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Implementation of an Intelligent Security System Based on Face Recognition

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ABSTRACT : *Biometric face recognition is used in a variety of applications, including security systems, access control systems, time and attendance systems, and public safety applications. The application system also requires a non-physical system that can be applied to certain parts to support the creation of a complete security system. As an important layer of the security system in the mixing process, authentication techniques for mixing participants may be required during mixing. Currently, the application of facial recognition is still being developed through the development of methods to increase the recognition rate of facial recognition based on facial position and expression. Based on the comparison of the results of the algorithms used, it is known that the CAMSHIFT algorithm has the best accuracy value with an accuracy of 99.51%. Based on the experimental results, information was obtained that the F-measure value for FASTER R-CNN and CAMSHIFT was 0.96, therefore it can be concluded that the Faster R-CNN method is a method that can be used to detect large numbers of objects, while the CAMSHIFT algorithm is ideal for use to support the authentication process on the face. In the future, a biometric-based security system can be implemented using the extended method to get better accuracy, resulting in speed and accuracy of detection and use in more dynamic conditions*

KEYWORDS - *Biometric, Face Recognition, Security System, Image Recognition*

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I. INTRODUCTION

Biometric face recognition is used in a variety of applications, including security systems, access control systems, time and attendance systems, and public safety applications. However, there are concerns about privacy and the potential for misuse of this technology, so it is important to use it ethically and with appropriate safeguards in place. The trial's security system has received widespread support through the construction of bulletproof buildings, but this is insufficient if no system protects the first most basic layers. All elements suitable for use should play a role in the judicial court security system so that the judicial trial can be conducted solemnly. In addition to physical systems, non-physical systems that can be applied to specific parts are required to support the development of a complete security system.

Terrorism is an act of open violence intended to spread terror or fear. However, there has been no agreement on the definition of terrorism itself until now [1]. Various small to large-scale attacks have occurred, including one on the judiciary, which has become a target for terrorists in their use of terror against the public. As a result, facial authentication techniques may be required for trial participants who work in real-time as an essential layer of the security system at court trials. Time for monitoring to continue throughout the trial. Face recognition has grown in popularity as an authentication method due to its advantages over other biometric features used for identity matching [2], which promises an authentication mechanism that is already widely available in the era of mobile computing [3].

Face detection is a fundamental process that determines the presence and position of a face in images and videos, which is referred to as a bounding box. Despite the development of new techniques and methods, the system needs to be enhanced to distinguish the real object's face from object spoofing with greater accuracy [4], therefore, in this research, a hybrid Faster R-CNN and Haar Cascade were conducted to authenticate the participants of the judicial trial in real-time so that the monitoring process through the computer system continues to be carried out when a trial is being carried out.

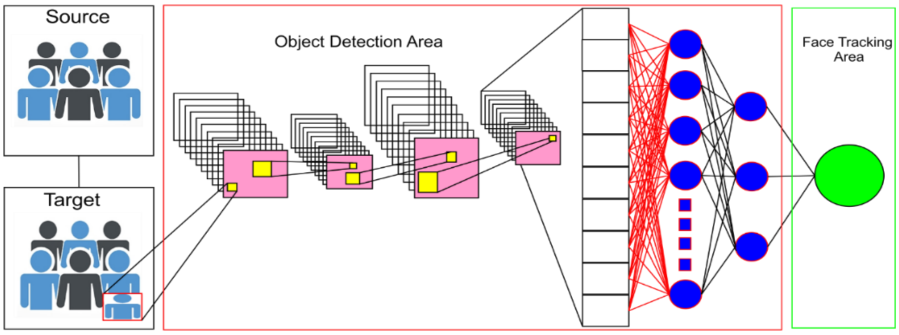

Fig 1. The research design for face recognition

Fig 1. shows an illustrative example illustrating the recognition process. Namely, to obtain object detection results, the face authentication process is carried out in real-time in stages designed using a combination of Faster R-CNN and Haar Cascade methods. In this case, the identification process uses the deep learning conceptual that aims to get the accuracy of face identification results, where personal profile data is stored in the database while saving face images to a file to be used as comparison material in the face identification process through the hidden layer. The authors summarize several studies on face recognition using different methods in Table 1.

