Gender Recognition - Check

by W navitas

Submission date: 30-Sep-2023 02:05PM (UTC+1000)
Submission ID: 2181144179
File name: 068_Wahyudi_cek.pdf (479.64K)
Word count: 4090
Character count: 21949

Gender Recognition Based on Face Image Using Deep Learning Method

1st Mochamad Wahyudi
Departement of Computer Science,
Universitas Bina Sarana Informatika,
Jakarta, Indonesia
wahyudi@bsi.ac.id

2nd Waeisul Bismi
Departement of Computer Science,
University Bina Sarana Informatika,
Jakarta, Indonesia
waeisul.wbn@bsi.ac.id

3rd Firmansyah
Departement of Computer Science,
University Bina Sarana Informatika
Jakarta, Indonesia
firmansyah.fmy@bsi.ac.id

4th Mugi Raharjo
Departement of Informatics,
University Nusa Mandiri,
Jakarta, Indonesia
mugi.mou@nusamandiri.ac.id

5th Untung Rahardja
Departement of Digital Business
University Raharja
Tangerang, Indonesia.
untung@raharja.info

6th Lise Pujiastuti
Departement of Information System,
STMIK Antar Bangsa
Tangerang, Indonesia.
lise.pujiastuti@gmail.com

***Abstract*— Gender recognition based on facial images is one of the interesting applications in the field of image processing and artificial intelligence. Deep Learning methods, particularly artificial neural networks, have emerged as an effective tool for extracting complex facial features and classifying gender with high accuracy. This research outlines a study that aims to develop an employee gender recognition system based on facial images using Deep Learning methods. The method used in this study proposes the inceptionV3 model as well as the OpenCV and matplotlib libraries in Python in involving the collection of facial image datasets covering different genders with a total of 1024 facial images, each with 40 attributes. This dataset was used to train a deep artificial neural network to recognize patterns and features that are unique to male and female genders and validated. Furthermore, the artificial neural network was tested with a dataset of never-before-seen facial images to evaluate the performance of the system. The results show that the InceptionV3 Deep Learning model has great potential in gender recognition based on facial images. The developed system was able to achieve a high level of accuracy in classifying the gender of individuals from facial images with a total accuracy of 94.8% against the test data, even in complex situations such as variations in facial expressions and lighting.**

Keywords—Gender recognition, Deep learning, InceptionV3

I. Introduction

Over time, facial image-based gender recognition is one of the important applications in the field of image processing and artificial intelligence. Technological advances in Deep Learning methods have opened up new opportunities to develop systems capable of automatically and accurately identifying the gender of individuals using only facial images that are included in biometric systems that utilize unique body parts to distinguish one person from another [1]. Biometrics comes from the Greek words bios, meaning life, and metron, meaning measurement. Biometrics is a method of recognizing people based on one or more unique physical or behavioral characteristics [2]. Gender recognition technology has now been widely used in various applications, including biological data recognition, searching and indexing digital image and video databases, and room security. Utilizing biological data, such as voice, face, fingerprints, or eyes, can provide information regarding the identification of each individual and distinguish them from others. Among these physical characteristics, the face is one of the most important differentiators of an individual's identity [3]. Biometric systems have been used for identification and verification purposes for a long time. These systems rely on a person's physiological and behavioral characteristics to recognize or prove their identity. Physiological characteristics include physical traits such as facial recognition, fingerprints, iris recognition, and hand geometry, while behaviors include handwriting, voice recognition, and signature recognition [4].

In the context of human resource management, employe gender recognition based on facial images can provide useful information for workforce analysis and human resource policies. Companies can use this system to monitor gender comparisons in different departments, so as to identify gender imbalances and take appropriate measures to encourage diversity. On the other hand, in the field of security, gender recognition systems based on facial images can be used to identify individuals trying to access restricted areas or sensitive data. There are a number of challenges that need to be overcome in the development of a facial image-based gender recognition system for employees. Some of these challenges include:

- Variability in Facial Imagery: Facial images can vary in many aspects, such as lighting, facial expression, and viewing angle. The system must be able to cope with these variations to get accurate results.
- Privacy Issues: The use of this technology must take into account privacy issues and strict data policies. Employee facial image processing should be done with due regard to privacy rules.
- Accuracy: The accuracy rate in recognizing gender should be very high, especially if the system is used in the context of security or human resource policies.
- Gender Comparison: The system should be able to recognize gender well, regardless of differences in ethnicity, age, or physical features of individuals.

