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Face Recognition to Determine Visitor Attraction Using Residual Deep Neural Network

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***Abstract*—The development of social media in the form of websites and android applications should be appreciated. The background of this research is the stage to develop the software needed to know the age range. The objective thing to observe is through the visitor's face on the web or application. The purpose is to avoid false information and get the proper process flow. The Technology used is deep learning for facial image recognition. The methods use Convolutional Neural Network with residuals because the advantage is using multi-branch layers but having a stable training process. The use of augmentation is needed to increase the variety of facial recognition image positions and to overcome unbalanced classes. The dataset used consists of seven categories, namely Children, Youth, Early Workers, Middle Ages, Pre-Retirement, Retirement, and Old People, which Bappenas regulate. Each folder contains about 1157 images with a total data of 8,105 images. The training process results can obtain a model with an average accuracy of 99.08% and a computational training time of about three hundred minutes. The model's accuracy is 99.08%, with MSE 0.0037, RMSE 0.0610, and MAE 0.0037. Testing time is about 2 seconds.**

Keywords: Face recognition, Visitor attraction, deep learning, residual network, data augmentation.

I. INTRODUCTION

The development of computer technology today leads to the use of applications and social media. It is attractive compared to conditions before the existence of devices to carry out social activities. At present, status updates are things that seem to be mandatory for application visitors. The offer offered by startups and web services also varies, ranging from online shopping applications, games, Tiktok, Instagram, and Facebook, personal meet-up applications, online chat, and so on. Often visitors use fake data to avoid identifying identities. However, if the application requires a cam, visitors will follow the process even though the identity submitted is false. Identification efforts were made by age. In addition, another requirement is that software developers can find out what visitors want using the concept of thinking or visitor desires [1].

Illustrative research shows how it can be used to develop students' critical thinking. It can be done using the graph theory of phenomena by understanding the concrete expressions of critical thinking, and it becomes a reference in developing the necessary features and menus [2].

There is research on how to get information from media in a way that attracts attention. The hope is that visitors will be willing to spend more time using the features and applications created by the developer. One way is to set the right business processes in the application, measure the value of customer satisfaction, and design the right content and display time [3].

Furthermore, there is visual research based on the literature on the experience of retail customers using the application by considering the four precursor dimensions. Aspects of customer satisfaction assessed on the application of retailers and loyal customers include cognitive, affective, relational, and sensory elements. The data collected were 545 samples and then analyzed using Partial Least Square-Structural. His research shows that improved visualization of appearances is crucial because it affects the affective dimension. Sensory experience in searching goes beyond even cognitive expertise. It can be concluded that various information related to customer desires can be obtained from the retailer's mobile application, which is the key to the success of retail applications. However, this research still needs further discussion related to retailer performance [4].

Research on facial extraction said an appropriate feature extraction method was needed to recognize faces well without changing other assumptions as humans age. The same person has a significant age difference in facial images, and the challenge in this research is age-related biological changes [5]. What external and internal variables can cause a substantial shift in facial characteristics between two photos? There are data taken at different ages but from the same person. Testing the addition of invariant techniques is carried out on deep learning-based methods as a feature extraction tool. It is seen that "aging" is becoming a challenging problem in facial recognition systems [6].

Subsequent research says that deep learning methods can be used in face recognition because they can address the problem of handling a heterogeneous variety of expressions, poses illumination effects, age, and face matching. A convolutional neural network (CNN) can handle these variations using deep learning. It can perform analysis and visualization on the feature maps layer related to the convolution process in facial images [7].

Research on coding skills for patterns and features of facial aging should be studied in depth using ground truth or sketches. Furthermore, these results are compared with the results of computer extraction carried out by Convolutional Neural Networks (CNN). The variation in facial appearance is quite significant, and several extrinsic and intrinsic factors affect the identification results. The comparison results show CNN performs better than handcrafted features. This research compares the ground truth of the handcraft results with the feature maps of the deep learning framework [8].

The research uses the R-Code autoencoder to predict facial attributes in deep learning. The Face recognition attribute can provide rich information and is used for various applications such as law enforcement regarding hoax accounts, ease of human interaction with computers, and target marketing. This research focuses on the proposed formulation by extending the input shortcut connection in the architecture. R-Code to get the loss function by combining the magnitude and direction of the image vector during the feature learning process. There is a facial attribute prediction framework that includes a weighting mechanism. The loss function is calculated by applying the Euclidean distance to the cosine similarity method. The aggregation-based method assigns a higher weight to the relevant weight for each attribute [9].

