International Journal of Current Innovations inAdvancedResearch
(International Multidisciplinary Tri-annual Research Journal)
Content Available at www.ijciar.com ISSN (O)2636-6282ISSN (P)2659-1553

AUTOMATE FACIAL PARALYSIS DETECTION USING VGG ARCHITECTURES

Abbas Khalifa Nawar*[1], Hadi Raheem Ali[2], Mothefer Majeed Jahefer[3], Sabah Abdulazeez Jebur[4]
Department of Computer Techniques Engineering, Imam Al-Kadhum College (IKC), Baghdad, Iraq

***Corresponding Author**
Abbas Khalifa Nawar

DOI: https://doi.org/10.47957/ijciar.v7i1.158

Received: 22 Nov 2023 Revised: 15 Dec 2023 Accepted: 17 Jan 2024

Abstract
Facial Paralysis (FP) is a debilitating condition that affects individuals worldwide by impairing their ability to control facial muscles and resulting in significant physical and emotional challenges. Precise and prompt identification of FP is crucial for appropriate medical intervention and treatment. With the advancements in deep learning techniques, specifically Convolutional Neural Networks (CNNs), there has been growing interest in utilising these models for automated FP detection. This paper investigates the effectiveness of CNN architectures to identify patients with facial paralysis. The proposed method leveraged the depth and simplicity of Visual Geometry Group (VGG)architectures to capture the intricate relationships within facial images and accurately classify individuals with FP on the YouTube Facial Palsy (YFP) dataset. The dataset consists of 2000 images categorised into individuals with FP andnon-injured individuals. Data augmentation techniques were used to improve the robustness and generalisation of the approach proposed. The proposed model consists of a features extraction module utilising the VGG network and a classification module with a Softmax classifier. The performance evaluation metrics include accuracy, recall, precision and F1-score. Experimental results demonstrate that the VGG16 model scored an accuracy of 88.47% with a recall of 83.55%, precision of 92.15% and F1-score of 87.64%. The VGG19 model attained level of precision of 81.95%, with a recall of 72.44%, precision of 88.58% and F1-score of 79.70%. The VGG16 model outperformed the VGG19 model in terms of accuracy, recall, precision, and F1-score. The results indicate that VGG architectures are effective in identifying patients with facial paralysis.
Keywords: Facial paralysis, Deep learning, YFP, VGG, CNN.

1. Introduction

Facial paralysis is a common condition characterized by droopingor reduced control of the affected part of the face. In addition to its impact on facial appearance, it can give rise to challenges related to feeding and emotional well-being[1]. The conventional diagnosis of facial palsy heavily depends on the subjective judgment of clinicians by instructing them to implement specific facial expressions using various scoring standards and their own clinical expertise[2]. However, this clinical method suffers from labour-intensive procedures and subjective assessments [3].

In recent years, computer-aided diagnosis approaches have gained significant attention in the field of healthcare by leveraging artificial intelligence and computer vision techniques [4][5]. These approaches have the potential to overcome the limitations associated with traditional clinical methods [6]. Notably, the advancements in computer-aided diagnosis methods for facial palsy have demonstrated impressive performance and garnered widespread interest[7]. These approaches involve the direct analysis of standardised 2D photographs or videos of facial palsy by utilising computer vision and machine learning techniques[8].

CNNs have exhibited excellent results in medical applications and various other domains[9][10].CNNs are a subset of Deep learning (DL) methods that have been designed for image and video recognition tasks. They consist of several layers. Each layer applying a set of filters to an input image. This hierarchical structure enables the network to extract complex features from the input data[11]. However, training a CNN to achieve optimal performance requires a substantial amount of data and the demand for high volumes of data poses a significant problem. To address this issue, researchers have increasingly embraced the concept of transfer learning as a promising solution.

Transfer learning involves utilising a pre-trained CNN model, which has already learned specific features for a particular task from a specific dataset, and fine-tuning it for a new task[12].The main contribution of this paper can be summarised as follows:

- Investigating the effectiveness of CNN architectures, particularly visual geometry group (VGG) networks, in identifying patients with facial paralysis.
- Proposing a deep CNN approach for facial paralysis detection, which comprises two modules: a feature extraction module utilising VGG networks and a feature classification module with a Softmax classifier. The VGG networks were adapted specifically for the task of facial paralysis detection.
- Addressing the issue of data scarcity by employing transfer learning and data augmentation techniques.

