Optimization of Heavy Point Position Measurement on Vehicles Using Support Vector Machine

Franky Melky [1], Siti Sendari [2], Ilham Ari Elbaith [2]
[1] Research Centre for Structural Strength Technology - National Research and Innovation Agency, Habibie Science Technology Area Building 220, South Tangerang 15314, Indonesia
[2] State University of Malang, Jl. Semarang No. 5, Malang 65141, Indonesia

INFO | **ARTICLE**

Article history:

Received May 23, 2023
Revised July 04, 2023
Published July 24, 2023

Keywords:

Hydraulic lift table;
Weight point testing;
LVDT;
Support vector machine

During this time, weight point testing is still done manually using a jack until now it has begun to be replaced with hydraulic equipment namely Lift Table Hydraulic (LTH) which is a portable table with a hydraulic system equipped with sensors (Loadcell and LVDT), powerpack control panel, powerpack, relay module and solenoid valve to adjust the table height. This portable table is one component of the heavy point measurement equipment system used for mining and plantation vehicles such as tractors, buses, trucks which are required to have a safe structure in heavy road conditions with rough or uneven surfaces with slopes up to an angle of 15 ° to 20 °. This emphasized research contributes to more accurate testing. Based on these problems, this research was conducted using Support Vector Machine (SVM) for the optimization of heavy point position measurement. The objects used are minibuses with 1 and 19 passengers and buses with 29 and 36 passengers on the proportion of datasets (training: testing) of 80% and 20% using linier kernel. From the experimental results, the accuracy in the condition of 1 passenger is 94.7%; minibus 19 passengers 98%; bus 29 passengers 98.1% and bus 36 passengers 97.4%. The highest accuracy obtains on 29 passengers minibus.

This work is licensed under a Creative Commons Attribution-Share Alike 4.0

Corresponding Author:

Franky Melky, Electrical Engineering, University Negeri Malang, Jl Semarang No 5, Malang, Indonesia
Email: franky.melky.2105348@students.um.ac.id

1. INTRODUCTION

During this time, weight point testing is still done manually using a jack until now it has begun to be replaced with hydraulic equipment namely Lift Table Hydraulic (LTH) which is a portable table comes with a hydraulic drives, sensors (Loadcell and LVDT), powerpack control panel, powerpack, hydraulic cylinder, relay module and solenoid valve to adjust the table height [1]. Hydraulic drives is chosen for their outstanding force and power density and drive stiffness. They are indispensable when heavy load applications have to meet strict demands on fast response and high precision [2]. In hydraulic drives, sensors used are Loadcell and LVDT. Firstly, Load cell is the main component in the weighing system which use pressure principles utilizing a strain gauge that will turn a mechanical shift into a change in resistance [3]. Secondly, Linear variable differential transformer (LVDT) is one of the most widely used transducers for the measuring linear displacement in a specimen which works on the principle of magnetic induction [4]. Furthermore, Solenoid is an Electrical device which works on the principle of an electromagnet (i.e. when an electric current is passed through a wire or a coil a magnetic field is produced). A solenoid being an electromechanical device is used for a wide array of industrial applications, including fluid power hydraulic systems, to control cylinders, process control systems, as cheap and robust switching components and manufacturing departments [5]. This portable table is one component of the heavy point measurement equipment system used for mining and plantation vehicles such as tractors, buses, trucks which are required to have a safe structure in heavy road conditions with rough or uneven surfaces with slopes up to an angle of 15° to 20° [6]. It works on the principle of fluid-pressure or Pascal Law is the principle in fluid mechanics that explain that the pressure applied anywhere in a confined incompressible fluid is transmitted equally in all directions throughout the fluid such that the pressure variations (initial differences) remain the constant. According to S. B. Bhalake, *et al.* [7] LTH contain five major components such as Platform, Base Platform, Scissor Legs, Hydraulic Cylinder and Motor.

The position of the vehicle's heavy point is very important to know in the context of vehicle planning, especially to ensure braking capacity and acceleration, planning the position of the body centre and aspects of vehicle stability, determining vehicle stability and the moment of inertia [8]. According to the research of Kardmiaji, *et al.*[9] One of the vehicle stability factors, especially to avoid rolling conditions due to height differences on both sides of the road until the vehicle tilts following the contours of the road, is the location of the weight point both vertically and in the horizontal direction to the fulcrum or tyres of the vehicle calculated from the road surface. The higher the location of the weight point from the road surface, the easier it is to change the horizontal and vertical bearing forces on the left and right vehicle tyres. This difference in bearing force occurs mainly when the vehicle is tilted so that it becomes unstable or the vehicle rolls over more easily. The COG of a minibus is one of the basic parameters that affect vehicle operation to maintain traffic safety. In addition, COG greatly affects vehicle manoeuvres to transfer loads between the front wheels and rear wheels such as when turning, braking and accelerating [10]. However, Karmiadji, *et al.* research has not yet implemented the use of SVM. By using SVM, It is expected that the measurement of the weight point position will be more accurate [11].

There are several machine learning algorithms or methods that can be used for weight point position measurement, including Naïve Bayes, Support Vector Machine (SVM) and K-Means clustering [12]. Support Vector Machine (SVM) is a technique for classification and regression and is in the same class as ANN in terms of functions and conditions of problems that can be solved and is included in the supervised learning class. SVM aims to separate two classes using support vector and margin to find the optimal classifier function that can separate two different classes. This technique attempts to find the best hyperplane among an infinite number of functions to separate two kinds of objects. The best hyperplane is the hyperplane that lies midway between two sets of objects from two classes [13]. The superiority of Support Vector Machine (SVM) comes from the ability to apply linear splitting to large-dimensional non-linear input data, and this is obtained by using the necessary kernel functions. The ability of Support Vector Machine (SVM) to process large-dimensional data is very suitable to be applied to text data which tends to be large-dimensional.

