IRJAEH
International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 941-948
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0134

A Novel Framework for Detection of Facial Paralysis Using Cascaded Convolutional Neural Networks

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Abstract
Early detection and accurate diagnosis of facial paralysis are vital because of timely medical treatment and improved patient outcomes. Traditional diagnostic techniques are based on subjective evaluations, thus leading to unnecessary delays in diagnosis. This work attempts to solve this challenge by introducing a cascaded convolutional neural network (CNN) for the automatic diagnosis of facial paralysis signs from recorded facial images in real-time. Our proposed system uses advanced image preprocessing and feature extraction techniques to classify facial paralysis symptoms with great accuracy. The model was trained on a dataset composed of diverse facial expressions; it achieved a training accuracy of 98% and a testing accuracy of 99.86%. The cascaded CNN architecture is capable of detecting very effectively by combining many feature layers for correct classification. This system has enormous applicability in real-time telemedicine, remote diagnostics, and in continuous monitoring of patients. Thus, the project will tackle a relevant gap between advanced machine learning technology and health by providing a more scalable and efficient solution, accessible to many.
Keywords: *Automated diagnosis; Cascaded CNN; Early Detection; Facial Paralysis; Healthcare AI; Image Classification; Real-Time Diagnosis; Telemedicine.*

1. Introduction
Facial paralysis, commonly referred to as Bell's palsy, is a condition characterized by extreme impairment of the individual's ability to control facial muscles. Oftentimes, such a condition could arise due to any damage caused by the seventh cranial nerve which could originate from trauma, brain tumors, or other neurological conditions such as stroke. The person suffering from paralysis of the face would have to bear severe complications, which include chronic pain, unhealed ulcers in the eyes, or deformities for life [1,2]. Clinical diagnosis for facial paralysis usually relies on mere observation and expert analysis called subjective criteria. Variability in expertise and the subtlety of early findings may lead to inconsistencies in the process of diagnosis. As a means of bridging this gap, the supply of an automated diagnostic tool allows a reasonable level of consistency in their analysis and objective measurement of facial asymmetry and movements [3,4]. It is becoming increasingly important to establish an early diagnosis as delayed intervention increases the risk of further nerve damage and consequent recovery time [5]. Deep learning approaches are revolutionizing medicine, including facial images, in medical imaging. Such Convolutional Neural Networks automatically extract relevant features from images of facial structure, dispensing with entirely manual annotations. Particularly for multi-stage processing cases, where a coarse-to-fine feature extraction is required, cascaded architectures have been effective [6,7]. In light of and on top of these advancements, this study presents a cascaded CNN-based framework for detecting facial paralysis with a very high degree of accuracy and reliability [8-12].

2. Literature Review
After exploring the topic of the approaches used for the detection of facial paralysis, a large group of them started to accumulate. The earliest efforts were largely derivative of traditional image-processing

techniques, which include the manual detection of features for the measurement of facial symmetry indices. However, those methods were hampered in their approaches due to their dependence on handcrafted features and the inability to deal with complicated cases involving facial asymmetry properly. More recent developments in deep learning are able to counteract such weaknesses. Chen et al. (2020) showed that the ResNet-based CNNs, with the capability to detect asymmetry of the face, have an accuracy of 92 percent in performing these tasks. The work showed the feasibility of deep feature extraction, catering for minute changes in the facial regions. Support Vector Machines (SVMs), as well, have been used here for classifying facial paralysis: however, with only an 85% accuracy [2], Table 1. A Gradient Boosting Trees based model for grading the severity of facial paralysis was presented by Zhao et al. in 2018, establishing the powers that machine learning strategies enjoy in clinical applications, specifically for visualizing changes in facial expressions. More recently, Wang et al. proposed the combination of CNN-SVM classifiers and utilized the capabilities of both to achieve an accuracy of 90% [4]. Another striking current development is the emergence of transfer learning as an idea. In a recent work, Silva and Rodriguez applied MobileNet, a small CNN architecture, making it feasible to detect facial paralysis in real-time. The system achieved an accuracy of 89%, showing the potential for deploying such models in resource-constrained settings [3].

