Masked Face Recognition and Temperature Monitoring Systems for Airplane Passenger Using Sensor Fusion

Feni Isdaryani[1], Noor Cholis Basjaruddin[2], Aldi Lugina[3]

***Abstract*—Transportation is currently an unavoidable necessity. However, the COVID-19 pandemic has impacted all lines of industry, including the Indonesian aviation transportation industry. Technology is one of the solutions to deal with these problems. The monitoring system of masked face recognition and body temperature detection for the check-in process of passengers at the airport is aimed to be developed in this research. The contribution of this research is that the system can distinguish the type of face mask used. Therefore, this monitoring system classified only medical masks and N95/KN95 respirator masks as 'Good Masked'. IP camera and thermal camera are used to identify a masked face and body temperature, respectively. The sensor fusion method was used for decision-making on passengers whether they can be departed or not. The decision was taken based on the measured body temperature, the use of standardized face masks, and the face recognition of the airport passengers. Convolutional neural network (CNN) method was used for face and face mask recognition. The CNN model training was conducted four times according to the four proposed scenarios. The CNN model that has been trained can distinguish a masked face and a face without a mask. The best results were obtained in the fourth scenario with the comparison of the training dataset to the testing dataset was 9:1 and the epoch was 500 times. The basic deep learning model used for face detection was the single shot multibox detector (SSD) using the ResNet-10 architecture. Meanwhile, the CNN method with the MobileNetV2 architecture was used to detect the use of masks. The accuracy of the CNN model for face recognition and mask recognition was 100%. All check-in monitoring and verification process data were displayed on the web application which was built on the localhost.**

***Keywords*—CNN, Face Recognition, Face Masks Detection, NFC, Sensor Fusion.**

I. INTRODUCTION

The COVID-19 pandemic has impacted all industry lines, including the Indonesian aviation transportation industry. The Ministry of Transportation Republic of Indonesia has instructed airlines to enforce health protocols at airports such as checking body temperature, wearing gloves, and wearing face masks [1]. Referring to the World Health Organization (WHO), the best way to use a face mask is to set the mask to cover the mouth, nose, and chin [2].

Due to health protocol regulations, a new problem arises, such as the large number of passengers who would check-in at the airport, causing the check-in time to be longer due to body temperature and face mask use verification. This problem can be solved by technology. Some research has been developed to provide solutions based on computer vision, such as facial detection and recognition technology. Computer vision is a multidisciplinary scientific field involving how a computer can increase the understanding of digital images and videos [3].

The face mask detection method used in [4] was deep learning. This research compared ResNet50 with Mobile Net model to find out which model had the most accurate detection. The results showed that the ResNet50 model generated more precise face detection. Reference [5] developed a face mask detection based on YOLOv3 technology, where the authors created a dataset named Properly Wearing Masked Face Detection Dataset (PWMFD). On [6], one stage face masked detection was performed by adding a neck and head recognition backbone. The researcher claimed that head and neck detection increased detection ability. On [7], face mask detection was conducted by removing the masked face from the image and then applying the convolutional neural network (CNN) method to extract features from the eye and forehead area.

Sensor fusion uses information from different sensors to increase all the system selection features and classifications performance. Research on sensor fusion in [8] was performed by combining heterogeneous information from three sensors, viz., triaxial accelerometers, micro-Doppler radar, and depth camera. These sensors were implemented to detect human activity and fall detection classification. Reference [9] proposed a multi-sensor fusion framework based on a body network to detect human health.

Another issue with using face mask detection technology in airports is that it not only detects masked faces, but also recognizes people who wear them. Its purpose is to make the verification process at the security checkpoint and check-in easier.

Therefore, this research focuses on developing a monitoring system for masked face recognition and body temperature for the check-in process of the passengers at the airport. These monitoring systems of the aircraft passengers were supported by a combination of sensors, namely near-field communication (NFC), IP camera, and thermal camera. The sensor fusion technique was applied to generate the right decision based on the information obtained by the sensors. CNN method was used for facial and face mask recognition. Meanwhile, NFC was used as wireless communication between passenger mobile devices and the aircraft passenger monitoring system.

The contribution of this research is that the system can distinguish the face mask type used. According to WHO, the face mask types with good protection are medical masks and respirator masks [10]. Hence, this research considered only

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medical masks and respirator (N95/KN95) masks as 'Good Masked'.

This paper is organized as follows: Section II discusses NFC, CNN, and sensor fusion; Section III describes the proposed method; Section IV is the result; and Section V is the conclusion.

II. NFC, CNN, and Sensor Fusion

A. Near-Field Communication (NFC)

Near-field communication (NFC) is a technology allowing two devices to exchange information wirelessly at a close range, approximately 20 centimeters under specific conditions. More precisely, NFC is a set of technical specifications and standards for transferring data between two proximate objects via the inductive coupling of radiofrequency fields at 13.56 MHz [11]. There have been many applications regarding NFC. Reference [12] applied NFC to the luggage tracking and management system. The system employed NFC technology and homomorphic cryptography to protect wireless communication and stored data. In [13], NFC technology was applied to passenger rail transport, especially ticket payment systems.

