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Automatic human height measurement system based on camera sensor with deep-learning and linear regression analysis

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ABSTRACT

This study proposes a new approach for automatically measuring human height using a camera sensor with deep learning and linear regression analysis. The camera sensor is used to capture real-time images of human objects. The image is then processed with a YOLO4-based convolutional neural network (CNN) to separate the region of interest (ROI) of the human object from the background. The pixel value of the ROI vertical line is then converted into height in centimeters by the linear regression equation. The system was tested on 40 primary samples, with 20 samples used as control data and 20 samples used as test data. From the results of testing 20 control data samples, the linear regression equation was obtained as y' = 0.4034x + 24.938, which was then applied to convert the system's predicted height in centimeters for 20 test samples. The test results for 20 test samples showed that an average F1_score was 1, the R_square obtained was 0.93, the root mean square errors (RMSE) was 0.02, and the percentage of accuracy was 99.00%. The test results showed that the system was able to automatically detect human height with a very high level of correlation/similarity and accuracy between actual and predicted height.

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1. INTRODUCTION

The word "anthropometry" comes from the greek words "anthropos" (meaning "human") and "metron" (meaning "measure"), anthropometry is defined as the measurement of the human body [1]. In a broad sense, anthropometry is defined as the measurement of the dimensions of the human body based on several parameters, including height, weight, body circumference, upper arm circumference, head circumference, chest circumference, and leg length [2]. Anthropometric data is used in a variety of fields. For example, in industry, anthropometric data is used to design workstations, work facilities, and product designs to ensure that the dimensions are appropriate and suitable for the dimensions of the human body that will use them [3], [4]. In the field of maritime and air transportation, anthropometric data is used to assess whether or not a person is eligible to board maritime and air transportation, such as airplanes and pioneer ships, which are indeed limited in height and weight [5], [6]. In the field of health, anthropometric data like body mass index (BMI) and mid-upper arm circumference (MUAC) classification is used to assess a person's nutritional status [7], whether it is in line with their growth development or whether they fall into the category of stunting [8].

Height, along with weight, is one of the most important anthropometric measurements in assessing a person's nutritional status. This is because height provides information about a person's linear growth and development, and can be used to determine a healthy weight [9]. Height measurement is also often used as a component of physical fitness tests used for job applications, civil service registrations, military and police registrations [10], or simply for periodic health checks along with weight measurement to determine the body mass index (BMI) score [11]. In general, height measurement is done manually using a special measuring device, such as a ruler or stadiometer. However, this manual method requires special measurement skills and can lead to significant measurement errors if not done correctly. Furthermore, manual height measurement is still risky, especially if the check is done at close range, because COVID-19 and other infectious diseases are still lurking around us. Even if the process uses strict COVID-19 protocols, it is not impossible that it will still be risky because the measurement process is done very closely, so even the slightest human error poses a risk of COVID-19 transmission [12].

To address this issue, a digital approach is needed to measure height, eliminating the need for direct interaction between the measurer and the person being measured. Digital approaches that have been used in recent years have used ultrasonic, infrared, load cell sensors, arduino, raspberry, or Android smartphones as microcontrollers/ microprocessors that control input/output and the sensors with wireless communication and tools display information [13]–[18]. The results of these studies have shown an average accuracy of height measurement of more than 90% to 99.99%, indicating that they are already good/suitable for use as height measurement devices. However, these studies require several sensor and microcontroller components that require significant costs and maintenance, as these components have a lifespan and are limited in the maximum height that can be measured. Currently, automatic height measurement systems based on camera sensors can be an alternative measurement technique to replace conventional measurements or measurements based on ultrasonic and infrared sensors. This system consists of a camera connected to a computer or smart device, such as a smartphone or tablet. The camera will take a picture of the person standing in front of it. Then, using computer vision techniques, the system will identify key points on the human body, such as the top of the head and the tips of the feet. After that, the system will calculate the distance between these two points and produce the height value in the unit selected by the user. This system is considered capable of simplifying and speeding up height measurement, especially for measuring the height of people simultaneously in a certain area. The development of this system is also driven by advances in camera technology and computer software, which allow for image capture with good quality and real-time image processing.

