Journal of Techniques, ISSN: 2708-8383, Vol. 5, No. 1, 2023, Pages 44-51
DOI: https://doi.org/10.51173/jt.v5i1.1133

JOURNAL OF TECHNIQUES

Journal homepage: http://journal.mtu.edu.iq

RESEARCH ARTICLE - ENGINEERING

Computer Vision System for Facial Palsy Detection

Ali Saber Amsalam [1*], Ali Al-Naji [1,2], Ammar Yahya Daeef [3], Javaan Chahl [2]

[1] Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq

[2] School of Engineering, University of South Australia, Mawson Lakes, SA 5095, Australia

[3] Technical Institute for Administration, Middle Technical University, Baghdad, Iraq

[*] Corresponding author E-mail: bdc0034@mtu.edu.iq

Article Info.

Article history:

Received
20 December 2022

Accepted
09 February 2023

Publishing
31 March 2023

Abstract

Facial palsy (FP) is a disorder that affects the seventh facial nerve, which makes the patient unable to control facial movements and expressions with other vital activities. It affects one side of the face, and it is usually diagnosed by the asymmetry of the two sides of the face through visual inspection by a doctor. However, the visual inspection is human-based, which is prone to errors because the doctor is exposed to omission due to fatigue and work stress. Therefore, it is important to develop a new method for detecting FP through artificial intelligence and use a more accurate computerized system to reduce the effort and cost of patients and increase the accuracy of diagnosis. This work aims to establish a safe, useful and high-accuracy diagnostic system for FP that can be used by the patient and proposes to detect FP using a digital camera and deep learning techniques automatically. The system could be used by the patient himself at home without needing to visit the hospital. The proposed system trained 570 images, including 200 images of FP palsy. The proposed FP system achieved an accuracy of 98%. This confirms the effectiveness of the proposed system and makes it an efficient medical examination tool for detecting FP.

Publisher : Middle Technical University

Keywords: Non-Contact Palsy Detection; Computer Vision; Deep Learning; Digital Camera.

1. Introduction

Facial palsy is a devastating neurological disease for patients, and it is one of the diseases that make the patient unable to control the voluntary muscles on one side of the face [1]. The rate per 100,000 population, FP affects 11 to 40 persons, and it is more common between the ages of 30 and 45 than the age groups, and about 37.7 out of 100,000 is the annual incidence of FP in the UK population [2]. The incidence of injury of FP reaches 1 in every 60 people in the community, with some symptoms including eyelid sagging, pain around the face and ear, hearing disturbance, dry eyes, and loss of taste [3]. There are many functions controlled by the left and right facial nerves, such as drooling, taste sensations, tears, smiling, and eyelid movement. Men are exposed to a large percentage of FP, as is the case with women, and 10% of those infected with this disease are from families with a history of it, and the people most susceptible to it are those with diabetes and pregnant women [4]. This disease causes embarrassment and inconvenience to the patient. In addition, the diagnosis in the traditional method through the visible signs on the patient's face with the doctor appointed is inaccurate and requires more time and effort from the patient side. Therefore, researchers had to go to a more accurate and fast diagnosis method that does not require effort from the patient, and here the transition from the traditional method to using computer vision systems by deep learning began to detect FP disease. In recent years, when switching from traditional methods to computer vision systems and deep learning techniques in face detection techniques, some problems have arisen in this technology. One of the forms of artificial intelligence that works on complex and well-designed image and pattern recognition tasks is CNN [5]. It is a network that can extract data features using convolutional structures and differs from traditional methods in feature extraction [6], 7]. It enables people to learn about things through computer vision, and in the field of deep learning, it has become one of the most representative neural networks [8]. Deep learning is one of the most advanced solutions to many problems, such as speech recognition, face recognition, visual recognition, and others [9]. It solves the problems of classification, detection and colorization of images in digital image processing applications [10]. The face recognition algorithms and monitoring techniques used in cameras, the performance is not convincing due to the problem of image blurring and low resolution [11]. Despite the great efforts by researchers, face recognition technology is still difficult and contains many problems because of its use in many fields. Achieving the optimal performance of these technologies is still challenging. There is no system that claims perfection to this technology [12]. In FP detection technology, there were few methodologies that worked on deep learning in particular [13]. Hence, another study proposed by [14] increased the image dataset and used randomly selected cells in the random scanning method to train the deep neural network. The dataset comprised 1555 samples divided into 1105 palsy faces and 450 normal faces with five subjects. The achieved accuracy ranged from 78.62 ± 5.65 to 99.35 ± 0.24%. However, the accuracy was not enough to evaluate the classifier on the unbalanced dataset.

