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Advanced home security: detecting unusual movements using the single shot detector technique

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Abstract
As area surveillance technology, the camera still needs to be suboptimal because it cannot detect suspicious human movement, and there is no real-time security alert. Although motion detection is implemented, it is only activated when a person passes the PIR sensor, triggering the camera to capture the object. Due to its lengthy process, it is less effective. This study aims to develop a home surveillance system that uses object detection technology to detect unusual human movements. The system is also equipped with real-time early warning through a Telegram Messenger application. The system is then tested using various parameters that may impact the precision of detection results, including object poses, camera height, and camera distance. The system can detect objects that make unusual movements in 69 images, or 57.5% of the tests, based on the analysis of 120 test data. By integrating object detection technology and real-time Telegram-based alerts, this home surveillance system significantly demonstrates the capability to accurately identify suspicious human motions, enhancing area surveillance effectiveness and adaptability to various environmental conditions.

Keywords:
Computer Vision;
Early Warning;
Movement Detection;
Single Shot Detector;

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INTRODUCTION

The increasing economic development towards a better city is one of the triggers for the increase in crime in the form of theft. This raises concerns for homeowners, shops, and other residences. Many thefts occur when homeowners travel and leave the house for a long time. Although some residential environments already have security officers, human limitations can be a gap for perpetrators of theft [1].

Many tools have been used for security systems that can be used as additional security at home, such as surveillance cameras to record or monitor the house's condition. In the current digital era 4.0, the function of cameras has been enhanced to record data and identify humans and other objects [2]. Generally, the function of cameras/CCTV is implemented as evidence after a crime has occurred and as a place to store activity data that can later be visually and audibly analyzed by humans [3][4]. One way to overcome crime by creating a better home security system is the application of a webcam camera on a security system embedded in object detection and early warning based on the application of the telegram messenger [5]. To practice the ability or intelligence of a surveillance camera with Computer Vision [6]. The Open Source Computer Vision library comprises various aspects such as Object Identification, Segmentation, Recognition, Face Recognition, Gesture Recognition, Motion Tracking, Motion Understanding, and Mobile Robotics [4, 7, 8].

Many studies have been conducted on detecting object movement using different methods. Among them is research on the frame difference method using a web server embedded in a motion detection application. The frame difference method works by comparing pixel values [9]. The frame difference motion detector is not required to recognize the type of object captured and trace the object's movement [10][11]. Furthermore, research has been conducted on home security systems based on Picamera and Raspberry Pi. This research focuses on how the system can monitor homes using motion sensor devices and a camera from a distance by utilizing the telegram application. This system will activate when the human object passes through the PIR sensor [12]. After that, it will activate the camera and require the user to log in with an ID in the security application [13][14].

Furthermore, the research discusses the single-shot detector method to detect moving objects. Single Shot Detector (SSD) is a method of detecting objects in images using artificial neural networks such as the human eye [15][16]. SSDs are easy to train and integrate into systems that use detection components. In some comparisons, the detection method. SSD has a higher accuracy and speed than other methods, YOLO is often used in real-time applications such as object detection in moving cameras or surveillance systems. While slower than YOLO, SSD tends to provide higher accuracy in some cases due to its multi-scale approach [17]. As a Convolution Neural Network (CNN) variant, SSD consumes significant computational power, yet it retains several advantages. It excels in efficiency by combining localization and classification in one pass, offering real-time performance crucial for applications like surveillance and robotics. Its multi-scale detection capability ensures accurate identification of objects of varying sizes, while its flexibility allows adaptation to diverse tasks and domains. Despite the computational demands, SSD's high accuracy and versatility make it a preferred choice in computer vision applications.

So, researchers proposed a security system with early warnings installed in outdoor areas. This system uses object detection with the SSD method to detect suspicious human movements, which are processed in real-time and pinned on the CCTV to maximize the CCTV's functionality [18].