According to A. Han etc [14] Support Vector Machine (SVM) has a higher accuracy than Neural Network and Linear Regression. Approximation models or commonly called kernels can help in overcoming the problem of feature space, and affect the accuracy of the classification method that will be generated. According to A. Z. Praghakusma and N. Charibaldi [15] there are several types of kernels in Support Vector Machine (SVM) besides the RBF kernel, namely linear kernel, polynomial, and sigmoid kernel. According to B. Sanjaa and E. Chuluun [16] training time of the linear kernel is faster than the other kernels and is suitable for the large-dimensional data. In the polynomial kernel, there is the use of adjustable degrees to increase the likelihood that the data can be linearly separated in a dimensional space without slowing down the model time [17]. In the sigmoid kernel, the use of gamma can be adjusted to increase the accuracy value but depends on the number of features used but depends on the number of features used [18].

Meanwhile, the method of measuring the position of the weight point requires the existence of lifting equipment for the vehicle to be measured and at the same time can adjust its position in such a way that measurements can be made precisely and accurately. Lastly, this research contributes to simplify the point of weight testing, making the test faster and more accurate.

2. METHOD

2.1. Weight Point Measurement

The weight point is expressed in terms of the three orthogonal axes x, y, z as shown in Fig. 1. As a reference point or coordinate (0,0,0) is the location of the tangent point of the right front wheel to the floor surface. The distance of the weight point in the longitudinal direction (X axis) is expressed as "l1", the transverse direction (Y axis) is expressed as "t", and the vertical direction (Z axis) is expressed as "h0" [19].

The distance between the longitudinal ($l1$) and transverse (c) weight points can be determined by measuring the mass (weight) of the vehicle through all four wheels. Measurement of the mass of the test object is done by placing the four wheels of the test object on the hydraulic lift table + Load Cell, then measuring the load without passengers (empty) and with passengers. The longitudinal and transverse weight points in Fig. 2 are calculated based on the moment equation as follows,

$$l1 = \frac{(P1 + P2)L1}{\text{Ptotal}} \tag{1}$$

where $l1$ is longitudinal weight point distance, $Ptotal$ is total weight of the vehicle in horizontal condition, $L1$ is distance between the centre point of the front and rear wheels, $P1$ is Weight on the right front wheel, $P2$ is weight on the left front wheel. The position of the vehicle's transverse direction (t) can be found through the following equation:

$$t = \left((P1 - P2)\frac{T1}{2} + (P3 - P4)\frac{T2}{2} \right) \frac{1}{Ptotal} \tag{2}$$

where t is transverse direction weight point distance, $P1$ is weight on the right front wheel, $P2$ is weight on the left front wheel, $P3$ is weight on the right rear wheel, $P4$ is weight on the left rear wheel, $T1$ is distance between right and left front wheel axes, $T2$ is distance between right and left rear wheel axes, $Ptotal$ is $Total$ weight of the vehicle in horizontal condition. If the value of t is negative, the vehicle's weight point is located to the right of the vehicle centre line in the transverse direction (Y axis).

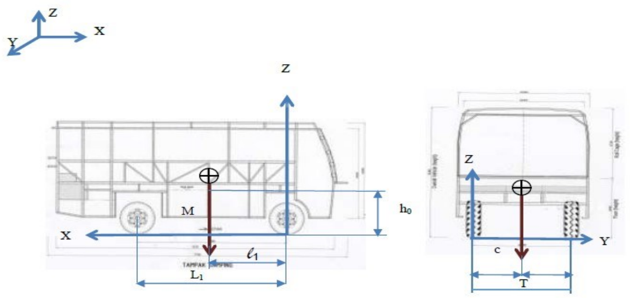

Fig. 1. Orthogonal Axis x, y, z

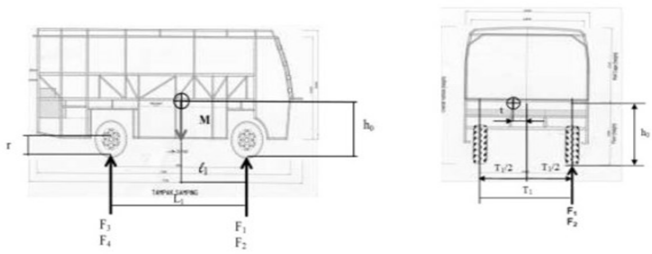

Fig. 2. Determination of the point of weight (COG) of the bus vehicle in the longitudinal and transverse directions

While the weight point in the vertical axis direction (h0), is done by measuring the weight of the vehicle with the condition of the test object lifted on both front wheels, as described in Fig. 3. The moment balance equation for these conditions is as follows [20],

$$\alpha = arcsin\left(\frac{H}{L1}\right)$$
$$h0 = r + \left(\frac{1}{tg\alpha}\right)\left(l1 - L1\frac{F1 + F2}{Ptotal}\right) \tag{3}$$

where $Ptotal$ is total weight of the vehicle in horizontal condition, $L1$ is Distance between the centre point of the front and rear wheels, H is height of jig for jacking, $l1$ is distance of the centre of gravity in the longitudinal direction, $F1$ is weight on the right front wheel, $F2$ is weight on left front wheel, $h0$ is Distance between the centre point of the front and rear wheels and the COG point, r is wheel radius, α is lift angle.

