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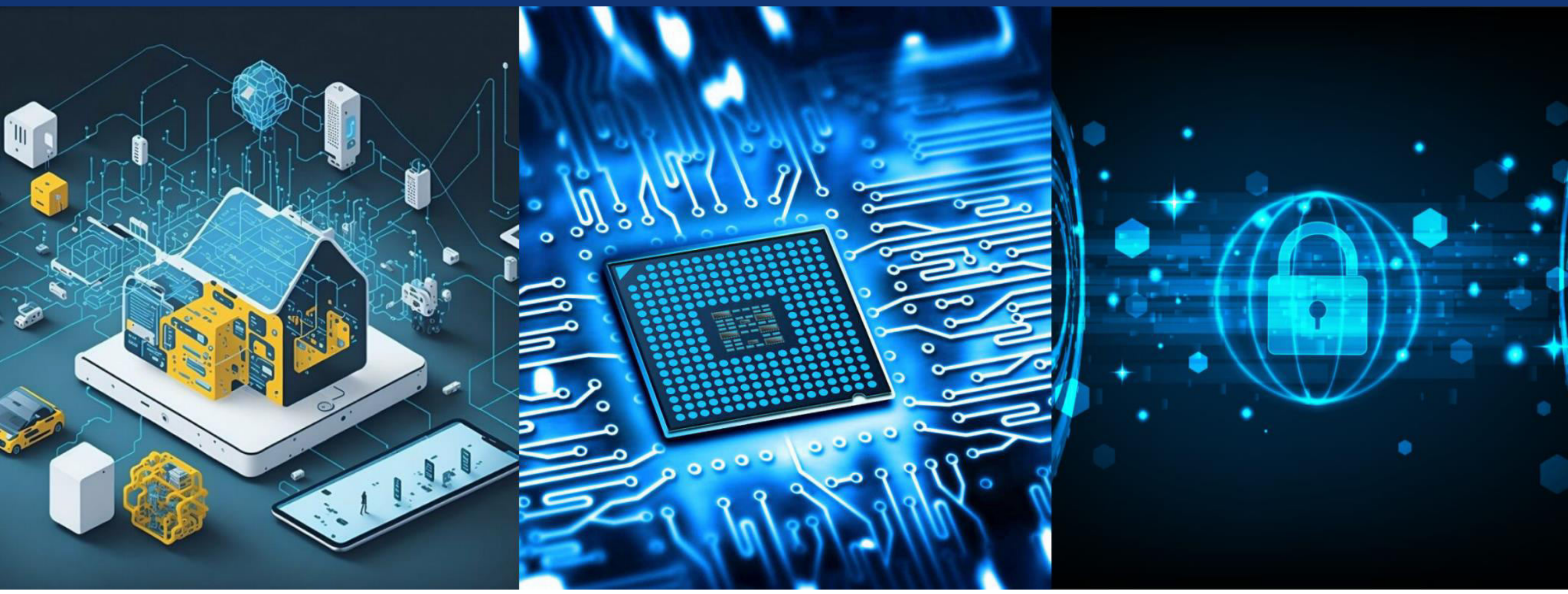

