Fall Detection System for Elderly Activity Daily Living using Modified 2D LiDAR as a Low-Cost Alternative to 3D LiDAR based on the Slice Feature Approach

Wijayanti[1]*, Herti Miawarni[2], Nova Eka Budiyanta[3], Dony Agus Rivai[4], and Mauridhi Hery Purnomo[5]*

[1]Department of Architecture, Faculty of Engineering, Universitas Diponegoro, Indonesia
[2.3.4.5]Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Indonesia
[5]Department of Computer Engineering, Institut Teknologi Sepuluh Nopember, Indonesia
[3]Department of Electrical Engineering, Unversitas Katolik Indonesia Atma Jaya, Indonesia
[5]University Center of Excellence on Artificial Intelligence for Healthcare and Society (UCE AIHeS), Indonesia
[1]wijayanti@lecturer.undip.ac.id*, [2]hertimiawarni.19071@student.its.ac.id, [3]7022211004@mhs.its.ac.id, [3]nova.eka@atmajaya.ac.id, [4]adonyrivai@gmail.com, [5]hery@ee.its.ac.id*

Abstract: This study aims to propose and implement a Fall Detection System (FDS) for the Elderly Activity Daily Living (ADL) based on the modified two-dimensional (2D) Light Detection and Ranging (LiDAR) method, inspired by slice feature on three-dimensional (3D) LiDAR data. LiDAR-based FDS is an ambient-based FDS that utilizes infrared laser light. This work is an improvement from our previous proposed method, namely FDS based on 2D LiDAR data. Previous work presents a research gap analysis of falling and not falling classes based only on footprint-scanned data. Therefore, detecting other essential fall activities is impossible, such as falling forward, backward, sideward, and others. The main points carried out in this paper are the design and realization of modified 2D LiDAR, primary dataset collection, an accuracy test using K-Nearest Neighbors (K-NN), Random Forest (RF), as well as Support Vector Machine (SVM) algorithms. This work is comparable to the previous work that uses Infrared Array-based FDS. The test results in this paper prove that the modified 2D LiDAR has better performance than the previous study, especially in terms of sensitivity and selectivity performance parameters. The test results show that FDS achieves optimal performance using the RF algorithm with 98.89% sensitivity and 99.38% selectivity. This percentage value is superior to the previous study, with 98% sensitivity and 93% selectivity. In addition, the results show that the modified 2D LiDAR is feasible to be used as an ambient-based FDS solution.

Keywords: Fall Detection System, Ambient-based, Elderly, 2D LiDAR, 3D LiDAR Slice Feature

1. Introduction

For the elderly, the older they get, the higher the risk of death due to falls [1]. Many elderly live alone at home while other family members are busy working. On the other hand, the elderly need direct and indirect technology-based supervision. Regarding technology-based indirect surveillance, FDS (Fall Detection System) has recently been developed to detect falls and transmit information to elderly families [2]. FDS has grown and become one of the implementations of the Internet of Things (IoT) [2-5] which is helpful for humanity.

FDS is classified into three sensor types: camera-based, wearable-based, and ambient-based [6]. In ambient-based FDS, various sensors are deployed, such as ultrasonic, motion, sound, and radar, to detect falling incidents in a room [7], [8]. It has been proposed using Infrared Radiation Change (IRC), a technique to detect the presence or activity of humans by utilizing differences in the intensity of infrared radiation emitted by humans [9]. The consequence of

Received: October 23th, 2022. Accepted: June 21st, 2023
DOI: 10.15676/ijeei.2023.15.2.8

using this technique is that detecting a fall incident requires at least four sensors with a complicated localization process.

For this reason, our previous study [10] proposes LiDAR (Light Detection and Ranging), especially 2D LiDAR (Two Dimensional LiDAR), as the primary sensor due to its capability in 360-degree scanning, and it does not require complicated localization. However, this previous work presents a gap in classifying FDS data, which is limited only to the footprint area of data scanning. Meanwhile, to analyze several fall activities such as fall forward, backward, sideward, and others, it is necessary for 2D LiDAR to scan body areas. Thus, in this study, 2D LiDAR is modified. Overall, the four steps of this study are:

1) Modification design of 2D LiDAR;
2) Primary dataset collection process;
3) Test the accuracy of fall incident detection using Machine Learning (ML) algorithms
4) Comparison with previous research, namely FDS based on Infrared Array [9].

Furthermore, the detail of previous research will be discussed in Section 2. The design and realization of the modified 2D LiDAR and the collection of a primary dataset will be discussed in Section 3. The accuracy test of fall incident detection using Machine Learning and its comparison to the previous research will be discussed in Section 4, while the final discussion of the conclusion is in Section 5.

2. IRC Based Fall Detection System in Previous Research

The working principle of FDS in the research proposed by Guan et al. [9] is to deploy several sensors to detect human activity. The sensor used is PIR (Pyroelectric Infrared), which can capture infrared light emitted by humans with a 5 to 14-micrometer wavelength. Figure 1 shows the concept adopted by Guan et al. The proposed model includes an object, radiation, and planned measurement space.