Table 1. Related studies on face recognition

Publication	Contribution	Comments
Girshick, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation (2014)	It is very effective to train the network with supervision and refine the network object detection process for image classification [5].	It was stated that it was essential to use a classic combination of tools from computer vision and deep learning to support the object detection process, so this study uses a hybrid Faster R-CNN and Haar cascade as a problem-solving method.
Elmahmud, Deep face recognition using imperfect facial data (2019)	founding that the parts of the face, including the eyes, nose, and cheeks, are the parts that have low recognition but are still able to produce a faster recognition rate when each part of the face is combined [6].	It is interesting to apply that before face authentication is performed, the image of the object on the face will be labelled first.
Kortli, Face recognition systems: A survey (2020)	From several experiences by researchers, it was found that the database can be used to support the face recognition process [7].	Interesting to apply the technique of using databases to support the face recognition process.
Adjabi, Taleb-Ahmed, Past, present, and future of face recognition: A review (2020)	The deep learning approach provides a reality for facial recognition research as a reference point for topics worth considering [8].	Lighting conditions and facial expressions are said to have an effect on face detection quality performance. As a result, in this study, lighting parameters and facial expressions will be used to evaluate the quality of face recognition.
Xiaochun, Faster R-CNN with Classifier Fusion for Small Fruit Detection (2018).	The Faster R-CNN Algorithm has the role of Five convolution screens that can be implemented to detect almonds [9].	This study will investigate the effectiveness of Faster R-CNN in improving object classification as a source of information.
Kollapudi, A Novel Faster RCNN with ODN-Based Rain Removal Technique (2022).	The foundation of the Densely Connected Networks Optimal Rain removal technique is the application of FRCNN-ODN is Faster R-CNN [10].	To produce high-quality regional proposals and assist the human object detection process, the Region Proposal Network (RPN) and Fast R-CNN model are elements that are also applied to FRCNN.

Based on the information collected from previous research in Table 1. The use of deep learning models for the object detection process can be implemented through the Faster R-CNN method or hybrid techniques with different methods to increase the accuracy value.

II. METHODOLOGY

2.1. Convolutional Neural Network (CNN)

Convolutional Neural Network is an artificial neural network development based on a human artificial neural network that is commonly used to detect and recognize objects in images and consists of neurons with weights, biases, and activation functions. The illustration process is shown in Fig 2. Modularity in deep learning frameworks used in CNN generally allows flexibility for adaptation to diverse architectures.

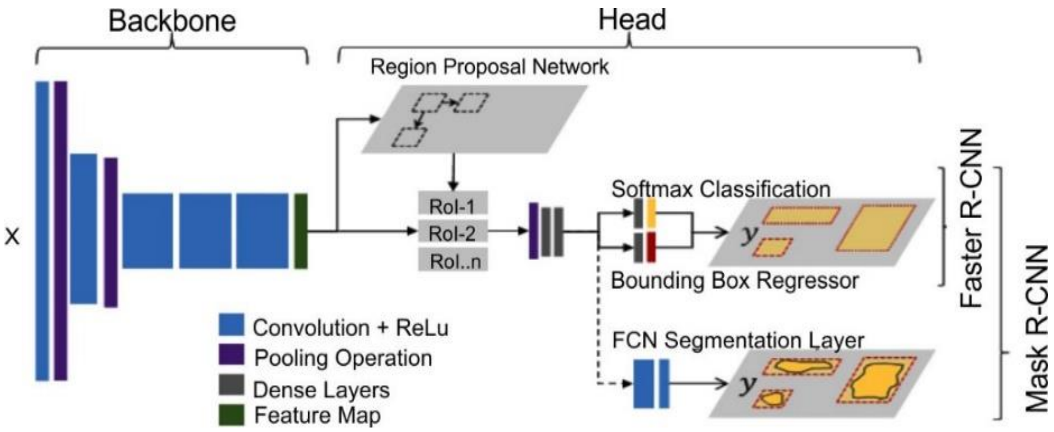

Fig 2. Faster-R-CNN and Mask-RCNN, respectively [11].

The R-CNN and Fast R-CNN methodology both have flaws, one of which is the complexity of calculating the proposal region of the RPN, which cannot match the computational speed of CNN [12]. The Regional Proposal Network(RPN) is a deep convolutional neural network that builds the area to be detected in Faster R-CNN. In the object detection process using Faster R-CNN, there is an RPN which is the module responsible for utilizing the proposed area [13]. The primary layer in Faster R-CNN is the convolutional layer component, which performs convolution operations on the kernel matrix or filter matrix to extract the element from an image. Edge detection and corner detection are two examples of image feature values.

The Number and size of filters can be changed, and the value of the filter matrix can be randomized to produce different convolution results. Faster RCNN combines the offered RPN and Fast R-CNN networks into a sole network with shared convolution features [14] so that it can improve the object tracking process's performance [15]. The specific flows are shown in Fig 3.

