IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 12, No. 3, September 2023, pp. 1019~1025
ISSN: 2252-8938, DOI: 10.11591/ijai.v12.i3.pp1019-1025

Face recognition in identifying genetic diseases: a progress review

Salsabila Aurellia[1], Siti Fauziyah Rahman[1,2]
[1]Department of Electrical Engineering, Faculty of Engineering, University of Indonesia, Depok, Indonesia
[2]Research Center for Biomedical Engineering, Faculty of Engineering, University of Indonesia, Depok, Indonesia

Article Info

Article history:

Received Jun 25, 2022
Revised Sep 19, 2022
Accepted Oct 11, 2022

Keywords:

2-dimensional
Artificial intelligence
Face recognition
Genetic disease
Identification

ABSTRACT

Genetic diseases vary widely. Practitioners often face the complexity of determining genetic diseases. In distinguishing one genetic disease from another, it is difficult to do without a thorough test on the patient or also known as genetic testing. However, in some previous studies, genetic diseases have unique physical characteristics in sufferers. This leads to detecting differences in these physical characteristics to assist doctors in diagnosing people with genetic diseases. In recent years, facial recognition research has been quite active. Researchers continue to develop it from various existing methods, algorithms, approaches, and databases where the application is applied in various fields, one of which is medical imagery. Face recognition is one of the options for identifying disease. The condition of a person's face can be said to be a representation of a person's health. Where the accuracy in early detection can be pretty good, so face recognition is also one of the solutions that can be used to identify various genetic diseases in collaboration with artificial intelligence. This article review will focus more on the development of facial recognition in 2-dimensional images, showing that different methods can produce different results and face recognition can also overcome complex genetic disease variations.

Corresponding Author:

Siti Fauziyah Rahman
Department of Electrical Engineering, University of Indonesia
Depok, West Java, Indonesia
Email: fauziyah17@ui.ac.id

1. INTRODUCTION

A genetic disease is a disease with differences in a person's genes or chromosomes. Genetic diseases consist of various diseases such as down syndrome, Noonan syndrome, Turner syndrome, Williams-Beuren syndrome, Cornelia de Lange, Klinefelter syndrome, and coronary artery disease (CAD). According to data from World Health Organization (WHO), out of 1,000 births, there is one who has down syndrome, with a total of 3,000-5,000 children born annually with this condition, and the estimated incidence in the population is about 1 in 1,000 live birth [1], [2]. As for the case of Turner syndrome, it is estimated that 1:2500 people worldwide suffer from it, especially in live female births [3]. If not known or detectable, the genetic disease can be dangerous for the individual who experiences it. In young children, genetic diseases can stunt growth, cause cognitive impairment, retard mental development, neurodevelopmental disabilities, cause differences in facial characteristics and body defects, and even cause death [4].

In the case of genetic diseases, it is usually necessary to carry out a genetic examination, commonly known as genetic testing. This test's results make it possible to identify changes or mutations in one or more chromosomes, genes, and proteins to determine the possibility of genetic disease [5]. Of course, this disease

needs to be confirmed by complex genetic testing, and genetic testing is only available and can be done in large hospitals. This examination takes a long time ranging from 2-3 weeks [6], but in some cases, it can take up to 8 weeks and the costs incurred are pretty significant. So, it is difficult for all groups to do this [7]. In addition, doctors sometimes perform a physical examination on specific physical characteristics such as facial features, and Geneticists mostly do physical examinations at an early stage.

The doctor will look at the facial dysmorphology and will make a diagnosis based on it. Previous studies have also explained that faces with genetic diseases have general characteristics. In people with Down syndrome, the typical features are small eyes, a round face, a small chin, Bushfield spots on the iris, a flat nose bridge, and abnormal or folded outer ears [8].

Meanwhile, Noonan syndrome has facial characteristics that can change depending on the sufferer's age. During childhood, facial characteristics experienced are a high forehead, short nose, slanted philtrum, hypertelorism, and thick hooded eyelids [9]. Then, when growing up, there is a deep curve between the nose and mouth, wide eye gaps, low-set ears, a small lower jaw, possibly crooked teeth, a curved inner palate, and transparent and thin skin on the neck. Even the face is expressionless [10].