2. Literature Review

This literature review offersan overview of several notable studies that propose novel methods for quantitative classification, severity assessment, gesture recognition and lesion analysis in facial paralysis.[13] introduced approach for quantitative classification and assessment of FP in facial images. This method combines iris segmentation and key point detection based on the localised active contour algorithm. The proposed approach provides a productive means of quantitatively assessing FP by measuring the facial symmetry using the ratio of iris area to the vertical spatial distances between key points. Furthermore, iris features are able to capture changes in iris exposure during facial expressions to highlight noticeable differences between the healthy and severely affected sides.

In [14], the authors proposed approach utilising deep convolutional networks for the objective assessment of unilateral peripheral facial paralysis. The article addressed the issue of confusion between neighbouring House–Brackmann (HB) degrees and achieving a classification accuracy of 91.25% for foreseeing HB degrees.

[15] presented a method for quantitatively assessing facial nerve paralysis (FNP) by combining a facial asymmetrical features (FAF)algorithm and a facial landmark estimation (FLE) algorithm extracted from facial movement images. The FLE algorithm enables automatic and precise detection of facial landmarks, while the FAF depends on the angles between key facial landmarks and the degree of mirroring in multiple facial regions. This approach captures the displacement and exposure changes of facial organs during facial movementswhich provides valuable insights for FNP diagnosis and personalised rehabilitation therapies.

In [16], a computer-based method for the objective and accurate classification of FNPwas proposed. The method utilised a CNN directly trained from imagesusing pixel data and disease labels as inputs. With a dataset of 1,049 clinical images categorised into seven classes, the CNN demonstrates a high level of accuracy when evaluated against neurologists' assessments as the ground truth.

The authors in[17] introduce the hierarchical detection network (HDN) as a DL-based method for facial palsy syndrome detection. Comprising three component networks for face detection, landmark detection and local palsy region detection, the HDN demonstrates efficient processing with reduced convolutional layers. The second component network utilises a 3D face alignment network for landmark localisation.

Research [18] suggests utilising a network on a comprehensive dataset to learn specific features related to facial palsy from face images. To address overfitting, a generative adversarial network is incorporated for data augmentation. The learned features are subsequently employed for classifying palsy diseases into five benchmarked grades.

In [19], an approach for classifying FP in facial images is introduced. Salient points and iris detection based on an ensemble of regression trees are used to learnkey features. The classification is performed using a regularised logistic regression combined with a classification tree classifier, which enables efficient quantitative assessment of facial paralysis.

3. Visual Geometry Group Networks (VGG)

After CNNs demonstrated their effectiveness in image recognition, Simonyan and Zisserman proposed the VGG, a straightforward and efficient design principle for CNN. VGG is a multi-layer model that delves deep into capturing the relationships between network representations. It adopts a layer of 3×3 filters stacked together, instead of using larger filters like 5×5 and 11×11. This innovative approach showed that the use of these smaller filters in parallel could achieve an equivalent impact to the larger ones while also reducing computational complexity through a decrease in the number of parameters[20]. Furthermore, VGG introduced 1×1 convolutions within the convolutional layers to regulate the network complexity, enabling the learning of linear combinations of subsequent feature maps. To maintain the spatial resolution, a max pooling layer was added after the convolutional layer, which implemented padding.

Overall, VGG gained a reputation for its increased depth, consistent topology and simplicity[21][22].VGG proposed two network architectures, namely VGG16 and VGG19, with the main difference being the depth of the network. VGG16 consists of 16 weight layers, while VGG19 has 19 weight layers. Both models share a similar structure, comprising a sequence of convolutional layers that are subsequently followed by fully connected layers. VGG16 comprisesfive convolution units and three fully connected layers. Each convolution unit is accompanied by a max pooling layer. The number of convolution channels starts at 64 in the first layer and doubles after each max pooling layer until reaching 512. Within each convolution unit, several convolutional layers are used with 3×3 kernels. This design reduces the number of parameters and enhances the network's ability to perform non-linear mapping, thereby improving its fitting capability[23][24]. Figure 1 provides a visual representation of the VGG16 architecture.