Nomenclature			
FP	Facial palsy	HBGS	House-Brackmann Grading System
DAN	Deep Alignment Network	VGGNet	Visual Geometry Group Network
UPFP	Unilateral Peripheral Facial Paralysis	CNN	Convolutional Neural Network
SVM	Support Vector Machine	GNBA	Gaussian Naive Bayes Algorithm
VLR	Very Low Resolution	VDRRE	Voronoi decomposition-based random region erasing
KNN	K-nearest neighbor	DHN	Deep Hierarchical Network
PBM	Photobiomodulation	FACS	Facial Action Coding System
HOG	Histograms of Oriented Gradient		

To address the abovementioned problems and limitations, increase accuracy and reduce time, computer vision technology and face detection techniques using a digital camera have been developed. Recent studies have proven that the solutions of computer vision and face detection techniques for FP detection were characterized by high accuracy, short time, and reduced effort of the patient. It is very useful in medical diagnosis and monitoring of the patient's condition. For example, a study by Dominguez et al. [15] presented several computer systems and technologies for detecting FP using advanced technologies to aid in diagnosis, medical treatment, and patient monitoring. These are patient-friendly, easy-to-use tools that could be used at home. Their study proposed a technique to detect FP through three models using a binary classifier and facial landmarks based on a multi-layer perceptron approach to determine facial asymmetry through facial features by using 640 samples with training time N =500 and achieved (94.06 to 97.22) % accuracy. However, the quality of the images in this study was not sufficient. Another study by Nguyen et al. [16] developed a new approach in deep learning to recognize facial expressions directly on 3D point cloud data, called geometric deep learning (Point Net++was applied). Two databases were used, Bosphorus database contains 65 subjects with 7 expressions (happiness, neutral, sadness, fear, disgust, surprise, and anger) and SIAT-3DFE database has 150 subjects and four basic expressions of facial (surprise, neutral, sadness and happiness). Training time was 31 minutes and achieved an accuracy of 69.01 to 85.85 %. The complexity of scanning three-dimensional faces and the time-consuming process were the main limitations of their technique. Also, a three-dimensional facial database was too small to draw reliable findings. Another work [17] proposed a new model in deep machine learning in parotid polyps' surgery to detect facial nerve palsy by using the k-nearest neighbor algorithm that achieved values specificity of more than 0.9 performance. This work used 345 patients from 356 patients with parotid gland tumors, containing 192 males and 153 females aged between 18 and 87. This work produced an accuracy of 25.08 to 97.14%. However, this method had some problems, including a low event rate comparatively, revision surgery is insularity, and the model was not casual. Another work by [18] proposed an imaging system based on dynamic three-dimensional stereo photogrammetry to objective grading FP severity. The work used facial asymmetry of sixteen patients, seven clinical FP of varying severity, with a time of about 5 sec and 73.2 to 91.1 % of accuracy. However, the stereo pod just used one problem for the facial image with the area of the central facial. Another work [19] used a new detection technique DAN of facial landmarks and imaging for objective assessment of UPFP. It used 116 samples with 34 subjects containing 69 males and 47 females with a short time of 2 seconds and achieved an accuracy of 56%. A HBGS is a prevalent scale that proposed to give results in face detection through face video, and it is one of the objective methods that used (Dlib) technique by using a model of 68-points for facial landmarks with a data set of (thirty-three) subjects and 88.9% accuracy but not a highly accurate method that proposed by [20]. By using support vector machine and multi-layer perceptron technique for problem classification to automatically diagnose of FP by using regional information from the photograph by using machine learning algorithms to diagnose FP. The datasets contained 144 images, the CK+ with 123 healthy subjects and 21 participants with FP from the (YouTube) Facial Palsy. The system achieved an accuracy of 95.05% in the eyes and 93.29% in the mouth. More complex and need high datasets was proposed by Parra-Dominguez et al. [21]. The VGGNet method was used to identify facial emotions in patients with FP. Trained with healthy subjects that contain 23,744 images achieved 85.97% accuracy. To confirm the classifier's performance, it was probable to use techniques of selection that were limited to this technique was also proposed by [22]. Using a new method to help identify facial asymmetry after FP, called 3D analysis method. Eighteen samples, 10 healthy (7 males and five females with 42.7 years old age, ranging from twenty-eight to sixty-seven years old and 8 patients; one male and seven females with mean age: sixty-one years old, ranging from thirty-three to seventh-four years old, with 10 sec time and 0.1 mm accuracy of the analysis but some of the problems in this mode such long time and low accuracy [23]. Another study by [24] proposed a method for automatic classification of central and primary FP by using machine learning of 68 facial landmarks on their face by SVM and GNBA. It used 103 images of peripheral palsy, including 60 healthy people and 40 central palsies, with achieved short processing time and 85.1 % of accuracy but considered more complex and low accuracy. The difference between the previous methods and the proposed system can be explained in terms of the technology used, the number of data used and system accuracy in Table 1.

