



Proposing Two Neural Networks Structures for Enhancing Laser Sensor Distance Accuracy

Karam Samir Khalid ¹, Rand Zuhair Khaleel ², Hind Zuhair Khaleel ^{1*}, Amjad Jaleel Humaidi ¹

¹ College of Artificial Intelligence Engineering, University of Technology, Baghdad, Iraq.

² Central Library, University of Technology, Baghdad, Iraq.

Emails:

Karam Samir Khalid | Rand Zuhair Khaleel | Hind Zuhair Khaleel | Amjad Jaleel Humaidi

Abstract:

The precision of distance measurement using a laser sensor significantly influences robot motion accuracy, localization, and obstacle avoidance. The present study proposes two artificial neural network (ANN) structures to enhance distance measurement accuracy using experimental data from a laser sensor. Both ANN structures are synthesized using the Multi-Layer Perceptron (MLP) model with different activation functions. The first structure utilizes the Rectified Linear Unit (ReLU), while the second employs the Hyperbolic Tangent function. Each ANN receives two inputs: the data has been gotten from laser sensor type VL53L0X and real measurements. The laser sensor is sensitive only to two colors (white and gray); as such, the gray and white obstacles are used. The ANNs are trained based on a dataset of 600 samples, with 80 percent for training, 20 percent for validation, and 20 percent for the testing. Measurement accuracy is evaluated with a Mean Squared Error (MSE) metric. The results based on the ReLU activation function showed higher accuracy than those with Tanh for the two colored objects. An ANN structure based on the ReLU function can be trained efficiently and accurately, making it suitable for robotic applications.

Keywords:

Accuracy; Distance measurement; Laser sensor; Mean Squared Error; Neural Network.

Highlights:

- Two ANN-based (MLP) approaches with two activation functions, ReLU and Tanh.
- An experimental setup using laser sensor data combined with ANN methodologies.
- Compare the performance of two proposed artificial intelligence techniques.

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Corresponding Author*:

Hind Zuhair Khaleel

College of Artificial Intelligence Engineering, University of Technology, Baghdad, Iraq.

1. INTRODUCTION

A sensor is a device that receives input from the external world and produces a signal proportional to the measured quantity. In robotic applications, distance sensors measure distances between obstacles and sensors to enable collision avoidance. In medical applications, the sensor is used to assess linear parameters of the Electrohysterograph (EHG) [1]. The ultrasonic sensor depends on the generated and reflected sound waves. It measured the distance between sensor and object, and it was useful for robot applications [2-5]. A time-of-flight (ToF) laser sensor is an optical sensor that utilizes laser light pulses to measure the time it incomes light and collapsible from sensor to the target and then back. This sensor is typically used for distance measurement, ranging, and depth-sensing applications [6-16]. Among different laser sensors, the VL53LoX is an efficient sensor that provides a reliable distance measurement solution. The VL53LoX is defined as the ToF laser type. The instrument demonstrated high accuracy in distance measurements despite various challenging factors, including noise, ambient light interference, and reflective surfaces [17, 18]. The VL53LoX laser sensor is utilized for distance measurement in Nano Sumo Robots [19]. Moreover, the VL53LoX sensor has been used in healthcare applications for COVID-19 detection, where the temperature of an affected person is monitored and tracked remotely via a mobile phone. It has been shown that the system's error was $< 1\%$ [20]. Another author presented low-cost health sensors connected to an Arduino microcontroller, which were monitored. Arduino is an open-source, user-controlled electronic microcontroller [21]. Another work proposed a low-cost security system that included a single door to control entry to an enclosed interior environment. An ESP32 microcontroller was used in conjunction with 2 VL53LoX laser Time-of-Flight sensors to power the system. Using Node-RED, the system tracks each room's occupancy and shares that information with a database and a dashboard [22]. The researchers in [23] depended on the VL53LoX sensor to measure flat surfaces. Neural Networks (NNs) are major element for Artificial Intelligence (AI) methodologies. Neural networks can learn complex patterns [24]. The multi-feed-forward NN method contains inputs, hidden, and output layers [25, 26]. Based on previous works, this study proposes an ANN-based predictor system to improve. The contribution of this work can be shortened by:

- 1) Develop a dual ANN-based Multi-Layer Perceptron (MLP) approach for predicting measurements derived from a real-world sensor.

- 2) Design and implement an experimental setup to achieve precise measurements using laser sensor data combined with ANN methodologies.
- 3) Execute a comparison between two proposed artificial intelligence techniques to evaluate their performance.

The respite of this research is prearranged as the follows: Section 2 designates the Methodology, Section 3 illustrates Distance Measurement based on the VL53LoX Sensor, Section 4 offerings Experimental Results and Discussion, the Section 5 represents the Test and Verification of MLP Estimator Methods based on the VL53LoX Sensor, and Section 6 validates the conclusion.