VGG19 refers to the VGG model with 19 layers. It follows a similar architecture as VGG16 but includes additional convolutional layers. Specifically, VGG19 has 16 convolutional layers and three fully connected layers[25]. Figure 2 illustrates the VGG19 architecture.

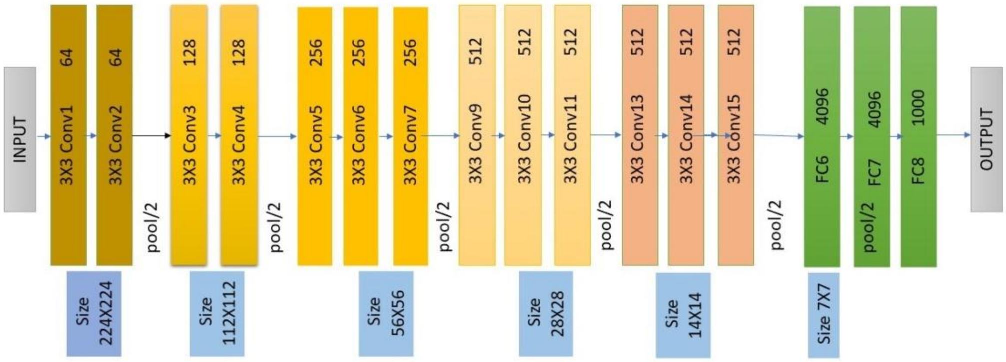


Figure 1. The architecture of VGG16

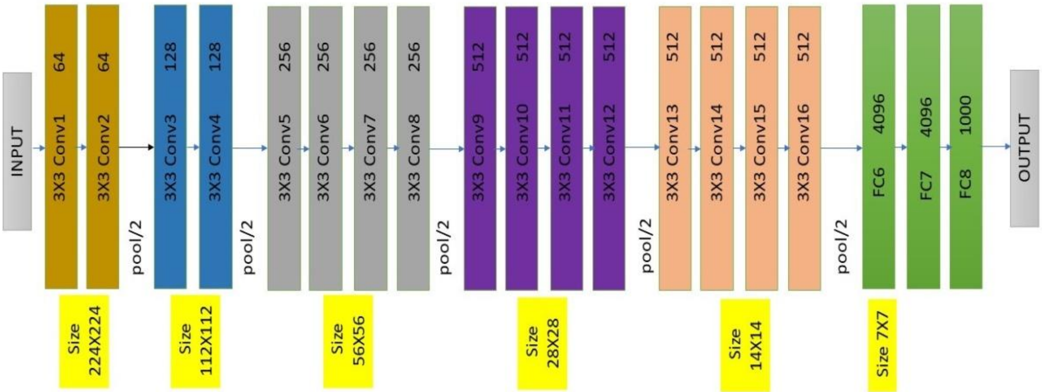


Figure 2. The architecture of VGG19

4. Materials and Methods

4.1 Dataset

This study utilised the YFPdataset as the primary dataset for the analysis[1]. This dataset encompasses 32 videos, featuring 21 patients that were collected from YouTube and meticulously annotated by medical specialists. The videos were subsequently converted into frames by the dataset authors, resulting in image sequences presented at a rate of six frames per second. The primary aim of the study was to evaluate the effectiveness of the proposed method in identifying patients with facial paralysis. To accomplish this, we utilised a total of 3,261 images that were categorised into two distinct classes: individuals with FP and non-injured individuals. The dataset was then divided into two groups, with 2,641 images allocated for training and the remaining 620 images reserved for testing. An exampleof facial palsy images is presented in Figure 3.