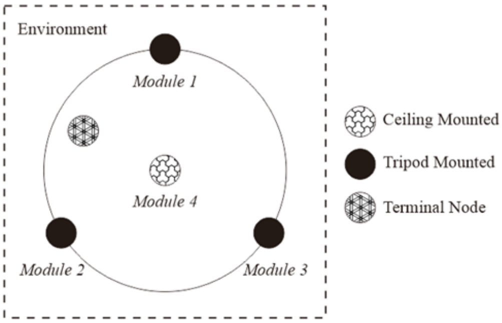


Figure 1. IRC-Based Fall Detection System in Previous Research

Human movement produces unique sensor data in each of its activities and actions. This study involved volunteers in demonstrating several activities, such as falling, walking, squatting, walking, running, and sitting, and resulted in a good fall detection performance, especially sensitivity parameters. In detecting human activities, especially the x-axis, performance parameters, especially sensitivity, reach up to 90% when using the SVM (Support Vector Machine) algorithm and 70% when using the K-NN (K-Nearest Neighbors) algorithm. Referring to the overall results from the calculation of the confusion matrix, the sensitivity score is 98%, and the specificity is 93%. These results are compared to our proposed method in the final discussion.

3. Proposed Fall Detection System

This section discusses the initial research proposal related to 2D-modified LiDAR for FDS. Specifically, this session discusses the design and realization of modified 2D LiDAR and the collection of a primary dataset.

A. 2D LiDAR Modification Design

This section discusses the initial research proposal related to 2D-modified LiDAR for FDS. Specifically, this session discusses the design and realization of modified 2D LiDAR and the collection of a primary dataset.

A.1. LiDAR Implementation for Fall Detection

LiDAR is an optical-based scanning technology to obtain distance information from an object [11]. In general, LiDAR is widely applied for navigation, such as in autonomous mobile robots [11-13], unmanned aerial vehicles [14], autonomous vehicles [15], [16], and autonomous guide vehicles [17], which have various detection objects. Thus, it will be beneficial if LiDAR is also implemented for FDS with less complex objects, namely humans, in an indoor environment. Simply speaking, the modified 2D LiDAR specific for FDS cases is the main contribution of this study.

A.2. Modification Design of 2D LiDAR

Two types of LiDAR are 2D LiDAR (Two-Dimensional Light Detection and Ranging) and 3D LiDAR (Three-Dimensional Light Detection and Ranging). 3D LiDAR has advantages over 2D LiDAR, namely the ability to scan at the azimuth and elevation angle. Meanwhile, 2D LiDAR can only do scanning at the azimuth angle. However, 3D LiDAR is at a disadvantage due to its high price [18].

In previous studies, mechanical modifications have been made so that 2D LiDAR can scan at the elevation angle using servo motor drives [18-19]. For LiDAR-based FDS to be built at a low cost, the primary sensor used in this study is modified 2D LiDAR, especially Slamtech RP LiDAR A1 M8, which has been modified. This product is a low-cost 2D LiDAR.

A.3. 2D LiDAR Physical Modification

Mechanical frame modification is required to enable 2D LiDAR scanning at an elevation angle. In previous studies, mechanical changes of LiDAR have been carried out so that it can scan at the elevation angle using servo motor drives [18-19]. Referring to the previous research, the servo motor is a mechanical solution for setting the elevation angle on 2D LiDAR. Technically, LiDAR elevation angle adjustment can be made by adjusting PWM (Pulse Width Modulation) on the servo motor. Figure 2 shows the realization of the 2D LiDAR modification.

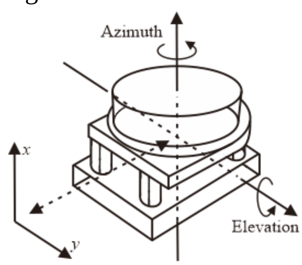


Figure 2. Realization Modification of 2D LiDAR Modification

A.4. Elevation Scanning

In this study, scanning at the elevation angle was limited to a rise of 0°, 10°, 20°, 30°, 40°, 50°, and 60°. At an angle >60°, it does not have important data because it is certain that the object scanned is the room’s ceiling. Figure 3 shows the LiDAR configuration illustration, specifically on object scanning at the elevation angle.

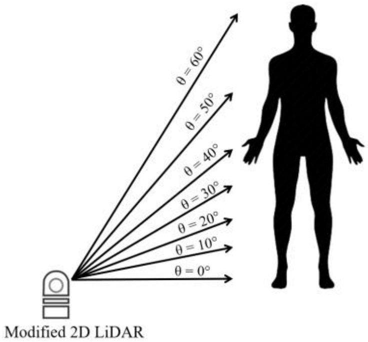


Figure 3. LiDAR Configuration at Elevation Angle

B. Primary Dataset Collection Process

Several steps must be taken to obtain the primary dataset, beginning with environmental scenarios, volunteering scenarios, and selecting sensor data to be used as a dataset.

B.1. Environmental Scenario

In the environmental scenario, a living room with 3 meters, a width of 3 meters, and a height of 3 meters, complete with furniture, were chosen as a test room. In order not to interfere with the activities of the elderly, LiDAR is installed on the edge of one side of the room wall. Thus, the sensor's scanning angle is assumed to be 180 degrees, even though the sensor can detect 360 degrees. Figure 4a shows the specifications of the test room. LiDAR is placed at the height of 10 cm from the floor surface to the "sensor's eye," as shown in Figure 4b.