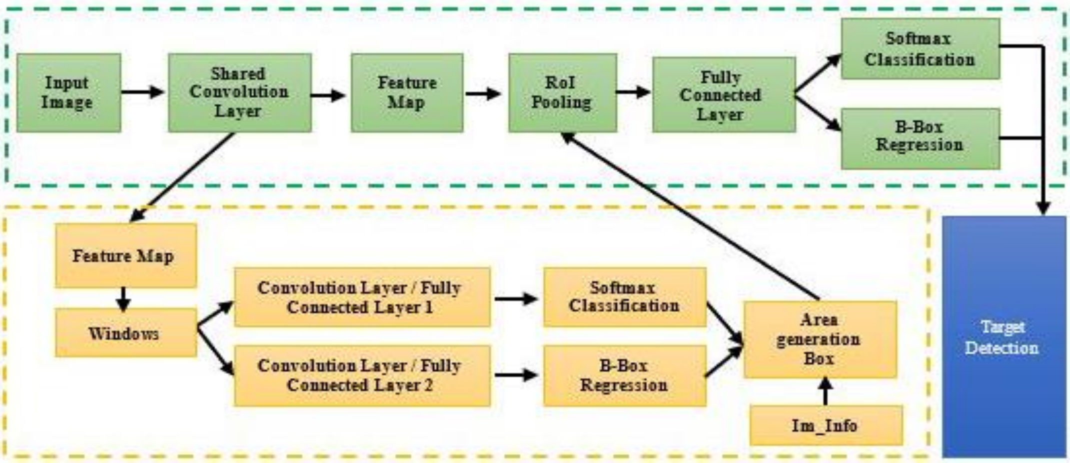

Fig 3. The Faster R-CNN algorithm framework [16]

In general, the training process of Faster R-CNN employs random weight initialization by sampling from the Gaussian distribution and all layers with an initial learning level of 0.0001, which is accomplished through four stages. In the first step, an initialized network is used to train the RPN to generate a proposal boundary box as a candidate mass. The second step is to separate the classifier network training process using the RPN bounding box. The third step initializes the RPN, but the shared convolution layer parameter is frozen with the learning speed set to 0, and the RPN has trained again by updating the RPN unique layer. The fourth step involves performing a joint layer refinement to train the classifier network using the bounding proposal box obtained by updating the unique layer contained in the Faster R-CNN [17].

2.2. Haar Cascade

The Haar Cascade is based on a convolutional neural network, so it can detect an object quickly and in real-time. [18]. Each stage classifier in the haar cascade is used to detect whether the image sub-window contains an object of interest [18]. The decision rules in the Haar Cascade filter sub-images from the main image for faster detection using the pixel value formula to detect and identify objects based on image features:

Pixel = (SDP / NDPs) – (SLPs / NLPs).. (1)

Description :

PV = Pixel.

SDPs = Sum Dark Pixels

NDPs = Accumulating The Dark Pixels

SLPs = Sum Light Pixels

NLPs = Accumulating The Light Pixels

The process of calculating each pixel in the image is carried out through an algorithmic algorithm that involves each pixel as a variable p and its eight neighbours compared to the pixel variable p, where each neighbour will be assigned a value of 1 if it contains a variable x greater than or equal to the variable p [20], as written in the formula:

$$LBP(XC, YC)=\sum_{p-0}^{p-1} 2ps(IP - IC) \quad (2)$$

Where XC and YC variable is the centre pixel, and IC variable is the brightness, and the IP variable is the brightness of the adjacent. The function defined is written : s(x)=1 if x≥0 and s(x) = 0 otherwise.

In this study, the face authentication process is based on spoofing, where the case of facial spoofing is significant to prevent security breaches in the face recognition system [21]. The researcher [22] stated discovered that facial spoofing data could be presented naturally in a video stream format that uses temporal consistency to consolidate pseudo-label reliability for specific images. In line with previous researchers' ideas, this study will perform facial authentication experiments on selected objects with the object selection process using Faster R-CNN. In contrast, the haar cascade is used in the facial spoofing process on selected objects. Fig 4 depicts an application of anti-spoofing technology.

