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RESEARCH ARTICLE

Real-time Facial Palsy with Age and Gender Detection

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Abstract

Facial palsy (FP) is a disease that affects the facial nerves, leading to deviation of the face towards the opposite direction of the injury, with an inability to control facial movements. Diagnosis is typically based on the clinician's judgment, considering the patient's age, gender, and treatment type. However, this method is prone to errors due to doctors' exposure to fatigue and other problems. Therefore, the use of computer vision (CV) systems to automatically detect FP has become crucial. Deep learning is a promising candidate for accurate and cost-effective FP detection. In this context, this work proposes a real-time system that uses a deep learning (DL) algorithm to detect FP, age, and gender. The proposed system could be used by patients at home or as a diagnostic tool for doctors. The proposed system achieves an accuracy of 98% by using datasets containing 19,239 normal images, 834 left palsy images, and 801 right palsy images.

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Keywords: Facial Palsy; Face Detection; Computer Vision; Machine Learning.

1. Introduction

Facial palsy (FP) is a neurological disease that affects the face, in which the patient loses the ability to control voluntary muscle movement and affects one side of the face [1]. It affects one out of every sixty people, and FP is accompanied by some symptoms, including dry eyes, hearing problems, lack of taste se
nation, sagging eyelids, and pain in the ears and around the face [2]. FP affects 11 to 40 people in every 100,000 population, with an annual incidence rate of 37.7 in the United Kingdom, and FP is more common among the age groups of 30-45 years [3]. About 10% of people who have been injured from this disease have a previous family history of it, and people with diabetes and pregnant women are more susceptible to FP [4]. For every 100,000 people, approximately 6.1 of them are children between the ages of one and fifteen years, and females are more likely to be affected than males [2]. Females are much more frequently affected by facial paralysis than males, and the percentage of infection on the right side of the face is lower than on the left side [5]. This disease is considered very distressing for patients because it causes them to lose control over facial movements and results in a distorted facial shape. Medical diagnosis still relies on traditional methods that require visual detection by a doctor, which can be time-consuming and require more effort from the patient. Therefore, it is necessary to use deep learning (DL) techniques to develop a rapid and highly accurate diagnostic system for detecting FP.

