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Original Article

Dual-Factor Indoor Identity Verification System Using Face Recognition and Height Detection with Raspberry Pi

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Abstract - *The purpose of this system was to verify identities and positions indoors by using image processing technology that detects a person's facial characteristics and height to increase identity verification accuracy. Data on people registered to use the system were stored in the Firebase database connected to Raspberry Pi boards, where cameras were installed at various positions of the test area for real-time monitoring and detection. Six cameras were installed, with three cameras being installed on two levels with an area of 746 square meters per level. Cameras were installed 0.40 meters from the ceiling or 2.1 meters from the floor. The system's main components consisted of Raspberry Pi4 boards, pocket WiFi, webcams, the Firebase database, and API linking data collection, detection, and warnings. Height was tested and determined by determining width compared to the reference size, and face testing was done using a 67-position model via processing with the MediaPipe library. System test results had a likeness of face verification from six cameras at a mean of 58.15-61.28%, while the mean height from measurements had a mean error of 0.14%-1.53%, which did not exceed 2% and was acceptable. In addition, the system was able to detect faces at a range of 0.5-4 meters when installed at heights of 1-2.5 meters, with the time of 8:30 am - 4:30 pm being the optimal time for facial recognition in the test area. Two-level identity verification was shown to be able to identify individuals effectively.*

Keywords - *Real-time identity verification, Image processing, Face recognition, Height detection, Indoor tracking system.*

1. Introduction

On identity verification via biometric technology, T.L. Johnson et al. stated that facial recognition developments and advancements have become widespread and applied in justice and law enforcement processes [1], particularly in missing person situations occurring from abduction, human trafficking, sexual exploitation, and other illegal activities. According to the latest statistical data from Thailand, Khaosod Online found 252 missing children reports in 2022, of whom 144 were girls and 108 were boys. The numbers have increased by 25% over the past four years [2]. Therefore, timely prevention methods, particularly if there are systems for tracking and identifying a person's position, can reduce damage from the aforementioned causes. Studies have been conducted on many types of technology used to identify a person's position in various places, such as RFID [3], Zigbee [4], and GPS [5]. However, currently, the highly advanced technology in use is image processing. Image processing can be used in various fields and industries. S. Sathiyamoorthy used image processing in production control, including testing the existence and non-existence of parts and finished products in production lines to improve production quality and reduce non-conforming products [6]. Moreover, P. Lerones et al. used three different computer systems to manufacture brake discs by casting in the automobile industry. These systems were a calibrated system for viewing 3D structural lights, an uncalibrated system for viewing 3D structural lights, and an ordinary 2D viewing system, which helped to make inspection work faster and more accurate [7]. In agriculture, A. Suksukont et al. developed a fruit ripeness analysis system using image processing technology to test fruits for ripeness in real-time and help farmers reduce potential fruit rot by using NI Vision Builder software with webcams [8]. M. P. Raj & P. R. Swaminarayan developed seed or grain and plant categorization by sorting to maintain consistency [9]. In another study conducted by M. A. Kashiha et al., an image processing system for tracking egg chickens in a laboratory used cameras to record images from above in order to monitor chicken movement and area selection behaviors, which helped to reduce data analysis time and expenses [10]. In medicine, N. Obukhova et al. used image processing for medical video systems with a focus on individual work in order to increase the speed and specificity of doctors' diagnoses by analyzing and automating diagnoses, performing statistical analyses, and using AI analyses [11]. In transportation and logistics, H. Borstell et al. used image processing in logistical systems to develop modern logistical solutions. Image processing enabled systems to collect, analyze, and communicate data effectively [12]. In another study conducted by G. Wu et al., a system for locating and tracking positions of small mobile robots by using image processing consisted of three main components, which were a system for collecting and processing images, a system for identifying positions using symbol memory, and a position tracking system. This enabled symbol detection to identify robot positions quickly and made systems suitable for use in complex and uncertain environments [13]. In identity verification, image processing has diverse uses. M. Wang & W. Deng studied to determine the accuracy of facial recognition in various conditions [14], and F. Schroff et al. developed a facial recognition algorithm capable of functioning in low light conditions or when there is motion, which was highly beneficial for field use such as in detecting suspects or missing persons in places with insufficient light and in identifying an individual within a large group with the “FaceNet” algorithm [15]. Additionally, in another study conducted by A. Nongvee et al., image processing technology was widely used. For example, facial recognition technology was used to log employee entry-exit times [16].

Moreover, S. Banlue et al. used CCTVs to detect faces in checking class attendance with face images by using the LBP technique [17], and K. Triprapin et al. used a web application developed with PHP, OpenCV, and Firebase to check class attendance with face images along with developing eye object detection by the method of using YCbCr color models and HSV color values to distinguish skin color from the background [18]. Recent advancements in AI-driven facial detection for biometric systems have been investigated across multiple studies. The development of real-time facial authentication frameworks is emphasized by Bertrand et al. [19], with significant improvements in recognition accuracy being achieved. In contrast, intelligent systems optimized for public safety applications are proposed by Siddiqui et al. [20], where robustness under variable environmental conditions such as lighting and occlusion is demonstrated.

