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Student Virtual Class Attendance Based on Face Recognition Using CNN Model

Abstrak

Attendance records are an important tool that can be used to include and broadcast member participation in an activity, including the learning process. In online learning classrooms, the process of recording attendance becomes challenging to do manually, thus an automatic attendance recording system is needed. The authentication process is important in developing an existing recording system to guarantee the correctness of the recorded data. In this research, a face authentication system was built to create a system for recording online class attendance to help integrate participant activities and participation in online class learning. The face recognition approach uses a Convolutional Neural Network (CNN) model specifically designed to automate student attendance in virtual classes. Student image data is taken from virtual classroom sessions and used to train a CNN model. This model can recognize and verify student identity in various lighting conditions and head positions. This research consists of several stages, namely data collection, artificial neural networks, use of facial recognition, dataset application stage, and facial recognition in video frames. The experimental results showed that there were 11193 samples studied and of these 11193 samples the distribution was even, namely 6.7%. In addition, the model performance results show an accuracy of 76.28%.

Keywords—*Attendance system, CNN, face regocnition, virtual smart classroom.*

1. INTRODUCTION

Since the COVID-19 pandemic, many educational institutions around the world have switched to distance learning by utilizing virtual classes. A virtual class is a class that is created by itself by utilizing internet technology and the help of third-party software, so that interactions between teachers and students can be created online [1]. With the shift in interaction between teachers and students from offline to online, the need to record student attendance in a virtual context is greater. In an online learning environment, recording student attendance becomes more difficult compared to physics classes. Students can experience problems such as turning off the camera, having someone else attend them, or even leaving class without notice. Meanwhile, as is known, to create effective learning, one of the requirements is the need to monitor student attendance, especially student attendance, which is used for student attendance, provide guidance if necessary, and ensure that they make maximum use of learning opportunities. So, an automated attendance system in virtual classes is very necessary to overcome these problems.

One of the attendance systems that can be used is face recognition technology. Facial recognition technology has become more sophisticated and accessible. Face recognition is a technology that identifies and verifies individuals based on their face features. Face recognition technology involves taking an image of a person's face and comparing it to a database of known faces to determine their identity [2]. The application of face recognition as an authentication system has quite a large potential [3]. Zho & Ye [4] say that face recognition technology has the potential to improve authentication systems, especially in the field of distance education. The current static "username + password" authentication method has several disadvantages, such as vulnerability to hacking and account sharing [4]. By applying face recognition, based on algorithm models and Convolutional Neural Network (CNN) models can be used to recognize faces in images and videos with high accuracy [5]. Face recognition technology for authentication

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systems for CNN models has advantages, such as having a high level of accuracy, providing a convenient and user-friendly authentication method, increasing security by providing unique identifiers that are difficult to imitate, non-intrusive because it does not require physical contact or procedures invasive, can be easily scaled to accommodate many users [6]. Other advantages include the ability to identify individuals without physical interaction, overcome fraud issues, and record attendance automatically, which can make it an efficient option in educational contexts. Apart from the education sector, face recognition technology has been successfully applied in various other sectors, such as security, attendance management, and authentication.

Several studies on face recognition using the CNN model have been carried out by previous researchers, including research conducted by Hussain *et al*. [7] regarding the application of the Internet of Things with a deep learning-based face recognition approach for authentication in medical control systems, research conducted by Castiglioni *et al*. [8] regarding the application of AI for medical images, research conducted by Clarke *et al*. [9] regarding the transparency of face recognition for mobile devices, research conducted by Nasution *et al*. [10] regarding face recognition login authentication for digital payment solutions during the COVID-19 pandemic, and research conducted by Chen *et al*. [11] regarding sensor-assisted face recognition for an enhanced biometric authentication system for smartphones.

In this research, we developed a CNN deep learning model to automate the attendance system for virtual classrooms. The CNN model was trained on the facial images of registered participants in the virtual class system. Therefore, participants must register on the system, and the system will record their images for the training process. After the CNN model is developed, all the online class attendance will be checked automatically by the system. However, to ensure the effectiveness of the system, the main contribution of this research is the architecture for developing a CNN model for face recognition, which is used to develop an automatic attendance system. The performance of the model is measured by the accuracy depicted in the confusion matrix.