In patients with Cornelia de Lange syndrome, the characteristic facial features are thick eyebrows, short nose, long philtrum, upturned nasal trip, concave nasal ridge, synophrys, thin upper lip, small widely spaced teeth, crescent-shaped mouth, and short neck [11], [12]. Then Turner syndrome is characterized by slanted eyes and skin folds at the corners of the eyes, ptosis or drooping eyelids, and a small lower jaw. A short neck is also a feature of Turner syndrome because the sufferer has bone abnormalities [13]. Meanwhile, Williams-Beuren syndrome (WBS) has classic facial characteristics, such as spiked hair, wide eyebrows, wide forehead, short nose, flat nasal bridge, long philtrum, and wide mouth [14]. As a result, practitioners sometimes find it difficult to distinguish physical characteristics whose differences are not significant when seen by the eye [15].

Face recognition is one of the biometric systems currently being developed to identify a person. This is because every individual has unique facial structures that can be used to identify someone, even twins [16]. The development of face recognition has been widely applied in various fields, such as health, security and law, education, and computer and human interaction [17]. When integrated with artificial intelligence, the information obtained from a person's face would greatly aid human work. However, of course, using a computer to identify faces is also not easy because human facial features vary, and a person's facial features can be either static or dynamic [18]. With the help of machine learning, the computer can distinguish facial dysmorphology which is associated with genetic diseases [8].

In some cases, early genetic disease diagnosis is critical in determining the following steps, accompanied by a complete examination. Therefore, computer-assisted development using artificial intelligence can be helpful in the accurate diagnosis of genetic diseases. Such artificial intelligence can increase the efficiency of early diagnosis work and provide valuable information to doctors and patients [7].

According to several previous studies, research has been carried out on the development of detecting genetic diseases using facial recognition [7], [19], [20]. In a study conducted by Liu *et al*. in 2021, researching the faces of patients with WBS using the convolutional neural network (CNN) showed promising results of 92.7% [7]. Then a study conducted by a research group from Turkey in 2012 with down syndrome patients produced a maximum accuracy of 97.34% using the Gabor wavelet transform and support vector machine (SVM) [19]. Meanwhile, research by Hong *et al*. also using CNN, can identify several genetic diseases with an accuracy of 88.6% from 456 children's facial data [20]. This means that the identification of genetic diseases from facial dysmorphology can be conducted and developed further. This review article aims to provide views and add insight to identify opportunities for further research in the application of artificial intelligence methods in identifying complex genetic diseases and finding out which artificial intelligence methods are the best in identifying genetic diseases.

2. DEVELOPMENT OF FACE RECOGNITION

Face recognition itself has developed since the 1950s and 1960s. In 1964, research on computer programming for semi-automatic facial recognition was carried out by Bledsoe and Wilson in seeing the mouth and eyes [21]. This was followed in 1970 by Takeo Kanade's study on facial matching systems with facial anatomical features, followed by the publication of a book on facial recognition technology seven years later [22].

Furthermore, there is the first successful research of facial recognition technology called "Eigenfaces" with a statistical method, namely principal component analysis (PCA), which was introduced by Turk and Pentland from the Massachusetts Institute of Technology in 1991. In this study, Turk and Pentland developed a model linear by combining factor analysis and the Karhunen–Loève theorem [23]. From here, it leads to the further development of "Fisherfaces," which is improved by using linear

discriminant analysis (LDA) [24]. Then it was continued in 1998 by the Defense Advanced Research Project Agency (DARPA), which developed facial recognition technology to assist intelligence security called facial recognition technology (FERET) [25]. This continued to grow until, in 2011, facial recognition using an artificial neural network was developed, which led to the development of DeepFace on Facebook's internal algorithm in 2014 [15].