In the past decade, significant advancements in computer vision and machine learning (ML) techniques have facilitated the emergence of various automated methods for identifying FP. For example, a study by [6] used the extracted facial features obtained from a dataset of palsy and healthy people with different facial expressions to train a system based on a fully convolutional deep neural network to detect 68 facial landmarks and detect the FP; however, real-time implementation and long execution time were the main limitations [7]. Another study by [8] employed a Facial Action Coding System (FACS) and utilized an Active Appearance Models (AAM) approach to conduct a detailed analysis of facial regions. The study investigated a dataset of 28 healthy individuals and 299 individuals with FP. The analysis examined the rules governing facial functions in terms of action units (AUs). However, it is important to note that the training process for this study incorporated data from healthy individuals exhibiting facial expressions similar to those observed in FP patients. Furthermore, the examination and analysis of each image required an average processing time of 108 milliseconds. Another study by [9] employed a quantitative estimation method to assess the severity of FP by calculating the dissimilarity between two facial images. The proposed method involved identifying salient points through K-MEANS clustering, followed by identifying key edge points using a Susan edge algorithm and face region detection for capturing facial features. In [10], A 3D imaging methodology was employed as an alternative to the conventional 2D approach to track facial features and perform numerical calculations of facial symmetry based on the movement of these features. Additionally, dynamic expressions were quantitatively analyzed. It is noteworthy that the training of the detection model utilized data from individuals without FP. Nevertheless, the presented method exhibited limitations in accurately diagnosing FP in certain patients. Azoulay et al. [11] employed a user-friendly mobile application for the diagnosis of FP and the identification of vital signs. Data acquisition was conducted using a mobile device, capturing information for a duration of 5 to 10 minutes from a cohort consisting of 31 healthy subjects and 14 subjects diagnosed with FP. The system demonstrated an impressive accuracy rate of 95.5%. A study by Jocelyn et al.[12] introduced a classification system designed for the detection of FP utilizing a dataset consisting of 325 facial images. The proposed system achieved a sensitivity rate of 93.6%. The study employed an iris segmentation method to extract key features, and the distances between these features were calculated using Dogman's integral differential algorithm. Another study by Marina et al. [13] proposed an evaluation methodology based on facial thirds for assessing facial asymmetry. The approach involved utilizing stereophotogrammetric devices to analyze differences and asymmetry in the face. The study incorporated a sample size of 30 patients diagnosed with unilateral FP alongside 40 healthy individuals. Another study by Storey et al. [14] presented a hybrid approach in their study, aiming to automatically generate a three-dimensional face model from a two-dimensional image for the purpose of detecting facial features using a computer vision system. The methodology incorporated engineering features, three-dimensional reconstruction, and two-dimensional face alignment techniques. The study achieved a notable level of accuracy in assembling facial features. However, it should be noted that errors arose during the assembly of mouth features when encountering asynchronous movements within a group, consequently affecting the overall accuracy of the system. Storey et al. [15] proposed a 3D CNN, named 3D palsyNet, for the classification of FP and oral movement. The methodology utilized two datasets and achieved an F1 score of 82% for mouth motion and 88% for FP. Another approach incorporated a ResNet backbone and employed a dataset containing various facial movements. The classification accuracy obtained ranged from 82% to 86%, with a training time ranging from 2 hours and 10 minutes to 4 hours and 25 minutes. Information extraction involved exploring facial features to evaluate FP, whereby the study relied on automatic prediction based on the severity of FP. The training data encompassed a mixture of paralyzed and normal faces, and a binary sequential process was employed for training the deep neural network model used in FP evaluation. The average accuracy for a study proposed by Wang et al. [16] was between 82% and 95.60%, with a classification of error between 8.72% and 18.88%. Barbosa et al. [17] conducted another study employing a set of regression trees for iris detection and regularized logistic regression (LR) to extract key features for FP analysis. The study utilized a dataset consisting of 440 FP images. Notably, the study achieved a satisfactory level of accuracy while maintaining a reduced processing time. Jiang et al. [18] used a computational image analysis technique for the detection of facial paralysis, utilizing three distinct machine learning methods: Support Vector Machines (SVM), k-Nearest Neighbors (K-NN), and Neural Networks (NN). The study utilized a dataset consisting of 8,000 facial images obtained from 80 participants. The accuracy rates achieved ranged from 87.22% to 95.69% in classifying the degree of injury. Dell'Olio et al. [19] used a FaraPy system and video data of six healthy subjects with different facial expressions to detect FP in real time and obtained acceptable accuracy and minimal losses. A study by Nguyen et al. [20] a study proposed a computer vision technique for the detection of facial expressions. The approach involved the application of deep learning techniques to analyze 3D point cloud data. The study achieved a detection accuracy ranging between 69.01% and 85.85%. Another study by Dominguez et al. [21] FP was detected using landmarks and a binary classifier for a dataset of 480 images. The classification accuracy was 94.06% when utilizing the freely available Massachusetts Eye and Ear Infirmary (MEEI) database, which contains a comprehensive range of facial photographs and videos covering both flaccid and nonflaccid FP. Additionally, a classification accuracy of 97.22% was achieved using the Toronto NeuroFace (TNF) database, which was specifically gathered for clinical evaluations. Recently, Estomba et al. [22] proposed a K-nearest neighbor algorithm to predict facial nerve paralysis by using a data set of 356 patients with a performance accuracy greater than 0.9. A recent study by Amsalam et al. [23] proposed a method for FP detection by computer vision system using deep learning by CNN and Python program. It used 570 images, including 200 images of FP palsy, 10 individuals (3 males and 7 females) with facial palsy participated. Their ages varied between 15 and 70 years with varying levels of FP and injury on different sides, with achieved short processing and detecting time and 98 % of accuracy. Still, it is considered not easy as it is not in real-time. Nevertheless, previous methods encountered some limitations, such as the lack of quantitative results or insufficient performance. Furthermore, many of these approaches relied on training models exclusively using data from healthy individuals and traditional facial feature detection techniques. This study proposes a real-time system to address these limitations by utilizing CNN and Python software-based deep learning algorithms. The proposed system aims to detect FP. Additionally, the proposed system aims to estimate the age and gender of patients accurately. The remainder of this paper is organized as follows: materials and methods are presented in section 2, followed by the evaluation metrics in section 3. The experimental results and discussion of the proposed system are presented in section 4. Finally, section 5 concludes the paper.