B. CNN-based Face Detection

CNN is biologically inspired network used in computer vision for image classification and object detection [14]. CNN comprises three main neural layers, namely convolutional, pooling, and fully connected layers; each type of layer plays a different role. Convolutional operations are performed on the convolutional layer. In the convolutional layer, image filter process is used to map the activation from a layer to the next layer. Every CNN layer transforms the input volume to an output volume of neuron activation, which eventually leading to the final fully connected layers and mapping the input data to a 1D feature vector.

The image classification process of the CNN method consists of two-stage, namely the training and testing stage. At the training stage, the input image will be processed according to the CNN architecture used. Previously, CNN has been successfully applied in various computer vision applications, such as object detection [15], face recognition [7], [16], and self-driving vehicles [17], [18].

C. Sensor Fusion

Sensor fusion uses information from different sensors to improve features selection and overall performance classifications or system interpretation. The main components of the sensor fusion frameworks are sensors, the process of fusing all measurements, and producing a one-state estimation that can be implemented in other applications [19]. In this research, sensor fusion was applied to aircraft passenger monitoring systems. In [20], a cost-effective 3D thermal model reconstruction was designed with two smartphones and a low-cost thermal infrared camera. The sensor fusion technique was applied to process infrared thermal images from IR thermal cameras and smartphone's visible images.

Reference [21] applied sensor data fusion to produce high-resolution ultrasonic oscillating temperature sensors (UOTS).

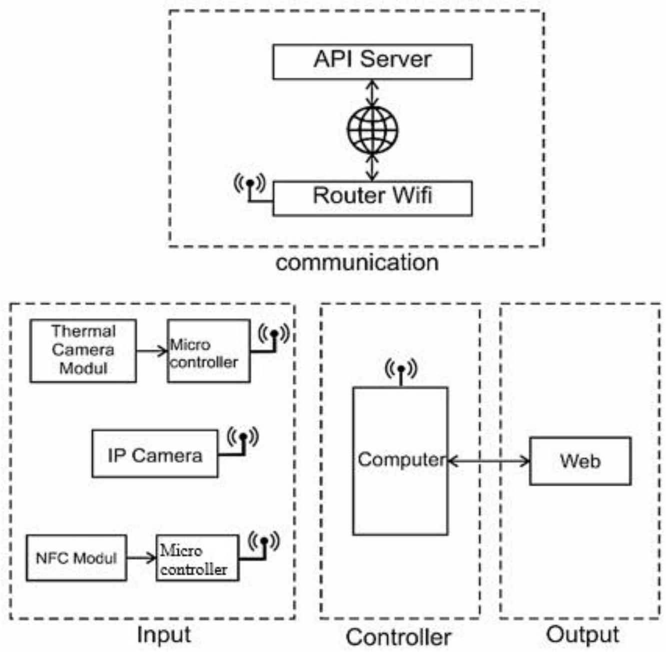

Fig. 1 Block diagram of the masked face and body temperature monitoring system.

The sensor data fusion procedure was made based on the first-order approach of the output frequency UOTS. The fused temperature was the current temperature frequency data and the previous frequency that has been stored.

III. Research Method

A. Concept of the System

The research concept is to create a system that can monitor the use of medical masks or respirator masks of the N95 / KN95 types and measure the body temperature of aircraft passengers. The monitoring system was deployed using three sensors, namely NFC, thermal camera, and IP camera. The NFC node was used to verify whether the passenger has a valid ticket.

The thermal camera was used to measure the body temperature of aircraft passengers. The body temperature limit for air travel following WHO recommendations for international traffic concerning COVID-19 is 38 °C. If the aircraft passenger's body temperature is above or equal to 38 °C, the prospective passenger is not allowed to depart. Meanwhile, an IP camera was used to monitor masks and face recognition of aircraft passengers. Passengers who are allowed to depart are passengers with valid tickets/boarding passes. Passengers recognized on the camera must match the boarding pass data, and the body temperature measured on the thermal camera must be below 38 °C.

This system uses the C++ programming language for microcontroller programming on NFC nodes and the Python programming language with the Django framework for developing web server applications (named e-flight apps) and API servers.

The diagram block of the proposed system is depicted in Fig. 1. It consists of input, controller, output, and communication blocks. The input block consists of a thermal camera, IP camera,

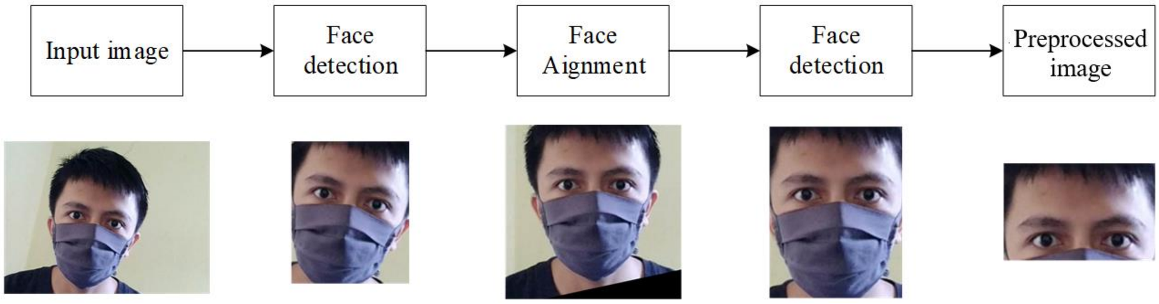

Fig. 2 Block diagram of face recognition dataset creation process.