Then research on facial recognition automatically using artificial intelligence continues to grow. Face recognition can be a solution to identification and verification problems. A person's face can be compared to determine a person's identity. Face recognition itself can be done using image-based or video-based [17], but this review will focus on image-based. Likewise, in determining disease, face recognition has been widely used in early screening or early diagnosis of a disease that can be distinguished from facial features. This continues to grow until now, where in this review, there are 13 studies related to facial recognition in the last ten years which are used to detect genetic diseases.

3. FACE RECOGNITION ALGORITHM

In general, there are three main steps in completing face recognition which can be seen in Figure 1, namely face detection, where the system must understand whether the detected image has a face or not, then which feature extraction step is to recognize distinctive features or characteristics that exist on the face. Finally, the face recognition step, which consists of identification and verification by comparing it with existing data. This process can be done with previously developed algorithms [26].

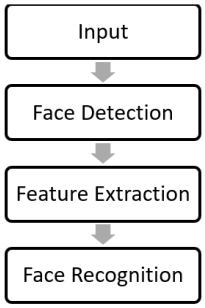

Figure 1. Shows the flowchart of the AI-based models and experimental methods applied

3.1. Gabor wavelet transform-based method

Gabor wavelet transform (GWT) itself is often used as a method to suppress noise in images [27]. Beginning with research conducted by Saraydemir [19], a study was conducted with data taken from one of the universities in Turkey and the down syndrome association. It starts with pre-processing the image and using GWT to extract the image's features. GWT is used because it has previously been proven that its robustness against local distortion is suitable for face recognition [28]. Gabor wavelets have been found to produce distortion-tolerant feature spaces for other pattern recognition tasks, including textures. Then the classification in this study uses k-NN and SVM, which have been used in several other studies because they are very good at classifying existing patterns. After the dimensions of the entire image have been adjusted, the classification accuracy is carried out by 96% and 97.34%, respectively, using the k-NN and SVM methods [19].

In contrast, Zhao *et al*. 2013 compared the combined features with geometric and Gabor jet and LBP-based geometric texture features on individuals with down syndrome from a variety of ethnic backgrounds. When combined and then assisted with SVM, both will get outstanding results with an accuracy of 0.970. According to the researchers, this solution is a simple, affordable, instant, and accurate solution for doctors [29].

Then a study conducted in the same year by Kosilek *et al*. was conducted for patients with Cushing's Syndrome in women who were on an outpatient basis at Mannheim University Hospital. Where the data used is a front view (frontal) and sideways with the camera. Then given, a label on each data obtained to make it easier when doing the classification later. The classification in this study compares the image's geometry and texture with Gabor Jet's help to determine the texture. This analysis obtained 91.7% accuracy with 92% specificity and 96% sensitivity. This study has strength in its simplicity by requiring only two photographs of each patient [30].

3.2. Texture analysis method

Several studies use semi-automatic methods in feature learning [31]–[33]. Research conducted by Basel-Vanagaite *et al*. for people with Cornelia de Lange syndrome in 2016 used Bayesian networks to calculate various local features such as the ratio of the distance from the face to identify or indicate dysmorphic features and to evaluate the similarity of the trained syndrome. Meanwhile, to capture the appearance of the entire face, local binary patterns (LBP) are used. This research finally resulted in the system being able to classify correctly by 87% greater than the previous research. In addition, a sensitivity of 86% and specificity of 89% were obtained. The system only makes errors in light cases three times, and the system consistently detects and continues to improve in terms of learning [31].

One year later, research was conducted by Hadj-Rabia *et al*. This study was conducted to detect X-linked hypohidrotic ectodermal dysplasia (XLHED) patients, including neonates and carriers of the XLHED gene, using facial dysmorphology novel analysis software (FDNA). FDNA itself has been widely used for various cases of genetic diseases. The result of this study is that this method can distinguish male and female XLHED patients with reasonable accuracy, with the sensitivity of all data obtained at 75% and specificity maintained at 99% [32].

