Enhancing Classification of Elderly Fall Detection System using Tuned RBF-SVM

Herti Miawarni
Dept. of Electrical Engineering, Faculty of Intelligent Electrical and Informatics Technology (F-Electics), Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
hertimiawarni.19071@mhs.its.ac.id

Tri Arief Sardjono
Dept. of Electrical Engineering, Dept. of Biomedical Engineering, Faculty of Intelligent Electrical and Informatics Technology (F-Electics), Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
sardjono@bme.its.ac.id

Eko Setijadi
Dept. of Electrical Engineering, Faculty of Intelligent Electrical and Informatics Technology (F-Electics), Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
ekoset@ee.its.ac.id

Agustinus Bimo Gumelar
Dept. of Electrical Engineering, Faculty of Intelligent Electrical and Informatics Technology (F-Electics), Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
bimogumelar@ieee.org

Wijayanti
Dept. of Architecture, Faculty of Engineering, Universitas Diponegoro,
Semarang, Indonesia
wijayanti@lecturer.undip.ac.id

Mauridhi Hery Purnomo
Dept. of Electrical Engineering, Dept. of Computer Engineering, Faculty of Intelligent Electrical and Informatics Technology (F-Electics), Institut Teknologi Sepuluh Nopember, The Science and Technology Center of Artificial Intelligent for Healthcare and Society (PUI AIHeS),
Surabaya, Indonesia
hery@ee.its.ac.id

***Abstract*— An elderly FDS or Fall-related incident Detection System can reduce the severity of late treatment after a falling incident by shortening the period between the inevitable fall and the proper medical care. A failure to comply the need of urgent medical attention to the falling victims can lead to painful death. But first, a machine must be trained to automatically and accurately detect a falling incident. The Support Vector Machine (SVM) is generally acknowledged as one of the best tree-based machine learning algorithms for classification and regression data analysis. This tree-based Deep Learning model has been used in fields, together with bioinformatics, face recognition, and image recognition, and urgent cases such as FDS. This paper defines a work of FDS using SVM. We used 16,261 instances and 33 attributes of fall simulation from eHomeSeniors dataset, in which the dataset employs the infrared thermal sensor. This dataset stated more than 15 classes of fall, to achieve best result in capturing falling incidents. We also set the gamma value from the default 0.01, to 0.9, with no normalization or standardization needed in the process. The training data and testing data are also split into the scale of 50:50, 60:40, 70:30, 80:20, and 90:10. Consequently, we were able to reached 84.62% accuracy and 50.32 seconds learning runtime at data split of 90:10.**

Keywords*— *Fall Detection System, Elderly, Infrared Thermal Sensor, eHomeSeniors, Support Vector Machine

I. Introduction

Recently, by using telemonitoring system it is possible to detect emergency situations of human physiological data in everyday living contexts. The fall detection system become a critical component of human body movement study for medical practitioners, academics, and healthcare businesses [1], and it is becoming increasingly popular. There are many sensor can be used to detect human from falling, for instance, infrared thermal data can be used to accurately detect the features of humans, allowing for the development of more reliable methods for combining long-term development into physiological observations throughout time. An extremely hazardous consequence of falling is the "long-lie," which is described as the victim suffering physiological reaction after remaining on the ground or floor for more than an hour after a fall [2]. According to research, the "long-lie" phenomenon is related with a high mortality rate in the elderly. It is envisaged that experts will introduce an FDS that will considerably limit the occurrence of the "long-lie" by shortening the interval between the fall and the emergence of medical aid [3], [4]. There are common types like forward and backward falls, there are also lateral falls, sit-and-stand falls, and stair falls [5]. These types of falls should be distinguished from Activity Daily Living (ADL). Falls can be recognized using proper classification algorithm, including tree-based Deep Learning model, such as Support Vector Machine (SVM) [6].

Deep Learning-based Support Vector Machine (SVM) algorithms will be used in this study in an effort to identify falls on a sensor-based fall detection system. There are a total of 15 distinct categories of fall occurrences. The infrared thermal sensor [7] provides the data used in the FDS. Accuracy, True Positive Rate (TPR), False Positive Rate (FPR), Area Under the Operating and Receiver Operating Characteristics, and learning runtime for both SVM were used to evaluate the classification results, as were.

This paper's structure is divided into several sections. Section 1 provides an introduction to fall incidents and the significance of designing a system that can recognise fall incidents automatically. Section 2 is a related paper that summarises past research on SVM-based fall incidence detection systems and how to evaluate the SVM's classification performance. Section 3 also includes an experiment design that details the sequence of Deep Learning-based fall incidence recognition tests (DL). Finally, Section 4 give a result and discussion that describes summarizes the results of our FDS by presenting the results of performance evaluation and SVM.