By understanding these challenges, further research and development in gender recognition based on employee facial images using Deep Learning methods is warranted.

II. Material and Methods

A. Research Method

This study uses Deep Learning methods with a model built from Inceptionv3 to perform gender recognition based on employee facial images. The method proposed in this study can be described as shown in Figure 1.

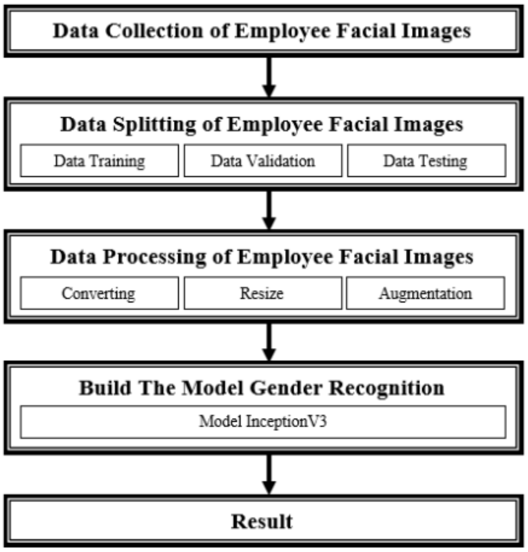

Fig. 1. Research Method.

B. Dataset

Face recognition is a personal identification system that uses a person's facial characteristics [5] . In this study, the dataset used in gender recognition is obtained from GENFACEES [6]. This dataset is a collection of facial attribute data with a total of 1024 employee images, each with 40 annotation attributes, the attribute label for each image "1" represents positive while "-1" represents negative [7]. The images in this dataset include a variety of female and male employee face images as well as a wide variety of poses and backgrounds. There are however more images of the Female gender than the Male gender in the data set. This gave us some insight into the need to balance the data in the next step. The following example of the employee face image used can be seen in Figure 2.

Fig. 2. Example Image of GENFACESS Dataset

The following is a Table 1 of attribute labels from each face image totaling 40 attributes which can be seen in table 1, as for the attribute value of each face image, namely 1 "represents positive while "-1" represents negative [7].

TABLE I. ATTRIBUTES OF EACH FACE IMAGES

No.	Attribute	No.	Attribute
1	Men	21	Oval Face
2	Women	22	Pale Face
3	Bald	23	Mouth slightly open
4	Bangs	24	Smile
5	Brown Hair	25	Bearded
6	Black Hair	26	Mustache
7	Gray Hair	27	Bearded
8	Blonde Hair	28	Glasses
9	Straight hair	29	Wearing a Hat
10	Curls	30	Wearing Lipstick
11	Curved Eyebrows	31	Wearing a Necklace
12	Thick Eyebrows	32	Wearing a Tie
13	Slanted eyes	33	Wearing Earrings
14	Bags of Eyes	34	Heavy makeup
15	Big nose	35	Wearing a Veil
16	Long nose	36	Old
17	Big lips	37	Young
18	Double chin	38	Fat
19	High cheekbones	39	Interesting
20	Cheek redness	40	Opaque

C. Splitting Data

In this study, we need to balance the number of images in each category (e.g., gender) so that the model is not biased toward a particular category. To accomplish this, the dataset is divided into three sets. Training data, validation data, and test data. The number of images in each set is determined based on model run time and dataset size.

The training set is used to train the model on the data set, the validation set is used to tune the model's hyperparameters to prevent overfitting, and the test set is used to check the model's performance on unseen data. used for evaluation. The data set is randomly partitioned into these sets so that the model generalizes well to new data. Balancing the number of images in each category and using well-designed dataset partitioning can improve model performance and avoid bias toward specific categories [8]. In addition, the uniform image size can also facilitate the recognition stage. Next, enter the data distribution which can be seen in Table 2.