Similarly, another study in the same year conducted by Liehr *et al*. 2017 also used FDNA for a different application, namely for patients with Emanuel syndrome and Pallister-Killian Syndrome. The results obtained in this study show that it can reduce the time in diagnosis and can differentiate Emanuel syndrome (ES) and Pallister-Killian syndrome (PKS) well. This study also proved that the solution used is cheap, can be used in places that do not have access to more sophisticated genetic approaches, and has the best accuracy of 92.8% [33].

3.3. Deep learning-based method

Deep learning is very often used in image analysis which is currently the focus of many researchers in its development. In deep learning, several hidden layers are interconnected, making the model learn to deliver the output, as shown in Figure 2. CNN is a type of deep learning algorithm. CNN itself has been widely applied to the development of artificial intelligence in the medical imaging field [34]. The various architectures of CNN itself successfully identify diseases from various medical images because of the high frequency and excellent recognition rate [35]. So, of course, in the last five years, many studies have focused on the development of CNN in detecting genetic diseases through facial recognition [7], [20], [36]–[40].

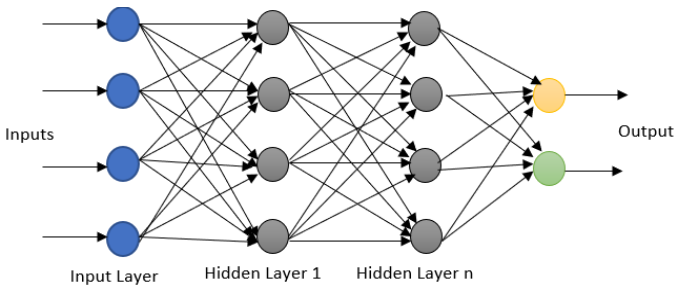

Figure 2. Deep neural network

Developments also lead to more complex problems, whereas Singh and Kisku in 2018 [36] and Gurovich *et al*. in 2019 [37] have identified various genetic diseases and the results obtained are pretty good. The research of Singh and Kisku [36] used CNN with visual geometric group (VGGFace) and residual network (ResNet) 50 architecture with the help of stochastic gradient descent (SGD) optimization to classify 12 genetic diseases. The architecture with SGD optimization is quite good when combined and produces an accuracy of 97.66%. Nevertheless, the research of Singh and Kisku [36] admits that it has shortcomings in the quality of the data used is not good. This model is not good in the classification of Marfan syndrome and 22q11. However, the overall accuracy is still reasonably good [36].

Meanwhile, the research of Gurovich *et al*. in the next year used deep CNN to solve more complex problems in 200 genetic diseases [37]. This is, of course, difficult to do, but Gurovich achieved an accuracy of 91% by outperforming physicians in three initial trials [37]. Likewise, Qin *et al*. in 2020 also used deep CNN to identify people with Down's Syndrome with very good accuracy of 95.87% and a specificity of 97.40%, which is helpful for early screening and prevention of disease progression [38].

Then the research in 2021 for facial recognition is quite a lot, coupled with the CNN method. This year it is pretty popular for all medical images. This was also done by Hong *et al*. by using the CNN architecture, namely visual geometric group-16 (VGG-16). The results were evaluated using five-fold cross-validation to detect genetic syndromes, with an accuracy of 88.6% and a specificity of 91.24% [20]. Followed up in the same year, Liu *et al*. [7] used several CNN architectures in order to compare which CNN architecture is the best in identifying Williams-Beuren syndrome, such as the VGG-16, VGG-19, ResNet 18, ResNet 34, MobileNet-V2, and ImageNet architectures from the 340 data obtained, this study produces the best accuracy at 92.7% of the VGG-19 architecture which means that other architectures are not suitable for the identification of Williams-Beuren syndrome. In contrast, the VGG-19 architecture is the most suitable for this disease [7].