2. METHODOLOGY

This segment designates the proposed flowchart for this work, then draws the proposed structure, and derives the equations for the proposed two ANN MLP estimator models. In the present work, the dataset size was 600 samples. The choice of activation functions (ReLU and Tanh) in the proposed ANN models was intended to enhance the ANN's performance in laser sensor distance measurement. The experimental limitation conditions for the VL53LoX laser sensor distance ranged from 0.02 to 2 meters.

2.1. The Proposed Flowchart

The proposed work presents the following flowchart, as shown in Fig. 1.

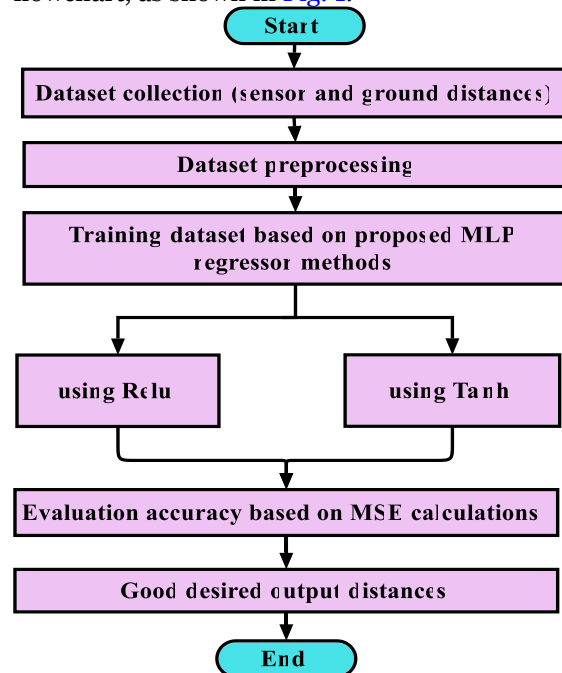
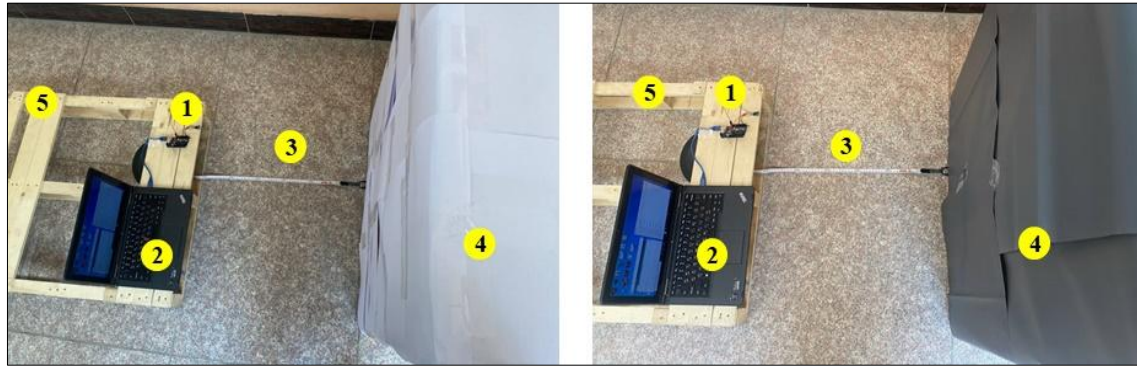


Fig. 1 A Proposed Structure of the Suggested MLP Estimator Methods.

- 1) Dataset Collection: The dataset was gathered. It contains distance measurements from the VL53LoX sensor, along with corresponding ground-truth distances. The data were collected by placing an object (a cartoon box) measuring 74×68×100 cm at different distances from

the sensor and recording the measurements. The distance measurement included two readings. The first reading is called the ground truth distance, measured from the length tool. The second reading, called the sensor reading, is obtained from the Arduino code and determined by Eq. (7) in the next section. The GY-530 VL53LoX laser sensor is sensitive to gray and white object colors; therefore, two objects (gray and white) were designed to test the

sensor's distance readings. Figure 2 shows the four parts of the hardware connection, labeled in yellow. The first part is the electrical circuit described in section 4. The second part is a laptop with Arduino code to read the dataset sensor and save the data on the laptop. The third part is called the length-measuring tool for ground-truth distance measurement. The fourth part is two objects (gray and white). The final part is the wooden box.



(a) White Object

(b) Gray Object

Fig. 2 An Experimental Work with Two Objects.

