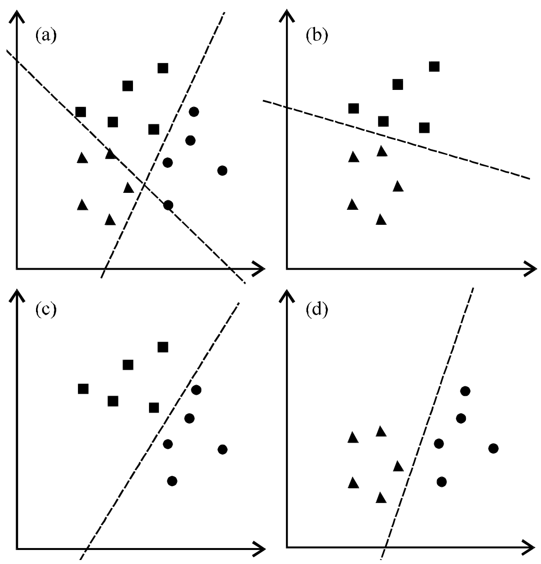

Fig. 5: Placement of smartphone which is on handheld horizontally (Dataset 2)

will be increased (Chawla *et al*., 2002). The flow (procedure) of the SMOTE application in this experiment is shown in Fig. 7. In this research, the rational of using SMOTE although the dataset seems to be balanced is because to generate more instances for both of the classes for better training purposes since the data are captured from a non-stationary device. Besides that, SMOTE is widely used in binary classes dataset application. To use SMOTE, there are few factors that should be considered. Mainly, there are 3 inputs that involve in generating the synthetic samples which are number of minority class samples, amount of SMOTE percentage and number of nearest neighbor to be used (Chawla *et al*., 2002). In the application, other requirement that need to understand is the number of factor of SMOTE. Using multiple factors on same SMOTE percentage produce different number of over-sampled instances. However, both of the class samples are increased instead of tweaking the percentage alone. The higher the number of factor used, both number of class samples would be over sampled and there would be greater difference between the number of generated over-sampled instances.

Algorithm 2: SMOTE:
Data: Z
Result: New synthetic instances generated from Z_+
1 while n <N in Z_+ do
2 Find its k-nearest neighbor
3 Randomly select some of the neighbor
4 For a line that is connected between neighbors, generate a new synthetic instance
5 end

Experimental setup: The experiment is divided into multiple levels as shown in Fig. 8.

Data collection: Data is collected while walking on the straight line where the distance is approximately 15 msec. The mobile phone is held by hand instead of locating the phone in the pocket or in a pouch. This is because, in real world situation, a person may not carry a pouch or even has a pocket to put the phone. The best solution is to hold it on hand. There are 30 subjects (person) which 15 of them are male and the rest are female. The age group is between 23-35 year old. The subject needs to walk on normal pace for about 15 m for three different poses for the training set. On the second day, the subject needs to walk again for three different poses for the testing set.

Although, the dataset seems to be small, this is just an exploratory research which it would open a new gateway for further exploitation using the mentioned