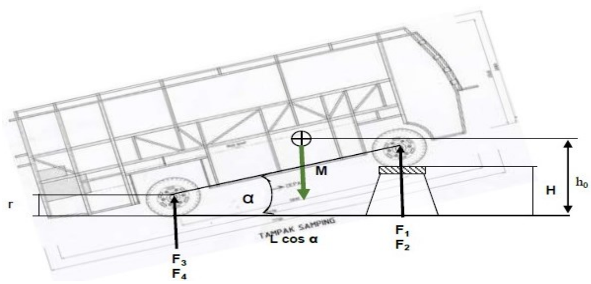

Fig. 3. Determination of the weight point (COG) of the bus vehicle in the vertical direction

2.2. Control System and Data Acquisition

The system is controlled by an electronic control system that drives both actuators and mechanical devices of the LTH [21]. The test object is placed on the LTH in such a way that the test object (measured vehicle) can be lifted and positioned by the controller from the computer according to the standard measurement *Australian Design Rule 59/00-Standards For Omnibus Rollover Strength 2017* where the passenger load per person is set at 70 kg [22]. Furthermore, at each specific position, the load is measured using a loadcell and the height (mm) is measured at a certain point using an LVDT, the results of these measurements are recorded by a Data Logger [23]. The circuit of the electronic control system, as well as the LVDT measuring equipment and hydraulic control can be shown in Fig. 4 [24], [25] with the usage of NI USB 6251 [26] and NI USB 9237.

Data acquisition is the process of converting sensor signals through hardware and then using software to read, convert and storage. According to the requirements of versatility and reliability for the heavy point position test, a data acquisition system with high sampling rate and general purpose is designed based on LabVIEW [27]. Because of that NI USB 9237, 4 channel ADC with 50kS/s sampling rate and 24bit resolution, is used [28].

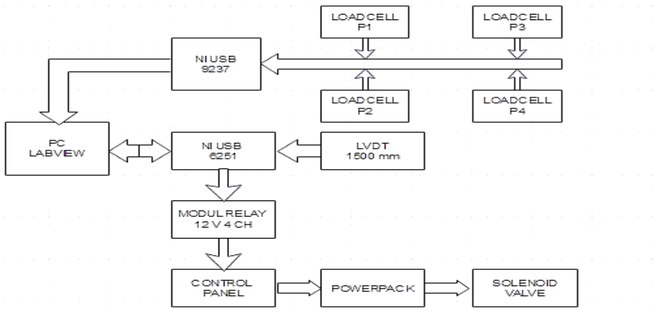

Fig. 4. Schematic of the Control System and Data Acquisition

Fig. 4 Description:

- 4 analogue inputs from Loadcell, into the input of NI USB 9237 module:
- Loadcell 1, P2 (Left front wheel)
- Loadcell 2, P1 (Right front wheel)
- Loadcell 3, P4 (Left rear wheel)
- Loadcell 4, P3 (Right rear wheel)
- The output of the NI USB 9237 module is processed into digital data by a computer with the Labview program.
- 1 analogue input from Displacement Transducer (LVDT) 1500mm, into the analogue input of NI USB module 6251, LVDT, placed on the front wheel lift tool.
- The output of the NI USB 6251 module is processed into digital data by a computer with the Labview programme, to control and monitor the height.
- From the NI USB 6251 output there are 8 Digital Output (DO), which are used 4 pieces to control the Power Pack through the Relay Module to turn off and turn on the powerpack (2 DO) and activate the Selenoid Valve Up / Down (2 DO) to move up or down.
- The lifting device is made to lift the front wheel simultaneously with the Hydraulic system [29].

2.3. Data Classification

From the explanation of the scheme, there is a potential error in measuring the position of the heavy point, especially in taking data on the X (l1), Y (t), Z (h0) values because the three values have not been classified. Therefore, it is necessary to use the Support Vector Machine (SVM) method to perform the data classification process [30]. The SVM method will classify the data into two classes, namely class 1 and class 2 where the division of this class refers to the *UNECER No. 66* standard [31]. The standard explains that the weight point measurement is more accurate if the lift angle is in the range of 15^0 to 20^0 as described in Table 1 [22].

Table 1. SVM Data Classification

	CLASS 1	CLASS 2
ANGLE	0^0-14^0	15^0-20^0
HEIGHT	0-895 mm	900-1390 mm

2.4. Dataset

By using mathematical (1),(2),(3) and moving the LVDT from a position of 200 mm up to 1300 mm until it returns to 200 mm then classifying the LVDT values into two different classes, a dataset is obtained where each research object gets a different dataset. The research objects used were minibuses with 1,19,29 to 36 passengers.

Vol. 9, No. 3, September 2023, pp. 673-683

Each dataset consists of 5 columns such as LVDT, X ($l1$), Y (t), Z ($h0$) and Class. Each dataset is simulated to get into .csv format (Table 2) [32] and will be optimized using support vector machine [33].

Table 2. Dataset in csv format

LVDT (mm)	X (l_1)	Y (t)	Z (h0)	Class
200				
300				
400				
500				
600				
700				
800				
900				
1000				
1100				
1200				
1300				

2.5. SVM

In this study using the SVM method to get the best accuracy value [34]. SVM (Support Vector Machine) is the technique for data classification. The data classification process mainly involves training and test datasets. Each element of dataset consists of multiple features and classification attributes. The principle of SVM is to create the model for predicting classification based on the given features of current element of test dataset [35] . The SVM algorithm can have various kernels, but the linear, polynomial, RBF, sigmoid are basically dominates [36]. Linear SVM have performed well on massive datasets with many features. In practice, the nonlinear SVM has inadequate result applying to data with more than 10000 entries. Therefore, linear SVM was chosen [37]. Classification of the data was then done by svm based on the training data given to it in the form of features for various dataset [38].

3. RESULTS AND DISCUSSION

In this study the object used are a mini bus on condition of a 1 passenger minibus, 19 passenger minibus, 29 passenger bus and 36 passenger bus. Each object will be placed on the Hydraulic Lift Table (LTH) to weigh the weight of the right and left front wheels and the right and left rear wheels and then measure L (Distance between the centre point of the front and rear wheels), T1 (Distance between the right and left front wheel axes), T2 (Distance between the right and left rear wheel axes), R (wheel radius) [39]. Data measurement shown in Table 3.

