Bell's Palsy: Automated Detection and Assessment Using Deep Learning

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Abstract

Bell's Palsy, a sudden facial paralysis caused by cranial nerve VII damage, significantly impacts daily life through impaired expressions, speech, and social interactions. This project proposes an automated system for detecting and assessing facial paralysis using facial landmark analysis and machine learning. By extracting 68 key facial points, computing symmetry metrics, and employing a multi-layer perceptron classifier, the system achieves high accuracy in classification (99.79%). The approach is computationally efficient, gesture-independent, and validated on public datasets, offering a scalable solution for early diagnosis and equitable healthcare access.

Introduction

Facial paralysis, characterized by unilateral muscle weakness, disrupts essential functions like communication and emotional expression. Traditional diagnostic methods rely on subjective clinical assessments, leading to delays and inconsistencies. This project addresses these challenges by developing an automated detection framework. Leveraging advancements in computer vision and machine learning, the system analyzes facial asymmetry through standardized landmark extraction, tilt correction, and symmetry measurements. The methodology aims to improve diagnostic accuracy, enable timely interventions, and reduce healthcare disparities in resource-limited settings.

Methodology:

The proposed methodology for assessing facial paralysis leverages facial symmetry features derived from facial landmarks to classify images into healthy, slight, and strong palsy categories. The process involves several key steps:

1. Face Detection: The input image undergoes face detection using the dlib library, which combines a linear classifier with Histogram of Oriented Gradients (HOG) and a sliding-window detection scheme.

2. Facial Landmark Extraction: The facial landmarks are extracted using a 68-point shape predictor model, specifically optimized for facial palsy patients by Guarin et al. Only 51 of these points are utilized in the analysis. The landmarks are corrected for head tilt using a similarity transform based on the eye corners.

3. Feature Calculation: From the extracted landmarks, 29 symmetry features are computed. These features capture asymmetry in the eyebrows, eyes, and mouth, and include angles, slopes, and ratios between key points. The features are designed to reflect facial symmetry and asymmetry, with ratios typically ranging from 0 (high asymmetry) to 1 (high symmetry).

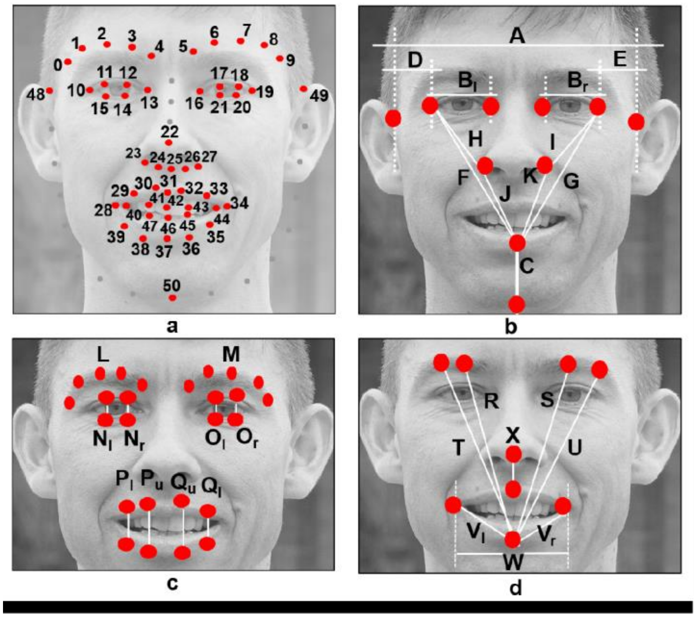

Figure 1. (a) The 51 key points inspired by the model proposed by Matthews and Baker [1]; (b–d) Facial distances to obtain spatial relations between facial landmark

4. Regional Information: The methodology explores the use of regional information, focusing on specific areas of the face (eyes, mouth) rather than the entire face. This approach aims to enhance the robustness of the analysis, especially in scenarios with partial occlusions.

5. Classification: Four classifiers—Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Multinomial Logistic Regression (MNLR)—are employed to classify the images. The classifiers are configured and optimized using the Weka machine learning toolkit. The 5-fold cross-validation technique is used to ensure robust evaluation.

6. Data Augmentation: To address class imbalance, data augmentation techniques are applied, including rotation of images to generate additional training samples.

7. Evaluation Metrics: The performance of the classifiers is evaluated using standard metrics such as accuracy, recall, precision, F1-score, true negative rate, false negative rate, and false positive rate.

The proposed methodology demonstrates high accuracy in detecting and assessing facial palsy, achieving up to 95.61% accuracy in binary classification tasks and 95.58% accuracy in multi-class classification tasks. This approach is adaptable to various datasets and can operate effectively with partial occlusions, provided face detection and landmark extraction are accurate.

