International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Age Identification Through Facial Images Using Gabor Filter and Convolutional Neural Network (CNN)

Zahra Nabila Izdihar[1], Simeon Yuda Prasetyo[2], Samuel Philip[3], Sani Muhamad Isa[4]

Submitted: 12/11/2022 **Accepted:** 16/02/2023

Abstract: Age prediction plays a very important role in helping prevent document falsification, identity fraud, age theft cases or other crimes. This research uses CNN to predict age, because CNN has a better performance in facial recognition. Then, the researcher also changed the filter in CNN using a Gabor filter to extract facial features to predict age. The Gabor filter method is often used in texture analysis because it is effective in recognizing patterns. Therefore, the Gabor filter method is known as a successful feature detector because it has the ability to eliminate facial variability. This research uses 8 types of experiments (CNN model only or a combination of CNN and Gabor filters) by comparing 4 types of CNN architecture, namely Standard CNN, VGG16, VGG19 and ResNet50. The best accuracy results are obtained from the VGG19 model which has an MAE value of 5.8235 with an execution time of 15 minutes 24 seconds. While the lowest computation time is obtained from the VGG16+Gabor model which is 7 minutes 4 seconds. Of the eight experiments that have been carried out, the Gabor filter has the advantage that it always has a lower computation time so that the Gabor filter is proven to be more efficient in predicting the age.

Keywords: *Age estimation, Computer Vision, CNN, Deep Learning, Face Recognition, Gabor filter*

1. Introduction

Technology can take advantage of the physical part of humans to identify a person. One of the physical parts that can be used to identify a person is the human face. The face is an important factor in identifying humans because the face is a multidimensional visual model of humans that can show a person's identity or emotions. On the other hand, humans have the ability to recognize thousands of faces and identify them with visual memory, but humans have limitations in remembering and recognizing changes in each human face. This is because changes in human visual appearance can be caused by several factors, such as aging, expressions, poses, illumination and other disturbances such as the use of glasses or changes in hairstyles [1]. Therefore, it is necessary to identify faces using face recognition technology. Human face identification is easier to do because facial image data is more widely available to the public compared to other human physical parts.

However, face recognition has a weakness, namely face identification must use a 1 to N matching technique. While the number of people is very much in one country. This of course will make it difficult to do facial recognition. So, face recognition will be more difficult to do when the number of N is increasing. Therefore, it is necessary to identify faces with more specific data, namely using facial image data based on age [2].

[1] Computer Science Department, BINUS Graduate Program, Bina Nusantara University – 11480, Jakarta, Indonesia
ORCID ID : 0000-3343-7165-777X
[4] Computer Science Department, School of Computer Science, Bina Nusantara University – 11480, Jakarta, Indonesia
** Corresponding Author Email: Zahra.izdihar@binus.ac.id*

In this study, identification was done through facial recognition based on age. Recognizing a person's face through age plays a very important role in preventing identity falsification in the form of age, falsification of important documents, identification of biometric passports, as well as preventing other crimes related to age. Therefore, research on age identification plays a very important role in identifying a person's identity.

Previously, several studies have been conducted on facial pattern recognition to identify age. However, these studies do not use the dataset used in these studies, it's just that the topic is the same.

One of the studies that predicts age uses public face databases and several Convolutional Neural Network (CNN) architectures. This research resulted in an accuracy of age prediction (regression), namely AlexNet with an MAE value of 8.98, VGG-16 with an MAE value of 7.77, ResNet-152 with an MAE value of 7.82, and Wide ResNet-16-8 with an MAE value of 7.52 [3]

Then, another similar study estimated the age of single person photos using the Convolutional Neural Network (CNN or ConvNet) and resulted in an overall prediction accuracy of 57% [4]

Then previously, there were also several studies that used the Gabor filter, but only to classify age instead of predicting age, and of course also used a different dataset from this study. One of them is research on age classification which has been categorized into several age groups (toddlers, adolescents, children, adults, elderly and seniors) from 250 facial images using ANN and Gabor filters. The results of this study resulted in an accuracy of 83% [5].

Therefore, based on previous studies, the researcher finally applied the Gabor filter in CNN to predict age because this second combination, namely CNN + Gabor filter, has never been used in other research cases related to age prediction, it has only been used for age classification.

The reason the CNN method was chosen is because CNN has better performance in face recognition and it has been proven in previous studies that it can produce better accuracy in the case of age prediction. The Gabor filter applied in the CNN model functions to extract facial features from the image dataset in this study. Features are things that distinguish an object, such as size, shape, composition, location, and so on [6]. The purpose of feature extraction is to find significant feature areas in an image that depend on intrinsic characteristics.