To address challenges in longitudinal recognition, Generative Adversarial Network (GAN)-based techniques for face aging simulation are leveraged by Anandhi et al. [21], resulting in age-related discrepancies being mitigated and long-term biometric system performance being enhanced. A hybrid approach integrating Faster R-CNN with CAMShift algorithms is introduced by Mulyadi et al. [22], with state-of-the-art accuracy in dynamic, real-world environments being reported. The adaptability and reliability of facial recognition technologies across diverse use cases are collectively advanced by these contributions. The reviewed literature highlights the growing significance of image processing and facial recognition technologies in enhancing the identification and tracking of individuals. Traditional tracking methods, such as RFID and GPS, are limited by reduced accuracy in indoor or densely populated environments. In contrast, image processing systems are recognized for their superior precision and real-time operational capabilities. These systems have already been implemented across diverse sectors, including agricultural, industrial, medical, and educational applications. In this research, Raspberry Pi boards equipped with six cameras are utilized to simultaneously detect facial features and anthropometric data, such as height. By integrating height measurements with facial recognition algorithms, the system’s identification accuracy is enhanced, and precise indoor localization is achieved. This approach is demonstrated to offer greater reliability, cost-effectiveness, and adaptability compared to conventional tracking methodologies, thereby improving its practical viability for real-world applications.

2. Relevant Literature

Image processing is a technology used to analyze and distinguish characteristics significant for identity verification. In general, identity verification depends on facial recognition, fingerprint testing or retinal scans, which are biological analysis techniques that can be used to identify individuals accurately.

2.1. Facial Recognition

Facial recognition is the process of processing detected images according to face detection steps used to confirm identity from still or motion images, as shown in Figure 1. As evidenced in the literature, face detection is achieved through analysing 68 distinct facial landmark coordinates employing KNN or SVM algorithms for classification. This preprocessing step precedes facial detection and enables systematic feature extraction, after which the data is stored in databases for subsequent retrieval or validation [23, 24].

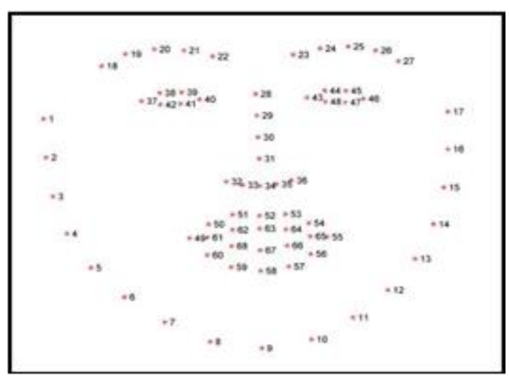

Fig. 1 Face verification location

From Figure 1, face detection is an advanced process focused on identifying the positions and boundaries of faces in still or motion images without considering personal identity or specific personal characteristics. The system consists of: 1) an algorithmic process which applies various algorithms such as Haar Cascades, Histogram of Oriented Gradients (HOG), Convolutional Neural Networks (CNN); 2) the processing step consisting of Step 1: Image data preparation from conversion into the grey level, image size adjustment, and image quality enhancement, and Step 2: Window slide image scanning and analysis of local characteristics; 3) Facial recognition, which is analysis of facial structures, identification of key physical points, and calculation of characteristic vectors before Euclidean comparison and categorization along with measuring similarities by using deep learning techniques [25, 26].

2.2. Height Measurement with Images

Height measurement uses the principle of pixel comparison by using images with clearly identified dimensions as a reference, such as A4 paper (21.0 x 29.7 cm), before using the measured values to calculate the person's height with characteristics of height measurement, as shown in Figure 2.

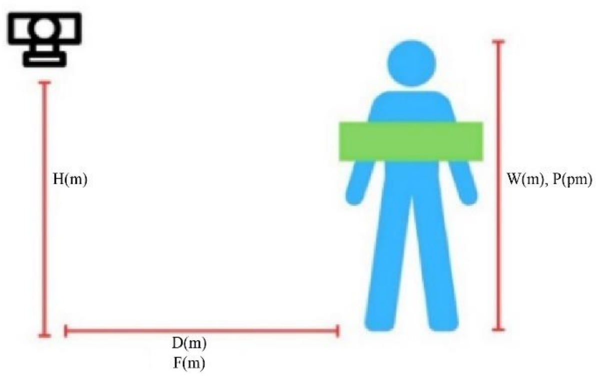

Fig. 2 High computation

From Figure 2, calculations for a person's height can be written in an equation as follows:

$$F = (D * P)/W \quad (1)$$

When W is the object's width with a unit in meters, P is the object's width within the image with a unit in pixels, D is the distance between the camera and the object with a unit in meters, and F is the image's focus range with a unit in pixels.

3. Proposed System

This study and creation of a system for in-door identity verification in real-time using image processing techniques used the principle of comparing faces and heights to verify identities and positions in real-time. The system's functions were divided into three parts as follows: 1) collection of data on individuals who registered via a Python interface (Package Tkinter Python) to provide a database; 2) search for individuals and positions by collecting images to test and find individuals through processing with MediaPipe's library [27], which was the comparison of faces and heights with a database that can be recorded.

This comparison was a two-level comparison, and six cameras were installed in this study, with three cameras installed on each of the two floors, and 3) search warning took images of individuals and displayed results on the search window to help facilitate searches for individuals.

3.1. System Working Principle

The system collected data on faces, heights, and other data in the database. The database was linked to the Raspberry Pi board via the internet and linked to cameras to detect faces and heights before comparison with the database, as shown in Figure 3.

Fintech Luminous C30 model cameras were applied, featuring a resolution of 2650×1440 pixels. The test area was on the 6th and 7th floors of Building 42, Phranakhon Rajabhat University, Thailand, each of which had an area size of 746 square meters, as shown in Figure 4.