To overcome the abovementioned limitations, this study aims to propose a useful diagnostic method for contactless detecting FP based on a computer vision system using CNN since this method is considered one of the modern methods in medical diagnosis with high accuracy, speed of performance, and cost-effectiveness.

The remainder of this paper is as follows: Section 2 describes the materials and methods of the study, including research ethics and participants, experimental setup, and system design. Section 3 includes the matrices of the proposed system. Section 4 presents the results and analysis of the proposed system performed on human participants with discussion. Finally, Section 5 concludes the paper.

2. Materials and Methods

2.1. Research Ethics and Participants

This study followed the guidelines of the Helsinki Declaration of Research Ethics (Finland 1964) and was approved by the Research Ethics Committee of the Dhi Qar Health Department, the Iraqi Ministry of Health (research protocol no.: 362/2022). The samples were collected in an information sheet for the participants after obtaining their consent. The participants were informed of the confidentiality of the information taken from them and that this information is protected and preserved by the research team. The total number of participants with facial palsy was 10 participants (3 males and 7 females), and the average age ranged between 15 and 70 years, with different degrees of FP and side injury, and they did not have other neurological diseases in the face. The cases were severe and moderate, and the subjects were fully aware of the steps and purpose of the examination. Due to the small number of people with facial paralysis, the difficulty of persuading the injured person, and the embarrassment of filming, these reasons made the data collection time longer, reaching two months, despite the patients being informed of the ethical procedures and data protection. The rest of the FP data were collected from free websites on the internet for system training purposes. Data on healthy cases in the training process were collected from the internet, and the used data was the FER-2013 dataset [25] and the UTKFace dataset [31] to train the computer to detect facial reactions using the Python program through a set of packages that used for detecting facial movements and expressions.

Table 1. The comparison between previous research and the proposed system

work	The used method	The used technique	datasets	Accuracy
[11]	Face Recognition	super-resolution method	10 images per class	30 % for VLR image
[13]	Facial Nerve Paralysis	CNN	1049 clinical images	97.5 %
[14]	Facial Palsy	VDRRE	21 patient	89.25 % to 99.07 %
[15]	Facial Paralysis	multi-layer perceptron	480 images	94.06 % to 97.22 %
[16]	facial expression recognition	geometric deep learning	215 subjects	78.70 % to 85.85 %
[17]	Facial Nerve Palsy	KNN	356 patients	above 0.9
[18]	Facial paralysis	dynamic3D-stereo photogrammetry	16 patients	73.2 **%** to 91.1 %
[19]	facial paralysis	DAN	116 patients	90.2 %
[20]	Facial Paralysis	HBGS	33 original facial videos	88.9 %
[21]	Facial Palsy	deep neural networks	21participants with 123 healthy subjects	93.29 % to 95.05 %
[22]	facial nerve paralysis	modified VGGNet	45 patients	66.58 % to 85.97 %
[23]	facial palsy	three-dimensional-digital model	8 patients with 10 healthy	0.1 mm
[24]	facial paralysis	deep neural network	103 peripheral palsy images	85.1 %
[2]	Facial Palsy	sensor-based digital technology	216 patients	___________
[13]	Facial nerve paralysis	CNN	1049 clinical images	97.5 %
[25]	Facial emotion recognition	CNN	35,887 images	65.97 %
[26]	Facial emotion recognition	CNN	35888 images	73.06 %
[27]	Emotion and Gender Classification	CNN	460,723 RGB images	66 % to 96 %
[28]	Facial Palsy	DHN	32 videos of 21 patients	87.5 %
[29]	Bell’s Palsy	PBM	14 patient	__________
[7]	Human Detection	HOG	1800 human images	84 % to 89 %
[30]	facial palsy	FACS	28 healthy and 299 patients	66 %
The proposed system	facial palsy	CNN	570 normal and 200 palsy images	**98 %**to 99 %

2.2. Experimental Setup

The experimental setup is able to detect facial palsy by a computer vision system where the patient sits directly in front of the camera. The images were captured at several positions, and the imaging session for the patient took five minutes using a digital camera for a Galaxy A70 mobile device. The data was then collected from the camera and divided into three parts, right palsy, left palsy and normal (They were set as 20% testing data and 80% training data) using the Python program version 3.9 through a special code on the comprehensive library of the Python program, which is the Anaconda Navigator version 2.3.2, and spider IDE version 5.3.2, including a set of packages (opencv, dlib, keras and numpy) after resetting the images to one size and one color, noting that the test images are not used with the training images. The general diagram of the proposed FP diagnostic system is shown in Fig. 1.