Table 1 Summary of Related Works

SNO	Previous Research Paper Details		
	Title/ Author	**Methodology**	**Key Findings**
1	Chen et al.(2020)	RegNet-based CNN	Extracted deep facial features to detect asymmetry
2	SVM-based Approach	Support Vector Machines (SVM)	Classified facial paralysis but had lower accuracy
3	Zhao et al. (2018)	Gradient Boosting Trees	Graded severity of facial paralysis
4	Wang et al.	CNN-SVM Hybrid Model	Combined deep learning and traditional ML for detection
5	Patel et al. (2021)	VGG-16 CNN Model	Improved classification of facial asymmetry using deep features
6	Silva & Rodriguez	MobileNet (Transfer Learning)	Enabled real-time detection in resource-limited environments

3. Methodology

3.1. Overview of Methodology

The general methodology of the facial paralysis detection system is shown in Figure 1. This diagram illustrates the sequential process, starting from data collection and preprocessing, followed by cascaded CNN feature extraction, model training, and final classification of facial paralysis. The multi-stage hierarchical feature extraction in the Cascaded CNN enhances the model's ability to detect subtle facial asymmetries with improved accuracy and robustness. complicated cases involving facial

3.2. Data Collection and Preprocessing

The dataset employed in this work consists of labeled facial expression images, comprising people with and without facial paralysis. Apart from public datasets, real-time video streams from OpenCV were employed to demonstrate variability in training samples. This guarantees a wide and representative dataset capturing various facial expressions, lighting conditions, and view angles for enhanced generalization. Several preprocessing procedures were applied to the data:

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- **Face Detection:** Haar cascades and DNN modules were used to accurately detect facial regions.
- **Resizing:** All images were resized to a uniform shape of (150,150,3) to maintain consistency.
- **Normalization:** Pixel values were scaled to the range [0,1] to reduce variations between individual samples and prevent overfitting.
- **Data Augmentation:** Various transformations, including rotation, flipping, shearing, zooming, and cropping, were applied using ImageDataGenerator() to increase dataset diversity and model robustness.
- **Class Weighting:** Class imbalance was addressed using class_weight.compute_class_weight() to ensure balanced learning from both categories.

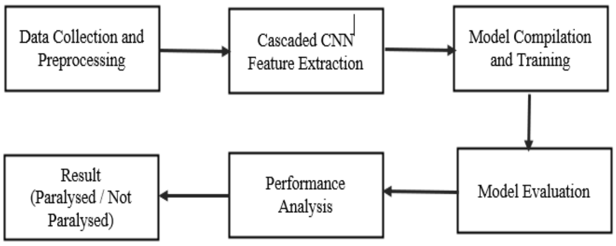

Figure 1 A Summary of The Recommended Facial Paralysis Detection Model

3.3. Cascaded CNN Feature Extraction

Cascaded Convolutional Neural Networks (CCNNs) are utilized for extracting hierarchical facial features from an image sequentially. Cascaded CNNs process the images in more than one step unlike typical CNNs, and feature extraction in each step enhances the amount to increase classification accuracy.

- **Convolution Layers:** It contains several blocks of convolution using filter sizes in increasing order (32, 64, 128, 256) each with ReLU activation to gain primary visual features.
- **Batch Normalization:** Utilized after each convolution layer for normalization of the activations and speedy training.
- **Pooling Layers:** Dimensions are reduced without losing major features through max-pooling layers, thereby inducing more computations.
- **Feature Concatenation:** Features from various convolutional blocks are concatenated to enhance the feature space and improve classification accuracy.
- **Dropout Regularization:** Dropout is applied to avoid overfitting by deactivating neurons randomly during training.

3.4. Model Compilation and Training

Post-feature extraction, the model is trained and built stepwise for the optimal performance.

- **Optimizer:** The weights are updated by Adam optimizer with the learning rate of 0.001.
- **Loss Function:** Binary cross-entropy for handling the two-class classification problem.
- **Early Stopping:** Training is monitored to terminate in the absence of an increase in validation accuracy in order to prevent overfitting.
- **ReduceLROnPlateau:** The learning rate gets automatically decreased whenever the performance gets stuck for best convergence.
- **Batch Size & Epochs:** It is trained on 32 batch sizes for 20 epochs.

It is trained with real-time data augmentation methods to provide real-world variability flexibility.

3.5. Model Evaluation

To confirm model efficacy, various performance measures are employed on the test data.

- **Accuracy:** It gauges the total accuracy of predictions.
- **Precision:** It measures the ratio of actual positive predictions out of all the positive classifications.
- **Recall:** It gauges the capability of the model to identify all positive cases correctly.
- **F1-Score:** It combines precision and recall to yield an overall performance measure.
- **Confusion Matrix:** It examines the errors in classifications and model efficiency in differentiating paralysis and non-paralysis cases.

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3.6. Performance Analysis

The model's learning behavior is analyzed through visualization techniques to assess its convergence and generalization ability.