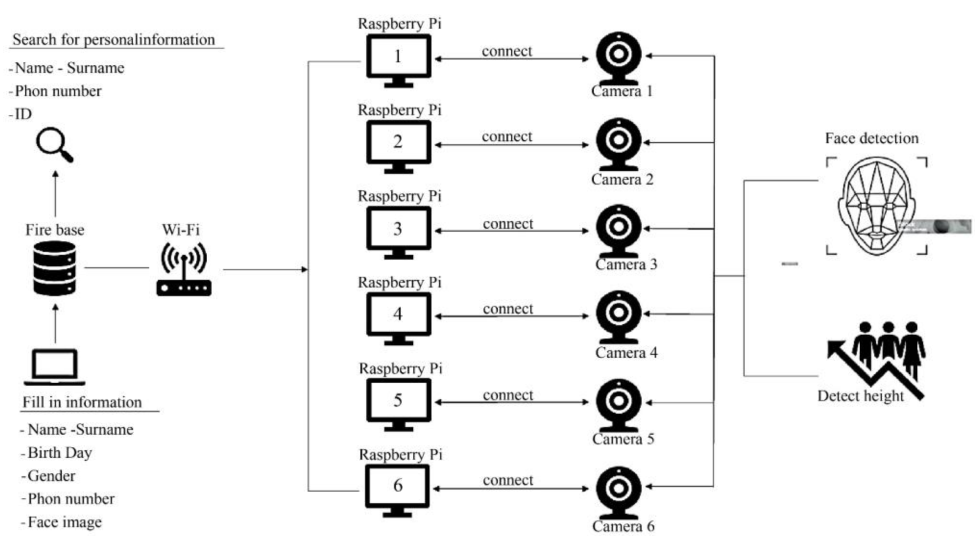

Fig. 3 System operation principles

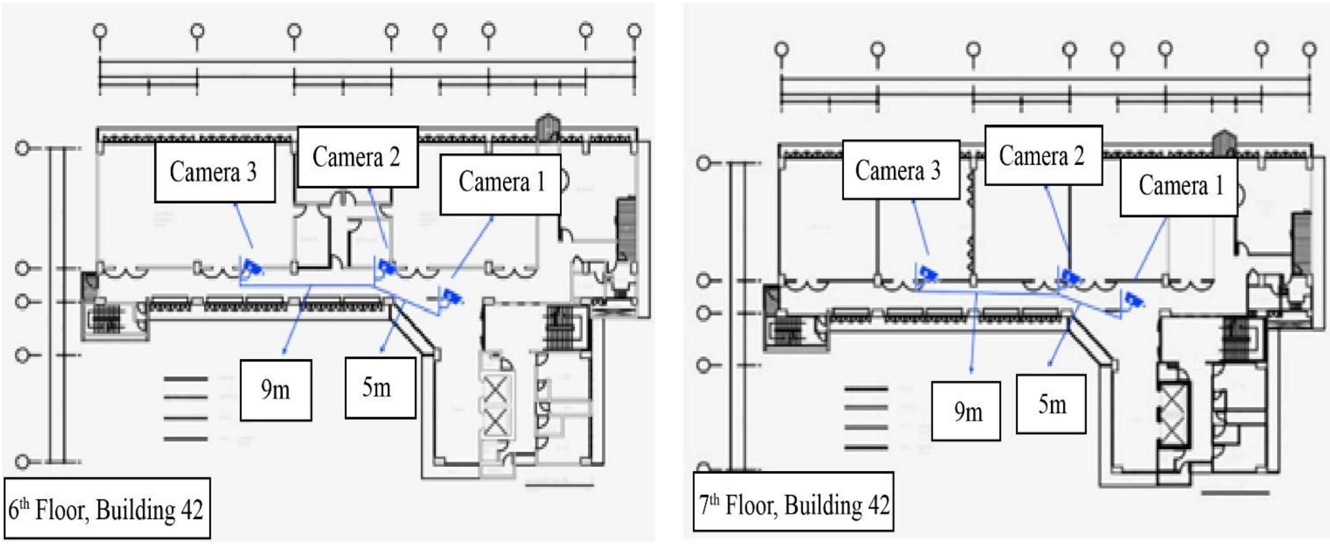

Fig. 4 Camera installation location for testing

3.2. Installation of System Cameras for Position Detection

The design of the camera and Raspberry Pi board installation structures required installations to be 40 cm from the ceiling or 2.10 meters from the floor.

Inexpensive materials were used as the structure and parts designed to install cameras, which created durability at the correct angle, as shown in Figure 5.

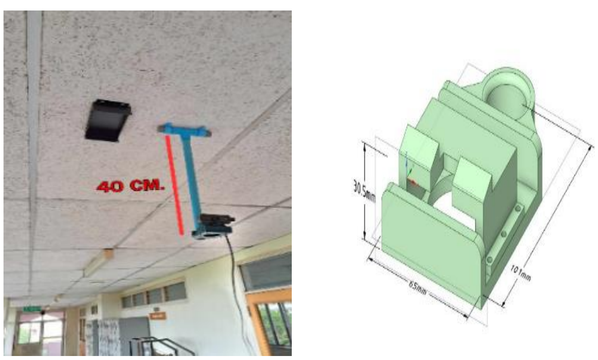

Fig. 5 Installation of cameras to detect system location

3.3. Hardware and Software Structure Design

The hardware structure connected equipment with four main components consisting of the Raspberry Pi4 board with a quad-core processing unit that supports high-level processing, the Pocket WiFi for connections with the Firebase database, the API used to connect data storage, detection, and warnings by using a 5V energy source capable of distributing 2.5A to 3A of electricity to supply the board and connect the 1080p (Full HD) webcam at 30 fps to Raspberry Pi4 in order to detect individual faces and heights as shown in Figure 6.

The software structure designed the working steps of the indoor identity verification system in real-time controlled by image processing techniques, as shown in Figure 7.