The digital camera was placed at a distance of approximately 1 to 3 meters from the patient. Taking into consideration the lighting of the room in which the photograph is taken and the direction of the face it should be in direct view with the camera in order to detect all parts of the face because the diagnosis will be by distinguishing between the signs and expressions of a healthy face and a palsy face. Also, a distinction is made between the two sides of the injury, whether the patient has the right or left side of the face. The code was programmed on the Python program on a computer type (MSI) with coreI7, 16 GHz of RAM to reduce training time and increase the speed of diagnosis.

2.3. System design

The proposed system consists of several stages, starting with the patient, a digital camera that works on photographing the patient and the data it's dataset and data acquisition collected through data collection. The program is then trained on the collected data after dividing it into three sections, namely, normal, right palsy and left palsy, after resetting the size of the data to be one size in order to make it easier for the program to read, so that the stage of face detection through artificial intelligence and machine learning begins. After the facial features are recognized by computer recognition, the disease is diagnosed. The person may have FP or be healthy, and if he is injured, the side of the injury is determined, is it the right or the left. Fig. 2 illustrates the structure of the proposed system.

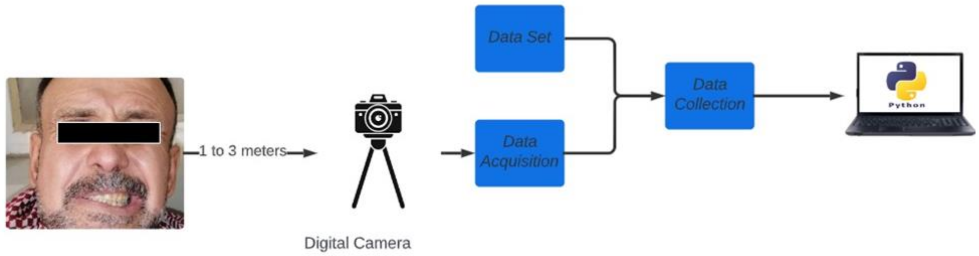


Fig. 1. Diagram of the proposed FP diagnostic system, which captures the patient's image by a digital camera and inserts it into the computer to diagnose it through the Python program

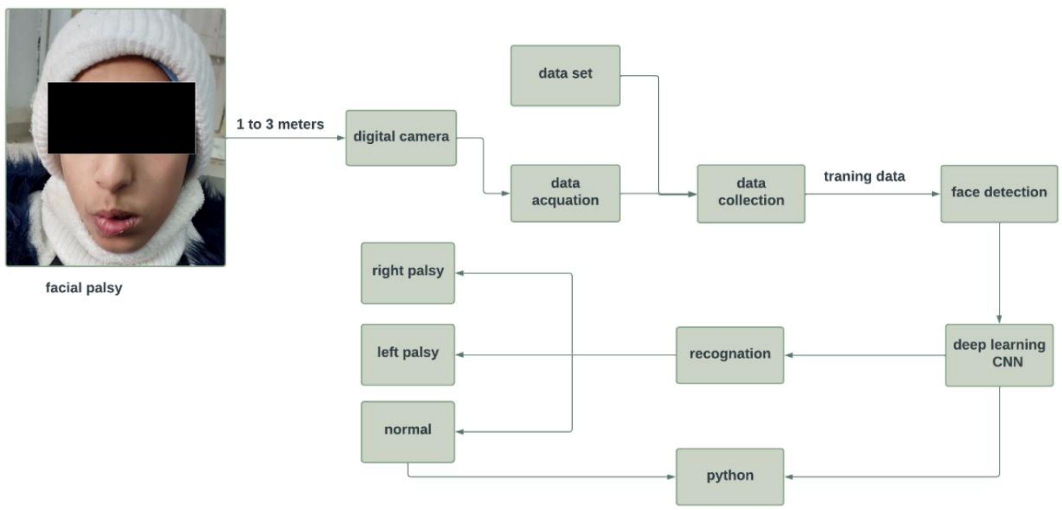


Fig. 2. The block diagram of the proposed computer vision system

When the data reaches the computer after it has been collected, the stage of programming this data begins within the Python program, where the packages for detecting the face features are defined in the program and determining the size of the image. The image was then stored and converted to grayscale color. Then the data was divided into three sections according to the storage folder and determined the shape of the image. The model was then created for the dimensions from the length, width and color of the image, then training the program using CNN on the existing data. After determining the number of epochs and doing a test for the model, the system decision and accuracy were obtained.

Face detection begins with feature extraction with image preprocessing, where the processor takes the shape of the face to discover the key points of the eyes, eyebrows and mouth [32]. Face detection technology depends on the difference in facial expressions, points, and distances on both sides of the face, where the face deviates to the healthy side due to the inability to control the facial muscles of the affected side. In addition, the eye is open on the side of the injury, and the patient cannot control its opening and closing, like that the eyebrow on the side of the injury, as shown in Fig. 3.