II. Related Work

A. Sensor-based Fall Detection System

Other publications have previously addressed the use of infrared sensor arrays for FDS, with architectures and proposed algorithms yielding varying degrees of accuracy. Low-resolution thermal sensors are a feasible alternative for FDS purpose since they are inexpensive, non-intrusive, and would provide a variety of information in a confined space, such as position, velocity, acceleration, and human body temperature.

Sixsmith et al. were among the first to use low-resolution infrared sensor arrays in their research (16×16 pixels). Their system train more than 10,000 vectors and 108 scenarios. They also use MLP or Multi-Layer Perceptron to as the Deep Learning model. A module for sending alerts via GSM card is also included in the system. Although their results were unimpressive due to their training set, the confidence of using thermal sensor is quite high due to the excellent user acceptance for privacy reason [8].

Taniguchi et al. employ two 16×16 pixels low-resolution sensor arrays. One sensor is mounted on the wall and the other in the ceiling. The algorithm of the system composed of accurately predicting body posture and detecting falls based on posture changes over time. The system's high accuracy was around 72.7 percent in its worst-case scenarios [9]. According to their findings, their system detects falls efficaciously and their system is also applicable for monitoring implementation. Fan et al. does the study on infrared sensors as one of the recent ones [10]. The research looks at how different Deep Learning methods, (such as LSTM and GRU) would perform on low-resolution infrared sensor arrays (8×8 pixels). The results can be improved, with the GRU-ATT algorithm reaching a pinpoint accuracy of 75 percent in the worst-case scenario and the LSTM algorithm attaining an accuracy of 85 percent [11].

B. *Support Vector Machine-based FDS*

Many things have been done by researchers to improve the performance of SVM as a classification algorithm, such as feature selection [12] and also studies to find optimal kernel [13]–[16]. Agarwal et al. evaluated the efficiency of the SVM classification algorithm in filtering junk or spam E-mails using linear kernel, polynomial kernel, sigmoid kernel, and Radial Basis Function (RBF) kernel, as well as C-SVC and nu-SVC parameters. A spam-based UCI repository dataset is used to implement the experiment. Their experiment achieves the highest accuracy when the linear kernel function and C-SVC are applied [13].

Fadel et al. used eleven mathematical functions known as kernels to implement SVM. This study was carried out using images of Arabic alphabetic characters [14]. A character image database was used in their paper. Gamma noise levels in the range of 0.1 to 0.9 are used. They found that efficiency of both linear kernel and polynomial kernel decreases as the noise level increases. Song et al. conducted comparative research to evaluate the linear kernel-based SVM and RBF kernel-based SVM for functional MRI (fMRI) classification with voxel selection schemes. The aforementioned article compares the accuracy and time required to understand complex brain patterns from fMRI data. Six different voxel selection methods were used to clearly define which fMRI data voxels would be included in SVM classifiers with linear kernel and RBF kernel in classifying four-category objects. According to their result, RBF-based SVM outperformed the linear-based SVM, but with low-dimension feature space. However, when it came to implementing a feature space with a high dimensionality, linear-based SVM out performed RBF-based SVM [15]. In another study, Kanpur used three datasets to investigate the SVM implementation for text independent speaker task with linear kernel, polynomial kernel, and RBF kernel. The SVM with polynomial kernel performed the best, according to Kanpur's results [16].

It should be noted, however, that this method of handling SVM by manually selecting kernels is highly dependent on the data [17]. As a result, the data used in this study may necessitate a different approach, while implementing only default RBF kernel. Furthermore, because SVM cannot be used for multilabel classification, the gamma value as the hyperparameter can be changed in favor of accuracy.

Our gamma-tuned SVM can also be used to address multiclass classification issues. Data from infrared heat sensors from users who fell by design was also used in our study [7]. A Sequential Minimization Optimization (SMO) software was used to build the SVM in this experiment [18]. The computation time for both training and testing stages of SVM was also included as a performance evaluation factor in our study.

C. *eHomeSeniors Public Dataset*

eHome Seniors is a public dataset that helps researchers to develop an ambient based Fall Detection System (FDS). This public dataset was published in 2019 by Requelme et. al. The eHomeSeniors dataset builds from two sensor data, Omron D6T-8L-06 and Melexis MLX90640. Both sensors are low cost and do not require a complicated calibration process like other sensors such as accelerometers [19].