2. METHOD

In building a CNN architectural model, researchers use several stages, from data collection, Pre-Processing data detection, building the CNN model, predicting, and finally validating. More detailed model-building steps are shown in Figure 1.

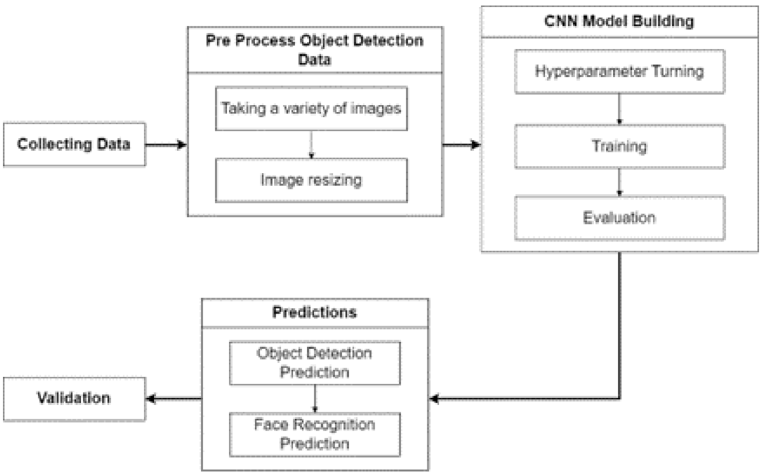

Figure 1. Stages of model building.

The detailed description of all the processes in Figure 1 is briefly explained in the following sections.

2.1. Collecting Data

The first stage of this research was the data collection process. The data used is image data in the format ('.jpg', '.png', '.PNG', '.JPG', '.jpeg', '.JPEG') which will later be used as a CNN training model. The data that was collected was obtained from the results of distributing the availability link to respondents. From the distribution link, 21 respondents were obtained from students. The 21 respondents consisted of 10 men and 11 women.

2.2. Pre-Processing object data

In detail, the data collection process was carried out by carrying out the following stages:

a. Taking a variety of imagines. The data recording process is carried out to collect a dataset in the form of facial images, which will be used to develop the CNN model. Data recording stages:
   1) Take a Face Screenshot from a video based on the specified pose.
   2) Collect facial screenshots from videos and save them in the folder provided.
   3) Each folder contains image data with a specific folder name (example folder name: respondent 1).
   4) Each image file in image format is given a name (respondent 1a_and so on).
   5) Each picture from each respondent has 16 different poses.

b. Imagine resizing and other preprocessing data. Imagine resizing is done to get data with images that have the same size. In this research, each image is converted so that it has a uniform size, namely 240 x 240 pixels with a grayscale image type. To solve problems with small datasets in some classes, we can augment the data to increase the number of samples. Image augmentation is a set of transformations like translation, rotation, grayscale color adjustment, etc. Furthermore, the data balancing process has been done in this process by adding more data to the class which has fewer sample data *3*.

2.3. CNN Modelling

The CNN model-building process is carried out to obtain the best prediction model. In general, the steps taken are determining the hyperparameters of the CNN architecture, training the model with the selected parameters, and evaluating the resulting model.

2.3.1. Hyperparameter tuning

The hyperparameter tuning process is carried out to get the best parameters used in the CNN architecture to produce the best CNN model. In this research, the CNN architecture used consists of:

a. 4 convolution layers: kernel size: 33, ac
b. 2 max-pooling layers
c. 1 flattening layer
d. 3 hidden layer NN
e. 1 output layer with 15 neurons

Other essential parameters chosen to build the CNN model:

a. The filters for the first 2 convolution layers are 64, and the next 2 convolution layers are 128. These filters indicate how many filters are used in the convolution layers process. Several filters are used to obtain important data from an image, such as image edge data and color variations.
b. The kernel_size used in the convolution layer is 3 x 3.
c. Input _size = (240, 240, 2).
d. Activation in convolution is 'relu'.
e. Activation on the flattening layer and hidden layer NN is soft-max.

f. Optimizer = 'adam'.
g. Epoch = 30.