Previous research on the use of camera sensors has shown high accuracy in measuring height. For example, the research by Tian *et al.* [19] using canny operator, histogram of gradient (HOG), and visible-light propagation through a camera in displacements. This research successfully with a maximum measurement-error percentage of 3.63% and an average of 1.90%. Then, the research by Kriz *et al.* [20] using edge line detection, though transform, vanishing points detection and HOG for human detection successfully achieved accuracies about 2.25±2.79 cm where the images of 19 subjects standing in the same type of environment were captured and processed. Then, the research by Abadi and Tahcfulloh [21] using grayscale, blur, and edge detection methods combined with least square regression analysis successfully achieved an accuracy of 99.41% at a distance of 200 cm, while with logarithmic power analysis it achieved an accuracy of 99.42%. However, from these studies, there are two main weaknesses, namely in the preprocessing and the conversion section of the region of interest region of interest (ROI) height pixel value into cm or m units. In the part of preprocessing real-time image to then obtain the ROI which will be calculated the pixel value into height is still conventional, namely with morphological processing spatially, for example by converting color to grayscale, blurring the image, edge detection, binary segmentation with otsu or manual threshold. The weakness of the histogram of gradient (HOG) features of an image, edge detection [19]–[21] and morphological processing [11] spatially is that it is very vulnerable to variations in body position and movement during image acquisition, poor lighting, or errors in recognizing points on the human body. This is evident from several of these studies when taking images, in terms of lighting, background or object shirt color are made with certain restrictions, not flexible. Further, in the part of converting ROI pixel values to cm or m units, for example in the research by Tian *et al.* [19], the formula works by comparing the height pixel size of an object in an image taken with different camera positions (in perpendicular and parallel diversity). This difference in pixel size is then used to calculate the height of the object. This system is less effective and impractical for taking height data, because each human object whose height will be measured must always be captured with a different camera position (in perpendicular and parallel diversity). Then, Abadi and Tahcfulloh [21] and Liu *et al.* [22] use regression analysis with an approximation approach with the concept of creating a mathematical equation model from the problem of converting pixel values to cm or m, this is because there is no standard formula for converting pixels to cm or m due to the fact that each camera device and PC used has different resolutions. However, in [22], the application of linear regression was only calculated using camera calibration and reference object techniques, from manually annotated images. But, in [21] reference objects have been successfully extracted from images automatically, but still using morphology and edge detection techniques that are susceptible to errors caused by varying clothing and background colors.

Therefore, based on the problems mentioned above, this study proposes a new method for automatically measuring human height using a camera sensor with deep learning approach and linear regression analysis. The camera sensor is used to capture real-time images of human objects. The images are then processed with a YOLO4-based convolutional neural network (CNN) to separate the ROI of the human object from the background. YOLOv4 follows a one-stage detector architecture comprised of four parts: input, backbone, neck, and dense prediction or head [23]. The input is the set of data we want to detect. The backbone is responsible for extracting features and uses the image dataset to make the object detector scalable and robust. It is comprised three parts: bag of freebies (BoF), bag of specials (BoS), and CSPDarknet53 [24]. The head uses same strategy as YOLOv3 [25]. BoF is a data augmentation technique used in YOLOv4 to improve the model's performance. This technique adds various distortions and transformations to the training images to generate more data variation. Important BoF strategies used in YOLOv4 include CutMix, mosaic data augmentation, label smoothing, IoU loss, and DropBlock regularization [23]. While, BoS to improve object detection accuracy by increasing a small amount of inference costs. Various techniques used in YOLOv4 include Mish activation, cross stage partial CSP connections, SPP-block, and PAN path-aggregation block [23]. YOLOv4 uses a CNN backbone architecture called CSPDarknet53 with input layers that are frames from moving images that are resized according to the configuration initialization [26]. CSPDarknet53 uses the CSP structure to improve the network's efficiency and performance [27]. It has several advantages, such as fast processing time for real-time video/images, the ability to detect multiple objects simultaneously with varying color variations in a single frame of image capture, and good and stable performance for low-light conditions and varying object angles [28]. The pixel value of the vertical line of the ROI generated by YOLOv4 is then converted to height in centimeters by a linear regression equation. Linear regression analysis is a technique for finding a mathematical modeling in a time series between predicted height data in pixels and actual height data in centimeters [21], [22]. The final result of the linear regression analysis is then the output value of the human height by the system. It is hoped that the proposed research design will produce an automatic height measurement system for real-time images of human objects that is effective and accurate with dynamic performance, and lightweight resources. In addition, the design of this system for measuring height will be able to reduce direct contact (less contact) between the measurer and the person being measured. This system can be used by many people without the need for special skills to operate it. In the future, this system can be applied in many fields, especially in the health field for the early detection of stunting cases.