From the research above, the researcher is interested in exploring various patterns of age identification to obtain an age range survey. The importance of this research is to avoid hoax information related to age and get process flow information that users or visitors want. GAP with research that has been studied previously is CNN non-sequential layer with residual combinations that have not been used to classify categories based on facial age. The weakness of the CNN architecture with the sequential layer method is the instability during the training process. While the advantage of using the residual layer is that there is a skip connection, so the computational burden is not as heavy as the branched layer architecture. The contribution of this paper is to obtain predictions of the age range of visitors from facial information so that visitors do not enter the wrong application or location. This application can be implemented at airports, tourist attractions, and cinemas to sort visitors based on age ranges. The research hopes there is a deep learning process with stability in the training process and optimal computing time to get the model.

II. Background

A. *Visitor attraction Survey using a range of age*

The research examines customer satisfaction using information systems and personal innovation. The survey results show that the business processes in the application significantly affect the intention to use the mobile shopping application. Its characteristics have adopted m-shopping using a mobile application. The type of device used depends on the age limit of the consumer [10].

This research shows the effects of moderation use on certain types of devices and ages in shopping applications. Respondents were divided into young ($\leqslant$35 years) and old (>35 years). As a result, responses to certain variables, perceived usefulness, satisfaction, and intentions among specific subgroups were considered. It shows the importance of age grouping for application development [11].

Research that Technology can be strengthened and made to produce more accessible and effective products. Cooperation regarding age grouping is more inclusiveness by getting a co-designer involving an adult or older as a learning model. The application should be right on target, according to the needs and ages of visitors. Research on mobile health (mHealth) was conducted on the elderly group and delivered through a smartphone application to improve the health behavior of active older people [12]. A sample of group age categories is shown in Fig. 1.

The Moving Up Method is a multi-featured application designed to determine the routine behavior of the elderly who are less active by increasing Performance analysis (PA). Regular or periodic behavior, stereotypes about aging, and knowledge of routines become the reference for developing the application, and I hope there is a correlation between the three inactive features [13].

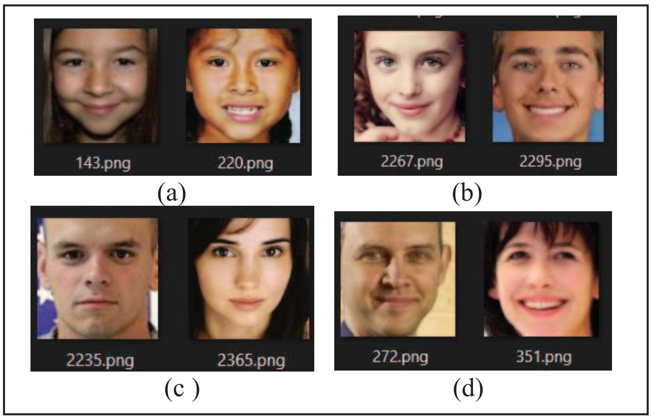

Fig. 1. Face recognition dataset (a) 10 years, (b) 15 years, (c) 25 years, (d) 40 years [14]

The results showed that the participants' mean age was 71 years using IOS users. There are eight women and twelve men. Performance analysis recommendations from older adults to design mHealth devices improve usability, and Apps for older adults generally show good usability and acceptance. Overall it will affect long-term behavior, for example, in people with disabilities or the elderly [15].

B. *Deep learning*

It is one of the machine learning algorithms whose algorithms are inspired by the structure of the human brain and carried out in depth. What needs to be considered is accuracy, training time, and level of stability.

C. *Residual Network*

It is one of the convolutional neural network architectures commonly abbreviated as ResNet. In its development, there are Resnet-18, Resnet-50, and Resnet-101 [16].

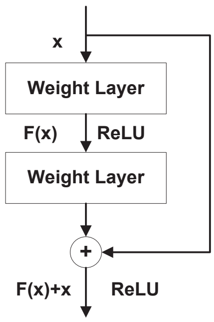

Fig. 2. Residual Network [17]

Residual network using skip connection or shortcut and features batch normalization, as shown in Fig. 2, allows training Neural Network with 152 layers. It can reduce complexity compared to VGGNet. The advantage of the ResNet model is that it does not decrease in performance even though the data types used have different characters and numbers, even though the learning architecture or layers are getting deeper. [18]. The coatings used in the Residual Network include:

- The Convolution Layer performs discrete multiplication between the source image matrix and the filter or kernel. The input matrix used has a size of [224 224 3], while the filter kernel has a length of 3x3, or 5x5.

$$h[x, y] = f[x, y] * g[x, y] \tag{1}$$

where $f[x, y]$=Matrix image, $g[x, y]$=matrix filter or kernel, and $h[x, y]$ =output convolution, x =rows, y=column [19].

