Fall Detection and Monitoring using Machine Learning: A Comparative Study

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***Abstract*—The detection of falls has emerged as an important topic for the public to discuss because of the prevalence and severity of unintentional falls, particularly among the elderly. A Fall Detection System, known as an FDS, is a system that gathers data from wearable Internet-of-Things (IoT) device and classifies the outcomes to distinguish falls from other activities and call for prompt medical aid in the event of a fall. In this paper, we determine either fall or not fall using machine learning prior to our collected fall dataset from accelerometer sensor. From the acceleration data, the input features are extracted and deployed to supervised machine learning (ML) algorithms namely, Support Vector Machine (SVM), Decision Tree, and Naive Bayes. The results show that the accuracy of fall detection reaches 95%, 97 % and 91% without any false alarms for the SVM, Decision Tree, and Naïve Bayes, respectively.**

***Keywords*—Fall detection; machine learning; acceleration data; SVM; decision tree; Naïve Bayes; IoT**

I. Introduction

Human falling is feared because it may have both physical and psychological consequences. Compared to younger individuals, elderly have a higher chance of fall [1]. According to the World Health Organization (WHO), elderly represent 20 percent of the world's population [2]. By 2030, the global population aged 60 and more is estimated to reach 1.4 billion, and by 2050, it is estimated to increase from 962 million to 2.1 billion, compared to 2017 [1]. Falls has perturbing influence on the elderly, which may shorten their life expectancy. People older than 65 years often experience a fall every year at a rate of around one-third of the population. In addition to ageing, falling incidents also caused by a few other variables, including environment, level of physical activity, and cardiovascular problems. This can cause bodily harm, and the treatment for these injuries often requires a long stay in medical healthcare centers. The fear of falling, which limits older individuals' ability to engage in their Activities of Daily Life (ADL), is the major physiological problem they face. This concern leads to activity limitation, which may lead to insufficient gait balance and reduced muscle, both of which hinder an older adult's mobility and independence. Therefore, remote wearable technologies are necessary to monitor, detect, and avoid falls to enhance the quality of life in general (QoL). As a result of this, a knowledge of falls may be split into two categories: fall prevention and fall detection. It is possible to consider fall detection to be the process of detecting a fall via the use of sensors or cameras to contact medical personnel. For the purpose of detecting and preventing falls, several systems that make use of a variety of sensors and algorithms have been created [2]. Referring to the dataset source [3], we learn that there is no machine learning applied, and SisFall dataset [4] are bias to western body structure, contras to this work preference that aims for Asian-based ADLs. For this reason, we have applied different machine learning algorithms to classify our previous collected data.

In this paper, we used the ASEAN experiments by own database, where do not depends on the other database and this is what distinguishes the work of this paper. Fig. 1 shows the overview of the system procedure.

Section II discusses the literature review. Section III overviews the machine learning algorithms employed in this work. The research methodology including data collection is explained in Section IV. Section V discusses the results. Section VI concludes this work.

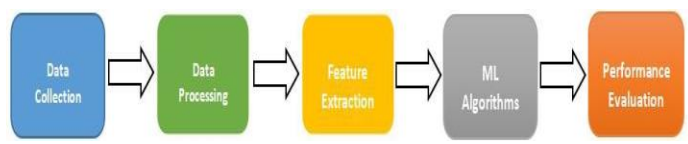


Fig. 1. The overview of system procedure.

II. Literature Review

Ali et al. [5] compared the classification accuracy and execution speed of the J48 and to AdaBoost classifiers for fall detection. The proposed fall prototype was built by varying many distinguishing parameters, including velocity, geometric orientation, and geometric location. The results showed that 99.03 % fall detection accuracy. The execution time of the J48 classifier was 0.01 milliseconds, whereas the execution time of the AdaBoost classifier was 0.025 milliseconds.