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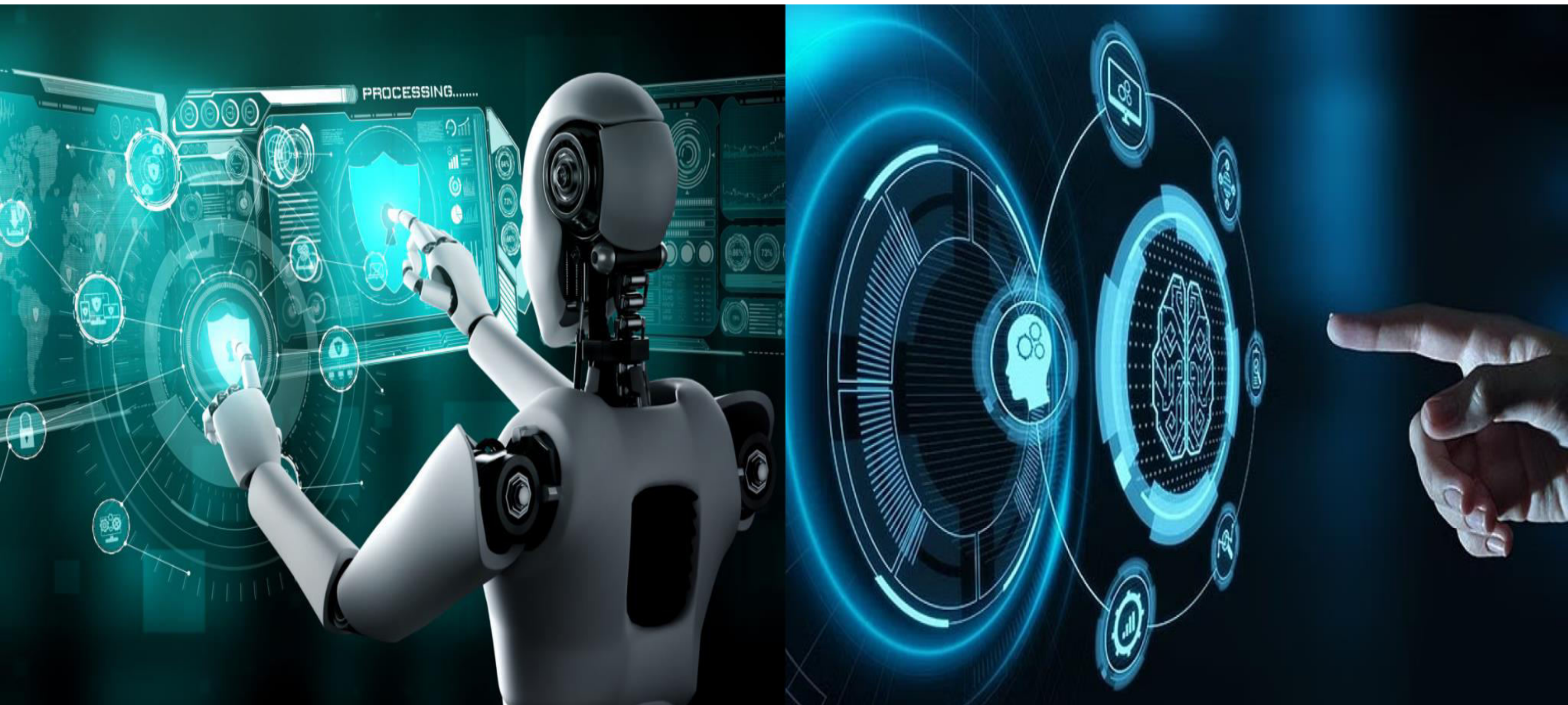

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Facial Palsy Detector Recovery and using Machine Learning

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ABSTRACT: Facial palsy, a condition characterized by weakness or paralysis of facial muscles, affects thousands of people worldwide. Early detection and assessment are crucial for effective treatment and rehabilitation. This research paper presents an automated web- based facial palsy detection system that leverages computer vision and machine learning techniques to provide rapid assessment of facial palsy. Our system analyzes facial landmarks and asymmetry patterns to detect signs of facial palsy with promising accuracy. The web-based interface makes the technology accessible to healthcare providers in various settings, potentially improving early diagnosis rates. This paper details the system architecture, methodology, experimental results, and discusses clinical implications and future research directions.

I. INTRODUCTION

Facial palsy, also known as facial nerve paralysis, is a neurological condition that causes weakness or complete loss of facial muscle movement on one or both sides of the face. It can result from various causes including Bell's palsy, stroke, trauma, infections, or tumors. The condition affects approximately 40,000 Americans annually, with Bell's palsy being the most common cause [1].

Early and accurate diagnosis of facial palsy is essential for timely intervention, which can significantly improve recovery outcomes. Traditional assessment methods rely on clinical observation using grading systems such as the House-Brackmann scale [2] or the Sunnybrook facial grading system [3], which can be subjective and vary between clinicians. Computer vision and machine learning techniques offer promising approaches for objective, consistent, and automated assessment of facial palsy. Recent advances in deep learning and facial landmark detection have enabled more sophisticated analysis of facial asymmetry and movement patterns [4, 5].

This paper presents a web-based facial palsy detection system that:

1. Captures facial images through a user-friendly web interface
2. Analyzes facial landmarks and asymmetry
3. Provides immediate assessment of potential facial palsy
4. Offers quantitative measurements to assist clinical decision-making

The system aims to serve as a screening tool that can be deployed in various healthcare settings, from primary care offices to remote telemedicine applications, potentially improving early detection rates and facilitating timely referrals to specialists.