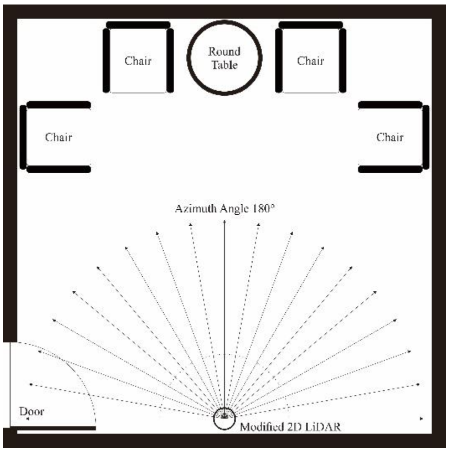


Figure 4a. Room Scenario Illustration

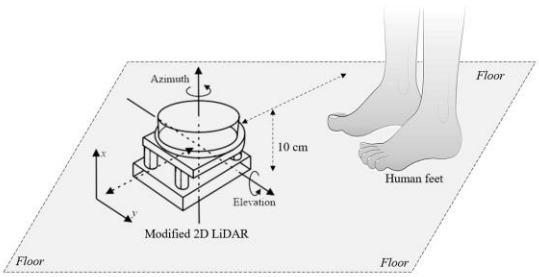


Figure 4b. LiDAR Placement

B.2. Volunteers Scenario

In this study, ten volunteers demonstrated various ADL and Fall activities, with height specifications between 160 to 180 cm and weight specifications between 55 to 85 kg. Volunteers consisted of seven men and three women.

B.3. Modified 2D LiDAR Data Outcome

Modified 2D LiDAR produces two types of data that have the potential to be used as a primary dataset, including 1) The 360° scanned data is in numerical form and technically is a file with the CSV (Comma Separated Value) extension that is used as the primary dataset, and 2) The 360° scanned data is also in the form of the point cloud that is only used as additional information when the sensor detects the presence of volunteers and is not used as a primary dataset. Our Primary Dataset Information can be seen in Table 1.

Table 1. Primary Dataset Information

Information	**Detail**
File Type	Comma Separated Values (CSV)
Volunteers Profile	• Ten people aged 20 to 35 years old • Height ranged from 160 to 180 cm. • Weight ranged from 55 to 85 kg. • Seven men and three women
Total Data	180 records (9 activities × 20)
Classes	ADL and Fall
ADL Class	An empty room, sitting, standing, picking up an object.
Fall Class	Fall forward using hands, fall forward using knees, sideward, backward, and lying down.

The dataset used in this study is a primary dataset directly obtained from LiDAR in a CSV file. Data acquisition during LiDAR scanning setup at an azimuth angle of 0° to 359° and the elevation angle of 0°, 10°, 20°, 30°, 40°, 50°, and 60°. Only data on the azimuth angle of 0° to 180° are used in the feature selection process. This is because LiDAR is placed on one side of the room wall (Figure 5a), so only data at 0° to 180° azimuth angle can describe the condition of the room.

Volunteers demonstrate several human activities, both fall activities and ADL (Activity Daily of Living). Activities presented by volunteers refer to previous research [11]. Each activity was demonstrated 20 times. Thus, 180 rows of data records were obtained (20 volunteers × nine activities). Each data record contains 181 distance information from azimuth angle (0° to 180°) and seven elevation angles (0°, 10°, 20°, 30°, 40°, 50°, and 60°). So, in one data record, there is 1267 distance information in millimeter units. All Activities Performed by Volunteers to gain all data can be seen in Table 2.

Table 2. All Activities Performed by Volunteers

Volunteer Activities	
ADL	Empty Room
	Standing
	Sitting
	Picking up an object
Fall	Fall forward using hands
	Fall forward using knees
	Fall backward
	Fall sideward
	Lying down

This study uses the point cloud as additional information on how modified 2D LiDAR detects objects. There are different data captured on each elevation angle tested in this experiment. To compare all object caught status, we run the modified 2D LiDAR and capture point cloud data on each elevation angle. The elevation angle object detected rate by point cloud data on modified 2D LiDAR based on volunteer activities can be seen in Table 3.

Table 3. Elevation Angle Object Detected Status by Point Cloud Data on Modified 2D LiDAR-based on Volunteer Activities

Volunteer Activities	**Elevation Angle Object Detected Status by Point Cloud Data on Modified 2D LiDAR**						
	0°	**10°**	**20°**	**30°**	**40°**	**50°**	**60°**
Empty Room	×	×	×	×	×	×	×
Standing	✓	✓	✓	✓	✓	✓	×
Sitting	✓	✓	✓	×	×	×	×
Picking up an object	✓	✓	✓	✓	×	×	×
Fall forward using hands	✓	✓	✓	×	×	×	×
Fall forward using knees	✓	✓	×	×	×	×	×
Fall backward	✓	✓	✓	×	×	×	×
Fall sideward	✓	✓	✓	×	×	×	×
Lying down	✓	×	×	×	×	×	×