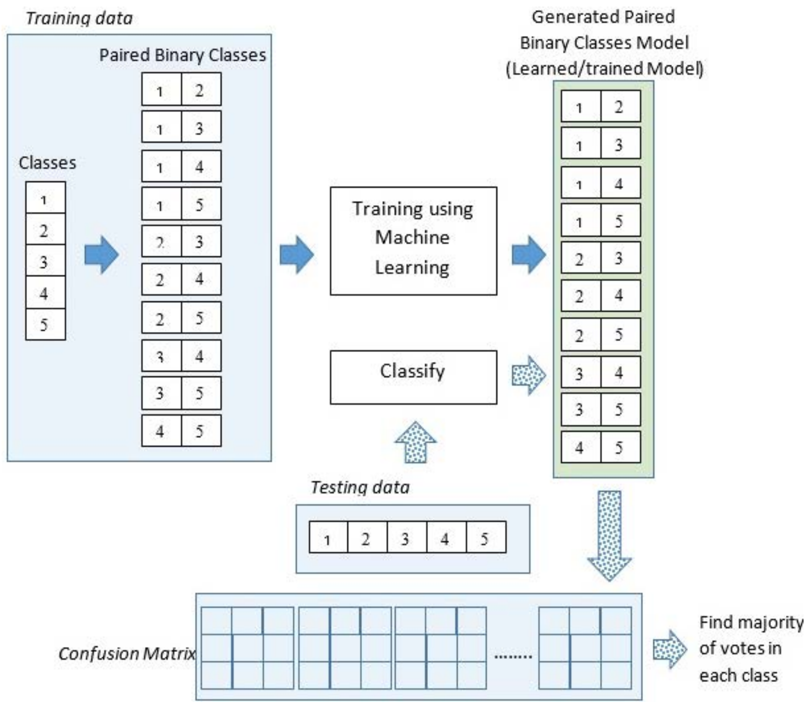

Fig. 6: OvO classification mapping

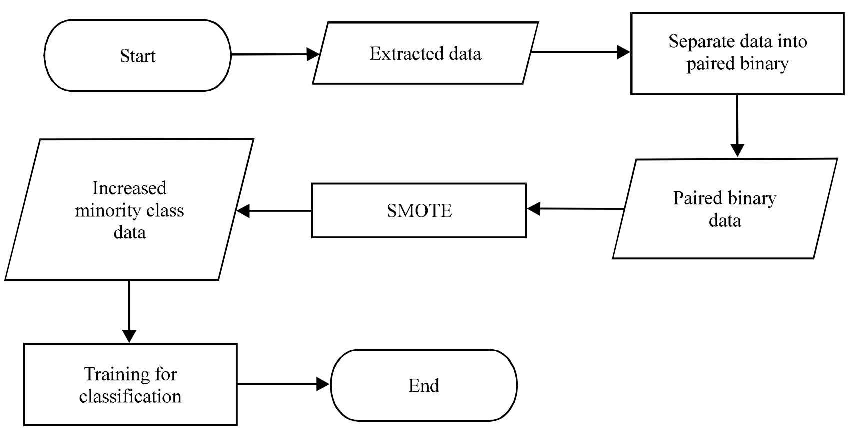

Fig. 7: The flow of SMOTE application procedure

model. In the research conducted by Ren *et al*. (2015), the amount of classes used were 26 subjects which is about the same with this research.

Preprocessing: The first step in the pre-processing is the linear interpolation. Since, the smartphone is not in a fix sampling rate, linear interpolation is applied to reproduce the sampling data over 1 sec (Hz) (Nickel and Busch, 2013; Hoang *et al*., 2013).

The second step is centering around 0. This is due to the smartphone which is not properly calibrated which the acceleration data in the stable position is not exactly zero or gravity (Nickel and Busch, 2013). The third step is the segmentation. The method used Fixed Size Overlapping sliding Window (FSOW) which was used by Keogh *et al*. (2001) and Bersch *et al*. (2014).

Feature extraction: Before the training and testing can be performed, the dataset need to undergo a feature extractions phase in-order to extract important features. The features involved. Minimum and maximum values

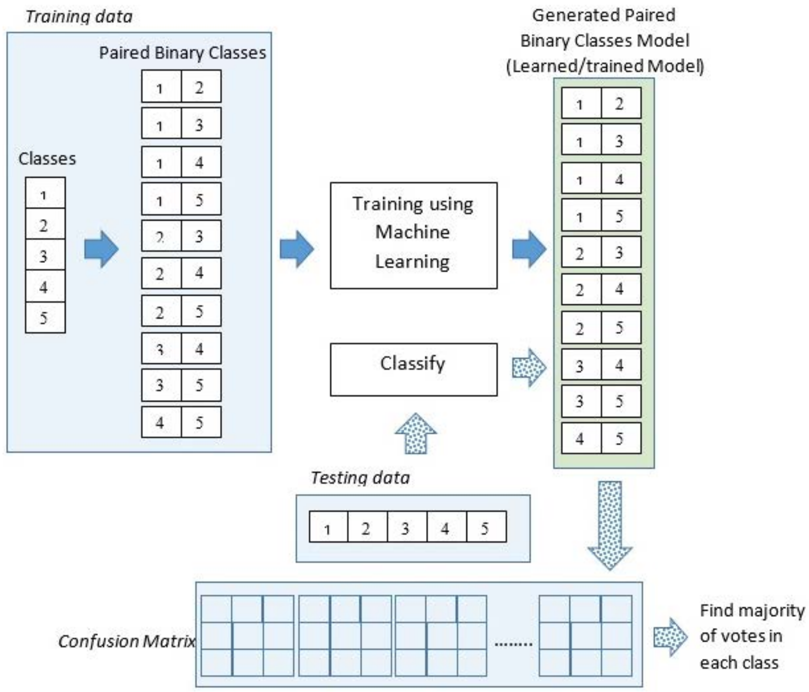

Fig. 8: The framework of the proposed experimentation

mean standard deviation correlation. Root mean square, signal vector magnitude, number of 0 crossing of the median, percentile rank.