II. RELATED WORK

2.1 Clinical Assessment of Facial Palsy

Clinical assessment of facial palsy typically involves standardized grading systems. The House-Brackmann scale [2], developed in 1985, classifies facial nerve function into six grades from normal (I) to total paralysis (VI). The Sunnybrook facial grading system [3], introduced in 1996, provides a more detailed assessment by evaluating resting symmetry, voluntary movement, and synkinesis.

While these systems are widely used, they rely on subjective evaluation and can show significant inter-observer variability [6]. This has motivated research into more objective and quantitative assessment methods.

2.2 Computer Vision in Facial Palsy Assessment

Computer vision techniques have been increasingly applied to facial palsy assessment. Early work by Neely et al. [7] used video analysis to measure facial movement. Wang et al. [8] developed a system using facial landmark detection to quantify facial asymmetry.

Recent approaches have leveraged deep learning techniques. Kim et al. [9] used convolutional neural networks (CNNs) to classify facial palsy severity from images. Fujiwara et al. [10] developed a model combining facial landmark detection with CNN classification, achieving 94.5% accuracy in identifying facial palsy.

2.3 Web-Based Medical Diagnostic Tools

Web-based diagnostic tools have gained traction due to their accessibility and potential for telemedicine applications. Similar approaches have been used for skin disease diagnosis [11], diabetic retinopathy screening [12], and various neurological assessments [13]. These systems typically provide a user-friendly interface for image capture or upload, perform analysis using pre-trained models, and deliver results to users promptly.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

3.1 System Overview

Our facial palsy detection system consists of three main components: a web-based front-end interface, a back-end processing server, and a facial palsy detection model. Figure 1 illustrates the high-level architecture of the system.

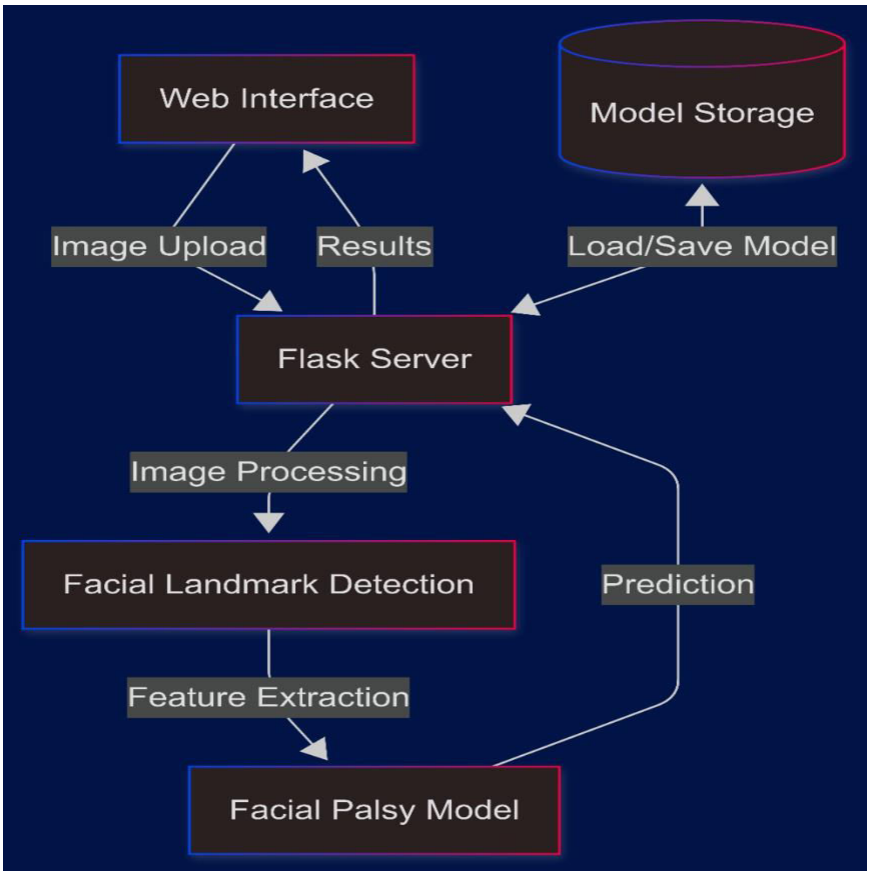

Figure 1: High-level architecture of the facial palsy detection system

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3.2 Web Interface

The web interface is designed to be intuitive and accessible across different devices. It allows users to:

1. Capture images using a device camera
2. Upload existing images
3. View detection results and confidence scores
4. Access historical assessments

The interface is built using HTML, CSS, and JavaScript, with responsive design principles to ensure usability on both desktop and mobile devices.