METHOD

Object Detection Method

The object detection used in this study is the Single Shot Detector method. SSD is a method of detecting objects in images using artificial neural networks such as the human eye. SSD is one object detector method that uses the principle of CNN, wherein in the process of detecting objects from an image, several mathematical calculation methods are carried out, such as convolution and pooling on each pixel. In the SSD object detection method, in general, two processes are carried out, namely the object classification process and object localization, where both processes are carried out simultaneously.

As shown in Table 1, SSD has a higher level of accuracy and speed than other detection methods in some comparisons.

In Figure 1, the SSD architecture uses the VGG16 network from conv1_1 to conv5_3. Furthermore, there are some modifications, such as the 224x224 input changed to 300x300. The changes are in the form of size (width and height) and thickness (color channel), then filter in pool5 with the size of 2x2s2 to 3x3s1, and change the entire fully connected layer into a convolution and sub-sample layer followed by detection and NMS (Non- Maxpression) layers. The stages of SSD convolution with VGG architecture start from conv4_3 38x38x512, conv7 19x19x1024, conv8_2 10x10x512, conv9_2 9x9x256, conv10_2 3x3x256 and conv11_2 1x1x256. The feature layer process will output the parameters, which the detection layer will then compare so that the detection layer will compute 8732 detection results and NMS of 74.3 Mean Average Precision (mAP) and 59 Frame Per Second (FPS) [19][20].

SSD operates with just an input image during inference and ground truth boxes for each object during training. It uses specific convolutional priors of varying aspect ratios and scales across different feature maps, like 8x8 and 4x4 grids. These priors are linked to predictions for object offsets (Δ(x1, y1, x2, y2)) and confidences for all object categories ((c1, c2, ..., cp)) based on the underlying 1x1 features. During training, these priors are matched with ground truth boxes, categorizing matches as positive (e.g., cat, dog) or negative. The loss is then computed as a weighted sum of localization loss (e.g., L2 loss) and confidence loss (e.g., multi-class logistic), and the error is backpropagated for training [22].

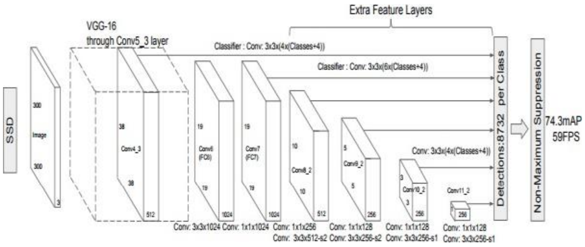

Figure 1. SSD Network Architecture [21]

For bounding box prediction, it has parameters in the form of pixel coordinates on the x-axis (Δcx), pixel coordinates on the y-axis (Δcy), width (w), and height (h). The bounding box prediction formed and accepted by the detection layer will be compared [23]. The bounding box prediction with the highest confidence value will be used as the bounding box at the actual output. In contrast, the bounding box predictions that intersect with the selected bounding box will be eliminated or ignored. As shown in Figure 2, the process is called Non-Maximum Suppression (NMS) [24].

System Planning

The design of this system uses a Logitech webcam to detect suspicious human movements or unusual movement detection. The system uses the Linux operating system and OpenCV with Python-based programming embedded in Raspberry Pi 3 b +. As shown in Figure 3, the system in this study detects suspicious movements and can send the results of these objects to the user via Telegram, where the device is connected to the internet [25].

The overall system design shown in Figure 3 is mounted on the tripod of a webcam, and Raspberry Pi is programmed with height and distance to adjust the house's fence. The programs that run on Raspberry Pi 3 can produce fast, lightweight, and accurate processing and detection [6]. Where the frame resolution on the input received by Raspberry Pi 3 will be changed to 300 x 300 pixels so that it can continue to use the SSD300 model, which will then be processed with several stages such as normalization, convolution, ReLU, pooling, SoftMax, thus providing object detection output (human) and their position. By knowing the object's position (human), the program will provide a boundary box around the human position in the frame.