Classification: Classification procedure has been explained in the proposed method section. The schematic diagram of the training and testing method can be seen in Fig. 8. The training data need to be binarized and applied with SMOTE algorithm for the training purposes. For the testing, the data is just leaved as it is as to resemble the real world application. The classifier involved in this research are k-Nearest Neighbor (k-NN), Multilayer Perceptron (MLP), Support Vector Machine (SVM) and Decision Tree (J48). The classifier is then paired in the OvO multiclass mapping for training and testing.

RESULTS AND DISCUSSION

In this experiment, a total of 180 Samples from 30 people were used with half of the potions were used for training and the other for testing. Every placement represents 30 Samples. So for 3 placements in the training set, the total would be 90 Datasets. Later the data is undergone for pre-processing that includes linear interpolation and filter around zero. Then, the segmentation is done using fixed size overlapping sliding window with the window size equivalent to 32. Features are then extracted. Then the dataset that is used for training are binarized. Since, there are 30 people, it means that the total of classes are 30. Based on the OvO formula, the total of generated binarized datasets are 435. Before the learning procedure is done, the datasets used for training are then applied with SMOTE. The number of factor did influence the number of generated data as can be seen in Table 1. For classifier algorithm, the first method used is k-NN. The search algorithm used is based on linear search with Euclidean distance as the object distance. The K value is set to 1.

The second classifier method is MLP with the number of hidden layer is 20. The learning rate is 0.3 with momentum = 0.2. For SVM, the coefficient is set to 0 with the cost equivalent to 1. The EPS (tolerance of the termination criterion), loss (epsilon for the loss function) and the degree of kernel are set to 0.001, 0.1 and 3, respectively. For J48, the seed is set to 1 and the number of fold is set to 3. After training with the classifier algorithm, there are 435 models generated for each of the classifier. To calculate the accuracy, voting is done to find the highest score (occurrence) from the 435 confusion

Table 1: The effect of SMOTE factor to the number dataset of a binary class using 100% SMOTE percentage

	Factors						
Classes	0	1	2	3	4	5	6
1	22	22	44	44	88	88	176
2	18	36	36	72	72	144	144

Table 2: Accuracy comparison on all smartphone's position using k-NN

	Datasets		
Smartphone position	1	2	3
Correct Recognition Rate (CRR)	29.0	25.0	23.0
Incorrect Recognition Rate (IRR)	1.0	5.0	7.0
Accuracy (%)	96.7	83.3	76.7

Table 3: Comparison of accuracy based on SMOTE factor on Dataset 2 using J48

SMOTE factor	0	1	2	3	4	5	6
CRR	26	24	25	26	27	27	27
IRR	4	6	5	4	3	3	3
Accuracy (%)	86.7	80	83.3	86.7	90	90	90

Table 4: Accuracy comparison on all classifier with OvO and traditional mapping on Dataset 1 (without SMOTE)

Machine learning algorithm	k-NN (%)	MLP (%)	SVM (%)	J48 (%)
OvO (CRR: IRR)	96.7 (29:1)	96.7 (29:1)	76.7 (23:7)	93.3 (28:2)
Traditional mapping (CRR: IRR)	93.3 (28:2)	96.7 (29:1)	73.3 (22:8)	90.0 (27:3)

Table 5: Accuracy comparison for k-NN and MLP, all position and with and without SMOTE. The data without bracket represents NO SMOTE and with bracket represents with SMOTE

Smartphone placement position (dataset)	k-NN D1	k-NN D2	k-NN D3	MLP D1	MLP D2	MLP D3
Classifier						
CRR	29 (29)	25 (27)	23 (24)	29 (29)	26 (27)	25 (25)
IRR	1 (1)	5 (3)	7 (3)	1 (1)	4 (3)	5 (5)
Accuracy (%)	96.7 (96.7)	83.3 (90)	76.7 (80)	96.7 (96.7)	86.7 (90)	83.3 (83.3)

Table 6: Accuracy comparison for SVM and J48, all position and with and without SMOTE. The data without bracket represents NO SMOTE and with bracket represents with smote

Smartphone placement position (dataset)	SVM D1	SVM D2	SVM D3	J48 D1	J48 D2	J48 D3
CRR	23 (24)	26 (27)	21 (22)	28 (29)	26 (27)	25 (26)
IRR	7 (6)	4 (3)	9 (8)	2 (1)	4 (3)	5 (4)
Accuracy (%)	76.7 (80)	86.7 (90)	70 (73.3)	93.3 (96.7)	86.7 (90)	83.3 (86.7)

matrix for a particular class. From Table 1, it can be seen that starting from Factor 1, the number of dataset increased from the generated synthetic for the minority class. Class B increase its total of dataset from 18-36. Class A's dataset count is still remain the same. While the SMOTE factor increased, the least dataset of the class grows. In factor 4, the dataset grows twice for both of the classes.