- 2) Dataset Preprocessing: Preprocessing the collected dataset included splitting it into train, validate, and test groups. The dataset consisted of 600 samples. The training set was 80%, the validation set was 20%, and the test set was 20%. The GY-530 VL53LoX distance sensor ranged between 20 mm and 2000 mm.
- 3) Training dataset based on the proposed two MLP Estimators: Neural network architecture designed for regression tasks. It is very suitable for this work. The two suggested MLP estimators were programmed in Python 3.7 using the Google Colab environment and MATLAB libraries [26]. In the present research, the maximum iteration is 100. The proposed Multi-Layer Perceptron (MLP) estimator in scikit-learn is a kind of ANNs that used to regression jobs. The proposed structure, specified by the number of input layers, had 2 inputs: sensor reading and ground reading. The number of neurons was 2. Two hidden Layers: each one consisted of 10 neurons. The proposed structure has been shown in Fig. 3. It implemented twice. The first time was implemented on the white dataset, and the second time on a gray dataset. The proposed structure was applied to two activation functions, and the results were compared between them in Section 4. These functions are used in both hidden layers: the Rectified-Linear-Unit (ReLU) and Tangent Hyperbolic

(Tanh). The Rectified Linear Unit is the activation function used in hidden layers of neural networks as below [27-29].

$$\text{ReLU}(x) = \max(0, x) \quad (1)$$

Tangent Hyperbolic is an activation function. The (x) is marked as input, which is charity in veiled layers of NN and deep learning. It squashed a real-valued number to the range (-1, 1), as in the formula below [27]:

$$\text{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (2)$$

In Eqs (1) and (2), x is marked as input of hidden layer. The structure of the MLP estimator with 2 hidden layers is presented in the equations below. Figures 3 and 4 show the explanation of the proposed ANN structures. An input layer collects two pieces of data and a bias. The number of neurons equals the number of input features; e.g., x_1 is a sensor reading, x_2 is a ground reading. The first and second hidden layers processed inputs using 10 neurons by one activation function (ReLU) from Eq. (1) (Fig. 3) and another activation function (Tanh) from Eq. (2) (Fig. 4) for each structure. Each instigation function transformed the sum of the ANN responses from the node to output, which was then delivered to the following layer and to the final output. The output layer contained the network's final predicted output. Additionally, MSE evaluates the variance between the expected and true outputs obtained from the experimental dataset.

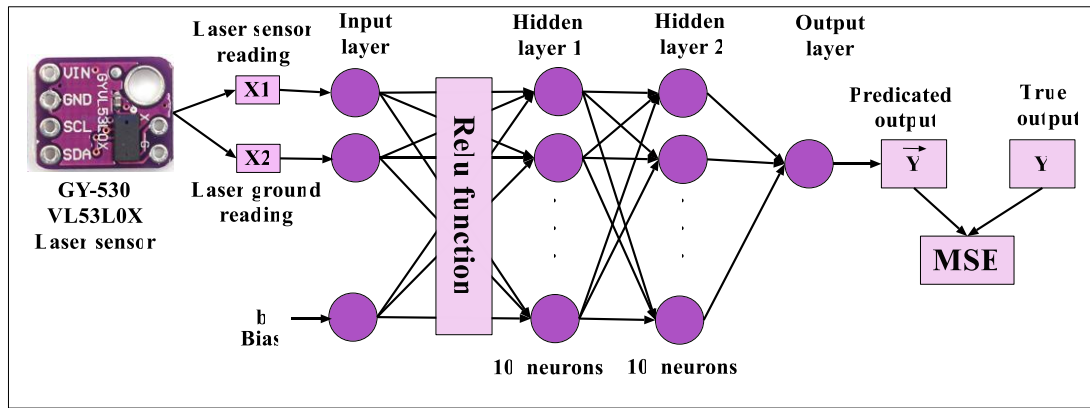


Fig. 3 The First Proposed Structure of the ANN Method using the ReLU Function.

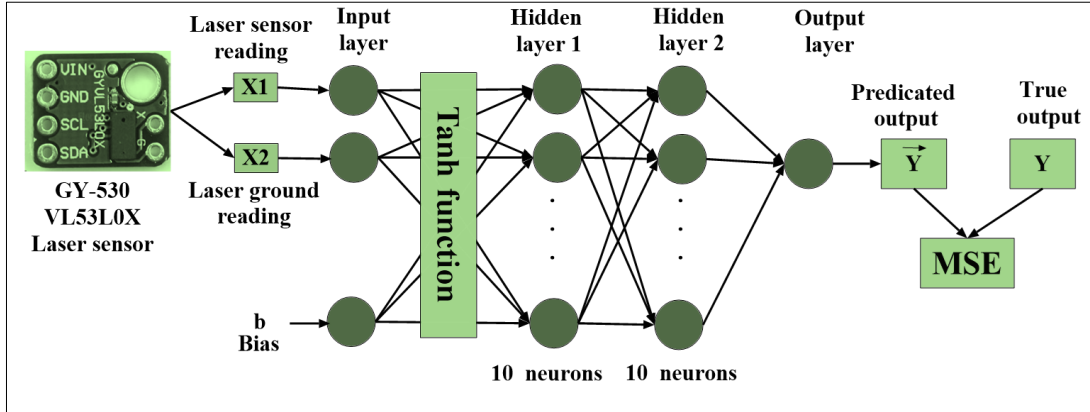


Fig. 4 The Second Proposed Structure of the ANN Method using the Tanh Function.