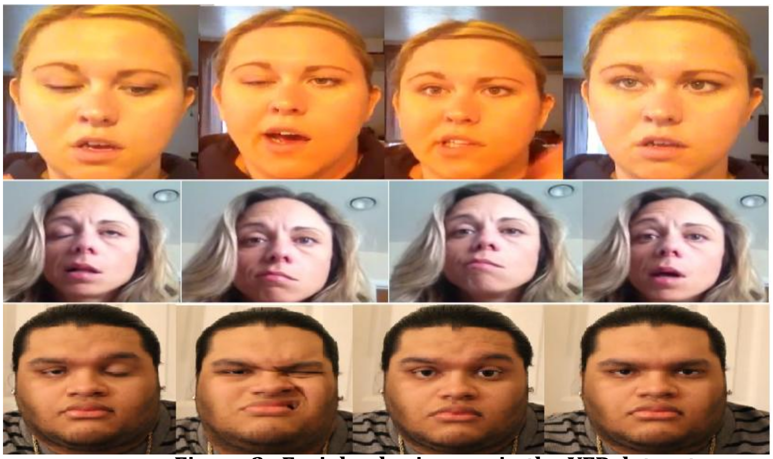


Figure 3. Facial palsy images in the YFP dataset

To ensure compatibility between the YFP dataset and the proposed model, the images in the dataset were resized to 224×224×3 (height, width, channels). This resizing was performed to align with the input size specifications of the VGG networks. In addition, a data augmentation method was employed to address the lack of data and enhance the robustness and generalisation. This technique aimed to increase the variety within the training dataset and grant the model the ability to learn more invariant and representative features. It involved generating altered versions of the existing data to artificially expand the training data. Various methods, including rotation, flipping, shifting and scaling, were employed to create these modified versions.

4.2 The Proposed Model

In this research, we propose a DL approach for classifying input medical images as either positive or negative. A positive result refers to facial paralysis, while a negative result refers to a normal condition. The model is composed of two modules: the feature extraction module, which utilises the VGG network to learn features from input images, and the classification module, which employs a Softmaxclassifier to assign class probabilities for distinguishing between individuals with FP and non-injured individuals. Figure 4 depicts a schematic diagram illustrating the proposed model.

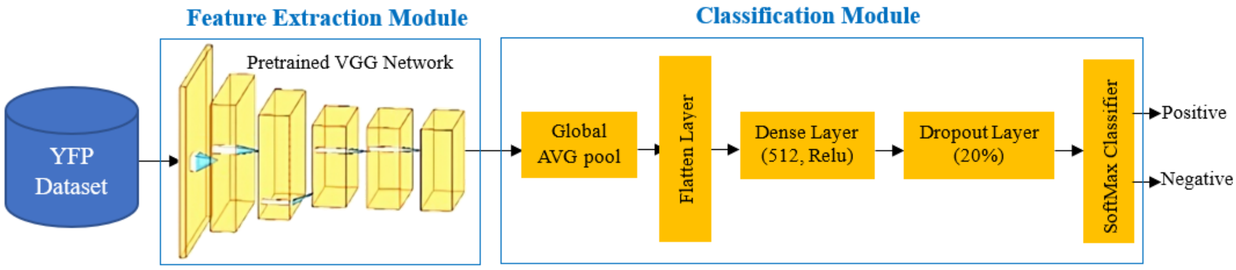


Figure 4. Schematic diagram of the Proposed Model

A. Feature Extraction Module

VGG networks, specifically VGG16 and VGG19, provide pre-trained models that have undergone training on large-scale datasets like ImageNet. These pre-trained models, which include learned features and weights, can be utilised by researchers as a starting point for their classification tasks. This approach, known as transfer learning, offers significant time and computational savings, particularly when dealing with limited labelled data. To ensure the suitability of the pre-trained VGG network for addressing the specific problem at hand, the classification layers are excluded. This exclusion allows for the incorporation of customised layers that are specifically designed for two-class classification. This adjustment makes it possible to tailor the models to the particular task, thus improving their performance in accurately distinguishing between the two classes.

B. Classification Module

The module for feature classification is responsible for training the weights of the characteristic vectors in order to identify injured individuals. This module consists of the following layers:

- **A global average pooling layer (GAP)** is applied to reduce the spatial dimensions of the input feature maps, generating a fixed-length feature vector. The GAP layer is represented by the formula:

$$G_i = \frac{1}{H \times w} \times \sum \sum f(i, j, k) \; Eq. (1)$$

In Eq. (1), the summation spans all spatial dimensions of the feature map denoted by j (ranging from 1 to H) and k (ranging from 1 to W). For a feature map (F) with dimensions H×W×C, where (H) is the height, (W) is the width, and (C) is the number of colour channels, the result of the GAP layer (G) is a vector of length (C). Each element (i) in this vector represents the average activation across all spatial dimensions.