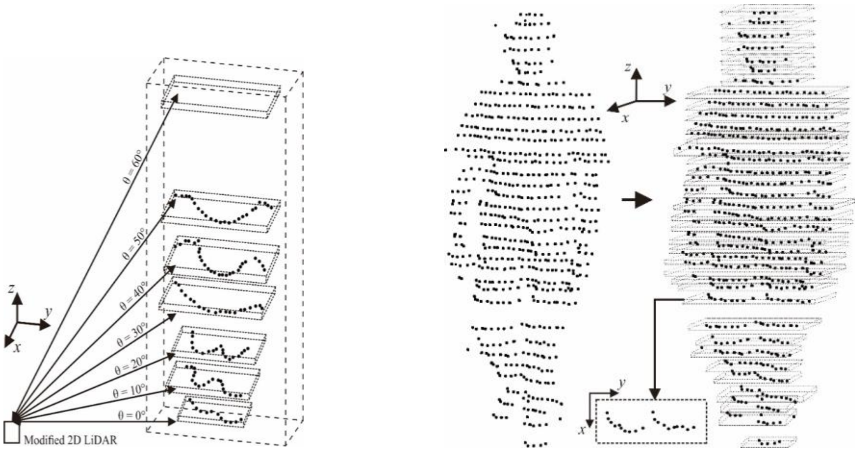
Note:
✓ : Object Detected
× : No Object Detected

B.4. Adapted 3D LiDAR Slice Feature

The distance measured in 2D LiDAR can be used to determine the x and y coordinates so that the location of each point on a 2-dimensional Cartesian plane can be known. As in 2D LiDAR, the distance measured in 3D LiDAR can also be used to determine the location of each point represented in x, y, and z coordinates. Determination of coordinates based on the distance measured in LiDAR can be determined using trigonometric equations [20].

The data structured by modified 2D LiDAR in this study, an environmental representation that resembles the data points of 3D LiDAR, is obtained. With the elevation angle on modified 2D LiDAR, several layers of distance data obtained from 2D LiDAR can be obtained. So, the coordinates of each point form not only a 2D space (x and y) but also a 3D (x, y, and z) because there is a 2D layer at each specified elevation angle.

The point collection data in each layer is similar to the coordinate data for each point obtained from 3D LiDAR. It is said that because it can be done by extracting slice features on 3D LiDAR point cloud data, point coordinates are obtained in 2D cartesian space at each layer of 3D LiDAR. The technique in the previous study was initiated to detect false positives from pedestrian objects reconstructed with a 3D LiDAR point cloud [21]. Thus, the formation of the layered slice is applied in this study by applying the elevation angle to the modified 2D LiDAR. For comparison, point cloud data representing people in a “Standing” position from the KITTI dataset was used in this study [22]. The visualization of the point cloud data formed from modified 2D LiDAR with an example of the “Standing” activity and the representation of the “Standing” activity data from 3D LiDAR taken from the KITTI dataset can be seen in Figure 5.



a) b)

Figure 5. Adapted 3D LiDAR Slice Feature for Modified 2D LiDAR Data Acquisition.
a) Modified 2D LiDAR Data Acquisition;
b) Adapted Slice Feature 3D LiDAR Data Acquisition [22]

C. Machine Learning Algorithms

The primary dataset that has been collected is then classified using Machine Learning algorithms. The K-NN algorithm is one of the machine learning algorithms commonly used for classification and detection. This algorithm is the easiest and simplest among other classification and detection algorithms [23]. In another study, K-NN (K-Nearest Neighbors), RF (Random Forest), and SVM (Support Vector Machine) have a good performance on FDS [24-27]. Especially for SVM, its key strength is the ability to apply the kernel method to handle a wide range of challenging problems [28]. In a previous study, KNN and SVM also proposed infrared array-based FDS [9]. RF algorithm has high accuracy in detecting human activities [29]. RF and K-NN are also well implemented in camera-based FDS by analyzing the human skeleton's point variation [30]. RF and K-NN have also been implemented in a smaller scope, such as detecting and classifying fall incidents from bed [31]. K-NN and RF are used as the proposed algorithm in the world-class FDS competition [32]. From those considerations, K-NN, RF, and SVM are used to process the primary dataset in this study.

The primary dataset collected and the three Machine Learning algorithms used need to be tested for their performance. For this reason, several parameters can be used as references in assessing performance, including sensitivity, selectivity, accuracy, precision, and FI-score [6], as shown in Table 4.

Table 4. Performance Parameter Formula [6]

Performance Parameters	**Formula**
$Sensitivity$	$\frac{TP}{TP+FN}\ x\ 100\%$
$Selectivity$	$\frac{TN}{TN+FP}\ x\ 100\%$
$Accuracy$	$\frac{TP+TN}{TP+FN+TN+FP}\ x\ 100\%$
$Precision$	$\frac{TP}{TP+FP}\ x\ 100\%$
$F_1\ Score$	$2 \times \frac{precision \times sensitivity}{precision + sensitivity}$

These parameters require a confusion matrix with attributes. TP (True Positive), which is the number of positive data correctly classified by FDS; TN (True Negative), which is the amount of negative data correctly classified by the system; FN (False Negative), which is the number of negative data but classified incorrectly by FDS; and FP (False Positive), which is the number of positive data but incorrectly classified by FDS.