Nevertheless, the effectiveness of these classifiers simplifies complex subjects, such as people wearing identical clothing or having the same backdrop colour. Min et al. [6] studied the area under the ROC curve (Receiver operating characteristic), they analysed the performance of faster recurrent neural network (RCNN). The proposed system identified falls by analyzing the situation. Based on deep learning and activity characteristics, they proposed a unique technique for recognizing human falls on furniture. Include other human characteristics, such as speed of motion, centroid, and aspect ratio. The outcome was an AUC of 0.941% and a precision of 93%. Zhang et al. [7] developed a fall detector using the Support Vector Machine (SVM) algorithm. The detector was equipped with a single accelerometer worn at the waist. Accelerations in both directions, variations in acceleration, and other factors were among the features for machine learning. Their method successfully detected falls approximately 96.7% of overall cases. The suggested approach included the incorporation of an accelerometer into a mobile phone for the purpose of determining the occurrence of falls. The body-fixed sensor made detection more difficult, putting the mobile phone in a pocket or wearing it around the neck made it more difficult. About 93.3% of occurrences, the mobile phone system properly triggered the warning.

Using five wireless accelerometers and a wireless heart rate monitor, Tapia et al. [8] developed a real-time method for automated detection not only of physical activities, but also in certain situations, by utilizing a wireless heart rate monitor and five separate triaxial accelerometers.. The shoulder, the wrist, the hip, the thigh, and the ankle were attached to the accelerometers. A predefined window size was used to recover the characteristics from the time and frequency domains of the signal. Some of these characteristics are the Fast Fourier Transform (FFT) peaks, variance, energy, and correlation coefficients. Classifiers, such as C4.5 and Naive Bayes were used in order to separate activity into the following three categories: postures (such as standing and sitting), activities (such as walking and cycling), and other activities (running, using stairs, etc.). When subject-dependent training was used, the recognition accuracy for these three classes was 94.6%, but subject-independent training resulted in just 56.3% of accuracy.

Xiong [9] also introduced a skeleton-based 3D consecutive-low-pooling neural network (S3D-CNN). Compared to existing methodologies, the proposed method fared the best on publicly available and user-collected datasets. Wang et al. [10] proposed a fall detection system comprised of many sensors. They used Multisource CNN Ensemble (MCNNE) architecture to enhance the accuracy of detection. They discovered that MCNNE outperforms both a single CNN structure and a multitude of ensembled bi-model structures. Hnoohom et al. [11] used sensor data from accelerometers and gyroscopes to compare the performance of conventional ensemble learning. Whether the sensor is placed on the arm or the waist, the study's results imply that strategies based on ensemble learning may improve detection accuracy.

Considering all the above aspects in the proposed system there is no analysis for the current data-set which used in this study. It shows the obtained results of comparison by using different machine learning algorithms to detect elderly fall.

III. Machine Learning Algorithms

ML gives the system the ability to learn from the dataset and the patterns in the data by using them as inputs. During the data gathering procedure, sensors offer information of several fall parameters. Then, machine learning techniques are employed to categorize or detect fall behaviour depending on the application requirements. The following is kinds of the machine learning (ML) algorithms that are commonly utilized for fall detection and prevention, and used in this work as well [2].

A. *Support Vector Machine*

The support vector machine (SVM), which is a kind of supervised machine learning model, may be used to determine the location of a hyperplane in a space that has n dimensions (where *N* is the number of features that distinctly divide the data). Although the support vector machine, also known as an SVM, may be used for both, classification and regression analysis, the former is where its principal application resides. Linear and non-linear support vector machines (SVM) are the two different types of this kind of machine. The linear classifier works on the assumption that all of the data points may be linearly divided into groups. As a consequence of this, it differentiates between the two classes by picking the hyperplane that maximizes the margin in the best possible way. Before determining a discriminant function, the non-linear classifier that is most usually employed maps the data using a kernel. This step is followed by the determination of the function. This discriminant function is linked to the hyperplane in the space that has been transformed. In addition to this, the kernel is used for pattern analysis in a number of other machine learning techniques [2]. Support Vector Machine (SVM) has one of the highest fall classification accuracies among the machine learning methods examined [12]. Where, the findings revealed that the linear SVM was one of the optimal classifiers for this cross-dataset validation strategy, as it accurately discriminated a fall event from typical day-to-day activities with a great accuracy rate and comparably high sensitivity and specificity [13].