2. METHOD

The focus of this research is to produce an automatic height measurement system based on a camera sensor with deep learning approach and linear regression analysis. In order for the research implementation not to deviate far from the needs of the proposed system, there are two designs that will be worked on, namely hardware and software designs as shown in Figure 1 and Figure 2. Figure 1 shows the hardware design of the system with 3 main hardware requirements, namely i) camera sensor; ii) PC/mini PC, and iii) camera sensor feet. The camera sensor is used as a tool to capture images of human objects. The PC/mini PC is used for processing the software of the proposed system. The camera sensor feet are used to place the camera sensor at the planned height of 150 cm. In addition, a marker is also prepared which is placed at a distance of 200 cm from the camera. This marker is used as the position or place where the human object to be photographed will stand. Then, regarding the minimum specifications of the mini PC and camera that will be used by this research, including: i) CPU: Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz or Core I5 8th 1,8 Ghz; ii) VGA: NVDIA Geforce 4 GB (optional); iii) RAM: 4 GB; iv) OS: Windows 11 or Raspberry Pi OS: v) OpenCV 4.2; vi) YOLOv4 or higher; and vii) camera: smartphone or stream webcam or similar, quad: 10 MP autofocus, resolution: full HD 720p/25fps.

Figure 2 shows the software design with the proposed core algorithm/method developed in this research, which can be seen in the boxes marked orange (CNN based on YOLOv4) and blue (linear regression analysis). In this design, there are 3 types of data collection that will be carried out, namely i) measurement of control image height; ii) measurement of actual height from control data, and; iii) measurement of testing image height. The measurement of control image height is carried out by taking several images of human objects as control data. These images are then processed using a YOLOv4-based CNN algorithm to generate a prediction value of whether the captured image only contains a human object or not. We did not create a custom dataset or perform re-weighting on the default YOLOv4 weight file, but we did modify the weight output, where only human objects will be marked with the ROI output, while non-human objects will be skipped. If there is a human object, the algorithm will then output the ROI of the object in the form of a bounding box. The number of pixels that make up the vertical ROI is calculated by the system to obtain the height in pixels. The measurement of actual height from control data is carried out by taking the actual height data in centimeters, using a stadiometer, tape measure, or ruler. This measurement is only carried out on control objects that have previously had their images taken and their heights obtained in pixels. The dataset of the results of the calculation of the height in pixels and the actual height in centimeters from the control data is then analyzed with linear regression to obtain a time series mathematical modeling that can convert pixel to cm values.