Nomenclature & Symbols	
AAM	Active Appearance Models
AUs	Action Units
BP	Bell's paralysis
CV	computer vision
CNN	Convolutional Neural Network
DL	Deep Learning
FACS	Facial Action Coding System
FP	Facial Palsy
KNN	K-Nearest Neighbors
KMC	K-MEANS clustering
LR	Logistic Regression
ML	Machine Learning
NN	Neural Networks
SVM	Support Vector Machine
MEEI	Massachusetts Eye and Ear Infirmary database
TNF	Toronto Neuro Face database

2. Materials and Methods

2.1. Research Ethics and data collection

This study followed the research ethics and guidelines of the Declaration of Helsinki on Research Ethics (Finland 1964), and an ethical protocol number was granted from a specialized committee at the Dhi Qar Health Department, Iraqi Ministry of Health (Protocol No. 362/2022). Consent was taken from the participants before sampling, and they were informed about the research procedures, the purpose of collecting samples, and the confidentiality of the collected information. Samples were collected from the Physiotherapy Center at Al-Rifai General Hospital. The participants were 20 people with FP, and the average age ranged from 10 to 70 years, with different sides and stages of facial palsy (ranging between medium and severe).

The remaining data were collected from [24,25] for facial palsy and normal people. The collected data were 2115 normal images, 834 left palsy images and 801 right palsy images. With regard to age and gender, a dataset consisting of 23,000 images depicting individuals of different age groups was used to train an algorithm capable of detecting age and gender. The dataset used in this investigation was obtained from [26] UTKFace dataset.

2.2. Experimental Setup

The experimental setup of detecting facial images and diagnosing FP is illustrated in Figure 1. The patient sits in front of the computer camera, and the device can directly diagnose the patient's condition, whether the patient has FP or not, and also detect the patient's age and gender in real-time. This process was done after training the system with three data, including normal data, right FP data, and left FP data. Each of these data was divided into training data (80%) and testing data (20%).

Python program (Version 3.9) was used and executed on Anaconda Navigator version 2.3.2, with some libraries (TensorFlow, Keras, NumPy, OpenCV and dlib) installed on a laptop.

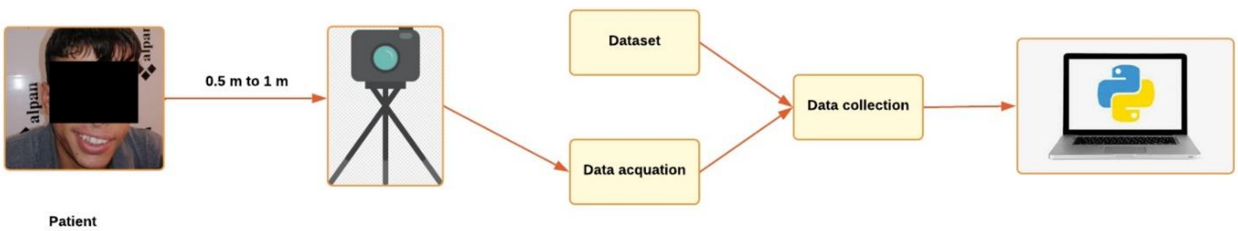

Fig. 1. The experimental setup of the proposed system.

The patient was photographed in several positions, such as opening the mouth, raising the eyebrows, and opening the eyes to obtain different images of the same patient after placing the camera at a distance of 0.5 to 1 meter. At the same time, adhering to some considerations, such as lighting the place of imaging and directing the patient in sight with the camera to achieve a clear image, making it easier for the proposed system to detect FP and its side easily.