Table 3. Data Measurement

	Measurement Result (kg)								
Load Type	**P1**	**P2**	**P3**	**P4**	**PTOTAL**	**L (mm)**	**T1 (mm)**	**T2 (mm)**	**R (mm)**
1-Passenger MINIBUS	989.10	1031.93	927.92	925.88	3874.86	3380	1540	1500	785
19- Passenger MINIBUS	1095.1	1205.28	1339.88	1463.27	5103.5985	3380	1540	1500	785
29-Passenger BUS	1578.5	1565.24	2373.86	2435.04	7952.6403	3380	1670	1760	785
36- Passenger BUS	1565.2	1658.03	2550.27	2720.56	8494.101	3380	1670	1765	785

The first dataset consists of 193 rows and 5 columns will be optimized on a proportion (training: testing) of 80% and 20%, namely a 1-passenger minibus with a data class classification between LVDT and Z in the form of an XY graph as shown in Fig. 5, a scatter plot and confusion matrix will be obtained as shown in Fig. 6 and Fig. 7. Scatter plot is one of the versatile, polymorphic and generally used for showing two or three variables on the 2D or 3D axes. It is very useful in the early stage of analysis for showing correlation and patterns in low dimensional data [40]. In the meantime, Confusion matrix is a tool for measuring the quality of classification system in the term of supervised learning which is each column of the matrix represents numbers of occurrences of an estimated class while each row represents the number of occurrences of a real class [41].

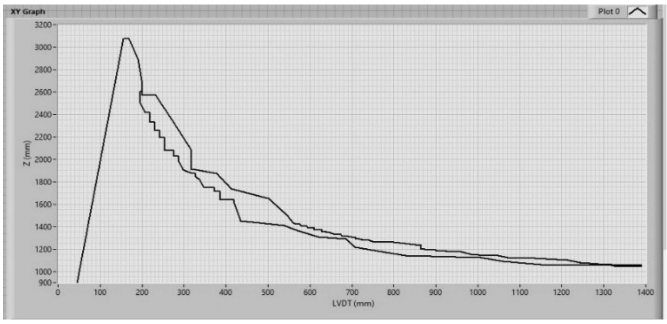

Fig. 5. XY Graph of LVDT and Z on 1-passenger minibus

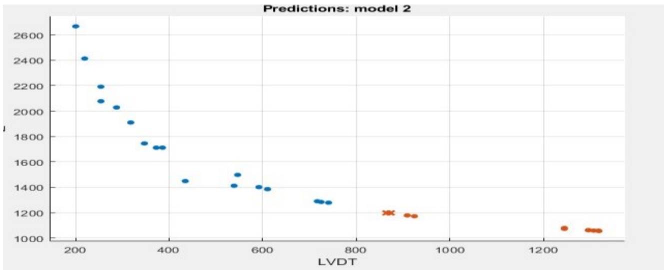

Fig. 6. Scatter Plot of 1 passenger minibus

Fig. 7. Confusion Matrix on 1-passenger minibus

From Fig. 7, it is known that the value of TP = 19; FP = 0; FN = 2; TN = 17. By using the following formula, the accuracy can be calculated.

$$Accuracy = ((TP + TN))/((TP + TN + FP + FN)) \times 100\%$$

$$Accuracy = ((19 + 17))/((19 + 17 + 0 + 2)) \times 100\%$$

$$Accuracy = 36/38 \times 100\%$$

$$Accuracy = 94.7\%$$

In the 1-passenger minibus dataset, the accuracy value is 94.7% [42]. This shows there is a 5.3% error in class prediction where it is predicted that there are 2 data entered into class 2 but incorrectly.

Second dataset consists of 254 rows and 5 columns will be optimized on a proportion (training: testing) of 80% and 20%, namely a 19-passenger minibus with a data class classification between LVDT and Z in the form of an XY graph as shown in Fig. 8, a scatter plot and confusion matrix will be obtained as shown in Fig. 9 and Fig. 10.

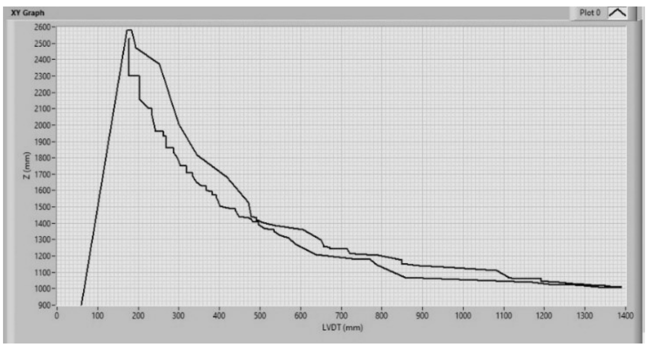

Fig. 8. XY Graph of LVDT and Z on 19-passenger minibus

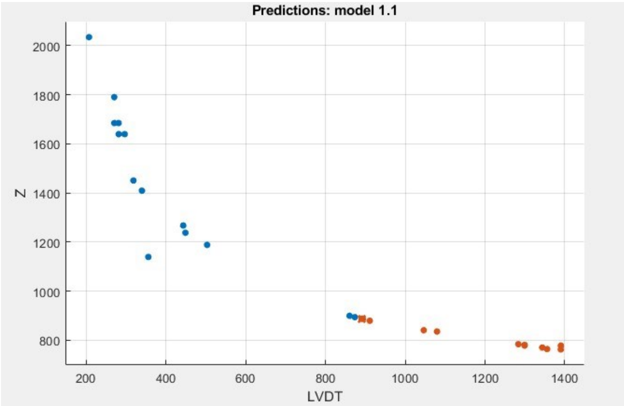

Fig. 9. Scatter Plot of 19-passenger minibus

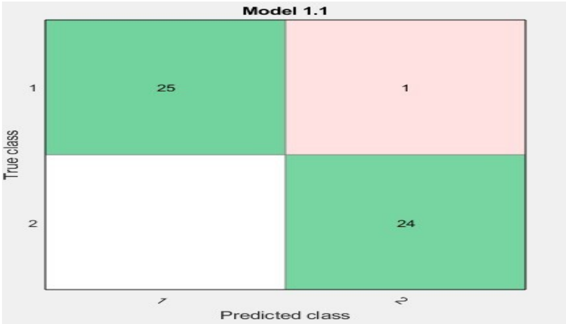

Fig. 10. Confusion Matrix Minibus 19 passengers

From Fig. 10, it is known that the value of TP = 25; FP = 0; FN = 1; TN = 24. By using the following formula, accuracy can be calculated.