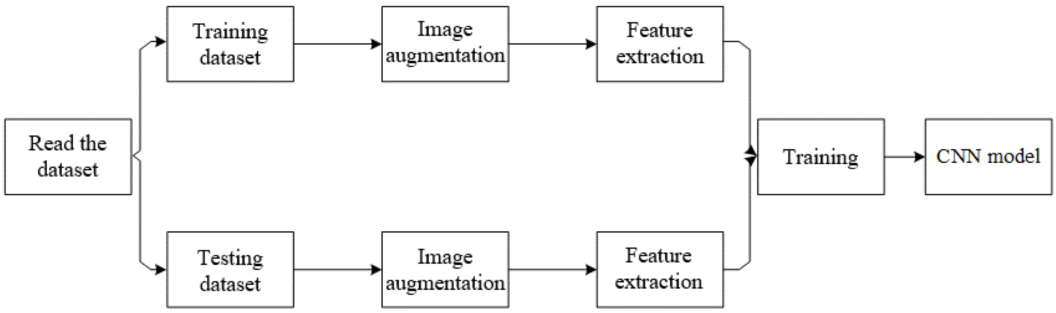

Fig. 3 Block diagram of CNN model training process.

and NFC node. The data sent from the input will be processed in the controller block, which is a computer. The output of the controller will be displayed on the web application (the output block). The communication block is used for communication between devices and the API server via the internet. The database on this system is stored on the API server.

B. Procedure of Sensor Fusion Design

The sensor fusion network deployed in this study was categorized based on the sensor configuration. The sensor configuration comprises complementary, competitive, and cooperative fusion configurations [19]. In this research, the sensor configuration used was complementary, consisting of three sensors (thermal camera, IP camera, and NFC) that worked together independently and performed their respective tasks. These data combinations from each sensor could complement each other and provided information for feature selection and decision level.

The decision on the check-in status of aircraft passengers was taken based on the results of the sensor fusion data. A check-in success status was generated when the masked passenger's face recognized on the camera matched 1) boarding pass data; 2) the type of masks, either medical or respirator mask of the N95/KN95 types; and 3) the maximum body temperature, which is 38 °C. The failed status occurred when certain conditions were not met after twenty seconds of the NFC tap process.

C. Design of Face Recognition Algorithm

Face recognition in this research was used to verify whether aircraft passengers matched the ticket data on the database. The CNN method was used in this face recognition process. The basic deep learning model used for face detection was the single shot multi-box detector (SSD) using the ResNet-10 architecture. SSD models can detect multiple objects in a single image frame. On the other hand, face detection in this research was conducted to determine the location of the face in the image. The ResNet-10 architecture was used to mark the face area and then crop the detected facial area.

The image collected could contain many unwanted elements. For this reason, the dataset of collected images must be preprocessed before its use as a training dataset. The dataset creating process is shown in Fig. 2. The adjustments on the images made the CNN model training process more optimal to produce a good model. The output of the process of creating this data set was a preprocessed image.

The preprocessed image was used for the training process on the CNN model of the face recognition stage. The preprocessed image was reproduced fifty times for each class/user, and image augmentation was carried out in the training process so that the training dataset was more varied. This output image was used for the training process on the CNN model. A block diagram of the CNN model's training process is depicted in Fig. 3.

The training process began with reading the dataset that has been created, then dividing the dataset into two parts, i.e., the dataset for training and the dataset for testing. The CNN model used the dataset for the training process, while the testing dataset was used as validation data to measure the accuracy of the CNN model training. After the dataset was separated, the image augmentation process was carried out. Image augmentation was used to make the image collection in the dataset more varied by changing several image parameters such as zooming, horizontal shifting, vertical shifting, and horizontal flipping. The whole augmentation process was done automatically and randomly. The feature extraction was then applied to the data that has been augmented, while the CNN method was used for the training.