4. Result and Discussion

A. FDS Accuracy using K-NN, RF, and SVM

In general, this trial aims to determine the feasibility of modified 2D LiDAR to be used as the primary sensor of FDS. In particular, this trial aims to assess the feasibility of the primary dataset generated by the sensor. The primary dataset collected is then processed using machine learning algorithms, namely K-NN, RF, and SVM, to determine the feasibility. After processing, we then performed a performance test.

The performance test starts by using the K-NN algorithm with the K-NN parameters setting, the value of K (number of neighbors) = 5, the distance calculation method using Euclidean, and uniform distribution. Setting these parameters produces 2 Class and 9 Class confusion matrix, as shown in Table in Table 5 and Table 6.

Table 5. K-NN 2 Class Confusion Matrix Result

		Predicted with K-NN	
		ADL	**Fall**
Actual	**ADL**	TP =240	FP =30
	Fall	FN =36	TN =444

Table 6. K-NN 9 Class Confusion Matrix Result

		Predict With K-NN								
		Empty Room	**Fall backward**	**Fall forward using hands**	**Fall forward using knees**	**Fall sideward**	**Lying down**	**Picking up an object**	**Sitting**	**Standing**
Actual	**Empty Room**	68	0	0	0	0	0	0	0	0
	Fall backward	0	69	0	0	0	0	0	0	0
	Fall forward using hands	9	0	49	12	0	0	0	0	0
	Fall forward using knees	0	0	13	42	0	0	5	5	3
	Fall sideward	0	0	0	0	69	0	0	0	0
	Lying down	4	0	0	0	1	192	1	2	0
	Picking up an object	0	0	0	4	0	0	60	0	4
	Sitting	12	0	0	2	9	17	5	23	0
	Standing	0	0	0	0	0	0	0	0	70

Performance testing is continued by using the SVM algorithm with SVM parameter settings, among others, Cost = 1.00, Epsilon Regression Loss = 0.10, Kernel RBF, Numerical tolerance = 0.001 and iteration limit = 100. FDS with our data and data and SVM produces 2

Class and 9 Class confusion matrix, as shown FDS with our data and SVM produces 2 Class and 9 Class confusion matrix, as shown in Table 7 and Table 8.

Table 7. SVM 2 Class Confusion Matrix Results

		Predicted with SVM	
		ADL	**Fall**
Actual	**ADL**	TP =267	FP =3
	Fall	FN =7	TN =473

Table 8. K-NN 9 Class Confusion Matrix Results

		Predict With K-NN								
		Empty Room	**Fall backward**	**Fall forward using hands**	**Fall forward using knees**	**Fall sideward**	**Lying down**	**Picking up an object**	**Sitting**	**Standing**
Actual	**Empty Room**	68	0	0	0	0	0	0	0	0
	Fall backward	0	69	0	0	0	0	0	0	0
	Fall forward using hands	0	0	70	0	0	0	0	0	0
	Fall forward using knees	0	0	0	68	0	0	0	0	0
	Fall sideward	0	0	0	0	69	0	0	0	0
	Lying down	0	0	0	0	0	198	0	0	2
	Picking up an object	0	0	0	0	0	0	68	0	0
	Sitting	0	0	0	0	0	0	0	68	0
	Standing	0	0	0	0	0	2	0	0	68

Performance testing is continued using the RF algorithm with the RF parameter setting Number of three = 10. FDS with our data and RF produces 2 Class and 9 Class confusion matrix, as shown in Table 9 and Table 10.

Table 9. RF 2 Class Confusion Matrix Result

		Predicted with RF	
		ADL	**Fall**
Actual	**ADL**	TP =267	FP =3
	Fall	FN =3	TN =477

Table 10. RF 9 Class Confusion Matrix Result

		Predict With K-NN								
		Empty Room	**Fall backward**	**Fall forward using hands**	**Fall forward using knees**	**Fall sideward**	**Lying down**	**Picking up an object**	**Sitting**	**Standing**
Actual	**Empty Room**	66	0	1	0	0	0	1	0	0
	Fall backward	0	69	0	0	0	0	0	0	0
	Fall forward using hands	0	0	70	0	0	0	0	0	0
	Fall forward using knees	0	0	0	68	0	0	0	0	0
	Fall sideward	0	0	0	0	69	0	0	0	0
	Lying down	0	0	0	0	0	200	0	0	0
	Picking up an object	0	0	0	0	0	0	68	0	0
	Sitting	0	0	0	0	0	0	3	65	0
	Standing	0	0	0	0	0	0	0	0	70

The confusion matrix results in Tables 5, 7, and 9 show that the overall performance parameters can be calculated, as shown in Figure 6.