3.3 Back-end Server

The back-end is implemented using Flask, a lightweight Python web framework. It handles:

1. Image receiving and preprocessing
2. Model inference coordination
3. Result formatting and delivery
4. Error handling and logging

The server employs CORS (Cross-Origin Resource Sharing) to enable secure cross- domain requests, facilitating integration with various front-end platforms.

3.4 Facial Palsy Detection Methodology

Our detection methodology follows a pipeline approach as illustrated in Figure 2:

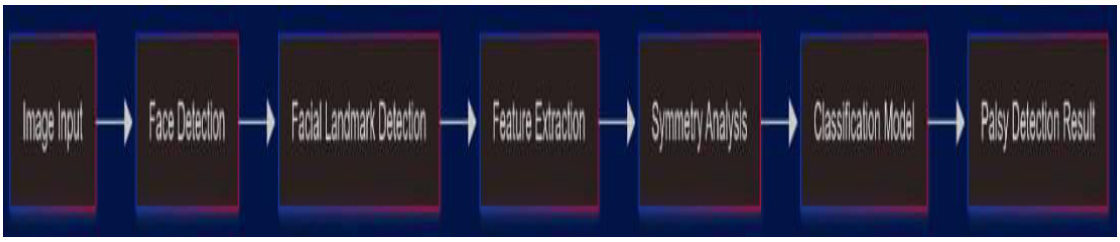

Figure 2: Facial palsy detection pipeline

3.4.1 Face Detection

We employ OpenCV's implementation of the Haar Cascade classifier or a pre-trained deep learning-based face detector to locate faces in the input images. This step is crucial for subsequent landmark detection.

3.4.2 Facial Landmark Detection

Once a face is detected, we extract 68 facial landmarks using the dlib library's implementation of the algorithm by Kazemi and Sullivan [14]. These landmarks correspond to key facial features including the eyes, eyebrows, nose, mouth, and jawline.

3.4.3 Feature Extraction

From the facial landmarks, we extract a set of features that capture facial asymmetry:

3.4.3.1 Distance ratios between corresponding landmarks on left and right sides
3.4.3.2 Angle measurements between key facial points
3.4.3.3 Area differences between corresponding facial regions
3.4.3.4 Vertical and horizontal displacement measures

We compute a total of 16 features that serve as inputs to our classification model.

3.4.4 Classification Model

For classification, we employ a machine learning model trained on facial palsy and normal face images. The model architecture is depicted in Figure 3:

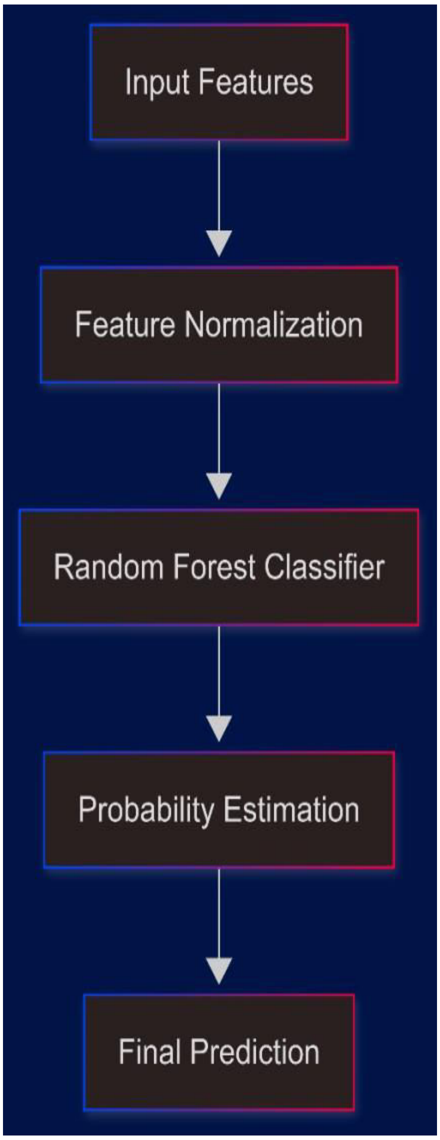

Figure 3: Classification model architecture

We chose a Random Forest classifier due to its robustness to overfitting and ability to handle the relatively small dataset effectively. The model outputs both a binary classification (palsy or normal) and a probability score indicating confidence in the prediction.