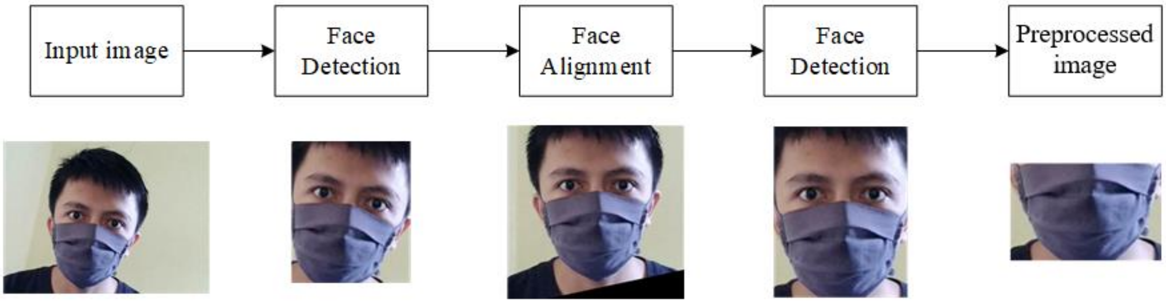

Fig. 4 Block diagram of the mask recognition dataset creation process.

TABLE I
PROPOSED CNN DIMENSIONS AND PARAMETERS SIZE

Layers	Output Dimension	Parameters
Conv2D	224 × 224 × 32	896
MaxPooling2D	112 × 112 × 32	0
Conv2D	112 × 112 × 32	9,248
MaxPooling2D	56 × 56 × 32	0
Conv2D	56 × 56 × 64	18,496
MaxPooling2D	28 × 28 × 64	0
Dropout	28 × 28 × 64	0
Flatten	50,176	0
Hidden	128	6,422,656
Output	70	1,290

The proposed CNN architecture consisted of three convolutional layers, three pooling layers for image data extraction, and a fully connected layer for image classification. The number of output neurons in the fully connected layer was the number of classes/users of the dataset used in training. The convolutional layer calculated the element-wise product of each word and multiplied by the weight associated with the convolutional filters. Consider the input matrix as in (1),

$$W = [w_1, w_2, \dots, w_n] \tag{1}$$

then the convolutional operation refers to (2),

$$w_i = f(W_t \cdot W_{[i:i+k-1]} + b) \tag{2}$$

where, $W_t \in R^{k*m}$ denotes a weight matrix, k denotes height of the convolutional kernel, m denotes a width of the convolutional kernel, b denotes an offset value, f denotes an activation function.

The resultant vector after convolutional operation is represented in (3),

$$W' = [w_1, w_2, \dots, w_i, \dots, w_{n-k+1}] \tag{3}$$

the pooling layer was applied after the convolutional operation. The types of pooling operation can be max and average pooling. In this research, the max pooling was used. For the input vector w_i, the k-max pooling operation is depicted in (4)-(5).

$$x = [x_1, x_2, \dots, x_i, \dots x_{m-k+1}] \tag{4}$$

$$x_i, = \max[w_i, w_{i+1}, \dots, w_{i+k-1}] \tag{5}$$

where, m is dimension of the vector w_i and max is the maximum function.

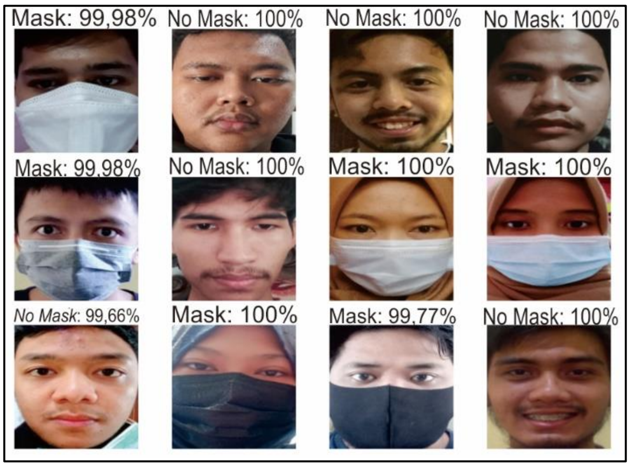

Fig. 5 Face mask detection result.

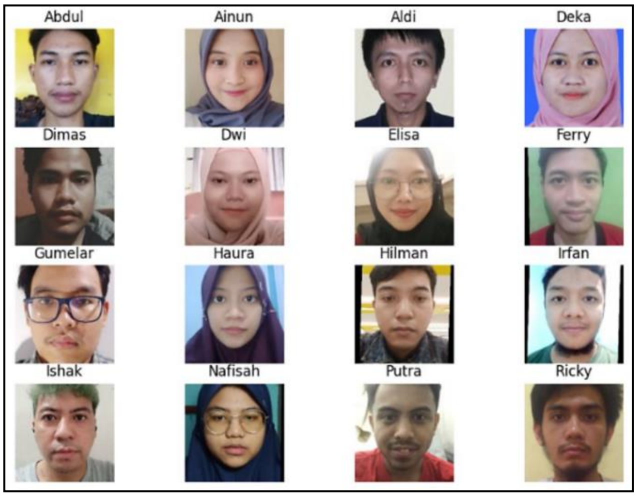

Fig. 6 Face recognition on the unmasked face.

Table I shows the size of the data and the parameters trained at each layer. The output dimension column in Table I shows the size of the input image after passing through the layers in the CNN model. Parameters indicate the number of parameters in the CNN model that change during the training. In this CNN model, the number of parameters being trained was 6,452,586 parameters.