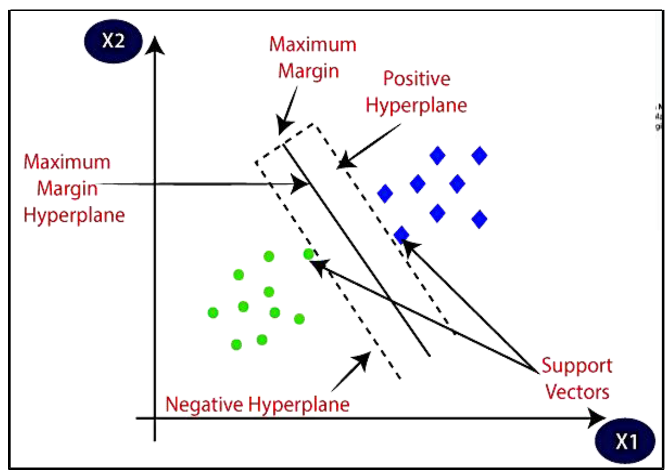


Fig. 2. Support vector machine.

Fig. 2 shows the classification of two distinct categories utilizing a decision boundary or hyperplane, which is this best decision boundary. Where, the aim of the SVM method is to generate the optimal line or decision boundary that divides n-dimensional space into classes, so that subsequent data points may be readily classified.

B. *Decision Tree*

A decision tree is a classifier that recursively splits the instance space. The decision tree consists of nodes that connect to form a rooted tree. This shows that the decision tree is a directed tree with a "root" node that lacks incoming edges.

Each internal node of a decision tree partitions the instance space into two or more sub-spaces according to a discrete function of the input attribute values. In the most common and straightforward example, each test examines a single attribute, splitting the instance space depending on the attribute's value. For quantitative attributes, the condition provides a range [3].

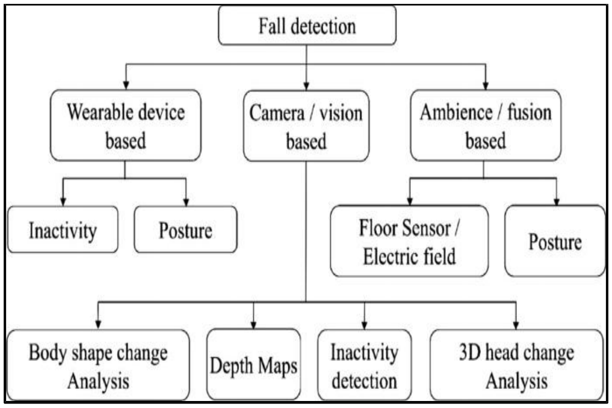


Fig. 3. Decision tree machine learning.

Fig. 3 illustrates different fall detection methods that make use of accelerometers, gyroscopes, or maybe both of them.

C. Naive Bayes

The Naive Bayes algorithm is another supervised learning technique based on the Bayes Theorem. It is one of the simplest and most extensively used classification algorithms that may provide accurate predictions quickly. The Bayes theorem is used to generate classifications based on probability. On the basis of classes, uneven gait and falls may be immediately and readily identified [2]. It is a probabilistic classifier, which means that it makes its predictions based on the likelihood that an item would be found.

In Fig. 4 that has been shown below, it is an example that illustrates how Naive Bayes classifier has distinguished between the data points that have a fine border. The Gaussian curve in its original form has been applied here.