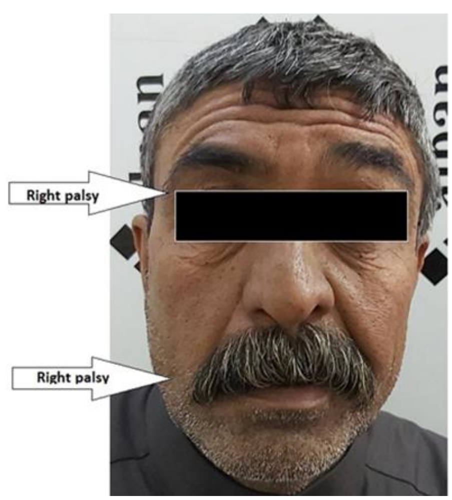


Fig. 3 Right palsy

3. Evaluation Metrics

The accuracy, sensitivity, precision and specificity of the system are computed respectively as evaluation metrics according to Eq. (1), (2), (3), and (4) [21], [33], [34].

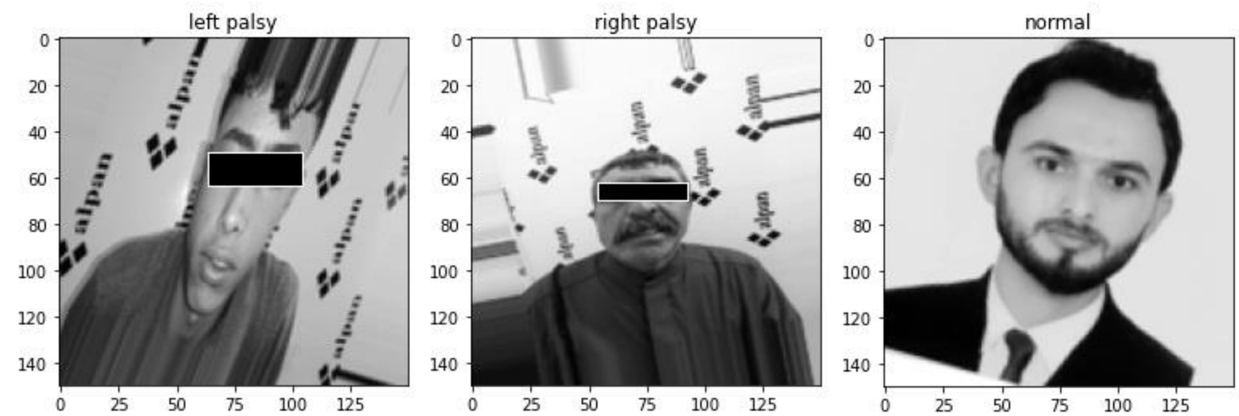
$$\text{"}Accuracy = \text{"}\ (TP + TN)/(TP + TN + FP + FN) \tag{1}$$
$$Sensitivity = TP/(TP + FN) \tag{2}$$
$$Precision = TP/(TP + FP) \tag{3}$$
$$Specificity = TN/(TN + FP) \tag{4}$$

Where TP stands for true positives, TN for true negatives, FP for false positives, and FN for false negatives.

4. Experimental Results and Discussion

To verify the results of the proposed system, the system was evaluated in comparison with other data and the diagnosis of the specialized doctor, where 10 patients were examined under the doctor's supervision, and their data was entered into the program, and the results appeared identical to reality.

Data were collected from different sources with 570 images for healthy people (normal face) and 100 images for people with left palsy and 100 images for people with right palsy. For images collected from the internet, we trained 80% of the collected data and testing 20%. The proposed system achieved an accuracy reached 98% on the collected data with a record time of several seconds. For images captured from 10 actual patients, the proposed system could detect all cases with an accuracy of 99%. As for the training time, it takes a longer time depending on the power of the computer processor where it reached 4 hours in the computer used for training. The typical results of applying the proposed FP detection system computer are shown in Fig. 4(a, b, and c).



a b c

Fig. 4. a) left palsy, b. right palsy, c. normal

It can be seen from Fig. 4 that the person has left FP, and this indicates the accuracy of the diagnosis, which is left facial palsy. In the second case, it can be noted that the person has the right FP, and the diagnosis was accurate, which is right facial palsy. In Fig. 4c, it is clear that the condition was healthy and the person was normal, so the system's diagnosis of the condition was correct and it is normal.

The confusion matrix records the number of repetitions of two types of classification, the predicted and true/actual classification, and is represented by a cross table of columns and rows, where the rows refer to the real original classification, while the columns refer to the prediction of the proposed model [34].