Gabor filter is a feature extraction technique that is often used in feature recognition [7]The gabor filter method connects the optimal representation of the direction of orientation with frequency (spatial domain). Gabor filter method is often used in voice detection, iris, fingerprints, texture analysis because it is effective in recognizing patterns. Therefore, the Gabor filter method is known as a successful feature detector because it has the ability to eliminate facial variability. Another advantage of using the gabor filter is that it is able to present images in angular orientation and frequency, so that the resulting image extraction will be more detailed [8].

2. Methods

In this study, researchers used the CNN method to identify age, because CNN has a better performance in face recognition. Then, this research will compare several CNN architectures such as CNN standards, VGG16, and VGG19.

The stages of this research consist of several stages, namely literature study, problem identification, identification of objectives, data collection, data pre-processing, and model development. After the deployment process is complete, it is then evaluated using MAE to measure the accuracy of the model. If accuracy has been reached, the predicted result image will appear.

At the initial stage, a literature study was conducted which aims to conduct a literature review to find out various problems related to the research topic and the solutions that have been used, which can be used as a reference for research topics. After that, they conducted a review of journals related to the topic of age identification research and theories regarding the Deep Learning method. Next, the problem identification stage is carried out which aims to identify problems related to the research topic and determine research objectives and find solutions to these problems. Then, collect data where the dataset used is a face image with a size of 48x48 pixels obtained from Kaggle. After that, the data is pre-processed so that it can be used to create a model. Then, carry out the implementation by creating a prediction model and evaluating the research results

2.1. Data Collection

The dataset in this research was obtained from Kaggle which was published in 2021 where the data is stored in the form of a csv file. The data contains thousands of grayscale images of human faces. The dataset consists of 27.305 rows and 5 columns consisting of “age”, “ethnicity”, “gender”, “img_name” & “pixels” (array to string of the image pixels). The "Gender" attribute consists of 2 labels, namely 0=Male and 1=Female. While the attribute "Ethnicity" there are 5 labels namely Asian, Black, Hispanic, Indian and White. Then for the age attribute, it consists of data ranging from 1 year to 116 years old.

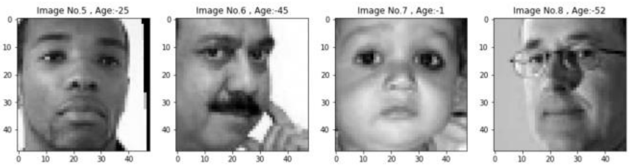

Fig 1. Sample of Facial Images

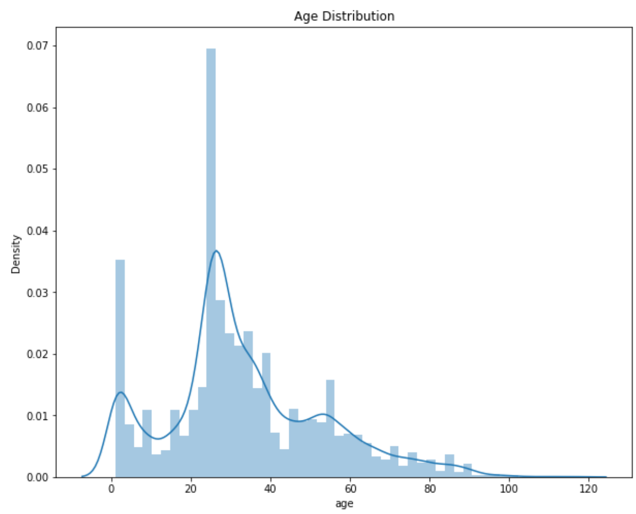

Fig 2. Age Distribution

Figure 2 shows the total distribution of age data. The highest amount of data is in the age range of 20-40 years.

2.2. Data Pre-Processing

The initial data processing that will be carried out in this study is the facial image dataset which will be divided into two parts, namely training data and testing data. The next process is data normalization and pre-processing the data by resizing the data to 48x48 pixels for the CNN architectures. The next process is training by determining the model to be used and the parameter list to be determined such as the learning rate and the number of training epochs. In this process the accuracy will be calculated using MAE and time execution. Then the testing process will be carried out after the training process is complete by providing testing data, so that an evaluation can be carried out to measure the accuracy of the CNN model performance. To train the performance of the CNN model, this study uses the open source frameworks Tensorflow and Keras.

2.3. CNN (Convolutional Neural Network) Model

Convolutional Neural Network (CNN) is the development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the type of Deep Neural Network because of its high network depth and widely applied to image data.