In addition, the most recent is the first by Yang *et al*. in 2021 to detect Noonan syndrome with deep CNN assisted by Additive Angular Margin (ArcFace) with a total of 430 data obtained from Guangdong Provincial People's Hospital [39]. This study outperformed the six doctors (reference) in accuracy, sensitivity, and specificity, by achieving an accuracy of 92.01% and 97.97%. This model has an excellent representation ability in predicting the output [39]. Second, the study by Geremek and Szklanny from 944 data from the facial collection site, UTKFace, classified 15 genetic diseases for children aged 5-12 years. The results of this study get an accuracy of 84%, where the model can detect abnormalities without requiring information about specific abnormalities. The system does not have to be trained with all genetic diseases to detect genetic features on existing faces [40]. A summary of all the research described can be seen in Table 1.

Table 1. Summary and comparison of facial recognition methods in identification of genetic diseases

Authors and Year	Genetic Disease	Algorithm	Dataset	Results
Saraydemir *et al*. (2012) [19]	Down Syndrome	Gabor Wavelet Transform and k-NN-support vector machine (SVM)	The dataset was taken from universities in Turkey and the Down syndrome association in Turkey.	Classification using SVM resulted in 96% and 97.34% accuracy.
Zhao *et al*. (2014) [29]	Down Syndrome	Local binary patterns (LBP), Gabor wavelet transform, and SVM.	130 Data from various ethnicities, 50 Down Syndrome; 80 healthy.	The highest accuracy was obtained at 0.967 with an F1 value of 0.956 with combined geometric and Gabor Jet features. The LBP accuracy is 0.970.
Kosilek *et al*. (2013) [30]	Cushing's Syndrome	Classification by comparing the texture (Gabor Jets) and geometry of the image.	20 female endocrine outpatients at Mannheim University Hospital	The accuracy of the software that can perform the classification is 91.7%.
Basel-Vaganite *et al*. (2016) [31]	Cornelia de Lange Syndrome	Local Binary Patterns and Bayesian Networks	Experiment 1: 31 data; Experiment 2: 17 Data	The detection rate of the system is 87%.
Hadj-Rabia *et al*. (2017) [32]	X-Linked Hypohidrotic Ectodermal dysplasia (XLHED)	Facial Dysmorphology Novel Analysis	27 frontal data	The sensitivity of all data obtained is 75%, and the specificity is 99%.
Liehr *et al*. (2017) [33]	Emanuel Syndrome and Pallister-Killian Syndrome	FDNA Technology	2,173 Data (Healthy, PKS, ES)	The average accuracy is 89.6%, and the best accuracy is 92.8%.
Singh and Kisku (2018) [36]	12 syndromes	VGGFace and ResNet 50 with SGD optimizer	1567 images	Produces an accuracy of 97.66%.
Gurovich *et al*. (2019) [37]	200 syndromes	Cascaded DCNN (DeepGestalt)	17,000 data	This technology only identifies a few disease phenotypes. DeepGestalt outperformed doctors in three initial trials with 91% accuracy.
Qin *et al*. (2020) [38]	Down Syndrome	Deep CNN	10,562 (training data), 405 (test data)	With accuracy is 95.87%, and specificity is 97.40% when identifying Down syndrome.
Hong *et al*. (2021) [20]	Genetic syndrome	CNN (VGG-16) and evaluated by five-fold cross-validation	456 data from Guangdong Provincial People's Hospital	The accuracy is 0.8860, the specificity is 0.9124, and the F1-Score is 0.8829.
Liu *et al*. (2021) [7]	Williams-Beuren Syndrome	CNN (VGG-16, VGG-19, ResNet-18, ResNet-34, Mobile Net-V2 and ImageNet).	340 data (Guangdong Provincial People's Hospital)	By using VGG-19, the best accuracy is 92.7%, where this architecture is the most suitable when diagnosing Williams-Beuren Syndrome.
Yang *et al*. (2021) [39]	Noonan Syndrom	Deep CNN and Additive Angular Margin (DCNN-Arcface model)	430 data from Guangdong Provincial People's Hospital	Achieved accuracy of 0.9201 and 0.9797.
Geremek and Szklanny (2021) [40]	15 genetic diseases	Multi-task Cascaded Convolutional Neural Network (P-Net, R-Net, and O-Net)	944 data, ranging from 5-12 years old from UTKFace.	The classification with the best accuracy was obtained at 84%.