2.3. System Design

The block diagram of the proposed system for detecting FP is shown in Figure 2.

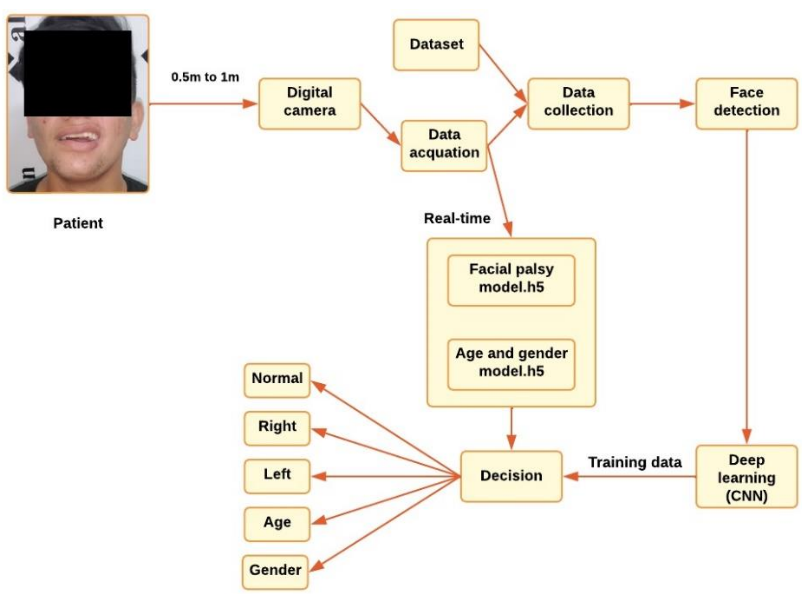

Fig. 2. The block diagram of system design.

The data was collected and stored in a special file inside the computer. There are three successive stages in the classification process of facial expressions, starting with face detection, then extracting facial features, and ending with a classification of facial expressions [23]. Features were extracted after detecting the face, as it detects the main points of the face, such as the mouth, eyes, and eyebrows after pre-processing the image [24]. The proposed system extracted 68 facial features that were identified using the Haar Cascades technology, which is one of the important technologies behind face detection technology. The facial features were determined, and a rectangle took the shape of the region and considering half of it is white and the other half is black due to the difference in the contrast of the facial regions. The white and dark regions were collected, and the result was subtracted one from the other, and the resulting value was whenever it was close to one or 255. This process was applied to the image after converting it to an integral image to reduce time complexity. The window size was then changed several times depending on the size of the feature. When the face is detected, all Haar features indicate the presence of a person. After collecting the features in each stage, the diagnostic algorithm for detecting facial features is then programmed and trained on this data using a set of packages for detecting facial features in the Python program. It was classified as True or Fuls, it exists, or it does not exist, and it searches for similar features in the images and matches them to reach the correct detection. It detects key features such as the nose, mouth, eyebrows, eyes and edges of the face.

2.4. Convolutional Neural Network (CNN)

CNN is a convolutional neural network that specializes in image and pattern recognition tasks. It is a hard-task network and is considered one of the forms of artificial intelligence [21]. It is one of the most representative neural networks in the field of deep learning, and it has the ability to recognize things and facilitate the identification of these things for people through computer vision [22]. It is a network that can extract data features using convolutional structures and differs from traditional methods in feature extraction [20,27].

Special features and all issues related to data pre-processing and extraction of features from the face were obtained. The selection of these features with their classification was overcome by using CNN, which is an advanced stage of artificial intelligence and machine learning in detecting facial features and identifying points of difference. Figure 3. shows the general architecture of the CNN.