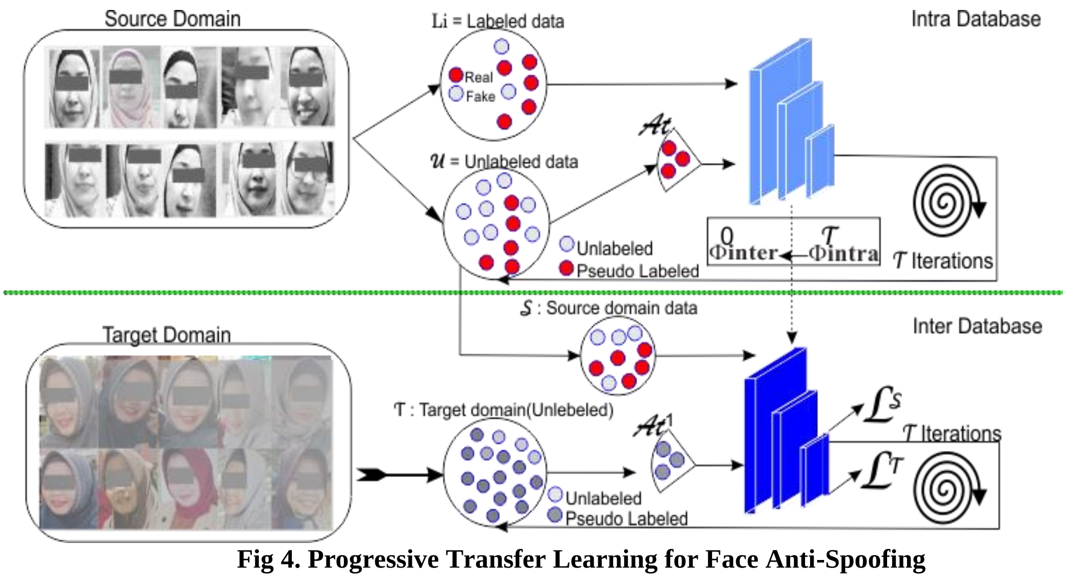

Fig 4. Progressive Transfer Learning for Face Anti-Spoofing

2.3. Continuously Adaptive Mean Shift (CAMSHIFT)

CamShift stands for Continuously Adaptive Mean Shift, which is a facial recognition algorithm that functions to adapt or adjust to the colour probability distribution which always changes every frame change of a video sequence. The user's head may be outside the image display, the user's facial color may change under different lighting conditions, and the user may differ in facial features such as moustaches and glasses [22], where The CamShift algorithm can be used for nose template matching for front facial posture recognition [23].

In the CamShift algorithm, after the process of determining the search for a face frame has been successfully carried out, the next step is to perform image processing of the image colour probability distribution, where the mean area of the framed object can be calculated using the formula :

Zeroth Moment :

$$Moo = \sum_x \sum_z I(x, y) \quad (3)$$

First Moment x,y

$$M_{1o} = \sum_x \sum_z I(x,y) \ and \ M_{01} = \sum_x \sum_z I(x,y) \qquad (4)$$

Mean Location in Centroid

$$X_c = \frac{M_{10}}{M_{00}} \ Y_c = \frac{M_{10}}{M_{00}} \qquad (5)$$

Second Moment :

$$M_{2o} = \sum_x \sum_z I^2(x,y) \ and \ M_{02} = \sum_x \sum_z y^2(x,y) \qquad (6)$$

Object Orientation :

$$\theta = \frac{arctan\left(\frac{2\left(\frac{M_{11}}{M_{00}} - XCYC\right)}{\left(\frac{M_{20}}{M_{00}} - X\frac{2}{C}\right) - \left(\frac{M_{02}}{M_{00}} - Y\frac{2}{C}\right)}\right)}{2} \qquad (7)$$

$$\mathrm{L} = \frac{\sqrt{(a+c)+\sqrt{b^2+(a-c)^2}}}{2} \qquad (8)$$

$$\mathrm{W} = \frac{\sqrt{(a+c)-\sqrt{b^2+(a-c)^2}}}{2} \qquad (9)$$

$$a = \left(\frac{M_{20}}{M_{00}} - X\frac{2}{C}\right) \ b = \left(\frac{M_{11}}{M_{00}} - x_c y_c\right) \ c = \left(\frac{M_{02}}{M_{00}} - y\frac{2}{C}\right) \qquad (10)$$

All stages of the CAMSHIFT algorithm produce values x, y, object rotation, length and width of the z region which are said to be the distance between the face and the camera position. Implementation the Camshift algorithm on face tracking use nose matching used in Fig 5.