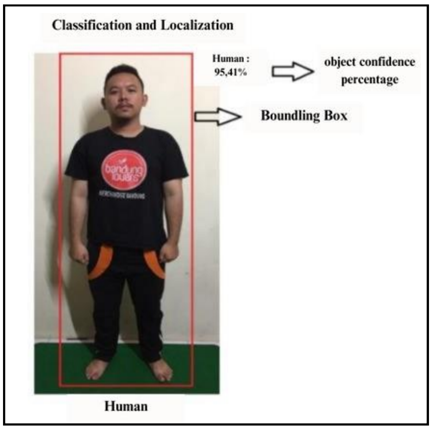

Figure 2. Output Object Detection

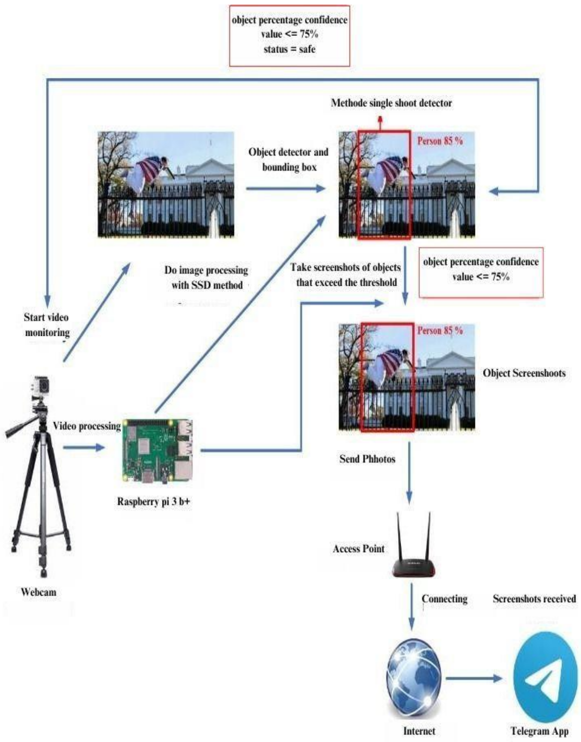

Figure 3. Overall System Design

In the threshold value system, the lowest confidence presentation is 50%. In comparison, the threshold value that triggers is 75% because the object indicated to do unusual movement is indeed considered human by the system. If the detected object has a confidence presentation below 75%, it will loop again in the initial process. This ensures that the detection results have a higher actual positive value and a lower false positive value. If the object is detected as suspicious, the system screenshot the monitoring video [6][26]. After that, the picture will be sent by Raspberry Pi, which is already connected to the internet, to the recipient or homeowner's telegram account. The main focus of this research is to know the factors that can affect the value of the belief in object presentation that can activate a screenshot of the image and then send it to a telegram account [27].

System Testing Scenario

At this stage, the system is accurately tested to detect suspicious movements when passing through the fence with predetermined parameters, such as distance, height, object pose, and testing time. To produce a system output or alert as a picture capture to the recipient with a telegram ID. Testing unusual movement detection systems is done by simulating the movement of people climbing the fence according to rain parameters [28][29].

The parameters that enter this testing phase are as follows: The position of the object when passing through the fence objects going up half the fence and objects up the entire fence. Camera position, camera distance: 3 m, 4 m, 5 m, and 6 m, camera height: 80 cm, 100 cm and 130 cm. Light brightness in the test environment: Day.

The steps to be taken in testing the system and collecting data are as follows: Install the device on a pole or tripod and adjust the pole's distance from the object and height, as shown in Figure 4.

Note the value of the light meter as a measure of light intensity, adjust the body position on the object, run the system, and monitor the system with SSH or VNC mode on the laptop, as shown in Figure 5.

Next, confidence data for object detection will be collected, the telegram application will be opened, and a photo of the detected object climbing the fence will be saved.