TABLE II. SPLITTING DATA

Image Id	Data
1- 820	Training
821 - 922	Testing
923 - 1024	Validation

Based on Table 2, the training and validation data is used in the process of training, tuning, and evaluating the model while the test data is used to test the performance of the training model. After obtaining an image with a uniform size and distribution of image data, then enter the classification stage.

D. *Pre-Processing*

Preprocessing is the initial stage of image data processing that aims to prepare the data to be processed by the model [9], which is an important step in improving image quality by reducing noise and enhancing relevant features, ultimately resulting in better model performance. Proper pre-processing can make the desired features in the image more prominent, which is essential for accurate classification. Before classification, a pre-processing analysis of the input data is performed to ensure the data is suitable for the model [10]. In the pre-processing of this study, the following are some steps to ensure that the input data is standardized and has enough variation to help the model generalize well to new data.

- Converting

Color image can be known from its constituent components, namely Red-Green-Blue. The basic colors of RGB are Red, Green, and Blue, each of which states the maximum value of its composition of 255. For example, if the color is red, then the matrix is [255 0 0], and so on. as well as for green and blue colors, respectively [0 255 0] and [0 0 255]. The RGB color standard is widely applied in image processing, but in OpenCV it is slightly different, namely Blue- Green- Red (BGR) to separate objects/subjects from their backgrounds [11] and aims to provide more color information to the image [12].

- Resize

Adjusting image dimensions refers to the steps to change the width and height of an image. This process is of high significance as the image may have various dimensions and if the dimensions are too large, it may interfere with the performance of the system during the subsequent processing stages [13]. The GENFACEES dataset has a variety of image dimensions, the step of changing the dimensions to 178 x 218 pixels is performed to ensure that all images have a uniform size, so that dimensional differences that may hinder system performance can be minimized [14].

- Augmentation

Enhancement is a process of processing image data, enhancement is the process of changing or editing an image in such a way that the computer detects the changed image as a different image, but humans can still know that the edited image is the same [15]. In training deep learning models, Augmentation helps to improve the collection of images, especially when there is a lack of sufficient image data. This technique is essential for achieving better testing accuracy and generating balanced data. Therefore, image data augmentation is an important step in the training process [16]. At this stage, image data augmentation is performed, as the original data is generated from the aggregated image data. The techniques implemented on image data include Rotation, Shift, Zoom, and Flipping. The following example of a face image that has been aggregated can be seen in Figure 3.

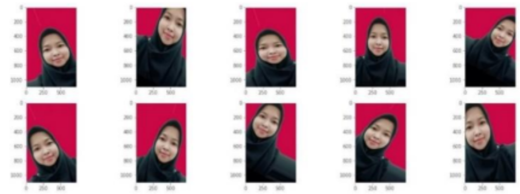

Fig. 3. Example of Augmented Image

E. *Deep Learning Models*

Deep learning is a field of machine learning based on artificial neural networks (JST) [17]. With the rapid development of deep learning innovations and improvements in computing power, deep learning has become widely used in the field of image classification [12]. In common, profound learning strategies frequently contain numerous trainable parameters and require a huge number of labeled tests to realize ideal execution, particularly convolutional neural organize (CNN) investigation [6].

The CNN show was to begin with created beneath the title NeoCognitron by Kunihiko Fukushima, a analyst from NHK Broadcasting Science Inquire about Research facilities, Kinuta, Setagaya, Tokyo, Japan [18]. The CNN Architecture model used in this research is the Inceptionv3 architecture model which uses several filters in its convolutional layer and this architecture is a model of a deep convolutional network developed by Google to follow the ILSRVC (ImageNet Large Visual Recognition Challenge) in 2012 [19], which can be seen in Figure 4.