The equations of the proposed two ANN MLP methods, depending on the structure of the Figs. 3 and 4, which are derived as follows: The input layer: $X = [x_1, x_2, \dots, x_n]$, where n = input features. In this case, $n = 2$. Hidden Layer one: $H1 = [h1_1, h1_2, \dots, h1_m]$, where m = neurons in the first hidden layer. In this case, $m = 10$. Hidden Layer 2: $H2 = [h2_1, h2_2, \dots, h2_k]$, where k = neurons in the second hidden layer. In this case, $m = 10$. Output Layer: $Y = [y_1, y_2, \dots, y_p]$, where p is the number of output values. In this case, for one output, $p = 1$. The equations are derived as follows:

- 1) Eq. (3) is the input to the first hidden layer:

$$H1 = \sigma_1 (W1 \cdot X + b1) \quad (3)$$

where $W1$ is the matrix of weight that connected to input layer to the first hidden layer, $b1$ is the bias vector and σ_1 is the activation function for the first hidden layer.

- 2) Eq. (4) is the first to second hidden layers:

$$H2 = \sigma_2 (W2 \cdot H1 + b2) \quad (4)$$

where $W2$ is the matrix-weight connecting this layer, $b2$ is the bias vector for the second hidden layer, and σ_2 is the activation function for the second hidden layer

- 3) Eq. (5) is the second hidden layer to the output layer:

$$Y = (W3 \cdot H2 + b3) \quad (5)$$

where $W3$ is the matrix of weight attached to this layer, and $b3$ is presented as the bias of the output. To calculate the accuracy of a

proposed regression model based on MSE calculations, the MSE calculated as in Eq. (6) is [2]:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y}_i)^2 \quad (6)$$

where y_i is a true value, $\bar{y}_i$ is a predicted value, and n is the number of samples. In this study, two NN-based structures have been designed and trained on the sensor's actual training dataset. The performances of sensor-based and ANN-based measurements are evaluated and compared to demonstrate the effectiveness of AI schemes.

3.DISTANCE MEASUREMENT BASED ON VL53LoX SENSOR

The GY-530 VL53LoX (Time-of-Flight) (ToF) sensor works depends on laser pulses. However, the sensor itself does not inherently differentiate between gray and white objects. Instead, it measures the distance to object's surface based on the time-of-flight principle. The sensor's output is typically a distance in millimeters, measured from the sensor to the object's surface. This distance value is obtained through signal processing and interpretation of the time-of-flight measurements. To evaluate VL53LoX sensor readings for gray and white objects, a simple mathematical equation or model can be used that incorporates factors such as distance to the obstacle surface reflectivity: The reflectivity or albedo of the object's surface, which can affect the amount of

light reflected to the sensor. Ambient light conditions: These can influence the sensor's performance. Noise: Any noise or uncertainty in the sensor readings can be modeled using a random variable. Here is a simplified Eq. (7) that can be used as a starting point to represent VL53LoX sensor readings [7-12]:

$$S_r = D \times S_f + N \quad (7)$$

where S_r denotes measurement sensor reading, D represents the distance from the sensor to the object, S_f denotes the reflected measurement of the sensor, which can be different for gray and white objects, and N represents the noise sensor [7-12]. In the present work, the GY-530 VL53LoX laser sensor, called a Time-of-Flight (ToF) for distance measurement module, powered by 5V, communicates with the

Arduino. The principle of operation of this sensor is shown in Fig. 5. The Laser's distance-measuring range was 3 cm to 200 cm. The dimensions of this sensor are 18×12×2 mm, and it operates at 5 V DC [7-12]. The pin for the laser sensor configuration connection in this work consists of (VCC), which is connected to 5V power supply on the Arduino. (GND) connects to the Arduino's GND (Ground) pin. Serial Clock Line (SCL) of sensor linked to SCL pin Arduino Uno, and finally, Serial Data Line (SDA) linked to SDA pin Arduino.

4.EXPERIMENTAL RESULTS AND DISCUSSION

4.1.The Experimental Work

The experimental work steps of the present paper are shown in Fig. 6.