- **A Flatten layer** is utilized to convert the output of the preceding layer into a 512-feature vector, which can then be forwarded to a fully connected layer. The fully connected layer comprises 512 neurons with a ReLU activation function, and each neuron is connected to 512 nodes of the feature vector.
- **ADropout layer** is introduced, with a dropout rate of 0.2, to address overfitting and enhance the model's generalization to new data. This drop rate signifies that during training, 20% of the neurons are randomly deactivated.
- **A Softmaxlayer**is utilized for feature classification, determining the final probability for the two classes in the YFP dataset. The Softmax activation function is defined as follows:

$$softmax(c_i) = \frac{e^{ci}}{\sum_{j=1}^{k} e^{ci}} \qquad Eq. (2)$$

5. Results and Discussion

5.1 Performance Evaluation Metrics

The proposed models were evaluated using the standard measures, including accuracy, precision, recall, and F1-score, to demonstrate its effectiveness. These measures are defined as follows:[11].

- **Accuracy**is a measure of the total correctness of the model. It calculates the ratio of correctly predicted samples to the total samples in the dataset. Accuracy is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad Eq. (3)$$

- **Precision**is the measure of the accuracy of the classifier in predicting positive samples. It is the ratio of true positives to the sum of true positives and false positives. Mathematically, precision is defined as:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad Eq. (4)$$

- **Recall**is the measure of the ability of a classification model to capture and correctly identify all the relevant samples (true positives) in the dataset. It is calculated as the ratio of true positives to the sum of true positives and false negatives. Mathematically, recall is defined as:

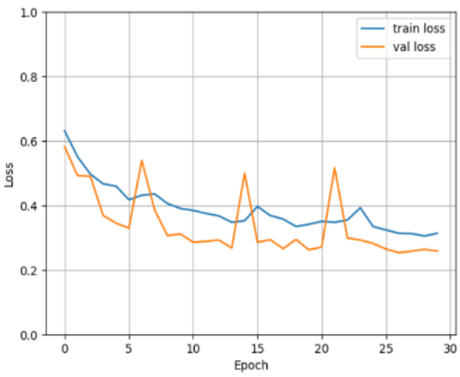
$$\text{Recall} = \frac{TP}{TP + FN} \qquad Eq. (5)$$

- **The F1 score**provides a balance between precision and recall, making it a useful metric when there is an uneven class distribution. Mathematically, It is defined as:

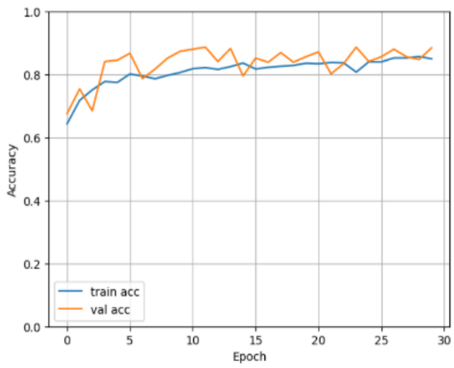
$$\text{F1 score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \qquad Eq. (6)$$

5.2 Analysis of Experimental Results

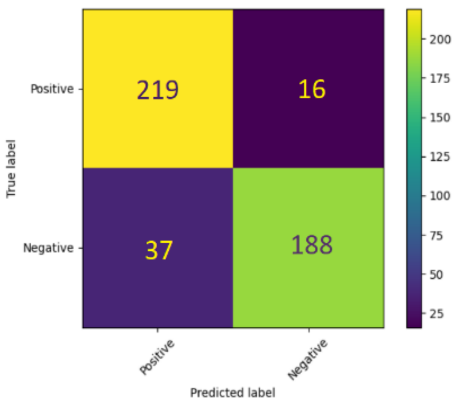
In this research, the effectiveness of the proposed method in identifying patients with FPwas evaluated using two deep CNN architectures, VGG16 and VGG19, on the YFP dataset. The training and validation set losses, accuracies and confusion matrices of the VGG16 and VGG19 models are illustrated in Figures 5 and 6, respectively. These figures provide a comprehensive representation of the models' performance during the training and validation phases. The detailed performance evaluation of these models on the YFP dataset is presented in Table 1. This evaluation reveals the models' performances.