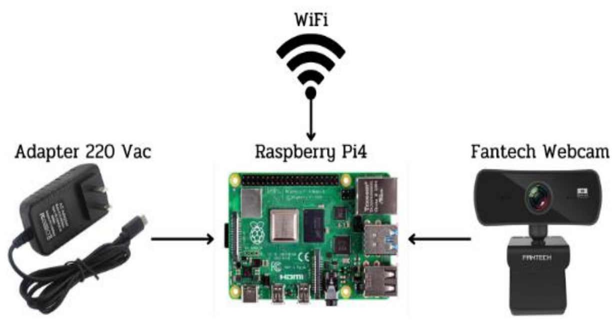

Fig. 6 Hardware structure

Figure 7 shows the system software structure, which used the Raspberry Pi4 board to connect to the database via the internet via the URL: "https://faceid-bcde3-default-rtdb.firebaseio.com/".

The registered data were in ten fields consisting of "name", "gender", "Contact number", "Height", "total_attendance", "last_attendance_time", "ID", "birth_date", "age", and "image_url.

Searches for individuals were then conducted by detecting faces and heights with the "if faceCutFrame" command, after which the system will check for matches with the database.

If the data matched, matches were tested with the "if matches [matchesIndex]" command and an alert was sent to Line Notify to report the position of the searched person.

The system will return to face and height detection if no matches are found. The software function window design was as follows:

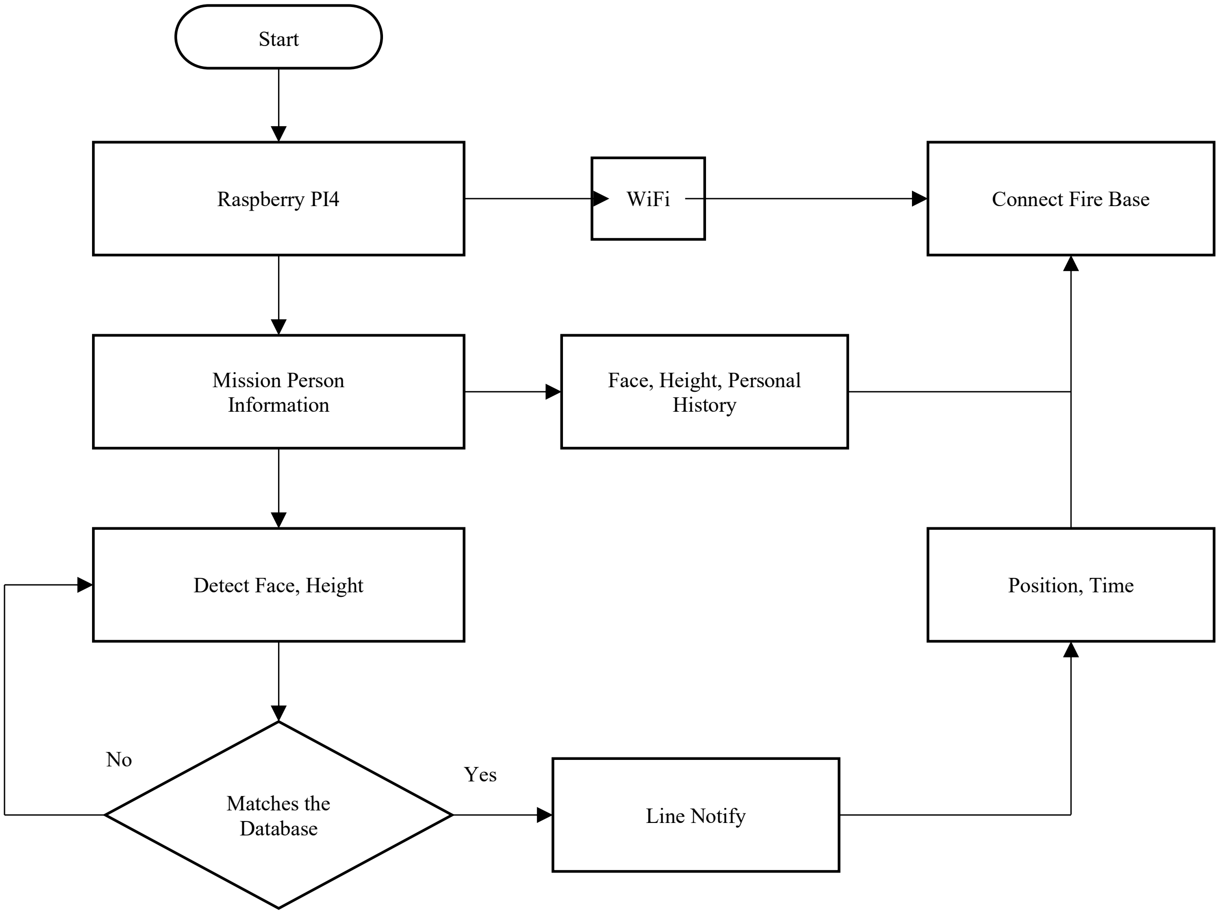

Fig. 7 Software structure flow

3.3.1. Registration Window and Position Search Window

The registration window consisted of necessary information entries for the information fields in the software structure. Data were stored in the database, as shown in Figure 8. The position search window for searching for individuals was used to make comparisons with the database of registered individuals by entering information, names, telephone numbers or IDs, as shown in Figure 9.

Fig. 8 Registration window form

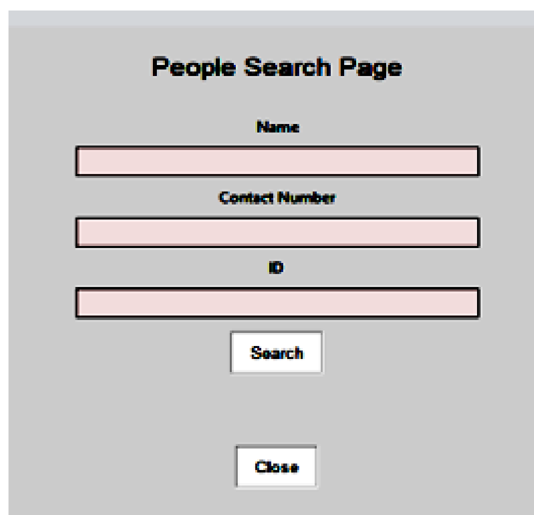

Fig. 9 Location search window form

3.3.2. Search Result Display Window

The search result display window displayed information on searched individuals according to registered information by displaying images of individuals and the position where the individual was found, as shown in Figure 10.