Omron D6T-8L-06 is a MEMS Thermal sensor that can measure the surface temperature of objects [20]. This sensor is a sensor array that has 8 channels and produces a thermal image with 1x8 pixels resolution. In eHomeSeniors dataset, this sensor is used to detect humans. MEMS Thermal sensors have advantages over conventional pyroelectric sensors. Pyroelectric sensors can be used to detect the movement of people based on the principle of detecting changes in the intensity of infrared light generated by the human body. but the sensing signal will be lost if there is no movement. On the other hand, the MEMS Thermal sensor will continue to generate a sensing signal when there is no movement.

The Melexis MLX90640 is a more advanced sensor than the Omron D6T-8L-06. This sensor is an FIR (Far Infrared) sensor array which has 768 channels which produces a thermal image with a resolution of 32 x 24 pixels and 16 fps (frames per second). This sensor is able to detect object temperatures from -40 degrees Celsius to 300 degrees Celsius [21].

In the development of further research, the eHome Seniors dataset has been proposed as a platform in the Non-Invasive Infrared Sensors to Classify Activities and Falls system [22]. The development of deep learning algorithm methods, especially CNN (Convolution Neural Network) has also been applied to this dataset with the aim of increasing the effectiveness of sensor resolution on human activity recognition [23].

III. Experiment Design

Figure 1 illustrated the experiment setup from data collection which we use the eHomeSeniors dataset, splitting data into conveniently putted in varying scenario, learning stage using SVM, and performance evaluation using its accuracy, TPR, FPR, AUC-ROC, as well as learning runtimes. In this study, a public dataset containing infrared-based fall data is used, namely the eHomeSeniors dataset. The eHomeSeniors dataset contains information gathered from infrared heat sensors in homes. Performing artists and ordinary young people work together to build it. It is constructed entirely by volunteers. However, for the performing artist, they are assisted by professional physiotherapists to emulate the real-life elderly fall conditions.

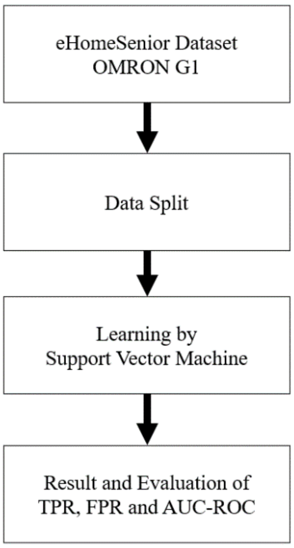

Fig. 1. Experiment Design of SVM-based Fall Detection System

Figure 2 shows illustration examples on how performing artist acting as elderly would fall, based on classes from eHomeSeniors dataset. Meanwhile, Figure 3 shows the Omron sensor setup (where the black screen is monitor), while Figure 4 illustrates how Omron sensor capture the body thermal by different degrees of 110 degrees, 124 degrees, and 6 degrees. According to eHomeSeniors dataset, this setup is fully able to detect falling incident [7]. Furthermore, Table 1 shows detailed information regarding the eHomeSeniors dataset, while Table 2 shows detailed information of 15 fall classes from eHomeSeniors dataset.

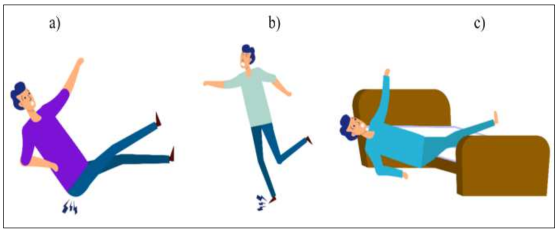

Fig. 2. Illustration of Elderly Falling by Classes of a) Backward Fall, b) Forward Fall, c) Falling from Bed.

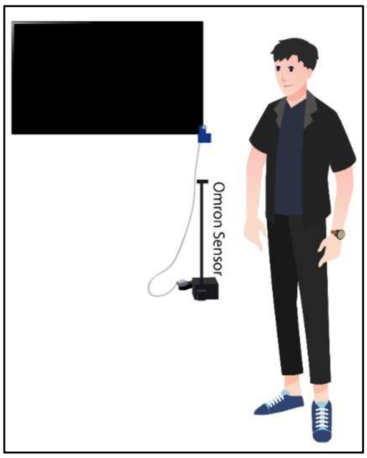

Fig. 3. Setup of Omron Sensor compared to Average-Height Man [7]