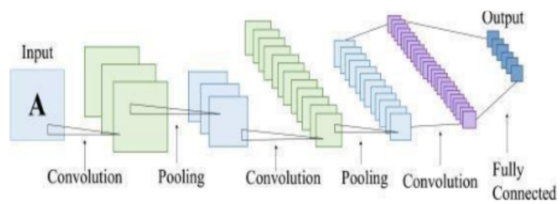

Fig. 4. InceptionV3 Model

III. RESULTS AND DISCUSSION

A. *Deep Learning Concepts*

Profound Learning calculation which is the advancement of Multilayer Perceptron (MPL) planned to handle information in two-dimensional shape [17], Multilayer Perceptron (MLP) implementation requires hidden layer parameters, activation, solver, and the maximum number of iterations while Convolutional Neural Network (CNN) implementation uses a hard library [20] CNN linear operations use convolution operations in the form of four dimensions, where the weights represent a collection of convolution kernels, rather than one dimension. The dimensions of CNN weights are input neurons x output neurons x height x width. [21]. The following example of MLP architecture and convolution process in CNN can be seen in Figure 5.

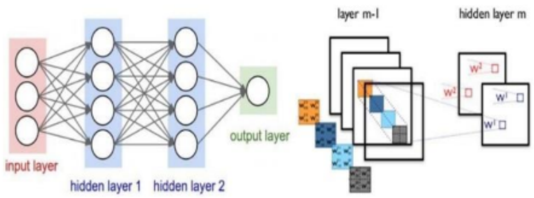

Fig. 5. MLP Architecture and Convulsive process in CNN

B. Deep Learning Architecture

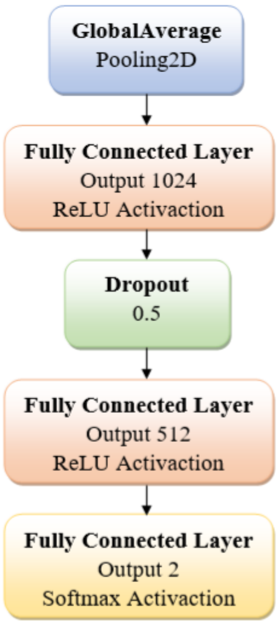

Fig. 6. Layers to be trained with the new model.

A JST consists of multiple layers and multiple neurons in each layer. This cannot be determined with exact rules and applies differently to different data. Based on its architecture, there are several main layers in CNN which can be seen in Figure 6. However, in this research only three layers are used, namely:

- Convolution Layer

The convolution layer performs the convolution operation on the yield of the past layer. This can be the most handle that underlies CNN. The weights of this layer decide the convolution part utilized so that the convolution bit can be prepared based on the input of the CNN. The objective of picture information convolution is to extricate highlights from the input picture. Convolution can make a straight transformation of the input information based on the spatial data contained within the information. The weights on the layer decide the convolution part utilized, so the convolution bit can be prepared based on the input of the CNN.

- Subsampling Layer

The method of decreasing the estimate of picture information. In picture handling, subsampling points to make strides the position invariance of highlights. Max pooling separates the yield of the convolutional layer into numerous little frameworks, at that point takes the greatest value of each lattice to make a compact picture framework. The results of the method can at that point be seen within the set of networks on the correct. Spangenberg et al. in their think about, they as it were utilized a pooling layer in a CNN to diminish the measure of the picture so that it can be effectively supplanted by a convolutional layer with the same walk as the pooling layer in address.

- Full Connected layer

The completely associated layer may be a layer commonly used in MLP applications and is expecting to convert the measurements of the information so that it can be classified in a direct way. Each neuron within the convolutional layer must to begin with be changed over to one-dimensional information some time recently it can be embedded into the completely associated layer. Since the information loses spatial data and is irreversible, a completely associated layer can as it were be conveyed at the conclusion of the organize. A convolutional layer with a part measure of 1 x 1 performs the same work as a completely associated layer but holds the spatial characteristics of the information.

The design of the profound learning show or CNN utilized in this ponder is the InceptionV3 design. The connected demonstrate can be seen in Figure 7

.