2.3.2 Model Evaluation

Model evaluation is used to determine the accuracy of the resulting model. This process is carried out using 15% validation data.

2.4. Prediction

2.4.1. Object Detection

Object detection prediction is a process for predicting objects in an image. The object prediction results are (class, position, and size). In this object detection process, there are several algorithms used, namely Haar Cascades [28], MTCNN (Multi-Task Cascade CNN) (see Figures 2 and 3).

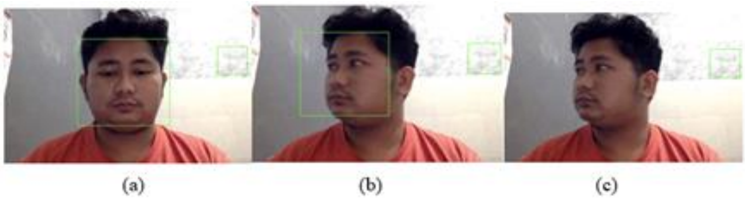

Figure 2. Object detection using haar cascades algorithm.

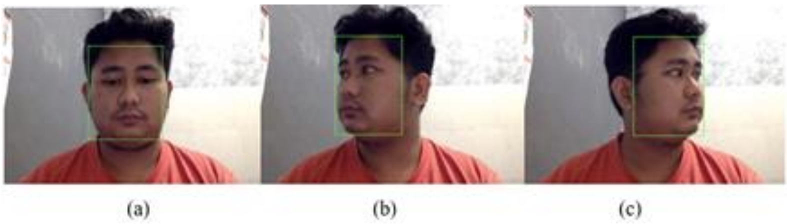

Figure 3. Object detection using MTCNN (Multi-Task Cascade CNN).

2.4.2. Face recognition

Face recognition is the process of recognizing facial objects that have been successfully detected based on certain labels (see Figure 4).

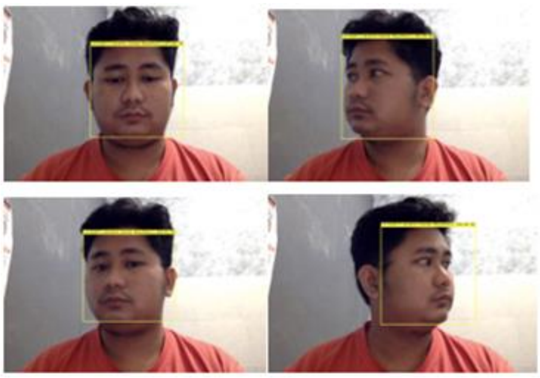

Figure 4. Face recognition sample.

3. RESULT AND DISCUSSION

3.1. Study Literature

3.1.1 Conventional Neural Network (CNN)

According to Hameed *et al*. [12], a Convolutional Neural Network (CNN) is a type of deep learning model specifically designed to process data in the form of images. Meanwhile, Wu [13] said that CNN is a type of deep learning model that is very effective for computer vision, such as image classification and object detection. CNNs are designed to mimic the visual processing of the human brain by using multiple layers of interconnected neurons.

The main function of CNN is to process and analyze images, extracting features and patterns of image data [12]. This process is carried out through a series of layers, such as convolutional layers, pooling layers, and fully connected layers [14]. CNN models are trained to learn and recognize certain objects or patterns in images, allowing the model to perform tasks such as image classification and semantic segmentation [15]. CNN models use mathematical principles and details to understand and interpret images.

In the CNN architecture, the convolutional layer functions to filter the input data and extract features from the image data, while the pooling layer extracts and reduces the number of features to reduce computational complexity. The fully connected layer performs the final classification or regression task.

CNN models have demonstrated excellent performance in various computer vision tasks and have been widely applied in various fields. CNN models can automatically learn and extract important features from raw input data, making them very effective in tasks such as image recognition and object detection.