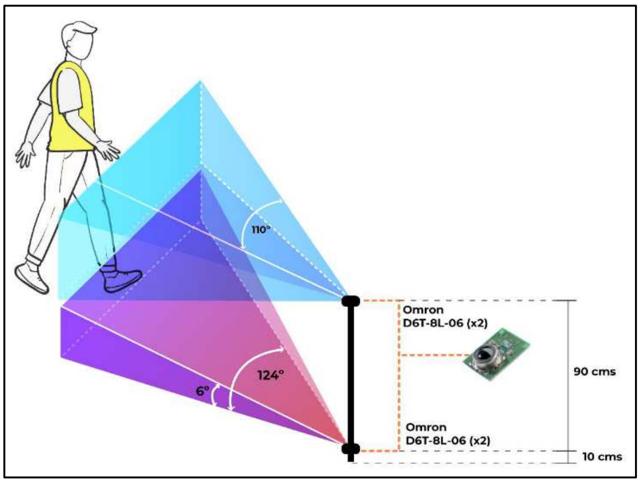

Fig. 4. Illustration on How Omron Sensor Capture Body Thermal [7]

TABLE I. PUBLIC DATASET EHOMESENIORS DETAILS

Information	**Details**
Dataset	eHomeSeniors [7]
File Type	Comma Separated Values (CSV)
Subjects	Young people and performing artist
Instances (used in this experiment)	16,621
Fall Incident Classes	15 classes
Attribute	33 attributes
Data distribution between Classes	Imbalanced

TABLE II. FALL CLASSES FROM EHOMESENIORS DATASET

Fall Class	**Fall Direction**	**From**	**Activity**
1	Backward	Walking backward	While walking caused by a trip
2	Forward	-	-
3	Slow lateral fall	-	Fainting
4	Backward	-	While trying to sit down (empty chair)
5	-	Bed	-
6	Backward	-	While legs are straight
7	Forward	-	While legs are straight
8	Forward	-	Flexed knee
9	Falling slowly backward	Standing	Flexed knee
10	Falling slowly forward	Standing	Flexed knee
11	Lateral fall	Standing	While legs are straight
12	Slow lateral fall	Standing	-
13	Falling slowly backward	-	Fainting/falling asleep
14	Falling slowly forward	-	Fainting/falling asleep
15	-	Chair	Fainting/falling asleep

IV. RESULT AND DISCUSSION

Table 3 shows the accuracy result from each data split, while Table 4 and Table 5 shows TPR and FPR result respectively from each data split. Furthermore, Table 6 shows the ability of SVM-based FDS in classifying 15 classes, in form of AUC-ROC. All the Tables 3, 4, 5 and 6 show results before and after the gamma value of the RBF kernel was fixed to 0.9, the default value of 0.01.

TABLE III. ACCURACY RESULT FROM SVM-BASED FDS (THE HIGHER THE BETTER)

Condition	Data Split (Training and Testing in percentage)				
	50:50	60:40	70:30	80:20	90:10
Default Gamma (0.01)	43.15%	46.16%	48.01%	49.7%	50.37%
After Gamma Fix (0.9)	78.93%	80.18%	81.73%	83.12%	84.62%

TABLE IV. TRUE POSITIVE RATE RESULT FROM SVM-BASED FDS (THE HIGHER THE BETTER)

Condition	Data Split (Training and Testing in percentage)				
	50:50	60:40	70:30	80:20	90:10
Default Gamma (0.01)	43.1%	46.2%	48%	49.8%	50.4%
After Gamma Fix (0.9)	78.9%	80.2%	81.7%	83.1%	84.6%

TABLE V. FALSE POSITIVE RATE RESULT FROM SVM-BASED FDS (THE LESSER THE BETTER)

Condition	Data Split (Training and Testing in percentage)				
	50:50	60:40	70:30	80:20	90:10
Default Gamma (0.01)	4.1%	3.9%	3.7%	3.6%	3.5%
After Gamma Fix (0.9)	1.9%	1.8%	1.7%	1.5%	1.4%

TABLE VI. AUC-ROC RESULT FROM SVM-BASED FDS (THE HIGHER THE BETTER)

Condition	Data Split (Training and Testing in percentage)				
	50:50	60:40	70:30	80:20	90:10
Default Gamma (0.01)	84.1%	85.2%	86%	86.7%	86.8%
After Gamma Fix (0.9)	94.3%	94.8%	95.2%	95.8%	95.9%