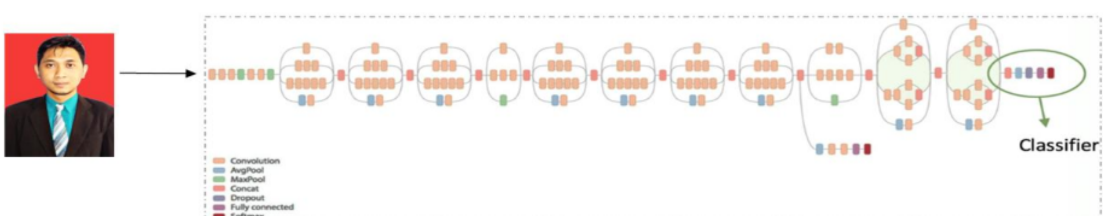

Fig. 7. InceptionV3 Model Architcture

C. Training Process

The preparing prepare is the organize where the CNN is prepared to urge higher exactness from the classification performed utilizing 820 representative confront pictures. At the arrange of the preparing handle, the bolster forward prepare and the backpropagation handle are carried out. To perform the feedforward prepare, the number and measure of layers to be shaped, the subsampling estimate, the vector picture gotten are decided. The result of the feedforward handle is the weight that will be utilized to assess the neural arrange process.

• Feedforward Process the feedforward prepare is the primary organize within the preparing prepare. This handle will deliver a few layers that are utilized to classify picture information utilizing weights and inclinations that have been overhauled from the backpropagation prepare.

• Backpropagation The backpropagation handle is the moment organize within the training handle. In this organize, as clarified, the comes about of the feedforward handle are traced from the yield layer to the primary layer.

• Angle Calculation The angle prepare for convolutional systems is the method of creating biast values and unused weights that will be required amid preparing.

D. Testing Process

The testing handle could be a classification handle that employments predisposition and weights from the comes about of the preparing prepare and the sum of data used for the 101 facial pictures. The most objective of the testing handle is to assess the execution, unwavering quality and in general quality of the framework or program that has been built, so that the conclusion result of this handle is the precision of the investigation. course is performed, the information that falls flat to be classified, the number of pictures that are not classified, and the shape of the arrange is shaped from the criticism prepare. The yield layer is totally associated to the existing name.

E. Validation Process

The validation process is an important stage to ensure that the resulting model can be used and produce relevant and accurate results and to obtain a level of confidence in the results of image interpretation [22] in facial image gender recognition. Validation is carried out using image data totaling 101 employee facial images.

F. Evaluation

By conducting a careful evaluation, this research will be able to determine the extent to which the Deep Learning method used is successful in gender recognition based on employee facial images. In the evaluation process, there are several parameters used for the IncepstionV3 model architecture in this study, the parameters used can be seen in Table 3.

TABLE III. PARAMETERS

Parameters	Description
Size (pixels)	178 x 218
Epoch	20 Epoch
Batch_Size	32
Optimizer	SGD
Learning_Rate	0.0001
Momentum	0.9
Loss	Categorical_crossentropy

The results of training and testing on the Inceptionsv3 model architecture using the GENFACESS dataset, get the results of the accuracy and loss curve or graph shown in Figure 8.

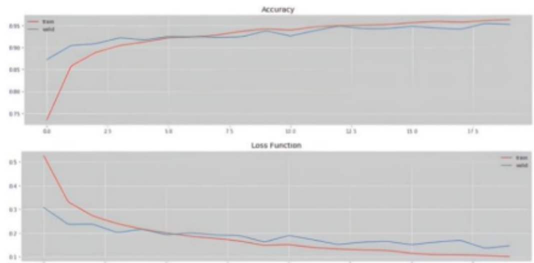

Fig. 8. Accuracy and Loss Graph Results

Based on the plot results on the applied inceptionsv3 model, it can be seen that training and validation increase close to a value of 1.0 as the epoch increases, resulting in a total accuracy of 94.8%. . Then, on the graph, the loss function value during the validation process is larger than the train loss function value during the process, which will be overfitting. And to know the classification efficiency, evaluation of the built model is performed as shown in Figure 9.