D. Design of Face Mask Detection and Recognition

In this system, the CNN method with the MobileNetV2 architecture was used to detect the use of masks which was available in the Keras library. Keras is a framework for deep learning written in the Python programming language. The training for this mask detection model used training data of 1,915 images each for training data without masks and training data with masks. Data training was carried out with twenty epochs.

Mask detection was used to monitor passengers whether they wore masks or not. In addition to mask detection, this algorithm must also be able to identify the type of mask used by passengers. The purpose of identification this type of mask was to ensure that passengers wore masks according to the standard, namely medical or N95/KN95 masks. Fig. 4 shows a block diagram of the dataset creation process for mask recognition.

Making a dataset for the detection of masks was done by performing two stages of face detection. The first face detection was done to cut the input image so that only the face area was obtained. The second face detection was done to get an image of the face area after straightening the face so that it was not tilted or straight. The preprocessed output in the creation of this dataset was the image of the mask section only.

The identification of masks in this system was divided into two classes, namely 'Bad Masked' and 'Good Masked'. 'Good Masked' class means that the masks used were surgical or N95/KN95 masks; the Bad Masked class means that the masks used were masks other than surgical or N95/KN95 masks.

IV. Experiment Results

The experiment tested in this study was divided into several test sub-systems. The first sub-system was testing the mask detection algorithm, the second was to use the CNN algorithm to demonstrate face recognition with and without masks. The third was testing the N95/KN95/surgical mask type recognition algorithm. The final step was to run the entire system to demonstrate the accuracy of the proposed sensor fusion algorithm's decisions.

A. Results of Face Mask Detection Algorithm

The mask detection was tested by predicting the image of a face with a mask or without a mask. The test result data is shown in Fig. 5. The label 'Mask' means the predicted image using a mask and the label 'No Mask' means the predicted image without a mask.

Fig. 5, shows that the CNN model that has been trained can distinguish a masked and an unmasked face with a very good accuracy. In the process of mask detection, the proposed CNN model has not been able to distinguish the types of face masks between surgical masks, respiratory masks (N95/KN95), and other masks.

B. Results of Face Recognition Algorithm

In the face recognition that was tested experimentally, the dataset used was 3,500 images consisting of seventy classes/users, with each class having fifty preprocessed images. The dataset was then divided into two parts, namely the training dataset and the testing or validation dataset. In creating the dataset, several training scenarios were applied, as shown in Table II. The results of the CNN model training based on the Table II scenarios are presented in Table III.

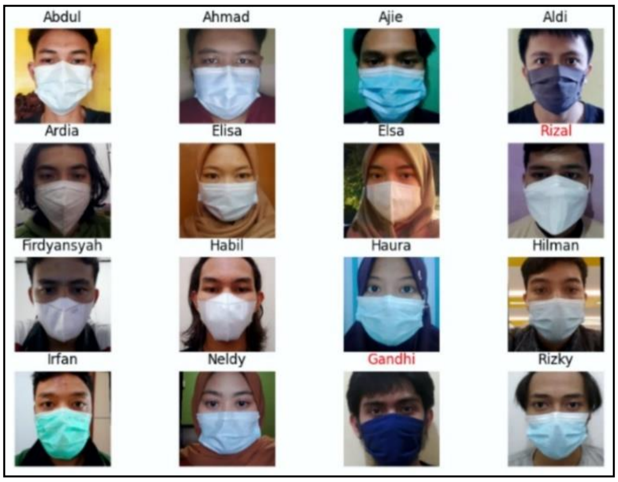

Fig. 7 Face recognition on a masked face using the second training scenario.

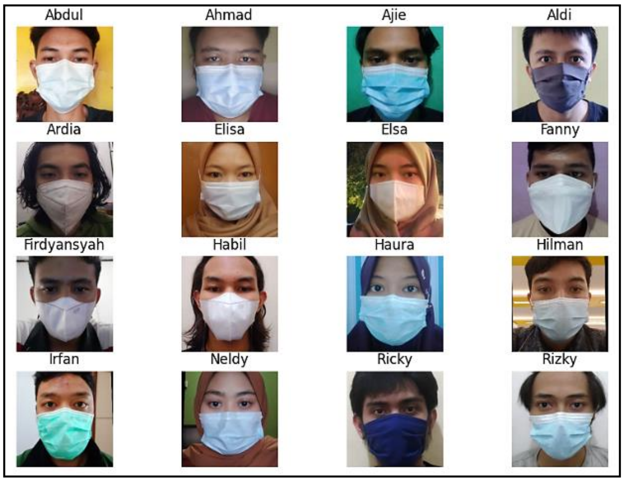

Fig. 8 Face recognition on a masked face using the fourth training scenario.