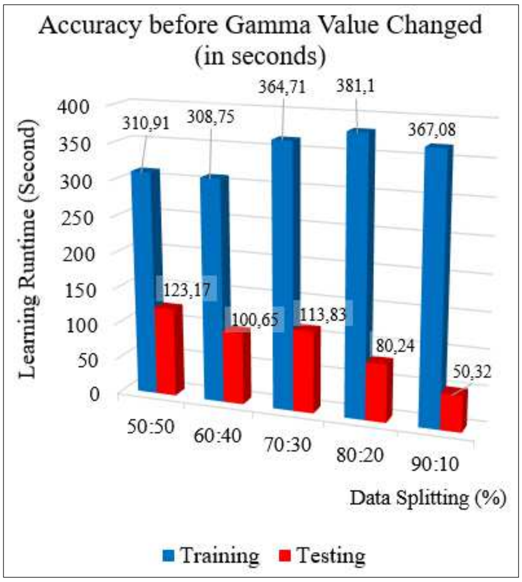

Fig. 5. Accuracy Result with 0.01 Gamma (the lesser the better)

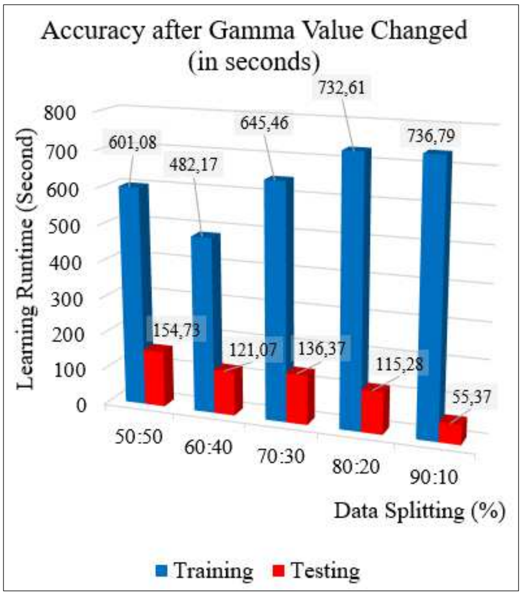

Fig. 6. Accuracy Result with 0.9 Gamma (the lesser the better)

To recap runtime learning, Figure 5 and Figure 6 illustrates seconds in which learning is calculated. Conclusively, the lesser learning runtime indicates the best SVM. Runtime learning is deceptively excellent before gamma value is changed, which is at 50.32 seconds. After the gamma value is changed, SVM is at best learns until 55.37 seconds. There is no explanation why the changed gamma value yields slower runtime, but we did the experiment by setting gamma value firstly to 0.9, then we changed it back to 0.01. Cache as WEKA's feature may did help for the learning runtime process at 0.01 gamma.

From the result shown in Table 3, accuracy indeed advancing to the better, after gamma value is changed into 0.9. Best accuracy value is shown at 90:10 data split, which is 84.62%. Whereas with default gamma value of 50.37%, accuracy is only at best of 50.37%. The same goes with TPR value shown in Table 4. Best TPR value is at 84.6% for 90:10 data split. FPR dictates that the lesser the value, the better. From Table 5, best FPR value is shown from 90:10 data split, which is 1.4% after gamma is changed to 0.9. Before gamma value is changed, FPR value is at best 3.5%. However, all AUC-ROC result, before and after gamma change is considered to be good. Any AUC-ROC value above 50% dictates that the SVM can indeed classify between the 15 classes, despite the SVM is naturally unable to classify two or more classes. Still, best AUC-ROC value is achieved by 0.9 gamma, which is at 95.9%.

CONCLUSION

This paper describes a fall detection system that employs SVM as Deep Learning models. In order to solve a classification issue that was not natural for SVM, such as the multiclass problem in conventional classification, SVM was selected. Using an infrared heat sensor, we analysed data from the eHomeSeniors dataset, which comprises 16,261 rows of data on falls among seniors. Additionally, there are 15 distinct classes of falling episodes in this dataset, each with its own unique collection of fall kinds, activities, and root causes.

These findings also indicate SVM's capacity to handle multiclass classification for a fall detection system under our gamma-tuned hyperparameter setup. SVM has a TPR score of 84.6 percent and an FPR score of 1.4 percent, according to our findings. This results in an accuracy rate of 84.62 percent for our gamma tuned SVM. Our SVM demonstrated the ability to handle multiclass classification with an AUC-ROC value of 95.9%. In addition, our experiment has a relatively short runtime in the training and testing stages, with 308.75 seconds and 50.32 seconds, respectively. Best data split is also found at 90:10, before gamma is changed to 0.9 and after gamma is changed. In the future, we plan to tweak the hyperparameter parameters of each DL model, including carefully choosing the kernels, in order to enhance the outcomes. An SVM's ability to handle a large number of classes and data samples may be improved by changing its additional mathematical characteristics.

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