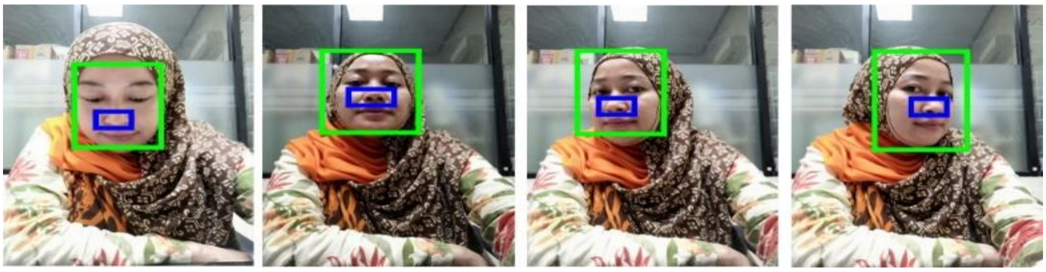

Fig 5. Nose Template Matching Method

In Fig 5. It is clearly demonstrated above that facial recognition through head movements is quite feasible via the dynamic face position.

2.4. Speeded Up Robust Feature (SURF**)**

The SURF algorithm is a development of the SIFT algorithm where SURF utilizes the computational speed of square filters by using an integral image which is a matrix image in which the value of each pixel is the accumulation of the top pixel values and left. Besides having data robustness, the SURF algorithm also introduces data aggregation and filter boxes in calculations, which increases the registration time[24]. The SURF Algorithm formula namely :

Citra Integral **:**

$$I(x,y) = \sum_{x=0}^{x} \sum_{y=0}^{y} N(x',y') \qquad (11)$$

Matrix Hessian **:**

D = (A+B+C+D)-(A+B)-(A+C)+A .... (12)

Determinant Hessian:

$$det\left(H_{approx} = D_{(xx)} D_{(yy)} - (0{,}9 D_{xy})^2\right) \qquad (13)$$

Scale-space :

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{dx^2} \qquad (14)$$

Extreme Space :

$$\hat{X} = \frac{\partial^2 D^{-1}}{\partial x^2} x \ \frac{\partial D}{\partial x} \qquad (15)$$

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In the SURF Algorithm, the integral is the cumulative sum of the pixel values and the zero padding adds zeros to the rows and columns of the image. The Hessian matrix consists of second-order Gaussian partial derivatives calculated from various filter box sizes using the octave scale as the image input. The SURF algorithm was implemented on employs the local maxima technique to detect interest points based on image pixel positions obtained by computing the determinant of the Hessian matrix. The next stage is carried out after the interesting point is detected, and a comparison is made between the threshold and the interesting point if there is a difference between the octave scales.

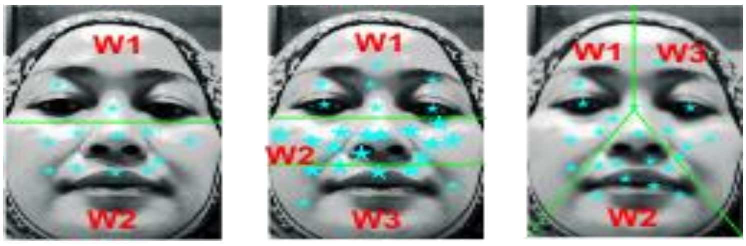

Fig 6. Face images of different clustering sub-regions in SURF Algorithm

In Fig 6. The left image illustrates The feature points are divided by a horizontal line. (b) The middle image The feature points are cluster-tired into three equal parts. (c) The right image The feature points are clustered and centred on the left eye, right eye, and centre of the mouth.

2.5. Confusion Matrix

The confusion matrix is a machine learning idea that contains information about the actual class and the classification system's predicted classification[26]. The confusion matrix generates information about a classification system's predictions and actuals using correct answer data. The results of testing the object detection and face recognition process using the Confusion Matrix calculation to obtain the values of rate accuracy, rate loss, precision, recall, and F1-Score were reported in this study. The explanation of the confusion matrix is shown in Table 2.

Table 2. Contingency determines the number of samples set as zero and alternative detectors [27].