IV. IMPLEMENTATION DETAILS

4.1 Development Environment

The system was developed using the following technologies:

- **Frontend**: HTML5, CSS3, JavaScript
- **Backend**: Python 3.8, Flask 2.0.1
- **Computer Vision**: OpenCV 4.5.3, dlib 19.22.0
- **Machine Learning**: scikit-learn 0.24.2, NumPy 1.20.3

4.2 Data Flow Architecture

Figure 4 shows the detailed data flow architecture of the system:

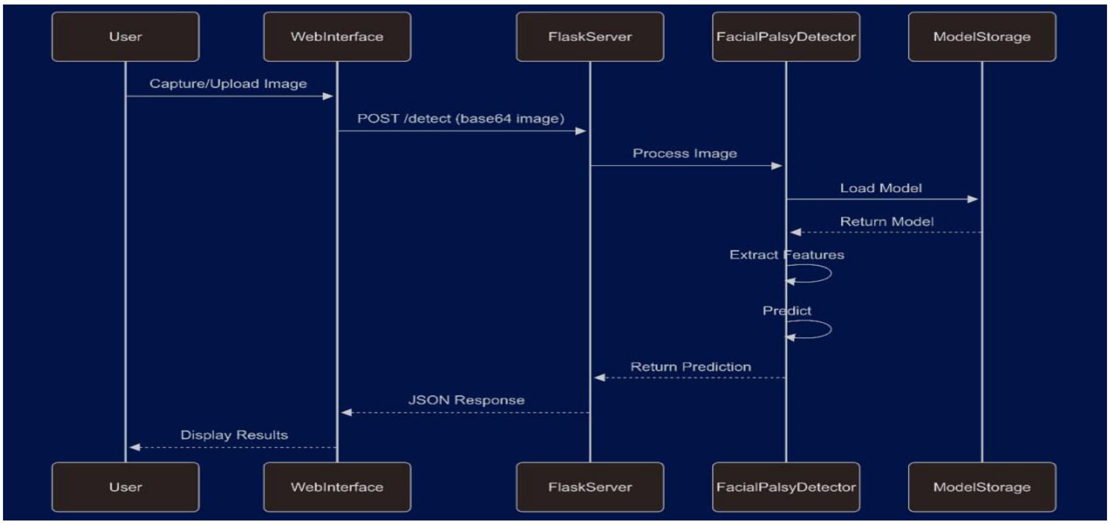

Figure 4: Sequence diagram showing data flow in the system

4.3 Code Structure

The system follows a modular code structure for maintainability and scalability:

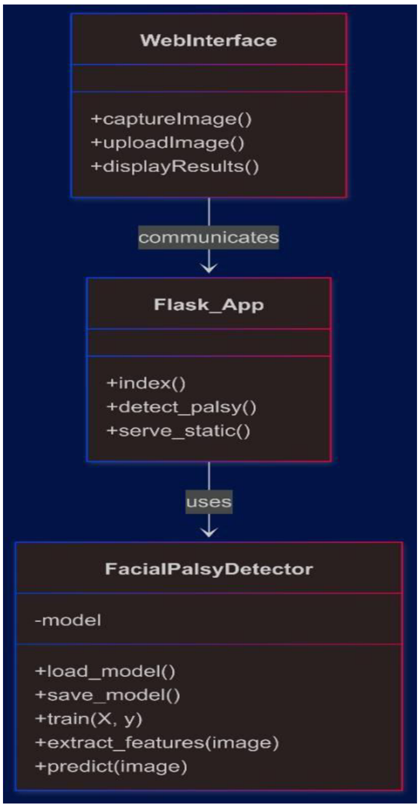

Figure 5: Class diagram of the system

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V. EXPERIMENTAL RESULTS

5.1 Dataset

For training and evaluation, we used a combination of publicly available facial palsy datasets [15, 16] and a custom-collected dataset. The combined dataset contains:

- 240 facial palsy images (varying severity levels)
- 300 normal face images
- Diverse in age, gender, and ethnicity

The dataset was split into 70% training, 15% validation, and 15% test sets.