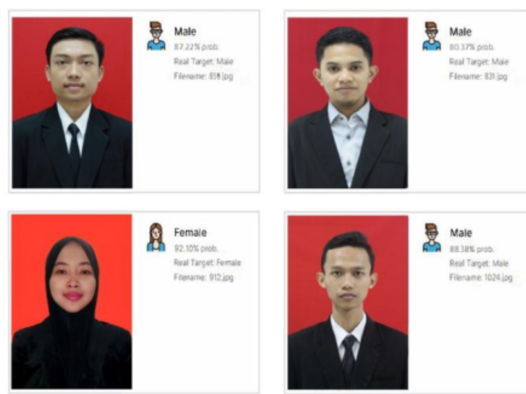

Fig. 9. Evaluation Results

IV. CONCLUSIONS

The results show that the model developed using the deep learning method with the InceptionV3 model base and the addition of a special layer can successfully identify gender in images that have certain characteristics with an accuracy rate of 94.8% when tested with the test dataset. However, there were some identified constraints and opportunities for improvement in the algorithm training process with the entire GENFACESS image dataset of 1024 images. Due to the limited computing resources available, the model was only trained with a small portion of the image dataset. With more powerful computing devices, the model can be trained with the entire image dataset, allowing it to gain a more comprehensive understanding of different types of images.

Thus, the model will be better trained to deal with images that it has never seen before. There is also the issue that most images almost exclusively feature the subject's face, which causes the model to be more accustomed to this type of image. In situations where the subject is only a small part of the image, the model is limited in its performance.

ACKNOWLEDGMENT

We thank the researchers for their hard work in successfully completing this research Gender Recognition Based on Face Image Using Deep Learning Method. We also thank colleagues who are willing to provide images or datasets for this study. Hopefully this research can be put to good use.

REFERENCES

[1] B. T. Wibowo and Kamilasari, "Sistem Identifikasi Wajah Manusia Berdasarkan Gender Dan Usia," *J. Teknol. Rekayasa*, vol. 22, no. 1, pp. 48–53, 2017.

[2] A. A. Andarinny, C. E. Widodo, and K. Adi, "Perancangan Sistem Identifikasi Biometrik Jari Tangan Menggunakan Laplacian Of Gaussian dan Ektraksi Kontur," *Youngster Phys. J.*, vol. 6, no. 4, pp. 304–314, 2017.

[3] R. A. Asmara, B. S. Andjani, U. D. Rosiani, and P. Choirina, "Klasifikasi Jenis Kelamin Pada Citra Wajah Menggunakan Metode Naive Bayes," *J. Inform. Polinema*, vol. 4, no. 3, p. 212, 2018, doi: 10.33795/jip.v4i3.209.

[4] abdul qowi Aziz, "Jurusan Teknik Elektro Fakultas Teknik Universitas Muhammadiyah Malang," *Digilibadmin.Unismuh.Ac.Id*, 2020.

[5] A. Budi, S. Suma'inna, and H. Maulana, "Pengenalan Citra Wajah Sebagai Identifier Menggunakan Metode Principal Component Analysis (PCA)," *J. Tek. Inform.*, vol. 9, no. 2, pp. 166–175, 2018, doi: 10.15408/jti.v9i2.5608.

[6] W. Bismi and M. Napiah, "Gender Face Of Employee," 2021. https://s.id/GenderFace-Of-Employess

[7] Z. Liu, P. Luo, X. Wang, and X. Tang, "Deep learning face attributes in the wild," *Proc. IEEE Int. Conf. Comput. Vis.*, vol. 2015 Inter, pp. 3730–3738, 2015, doi: 10.1109/ICCV.2015.425.

[8] P. Hensman and D. Masko, "The Impact of Imbalanced Training Data for Convolutional Neural Networks," *PhD*, 2015, [Online]. Available: https://www.kth.se/social/files/588617ebf2765401cfcc478c/PHensmanDMasko_dkand15.pdf

[9] I. A. Dly, S. Sanjaya, L. Handayani, and F. Yanto, "Klasifikasi Citra Daging Sapi dan Babi Menggunakan CNN Alexnet dan Augmentasi Data," vol. 4, no. 4, pp. 1176–1185, 2023, doi: 10.47065/josh.v4i4.3702.