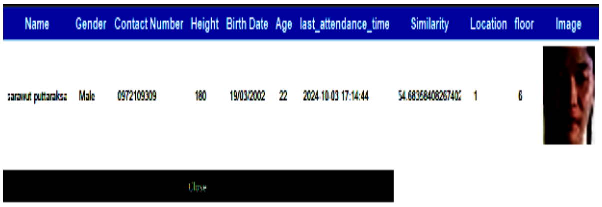

Fig. 10 Search result window

4. Results and Discussion

4.1. Results from Height Measurements with Image Processing

The height measurements while camera positions were at heights of 1-2.5 meters, and the distance between the camera and individuals was 0.5-5 meters, as shown in Figure 11 and Table 1.

Fig. 11 Visual height measurement testing

Table 1. Average height measurements using image processing via camera

		Camera Installation Height (meters)			
	0	**1**	**1.5**	**2**	**2.5**
Distance between the Camera and the Person to be Measured (meters)	**0.5**	0	1727.57	1034.81	414.18
	1	0	980.63	882.55	569.24
	1.5	633.76	618.156	581.97	328.09
	2	460.76	462.63	432.85	312.16
	2.5	374.39	352.30	330.69	271.14
	3	304.68	298.43	274.63	246.67
	3.5	258.10	249.54	240.61	221.03
	4	226.55	219.77	213.06	191.85
	4.5	198.09	192.79	187.65	177.87
	5	177.36	171.74	169.20	145.87

Table 1 shows mean height measurements from processing camera images with a distance of 0.5-5 meters between the camera and the person, while the positions where cameras were installed were 1-2.5 meters. The person's height was calculated using images using Equation (1).

$$\text{High} = \sqrt{(\boldsymbol{C}\text{X2 - CX1 })^2 + (\boldsymbol{C}\text{Y2 - CY1})^2} \tag{1}$$

When "High" is the height detected by the camera and "CX2, CX1" is the longitude and "CY2, CY1" is the latitude. Height calculations from Equation (1) had significant errors, necessitating a compensation equation to reduce height calculation errors, as shown in Equation (2).

$$\boldsymbol{RangeHigh} = \frac{(\boldsymbol{CY1-CY1\_Max}) * ((\boldsymbol{Hight\_Min/X}) - (\boldsymbol{Hight\_Max/X}))}{(\boldsymbol{CY1\_Min-CY1\_Max}) + (\boldsymbol{Hight\_Max/X})} \tag{2}$$

When "Range High" is the compensated distance, "CY1_Max" is the maximum latitude, "CY1_Min" is the minimum latitude, "High_Max" is the maximum height detected via camera, and "High_Min" is the minimum height detected via camera. Height compensation data are shown in Table 2.

Table 2. Height compensation value

CY1_Max	CY1_Min	Range_Min	Range_Max
1025.7	668.7	0.215200994	0.355090013
668.7	543.4	0.355090013	0.458766826
543.4	458.5	0.458766826	0.562266923
458.5	408	0.562266923	0.649648869
408	365	0.649648869	0.750379355
365	335	0.750379355	0.845495931
335	308.4	0.845495931	0.950859182
308.4	287.1	0.950859182	1.071856986

From Table 2, the data used in compensations to determine the height at the range were "CY11_Max", which was the maximum latitude; "CY1_Min", which was the minimum longitude; "Range_Min", which was the minimum height compensation; and "Range_Max", which was the maximum height compensation. The calculated data from Equation (1), Equation (2), and Table 2 were then processed, thereby enabling the calculation of compensated height from Equation (3), where "High Human" was each person's height after height compensation.

$$\text{High Human} = (\text{Hight} * \text{Range High}) \tag{3}$$

4.2. Search Test Result

Results from test searches of individuals in the area were as follows: 1) Cameras installed at heights of 2.5, 2, and 1.5 meters were able to detect faces at ranges of 0.5 to 4 meters; 2) Cameras installed at the height of one meter were able to detect faces at ranges of 1.5 to 4 meters; 3) testing of times with effects on face detection showed detection was possible from 8:30 am to 4:30 pm. At 8:30 am, the detection range was 0.5 meters longer than other times at 4.5 meters, as shown in Figure 12. From Figure 12, individual searches with the system compared data stored in the database for likeness and height. Likeness values measured from cameras were shown in Table 3, and height measurements from cameras were shown in Table 4. From Table 3, mean likeness scores from all six cameras were at 58.15%, 51.92%, 61.24%, 58.65%, 57.92%, and 61.28%, respectively, with a standard deviation of 6.59, 6.98, 6.81, 5.31, 3.60, and 5.69, respectively.