For the hand placement, it can be seen that Dataset 1 (hand placement touching the abdomen) does produced the best accuracy which is 96.7% using k-NN compared to other placements as can be seen in Table 2. This could be due to the stability gained by securing the smartphone's movement to the person's abdomen. For the dataset 2 and Dataset 3, the accuracy dropped 83.3 and 76.7%, respectively. This is due to the high amount of shake as can be seen in Fig. 9. According to the result in Table 3, the number of SMOTE application factor does reflect the overall result of classification.

When the SMOTE is applied once (Factor 1), the accuracy dropped as only 1 class are affected. When the SMOTE is applied again (Factor 2), the accuracy increased until Factor 4 is achieved. After that, the accuracy is maintained until Factor 6 as can be seen in Fig. 9. According to Table 4, using OvO does increase the performance accuracy for k-NN, SVM and J48 slightly by 1 CRR (correct recognition rate) except for MLP, the accuracy is same.

From the result in Table 5 and 6 the accuracy scores that are in bold are consider as the best in a particular dataset or sensor placement. It can be seen that using OvO could yield high result and using hand placement sensor, it is viable in the gait identification. Using SMOTE produce a relatively subjective result which in most cases, the final accuracy increased. In k-NN and MLP in dataset 1, the performance does not increase as it has reached its accuracy limit. For MLP in dataset 3 using SMOTE does not increase the accuracy although it is consider as the highest among other classifiers. For SVM and J48, the usage of SMOTE does increased all the accuracy score in all datasets. Rom the Table 4 and 5, it can be seen that MLP and J48 produced the best accuracy score in all dataset after the SMOTE has been applied. k-NN is also good in Dataset 1 and 2. SVM is only good in Dataset 2.

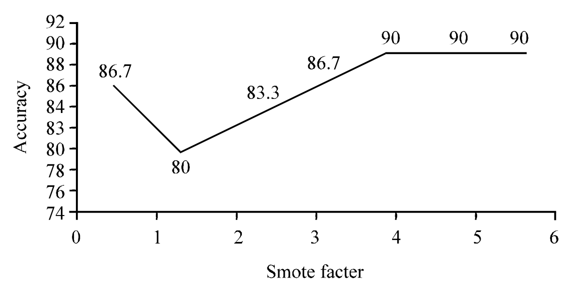

Fig. 9: Pattern of SMOTE's factor accuracy

CONCLUSION

In this study, gait recognition has been implemented using smartphone which is handheld. Data from 3 different positions have been collected and analyzed. The training data are splitted into binarized format to satisfy the OvO concept. The effect of SMOTE application is also analyzed. Lastly, the best classifier has been compared that is works best with OvO architecture.

Based on the result, capturing the gait signal from a hand placement smartphone is possible for the gait identification which means that there is no need to use any other tools such as the bag, pouch or pocket. From the conducted experiment, the best placement for the handheld position is to hold the smartphone while its bottom touches the abdomen. The rational of this method is to secure the phone from recording other unwanted acceleration signal due to the hand shake.

In the Dataset 1, one of the subject's dataset is tampered as the training set and the testing set are totally different pattern at all. This could be due to the error of management during the data collection day. However, it is difficult to replicate or to obtain new data as the situation, venue and the surrounding might be different from the original data collection. However, it would be easier if the tampered data is discarded but it would reduce the quantity of subject's data from 30-29 only in Dataset 1. It is proven when the tempered dataset is removed, the accuracy could reach 29/29 which is 100%.

It is noticed that using the SMOTE application, the accuracy increased. This is because the number of data for a class is increased and the pattern of the newly generated data resembles the original dataset. Although, SMOTE is widely used for imbalanced class problem, it is shown that SMOTE is also good in tackling nonstationary data like gait signal.

However, the number of SMOTE factor is an issue to be considered as the amount of factor does affect the overall accuracy of the classification. From the conducted experiment, it can be seen that once a SMOTE is applied, the accuracy is dropped but the accuracy will increase when the SMOTE factor is increased. After applies a certain SMOTE factor, the accuracy will be same although the factor is increased. This shows that the dataset and the classifier have achieved an optimum classification condition.

For the classification model, OvO layout model is able to identify a class or a person in this experiment. This is an option instead of using a traditional (single) classifier layout. However, there is a drawback by using this method in which the training time takes a longer time since there are many models that needs to be developed and trained according to the Eq. 1. For the testing phase, the time taken is fast. For future works, other data samples could be used to identify the effectiveness of the proposed model. At the same time, the number of subjects could be increased for further investigation. Besides that other types of aggregation method could be evaluated in the OvO classification mapping in this area of study.

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