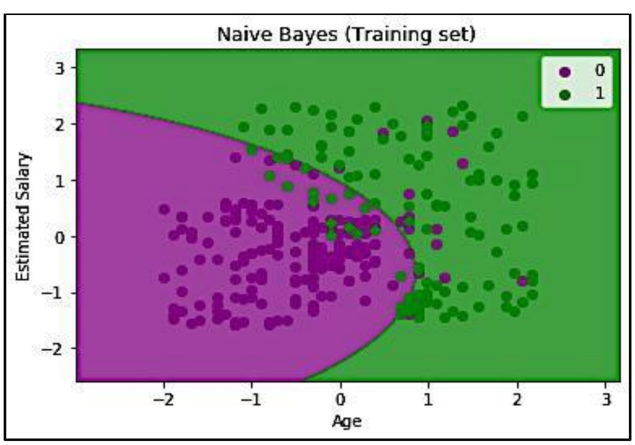


Fig. 4. Naive Bayes machine learning.

The preceding algorithms are generally used in fall detection and prevention applications. Additionally, there are other algorithms such as Logistic Regression and Dynamic Time Wrapping, exist for similar applications (DTW). Another method for recognizing falls is to see them as an anomaly detection issue. Auto-encoders are utilized to detect falls in such systems. Auto-encoder learns features via ADL model training. Based on the reconstruction inaccuracy, fall actions are thus classified as an abnormality. It includes an encoder, a decoder, and a code layer. An encoder learns and compresses the input's essential characteristics. The code layer is the intermediate layer that includes important and compressed data information. In contrast, the decoder converts the data back into the original input. This approach may aid in reducing the complexity of data, obtaining required gait characteristics, and detecting unobserved falls [2].

IV. Methods

A. Hardware Device Setup

The hardware involves a wearable device known as transmitter (FDS-Tx), which consist of the main controller (Arduino Pro mini), the wireless transmission module (XBee Pro) and the main component, a sensor (ADXL335 accelerometer). Before start the data collection, FDS-Tx will be attached to the volunteers' garment, specifically slightly above the right chest area. The device working system is, upon start, the user/volunteers' movements data will be recorded by accelerometer and sent to the receiver (FDS-Rx) via wireless transmission medium to the workstation. There, the computation take place to get the results of the volunteer's conditions (Fall or Normal). Details of the hardware description can be referred to work in [14]. Fig. 5 illustrates the setting of sensor on the user 0.

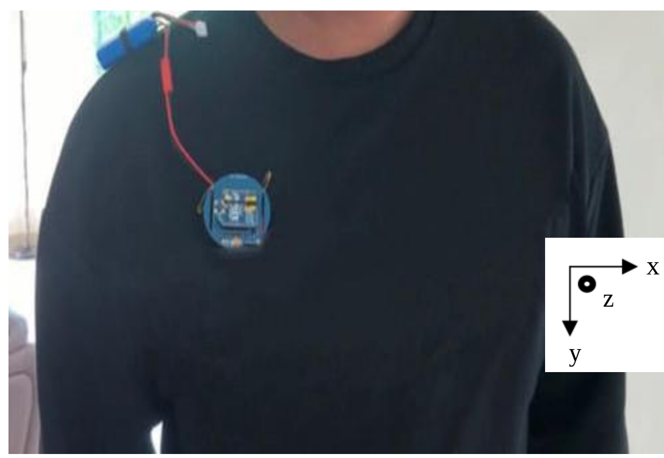


Fig. 5. Location of FDS-Tx on the user [26].

B. Data Acquisition

ADXL335 three-axis accelerometer provides analogue voltage readings for X, Y, and Z acceleration (Fig. 6). An accelerometer can determine the tilt angle touching the earth by detecting the acceleration due to gravity. By measuring the dynamic acceleration, the accelerometer can determine the device's speed and direction of movement. Accelerometer with an analogue interface show accelerations by a range of voltage levels. In general, these values oscillate between the ground and the supply voltage. The micro-controller's ADC may then be used to read this value. For detecting a fall using accelerometer, presently, there are two sorts of detection approaches: analytical methods and machine learning methods [15]. The X and Y axes have a bandwidth selection range of 0.5 Hz to 1600 Hz, while the Z axis has a bandwidth selection range of 0.5 Hz to 550 Hz. In general, accelerometer is low-power devices. Typically, the needed current is between a micro to milli amp [16].