$$Accuracy = ((TP + TN))/((TP + TN + FP + FN)) \times 100\%$$
$$Accuracy = ((25 + 24))/((25 + 24 + 0 + 1)) \times 100\%$$
$$Accuracy = 49/50 \times 100\%$$
$$Accuracy = 98\%$$

In the minibus dataset with 19 passengers, the accuracy value is 98%. This shows there is a 2% error in class prediction where it is predicted that there is one data entered into class 2 but incorrectly.

Third dataset consists of 262 rows and 5 columns will be optimized on a proportion (training:testing) of 80% and 20% minibus with 29 passengers with classifying the data class between LVDT and Z in the form of XY graph as shown in Fig. 11, a scatter plot and confusion matrix will be obtained as shown in Fig. 12 and Fig. 13. From Fig. 13, it is known that the value of TP = 27; FP = 0; FN = 1; TN = 24. By using the following formula, accuracy can be calculated.

$$Accuracy = ((TP + TN))/((TP + TN + FP + FN)) \times 100\%$$
$$Accuracy = ((27 + 24))/((27 + 24 + 0 + 1)) \times 100\%$$
$$Accuracy = 51/52 \times 100\%$$
$$Accuracy = 98.07\%$$

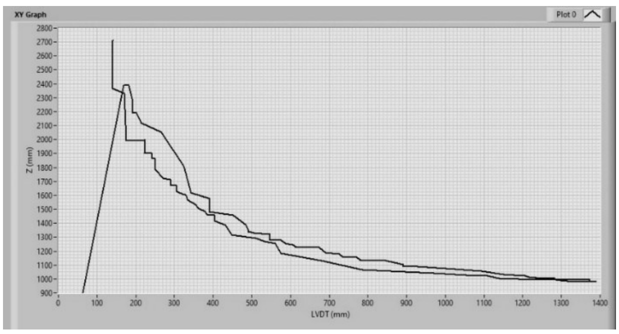

Fig. 11. XY Graph of LVDT and Z on 29-passenger minibus

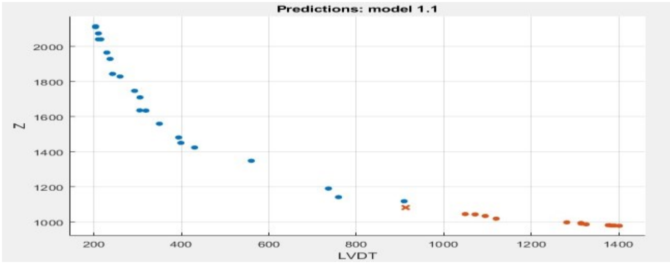

Fig. 12. Scatter Plot of 29-passenger minibus

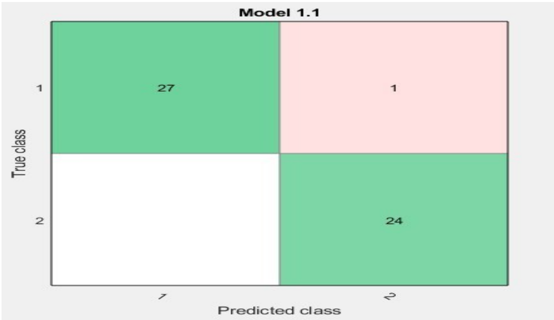

Fig. 13. Confusion Matrix Minibus 29 passengers

In the minibus dataset with 29 passengers, the accuracy value is 98.1%. This shows there is a 1.9% error in class prediction where it is predicted that there is one data entered into class 2 but incorrectly.

Fourth dataset consists of 195 rows and 5 columns will be optimized on a proportion (training:testing) of 80% and 20% of minibuses with 36 passengers with classifying the data class between LVDT and Z in the form of an XY graph as shown in Fig. 14, a scatter plot and confusion matrix will be obtained as shown in Fig. 15 and Fig. 16.

From Fig. 16, it is known that the value of TP = 23; FP = 1; FN = 0; TN = 15. By using the following formula, accuracy can be calculated.

$$Accuracy = ((TP + TN))/((TP + TN + FP + FN)) \times 100\%$$
$$Accuracy = ((23 + 15))/((23 + 15 + 1 + 0)) \times 100\%$$
$$Accuracy = 38/39 \times 100\%$$
$$Accuracy = 97.43\%$$

In the minibus dataset with 36 passengers, the accuracy value is 97.4%. This shows there is a 2.6% error in class prediction where it is predicted that there is one data entered into class 1 but incorrectly.