3.1.2 Attendance System

An attendance System is a technology used to record and track the presence or absence of individuals, which is usually used in classrooms or workplaces [16]. Attendance systems are used to monitor and manage attendance for various purposes, such as tracking student attendance at school or recording employee attendance in organizations [17]. The system can be manual, where individuals log in or mark their presence on a piece of paper, or automated, with technology such as biometric verification or facial recognition used to record attendance automatically. Automated attendance systems offer advantages such as accuracy, efficiency, and real-time data collection. They can integrate with other systems and provide easy access to attendance records for analysis and reporting purposes. Authentication systems are typically implemented in three main domains: time attendance and employee management systems, visitor management systems, authorization systems, and access control systems [16].

According to Kar *et al*. [16], attendance systems have several characteristics, namely:

1. Automatic Logging
2. Integration with Facial Recognition Technology
3. Log Maintenance
4. Biometric Authentication
5. Efficiency and Convenience
6. Non-Invasive Nature
7. Application in Various Domains

Kar *et al*. [16] also stated that attendance systems are used to track individual presence in certain places, such as classrooms or workplaces. The attendance system has several important objectives [16], such as:

1. Logging: The attendance system helps maintain a log file that records the entry and exit of everyone concerning to universal system time. These log files provide reliable attendance records, helpful for various administrative and organizational purposes.

2. Efficiency: Using an automated attendance system, such as one based on facial recognition technology, can significantly reduce the time and effort required for manual attendance recording. This eliminates the need for paper-based attendance sheets and allows fast and accurate attendance recording.
3. Authentication: An attendance system based on facial recognition technology ensures that only registered individuals are recorded as present. By authenticating an individual's identity through facial recognition, the system can prevent unauthorized attendance recording and ensure the accuracy of attendance data.
4. Convenience: The automatic attendance system provides convenience for students and lecturers. Students can easily log in and out without needing to log in manually, while lecturers can access attendance information easily through the system.

3.1.3 Face Recognition

Facial recognition refers to the process of automatically identifying or verifying a person's identity by analyzing and comparing their facial features with a database of known individuals [18]. Facial recognition is a technology that has received great attention in recent years due to its wide application in the commercial and security sectors. Facial recognition systems use algorithms to detect and extract facial features from images, then match them against a stored model to determine the person's identity. Face recognition has the potential to provide a user-friendly and secure solution for various applications, such as access control, surveillance, and personal identification [19].

Facial recognition is a technology that aims to identify and verify individuals based on their facial features [20]. This has important consequences for engineers designing algorithms and systems for machine recognition of human faces. The main function of facial recognition is to automatically detect and recognize faces in images or video clips [21]. This involves several steps, including face detection, feature extraction, and matching against a database of known faces. The main goal is to achieve accurate and reliable identification of individuals for various applications, such as security, surveillance, and access control.

According to Zhao *et al*. [18], there are several steps involved in implementing a facial recognition system, namely:

1. Face Detection: The first step is to detect faces in the image. This involves identifying the presence and location of faces in an image.
2. Feature Extraction: Once a face is detected, various features are extracted from the face image. These characteristics can include shape, texture, and facial appearance.
3. Face Representation: The extracted features are then used to create a unique representation of each face. This representation usually takes the form of a numerical vector that captures facial characteristics.
4. Face Matching: In the face matching stage, the detected face representation is compared with a database of known faces. This involves measuring the similarity between the extracted features and the features stored in the database.
5. Recognition and Verification: Based on the similarity score obtained from the face-matching stage, the system can perform face recognition or face verification. In facial recognition, the system identifies the person by matching the detected face with a known identity in the database. In face verification, the system verifies whether the detected face matches the claimed identity.

Integration with Other Systems: Facial recognition systems can be integrated with other systems, such as access control systems, surveillance systems, or authentication systems. This enables the use of facial recognition as an identification or verification tool in a variety of applications.