The data acquisition is based on the Activity list as in the Table I. Three (3) activities are performed for 3 times each for better analysis process which will be discussed in the next section [3].

TABLE I. TEST SCRIPT

Code	Activity	Trial s	Duration (s)
F01	Fall forward while walking caused by a trip	3	15
F02	Fall to the right while walking caused by a trip	3	15
F03	Fall to the left while walking caused by a trip	3	15

Equipment setup are consisting of the FDS-Tx and FDS-Rx hardware, and safety mats in a closed venue with adequate sizes for 10 to15 seconds of straight walk. 10 volunteers are involved in this session with the detail of age, height, weight and gender are recorded for further analysis reference. During data acquisition, volunteers will walk straight on the normal carpeted composite structure, and then falls on a safety mats to reduce the forces during fall impact. Fig. 6 demonstrates the volunteer performing one of the activities.

Fig. 6. A volunteer performing F03 activity under researcher supervision [15].

In this part, we present an overview of the framework used to identify ADLs and falls occurrences, as well as an explanation of the activity recognition technique (Fig. 7).

C. Data Processing

Data implementation: Google Colab product used for machine learning applications was used to process the available data [12]. After the data was collected and the needed libraries and packages were obtained and imported, the process of implementing the coding started. As a precaution, a unique ID of the data-set was specified within the drive to allow a seamless download. The data on the status activities of the elderly consists of four input features (X-axis, Y-axis, Z-axis accelerations, and total MAG) and 1 output feature (STATUS), which are viewed through the panda's package.

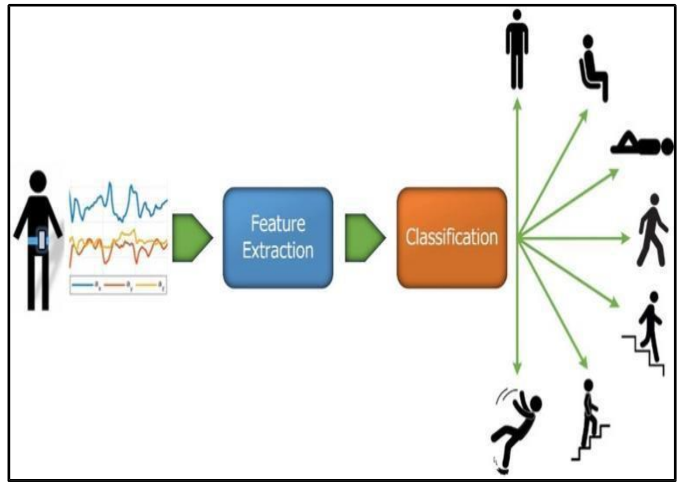
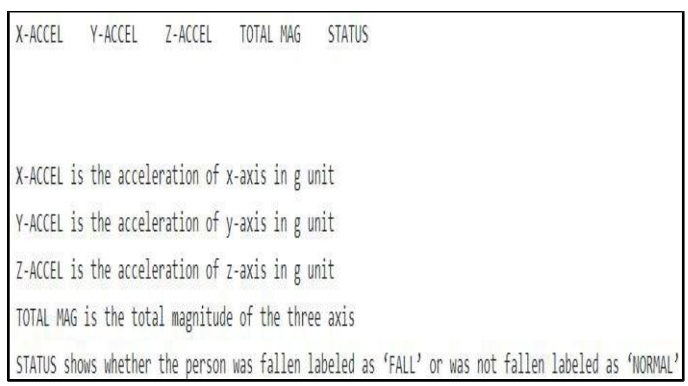


Fig. 7. Illustration of the activity recognition framework.

The data was distributed into Normal and Fall activities. Among 2245 activity, 1788 was Normal, and 457 was for Falling. Using Google Colab software, a categorical feature encoding was used. This feature converts non-numeric features to numbers for ease of machine learning. The STATUS of the Normal activity is precisely encoded as 1, while Fall activity is encoded as 0.