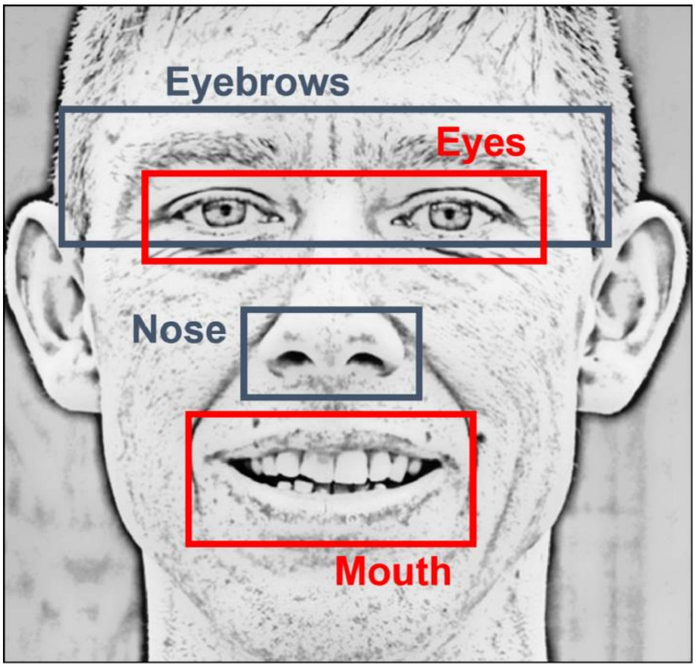

Figure 2. Example of a face image divided into four facial regions.

Experimental Outcomes:

Achieved **99.79% accuracy** for whole-face analysis and **97.22%** for region-specific assessments (eyes/mouth).

Confusion matrices (Figure 4) highlight precision in distinguishing palsy severity.

Facial symmetry metrics (Figure 1–3) demonstrate clear differentiation between healthy and affected cases.

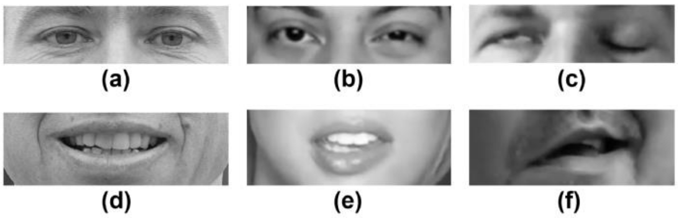

Figure 3. Facial analysis: (a) healthy eyes, (b) slight palsy and (c) strong palsy eyes; (d) healthy
mouth, (e) slight palsy, and (f) strong palsy mouth. Palsy images were obtained from

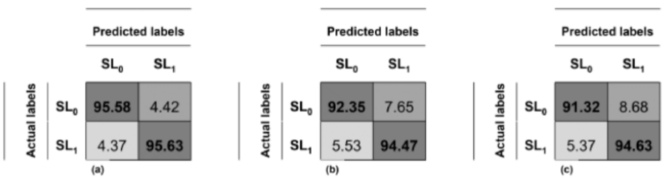

Figure 4. Confusion matrix of the detection of the palsy: (a) on the entire face, (b) on the eyes region and (c) on the mouth region.

Societal Impact

Early Diagnosis: Enables prompt treatment, improving recovery outcomes.

Cost-Effective: Utilizes open-source tools (e.g., OpenCV) for scalable deployment.

Accessibility: Reduces reliance on specialized clinicians, benefiting rural or underserved areas.

Future Work:

In future work, we plan to enhance the accuracy and efficiency of facial paralysis detection systems. One approach involves incorporating advanced deep learning techniques, such as convolutional neural networks (CNNs), to extract more discriminative features from facial images. Additionally, we aim to explore the use of temporal information by analyzing sequences of images to capture dynamic facial movements, which can provide valuable insights into the severity of paralysis. Furthermore, we intend to collaborate with medical professionals to validate our methods on a larger and more diverse dataset, ensuring that our system is robust and generalizable across different populations. Another direction is to develop a user-friendly mobile application that allows patients to self-assess their facial paralysis symptoms using their smartphones, facilitating early detection and monitoring. Finally, we plan to investigate the integration of our system with other modalities, such as electromyography (EMG), to improve the overall diagnostic accuracy and provide a comprehensive assessment of facial nerve function.

Conclusion

This project establishes a robust framework for automated facial paralysis detection using machine learning. By achieving high accuracy and computational efficiency, the system bridges gaps in healthcare accessibility and diagnostic consistency. Future enhancements, such as real-time analysis and severity grading, could revolutionize clinical workflows, empowering both patients and practitioners.

References

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[2]G. Bradski, "The OpenCV Library," Dr. Dobb's Journal of Software Tools, 2000. Available: https://opencv.org/.
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