3.1.4 Authentication system research for face recognition

Several researchers have conducted review studies regarding the implementation of authentication systems for face recognition [22-27]. Research conducted by Battaglia *et al*. [22] identified the use of Visilab FaceRec as a multifactor authentication system based on a combination of two-stage tiered classifiers for biometric identification with encrypted RFID tags for token-based authentication. False simultaneously, thanks to an innovative approach to calculating decision thresholds for both discriminators. Visilab FaceRec has been implemented on commercial boards for embedded computing and proven capable of running in near real-time. Abozaid *et al*. [23] identified the use of multimodal biometrics for human authentication tools based on the fusion of facial and voice recognition. In his research it was said that better results were given in the case of using cepstral coefficients and statistical coefficients for speech recognition and in the case of faces, Eigenface and SVM experiments gave better results for face recognition.

Moreover, in the proposed multimodal biometric system, the score fusion performance is better than in other scenarios. McKenna and Gong [24] identified face recognition in security applications based on closed-circuit television (CCTV). In his research, it was said that the application of face recognition on CCTV achieved accurate face tracking in various scenarios. The scenario in question combines two visual cues that complement each other, from movement to facial appearance. Hwang *et al*. [25] identified standardization and understanding of face recognition and technology trends to overcome the weaknesses of ID-based authentication. Zulfiqar *et al*. [26] identified a convolutional neural network-based face recognition system that detects faces in input images using the Viola-Jones face detector and automatically extracts face features from the detected faces using a trained CNN for recognition. In his research, it was said that the overall accuracy results obtained were 98.76%. In addition, with the accurate results obtained, a depiction of the effectiveness of face recognition in an automatic biometric authentication system can be carried out. Battaglia *et al*. [27] identified authentication based on face recognition and pattern-matching algorithms. In his research, it is said that pattern matching is used to provide high reliability and resistance to fraudsters. Additionally, pattern matching also stores in personal radio frequency identification (RFID) tags.

3.2. Implementation

3.2.1 CNN model

The results of computer vision trials for face detection were carried out using deep learning analysis. Based on the analysis by determining the minimum requirement for respondent data used, if there are 32 image examples, then from 21 respondents, only 15 respondents' data will be used for a total of 533 facial data samples. The number of the participants here will indicate the number of the class that will be used in this modelling process. The face sample data augmentation process is carried out to duplicate images with unique positions. Duplication is carried out by paying attention to the rotation and light-dark intensity of the facial image sample. The augmentation sample results are 10660 images. The augmented images were combined with original facial image samples using the extended array list function, resulting in 11,193 facial samples used in this research. Details of the number of samples of facial images for each respondent are shown in Table 1.

Table 1. Total Details of Face Image Samples

Respondent Folder Name	Number of Samples Image
Respondent 1	672
Respondent 2	672
Respondent 3	672
Respondent 4	672
Respondent 5	672
Respondent 6	1092

Respondent Folder Name	Number of Samples Image
Respondent 7	672
Respondent 8	672
Respondent 9	672
Respondent 10	1344
Respondent 11	672
Respondent 12	693
Respondent 13	672
Respondent 14	672
Respondent 15	672

When training class CNN Python deep learning data, the number of samples for each object must be the same to increase and optimize the training accuracy process. Therefore, we reduced the sample size per class using NumPy random choice. The results of the reduced sample size are shown in Figure 5. Based on Figure 5, it is known that the entire amount of data is distributed evenly, with each class having a sample distribution of 6.7%.

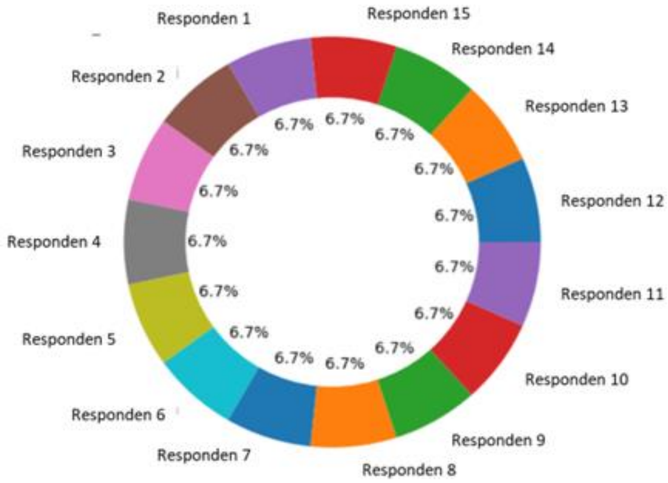

Figure 5. Data distribution after the reduced sample size function is carried out.