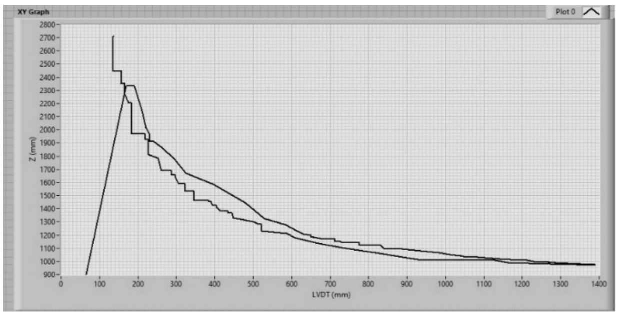

Fig. 14. XY Graph of LVDT and Z on 36-passenger minibus

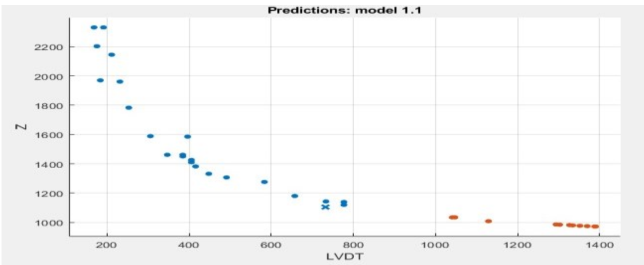

Fig. 15. Scatter Plot of 36-passenger minibus

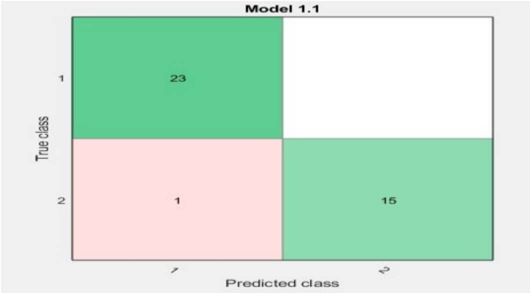

Fig. 16. Confusion Matrix Minibus 36 passengers

4. CONCLUSION

From the four experiments, it can be concluded that measuring the position of the heavy point with a proportion of 80% and 20% datasets on a minibus with 1 and 19 passengers and a bus with 29 and 36 passengers using the Support Vector Machine method, the highest accuracy is obtained on a minibus with 29 passengers by 98.1%. It means that 98.1% were predicted accurately and only 1.9% of errors occurred in class prediction where there was only one data that was predicted to be in class 1 but was wrong.

Acknowledgments

Firstly, I would like to express my deepest appreciation to Agency for Research and Inovation for their support which has contributed funding to conduct this research through SAINTEK scholarship. I am also thankful to OR-TKS which has contributed to supporting laboratory facilities. Lastly, I'd like to mention Universitas Negeri Malang and Universitas Ahmad Dahlan for their collaboration in writing this journal.

REFERENCES

[1] G. C. Semassou, R. Ahouansou, E. C. Vodounnou, and G. T. Clotilde, "Study and Design of a Mobile Hydraulic Lift Table with Single Scissors," *Phys. Sci. Int. J.*, vol. 25, no. 8, pp. 32–43, 2021, https://doi.org/10.9734/psij/2021/v25i830276.

[2] E. Lukachev and R. Scheidl, "Hydraulic Switching Type Position Control of A Large Cylinder Drive," *2018 Glob. Fluid Power Soc. PhD Symp. GFPS 2018*, pp. 1–6, 2018, https://doi.org/10.1109/GFPS.2018.8472402

[3] D. Yendri, Adrizal, Derisma, and H. Afif, "Design of cow cattle weighing system technology and automatic giving feed," *2020 Int. Conf. Inf. Technol. Syst. Innov. ICITSI 2020 - Proc.*, pp. 185–191, 2020, https://doi.org/10.1109/ICITSI50517.2020.9264977.

[4] S. Saurav and S. Murugan, "Selection of Material for Magnetic Core of LVDT for High Temperature Application," *2019 2nd Int. Conf. Intell. Comput. Instrum. Control Technol. ICICICT 2019*, vol. 255, pp. 125–128, 2019, https://doi.org/10.1109/ICICICT46008.2019.8993181.

[5] P. Mahajan, P. P. Kalkundri, and A. Sultana Shaikh, "Precision Actuator Control for on/off Type Solenoid Valves using Pid Control Loop," *2019 IEEE 5th Int. Conf. Converg. Technol. I2CT*, pp. 1–4, 2019, https://doi.org/10.1109/I2CT45611.2019.9033834.

[6] G. Park and S. B. Choi, "An Integrated Observer for Real-Time Estimation of Vehicle Center of Gravity Height," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 9, pp. 5660–5671, 2021, https://doi.org/10.1109/TITS.2020.2988508.

[7] S. B. Bhalake, A. Gade, and N. Bhapkar, "Review on Hydraulic Scissor Lift," *International Research Journal of Engineering and Technology (IRJET),* vol. 7, no. 8, pp. 1918–1921, 2020, https://www.irjet.net/archives/V7/i8/IRJET-V7I8318.pdf.

[8] Y. Gu, H. Wang, and Y. Yu, "Stability and synchronization for Riemann-Liouville fractional-order time-delayed inertial neural networks," *Neurocomputing*, vol. 340, pp. 270-280, 2019, https://doi.org/10.1016/j.neucom.2019.03.005.

[9] D. W. Karmiadji, M. Gozali, M. Setiyo, T. Raja, and T. A. Purnomo, "Comprehensive Analysis of Minibuses Gravity Center: A Post-Production Review for Car Body Industry," *Mech. Eng. Soc. Ind.*, vol. 1, no. 1, pp. 31–40, 2021, https://doi.org/10.31603/mesi.5250.

[10] T. Skrucany, F. Synák, Š. Semanová, J. Ondruš, and V. Rievaj, "Detection of road vehicle's centre of gravity," *11th Int. Sci. Tech. Conf. Automot. Safety, Automot. Saf. 2018*, pp. 1–7, 2018, https://doi.org/10.1109/AUTOSAFE.2018.8373334.

[11] H. Talabani and E. Avci, "Performance Comparison of SVM Kernel Types on Child Autism Disease Database," *2018 Int. Conf. Artif. Intell. Data Process. IDAP 2018*, pp. 1–5, 2019, https://doi.org/10.1109/IDAP.2018.8620924.