According to Table III, the trained CNN model for face recognition can recognize faces with the highest accuracy for face recognition without a mask and face recognition with a mask being in the fourth scenario. The ratio of 9:1 on the testing dataset to the training dataset results in more training datasets and has represented the data in the testing dataset as a whole so that the CNN model can predict well. Fig. 6 shows the result of face recognition when people are not wearing face masks. Fig. 7 (second scenario) and Fig. 8 (fourth scenario), shows the result of testing the CNN model for face recognition when people are wearing face masks. The face recognition accuracy (while using face masks) of the second scenario is 87.5%, while the accuracy of the fourth scenario is 100%.

C. Results of Face Mask Recognition Algorithm

The results of the CNN model training in recognizing the types of face mask used by the prospective passenger are presented in Table IV. The accuracy testing of mask recognition is conducted based on the scenarios in Table II.

Based on Table IV, the CNN model for mask recognition can distinguish the types of masks with accuracy in the first scenario is 100%, the second scenario is 100%, the third scenario is 93.75%, and in the fourth scenario is 100%. Fig. 9,

TABLE II
TRAINING SCENARIOS OF CNN MODEL

Scenario	EPOCHS	Training Dataset	Testing Dataset
1	100	80	20
2	100	90	10
3	500	80	20
4	500	90	10

TABLE III
FACIAL RECOGNITION TEST ACCURACY

Scenario	Accuracy (%)	
	Without Mask	*With Face Mask*
1	56.25	93.75
2	68.75	87.50
3	93.75	93.75
4	100.00	100.00

TABLE IV
THE ACCURACY OF MASK TYPE RECOGNITION RESULT

Scenario	Accuracy (%)
1	100.00
2	100.00
3	93.75
4	100.00

shows a sample of CNN model testing for face mask type recognition.

D. Results of Integrated System

Integrated experiment testing consisted of the check-in process of prospective passengers. First, prospective passengers used their smartphones to log in to the flight web and tap on the NFC terminal. Then, the thermal and IP cameras conducted the face and the type of mask detection process. This integrated experiment was represented in the diagram block of the system in Fig. 1.

The flight web application was intended for the administration of aviation providers. The web application was made into three pages, namely the registration, the login, and the monitoring page. This flight web application ran on a local computer with IP address 192.168.0.102/127.0.0.1 (localhost). On the registration page, there was several data that must be filled in, namely the user's email address and password. If the registration was successful, the log in page would be displayed.

Fig. 10 is the main page of the flight web. There are two windows to display images from IP cameras and thermal cameras. The table shows a list of airline passengers who have registered and have tickets. There are columns that provide information regarding the name and the condition of the passengers. In security check point 1 (SCP1) column, there are several columns for measuring various parameters as a condition for departure. The verification column indicates whether the passenger checking in is the ticket owner, as detected through face recognition on the IP camera. The temperature column shows the condition of the passenger's body temperature as measured using a thermal camera. The

Fig. 9 Recognition of mask types.

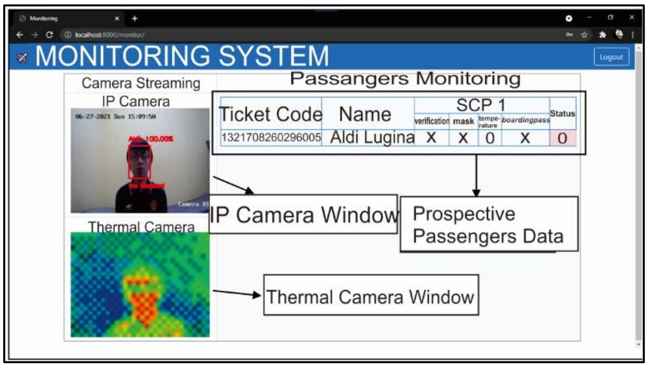

Fig. 10 Main page of the flight web.

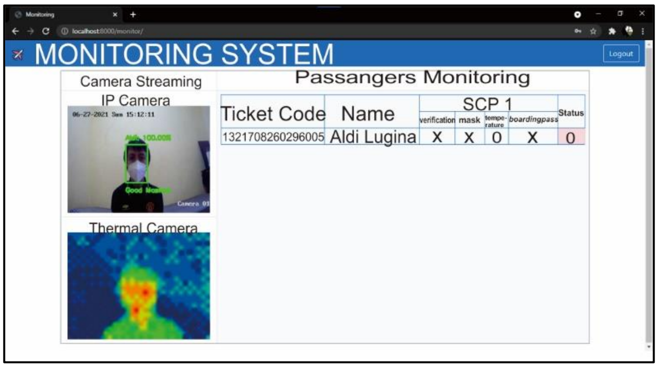

Fig. 11 Check-in process without NFC tap.

boarding pass column shows the boarding pass verification on the NFC node. The passenger who failed to check-in due to the discrepancy in the measured parameters is indicated by the red status column, which will turn green if all the measured parameters are in accordance with the provisions.

Fig. 11 indicates that the passenger is well recognized and wearing a mask according to the provisions, however, the status column still looks red. It happened because passengers did not tap on the NFC node/terminal, so the system did not take measurements. For the system to take measurements, it is necessary to put the mobile phone to the NFC node (as shown in Fig. 12, and the mobile phone must have the e-flight application installed.