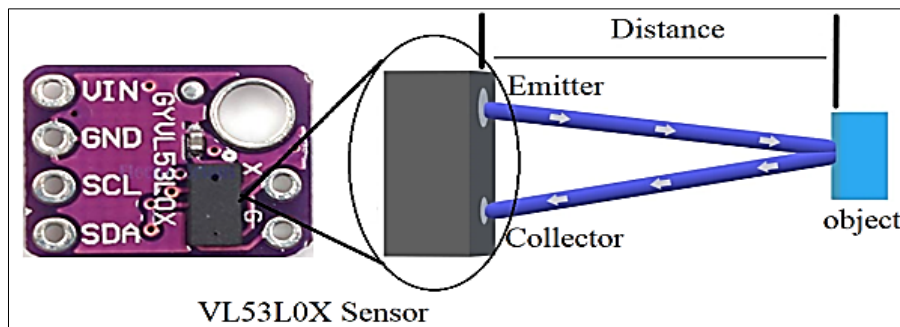
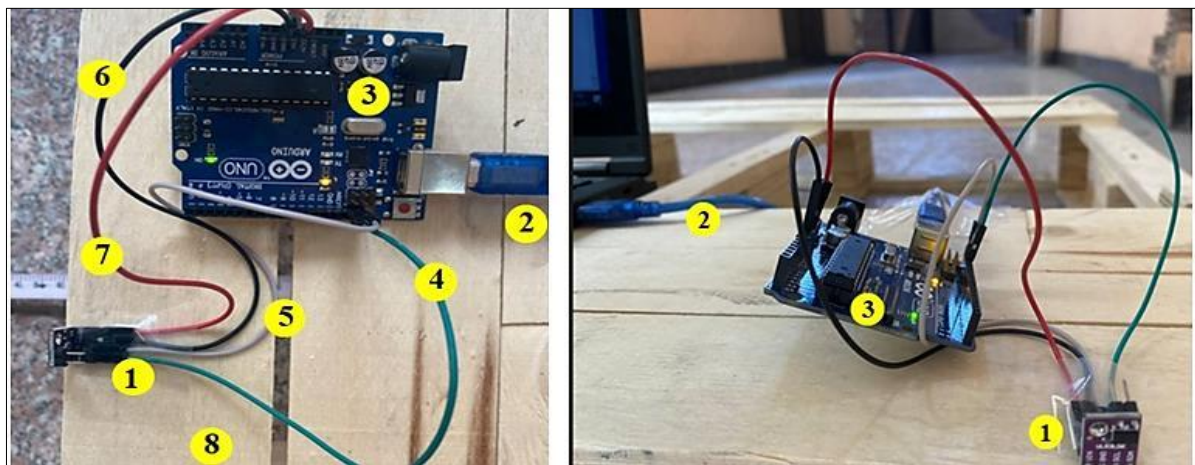


Fig. 5 The GY-530 VL53LoX Laser Sensor.



(a) Front View.

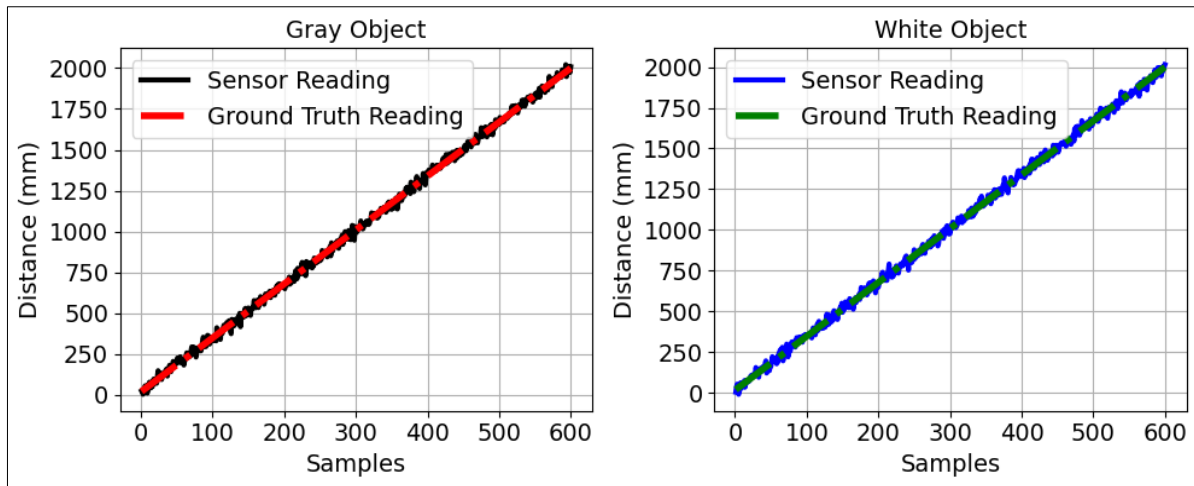
(b) Side View.

Fig. 6 An Experimental Connection from Two Sides.

Figure 6 shows the labels as follows: (1) yellow, which indicates the GY-530 VL53LoX laser sensor, (2) Blue cable connected between the laptop and Arduino Uno, (3) Arduino Uno microcontroller, which is supplied by 5 V from the laptop using the cable mentioned in step 2. The label (4) Green wire is linked between the SDA pins of the sensor and the Arduino Uno. (5) Gray wire is linked between the SCL pins of the sensor and the Arduino Uno. (6) Black wire is attached to GND on Arduino Uno. (7) The red wire is attached to 5 V (VCC) on the Arduino Uno. (8) Wooden box with 76×70×12 cm dimensions, and it presents a stand for all electrical circuits.