Predicted	**Actual**	
	Negative (null detection)	Positive (alternate detection)
Negative (null detection)	TN	FN
Positive (alternate detection)	FP	TP

TP = Number of human objects detected.
TN = Number of other objects detected.
FP = Number of other objects detected as human objects.
FN = Number of human objects detected as other objects

III. RESULTS

The first step in this study is to collect judicial participant data into a database. The database contains two types of data: biodata and biometrics of judicial participants. Then, high-resolution cameras are used to produce high-quality images. When the trial is carried out, the camera will send video files in real-time, allowing the person's object to be identified when the authentication process is carried out. The selected face will then be compared to the facial image in the database. Several comparisons with commonly used facial recognition methods demonstrate the proposed approach's effectiveness and superiority [27]. To obtain the correct image matching results, the authentication process is repeated with different facial expressions

3.1. Detection Quality:

Object detection is all about detecting the bounding box with the highest detection score for a given input image [28]. To implement object detection in this study, the Faster R-CNN technique was used with video data converted into images. A text file containing information about the figure name, the bounding box size, and class is provided before beginning the training process. Nine anchors are used based on the Faster R-CNN default anchor value. In this study, the video file becomes the input as an initial stage, where the video will be processed by convolution, and a pre-trained image will be made. A feature map is also created during this process to collect all information related to the vector representation of the input data. After gathering all information on the feature map, the Proposed Region Network will process the data to predict the image areas considered person objects and bounding boxes in the image area considered person objects. After that, the initial feature map information and the feature map information uploaded to the RPN will go to RoI Pooling.

In this study, the procedure for collecting RoI Pooling, where a new data set from real-time video footage is used for the analysis phase. The data set consisted of a video sequence shot during the trial in which participants moved around to create various patterns. Video is shot at 50 frames per second in 1920 x 1080 resolution. To address the computational complication problem in video handling, video sequences captured for investigation are 20 to 50 seconds long and contain vital factors that may be present in longer video sequences.

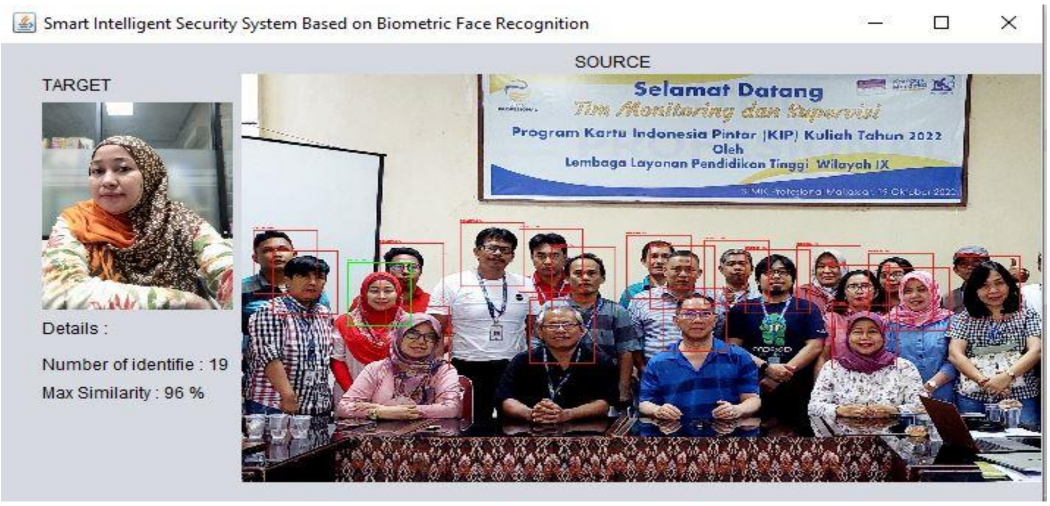

Fig 7. Results of the detection object

According to Fig 7. using training results in an accuracy rate of 96.0%, indicating that the Faster R-CNN is suitable for object detection processing. The test results on 10 sample videos are shown in Table 3.

Table 3. Results of testing detection participant object

Input	Data	Participant	Detected	Undetected
1	Video[1]	20	19	1
2	Video[2]	28	27	1
3	Video[3]	18	18	0
4	Video[4]	30	30	0
5	Video[5]	40	38	2
6	Video[6]	18	15	3
7	Video[7]	16	16	0
8	Video[8]	20	20	0
9	Video[9]	35	35	0
10	Video[10]	23	22	1
Number		**248**	**240**	**13**

Table 3. shows the results of object participant detection are shown: TP is worth 248, TN is worth 0, FP is 0, FN is worth 13, and then the value of the confusion matrix calculation is obtained.

Table 4. Result of Confusion Matrix

Accurate	*0.96*
Precicion	1
Recall	0.96
F1-Score	0.97
Rate Accurate	96.0
Rate Loss	4.70

Table 4. shows the overall average accuracy of all image types tested was 96%. Due to lighting factors, the image quality of a participant in the back position may result in accuracy that is not maximized.