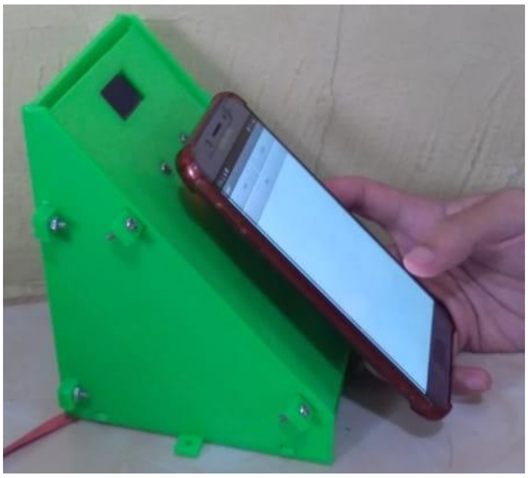

Fig. 12 NFC tapping process.

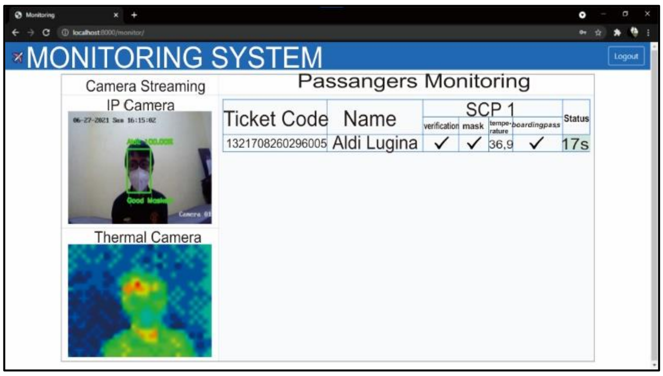

Fig. 13 Check-in process with NFC tap.

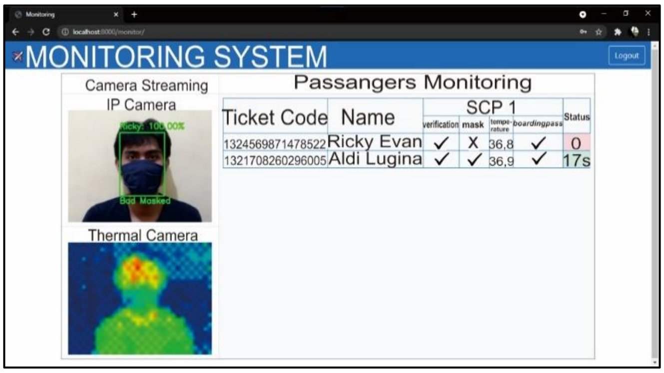

Fig. 14 Non-standardized face masks are detected.

After putting the NFC device within the range of the terminal, on the passenger monitoring web, the status changed to green, the use of masks and body temperature was verified. The interface of the monitoring website is shown in Fig. 13. The mask and boarding pass status changed from a cross to a tick. The measured body temperature was below 38 °C, indicating that the passenger who checked-in had met the requirements so that the status column turned green with check-in processing time of 17 seconds. The green status column indicates that the passenger has passed SCP1. Fig. 14 displays measurements on different prospective passengers.

In Fig. 14, even though the passenger has tapped the boarding pass marked with a check mark in the boarding pass column and the recognized face matches the boarding pass owner's data, the status column is red. The red color in the status column was caused by the type of mask used not complying with the provisions, specifically the type of cloth mask, so the passenger was rejected to pass the security check point 1. This result shows that the sensor fusion on the decision level has a good decision-making performance.

V. Conclusion

The body temperature monitoring system and mask use detection for airplane passengers at the airport have been realized. The proposed web application for this monitoring system, which was called by e-flight apps and designed in localhost, was successfully created and worked to display the list and check-in status of aircraft passengers.

The best CNN model for face and mask recognition was found in the fourth scenario with the ratio of the training dataset to the test dataset was 9:1 and the epoch was 500 times. In the face recognition experimentally tested, the dataset used was 3,500 images consisting of seventy users. Meanwhile, the training for mask detection model used training data accounting for 1,915 images each for training data without masks and training data with masks. The CNN model training accuracy for face recognition and mask recognition reached 100%.

The proposed sensor fusion method was developed using a complementary configuration consisting of three sensors (IP camera, thermal camera, and NFC). The decision level carried out in this study was able to determine the verification of the check-in status of airplane passengers based on three provisions including the value of body temperature, the type of face mask worn, and the face accuracy on the prospective passengers' boarding pass ticket.

Conflict of Interest

The authors declare no conflicts of interest. All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. All information delivered is the actual result obtained from conducting research
and is not influenced by personal opinion or interest.