[12] H. F. Chen, "In silico log p prediction for a large data set with support vector machines, radial basis neural networks and multiple linear regression," *Chem. Biol. Drug Des.*, vol. 74, no. 2, pp. 142–147, 2009, https://doi.org/10.1111/j.1747-0285.2009.00840.x.

[13] I. Monika Parapat and M. Tanzil Furqon, "Penerapan Metode Support Vector Machine (SVM) Pada Klasifikasi Penyimpangan Tumbuh Kembang Anak," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 2, no. 10, pp. 3163–3169, 2018, https://docplayer.info/80265516-Penerapan-metode-support-vector-machine-svm-pada-klasifikasi-penyimpangan-tumbuh-kembang-anak.html.

[14] A. Han, R. Jifan, and Z. Mengyang, "The Impact Factors of Online Book Reviews Usefulness: An Empirical Comparison

between ANN and SVM," *2018 15th Int. Conf. Serv. Syst. Serv. Manag. ICSSSM 2018*, pp. 1–6, 2018, https://doi.org/10.1109/ICSSSM.2018.8464990.

[15] A. Z. Praghakusma and N. Charibaldi, "Komparasi Fungsi Kernel Metode Support Vector Machine untuk Analisis Sentimen Instagram dan Twitter (Studi Kasus : Komisi Pemberantasan Korupsi)," *JSTIE (Jurnal Sarj. Tek. Inform.*, vol. 9, no. 2, p. 88, 2021, https://doi.org/10.12928/jstie.v9i2.20181.

[16] B. Sanjaa and E. Chuluun, "Malware detection using linear SVM," *8th Int. Forum Strateg. Technol. 2013, IFOST 2013 - Proc.*, vol. 2, pp. 136–138, 2013, https://doi.org/10.1109/IFOST.2013.6616872.

[17] G. L. Prajapati, "Personalizing Kernel and Investigating Parameters for the Classification with SVM," *12th IEEE Conference on Industrial Electronics and Applications (ICIEA),* pp. 1695–1700, 2017, https://doi.org/10.1109/ICIEA.2017.8283112.

[18] L. Grama, L. Tuns, and C. Rusu, "On the optimization of SVM kernel parameters for improving audio classification accuracy," *2017 14th Int. Conf. Eng. Mod. Electr. Syst. EMES 2017*, pp. 224–227, 2017, https://doi.org/10.1109/EMES.2017.7980420/

[19] M. Wang, J. Wang, W. Tang, X. Zhang, Y. Peng, and Z. Li, "Mass and center of gravity measurement of large size revolving bodies and error separation method," *Proc. 2019 IEEE 3rd Inf. Technol. Networking, Electron. Autom. Control Conf. ITNEC 2019*, pp. 1638–1641, 2019, https://doi.org/10.1109/ITNEC.2019.8729523.

[20] United Nations Economic Commission for Europe, "Review and Revision of UN-ECE Regulation No. 66," no. 66, p. 38, 2002, https://unece.org/DAM/trans/doc/2002/wp29grsg/TRANS-WP29-GRSG-83-inf08e.pdf.

[21] M. S. Nedeljkovic, D. S. Cantrak, N. Z. Jankovic, D. B. Ilic, and M. S. Matijevic, "Virtual instruments and experiments in engineering education lab setup with hydraulic pump," *IEEE Glob. Eng. Educ. Conf. EDUCON*, pp. 1139–1146, 2018, https://doi.org/10.1109/EDUCON.2018.8363358.

[22] Vehicle Safety Standards, "Vehicle Standard (Australian Design Rule 59 / 00 – Standards For Omnibus Rollover Strength) 2007," pp. 1–77, 2012, http://www.puntofocal.gov.ar/notific_otros_miembros/aus49_t.pdf.

[23] H. Zhengbing, M. Mykyichuk, O. Kochan, R. Kochan, S. Jun, and L. Risna, "Experimental study of the input parameters of the data acquisition device NI USB 6009," *2017 11th Int. Conf. Meas. Meas. 2017 - Proc.*, pp. 155–158, 2017, https://doi.org/10.23919/MEASUREMENT.2017.7983559.

[24] G. Kumar, and N. P. Mandal, "Experimental Analysis of Square Position on Variable Displacement Electrohydraulic Actuation System by Open Loop Control," *International Journal of Engineering*, vol. 36, no. 6, pp. 1185-1192, 2023, https://doi.org/10.5829/ije.2023.36.06c.17.

[25] A. Entezari and A. Afifi, "A PID for needle valve output pressure control based on servo motor & LabVIEW," *2017 IEEE 4th Int. Conf. Knowledge-Based Eng. Innov. KBEI 2017*, pp. 0151–0155, 2018, https://doi.org/10.1109/KBEI.2017.8324962.

[26] D. Wang and C. Hao, "Hull deformation measurement equipment based on LVDT sensor," 2022 IEEE 6th Advanced Information Technology," *Electronic and Automation Control Conference (IAEAC*), pp. 1494-1497, 2022, https://doi.org/10.1109/IAEAC54830.2022.9930079.

[27] J. Du, W. Li, and J. Guo, "Design of LabVIEW based general data acquisition system," *Proc. 2017 IEEE 2nd Inf. Technol. Networking, Electron. Autom. Control Conf. ITNEC 2017*, pp. 1235–1239, 2018, https://doi.org/10.1109/ITNEC.2017.8284973.

[28] "NI USB-9237", https://manualsbrain.com/en/manuals/1187015/.

[29] G. Zenan and P. T. Szemes, "Hydraulic system with PID control under photovoltaic panel supply using LabVIEW," *2020 3rd Int. Symp. Small-Scale Intell. Manuf. Syst. SIMS 2020*, vol. 1, no. 2, 2020, https://doi.org/10.1109/SIMS49386.2020.9121415.