4. CONCLUSION

Facial recognition for genetic diseases has been demonstrated in this systematic review's studies over the last ten years. It can be seen in this review that facial recognition for genetic diseases is perfect and

can recognize genetic diseases that are increasingly complex in recent studies. Even various existing methods, such as the GWT approach, texture analysis, and even deep learning, it has been developed, and it has been proven that in several studies, it is said to be able to simplify the work of doctors and reduce diagnosis time which, of course without the help of artificial intelligence would take weeks. This, in the future, still opens up opportunities for researchers to continue to develop data, methods, and algorithms in a photo and facial video recognition and perhaps can be combined with other biometrics.

ACKNOWLEDGEMENTS

We gratefully acknowledge the funding from Kementerian Pendidikan, Kebudayaan, Riset Dan Teknologi through Penelitian Tesis Magister 2022 No. NKB-1037/UN2.RST/HKP.05.00/2022.

REFERENCES

[1] H. A. Audya Tyas Regita, Risti Saptarini Primarti, Eriska Riyanti, "Relationship between maternal age and the incidence of down syndrome," *International Journal of Pharmaceutical Research*, vol. 12, no. sp3, 2020, doi: 10.31838/ijpr/2020.sp3.105.

[2] A. Asim, A. Kumar, S. Muthuswamy, S. Jain, and S. Agarwal, "Down syndrome: An insight of the disease," *Journal of Biomedical Science*, vol. 22, no. 1, 2015, doi: 10.1186/s12929-015-0138-y.

[3] X. Cui, Y. Cui, L. Shi, J. Luan, X. Zhou, and J. Han, "A basic understanding of Turner syndrome: Incidence, complications, diagnosis, and treatment," *Intractable and Rare Diseases Research*, vol. 7, no. 4, pp. 223–228, 2018, doi: 10.5582/irdr.2017.01056.

[4] M. H. Wojcik, J. E. Stewart, S. E. Waisbren, and J. S. Litt, "Developmental support for infants with genetic disorders," *Pediatrics*, vol. 145, no. 5, 2020, doi: 10.1542/PEDS.2019-0629.

[5] H. Deng, P. Riederer, H. X. Deng, W. Le, W. Xiong, and Y. Guo, "Human genetic diseases," *BioMed Research International*, vol. 2015, 2015, doi: 10.1155/2015/315216.

[6] S. Oliveri, F. Ferrari, A. Manfrinati, and G. Pravettoni, "A systematic review of the psychological implications of genetic testing: A comparative analysis among cardiovascular, neurodegenerative and cancer diseases," *Frontiers in Genetics*, vol. 9, 2018, doi: 10.3389/fgene.2018.00624.

[7] H. Liu *et al.*, "Automatic facial recognition of Williams-Beuren syndrome based on deep convolutional neural networks," *Frontiers in Pediatrics*, vol. 9, 2021, doi: 10.3389/fped.2021.648255.

[8] J. Y. R. Cornejo, H. Pedrini, A. Machado-Lima, and F. de L. dos S. Nunes, "Down syndrome detection based on facial features using a geometric descriptor," *Journal of Medical Imaging*, vol. 4, no. 04, p. 1, 2017, doi: 10.1117/1.jmi.4.4.044008.

[9] J. E. Allanson *et al.*, "The face of Noonan syndrome: Does phenotype predict genotype," *American Journal of Medical Genetics, Part A*, vol. 152, no. 8, pp. 1960–1966, 2010, doi: 10.1002/ajmg.a.33518.

[10] A. A. Romano *et al.*, "Noonan syndrome: Clinical features, diagnosis, and management guidelines," *Pediatrics*, vol. 126, no. 4, pp. 746–759, 2010, doi: 10.1542/peds.2009-3207.

[11] A. D. Kline *et al.*, "Diagnosis and management of Cornelia de Lange syndrome: First international consensus statement," *Nature Reviews Genetics*, vol. 19, no. 10, pp. 649–666, 2018, doi: 10.1038/s41576-018-0031-0.