CNN is a deep learning algorithm in 3 dimensions. Therefore, we carry out Label Encoding & categorization of sample data, so that a 3-dimensional matrix is formed. Label encoding refers to the process of transforming word labels into numerical form. The categorization process is carried out with a function in the numpy utility library, namely to_categorical(). The to_categorical method allows a numpy array (or) vector that has integers representing various categories, to be converted into a numpy array (or) matrix that has binary values and has columns equal to the number of categories in the data.

The following process is to split the data set. A split dataset is carried out to categorize data into two groups, namely the training group and the test group. The test sample group was taken as 15% of the total sample per class. Meanwhile, training samples were taken as much as 75% of the total samples per class. The total samples from each group were 8568 training samples and 1512 test samples.

Training data is carried out based on samples that have been obtained. Training data is carried out using the CNN algorithm. Figure 6 shows the results of training data with the complex sequential model. Sequential model classes provide training and inference features on samples of each class. The number 10368 in the flatten layer is a number obtained from multiplying the previous dimensions, namely 9×9×128=10368 and in the dense layer 128 is a number that shows the number of neurons used (see Figure 6). The total parameters obtained from the model created are 1595471. In CNN modelling, the feature extraction simply is performed by the network through convolution and pooling layer which extract the relevant feature. Therefore, the training process is carried out with `EPOCHS` and `BATCH_SIZE` which have been set. In this research, EPOCHS was carried out 30 times with BATCH_SIZE 32. BATCH_SIZE is the number of samples that will be propagated into the Network. Using a BATCH_SIZE that is too small can result in fluctuating gradient updates.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_12 (Conv2D)          (None, 48, 48, 64)        640

 conv2d_13 (Conv2D)          (None, 46, 46, 64)        36928

 max_pooling2d_6 (MaxPoolin  (None, 23, 23, 64)        0
 g2D)

 conv2d_14 (Conv2D)          (None, 21, 21, 128)       73856

 conv2d_15 (Conv2D)          (None, 19, 19, 128)       147584

 max_pooling2d_7 (MaxPoolin  (None, 9, 9, 128)         0
 g2D)

 flatten_2 (Flatten)         (None, 10368)             0

 dense_7 (Dense)             (None, 128)               1327232

 dense_8 (Dense)             (None, 64)                8256

 dense_9 (Dense)             (None, 15)                975

 activation (Activation)     (None, 15)                0

=================================================================
Total params: 1595471 (6.09 MB)
Trainable params: 1595471 (6.09 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 6. Results of sequential training data models using the CNN algorithm.

3.2.2 Model Performance

Figure 7 shows learning curves for diagnosing model performance. Figure 7a shows the performance model from the accuracy value, while Figure 7b shows the performance model from the loss value. A learning Curve is a model plot of learning performance against experience or time. Learning curves are a diagnostic tool widely used in machine learning for algorithms that learn from training data sets incrementally. The model can be evaluated on the training dataset, and on the validation dataset after each update during training and plots of the measured performance can be created to show the learning curve.

In this research a learning curve was carried out to diagnose the data set. Figure 7a shows the learning curve for the training accuracy value. Based on Figure 7a, it is known that the accuracy value between the training samples and validation samples is quite good. This means the distance between the training and validation samples is quite visible. Based on 30 epoch, the smallest accuracy value was obtained, namely 0.4175 for the training sample and 0.4323 for the validation sample. Meanwhile, the most considerable accuracy value is 0.8256 for the training sample and 0.7628 for the validation sample.