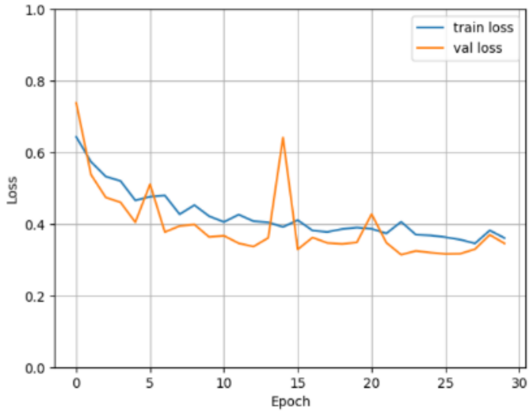
(a) Loss with varying epochs



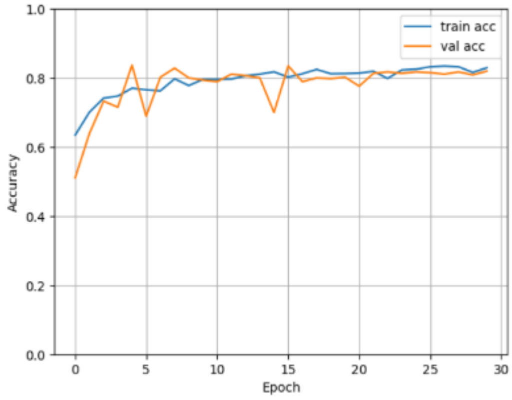
(b) Accuracy with varying epochs



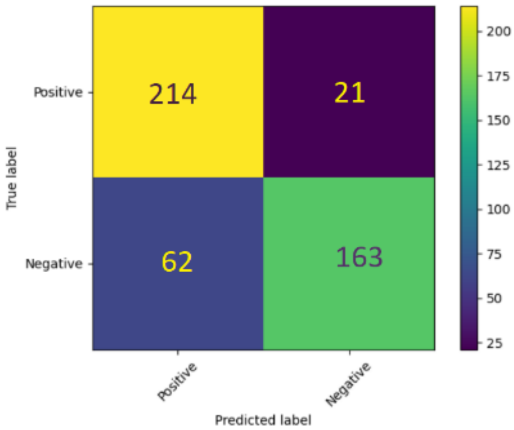
(c) Confusion matrix



(a) Loss with varying epochs



(b) Accuracy with varying epochs



(c) Confusion matrix

Figure 6. Experimental results using the VGG19 Model

Table 1: Experimental on YFP dataset using VGG16 and VGG19 models

Model	Accuracy %	Recall %	Precision %	F1-score %
VGG16	88.47	83.55	92.15	87.64
VGG19	81.95	72.44	88.58	79.70

The results of the first experiment using the VGG16 network for feature extraction showthat it achieved an accuracy of 88.47%, which means that the model correctly classified 88.47% of the input images. The recall, which measures the model's ability to accurately determine positive instances, was 83.55%. The precision, which represents the model's ability to correctly label instances as positive, was 92.15%. The F1-score, which is a harmonic indicate of precision and recall, was 87.64%. In the second experiment, the VGG19 network was used for feature extraction. The accuracy achieved by this model was 81.95%, which is slightly lower than the VGG16 model, and the recall was 72.44%, indicating that the model had a lower ability to correctly identify positive instances compared to the VGG16 model. The precision, however, was 88.58%, which indicates that the model had a higher ability to correctly label instances as positive compared to the VGG16 model. The F1-score was 79.70%.Based on these results, it can be concluded that the VGG16 model outperformed the VGG19 model in terms of accuracy, recall, precision, and F1-score.Overall, these results demonstrate that VGG architectures are an effective approach for identifying patients with facial paralysis.

5.3 Comparative Analysis

For evaluating the performance of the proposed method against some other studies, a precise comparison has been accomplished, as shown in Table 2. The performance of the methods was measured according to metrics of accuracy, recall, precision, and F1-score. All methods intended to achieve considerable results regarding the classification of individuals into non-facial palsy and facial palsy patients. The presented results clearly show that the performances of these methods are different. Results also show that the performance of the proposed method outperforms other considered methods in references [4] and[26]. However, the performance of the reference [27] is the best among others. Finally, it is more important to mention that facial palsy detection is an optimization problem. Therefore, there is a need for continuing research on that truck. Besides, factors such as the size of the dataset, dataset diversity, and the quality of images have an effectiveness on the conducted approaches.