- Batch normalization accelerates deep learning training by reducing internal covariate shifts.

$$output = \frac{W-N+2P}{S} + 1 \tag{2}$$

With W = Length of Input, N = High of Filter, P = *Zero padding,* and S = *Stride* [20].

- ReLU (Rectified Linear Unit) is a linear function that converts a negative value to 0 [21].

D. Confusion Matrix

It is a method to visualize the performance of predictive models in supervised learning. Each data from each class in the confusion matrix table shows the number of predictions made to classify the class as right or wrong, as shown in Fig. 3.

		Predicted Class	
		Positive	Negative
Actual Class	Positive	TP	FN
	Negative	FP	TN

Fig. 3. Confusion matrix [22]

Precision is the level of accuracy between the information and the results detected by the system [23].

$$Spesifity = \frac{TN}{TN+FP} \tag{3}$$

TN (True Negative) are those whose tests are negative and are not included in the class. FP (False Positive) is a collection of populations whose test results are positive when the population is not available in class [24].

Augmentation Data

Data augmentation is a strategy that allows practitioners to significantly increase the diversity of data available for a training model without collecting new data [25].

$$A=\begin{bmatrix} C_x & 0 & 0 \\ 0 & C_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

With C_x =scaling horizontal, C_y =scaling vertical, A=kernel for mounting. In addition, rotation, shears, and reflection are used [26].

E. Error Calculation

Accuracy is the similarity of the predicted value results with the actual value. It shows in Mean Square Error(MSE) and Means Absolute Area (MAE) [27].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \tag{5}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{6}$$

With N=number of sample data, j=indexing, y_j=actual label, and $\hat{y}_j$ Prediction label [28].

III. Research Methods

The research methodology is described according to the flowchart.

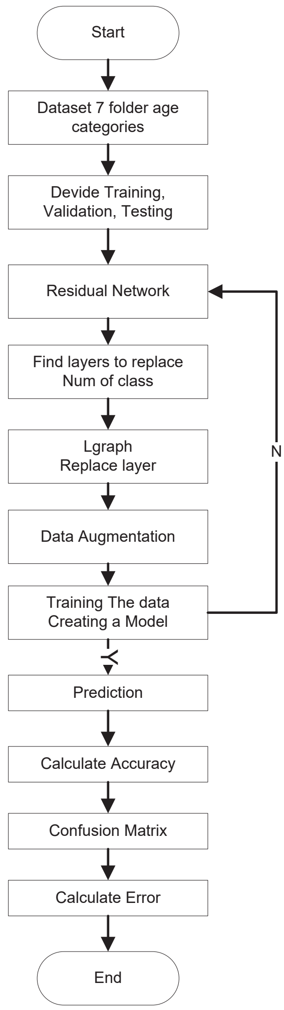

Fig. 4. CNN Residual Network Flowchart

Fig. 4 shows the classification process using a residual network where there is a layer update using graph and layer replacement so that the layer order becomes a priority when the weight changes to determine whether or not to skip the connection. It makes the residual network also work to reduce the computational load carried out by the parallel branch layer.

A. Dataset

The secondary dataset from Kaggle.com contains seven folders stating age; each folder contains 40 face images. Image size 200x200 pixels, with a depth of 24 bits. Data were taken from the link https://www.kaggle.com/datasets /frabbisw/facial-age. Meanwhile, according to Bappenas, the age group is under 15: Age group of children 1837 files, 15-24 years old: Young age group 1358 files. 25-34 years old: Age group of early workers 1336 files, 35-44 years old: Middle age group 858 files. 45-54 years: Pre-retirement age group 910 files, 55-64 years: Retirement age group 738 files, 65 years and over 1068 files: Elderly age group according to the link https://sepakat.bappenas.go.id/wiki/Kelompok_Usia. The composition is 80% data training, 20% data testing, and data validation 20%-80%.

B. Software and Hardware Requirements

The software used in this research is Matlab 2020. The hardware specifications are Intel Core i-7, 12GB RAM, and Nvidia Geforce GTX1050.