D. Data Set

Collected Data-set: The real datasets should be created, as current datasets including samples from 10 people that are physically different and with 3 different activities. Where number of trials for each activity is 3, and the total number of data is 84. Two (A01 and A02) out of ten participants only perform 2 activities because of personal health problem. To be clarified, the data set has been arranged as shown below in Fig. 8:



X-ACCEL Y-ACCEL Z-ACCEL TOTAL MAG STATUS

X-ACCEL is the acceleration of x-axis in g unit

Y-ACCEL is the acceleration of y-axis in g unit

Z-ACCEL is the acceleration of z-axis in g unit

TOTAL MAG is the total magnitude of the three axis

STATUS shows whether the person was fallen labeled as 'FALL' or was not fallen labeled as 'NORMAL'

Fig. 8. Arranging of data set.

Accuracy measurement: To validate the accuracy of the results, the SVM machine learning algorithm was used and compared with the Decision Tree and Naive Bayes machine learning algorithms. The data is divided into 80-20% training-testing set splits where 1796 and 449 samples are used for training and testing, respectively.

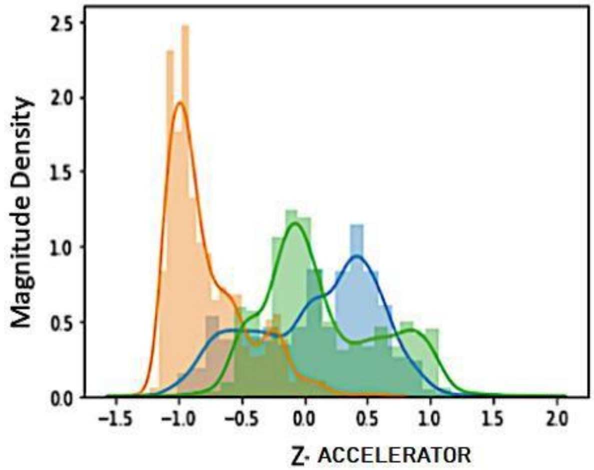


Fig. 9. Accelerometer input features.

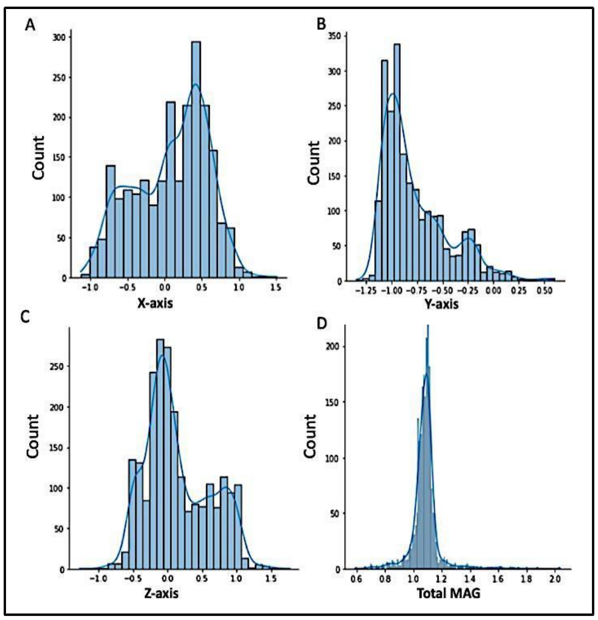


Fig. 10. Accelerometer input features of x-, y-, z- axes accelerations, and total MAG.

V. Results and Discussion

A. Input Features Distribution

The data distribution of the X, Y, Z, and total MAG was assessed before applying the machine learning algorithms and found that the data was skewed and abnormally distributed (Fig. 9). A separate axial distribution of each axis was plotted and presented abnormal distribution (Fig. 10A, B, and C). However, the total mag feature exhibits a normal distribution (Fig. 10D). These results suggest that the dataset used in this study composes a suitable confusion matrix, which can be used to understand the classification model and correctly predict the possible errors.