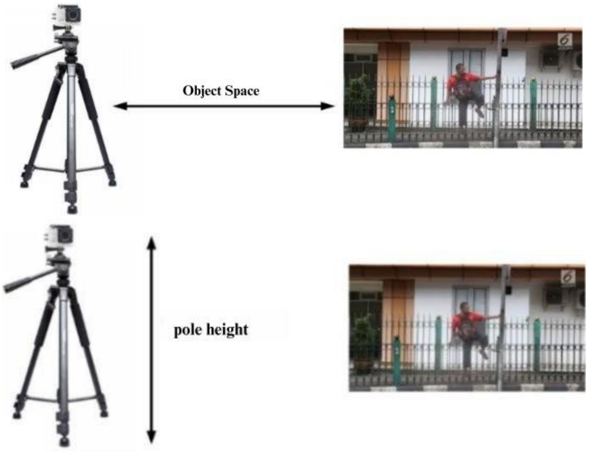

Figure 4. Adjusting The Distance and Height of The Pole

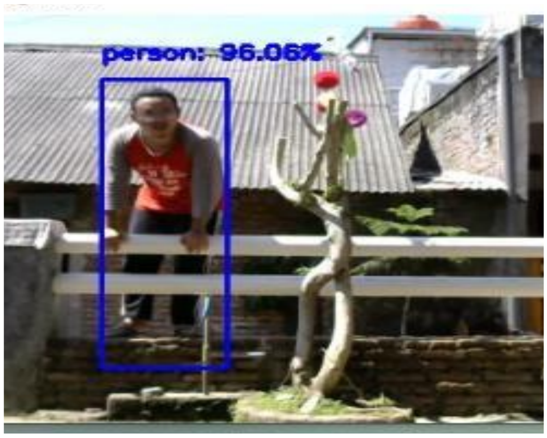

Figure 5. Video Monitoring on The Xming Viewer Display

RESULTS AND DISCUSSION

In this section, the researcher will describe several tests and analyze the system designed and made in this study. The data from the test results will be analyzed so that a conclusion can be drawn [30][31].

System Testing Results

System testing activities are carried out on the home page, with a fence height of 130 cm. Testing is only done during the day with an intensity of 10970 lux sourced from direct sunlight. The tested camera distance is 300 cm, 400 cm, 500 cm, and 600 cm. The height of the tested cameras is 80 cm, 100 cm, and 130 cm. In testing the system visualization using Xming Viewer with SSH mode, the results of detection and localization of objects considered humans by the system are shown in Figure 6.

The system will give the human-considered object a blue box accompanied by the detection confidence value in the right corner of the object [10][32]. If the accuracy of the object exceeds the 75% threshold limit, then the system will capture the image directly and then send it to the Telegram account via a Telegram bot aimed at Figure 7. The object image data received by the telegram account and performing unusual movements is shown in Figure 8.

If the object detected as a human is below 75% in the system, it will detect it again and is not considered a warning. As shown in Figure 9, the detected object only moves behind the fence. The system's minimum limit for objects that can be detected as humans is 50%; if it is under 50%, the system ignores it. As in Figure 10, at a distance of 6 m, bounding boxes to detect objects do not appear in the video monitoring

Test Data Results

The test is carried out with the previously mentioned test parameters. In one sample of the variable studied, the test was repeatedly tried 30 times with the pose of object one, namely climbing half a fence, and the pose of object two, namely climbing an entire fence [33].

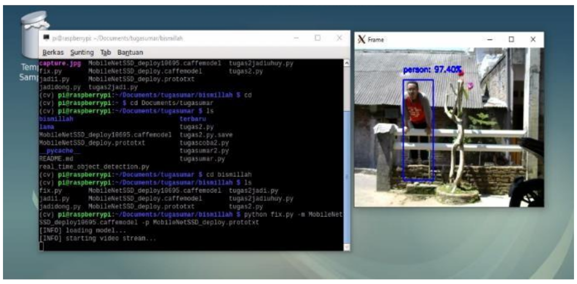

Figure 6. Video Monitoring Display in Xming Viewer

Data Table 2 shows the results of detection testing at testing distances of 3m, 5m, and 6m with height parameters at 100 cm and 130 cm.