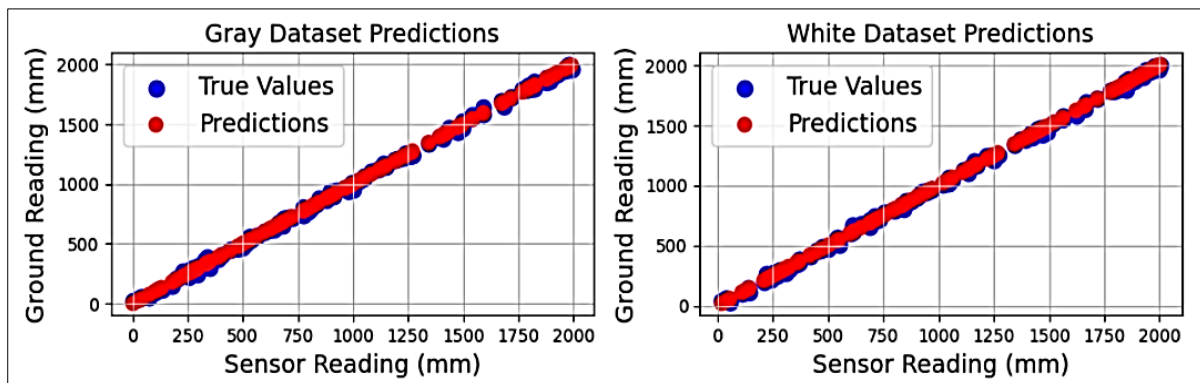
4.2.The Simulation Results

Python 3.7 and Google Colab software have been used to verify the proposed regression techniques to improve distance-measurement accuracy with an intelligent laser sensor. Figure 7 shows the dataset collection and creation from experimental work before applying the suggested MLP models. The y-axis shows the practical distances of the sensor, ranging from 20 mm to 2000 mm, while the x-axis shows the number of dataset samples: 600 for both Gray and White objects. Each object detected by the sensor contains two readings: sensor (measured by the Arduino Uno) and ground (measured by the length-measuring tool).



(a) Gray Object.

(b) White Object.

Fig. 7 Sensor and Ground Reading Vs Samples in Both Gray and White Objects before the Suggested Two MLP Models.

(a) Gray Object.

(b) White Object.

Fig. 8 Sensor Vs Ground Reading in both Gray and White Objects using the First Suggested MLP Estimator Method (ReLU).

Figure 8 shows the results of both states: Gray and White objects for ground and sensor readings in each state. These results are based on the training dataset for the first suggested MLP estimator method with the ReLU activation function, as mentioned in Eq. (1) and Eqs. (3-6). The blue lines are the true values (input distances readings), and the red lines are predictions (output distances readings). From Fig. 8, it can be concluded that the first suggested MLP estimator method with ReLU is a very good curve-fitting regression method, with results ranging from 20 to 2000 mm across 100 iterations. Figure 8 also shows the results based on the training dataset for the first suggested MLP estimator method with Eq. (2) activation function as mentioned in Eqs. (2-6). It can be concluded that the second suggested MLP estimator method with activation function, Eq. (2), is a poor curve-fitting regression method, with results ranging from

20 to 2000 mm across 100 iterations. The comparison results between Fig. 8 and Fig. 9 show the results for the dataset using the first and second suggested ANN MLP methods, respectively. The curve-fitting in Fig. 8 using ReLU is better than that in Fig. 9 using Tanh. This result is because ReLU outperforms Tanh in many scenarios: it avoids the vanishing gradient problem, encourages sparsity, speeds up training, and simplifies optimization. After training the dataset, the MSE was computed as (7) between the gray and white datasets against 100 iterations using the two proposed MLP estimator methods, as shown in Fig. 10. The gray and white output readings are marked as blue and red lines, respectively. Figure 10 and Table 1 show the minimum MSE results of the first proposed MLP estimator method. ReLU has fewer errors and better results than the MSE of the second proposed MLP estimator (Eq. (2)).