B. Machine Learning Accuracy Measurement

The training and testing accuracy of the proposed machine learning algorithms (SVM, Decision Tree, and Naive Bayes) was measured. However, the testing accuracy was used to rank the algorithms as it offers consistent and more reliable results. Surprisingly, the Decision Tree algorithm provided the best accuracy (97%). SVM algorithm showed a relatively high accuracy of 95% as well (Fig. 11). Taken together, current measurements suggest that the best algorithm for fall detection is the Decision Tree machine learning algorithm. Indeed, employing Decision Tree will result in 100 % accuracy since a portion of training data is utilised for testing. The decision tree learns about the data during training, and if the same data is used to forecast today, it will provide the same outcome.

Therefore, a decision tree outperforms other machine learning algorithms.

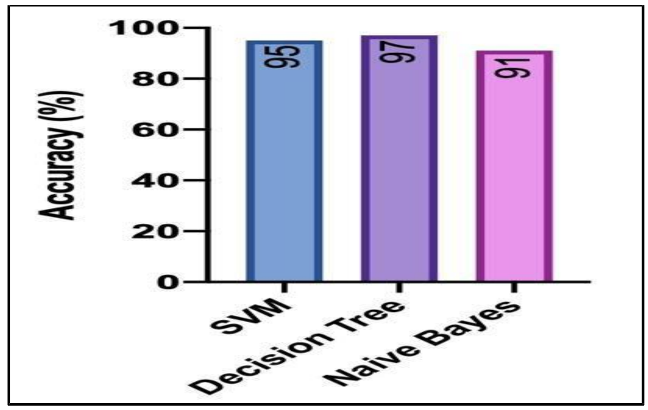


Fig. 11. Comparison of algorithms accuracy.

Fig. 12 shows the confusion matrix of the predicted results for Naive Bayes, SVM and decision tree algorithms. Where, DT carried out best performance comparative the other classification methods by getting 97% accuracy, whereas Naive Bayes shows the least performance by attaining 91% accuracy.

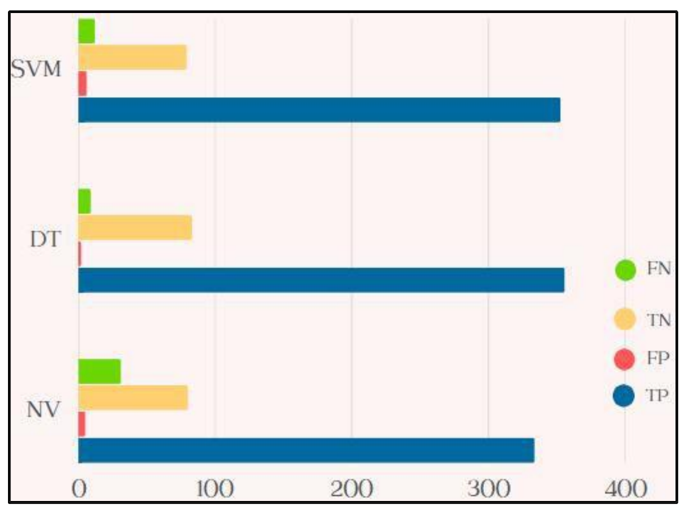


Fig. 12. Classification results using confusion matrix.

VI. Conclusion

The purpose of this research is to compare some ML-based fall detection system as offline. It examines the systems based on a variety of characteristics including data-sets, confusion matrix and accuracy. The performance accuracy of the SVM, Decision Tree, and Naive Bayes classification algorithms was tested using real-world acceleration data gathered from public databases. Using the training data, the internal parameters of these algorithms have been enhanced. Thereafter, the performance of the trained algorithms has been evaluated using the test data. The findings exposed that the SVM, Decision Tree, and Naive Bayes algorithms achieve an overall accuracy of 95%, 97%, and 91%, respectively. As next steps, it can be work on data generated by a combination of different types of sensors and vital signs sensors which may be worn by elderly people staying in old-age care homes or even their own homes. Also, the system may have another machine learning algorithms to support the end-to-end functionality.

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