Figure 7. Telegram Bot Sends Image Capture

Figure 8. Detected Object Performs Unusual Movement

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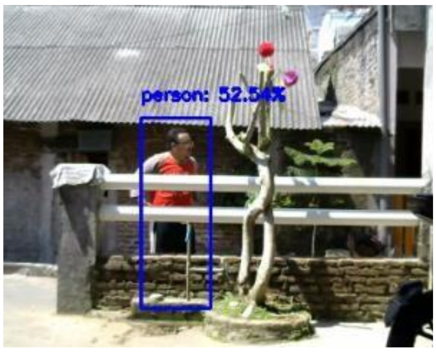

Figure 9. Objects that do the usual movement

Figure 10. Objects That Are Not Detected as Humans by The System

With the same lux intensity and for pose types 1 and 2, differences in accuracy and notification commands from the security system (detection) were obtained.

Distance Testing Results in 3 m: A sample of variables was studied in testing with a distance of 300 cm. The test was tried 30 times over and over with data on object one pose, which is climbing half a fence, and object pose two, which is climbing all fences. Figure 11 shows that the system detects objects that do unusual movements.

In Table 2, the height of the 100 cm camera shows that the results of pose one and pose the system can detect one as humans. In testing with pose 1, the system captures three images. From testing pose two, the system can capture all images. Images captured by the system from the object are sent to the telegram application [34]. This is because the confidence level, when detected, has exceeded the threshold limit of 75%. If the object detected as a human is below 75% in the system, it will detect it again and not be considered a warning. As shown in Figure 12, the detected object only carries behind the fence.

Distance Testing Results in 5 m: A sample of variables was studied in testing with a distance of 500 cm. The test was tried 30 times over and over with data on object one pose, which is climbing half a fence, and object two pose, which is climbing all fences. Figure 13 shows that the system detects objects that do unusual movements.

Figure 11. Example Test with a Distance of 3 m

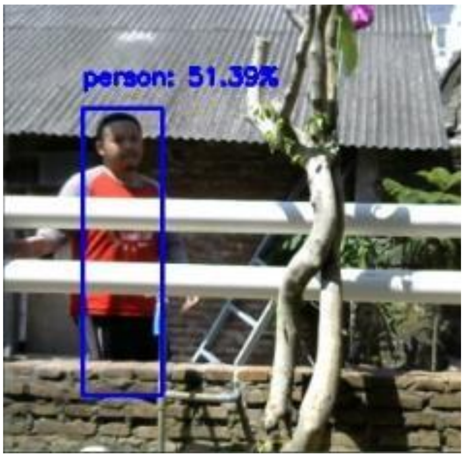

Figure 12. Detected Objects Perform Usual Movement

From Table 2, it is done on a 100 cm camera height. The results obtained in poses one and two can all be detected as a human system. For testing with pose one, the system successfully captured three tests. From testing pose two, the system can capture all testing. On testing a distance of 5 meters, objects that do the usual movement cannot be detected as humans because the level of confidence in the object is below 50% in the system. Then, it will be ignored and then detected again. As shown in Figure 14, the detected object runs behind the fence.

Test Results Distance of 6 m: One sample variable was studied in a test with a distance of 600 cm. The test was repeated 30 times with the pose of object one, namely climbing half a fence, and object pose two, namely climbing the entire fence. Figure 15 shows that the system detects objects that make unusual movements.

From Table 2, the camera is 130 cm high. Obtaining the results of testing pose one and testing pose two can all be detected as a human system. When testing with pose one, no images were captured by the system.

Figure 13. Example Test with a Distance of 5 m

Figure 14. Objects Ignored by The System as Humans

Figure 15: Example Test with a Distance of 6 m

From testing pose 1, only 1 picture can be captured by the system, with a confidence level of 78.22%. On testing a distance of 6 meters, objects that do the usual movement cannot be detected as humans. Then, it will be ignored and then detected again.