The main layers to build a CNN architecture are Convolutional Layer (CONV), ReLU, Pooling Layer (POOL), and Fully-Connected Layer (FC) [9]. The convolution and pooling layers are layers that aim to study features in the image, while the fully connected layer will perform image identification.

In general, the CNN architecture is divided into 2 major parts, the Feature Extraction Layer and the Fully-Connected Layer (MLP). The process that occurs in this section is "encoding" from an image into features in the form of numbers that represent the image (Feature Extraction)

The VGGNet architecture was popularized by Simonyan and Zisserman in their 2014 research paper [10]Visual Geometry Group (VGG), was runner up for ILSFRC 2014. The VGG architecture consists of two convolution layers, both of which use the ReLU activation function. Following the activation function is the single max pooling layer and several fully connected layers also use the ReLU activation function. The last layer of the model is the Softmax layer for classification. In VGG-E the size of the convolution filter is changed to a 3x3 filter.

Three models VGG-E, VGG-11, VGG-16, and VGG-19; proposed a model in which each has 11, 16, and 19 layers. All versions of the VGG-E model end up with three fully connected layers. However, the number of convoluted layers varies. VGG-11 consists of 8 convolution layers, VGG-16 has 13 convolution layers, and VGG-19 has 16 convolution layers. The VGG-19, the most expensive computing model, weighs 138 million and has 15.5 million MAC.

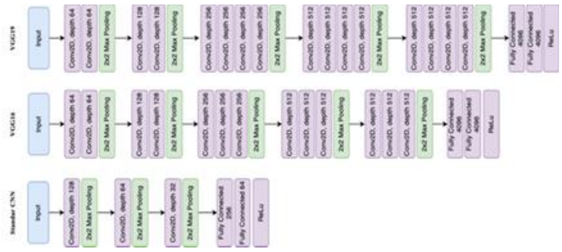

Fig. 3. CNN Architectures (CNN Standard, VGG16 and VGG19)

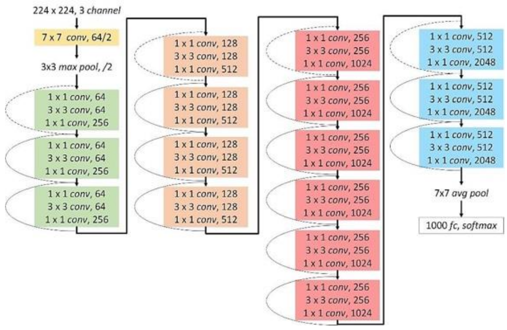

Fig. 4. ResNet Architecture

Figure 3 and Figure 4 show the structure of the CNN architectures used in this study.

2.4. Gabor Filter Implementation

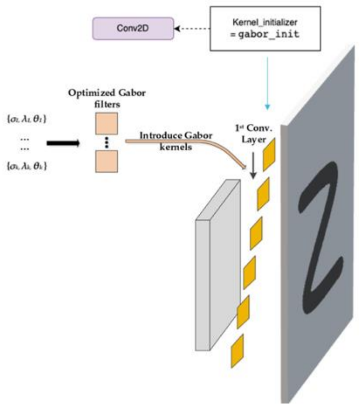

Fig 5. Illustration of Implementation the Gabor Filter in the CNN model

Figure 5 illustrates the process of changing the Gabor Filter into the existing filter in CNN. So, this Gabor filter replaces the existing Glorot_uniform filter in CNN and the Gabor filter will be applied in the Kernel_initializer on the Convolution layer. In addition, the size of the Gabor filter will automatically be adjusted to the length and width of each filter in the convolution layer according to the CNN architecture and this study uses a 3x3 filter.

Then, after all the CNN architectural designs have been designed, the next step is to train the model. The Gabor filter will be implemented into the CNN model where the Gabor filter will be implemented in the Kernel_initializer on the

CNN architecture, then a training process is carried out using the age dataset.

3. Experimental Results dan Evaluation

The accuracy value of a model can be determined after the model parameters have been studied and improved until the training process has been completed. Then, testing and evaluation is carried out. In the evaluation stage, the number of errors made by the model will be compared with the actual target. Then, the percentage of misclassification is calculated.

In the training process, there is a division of the dataset into training, validation, and testing data with a percentage of 80% training, 10% validation and 10% testing.