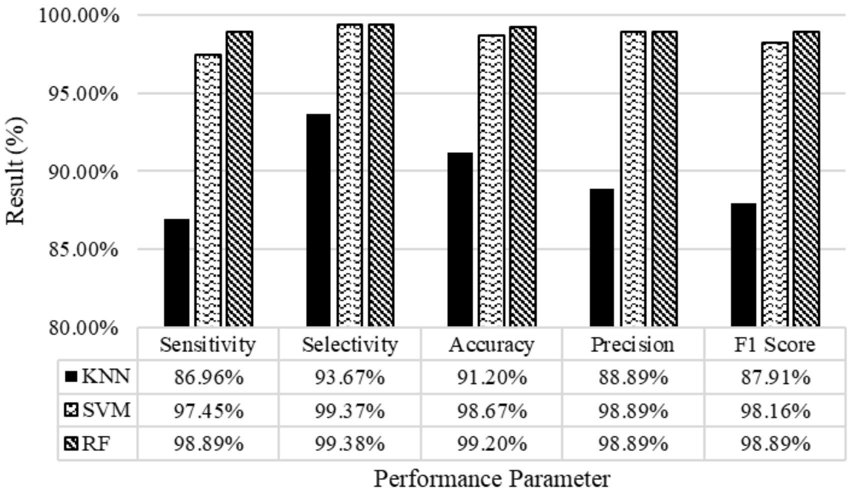


Figure 6. Performance Result

From the performance calculation result, it can be concluded that the RF algorithm performs better than KNN and SVM. The RF algorithm performs best based on three parameters: sensitivity, accuracy, and F1 Score. Meanwhile, the SVM algorithm only has two best performances based on three parameters: selectivity and precision.

B. Result Comparison with Previous Work

After getting the performance results, as shown in Figure 6, a comparison was made between the results of the previous study [9] and our proposed study using KNN-SVM-RF, as represented in Figure 7.

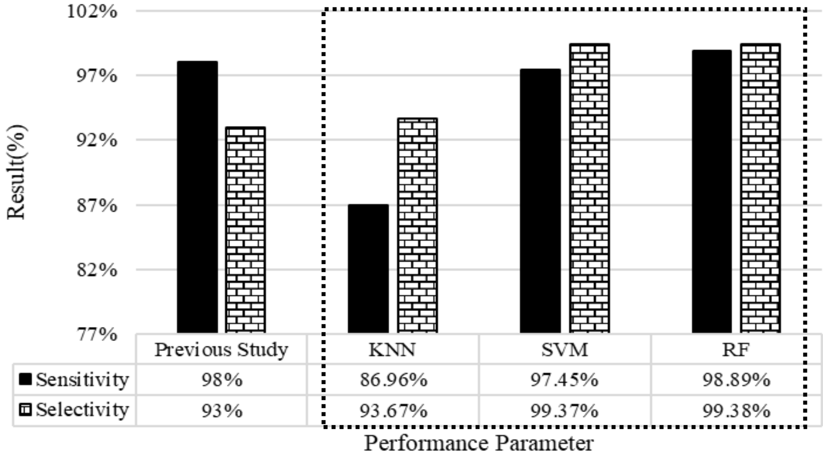


Figure 7. Result Comparison

As seen in Figure 7, the sensitivity and selectivity of this proposed study got higher performance than those in the previous research. This higher result is obtained when using the RF algorithm.

In general, these results indicate that the primary dataset in the proposed study is feasible to use and that modified 2D LiDAR has been successfully implemented as the primary sensor in FDS as a Low-Cost Alternative to 3D LiDAR. Thus, modified 2D LiDAR can be used as an ambient-based FDS solution in addition to those proposed by previous researchers [7 – 9].

5. Conclusion

In general, this study proposes a Modified 2D LiDAR-based FDS for the elderly. Modified 2D LiDAR inspired by slice feature on 3D LiDAR data is proposed as an ambient-based FDS solution in addition to those proposed by previous researchers [7 – 9]. Overall, this study involves designing and realizing modified 2D LiDAR, collecting the primary dataset, testing fall detection accuracy using machine learning algorithms, and comparing it to the previous research, namely FDS based on Infrared Array [9]. The test results show that FDS achieves optimal performance using the RF algorithm with 100% sensitivity and 99.4% selectivity. This percentage value is superior to the previous study, with 98% sensitivity and 93% selectivity [9]. Thus, modified 2D LiDAR can be used as an ambient-based FDS solution in addition to those proposed by previous researchers.

6. Acknowledgement

This study is supported by the Deputy of Strengthening Research and Development Ministry of Research and Technology / National Research and Innovation Agency by Master Contract and Implementation Contract Amendments, Post-Doctoral Research, Master Contract Number: 3/ E1/KP.PTNBH/2020, March 18, 2020, Amendment Number Master Contract: 3 / AMD / E1 / KP.PTNBH / 2020, dated 11 May 2020.

7. References

[1]. M. Cheffena, "Fall Detection Using Smartphone Audio Features," in *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1073-1080, July 2016.

[2]. W. Saadeh, S. A. Butt, and M. A. B. Altaf, "A Patient-Specific Single Sensor IoT-Based Wearable Fall Prediction and Detection System," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 5, pp. 995-1003, May 2019.

[3]. N. B. Joshi and S. L. Nalbalwar, "A fall detection and alert system for an elderly using computer vision and Internet of Things," *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore*, 2017, pp. 1276-1281.