[12] S. Rohatgi *et al.*, "Facial diagnosis of mild and variant CdLS: Insights from a dysmorphologist survey," *American Journal of Medical Genetics, Part A*, vol. 152, no. 7, pp. 1641–1653, 2010, doi: 10.1002/ajmg.a.33441.

[13] C. A. Bondy, "Clinical practice guideline: Care of girls and women with Turner syndrome: A guideline of the Turner Syndrome study group," *Journal of Clinical Endocrinology and Metabolism*, vol. 92, no. 1, pp. 10–25, 2007, doi: 10.1210/jc.2006-1374.

[14] P. Poornima, P. S. Patil, V. V. Subbareddy, and G. Arora, "Dentofacial characteristics in William′s syndrome," *Contemporary Clinical Dentistry*, vol. 3, no. 5, pp. S41–S44, 2012, doi: 10.4103/0976-237X.95103.

[15] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the gap to human-level performance in face verification," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 1701–1708, 2014, doi: 10.1109/CVPR.2014.220.

[16] S. Richmond, L. J. Howe, S. Lewis, E. Stergiakouli, and A. Zhurov, "Facial genetics: A brief overview," *Frontiers in Genetics*, vol. 9, no. OCT, 2018, doi: 10.3389/fgene.2018.00462.

[17] M. Taskiran, N. Kahraman, and C. E. Erdem, "Face recognition: Past, present and future (a review)," *Digital Signal Processing: A Review Journal*, vol. 106, 2020, doi: 10.1016/j.dsp.2020.102809.

[18] L. M. Vaina, J. Solomon, S. Chowdhury, P. Sinha, and J. W. Belliveau, "Functional neuroanatomy of biological motion perception in humans," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 98, no. 20, pp. 11656–11661, 2001, doi: 10.1073/pnas.191374198.

[19] Ş. Saraydemir, N. Taşpınar, O. Eroğul, H. Kayserili, and N. Dinçkan, "Down syndrome diagnosis based on Gabor wavelet transform," *Journal of Medical Systems*, vol. 36, no. 5, pp. 3205–3213, Oct. 2012, doi: 10.1007/s10916-011-9811-1.

[20] D. Hong *et al.*, "Genetic syndromes screening by facial recognition technology: VGG-16 screening model construction and evaluation," *Orphanet Journal of Rare Diseases*, vol. 16, no. 1, 2021, doi: 10.1186/s13023-021-01979-y.

[21] Bledsoe and W. Wilson, "The model method in facial recognition," *Panoramic Research Inc., Palo Alto, CA, Rep. PR1*, vol. 14, pp. 47–48, 1966.

[22] K. de Leeuw and J. Bergstra, "The history of information security: A comprehensive handbook," *The History of Information Security: A Comprehensive Handbook*, pp. 1–887, 2007, doi: 10.1016/B978-0-444-51608-4.X5000-7.

[23] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, vol. 3, no. 1, pp. 71–86, 1991, doi: 10.1162/jocn.1991.3.1.71.

[24] D. W. J. Wang, L. Chan, "Neural information processing: 13th International Conference," *13th International Conference ICONIP 2006*, p. 198, 2012, doi: 10.1007/11893028.

[25] P. J. Phillips, H. Wechsler, J. Huang, and P. J. Rauss, "The FERET database and evaluation procedure for face-recognition algorithms," *Image and Vision Computing*, vol. 16, no. 5, pp. 295–306, 1998, doi: 10.1016/s0262-8856(97)00070-x.

[26] M. Chihaoui, A. Elkefi, W. Bellil, and C. Ben Amar, "A survey of 2D face recognition techniques," *Computers*, vol. 5, no. 4, 2016, doi: 10.3390/computers5040021.