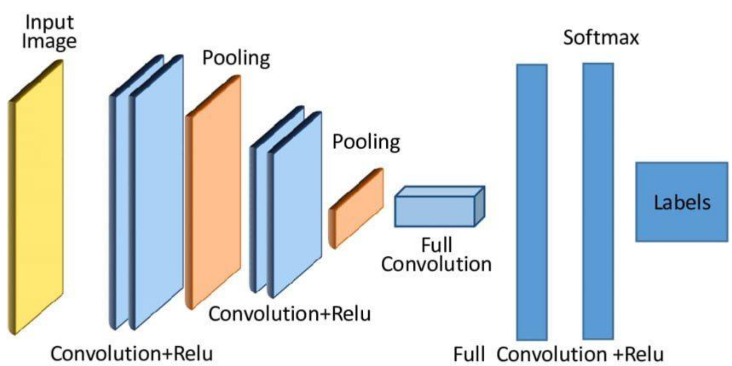

Fig. 3. The general architecture of the CNN [28].

After the image was input into the CNN, the convolutional layer was combined with an activation function (Relu) along with its variables, subsampling layers such as max-pooling, another convolutional layer, a dense layer, and ending with the soft-max layer. The practical algorithm works by inputting both the test and training data, and the process involves training the model using the training data, which the CNN processes to extract facial features. After evaluation, the training model is produced for the maximum epoch. The trained data is then compared with the test data to achieve an actual and accurate prediction of facial expressions.

The techniques for detecting facial features depend on identifying differences in both sides of the face, including different expressions, distances, and key points on the face. This is because the patient cannot control the affected side of the face due to the inability to control the muscles on that side. As a result, the patient cannot raise an eyebrow, close the eye, or move the mouth on the side of the injury. This deviation from the healthy side is caused by the loss of control of the muscles on the affected side, as shown in Figure 4.

Fig. 4. An example for a patient with right palsy.

FP, age, and gender can be simultaneously predicted using a CNN on the UTKFace dataset. The dataset contains more than 20,000 facial images with annotated information on age and gender. To achieve this, the data can be preprocessed by resizing the images and normalizing pixel values, defining a CNN architecture consisting of several convolutional layers, pooling layers, and fully connected layers, training the CNN on the dataset using an optimization algorithm, and evaluating its performance on the test set using metrics such as accuracy, precision, recall, F1 score, or mean absolute error. Using a softmax output layer for FP data and a linear or sigmoid output layer for age and gender, the three traits can be predicted on new facial images.

2.5. Evaluation Metrics

Depending on the combination of expected and an actual class of FP diagnosis, results can be divided into four cases: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). According to the confusion matrix, five variables are used to evaluate the proposed system's diagnostic ability: accuracy, sensitivity (Recall), Specificity, Precision, and F1 Score. These variables can be defined as follows: [6,29-31]

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

$$Sensitivity = TP/(TP + FN) \tag{2}$$

$$Specificity = TN/(TN + FP) \tag{3}$$

$$Precision = TP/(TP + FP) \tag{4}$$

$$Error\ rate = (FP + FN)/(TP + FP + FN + TN) \tag{5}$$

$$F1\ Score = 2 \times (Precision \times Recall) / (Precision + Recall) \tag{6}$$

3. Experimental Results

To evaluate the proposed system and verify its results, a comparison was made with the diagnosis of ten other patients who were examined and diagnosed by a specialist doctor. The program was trained using 80% of the data and the remaining 20% for testing. The proposed system achieved an accuracy of 98%. For actual patient data, the system had a detection accuracy of 99% for all cases. The diagnostic time was a few seconds, while training required a longer time of up to 6 hours, depending on the computer processor's power. Figure 5 shows the typical result of the proposed system, as it classified the images according to the diagnosis of right palsy, left palsy, and normal. Upon examining the three images, it becomes evident that the proposed system's diagnosis was accurate and efficient.