[30] M. Pal, Akshay, H. Rohilla, and B. C. Teja, "Patch Based Land Cover Classification: A Comparison of Deep Learning, SVM and NN Classifiers," *Int. Geosci. Remote Sens. Symp.*, pp. 1933–1936, 2020, https://doi.org/10.1109/IGARSS39084.2020.9323755.

[31] S. A. Hasan, *et al*., "Classification of Multi-Labeled Text Articles with Reuters Dataset using SVM," *2022 Int. Conf. Sci. Technol.*, pp. 01–05, 2022, https://doi.org/10.1109/ICOSTECH54296.2022.9829153.

[32] H. Lala, S. Karmakar, and A. K. Singh, "MATLAB-Based GUI Development for the Detection and Localization of Faults in Transmission Line," *Proc. 2019 IEEE Reg. 10 Symp. TENSYMP 2019*, vol. 7, pp. 654–659, 2019, https://doi.org/10.1109/TENSYMP46218.2019.8971303.

[33] C. Hortinela *et al.*, "Classification of Cane Sugar Based on Physical Characteristics Using SVM," *2019 IEEE 11th Int. Conf. Humanoid, Nanotechnology, Inf. Technol. Commun. Control. Environ. Manag. HNICEM*, 2019, https://doi.org/10.1109/HNICEM48295.2019.9072699.

[34] M. Ayad, H. Kanaan, and M. Ayache, "Diabetes disease prediction using artificial intelligence," *Proc. - 2020 21st Int. Arab Conf. Inf. Technol. ACIT*, 2020, https://doi.org/10.1109/ACIT50332.2020.9300066..

[35] G. M. Shahariar, S. Biswas, F. Omar, F. M. Shah, and S. Binte Hassan, "Spam Review Detection Using Deep Learning," *2019 IEEE 10th Annu. Inf. Technol. Electron. Mob. Commun. Conf. IEMCON,* pp. 27–33, 2019, https://doi.org/10.1109/IEMCON.2019.8936148.

[36] M. Duan, "Short-time prediction of traffic flow based on PSO optimized sVM," *Proc. - 3rd Int. Conf. Intell. Transp. Big Data Smart City, ICITBS 2018*, pp. 41–45, 2018, https://doi.org/10.1109/ICITBS.2018.00018.

[37] A. Goel and S. K. Srivastava, "Role of kernel parameters in performance evaluation of SVM," *Proc. - 2016 2nd Int. Conf. Comput. Intell. Commun. Technol. CICT 2016*, pp. 166–169, 2016, https://doi.org/10.1109/CICT.2016.40.

[38] H. Krishnan, K. Priyadharshini, M. Gowsic, N. Mahesh, S. Vijayananth, and P. Sudhakar, "Plant disease analysis using image processing in MATLAB," *2019 IEEE Int. Conf. Syst. Comput. Autom. Networking, ICSCAN*, pp. 1–3, 2019, https://doi.org/10.1109/ICSCAN.2019.8878753.

[39] H. Sar and P. Fundowicz, "Empirical equations for determining the height of the center of mass of a passenger car," *11th Int. Sci. Tech. Conf. Automot. Safety, Automot. Saf. 2018*, no. 2, pp. 1–4, 2018,

https://doi.org/10.1109/AUTOSAFE.2018.8373325

[40] Q. V. Nguyen, M. Lin Huang, and S. Simoff, "Enhancing Scatter-plots with Start-plots for Visualising Multi-dimensional Data," *Proc. Int. Conf. Inf. Vis.*, pp. 80–85, 2020, https://doi.org/10.1109/IV51561.2020.00023.

[41] D. E. Zomahoun, "A semantic collaborative clustering approach based on confusion matrix," *Proc. - 15th Int. Conf. Signal Image Technol. Internet Based Syst. SISITS 2019*, pp. 688–692, 2019, https://doi.org/10.1109/SITIS.2019.00112.

[42] N. Pratiwi and Y. Setyawan, "Analisis Akurasi Dari Perbedaan Fungsi Kernel Dan Cost Pada Support Vector Machine Studi Kasus Klasifikasi Curah Hujan Di Jakarta," *J. Fundam. Math. Appl.*, vol. 4, no. 2, pp. 203–212, 2021, https://doi.org/10.14710/jfma.v4i2.11691.

BIOGRAPHY OF AUTHORS

Franky Melky is an employee on study assignment who is currently pursuing a postgraduate program at State University of Malang, Malang. He majored in Electrical Engineering. His research interests include Control, Data Acquisition, and Machine Learning.
Email: franky.melky.2105348@students.um.ac.id.

Siti Sendari received the B.Eng. on Electrical Engineering from Brawijaya University, Malang, Indonesia in 1996, the M.Eng. on Electrical Engineering from Gajah Mada University, Yogyakarta, in 2005, the M.Eng on Information, Production and System Engineering from Waseda University in 2013. Since 1998, she has joined State University of Malang as a lecturer in the Departement of Electrical Engineering. His research interests include Dynamic System, Control and Robotic. Scopus ID: 36810359400, Orcid ID: https://orcid.org/0000-0002-8681-7024. Email: siti.sendari.ft@um.ac.id.

Ilham Ari Elbaith received the B.Eng. on Electrical Engineering from Brawijaya University, Malang, Indonesia in 2005, the M.Eng. on Electrical Engineering from Brawijaya University, Malang, in 2012, the Ph.d on Electrical Engineering from Southern Taiwan University of Science and Technology in 2017. Since 2006, he has joined State University of Malang as a lecturer in the Departement of Electrical Engineering. His research interests include Biomedical Electronic, Signal Processing, Machine Learning. Scopus ID: 56825950400, Orcid ID: https://orcid.org/0000-0001-9665-8613. Email: ilham.ari.ft@um.ac.id.