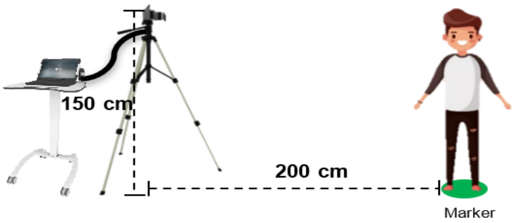

Figure 1. The proposed hardware design

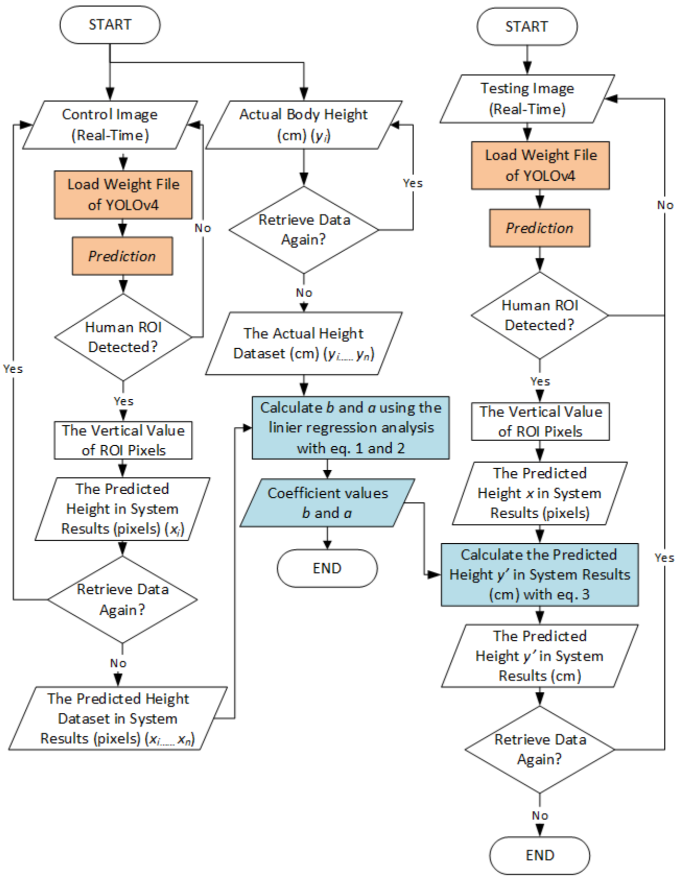

Figure 2. The proposed software design

Linear regression is one of the many regression analysis methods used to solve mathematical problems that cannot be solved analytically/by textbook formulas. This method models the relationship between several variables according to the form of a time series or linear equation [29]. It helps in analyzing the strength of the association between the outcome (dependent variable) and predictor variables [30]. It has the form of an equation as shown in (1)-(3). Where x_i is the vertical pixel data of ROI object-*i* predicted by the proposed system. y_i is the actual height data in cm of object-i taken from a standardized measuring device. b is coefficient of variable x. a is constant. y' is the predicted height data in cm by the proposed system [21], [22].

$$b = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{n\sum x_i{}^2 - (\sum x_i)^2} \tag{1}$$

$$a = \bar{y} - b\bar{x} \tag{2}$$

$$y' = a + bx \tag{3}$$

The measurement of testing image height is carried out by taking several images of human objects as testing data. The processing of testing image height is almost similar to the measurement of control image height. The only difference is that the output of the height in pixels will be automatically converted by the system into the height in centimeters using the formula from the linear regression analysis of the control image data. The calculation result of the formula from the mathematical modeling is what will eventually display the notification of the system's predicted height value in centimeters.

In this research, the testing was conducted on two sets of data, namely control data and test data. The control data was used to build the mathematical modeling produced by deep learning and linear regression analysis to convert the height data from the system's prediction results in pixel units to cm units, while the test data was used to determine the performance of the mathematical modeling produced by the proposed system in more realistic conditions. Data collection was carried out through direct observation/observation (primary data) of real-time images of human objects and actual height that will be processed. The total data to be processed is 40 primary samples, with 20 control data samples and 20 testing data samples. The sampling for control and testing data was carried out by random sampling related to the background of the image capture and the color of the clothes worn by the object in order to see the ability of the proposed system to recognize objects with variations in background and clothing color.