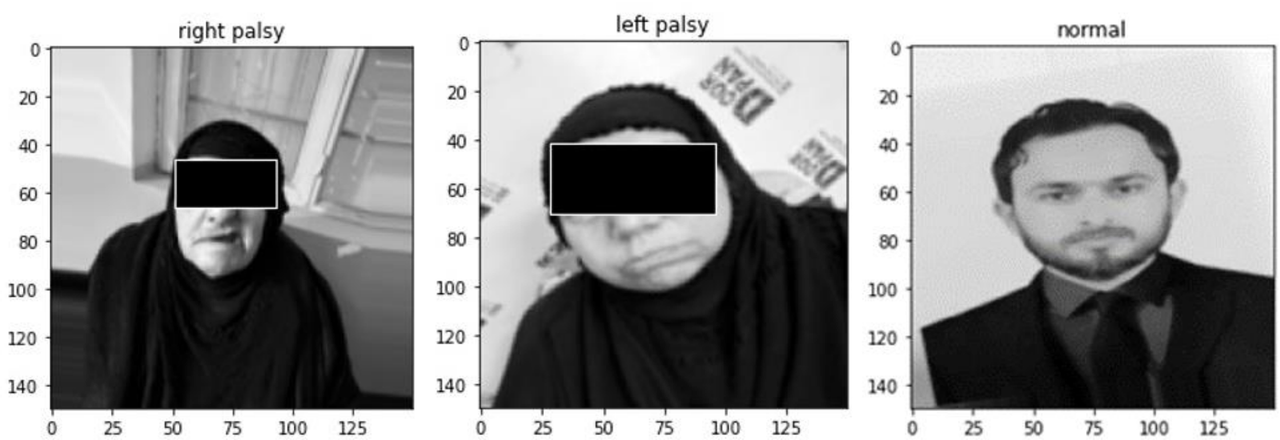

Fig. 5. The typical result of the proposed diagnostic system for different cases.

When the proposed system was applied in real-time, the results showed whether the person has FP, his age, and gender, as demonstrated in Figure 6. The proposed system also successfully detected the case of a healthy person without FP, along with his age and gender, as shown in Figure 7.

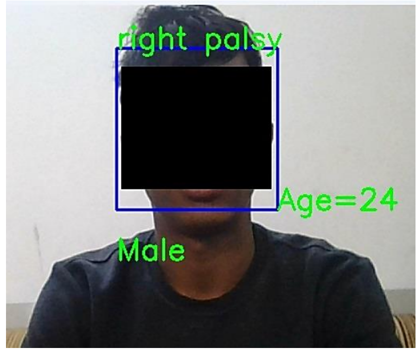

Fig. 6. Real-time diagnosis of the proposed system for a right FP patient with age and gender detection.

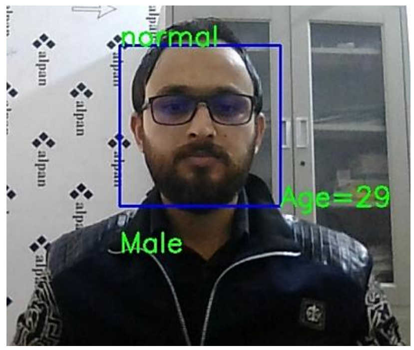

Fig. 7. Real-time diagnosis of the proposed system for a normal person with age and gender detection.

The confusion matrix is based on the actual classification and the expected classification, determined by the number of iterations. The two classifications, actual and expected, are represented by rows and columns in a cross table. The rows indicate the actual classification, while the columns indicate the classification expected by the proposed system [30]. Figure 8 shows the confusion matrix divided into three sections according to the classification of the test data. It consists of 3 rows and 3 columns, with each row and column representing one of the classifications of the test data. The data was either correctly classified or misclassified by the proposed system. The confusion matrix shows the actual value and the predicted value of the program, which classifies the values into an actual value (the real rating value) and a prediction value (predicted by the program). The program's prediction should be similar to the input values; when a positive or negative real value was entered in the training data, the program should predict the same value in the test data after completing the training process. In order for the model to be approved, the results must match the classification of the data stored in the program. The proposed system's accuracy, sensitivity, precision, specificity and F1 Score were 0.93.78, 1, 0.97, 0.8 and 0.984, respectively, with an error rate of 6.22. These results when using 20 % from total datasets and these results indicated that the proposed system has acceptable results with high diagnostic accuracy.