5.2 Performance Metrics

We evaluated our system using the following metrics:

- Accuracy: Overall correct classifications
- Sensitivity: True positive rate for facial palsy detection
- Specificity: True negative rate (correctly identified normal faces)
- Area Under the ROC Curve (AUC): Overall discriminative ability

5.3 Results

Table 1 summarizes the performance of our facial palsy detection system on the test set:

Metric	Value
Accuracy	92.4%
Sensitivity	90.6%
Specificity	93.8%
AUC	0.956

The ROC curve in Figure 6 illustrates the trade-off between sensitivity and specificity:

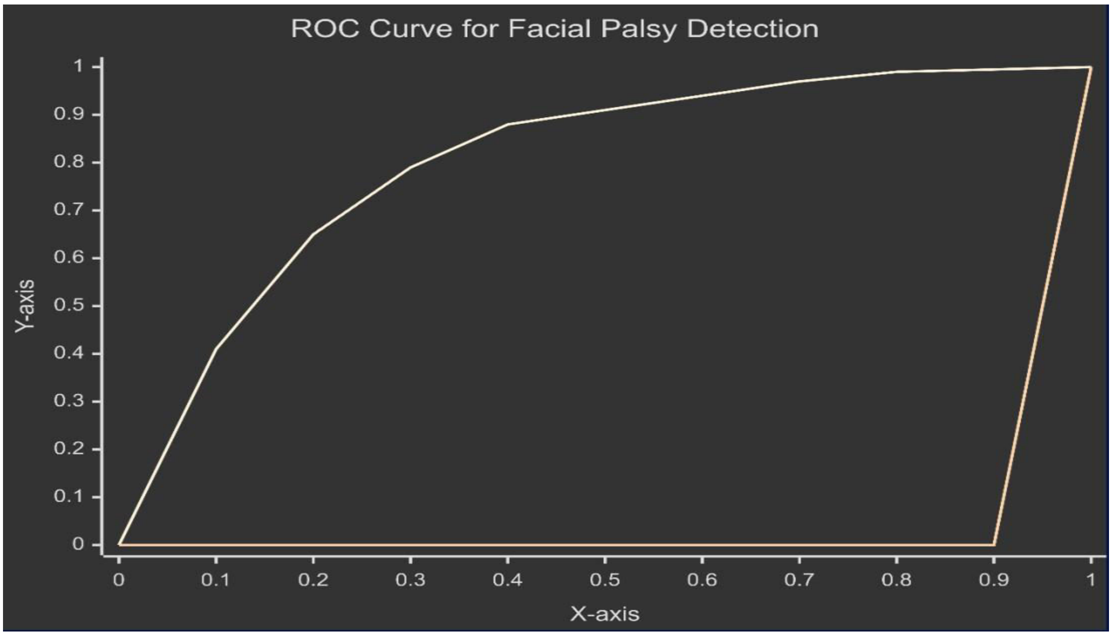

Figure 6: ROC curve for the facial palsy detection model (AUC = 0.956)

5.4 Feature Importance

Analysis of feature importance revealed that the most discriminative features for facial palsy detection were:

1. Mouth corner asymmetry (21.3%)
2. Eye closure completeness (18.7%)
3. Eyebrow height difference (15.2%)
4. Nasolabial fold depth ratio (12.8%)