Next, the performance evaluation technique was carried out in two stages for both the control data and the test data samples. The first stage of the evaluation was carried out to assess the performance of the proposed system in detecting human objects or not using the F1_score formula as in (4). Where, F1_score is the harmonic mean of precision and recall, where the best score is close to 1 and the worst score is close to 0.

$$F1\_score = \frac{2 \times precision \times recall}{(precision + recall)} \tag{4}$$

The second stage of the evaluation was carried out to assess the performance of the proposed system in detecting the height based on the real-time image of human objects by comparing the height from the proposed system with the actual height using the R_Square, root mean square errors (RMSE), and average accuracy percentage formulas [21]. The formulas for these three equations can be seen in (5), (6), and (7).

$$R^2 = \frac{(\sum_{i=1}^{n}(y_i - \overline{y_i})^2) - (\sum_{i=1}^{n}(y_i - y_i')^2)}{(\sum_{i=1}^{n}(y_i - \overline{y_i})^2)} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i' - y_i)^2}{n}} \tag{6}$$

$$Accuracy(\%) = 100\% - \frac{\sum_{i=1}^{n}\left|\frac{y_i - y_i'}{y_i}\right| \times 100\%_i}{n} \tag{7}$$

Where y is the actual height in cm, y' is the predicted height in cm as output from the proposed system, R_square is the correlation coefficient that shows the degree of strength/similarity of the relationship between data y and y'. The value of this correlation coefficient is in the range of 0 to 1, where 0 indicates no relationship between the two data sets, while 1 indicates a very strong similarity between the two. RMSE is used to measure the error rate of a model in predicting quantitative data. The smaller the RMSE value approaches 0, the more accurate the model is in predicting data. RMSE is calculated by taking the square root of the average squared error between the actual value y and the predicted value y'. Accuracy is the value of one hundred percent minus the percentage value of the average error of the system in predicting the calculation model.

3. RESULTS AND DISCUSSION

Figure 3 shows the implementation of the proposed hardware design. The camera sensor is mounted on a tripod with a height of 150 cm from the surface. The camera sensor is then connected to a laptop/PC using a USB type C cable. It is then pointed vertically facing forward to capture real-time images of human objects in front of it at a distance of 200 cm. Then, the implementation of the proposed software design was divided into three phases. The first phase, which has been successfully completed, involved the implementation of the YOLOv4-based CNN algorithm into the system. This enabled the system to detect full-body human objects in a variety of background and clothing color, as shown in Figure 4. Figure 4 shows the ability of the proposed algorithm to accurately detect the ROI of human objects and their pixel size. It shows that some samples have a variety of clothing colors and background noise, but the system is able to detect full-body human objects. Even if the human object is obscuring its face, the system is still able to detect the human object. Figure 5 shows that the proposed system is able to capture and detect the ROI of human objects from all real-time control data images tested (20 samples) with an average F1_score of 1 or 100%. The proposed system is also able to automatically generate the object's height in pixels based on the ROI vertical line of the human object captured during the measurement. In Figure 5, we found that the predicted height in pixels obtained by the proposed system is highly correlated with the actual height in cm measured using a stadiometer. The deep learning method using the YOLOv4-based CNN algorithm in this study tends to have a much higher proportion of linear detection accuracy compared to morphology and edge detection techniques [11], [18]–[21].

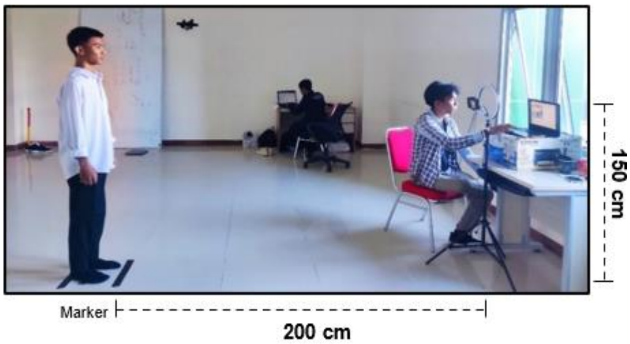

Figure 3. Implementation of the proposed hardware design

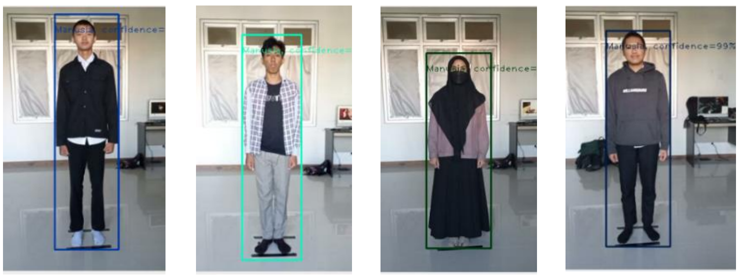

Figure 4. The proposed algorithm (YOLOv4-based CNN) is able to detect full-body human objects in a variety of background and clothing color