Author Contribution

Conceptualization, Noor Cholis Basjaruddin; methodology and design, Feni Isdaryani; software and data collection, Aldi Lugina; analysis and interpretation of results: Feni Isdaryani, Aldi Lugina; draft manuscripts preparation: Feni Isdaryani, Aldi Lugina. All authors reviewed the results and approved the final version of the manuscript.

References

[1] "Kriteria dan Persyaratan Perjalanan Orang dalam Masa Adaptasi Kebiasaan Baru Menuju Masyarakat Produktif dan Aman Corona Virus Disease 2019 (COVID-19)," Surat Edaran Gugus Tugas Percepatan Penanganan COVID-19 Nomor 7, 2020.

[2] (2020) "Coronavirus Disease (COVID-19): When and How to Use Masks," [Online], https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/when-and-how-to-use-masks, access date: 10-Feb-2021.

[3] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep Learning for Computer Vision: A Brief Review," *Comput. Intell., Neurosci.*, Vol. 2018, pp. 1-13, 2018.

[4] S. Sethi, M. Kathuria, and T. Kaushik, "Face Mask Detection Using Deep Learning: An Approach to Reduce Risk of Coronavirus Spread," *J. Biomed. Inform.*, Vol. 120, pp. 1-12, 2021.

[5] X. Jiang, T. Gao, Z. Zhu, and Y. Zhao, "Real-Time Face Mask Detection Method Based on YOLOv3," *Electron.*, Vol. 10, No. 7, pp. 1-17, Apr. 2021.

[6] M. Jiang, X. Fan, and H. Yan, "RetinaFaceMask: A Single Stage Face Mask Detector for Assisting Control of the COVID-19 Pandemic," 2020, *arXiv:2005.03950*.

[7] W. Hariri, "Eficient Masked Face Recognition Method during the COVID-19 Pandemic," 2021, *arXiv:2105.03026*.

[8] H. Li, *et al*., "Multisensor Data Fusion for Human Activities Classification and Fall Detection," *2017 IEEE SENSORS*, 2017, pp. 1-3.

[9] R. Gravina, P. Alinia, H. Ghasemzadeh, and G. Fortino, "Multi-Sensor Fusion in Body Sensor Networks: State-of-the-Art and Research Challenges," *Inf. Fusion*, Vol. 35, pp. 68-80, 2017.

[10] (2020) "Coronavirus Disease (COVID-19): Masks," [Online], https://www.who.int/news-room/q-a-detail/coronavirus-disease-covid-19-masks, access date: 6-Feb-2021.

[11] S. McHugh and K. Yarmey, *Near Field Communication Recent Developments and Library Implications*. San Rafael, USA: Morgan & Claypool Publishers, 2014.

[12] N. Álvarez-Díaz, P. Caballero-Gil, and M. Burmeste, "A Luggage Control System Based on NFC and Homomorphic Cryptography," *Mobile Inf. Syst.*, Vol. 2017, pp. 1-11, 2017.

[13] H. Komsta, E. Brumercikova, and B. Bukova, "Application of NFC Technology in Passenger Rail Transport," *Transp. Probl.*, Vol. 11, No. 3, pp. 43-53, 2016.

[14] C.C. Aggarwal, *Neural Networks and Deep Learning*. Cham, Switzerland: Springer, 2018.

[15] H. Yanagisawa, T. Yamashita, and H. Watanabe, "A Study on Object Detection Method from Manga Images Using CNN," *Int. Workshop Adv. Image Technol. (IWAIT)*, 2018, pp. 1-4.

[16] Z. Ouyang, J. Niu, Y. Liu, and M. Guizani, "Deep CNN-Based Real-Time Traffic Light Detector for Self-Driving Vehicles," *IEEE Trans. Mob. Comput.*, Vol. 19, No. 2, pp. 300-313, 2020.

[17] A.R. Syafeeza, M. Khalil-Hani, S.S. Liew, and R. Bakhteri, "Convolutional Neural Network for Face Recognition with Pose and Illumination," *Int. J. Eng., Technol. (IJET)*, Vol. 6, No. 1, pp. 44-57, 2014.

[18] M.G. Bechtel, E. Mcellhiney, M. Kim, and H. Yun, "DeepPicar: A Low-Cost Deep Neural Network-Based Autonomous Car," *IEEE 24th Int. Conf. Embedded, Real-Time Comput. Syst., Appl. (RTCSA)*, 2018, pp. 11-21.

[19] D. Galar and U. Kumar, *eMaintenance - Essential Electronic Tools for Efficiency*, J. Laurence, Ed., Cambridge, USA: Academic Press, 2017.

[20] M.-D. Yang, T.-C. Su, and H.-Y. Lin, "Fusion of Infrared Thermal Image and Visible Image for 3D Thermal Model Reconstruction Using Smartphone Sensors," *Sensors*, Vol. 18, No. 7, pp. 1-19, 2018.

[21] A. Hashmi, A.N. Kalashnikov, "Sensor Data Fusion for Responsive High Resolution Ultrasonic Temperature Measurement Using Piezoelectric Transducers," *Ultrasonics*, Vol. 99, pp. 1-8, 2019.