[10] J. E. Widyaya and S. Budi, "Pengaruh Preprocessing Terhadap Klasifikasi Diabetic Retinopathy dengan Pendekatan Transfer Learning Convolutional Neural Network," *J. Tek. Inform. dan Sist. Inf.*, vol. 7, no. 1, pp. 110–124, 2021, doi: 10.28932/jutisi.v7i1.3327.

[11] A. Dwarakanath *et al.*, "Identifying implementation bugs in machine learning based image classifiers using Metamorphic Testing," *ISSTA 2018 - Proc. 27th ACM SIGSOFT Int. Symp. Softw. Test. Anal.*, pp. 118–128, 2018, doi: 10.1145/3213846.3213858.

[12] D. Riana, S. Rahayu, S. Hadianti, Frieyadie, M. Hasan, and R. Pratama, "Identifikasi Citra Pap Smear RepoMedUNM dengan Menggunakan K-Means Clustering dan GLCM," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 5, pp. 1–2, 2022.

[13] M. Qomaruddin, D. Riana, and A. Anton, "Segmentasi K-Means Citra Daun Tin Dengan Klasifikasi Ciri Gray Level Co Occurance Matrix," *J. Sist. dan Teknol. Inf.*, vol. 9, no. 2, p. 223, 2021, doi: 10.26418/justin.v9i2.44139.

[14] N. Nurdin, D. Hamdhana, and M. J. Setiawan, "Sistem Pendeteksi Pola Lafadz Allah Dan Muhammad Pada Citra Al-Qur'an Menggunakan Metode Peirce," *TECHSI - J. Tek. Inform.*, vol. 9, no. 2, p. 78, 2017, doi: 10.29103/techsi.v9i2.215.

[15] K. H. Mahmud, Adiwijaya, and S. Al Faraby, "Klasifikasi Citra Multi-Kelas Menggunakan Convolutional Neural Network," *e-Proceeding Eng.*, vol. 6, no. 1, pp. 2127–2136, 2019.

[16] N. E. Khalifa, M. Loey, and S. Mirjalili, "A comprehensive survey of recent trends in deep learning for digital images augmentation," *Artif. Intell. Rev.*, no. 0123456789, 2021, doi: 10.1007/s10462-021-10066-4.

[17] A. Willyanto, D. Alamsyah, and H. Irsyad, "Identifikasi Tulisan Tangan Aksara Jepang Hiragana Menggunakan Metode CNN Arsitektur VGG-16," vol. 2, no. 1, pp. 1–11, 2021.

[18] A. Rodliyah, D. A. Sani, and M. F. Arif, "Perancangan Aplikasi Pembelajaran Ilmu Tajwid Berbasis Mobile," *J I M P - J. Inform. Merdeka Pasuruan*, vol. 5, no. 1, pp. 32–37, 2020, doi: 10.37438/jimp.v5i1.247.

[19] M. F. D. Ryandra, "Perbandingan Arsitektur Resnet-50 dan Inceptionv3 dalam Klasifikasi Covid 19 Berdasarkan Citra X Ray," Medan Area Univerity, 2022. [Online]. Available: https://repositori.uma.ac.id/handle/123456789/17072%0Ahttps://repositori.uma.ac.id/jspui/bitstream/123456789/17072/1/178160047 - Muhammad Farhan Dwi Ryandra - Fulltext.pdf

[20] M. F. Naufal *et al.*, "Analisis Perbandingan Algoritma Klasifikasi MLP dan CNN pada Dataset American Sign Language," *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 5, no. 3, pp. 489–495, 2021, doi: 10.29207/resti.v5i3.3009.

[21] K. Arisudana, A. X. LEJ, W. Kurniawan, and ..., "Sistem Pendeteksi Kerusakan Luar Angkutan Umum," *Lomba Karya Tulis ...*, pp. 175–187, 2020.