C. Training Parameter

The optimization training used is adam adam (adaptive moment), sgdm (gradient descent), and rmsprop (root mean square) with a learning rate of $3x10^{-4}$, minibatch size = 10, MaxEpochs = 30.

D. Trial Scenario

The test scenario in this research is to change the value of the training optimization and the value of the training parameters used. In addition, a trial was carried out by comparing the accuracy and computational time with other architectures.

E. Evaluation Process

Minimum Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

IV. Results and Discussions

The trial scenario is carried out by following the following steps::

A. Data Preparation

Preparation is done by checking all files used for the training process, and all data must have the exact file size dimensions with the same color depth level. In addition, age grouping is carried out so that the number of classes is not too many but focuses on what is sought, namely the range of age. All files in the folder are equal in size [200 200 3], which means a matrix with rows of 200 pixels in size, columns of 200 pixels, and a depth of 24 bits.

B. Data augmentation

In the Augmentation step, improvements are made to datasets that are not balanced in number. The actions performed are scaling, rotation, flip, and projection. This step is carried out to obtain various variations of the image dataset display that will be used. Namely, the augmentation process will balance data groups that do not meet their top class through the augmentation process. The amount of augmented data cannot be determined, meaning that if more data is lacking in a class, the amount of data created will increase.

There are four techniques include scale, rotation, shears, and reflection. All data that will be processed by training is processed first before the process is carried out to get the model. The Matlab source code definition is shown in Fig. 5

```
augmenter = imageDataAugmenter( ...
        'RandRotation',[0 90], ...
        'RandScale',[0.5 1], ...
        'RandXScale',[1 1])
imageSize = [224 224 3];auimds =
augmentedImageDatastore(imageSize,imdsTrain,'DataAug
mentation',augmenter)
minibatch = preview(auimds);
imshow(imtile(minibatch.input));
```

Fig. 5. Source code program of data augmentation

The Output of the program has shown in Fig. 6

(a) (b)

Fig. 6. Data Augmentation (a) Scale (b) Rotation

C. Training Process

The training on the CNN residuals shows that the training process required to obtain the model is around 300 minutes, with an accuracy of about 99.08%. This training process takes a long time, considering that of the seven classes observed, it has about 1.157 data in each folder or about 8.105 data.

D. Confusion Matrix

The training process results are then compiled to obtain a learning model. The step is to map each class image to the appropriate class; some are wrong or inappropriate classes, as shown in Fig 7.

Fig. 7. Confusion Matrix

E. Prediction

The training results are arranged and formed as a model and become a reference at this stage. From Fig. 8, the first picture, if beliefs are 40.9%, there is a possible test image inserted into the wrong class.

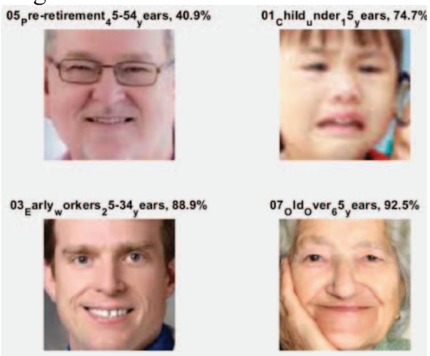

Fig. 8. Prediction test 01

The second picture of small children is 74.7% correct. In the third picture, workers 25-34 years, 88.9% are valid, and the fourth picture is in the elderly category with a confidence level of 92.5% correct.

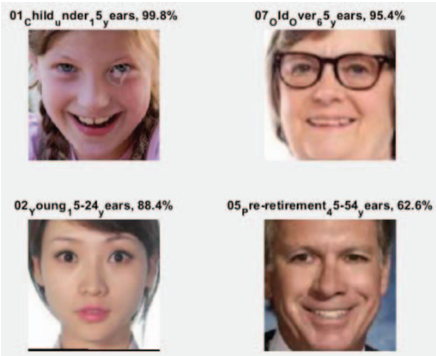

Fig. 9. Prediction test 02

In prediction test 02, Fig 9, the result shows a prediction of the children is correct at 99.8%, the second picture of older men with believes 95.4%, the third picture of girls 15-25 years right with believes 88.4%, and the last pre-retirement man 45-54 years with feels 62.6% is correct.

F. Classification Error Rate Measurement

After getting the prediction results, the error rate can be calculated by compiling the confusion matrix. Root Mean Square (RMSE) :

$$RMSE = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}(y_k - \hat{y}_k)^2} \quad (7)$$

With N_d = number of sample data, i=indexing, y_k =actual label, and $\hat{y}_k$ = Prediction label. This error calculation is needed to find out how much precision is built.