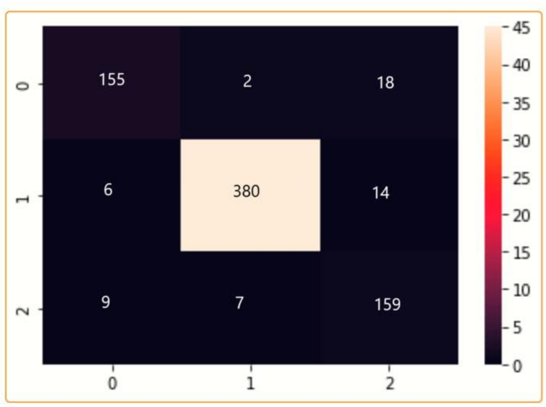

Fig. 8. Real-time diagnosis of the proposed system for a normal person with age and gender detection.

The images used must have the same size, color, and extension to make it easier for the program to read them without any loss. The more data and clearer the images used, the higher the accuracy of the proposed system and the fewer losses in unreadable images from the proposed system. The typical result of high accuracy in the training process is clearly shown in Figure 9. The proposed system's accuracy reached 98% when using total datasets, indicating that it is an acceptable diagnostic system with few losses. The amount of loss in the training data was 2%, which indicates that the proposed system has low loss and high accuracy, as shown in Figure 10.

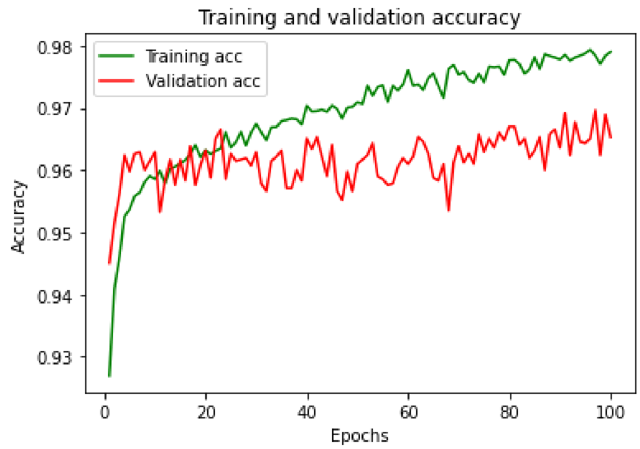

Fig. 9. The training and validation accuracy.

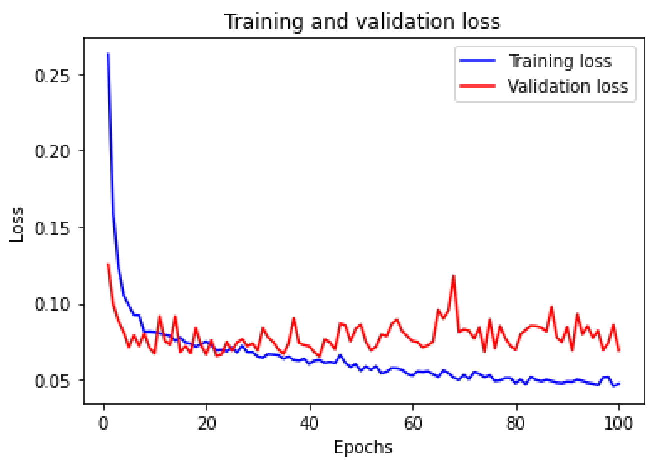

Fig. 10. The training and validation loss.

It is possible to reduce losses further and increase accuracy by using higher-resolution images and removing low-resolution images. Although the proposed diagnostic system provided acceptable results for FP, age, and gender detection, there were some limitations, including consideration of subject movement, difficulty in differentiating between an impersonator of FP and an actual patient, and the challenge of diagnosis in the case of tilting the face or moving away from the camera. Additionally, general restrictions such as patient embarrassment and annoyance with imaging made it challenging to collect data for palsy patients.

4. Conclusion

In this paper, an advanced and high-accuracy system was presented to detect FP that occurs on one side of the right or left face without the doctor needing a visual inspection. In the proposed system, FP, age, and gender were precisely detected in real-time based on CNN. The proposed system provided high accuracy in diagnosis, reaching 98% after training the collected data. The proposed system can be used by specialized staff in hospitals. In addition, it can be used in homes by the injured patients themselves without going to the hospital, thus reducing patient time, effort and cost.

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