3.2. Face Tracking Quality:

Facial biometric data has been used as a method of human identification and authentication with a high level of security in various applications, where developments continue to be made through advances in computer vision technology and pattern recognition technology [29]. As in this study, facial recognition is used to aid in the identification of trial participants, with the results shown in Fig 8.

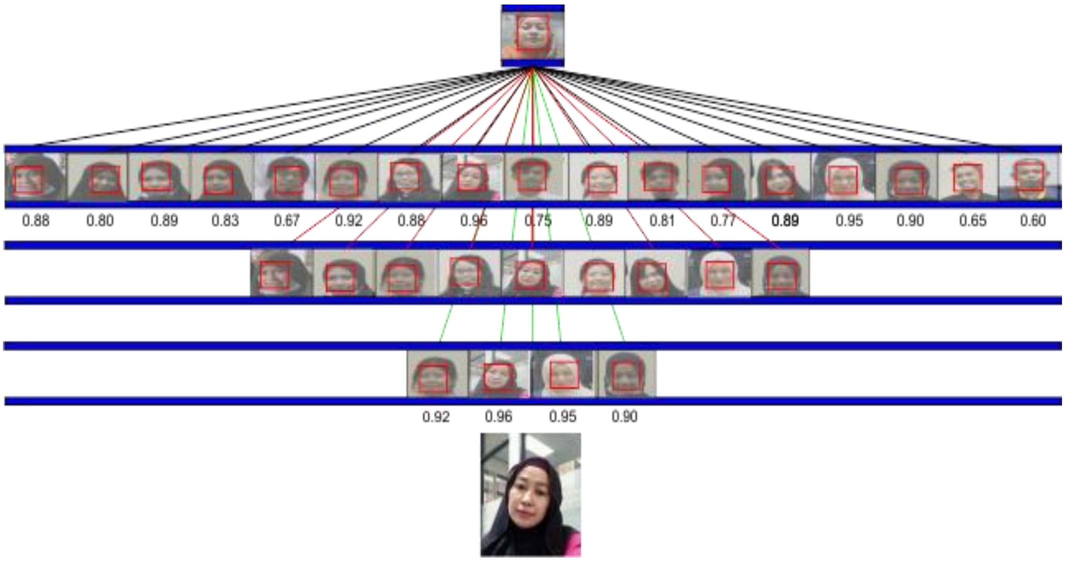

Fig 8. Result tracking of Face identified.

The Figure 8. shows the facial data tracking process based on the selected input image where each dataset will be compared with the input until the greatest similarity value is obtained. Tests are carried out on each algorithm that is determined by using time and accuracy as variables, where the results are shown Table 5.

Table 5. Result of Comparison Algorithm

OBJECT	TIME (sec/frame)	CAMSHIFT	SURF	HAAR-LBP
		Accurate (%)		
1	0.35084	99.53	89.70	94.58
2	0.35282	99.42	90.50	96.35
3	0.47714	99.61	89.87	94.18
4	0.43022	99.05	90.88	96.02
5	0.47453	99.98	89.82	93.28
6	0.36288	99.57	92.89	95.95
7	0.35387	99.86	89.99	93.07
8	0.47680	99.48	91.25	96.74
9	0.44890	99.53	92.27	94.10
10	0.35156	99.10	89.60	93.47
Average		**99.51**	**90.68**	**94.77**

Based on a comparison of the results of the algorithm used, it is known that the CAMSHIFT algorithm has the best accuracy value with a value of 99.51%, therefore the authors decide that the FASTER-RCNN algorithm is ideal for use with the CAMSHIFT algorithm to carry out the process of identifying and recognizing faces

IV. DISCUSSION

In this study, testing was carried out through an iteration process to determine the greatest accuracy value and the ideal time to use. The resulting learning rate value between 0-1 can be used as a measure of the speed of the ongoing training process. Another factor to consider is that if the learning rate is too large, the training process may exceed the optimal state when it reaches the minimum error value. In this study, testing was carried out to see the results obtained based on 150 with a learning rate of 0.0001. The test results can be seen in Fig 9 and 10.