3.1. Experimental Results

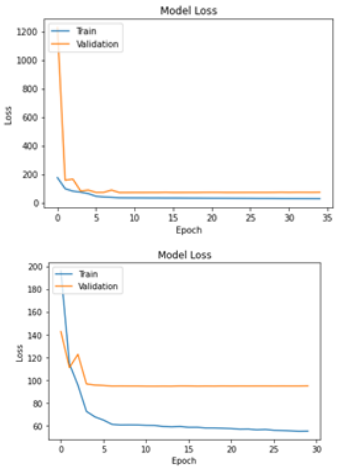

Fig. 6. The Loss Graph of the Standard CNN (Left) vs Standard CNN+Gabor filter (Right)

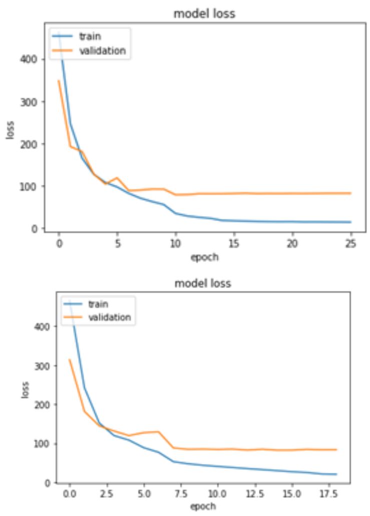

Fig. 7. The Loss Graph of the VGG16 architecture (Left) vs VGG16 + Gabor filter (Right)

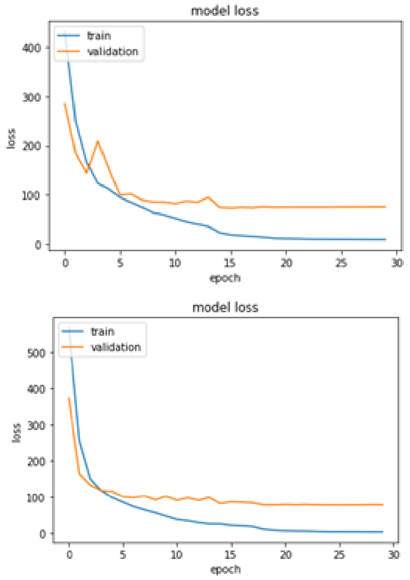

Fig. 8. The Loss Graph of the VGG19 (Left) vs VGG19 + Gabor filter (Right)

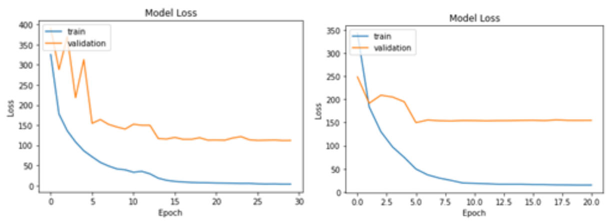

Fig. 9. The Loss Graph of the ResNet50 (Left) vs ResNet50 + Gabor filter (Right)

Loss Graph of Fig. 6, Fig. 7, Fig. 8 and Fig. 9 shows the Loss value of the prediction model using the Standard CNN, VGG16, VGG19 and ResNet50 architectures. From the four images it can be shown if it has converged at a certain epoch and it has reached the lowest MAE value for the training and validation models.

3.2. Model Evaluation

This study uses several architectures in CNN such as CNN Standard, VGG16, VGG19 and ResNet. In addition, the four architectures are also combined by replacing the existing filters in CNN with the Gabor filter. So there will be 8 types of experiments in this study. Then, we will see a comparison of the performance of the 8 types of experiments to be able to see how good the results of the architectures of the resulting prediction model are. In addition, the results of applying the Gabor filter to the CNN model will also be seen.

Table 1. Comparative Evaluation of Results from Experiments

Model	Loss	MAE	Time Execution
Standard CNN	74.3299	6.2128	1 hour, 55 mins, 7 secs
GABOR + Standard CNN	87.4337	6.8168	1 hour, 17 mins, 22 secs
VGG 16	72.6596	6.1170	7 mins 40 secs
GABOR + VGG 16	79.4300	6.3804	7 mins 4 secs
VGG19	69.8154	5.8235	15 mins 24 secs
GABOR + VGG 19	71.6733	5.9027	15 mins 23 secs
ResNet50	109.1317	7.2271	10 mins 28 secs
ResNet50 + Gabor	155.3902	8.6633	7 mins 14 secs

Table 1 displays the Loss, MAE and computation time values of the 8 experiments that have been carried out. From Table 1 it can be seen that the lowest Loss and MAE values are obtained from the VGG19 Model, which produces an MAE value of 5.8235 and a Loss of 69.8154 with a computation time of 15 minutes 24 seconds. The second best result was obtained from the VGG19+Gabor model which has an MAE value of 5.8235 and a Loss value of 69.8154. But on the other hand, in terms of computation time, VGG16+Gabor is superior in time efficiency because it has the lowest computation time.