[4]. S. C. Chavan and A. Chavan, "Smart wearable system for fall detection in elderly people using Internet of Things platform," *2017 International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai*, 2017, pp. 1135-1140.

[5]. S. A. Waheed and P. Sheik Abdul Khader, "A Novel Approach for Smart and Cost Effective IoT Based Elderly Fall Detection System Using Pi Camera," *2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), Coimbatore*, 2017, pp. 1-4.

[6]. F. Hussain, F. Hussain, M. Ehatisham-ul-Haq and M. A. Azam, "Activity-Aware Fall Detection and Recognition Based on Wearable Sensors," *in IEEE Sensors Journal*, vol. 19, no. 12, pp. 4528-4536, June 15, 2019.

[7]. E. Cippitelli, F. Fioranelli, E. Gambi and S. Spinsante, "Radar and RGB-Depth Sensors for Fall Detection: A Review," in *IEEE Sensors Journal*, vol. 17, no. 12, pp. 3585-3604, June 15, 2017.

[8]. F. De Backer et al., “Towards a social and context-aware multi-sensor fall detection and risk assessment platform,” *Comput. Biol. Med*., vol. 64, pp. 307–320, Sep. 2015.

[9]. Q. Guan, X. Yin, X. Guo, and G. Wang, "A Novel Infrared Motion Sensing System for Compressive Classification of Physical Activity," in *IEEE Sensors Journal*, vol. 16, no. 8, pp. 2251-2259, April 15, 2016.

[10]. Miawarni et al., "Fall Detection System for Elderly based on 2D LiDAR: A Preliminary Study of Fall Incident and Activities of Daily Living (ADL) Detection," *2020 International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, 2020, pp. 1-5.

[11]. Hutabarat, M. Rivai, D. Purwanto, and H. Hutomo, "Lidar-based Obstacle Avoidance for the Autonomous Mobile Robot," *2019 12th International Conference on Information & Communication Technology and System (ICTS)*, Surabaya, Indonesia, 2019, pp. 197-202.

[12]. D. Ghorpade, A. D. Thakare, and S. Doiphode, "Obstacle Detection and Avoidance Algorithm for Autonomous Mobile Robot using 2D LiDAR," *2017 International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune*, 2017, pp. 1-6.

[13]. S. Gatesichapakorn, J. Takamatsu and M. Ruchanurucks, "ROS based Autonomous Mobile Robot Navigation using 2D LiDAR and RGB-D Camera," *2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP)*, Bangkok, Thailand, 2019, pp. 151-154.

[14]. L. Zheng, P. Zhang, J. Tan, and F. Li, "The Obstacle Detection Method of UAV Based on 2D LiDAR," *in IEEE Access*, vol. 7, pp. 163437-163448, 2019.

[15]. A. N. Catapang and M. Ramos, "Obstacle detection using a 2D LIDAR system for an Autonomous Vehicle," *2016 6th IEEE International Conference on Control System, Computing and Engineering (ICCSCE), Batu Ferringhi*, 2016, pp. 441-445.

[16]. V. Vaquero, A. Sanfeliu and F. Moreno-Noguer, "Deep Lidar CNN to Understand the Dynamics of Moving Vehicles," *2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD,* 2018, pp. 4504-4509.

[17]. Yılmaz, Abdurrahman and Hakan Temeltas. “Self-adaptive Monte Carlo method for indoor localization of smart AGVs using LIDAR data.” *Robotics Auton*. Syst. 122, 2019.

[18]. P. Queralta et al., "FPGA-based Architecture for a Low-Cost 3D Lidar Design and Implementation from Multiple Rotating 2D Lidars with ROS," *2019 IEEE SENSORS, Montreal, QC*, Canada, 2019, pp. 1-4.

[19]. Harchowdhury, L. Kleeman and L. Vachhani, "Coordinated Nodding of a Two-Dimensional Lidar for Dense Three-Dimensional Range Measurements," in *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 4108-4115, Oct. 2018.

[20]. J. P. Queralta et al., FPGA-based Architecture for a Low-Cost 3D Lidar Design and Implementation from Multiple Rotating 2D Lidars with ROS, 2019 *IEEE SENSORS*, 2019, pp. 1-4, DOI: 10.1109/SENSORS 43011.2019.8956928.

[21]. K. Kidono, T. Miyasaka, A. Watanabe, T. Naito, and J. Miura, "Pedestrian recognition using high-definition LIDAR," *2011 IEEE Intelligent Vehicles Symposium (IV)*, 2011, pp. 405-410, DOI: 10.1109/IVS.2011. 5940433.

[22]. A. Geiger, P. Lenz, C. Stiller, R. Urtasun. Vision meets Robotics: *The KITTI Dataset, International Journal of Robotics Research (IJRR)*. 2013

[23]. Okfalisa, I. Gazalba, Mustakim, and N. G. I. Reza, "Comparative analysis of k-nearest neighbor and modified k-nearest neighbor algorithm for data classification," *2017 2nd International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, Yogyakarta, 2017, pp. 294-298.