Based on the results of the learning curve with loss values in Figure 7b, in this study the data sample is included in the Unrepresentative Train Dataset group. An unrepresentative training dataset means that the training dataset does not provide enough information to study the problem, relative to the validation dataset used to evaluate it. This is caused by the training dataset having too little. These results are concluded by identifying that the learning curve for training loss (Figure 7b) shows an increase (drawing a decreasing curve line) and the learning curve for validation loss which shows an increase (drawing a decreasing curve line), but there is a large gap between the two curves.

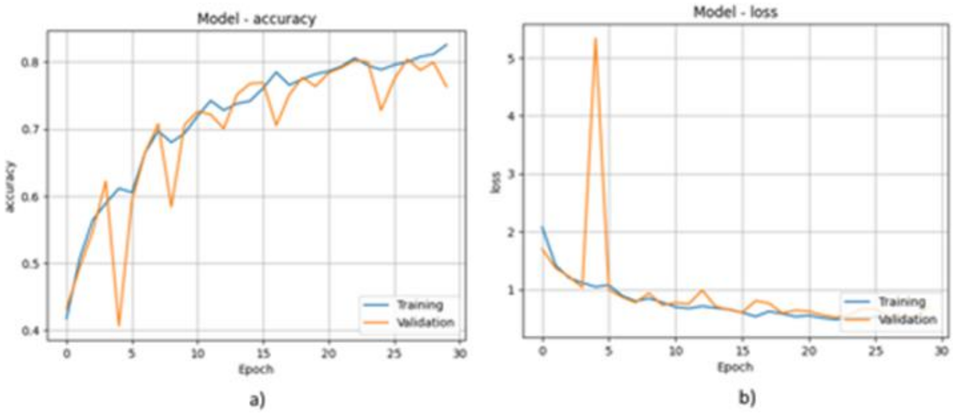

Figure 7. Learning curves for diagnosing model performance, a) model accuracy graph and b) model loss graph.

Figure 8 shows the results of the confusion matrix. Confusion matrix is a table that has 4 (four) combinations of predicted values and actual values[29]. The observed object (Sample face image) is represented by the middle blue zone of the matrix, and this blue zone is contained in the "true" and "predicted" categories of the confusion matrix. This means the model correctly predicted the existence of the object in that case. The values in other matrix zone represent the model's performance in detecting the object of interest in different cases.

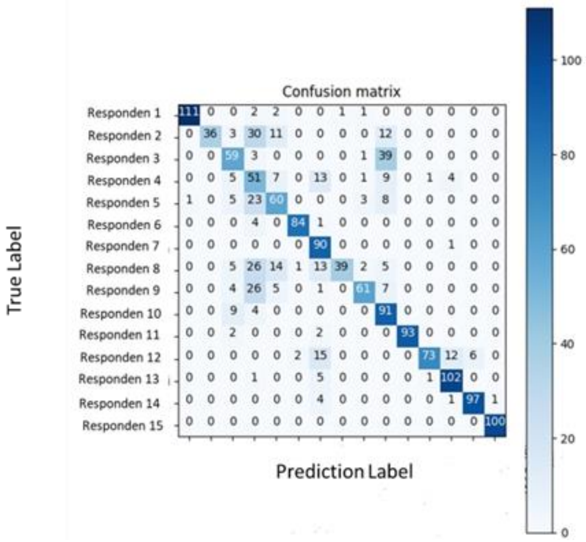

Figure 8. Confusion Matrix.

4. CONCLUSION

Based on the research results, it was found that in creating an authentication system for face recognition using the Convolutional Neural Network (CNN) model, it consists of several stages, namely neural network, face recognition using, applying our dataset phase, and face recognition on video frames. At each stage there is a process for entering the dataset, creating a model, and testing the model. The test results showed that there were 10660 images that were used as sample augmentation results. From 10660, after combining it with the extended arraylist function, 11193 samples were obtained which were used in the research. Apart from that, in this research it was also found that after the process of reducing the sample size it was discovered that the entire amount of data was distributed evenly, with each class having a sample distribution of 6.7%. Model performance was also tested in the research. Based on the results of the model performance diagnosis, it was found that the accuracy value between the training samples and validation samples was quite good, with an accuracy value of 0.8256 for the training samples and 0.7628 for the validation samples.

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