[27] B. Ergen, "A fusion method of gabor wavelet transform and unsupervised clustering algorithms for tissue edge detection," *The Scientific World Journal*, vol. 2014, 2014, doi: 10.1155/2014/964870.
[28] L. Shen and L. Bai, "A review on Gabor wavelets for face recognition," *Pattern Analysis and Applications*, vol. 9, no. 2–3, pp. 273–292, Sep. 2006, doi: 10.1007/s10044-006-0033-y.
[29] Q. Zhao *et al.*, "Digital facial dysmorphology for genetic screening: Hierarchical constrained local model using ICA," *Medical Image Analysis*, vol. 18, no. 5, pp. 699–710, 2014, doi: 10.1016/j.media.2014.04.002.
[30] R. P. Kosilek *et al.*, "Automatic face classification of Cushing's syndrome in women - a novel screening approach," *Experimental and Clinical Endocrinology and Diabetes*, vol. 121, no. 9, pp. 561–564, 2013, doi: 10.1055/s-0033-1349124.
[31] L. Basel-Vanagaite *et al.*, "Recognition of the Cornelia de Lange syndrome phenotype with facial dysmorphology novel analysis," *Clinical Genetics*, vol. 89, no. 5, pp. 557–563, 2016, doi: 10.1111/cge.12716.
[32] S. Hadj-Rabia *et al.*, "Automatic recognition of the XLHED phenotype from facial images," *American Journal of Medical Genetics, Part A*, vol. 173, no. 9, pp. 2408–2414, 2017, doi: 10.1002/ajmg.a.38343.
[33] T. Liehr *et al.*, "Next generation phenotyping in Emanuel and Pallister-Killian syndrome using computer-aided facial dysmorphology analysis of 2D photos," *Clinical Genetics*, vol. 93, no. 2, pp. 378–381, 2018, doi: 10.1111/cge.13087.
[34] N. Tajbakhsh *et al.*, "Convolutional neural networks for medical image analysis: Full training or fine tuning?," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1299–1312, 2016, doi: 10.1109/TMI.2016.2535302.
[35] K. M. M. Aneesa, N. Saabina, "Face recognition using CNN: A systematic review," *Int J Eng Res Tech.*, vol. 11, no. 6, 2022.
[36] A. Singh and D. R. Kisku, "Detection of rare genetic diseases using facial 2D images with transfer learning," *Proceedings of the 2018 8th International Symposium on Embedded Computing and System Design, ISED 2018*, pp. 26–30, 2018, doi: 10.1109/ISED.2018.8703997.
[37] Y. Gurovich *et al.*, "Identifying facial phenotypes of genetic disorders using deep learning," *Nature Medicine*, vol. 25, no. 1, pp. 60–64, 2019, doi: 10.1038/s41591-018-0279-0.
[38] B. Qin, L. Liang, J. Wu, Q. Quan, Z. Wang, and D. Li, "Automatic identification of down syndrome using facial images with deep convolutional neural network," *Diagnostics*, vol. 10, no. 7, 2020, doi: 10.3390/diagnostics10070487.
[39] H. Yang *et al.*, "Automated facial recognition for Noonan syndrome using novel deep convolutional neural network with Additive Angular Margin Loss," *Frontiers in Genetics*, vol. 12, 2021, doi: 10.3389/fgene.2021.669841.
[40] M. Geremek and K. Szklanny, "Deep learning-based analysis of face images as a screening tool for genetic syndromes," *Sensors*, vol. 21, no. 19, p. 6595, Oct. 2021, doi: 10.3390/s21196595.

BIOGRAPHIES OF AUTHORS

Salsabila Aurellia holds a Bachelor of Engineer degree from Airlangga University, Indonesia, in 2020. She is currently a master's student at Universitas Indonesia. Her research interests are image analysis and artificial intelligence. She has published three papers in international journals and conferences. She can be contacted at email: salsabila.aurellia11@ui.ac.id.

Siti Fauziyah Rahman holds a Bachelor of Engineer degree from Universitas Indonesia in 2010. She also received her M.Eng and Ph.D. from Chonnam National University, South Korea, in 2012 and 2016. She is currently a lecturer at the Department of Electrical Engineering at Universitas Indonesia. Her research includes biosensors, biotechnology, and biomaterial. She has published over 30 papers in international journals and conferences. She can be contacted at email: fauziyah17@ui.ac.id.