From the comparison table it can be concluded that the computation time of models that only use CNN always takes longer, compared to models that use Gabor filters. Therefore, the Gabor filter is more efficient in predicting age using a dataset of 27,300 images.

4. Conclusion

This study examines how the use of the Gabor filter can affect the performance of age prediction on the CNN model that has been created. The best age prediction results are using the VGG19 architecture without using the Gabor filter which produces an MAE value of 5.8235 and a computation time of 15 minutes 24 seconds. The second best result was obtained from the VGG19+Gabor model which has an MAE value of 5.8235 and a Loss value of 69.8154. But on the other hand, in terms of computation time, VGG16+Gabor is superior in time efficiency because it has the lowest computation time, which is 7 minutes 4 seconds.

However, there are other findings, namely that the Gabor filter can produce better age predictions for certain categories such as facial images of men aged 20-40 years, when compared to just using regular CNN without using the Gabor filter. This study also found that the Gabor filter also always has a much faster time efficiency in the four CNN architectures (Standard, VGG16, VGG19 and ResNet50) that have been used to predict age, even with a very large amount of data, namely around 27,300 images.

5. References and Footnotes.

Acknowledgements

This research was supported by BINUS University. We thank our colleagues from BINUS University who provided insight and expertise that greatly assisted the research, although they may not agree with all of the interpretations/conclusions of this paper. We thank Simeon Yuda Prasetyo and Samuel Philip for assistance with coding and methodology, and Sani Muhamad Isa for comments that greatly improved the manuscript.

Author contributions

Zahra Nabila Izdihar: Conceptualization, Methodology, Data curation, Writing-Original draft preparation, Implementation

Simeon Yuda Prasetyo: Coding, Implementation, Validation

Samuel Philip: Data Visualization, Writing-Reviewing and Editing.

Sani Muhamad Isa: Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] W. Liu, L. Chen, and Y. Chen, “Age Classification Using Convolutional Neural Networks with the

Multi-class Focal Loss," in *IOP Conference Series: Materials Science and Engineering*, Oct. 2018, vol. 428, no. 1. doi: 10.1088/1757-899X/428/1/012043.

[2] H. Tin, "Subjective Age Prediction of Face Images Using PCA," *International Journal of Information and Electronics Engineering*, 2012, doi: 10.7763/ijiee.2012.v2.102.

[3] K. Ito, H. Kawai, T. Okano, and T. Aoki, "Age and Gender Prediction from Face Images Using Convolutional Neural Network," in *Asia-Pacific Signal and Information Processing Association APSIPA) Proceedings*, Nov. 2018, pp. 1–11.

[4] A. M. Abu. Nada, Eman. Alajrami, A. A. A. l-Saqqa, and S. S. Abu-Naser, "Face detection in color images," *IEEE Trans Pattern Anal Mach Intell*, vol. 4, no. 8, pp. 21–24, May 2020, doi: 10.1109/34.1000242.

[5] A. N. Rohmah, D. Putra Pamungkas, and A. B. Setiawan, "Implementasi Ekstraksi Ciri Filter Gabor Dan Ann Dalam Klasifikasi Citra Wajah," 2021.

[6] H. el Khiyari and H. Wechsler, "Age Invariant Face Recognition Using Convolutional Neural Networks and Set Distances," *Journal of Information Security*, vol. 08, no. 03, pp. 174–185, 2017, doi: 10.4236/jis.2017.83012.

[7] A. Syarif, A. R. Tanjung, R. Andrian dan, and F. R. Lumbanraja, "Implementasi Metode Ekstraksi Fitur Gabor Filter dan Probablity Neural Network (PNN) untuk Identifikasi Kain Tapis Lampung," *Jurnal Komputasi*, vol. 8, no. 2, 2020.

[8] Lussiana ETP, S. Widodo, and D. A. Pambayun, "Penerapan Filter Gabor untuk Analisis Tekstur Citra Mammogram," *Seminar Nasional Aplikasi Teknologi Informasi*, pp. 17–18, 2011.

[9] B. Muharom, H. Hidayat, and R. E. Putra, "Penerapan CNN dengan Filter Gabor sebagai feature extractor untuk Content-Based Image Retrieval," 2019.

[10] A. Dhomne, R. Kumar, and V. Bhan, "Gender Recognition Through Face Using Deep Learning," in *Procedia Computer Science*, 2018, vol. 132, pp. 2–10. doi: 10.1016/j.procs.2018.05.053.