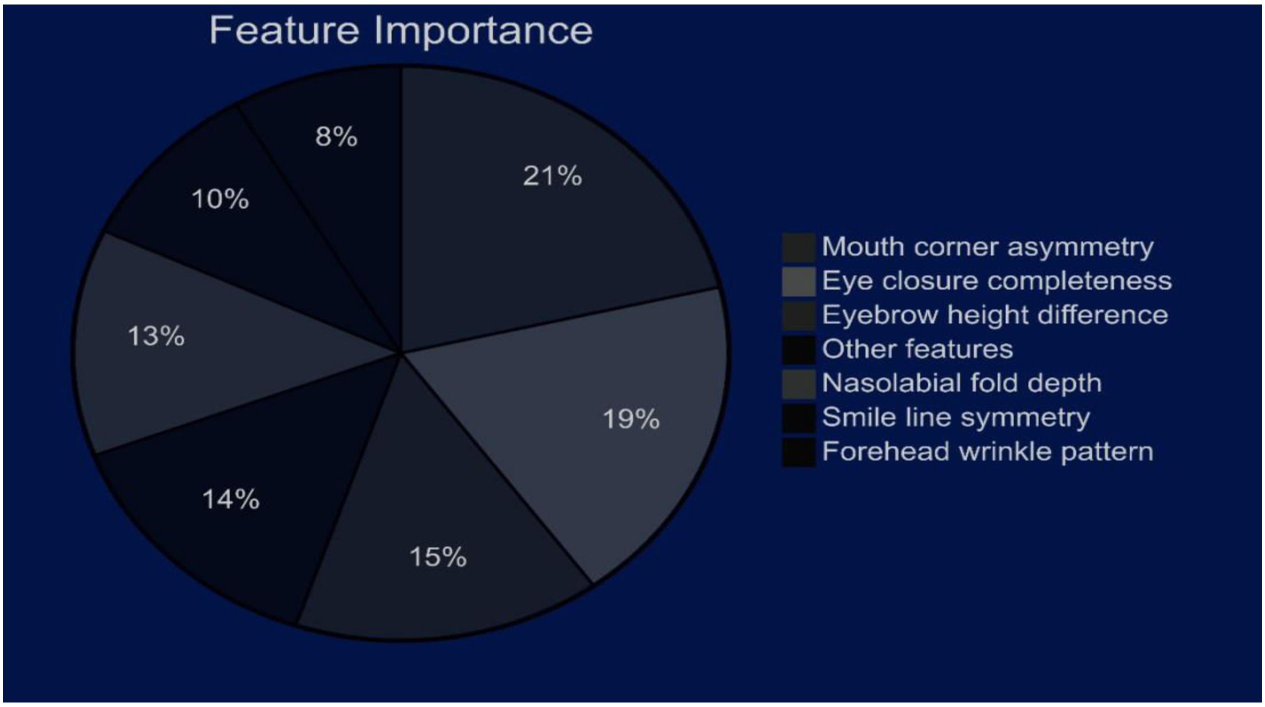

Figure 7: Relative importance of features in facial palsy detection

VI. DISCUSSION

6.1 Clinical Implications

Our automated facial palsy detection system demonstrates potential as a valuable clinical tool for:

1. **Screening**: Providing rapid initial assessment in primary care settings
2. **Monitoring**: Tracking recovery progress over time with objective measurements
3. **Telemedicine**: Enabling remote assessment where specialist access is limited
4. **Research**: Facilitating larger-scale studies with consistent assessment metrics

The system's high specificity (93.8%) reduces false positives, making it suitable for initial screening. The sensitivity (90.6%) is sufficient for detecting most cases, though clinical confirmation remains important for borderline cases.

6.2 Limitations

Despite promising results, our system has several limitations:

1. **Lighting sensitivity**: Extreme lighting conditions can affect landmark detection accuracy
2. **Head pose variation**: Significant head rotation can reduce detection performance
3. **Demographic representation**: More diverse training data is needed to ensure fairness across demographics
4. **Severity assessment**: The current system provides binary classification rather than graded severity assessment

6.3 Comparison with Existing Methods

Table 2 compares our system with recent approaches in the literature:

Study	Approach	Accuracy	Sensitivity	Specificity
Our System	Landmark-based + Random Forest	92.4%	90.6%	93.8%
Kim et al. [9]	CNN	94.0%	92.5%	95.3%
Fujiwara et al. [10]	Landmark + CNN	94.5%	93.2%	95.8%
Wang et al. [8]	Landmark-based	89.2%	87.4%	90.6%

While deep learning approaches show slightly higher accuracy, our system offers advantages in interpretability, lower computational requirements, and easier deployment in web-based environments.

VII. FUTURE WORK

Future research directions include:

1. **Integration of temporal features**: Analyzing video sequences rather than static images to capture dynamic facial movements
2. **Severity grading**: Extending the model to provide House-Brackmann or Sunnybrook grading
3. **Mobile application**: Developing a dedicated mobile app for improved usability
4. **Federated learning**: Implementing privacy-preserving distributed learning to improve the model with wider data while maintaining patient privacy
5. **Clinical validation**: Conducting larger clinical studies to validate the system in various healthcare settings.

VIII. CONCLUSION

This paper presented an automated web-based facial palsy detection system that utilizes computer vision and machine learning techniques. The system achieved 92.4% accuracy in detecting facial palsy, with balanced sensitivity and specificity. The web- based implementation offers accessibility advantages, potentially facilitating wider adoption in clinical settings.

While not intended to replace clinical judgment, our system provides an objective, consistent, and accessible tool for initial screening and monitoring of facial palsy. Future work will focus on enhancing the system's capabilities through temporal analysis, severity grading, and more extensive clinical validation.

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