Thus, we can create a mathematical equation of linear regression as shown in Figure 6. Figure 6 shows that the predicted height in pixels with the actual height in cm form a linear function/straight line with the equation $y' = 0.4034x + 24.938$. The analysis showed that the R_square correlation coefficient and the percentage accuracy of the equation are very high, reaching 0.99 and 99.40%, respectively. This indicates that the equation is a very good fit for the data and that the system is very accurate in predicting the height of data control. The RMSE score is also very low, at 0.19. This indicates that the predicted height is very close to the actual height of the data control. The linear regression equation obtained from the data control modeling was then integrated into the proposed system and evaluated on 20 samples of test data obtained by random sampling. Table 1 shows the performance of the proposed system against 20 test data samples was excellent. The system was able to predict the test results correctly with an average of F1_score was 1, the R_square obtained was 0.93, the RMSE value was 0.02, and the percentages of average error and accuracy were 1.0% and 99.00%, respectively.

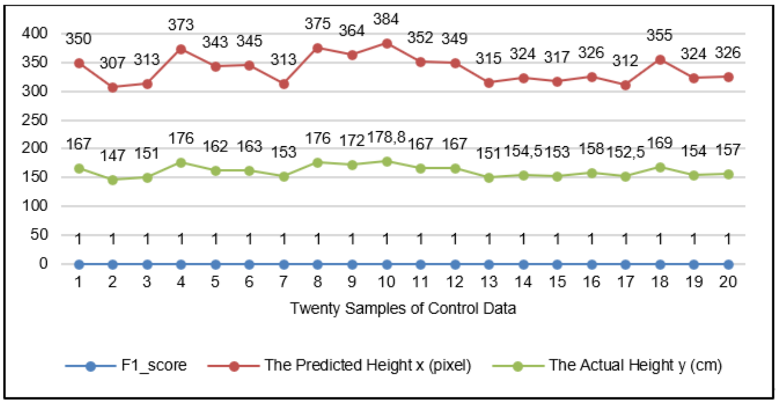

Figure 5. The F1_score, the predicted height of the proposed system (pixel), and the actual height taken using a stadiometer (cm) for 20 control samples

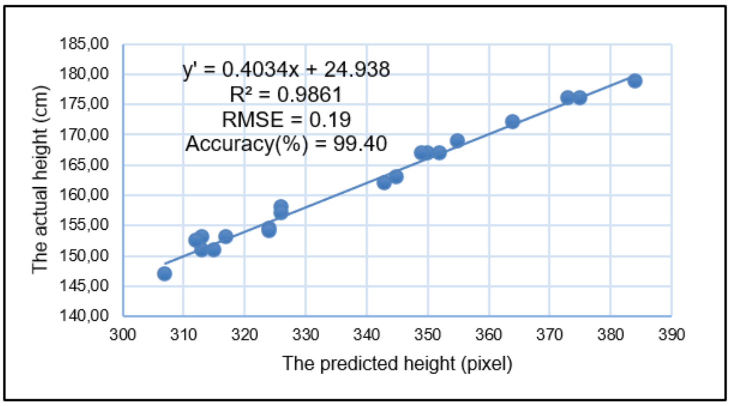

Figure 6. Linear regression modeling to find the equation of predicted height in centimeters

Table 1. The performance of the proposed system was evaluated on 20 testing data samples

Sample-i	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
x	345	343	375	321	345	353	346	330	386	308	366	345	353	359	351	355	344	352	366	364
y	164.0	162.3	177.5	155.0	162.5	170.0	162.0	161.0	179.0	148.0	173.0	161.0	167.5	171.0	163.5	168.3	161.0	165.5	173.0	167.2
y' = 0.4034x + 24.938	164.1	163.3	176.2	154.4	164.1	167.3	164.5	158.1	180.6	149.2	172.6	164.1	167.3	169.8	166.5	168.2	163.7	166.9	172.6	171.8
F1_score	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Error (%)	0.07	0.62	0.73	0.37	0.99	1.57	1.55	1.83	0.92	0.80	0.24	1.93	0.10	0.73	1.85	0.09	1.68	0.87	0.24	2.74
Average F1_score	1.00																			
R_square	0.93																			
RMSE	0.02																			
Accurary (%)	99.00																			