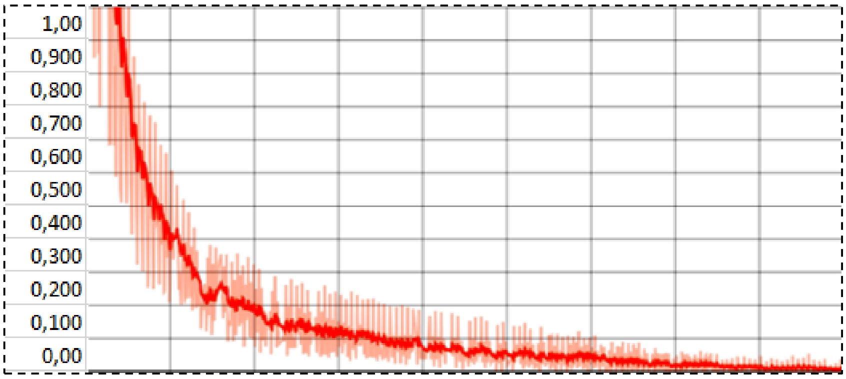

Fig 9. Training Loss of 150 iterations in Learning rate 0.0001.

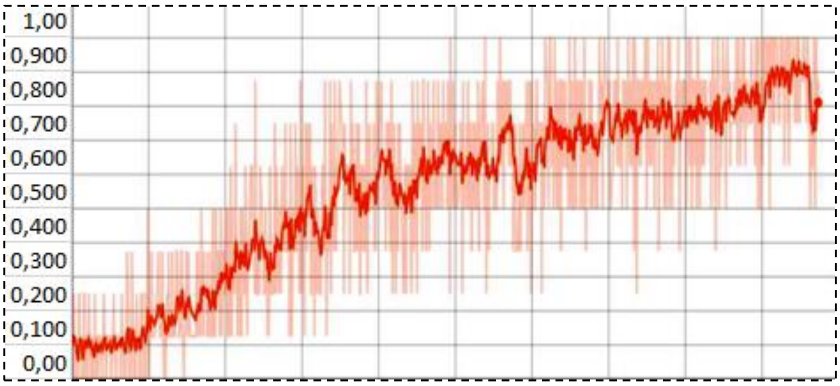

Fig 10. Training Accuracy of 150 iterations in Learning rate 0.0001

After obtaining the object detection process results, the next step is calculating value of the selected object to be used as the comparison accuracy value between the participant data in the database and image extraction.

When conducting trials for face identification and labelling, we considered many of the adapted datasets in Table 6. The main data set involves of all photos taken at the Makassar District Court Office. The second data set consists of images with various facial orientations consisting of several photos containing images last data set comprises photos of some population data in the downtown area of Makassar city.

Table 6. The data set used for face detection and tagging.

Data Set Name	*Total Images*
Participans on District Court office	800
Custom Different Oriented Facess	1019
Randomly Selected Makassar People	1500

To investigate the efficacy of the planned method, we compute precision, recall, and F-measure values[30], which are defined as:

Precision (P) is the section of rescued documents that are relevant.

$$\text{Precision(P)} \; \frac{\text{TruePositives}}{\text{TruePositives + FalsePositives}} \quad \ldots (16)$$

Recall (R) is the section of pertinent documents that are retrieved.

$$\text{Recall(R)} \; \frac{\text{TruePositives}}{\text{TruePositives + FalseNegatives}} \quad \ldots (17)$$

The F-measure (F) is clear as a harmonical mean of Precision (P) and Recall (R).

$$\text{F-measure(F)} \; \frac{2PR}{\text{Precision+ Recall}} \quad \ldots (18)$$

These notions can be made clear by examining Table 7.

Table 7. Results for face tagging

Data Set Name	*TP*	*TN*	*FP*	*FN*	*P*	*R*	*F*
Participants on the District Court	700	50	30	20	0.9589041	0.9722222	0.9655172
Custom Different-Oriented Faces	796	80	73	70	0.9159954	0.9191685	0.9175792
Randomly Selected People	1176	150	101	73	0.9209083	0.9415532	0.9311163

Based on the data in Table 7. information is obtained that the F-measure value of the results of the FASTER R-CNN and CAMSHIFT experiments is 0.96%. Therefore it was stated that the system could be used to support a security software-based security system at the district court office of Makassar City.

V. CONCLUSION

This study concludes that the main layer security system in court can be implemented by using object detection and face detection features. Based on the test results, the face detection accuracy value with the best accuracy value is using the CAMSHIFT algorithm with a value of 99.51%. Faster R-CNN is a suitable method for detecting large numbers of objects because it has good accuracy. Therefore it is said to be ideal when used simultaneously with the CAMSHIFT algorithm to support the process of object detection and face tracking, where from the experimental results obtained the value of F- Measures 0.96. In the future, biometric-based security systems can be implemented using extended methods to obtain better accuracy results and use in more dynamic case studies.

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