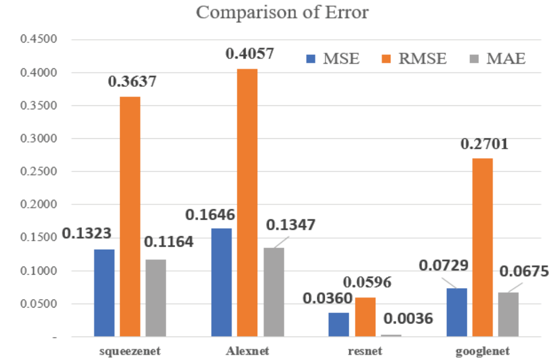

Fig. 10. Error Comparison

The comparison results in Fig. 10 show the MSE, RMSE, and MAE values from comparing with three other architectures used in the scenario, including squeezenet, alexnet, and googlenet. The result shows resnet-50 is better. The model accuracy value is 99.08%, and the training process's computation time shown in Fig. 11 is 300 minutes. Testing time using data experiments after a model has been built needs a second.

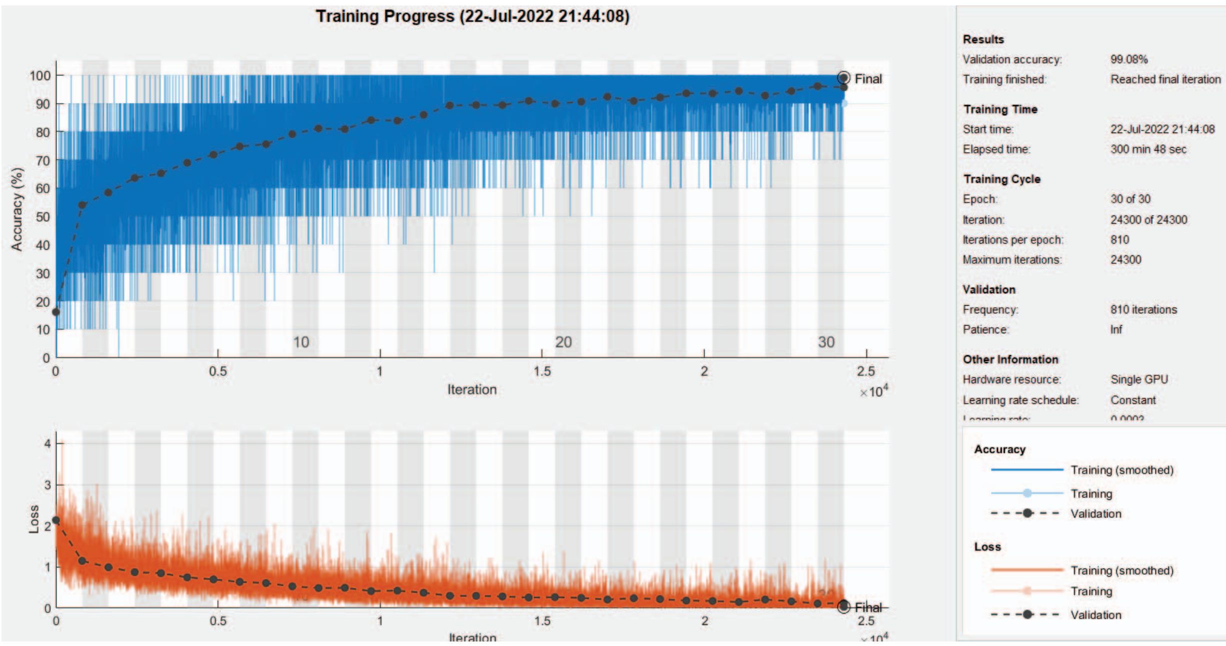

Fig. 11. Training Residual Network CNN

V. CONCLUSION

The results show that the system can recognize facial objects well and classify the visitor's face based on their age range. The method used is deep learning with resnet-50 architecture. The method selection is based on the data format: faces with seven folders, each class totaling 1068 data. Resnet has a skip connection, so it helps ease computing during the training process. The results obtained are models with an accuracy of 99.08% with an average value of MSE 0.0037, RMSE 0.0610, and MAE 0.0037. The computation time required is around three hundred minutes, while in the testing process, the needed average time is 2 seconds.

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