In real-time object detection, such as that applied to single-shot detectors (SSD), distance can affect the elevation position or accuracy of object detection. In this study, for distances of 3m and 5m, the elevation was designed at 100 cm to adjust to the boundary of the captured objects. Meanwhile, at 6 meters, the elevation was designed at 130 cm because, with increasing distance, the system needs to recognize object boundaries by raising the elevation by 30 cm. Several factors contribute to this, including Perspective and Resolution: The farther an object is from the camera, the smaller the proportion of the image dominated by that object. This can cause objects to appear smaller and less clear in the image. Parameter Adjustment: The detection system requires parameter adjustments depending on the distance of the object.

Testing Data Analysis

The test data that has been obtained can be analyzed to test unusual movement detection systems. Based on 30 tests at each distance, the percentage of objects detected by humans and those ignored by the system results. In the testing distance of 3 m, 4 m, and 5 m, the system's detection results indicate that all objects are correctly detected as humans in a total of 35 tests. However, in the 6-meter distance test results, 46.66% or 14 out of 35 tests were detected as humans, while the system ignored 53.34% or 16 out of 35 tests. Refer to the following Figure 16. Meanwhile, to compare the results of telegram data received at a distance of 3 m are 22 image data, at a distance of 4 m is 26 data, at a distance of 5 m is 16 data and at a distance of 6 m only one image data, refer to Figure 17. Overall, the test data analysis indicates a promising detection system for close-range human identification. However, significant performance degradation at larger distances necessitates further investigation into the underlying causes and potential mitigation strategies.

The two graphs above show the prominent effect of the camera's distance with the object detected. The closer testing distance will make it easier for the system to recognize human objects and capture images of objects with a high level of confidence.

Meanwhile, the results of the telegram data received at all test distances were compared. The data received in pose 1 is 27 image data, and pose 2 is 42 image data, shown in Table 3. This indicates that the object's pose is a factor in how well the system captures its image, alongside the distance from the camera. By delving deeper into how pose affects the data and analyzing it more thoroughly, researchers can fine-tune the system's performance and improve strategies for collecting data.

After the translation of the test data and the results of the initial analysis, then the statistical analysis process is carried out using SPSS software with a binary logistic regression test method.

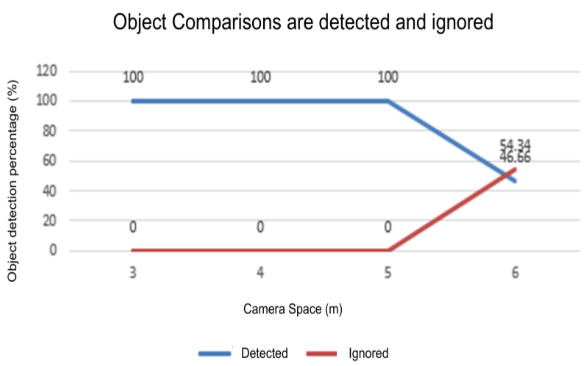

Figure 16. Comparison of Object Detection Results Graph

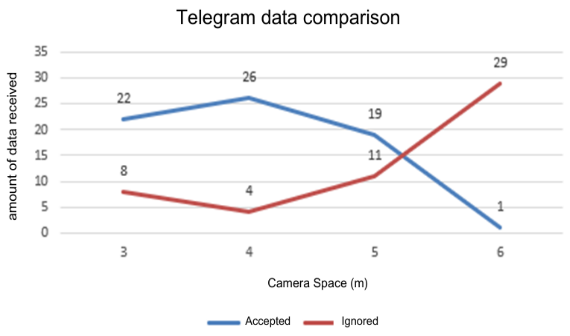

Figure 17. Comparison Graph of Telegram Data Results with Distance

That is because the dependent variable or Telegram is categorical and has image data with the state of the picture "accepted" or "no." For telegram data made into binary "received = 1" and "not = 0", one pose variable has one category, which is reduced to 1 only. With the condition if the pose is done = 1, otherwise it becomes 0. Then, an analysis of binary logistic regression methods with test data can be seen in Table 4. The results show that the data from the p-value or Sig has a value of 0.00, which explains that the independent variable is very influential on the results of the telegram image data with this test method because the P-Value <a: (0,000 <0.05).