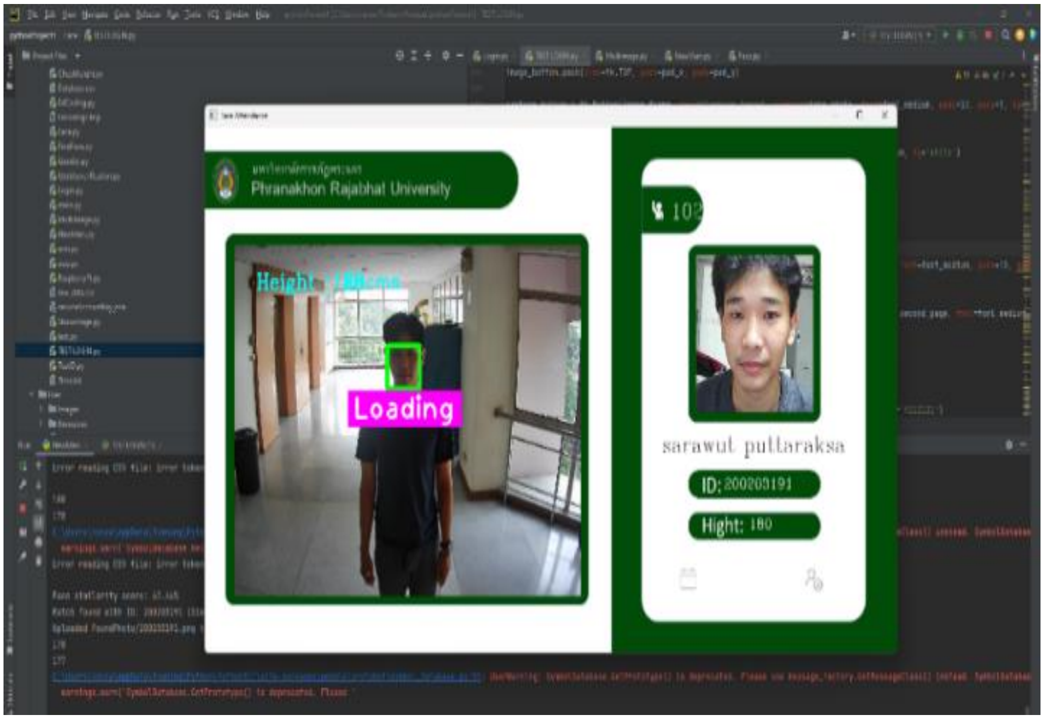

Fig. 12 Search test result

Table 3. Face identification test results from camera no. 1 to 6

Similarity (%)						
Range (meters)	**Camera No.**					
	1	**2**	**3**	**4**	**5**	**6**
1	63.92	49.97	64.81	57.00	59.22	67.76
1.5	62.46	63.50	70.15	63.36	59.05	65.38
2	62.31	56.53	70.73	68.37	62.8	68.63
2.5	62.43	51.76	62.74	50.65	61.93	60.77
3	62.95	49.69	56.33	59.17	53.31	58.29
3.5	47.76	41.32	55.51	57.41	52.91	59.84
4	52.55	45.65	54.93	57.98	57.06	57.79
4.5	50.78	56.93	54.68	55.22	57.11	51.77
Average	58.15	51.92	61.24	58.65	57.92	61.28
SD.	6.59	6.98	6.81	5.31	3.60	5.69

Table 4. Average results of height measurement test from camera no. 1 to camera no. 6

Height (centimeters)						
Range (meters)	**Camera No.**					
	1	**2**	**3**	**4**	**5**	**6**
1	180	182	178	180	182	178
1.5	178	182	175	178	182	175
2	180	181	175	180	181	175
2.5	179	180	177	179	180	177
3	178	180	176	178	180	176
3.5	179	178	180	179	178	180
4	180	176	179	180	176	179
4.5	177	179	178	177	179	178
Average	178.88	179.75	177.25	178.75	179	177.5
SD.	1.13	2.05	1.83	3.45	1.51	3.38
Error(%)	0.67%	0.14%	1.53%	0.69%	0.56%	1.39%

From Table 4, the height measurements from 6 cameras were at mean scores of 178.88, 179.75, 177.25, 178.75, 179, and 177.5, respectively, with standard deviations of 1.13, 2.05, 1.83, 3.45, 1.51, and 3.38, respectively, and mean height measurement errors at 0.67%, 0.14%, 1.53%, 0.69%, 0.56%, and 1.39%, respectively, as shown in Figure 13 to Figure 18.