This study has successfully investigated the effect of combining two approaches, namely deep learning with YOLOv4-based CNN algorithm and linear regression analysis to automatically measure human height based on real-time images of human objects obtained from camera sensors. These results indicate that the proposed system was able to successfully detect the height in pixels from real-time images of human objects and was able to automatically convert it to height in centimeters with a very high similarity between the actual height in centimeters and the predicted height in centimeters based on the percentage of correlation coefficient and accuracy, as well as the very low RMSE and average error percentages. The proposed system is capable of replacing conventional methods of measuring a person's height or measuring height using microcontrollers and infrared or ultrasonic sensors [13]–[18].

The use of a camera sensor integrated with deep learning using CNN based on YOLOv4 and linear regression analysis, can be a new combination method for measuring a person's height in a less contact way easily and accurately. The use of linear regression analysis to create a modeling formula for converting the predicted height of the system in pixels to centimeters from a series of tests, both on control and testing data, has been proven to be accurate and effective in overcoming the conversion of unstandardized values that do not have a direct connection. Moreover, if the comparison between the predicted height of the system in pixels and the actual height in centimeters is in the form of a linear curve, then linear regression analysis can be a solution for building conversion modeling. Our findings are consistent with earlier studies have explored the impact of linear regression analysis for height estimation, but they have relied on manual annotation [22] and used morphology and edge detection with the constraint that the background and clothing color must be uniform to obtain the ROI of the human object [21]. This makes them inflexible and prone to measurement errors. This study suggests that the proposed method can automatically measure height and maintain accuracy that is not associated with poor performance in areas with varying background and clothing colors conditions.

However, further and in-depth studies may be needed to confirm the development of the proposed system in detecting human objects and performing the conversion of predicted height from pixels to centimeters more accurately, flexibly, and without distance limitations, especially regarding the use of linear regression analysis. This is because the weakness of the linear regression analysis is that the distance, height, and resolution of the camera in the testing data acquisition must be the same as the acquisition on the control data. If the distance and height of the camera experience a slight change in position, then the modeling formula for converting the predicted height of the system from pixels to centimeters needs to be recalculated again. Not to mention if the human object whose data is taken does not stand on the marker correctly or the marker position changes, then this adds to the system's error in detecting the height of the human object in centimeters. This is evident in the control data, there are still 4 out of 20 samples that have an error percentage of more than 1% with the highest error of 1.21%, while in the testing data, there are still 7 out of 20 samples that have an error percentage of more than 1% with the highest error of 2.74%. For that, future studies may explore alternative methods to replace linear regression with feasible ways to produce height estimates that are robust and flexible in variations of distance, height, and resolution of the camera.

4. CONCLUSION

This research successfully developed an automatic height measurement system based on a camera sensor with deep-learning approach and linear regression analysis. The proposed system uses a camera sensor to capture real-time images. The captured images are then processed using a deep learning with YOLOv4-based CNN algorithm to recognize whether the image contains a full-body human object or not. If so, the system automatically calculates the number of pixels in the vertical ROI of the full-body human object. Then, the equation of the linear regression analysis is used to convert it into the predicted height of the system in centimeters. The experimental results on 20 test data samples taken in real-time images and random sampling proved that the proposed system successfully performed automatic detection and measurement of human height with an average of F1_score was 1, the R_square obtained was 0.93, the RMSE was 0.02, and the percentage of accuracy was 99.00%. These results suggest that the system successfully detected the height in pixels from the entire real-time test image of human objects and was able to be automatically converted into height in centimeters with a high degree of similarity between the actual height in centimeters and the predicted height in centimeters based on the percentage of the correlation coefficient and accuracy, as well as the very low RMSE.

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