Table 2. A comparison of the proposed method's performance against other methods

Year, [Ref.]	Method	Accuracy%	Recall%	Precision%	F1-Score%
2019, [4]	End-to-End Training	82.90	82.53	83.41	82.96
2022, [26]	Support Vector Machine(SVM)	76.87	-	-	-
2023, [27]	Convolutional Neural Network (CNN)	95.80	100.00	99.00	99.49
The Proposed Method(VGG16)		**88.47**	**83.55**	**92.15**	**87.64**

6. Conclusion

This paper has explored the effectiveness of the VGG models, specifically VGG16 and VGG19, in identifying patients with FP when experiments were conducted on the YFP dataset. The results showed that the VGG16 model achieved an accuracy of 88.47%, a recall of 83.55%, a precision of 92.15% and an F1-score of 87.64%. In contrast, the VGG19 model achieved slightly lower performance metrics, with an accuracy of 81.95%, a recall of 72.44%, a precision of 88.58% and an F1-score of 79.70%. These findings indicate that the VGG architectures are effective in accurately identifying patients with facial paralysis. By leveraging pre-trained VGG models and transfer learning techniques, the proposed approach demonstrates the potential of DL in medical image analysis. Data augmentation strategies were employed to increase the enhancement of the robustness and generalisation of the proposed method.Further research could focus on optimising the VGG models or exploring other advanced DL architectures to improve the classification performance. Additionally, the inclusion of more diverse and larger datasets could enhance the models' robustness and generalisation capabilities.

Funding

No Funding

Informed Consent

Not Applicable

Ethical Statement

Not Applicable

Author Contribution

Study conception and design: Hadi Raheem Ali, Abbas Khalifa Nawar, Sabah Abdulazeez Jebur, Mothefer Majeed Jahefer; analysis and interpretation of results: Abbas Khalifa Nawar, Sabah Abdulazeez Jebur, Mothefer Majeed Jahefer; draft manuscript preparation: , Abbas Khalifa Nawar, Sabah Abdulazeez Jebur. All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors have no conflicts of interest directly relevant to the content of this article

References

1. G.-S. J. Hsu, J.-H. Kang, and W.-F. Huang, "Deep hierarchical network with line segment learning for quantitative analysis of facial palsy," *IEEE Access*, vol. 7, pp. 4833–4842, 2018.
2. Y. Xia, C. Nduka, R. Y. Kannan, E. Pescarini, J. E. Berner, and H. Yu, "AFLFP: A Database With Annotated Facial Landmarks for Facial Palsy," *IEEE Trans. Comput. Soc. Syst.*, 2022.
3. G. S. Parra-Dominguez, 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*, vol. 12, no. 7, p. 1528, 2022.
4. T. Wang, S. Zhang, L. Liu, G. Wu, and J. Dong, "Automatic facial paralysis evaluation augmented by a cascaded encoder network structure," *IEEE Access*, vol. 7, pp. 135621–135631, 2019.
5. H. Kim, J. Park, H. Kim, E. Hwang, and S. Rho, "Robust facial landmark extraction scheme using multiple convolutional neural networks," *Multimed. Tools Appl.*, vol. 78, pp. 3221–3238, 2019.
6. X. Liu, Y. Xia, H. Yu, J. Dong, M. Jian, and T. D. Pham, "Region based parallel hierarchy convolutional neural network for