[22] I. Crystiana, T. M. Susantoro, and N. Firdaus, "Pengolahan Data Citra Satelit untuk Mengidentifikasi Potensi Jebakan dalam Kegiatan Eksplorasi Migas," *Lembaran Publ. Miny. dan gas bumi*, vol. 49, no. 1, pp. 41–51, 2019, doi: 10.29017/lpmgb.49.1.235.

Gender Recognition - Check

ORIGINALITY REPORT

10%	7%	8%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	repository.ubharajaya.ac.id Internet Source	1%
2	Mochamad Wahyudi, Hengki Tamando Sihotang, Syahril Efendi, Muhammad Zarlis, Herman Mawengkang, Desi Vinsensia. "A stochastic approach for evaluating production planning efficiency under uncertainty", International Journal of Electrical and Computer Engineering (IJECE), 2023 Publication	1%
3	Matthew Sjarah, Winda Astuti, Lie Zener, Ari Fadli. "Development of automatic rice plant pest detection system based on convolutional neural network", AIP Publishing, 2023 Publication	1%
4	Submitted to Liverpool John Moores University Student Paper	1%
5	www.mdpi.com Internet Source	1%

www.gteknologies.com

6 Internet Source <1%

7 Lecture Notes in Computer Science, 2015.
Publication <1%

8 Submitted to University of Hertfordshire
Student Paper <1%

9 journal.ugm.ac.id
Internet Source <1%

10 www.img.ufl.edu
Internet Source <1%

11 www.frontiersin.org
Internet Source <1%

12 journal.uad.ac.id
Internet Source <1%

13 Haonan Qin, Weiying Xie, Yunsong Li, Kai Jiang, Jie Lei, Qian Du. "Weakly supervised adversarial learning via latent space for hyperspectral target detection", Pattern Recognition, 2023
Publication <1%

14 pdfs.semanticscholar.org
Internet Source <1%

15 Mamluatul Hani'Ah, Ika Kusumaning Putri, Ariadi Retno Tri Hayati Ririd. "Parameter Optimization Of Holt – Winters Exponential <1%

Smoothing Using Golden Section Method for Predicting Indonesian Car Sales", 2021 International Conference on Electrical and Information Technology (IEIT), 2021
Publication

16	Muhammad Taqiyuddin, Yudi Eko Windarto, Wahyul Amien Syafei, Ike Pertiwi Windasari, Agung Budi Prasetijo. "Accuracy Improvement of CNN MobileNet-V1 and Residual Network 50 Layers Models using Adam setting for Car Type Classification", 2022 International Symposium on Electronics and Smart Devices (ISESD), 2022 Publication	<1 %
17	Rika Ismayanti, Faza Alameka, Dedy Mirwansyah, Nariza Wanti Wulan Sari, Abdul Rahim, Riyayatsyah. "Identification of Pests on Black Orchid Plants Using Naïve Bayes Method Based on Leaf Image Texture", 2022 International Conference of Science and Information Technology in Smart Administration (ICSINTESA), 2022 Publication	<1 %
18	Wahyutama Fitri Hidayat, Muhammad Fahmi Julianto, Yesni Malau, Ahmad Setiadi, Sriyadi. "Implementation of LSTM and Adam Optimization as a Cryptocurrency Polygon Price Predictor", 2023 International	<1 %

	Conference on Information Technology Research and Innovation (ICITRI), 2023 Publication	
19	repositori.uma.ac.id Internet Source	<1 %
20	repository.tudelft.nl Internet Source	<1 %
21	www.jurnal.polgan.ac.id Internet Source	<1 %

Exclude quotes	On	Exclude matches	Off
Exclude bibliography	On		

Gender Recognition - Check

PAGE 1

PAGE 2

PAGE 3

PAGE 4

P/V You have used the passive voice in this sentence. Depending upon what you wish to emphasize in the sentence, you may want to revise it using the active voice.

PAGE 5

PAGE 6