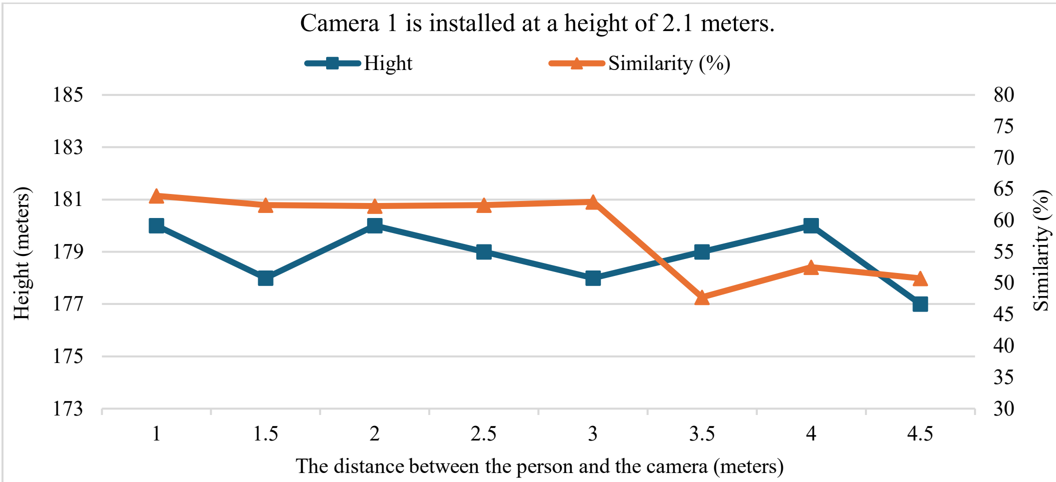

Fig. 13 Height measurement vs similarity from camera No.1

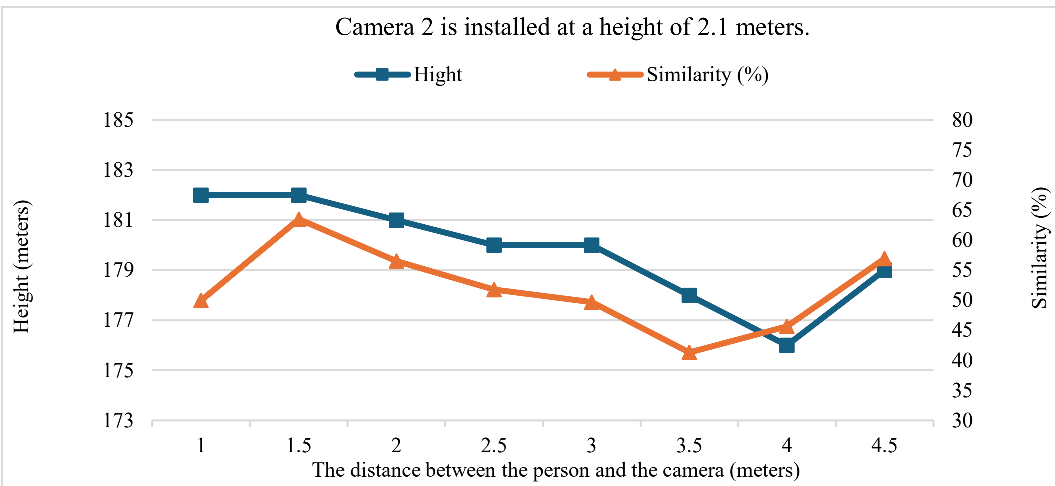

Fig. 14 Height measurement vs similarity from Camera No.2

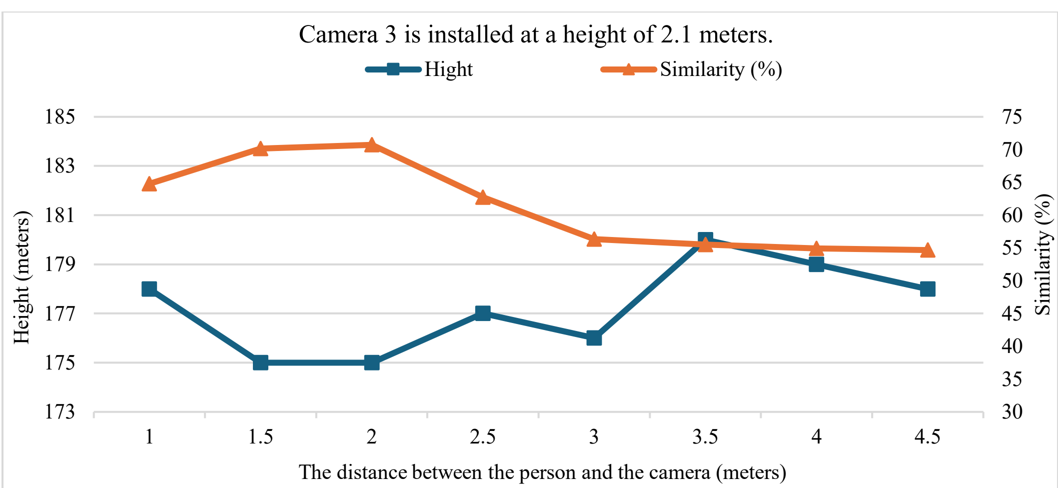

Fig. 15 Height measurement vs similarity from Camera No.3

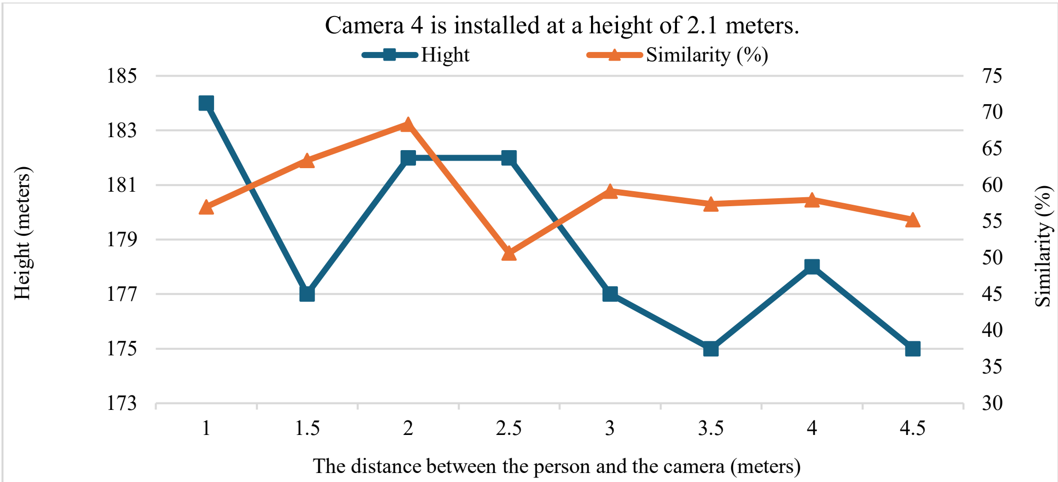

Fig. 16 Height measurement vs Similarity from camera No.4

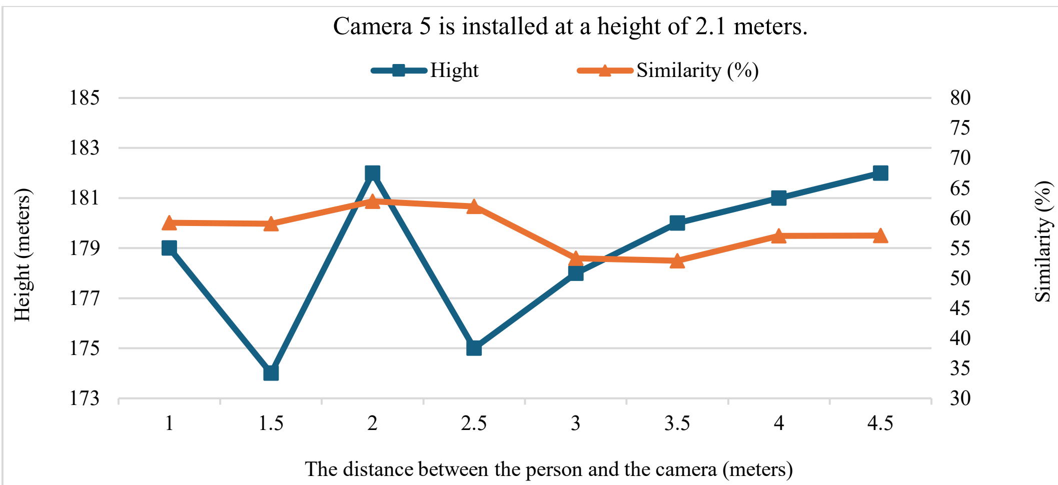

Fig. 17 Height measurement vs Similarity from camera No.5

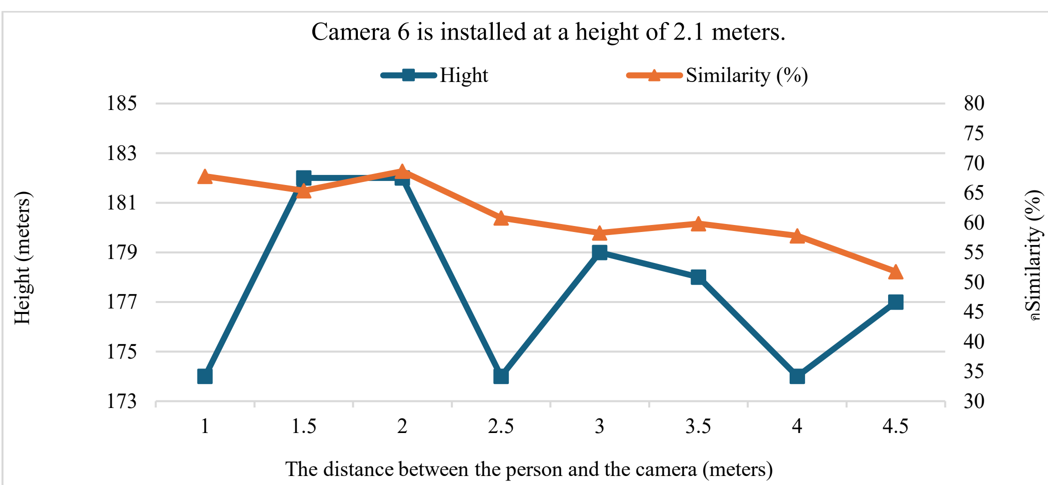

Fig. 18 Height measurement vs similarity from camera No.6

5. Conclusion and Recommendations

This study developed an indoor real-time identity verification system using image processing techniques and inexpensive equipment such as Raspberry Pi and high-resolution webcams. The system effectively detected faces and heights for identity verification in the test area, with mean scores for face detection at 58.15%-61.28% and a mean height measurement error range of 0.14%-1.53%, which are acceptable levels. Furthermore, the system could function at ranges of 0.5-4 meters, with the most suitable time being 8:30 am to 4:30 pm. The system was able to detect individuals consistently within the designed test area. The system showed capacity for applications for identity verification in controlled environments such as office buildings, schools, and government facilities. The findings can be summarized as follows:

- Mean scores from all six cameras used to measure facial likenesses were as follows: mean likenesses of Cameras 1 to 6 were at 58.15%, 51.92%, 61.24%, 58.65%, 57.92%, and 61.28%, respectively, with standard deviation at 6.59, 6.98, 6.81, 5.31, 3.60, and 5.69, respectively, showing the accuracy and consistency of face identifications via all six cameras.