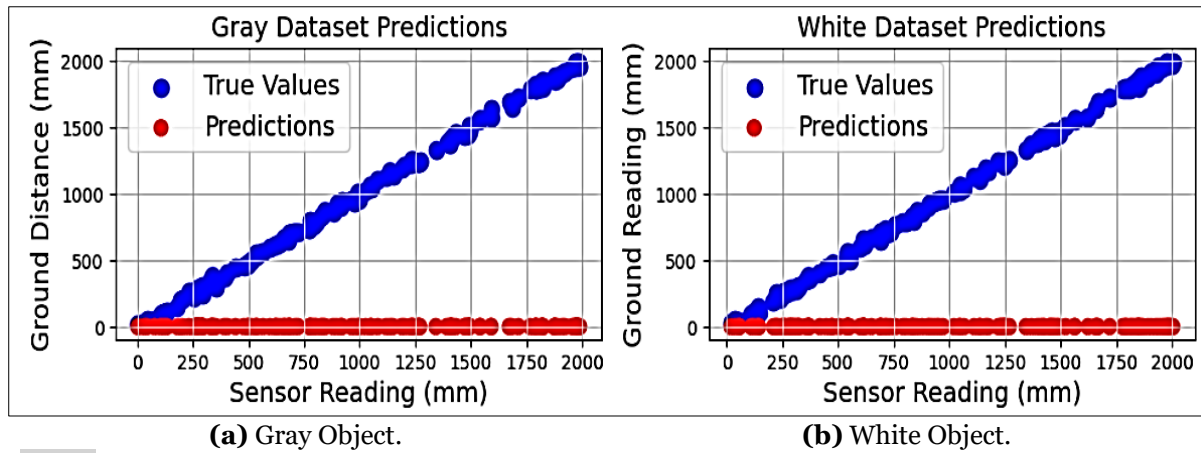
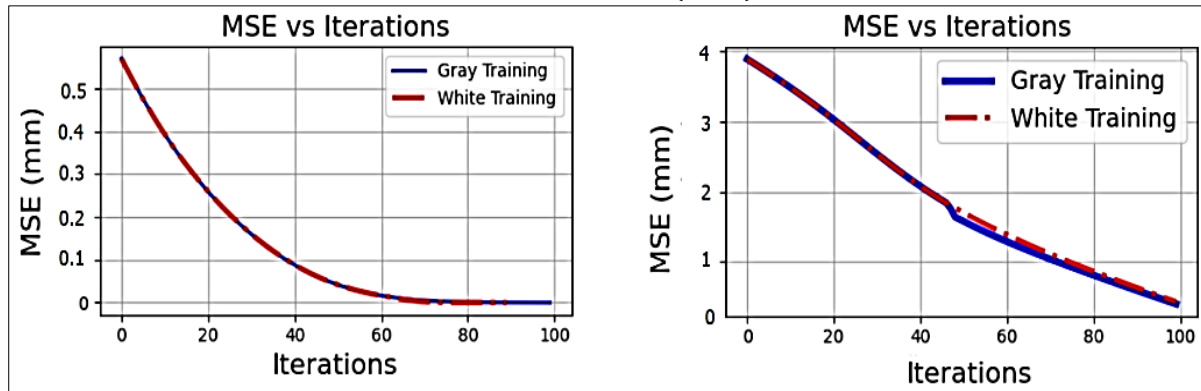


Fig. 9 Sensor Vs Ground Reading in both Gray and White Objects using the Second Suggested MLP Estimator Method (Tanh).



(a) MSE for Suggested ANN MLP with ReLU, (b) MSE for Suggested ANN MLP with Tanh

Fig. 10 The MSE vs. Iterations between the Gray and White Datasets.

4.3. The Comparison between the Two MLP Proposed Methods

The MSE values of the two proposed methods are illustrated in Table 1. From these results, it can be concluded that the MLP estimator with ReLU achieves more accurate performance than the MLP estimator with Tanh.

Table 1 The MSE Results Comparison for Both Methods of Training Datasets.

The proposed MLP estimator methods	MSE
Gray and white dataset in ReLU	0.00013
Gray and white dataset in Tanh	0.2600

5. TEST AND VERIFICATION OF MLP ESTIMATOR METHODS BASED ON VL53LoX SENSOR

This case study demonstrates the practical application of using two proposed MLP estimator methods to enhance the accuracy of distance measurements from a VL53LoX sensor. By evaluating the MSE and plotting the results, insights into the model's performance and its ability to predict good desired distances outputs can be gained. Figure 11 shows the case study of the proposed testing practical work in two cases. The VL53LoX sensor detected the white and gray objects, with a distance of 180 cm between each object and the sensor.

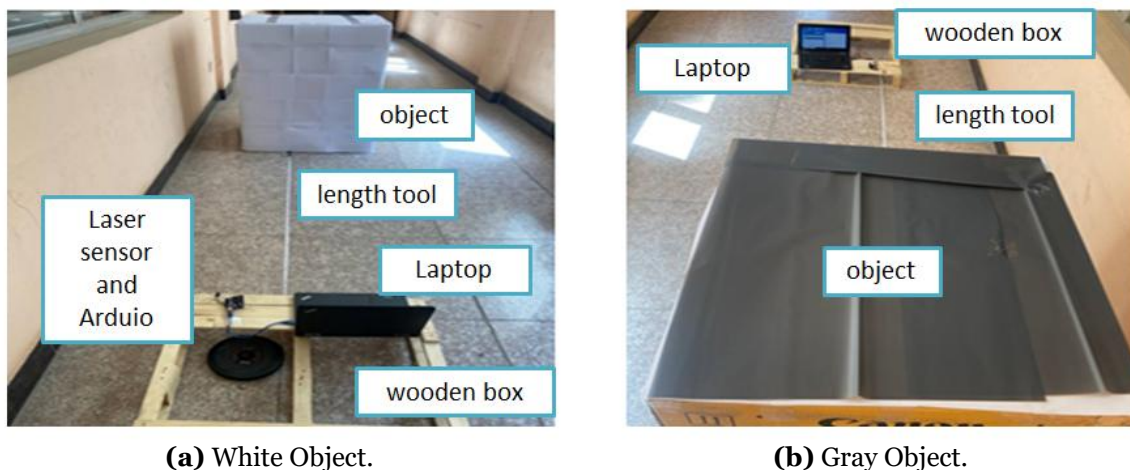


Fig. 11 Testing Proposed Experimental Work in 2 Cases with 180 cm.