automatic facial nerve paralysis evaluation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 10, pp. 2325–2332, 2020.
7. O. O. Abayomi-Alli, R. Damaševičius, R. Maskeliūnas, and S. Misra, "Few-shot learning with a novel voronoi tessellation-based image augmentation method for facial palsy detection," *Electronics*, vol. 10, no. 8, p. 978, 2021.
8. Z. Guo, W. Li, J. Dai, J. Xiang, and G. Dan, "Facial imaging and landmark detection technique for objective assessment of unilateral peripheral facial paralysis," *Enterp. Inf. Syst.*, vol. 16, no. 10–11, pp. 1556–1572, 2022.
9. S. A. Jebur, M. A. Mohammed, and A. K. Abdulhassan, "Covid-19 detection using medical images," in *AIP Conference Proceedings*, 2023, vol. 2591, no. 1, p. 30030.
10. L. R. Ali, S. A. Jebur, M. M. Jahefer, and B. N. Shaker, "Employing Transfer Learning for Diagnosing COVID-19 Disease.," *Int. J. Online Biomed. Eng.*, vol. 18, no. 15, 2022.
11. S. A. Jebur, K. A. Hussein, H. K. Hoomod, L. Alzubaidi, and J. Santamaría, "Review on Deep Learning Approaches for Anomaly Event Detection in Video Surveillance," *Electronics*, vol. 12, no. 1, p. 29, 2022.
12. S. A. Jebur, K. A. Hussein, and H. K. Hoomod, "Abnormal Behavior Detection in Video Surveillance Using Inception-v3 Transfer Learning Approaches," *IRAQI J. Comput. Commun. Control Syst. Eng.*, vol. 23, no. 2, pp. 210–221, 2023.
13. J. Barbosa *et al.*, "Efficient quantitative assessment of facial paralysis using iris segmentation and active contour-based key points detection with hybrid classifier," *BMC Med. Imaging*, vol. 16, no. 1, pp. 1–18, 2016.
14. Z. Guo *et al.*, "Deep assessment process: Objective assessment process for unilateral peripheral facial paralysis via deep convolutional neural network," in *2017 IEEE 14th international symposium on biomedical imaging (ISBI 2017)*, 2017, pp. 135–138.
15. S. Anping, X. Guoliang, D. Xuehai, S. Jiaxin, X. Gang, and Z. Wu, "Assessment for facial nerve paralysis based on facial asymmetry," *Australas. Phys. Eng. Sci. Med.*, vol. 40, pp. 851–860, 2017.
16. A. Song, Z. Wu, X. Ding, Q. Hu, and X. Di, "Neurologist standard classification of facial nerve paralysis with deep neural networks," *Futur. Internet*, vol. 10, no. 11, p. 111, 2018.
17. G.-S. J. Hsu, W.-F. Huang, and J.-H. Kang, "Hierarchical Network for Facial Palsy Detection.," in *CVPR Workshops*, 2018, pp. 580–586.
18. M. Sajid, T. Shafique, M. J. A. Baig, I. Riaz, S. Amin, and S. Manzoor, "Automatic grading of palsy using asymmetrical facial features: a study complemented by new solutions," *Symmetry (Basel).*, vol. 10, no. 7, p. 242, 2018.
19. J. Barbosa, W.-K. Seo, and J. Kang, "paraFaceTest: an ensemble of regression tree-based facial features extraction for efficient facial paralysis classification," *BMC Med. Imaging*, vol. 19, no. 1, pp. 1–14, 2019.
20. S. A. Jebur, K. A. Hussein, H. K. Hoomod, and L. Alzubaidi, "Novel Deep Feature Fusion Framework for Multi-Scenario Violence Detection," *Computers*, vol. 12, no. 9, p. 175, 2023.
21. L. Alzubaidi *et al.*, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *J. big Data*, vol. 8, no. 1, pp. 1–74, 2021.
22. L. R. Al-Khazraji, A. R. Abbas, and A. S. Jamil, "The Effect of Changing Targeted Layers of the Deep Dream Technique Using VGG-16 Model.," *Int. J. Online Biomed. Eng.*, vol. 19, no. 3, 2023.
23. E. M. Imah and A. Wintarti, "Violence Classification Using Support Vector Machine and Deep Transfer Learning Feature Extraction," in *2021 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, 2021, pp. 337–342.
24. J. Xia, Y. Ding, and L. Tan, "Urban remote sensing scene recognition based on lightweight convolution neural network," *IEEE Access*, vol. 9, pp. 26377–26387, 2021.
25. A. Kareem, H. Liu, and V. Velisavljevic, "A federated learning framework for pneumonia image detection using distributed data," *Healthc. Anal.*, p. 100204, 2023.
26. A. Arora, A. Sinha, K. Bhansali, R. Goel, I. Sharma, and A. Jayal, "SVM and Logistic Regression for Facial Palsy Detection Utilizing Facial Landmark Features," in *Proceedings of the 2022 Fourteenth International Conference on Contemporary Computing*, 2022, pp. 43–48.
27. C. A. Sari, F. A. Bachtiar, L. Muflikhah, and A. Widayati, "Facial Palsy Detection Through Changes in Facial Muscle Functionality Using CNN Algorithm," in *2023 6th International Conference of Computer and Informatics Engineering (IC2IE)*, 2023, pp. 297–302.