[24]. A. Rezaei et al., "Unobtrusive Human Fall Detection System Using mmWave Radar and Data Driven Methods," in *IEEE Sensors Journal*, vol. 23, no. 7, pp. 7968-7976, 1 April1, 2023, doi: 10.1109/JSEN.2023.3245063.

[25]. R. Maryam, A. Shahzad, M. Bashir, L. A. Caceres-Najarro and M. Kim, "A Fall Detection Algorithm for Thigh mounted Smartphones using Random Forest and Feature Selection Techniques," *2022 17th International Conference on Emerging Technologies (ICET)*, Swabi, Pakistan, 2022, pp. 48-53, doi: 10.1109/ICET56601.2022.10004626.

[26]. A. Taha, M. M. A. Taha, B. Barakat, W. Taylor, Q. H. Abbasi and M. Ali Imran, "AI-Based Fall Detection Using Contactless Sensing," *2021 IEEE Sensors, Sydney, Australia*, 2021, pp. 1-4, doi: 10.1109/SENSORS47087.2021.9639715.

[27]. S. Peng, B. Yang and Q. Peng, "Elder Fall Detection System Based on Two-level SVM Algorithm," 2022 *37th Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, Beijing, China, 2022, pp. 1308-1312, doi: 10.1109/YAC57282.2022.10023910.

[28]. Fathimah Al-Ma’shumah, Mostafa Razmkhah, Sohrab Effati, “Expectation-based and Quantile-based Probabilistic Support Vector Machine Classification for Histogram-Valued Data”, *International Journal on Electrical Engineering and Informatics* - Volume 14, Number 1, March 2022, pp. 234-253 [DOI Number: 10.15676/ijeei.2022.14.1.15].

[29]. Gjoreski H. et al. (2020) Wearable Sensors Data-Fusion and Machine-Learning Method for Fall Detection and Activity Recognition. In: Ponce H., Martínez-Villaseñor L., Brieva J., Moya-Albor E. (eds) Challenges and Trends in Multimodal Fall Detection for Healthcare. *Studies in Systems, Decision, and Control*, vol 273. Springer, Cham.

[30]. A. Y. Alaoui, S. El Fkihi, and R. O. H. Thami, "Fall Detection for Elderly People Using the Variation of Key Points of Human Skeleton," in *IEEE Access*, vol. 7, pp. 154786-154795, 2019.

[31]. F. Zhao, Z. Cao, Y. Xiao, J. Mao, and J. Yuan, "Real-Time Detection of Fall From Bed Using a Single Depth Camera," in *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 3, pp. 1018-1032, July 2019.

[32]. Ponce H., Martínez-Villaseñor L. (2020) Approaching Fall Classification Using the UP-Fall Detection Dataset: Analysis and Results from an International Competition. In: Ponce H., Martínez-Villaseñor L., Brieva J., Moya-Albor E. (eds) Challenges and Trends in Multimodal Fall Detection for Healthcare. *Studies in Systems, Decision, and Control*, vol 273. Springer, Cham.

Wijayanti is a senior lecturer at the Department of Architecture, Diponegoro University. Since 1992 – now, she done a lot of research in the housing sector focusing on the competence of the disabled and the elderly in several cities in Indonesia and Japan, supported by Monbusho scholarships, Universe Foundation Japan, Sumitomo Foundation, and DIKTI. As a member of the IEEE, she is currently involved in a research team that focuses on Artificial Intelligence for the Elderly in Public Housing based on Local Wisdom, which is supervised by Prof.Dr.Ir. Mauridhi Hery Purnomo, M.Eng. from the Institut Teknologi Sepuluh Nopember.

Herti Miawarni currently is Ph.D candidate from Institut Teknologi Sepuluh Nopember. She has experience in data acquisition system. She is also a lecturer of Dept. of Electrical Engineering, Universitas Bhayangkara Surabaya Indonesia, concerned with machine learning for instrumentation and measurement.

Nova Eka Budiyanta currently is Ph.D candidate from Institut Teknologi Sepuluh Nopember. He has experience in hardware-software programming. He is also a lecturer of Dept. of Electrical Engineering, Universitas Katolik Indonesia Atma Jaya, concerned with image processing, robotics, and artificial intelligence for computer vision research field.

Dony Agus Rivai, is from Dept, of Electrical Engineering, Faculty of Intelligent Electrical and Informatics Technology (F-Electics), Institute Technology Sepuluh Nopember Surabaya, Indonesia. He holds a Master Degree from Multimedia Intelligent Network, Institute Technology Sepuluh Nopember Surabaya. His current research interest include machine learning, artificial intelligence, image processing and data mining.

Mauridhi Hery Purnomo (Senior Member, IEEE) received the B.S. degree from the Electrical Engineering Institut Teknologi Sepuluh Nopember (ITS), Surabaya in 1984, the M.S. degree in 1989 and the Ph.D degree from the Electrical Engineering Osaka City University, Japan in 1995. He is a Professor with the ITS and involved in teaching on research philosophy, artificial intelligence, neural network, and image processing. His research interests include smart grid, renewable energy, artificial intelligent application on healthcare and power systems. He is the Chief Executive of University Center of Excellence on Artificial Intelligence for Healthcare and Society (UCE AIHeS) in ITS.