Fig. 5, shows the confusion matrix that illustrates a triple matrix depending on the number of classifications in the test data. Where the data in this matrix was divided into three columns and three rows, each row or column belongs to one of the sections of the examination data. The real number of data used in the examination appears with the number of unread data in which the error occurred. The confusion matrix works on categorizing the test values into an actual value and the prediction value of the program, where when we give the program a true positive value, it predicts the same actual value found in the training data from the test data after the training process. In the same way, when we give the program the true negative value, it predicts the same true negative value after the training process, in the same way, when we give the program that the actual value is true negative, it is predicted by the same actual value, true negative, after the training process. The data was divided into two sections, 80% for training and 20% for testing, and based on the test data, the system prediction results were as follows (accuracy = 0.98, sensitivity = 1, precision = 0.968 and specificity = 0.947). From these results, we make sure of the accuracy of the prediction of the proposed system.

It can be seen from the abovementioned figure that the higher number of data used and the closer and clearer the images, the more accurate result of the proposed system diagnosis. The more consistent the data in color, size, and image extension, the less loss of unread data from the system. The typical results of validation accuracy and validation loss are shown in Figs. 6 and 7.

In Fig. 6, the accuracy of the system reached 98% with 80 epochs, which showed that the proposed system had high accuracy at this point.

In Fig. 7, the percentage of missing data was very small at the same epoch, which was 0.02, due to the blurring of some images in the training data, and this indicated that the proposed system had few losses and errors.

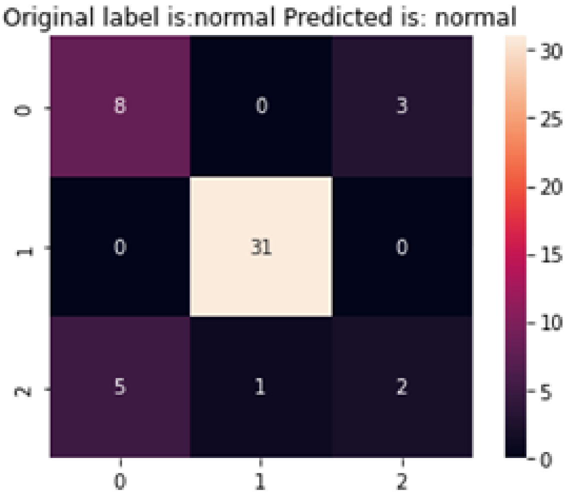


Fig. 5. The confusion matrix

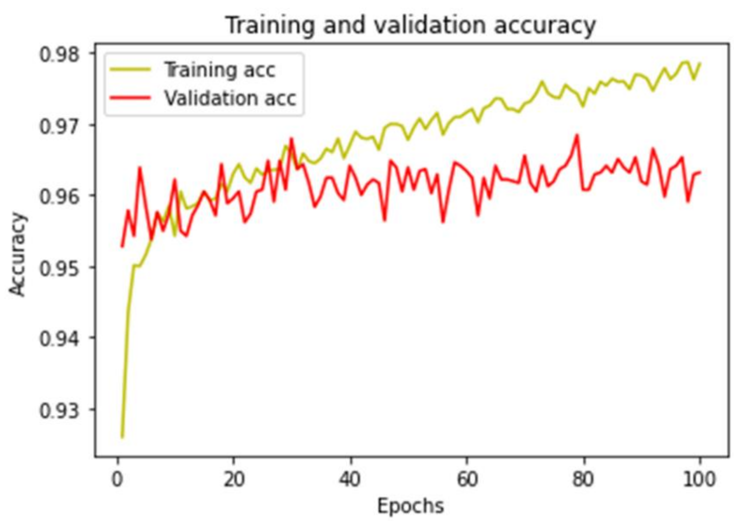


Fig. 6. The training and validation accuracy

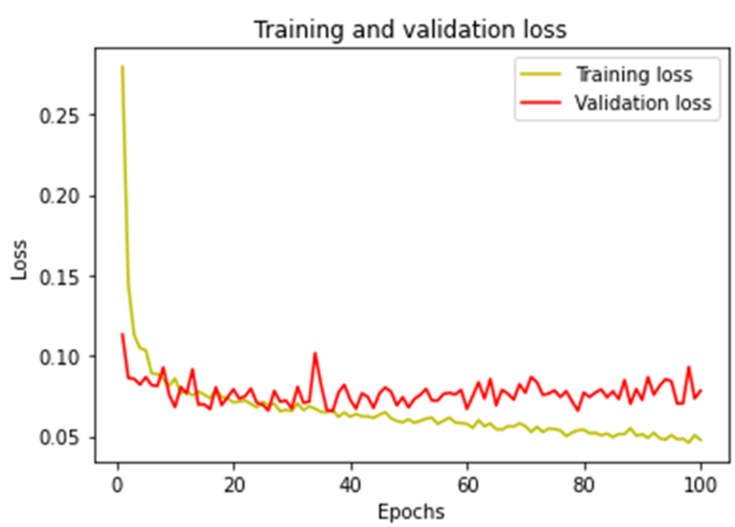


Fig. 7. The training and validation loss

It is possible to increase the system's accuracy and reduce the error further by deleting distorted and unclear images and limiting them to clear and high-resolution images. The user himself can reduce the error in diagnosis to the lowest percentage by photographing the patient in a bright place and using a high-resolution camera.