Then, the data obtained from the binary logistic regression test process can be seen in Table 5. Where the p-value or Sig. Seen that the distance between the camera and object pose 2 has a value of <0.05 or <5%, so the independent variable can be said to be very influential on the dependent variable. At the same time, the high variable has a value above 0.05, so it does not affect the dependent variable. From Table 5, we can see the value of the influence of the independent variables on the dependent variable.

The study involved 120 test data with a minimum 50% detection rate of objects, featuring two object poses, four test distances, and three different test camera heights. The system detected objects as humans in 86.667% or 104 tests, while it ignored them in 13.333% or 16 tests. Regarding image data received from Telegram, out of 120 tests with a 75% threshold, 69 images were received (57.5%), while 51 tests were not (42.5%). Other influencing factors analyzed include good light intensity and low FPS speeds (0.4 to 0.8 FPS) during real-time video monitoring.

Our research enhances home security by detecting unusual human movements. This differs from Kommey [34], which focuses on identifying authorized individuals.

Table 1. Comparison of Methods for Detecting Objects

Method	MAP	FPS	Batch Size	#Boxes	Input Resolution
Faster R-CNN (VCG16)	73.2	7	1	~ 6000	~ 1000 x 60
Fast YOLO	52.7	155	1	98	448 x 448
YOLO (VGG16)	66.4	21	1	98	448 x 448
SSD300	74.3	46	1	8732	300 x 300
SSD512	76.8	19	1	24564	512 x 512
SSD300	74.3	59	8	8732	300 x 300
SSD512	76.8	22	8	24564	512 x 512

Table 2. Testing Data with a Distance of 3,5,6 Meters

Parameter			Object Pose Accuracy (%)		Telegram Alert Received (1) or Not Received (0)	
Height (cm)	Distance (m)	Light Intensity (Lux)	Pose 1	Pose 2	Pose 1	Pose 2
		10970	70.28	81.06	0	1
		10970	96.23	85.12	1	1
100	3	10970	72.89	87.62	0	1
		10970	81.6	87.47	1	1
		10970	77.37	83.03	1	1
		10970	93.83	91.68	1	1
		10970	92.58	99.14	1	1
100	5	10970	55.24	92.58	0	1
		10970	79.8	93.49	1	1
		10970	59.41	95.51	0	1
		10970	58.18	59.55	0	0
		10970	72.54	78.22	0	1
130	6	10970	66.79	56.28	0	0
		10970	68.22	66.49	0	0
		10970	65.19	72.33	0	0

Table 3. Telegram Data Received Based on Object Pose

Status	Pose 1	Pose 2
Data Received (√)	27	42
Data Not Received (-)	33	18

Table 4. Independent Variable Influence Test

		Chi-square	df	Sig.
Step 1	**Step**	46.002	3	.000
	Block	46.002	3	.000
	Model	46.002	3	.000

Table 5: Independent Variable Influence Data

Variables In the Equation									
								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp (B)	Lower	Upper
Step 1[a]	**Pose_2**	1.409	.480	8.615	1	.003	4.091	1.597	10.479
	Range	-1.272	.243	27.415	1	.000	.280	.174	.451
	Height	.002	.011	.022	1	.883	1.002	.980	1.024
	Constant	5.261	1.577	11.126	1	0.001	192.710		

CONCLUSION

Based on the system design and testing conducted in this study, it can be concluded that this unconventional motion detection system is capable of identifying objects like humans up to a distance of 6 meters. Specifically, it was observed that accurate detection could be achieved at distances of 3 and 5 meters under pose conditions 1 and 2. However, at the 6-meter distance, no detection was recorded under pose condition 1, and under pose condition 2, the detection was achieved with low accuracy, yielding only one successful data point out of 5 test runs. The primary factor influencing detection accuracy is the spatial gap between the detected object and the camera. Several recommendations are provided to enhance future research endeavors. Improving hardware capabilities is essential to expedite the object detection process due to the low frames per second (FPS) currently achieved. Furthermore, the utilization of superior camera equipment is necessary to enhance object detection precision and effectiveness.

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