- Individual height measurements were measured from all six cameras by calculating height using Equations (1)-(3). Equation (2) was the equation used in height compensation at the distance between the camera and the individual. Mean heights were as follows: the mean heights from Cameras 1 to 6 were 178.88 centimeters, 179.75 centimeters, 177.25 centimeters, 178.75 centimeters, 179 centimeters, and 177.5 centimeters. Mean error of height measurements from Cameras 1 to 6 were 0.67%, 0.14%, 1.53%, 0.69%, 0.56% and 1.39%, respectively.

The proposed system was employed to compare facial features and the height of the human body parameters for identity verification, achieving a margin of error not exceeding 2%. By integrating facial recognition with height measurement, the framework enhances the reliability of indoor identity verification systems. While moderate facial similarity scores were observed, measurement inaccuracies were mitigated through height compensation values. Variability in camera positioning and illumination conditions was identified as a critical factor influencing accuracy, demonstrating the feasibility of implementing robust biometric systems using cost-effective hardware. These results demonstrate the system's viability and potential for future implementations.

In future research, Artificial Intelligence (AI) can be developed to improve accuracy in face detection and height measurement by using deep learning techniques such as Convolutional Neural Networks (CNN) or hybrid meta-heuristic methods with ANN to increase capabilities in analyzing images in diverse light conditions and camera views.

Furthermore, testing should be expanded to include complex environments such as areas with changes in light or numbers of people to assess the system's capabilities in situations similar to real use. In addition, test factors such as fingerprints or voice can be added for increased identity verification accuracy, along with software development to support parallel processing of large numbers of users in large environments such as department stores or airports.

Finally, the system may have security applications, such as detecting suspects or abnormal events, in order for the system to be ready for use on an industrial scale.

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