Although the previous studies are important and acceptable and contribute to the process of detecting facial paralysis, there are some problems, such as identifying the side of the injury, the speed of diagnosis, the accuracy of the system, and the diagnosis of all cases with their different degrees. All these limitations make the previous methods less accurate in diagnosis. Thus, these problems were addressed in the proposed system. As illustrated in Table 1, the difference between previous systems and the proposed system was clear, where CNN technology was used to detect facial features and diagnose FP. The training data were 570 images of healthy people and 200 images of people with FP. The accuracy of the system in diagnosis was 98% for the training data that was collected from multiple sources, and the accuracy of the system reached 99% for the study data collected by the researchers. The proposed system was better than the previous methods because it classifies the diagnosis according to the side of the injury into right palsy and left palsy. It also achieved high accuracy rate that was higher than the previous methods, and it could diagnose all severe, medium and mild cases with few errors.

Although the proposed system provides acceptable accuracy and beneficial results, however, there are some limitations, including when moving away from the camera or tilting the face to one of the sides, the accuracy of the diagnosis decreases. Another limitation was the difficulty in distinguishing between a person with FP and a person impersonating a person with FP. Also, the difficulty of collecting information about patients with FP and its unavailability directly and embarrassing patients from photography and cameras. In future work, increasing the accuracy of the system and the training data to convert the program to real-time and add age and gender detection for patients.

5. Conclusions

In this paper, a newly developed imaging method was presented for detecting facial palsy disease that affects one side of the face. In contrast to the previous traditional methods, which were based on visual inspection and the apparent symptoms of the disease. In this study, deep learning-based CNN was used with face detection technology through computer vision and using a high-resolution digital camera to obtain an accuracy of diagnosis of up to 98%, which was an excellent method in diagnosing FP. The proposed system showed its high effectiveness in detecting FP in all its mild, medium and severe cases and identifying the side of the injury with high accuracy compared to other methods. The proposed system may be beneficial in the medical field and a useful tool to help the doctor diagnose and treat. It could be used at home by the patient himself, saving the patient a lot of time, effort and cost. There is ample space for the development of this system, and further development processes are still needed for this system to reach more accurate results and implement it in real-time after developing the algorithm and increasing the number of cases of FP. Adding age and gender to the diagnosis process and the diagnosis of some other diseases that affect the face can be added to the system to become a diagnostic system for several diseases at the same time.

Acknowledgment

The authors would like to acknowledge the cooperation and assistance they received from Al-Rifai General Hospital in Thi-Qar, Iraq.

References

[1] Barbosa, J., et al., Efficient quantitative assessment of facial paralysis using iris segmentation and active contour-based key points detection with hybrid classifier. BMC medical imaging, 2016. 16(1): p. 1-18.
[2] Szczepura, A., et al., Raising the digital profile of facial palsy: National surveys of patients' and clinicians' experiences of changing UK treatment pathways and views on the future role of digital technology. Journal of medical Internet research, 2020. 22(10): p. e20406.
[3] Baugh, R.F., et al., Clinical practice guideline: Bell's palsy. Otolaryngology–Head and Neck Surgery, 2013. 149(3_suppl): p. S1-S27.
[4] Ahmed, A., When is facial paralysis Bell palsy? Current diagnosis and treatment. Cleve Clin J Med, 2005. 72(5): p. 398-401.
[5] O'Shea, K. and R. Nash, An introduction to convolutional neural networks. arXiv preprint arXiv:1511.08458, 2015.
[6] Lindeberg, T., Scale invariant feature transform. 2012.
[7] Dalal, N. and B. Triggs. Histograms of oriented gradients for human detection. in 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05). 2005. Ieee.
[8] Li, Z., et al., A survey of convolutional neural networks: analysis, applications, and prospects. IEEE transactions on neural networks and learning systems, 2021.
[9] Gu, J., et al., Recent advances in convolutional neural networks. Pattern recognition, 2018. 77: p. 354-377.
[10] O'Mahony, N., et al. Deep learning vs. traditional computer vision. in Science and information conference. 2019. Springer.
[11] Zou, W.W. and P.C. Yuen, Very low resolution face recognition problem. IEEE Transactions on image processing, 2011. 21(1): p. 327-340.
[12] Hassaballah, M. and S. Aly, Face recognition: challenges, achievements and future directions. IET Computer Vision, 2015. 9(4): p. 614-626.
[13] Song, A., et al., Neurologist standard classification of facial nerve paralysis with deep neural networks. Future Internet, 2018. 10(11): p. 111.
[14] Abayomi-Alli, O.O., et al., Few-shot learning with a novel Voronoi tessellation-based image augmentation method for facial palsy detection. Electronics, 2021. 10(8): p. 978.
[15] Parra-Dominguez, G.S., R.E. Sanchez-Yanez, and C.H. Garcia-Capulin, Facial paralysis detection on images using key point analysis. Applied Sciences, 2021. 11(5): p. 2435.
[16] Nguyen, D.-P., M.-C. Ho Ba Tho, and T.-T. Dao, Enhanced facial expression recognition using 3D point sets and geometric deep learning. Medical & Biological Engineering & Computing, 2021. 59(6): p. 1235-1244.