The proposed testing of the suggested two ANN MLP structures is shown in Fig. 12. The number of samples was 120 for each white and gray reading—the MSE between white and gray for Eqs. (1) and (2) against the 100 iterations were displayed to visualize the testing process of the proposed experimental MLP estimator methods. This approach captures the model's performance of test at each iteration, showing

how the model improves over time. Figure 12 and Table 2 compare the MSE results of Eqs. (1) and (2) functions. The proposed MLP estimator method with ReLU was better and had fewer errors than the MSE result of Eq. (2). Besides that, the curve of MSE is fitting 100% in ReLU, while in Eq. (2), the MSE curve failed to fit in the region from 45 to 53 iterations as in Figure 12.

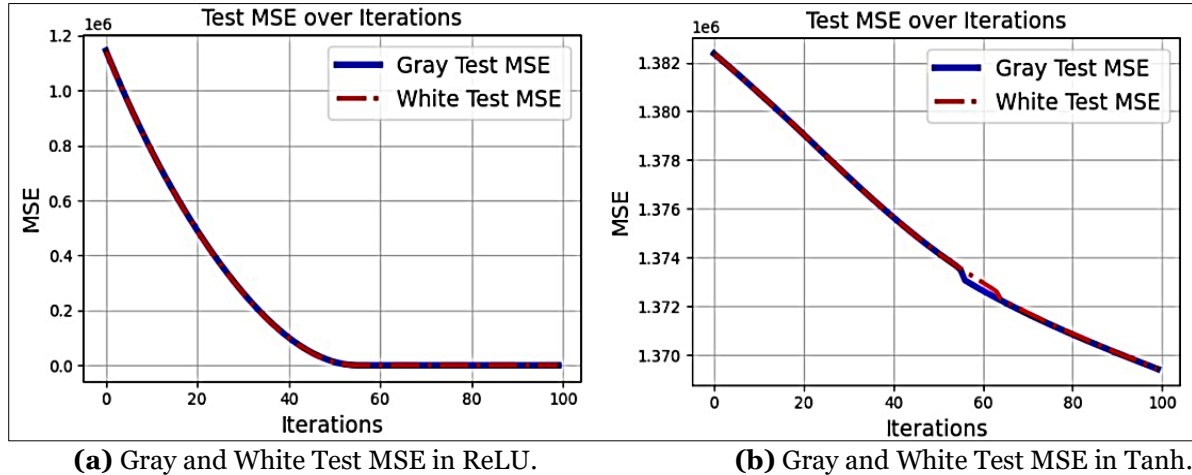


Fig. 12 Gray and White Test MSE in ReLU and Tanh vs Iterations of Proposed Experimental Work.

Table 2 shows that the ANN with ReLU achieved higher accuracy than the one with Tanh.

Table 2 The Comparison of the Minimum Results of MSE Using the Two Proposed Methods of the Proposed Experimental Work Testing.

The proposed ANN MLP estimator methods	MSE
Gray and white dataset in ReLU	1.84×10^{-6}
Gray and white dataset in Tanh	1.27

The actual experimental description of the laser sensor type VL53LoX is shown in Table 3 [10].

Table 3 The Experimental Description for Laser Sensor Type VL53LoX [10].

Description	Details
Distance measurement	0.02-2m
Frequency	33Hz
Size	4.4×2.4×1mm
Voltage	2.6 - 3.5 V
Temperature operating	From 20-70 °C
Emitter of an IR laser	940nm
Low power consumption	20mW

6.CONCLUSION AND FUTURE WORK

The contribution of the present research is the design and implementation of two MLP-based ANN measurement estimators. Two ANN structures were proposed using different activation functions. The training dataset was measured using a laser-based distance sensor type (GY-530 VL53LoX). The sensor was devoted to detecting two colors: gray and white. To demonstrate the effectiveness of the proposed estimator, the AI estimator's measurements were compared with real sensor measurements. This work is devoted to the design of two ANN-based estimators for

measuring the distance between the sensor and colored objects. The distance between the sensor and the object ranged between 0.02 and 2 m. Using the MSE metric, the results showed that the ANN structure based on ReLU(x) achieved higher accuracy than that based on Tan(x). Quantitatively, the value of MSE was 1.27 in a case of the ReLU activation function, while the value of MSE was 1.84×10^{-6} in a case of the Tanh activation function.

These accurate measurements from the laser sensor will be utilized in the future, such as in robot navigation and path-planning scenarios, including navigation, localization, and obstacle avoidance [30-46].

NOMENCLATURE

e^x	Exponential
k	Number of neurons in the first hidden layer
S_r	Measurement sensor reading
S_r	Reflected sensor reading
m	Number of neurons in the second hidden layer
n	Number of samples
N	Noise sensor
p	Number of output values
y_i	True output value
$\hat{y}_i$	Predicted output value

Greek symbols

σ	Activation function
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Subscripts

b	Bias
D	Distance from the sensor to the object
H	Hidden Layer
$\max$	Maximum value
x	Input distance measurement
W	Weight
m	meter

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