[17] Chiesa-Estomba, C.M., et al., Machine learning models for predicting facial nerve palsy in parotid gland surgery for benign tumors. journal of surgical research, 2021. 262: p. 57-64.
[18] Alagha, M.A., et al., Objective grading facial paralysis severity using a dynamic 3D stereo photogrammetry imaging system. Optics and Lasers in Engineering, 2022. 150: p. 106876.
[19] Guo, Z., et al., Facial imaging and landmark detection technique for objective assessment of unilateral peripheral facial paralysis. Enterprise Information Systems, 2021: p. 1-17.
[20] Liu, Y., et al. Automatic Assessment of Facial Paralysis Based on Facial Landmarks. in 2021 IEEE 2nd International Conference on Pattern Recognition and Machine Learning (PRML). 2021. IEEE.
[21] Parra-Dominguez, G.S., C.H. Garcia-Capulin, and R.E. Sanchez-Yanez, Automatic Facial Palsy Diagnosis as a Classification Problem Using Regional Information Extracted from a Photograph. Diagnostics, 2022. 12(7): p. 1528.
[22] Xu, C., et al., A novel facial emotion recognition method for stress inference of facial nerve paralysis patients. Expert Systems with Applications, 2022. 197: p. 116705.
[23] Azuma, T., et al., New method to evaluate sequelae of static facial asymmetry in patients with facial palsy using three-dimensional scanning analysis. Auris Nasus Larynx, 2022.
[24] Vletter, C., et al., Towards an Automatic Diagnosis of Peripheral and Central Palsy Using Machine Learning on Facial Features. arXiv preprint arXiv:2201.11852, 2022.
[25] Zahara, L., et al. The facial emotion recognition (FER-2013) dataset for prediction system of micro-expressions face using the convolutional neural network (CNN) algorithm based Raspberry Pi. in 2020 Fifth international conference on informatics and computing (ICIC). 2020. IEEE.
[26] Khaireddin, Y. and Z. Chen, Facial emotion recognition: State of the art performance on FER2013. arXiv preprint arXiv:2105.03588, 2021.
[27] Arriaga, O., M. Valdenegro-Toro, and P. Plöger, Real-time convolutional neural networks for emotion and gender classification. arXiv preprint arXiv:1710.07557, 2017.
[28] Hsu, G.-S.J., J.-H. Kang, and W.-F. Huang, Deep hierarchical network with line segment learning for quantitative analysis of facial palsy. IEEE Access, 2018. 7: p. 4833-4842.
[29] Pasquale, C., et al. Recovery from Idiopathic Facial Paralysis (Bell's Palsy) Using Photobiomodulation in Patients Non-Responsive to Standard Treatment: A Case Series Study. in Photonics. 2021. MDPI.
[30] Haase, D., et al., Automated and objective action coding of facial expressions in patients with acute facial palsy. European Archives of Oto-Rhino-Laryngology, 2015. 272(5): p. 1259-1267.
[31] Chandaliya, P.K., et al. Scdae: Ethnicity and gender alteration on clf and utkface dataset. in International Conference on Computer Vision and Image Processing. 2019. Springer.
[32] Barbosa, J., W.-K. Seo, and J. Kang, paraFaceTest: an ensemble of regression tree-based facial features extraction for efficient facial paralysis classification. BMC Medical Imaging, 2019. 19(1): p. 1-14.
[33] Wang, T., et al., Automatic facial paralysis evaluation augmented by a cascaded encoder network structure. IEEE Access, 2019. 7: p. 135621-135631.
[34] Grandini, M., E. Bagli, and G. Visani, Metrics for multi-class classification: an overview. arXiv preprint arXiv:2008.05756, 2020.