- **Training vs. Validation Accuracy:** Identifies potential overfitting or underfitting issues.
- **Training vs. Validation Loss:** Monitors model convergence and stability over epochs.

These analyses provide insights into improving hyperparameter tuning and model architecture for better real-world deployment.
epochs.

4. Cascaded Convolutional Neural Networks

Cascaded convolutional neural networks (CNNs) stand tall as one of the most novel approaches to deep learning and hierarchical feature learning tasks. Architectures link together multiple CNN architectures in a cascade manner, progressively yielding predicted results. While exploiting the feature extraction powers of CNN architecture, the approach overcomes some limitations associated with one-stage processing [17]. Initial stages would recognize rather global patterns, like coarse facial asymmetry, while subsequent stages undertake to detect more localized details so as to enhance the model's accuracy as well as robustness [18]. In cascaded CNNs, each stage builds on the outputs of its preceding counterparts, providing a mechanism for coarse-to-fine analysis. In facial paralysis, the first stage might involve establishing the general contour of the face, while further stages could focus on zones like the eyes, lips, and cheeks, all areas where asymmetry could be quite easily detected [18]. This architecture allows for the similitude of initial processes to extract important low-level features, such as edges and textures that are significant for detecting slight irregularities in facial structure [19]. The advantages of cascaded CNNs include reduced false positives and tighter classification boundaries. Each stage of the cascade can be viewed as a filter allowing the model to rule out certain classes based on a more complex feature hierarchy. This property has been successfully used in applications such as facial expression recognition, with cascaded architectures showing great performance as they focus on higher-order complex features of the input image [20]. These architectures permit modularity in the sense that components may be bootstrapped in different sequences and training configurations. For example, a cascaded CNN framework may resort to the use of different CNN architectures, such as ResNet and MobileNet, thus retaining the strengths of these architectures in deep feature extraction and computational efficiency. By using techniques like transfer learning and due to data augmentation, cascaded CNNs are scalable solutions to complex tasks such as setting real-time paralysis detection and emotion analysis [20,21], Figure 2.

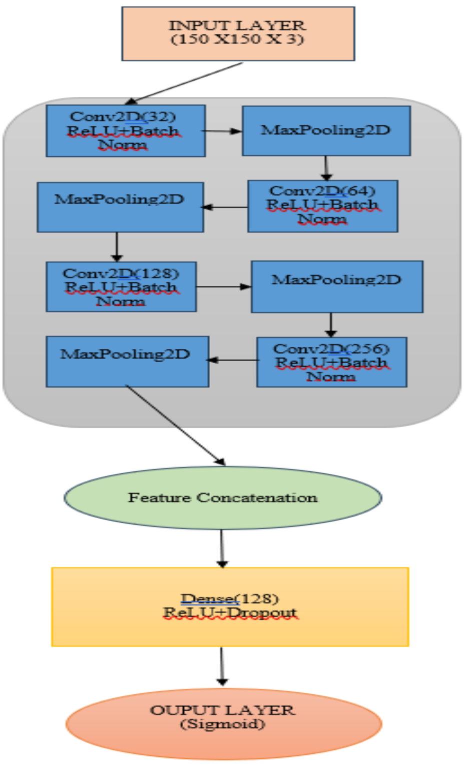

Figure 2 Architecture of the Cascaded

5. Convolutional Neural Network

A feature map representing the existence of specific features identified by the filters, subjected to an activation function such as ReLU to introduce non-linearity, is the result of the convolution process. By learning to recognize complex patterns such as facial characteristics (eyes, nose, and mouth) and spatial relationships, the second multilayer operation expands on the features extracted by the initial filters. In deeper layers, convolutional filters grow increasingly specialized, capturing higher-level data

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such as particular emotional expressions. These layers enable the network to concentrate on abstract data, progressively refining its ability to identify patterns corresponding to facial asymmetry or paralysis. Pooling operations like max pooling minimize the dimensions of feature maps without discarding critical information, while fully connected layers classify the features into respective categories [11,12]. Another explanation is illustrated in Figure 3, which shows the architecture of the proposed cascaded CNN [13-16].

Model: "functional_1"

Layer (type)	Output Shape	Param #	Connected to
input_layer_1 (InputLayer)	(None, 150, 150, 3)	0	-
conv2d_4 (Conv2D)	(None, 150, 150, 32)	896	input_layer_1[0][0]
batch_normalization_5 (BatchNormalization)	(None, 150, 150, 32)	128	conv2d_4[0][0]
activation_5 (Activation)	(None, 150, 150, 32)	0	batch_normalization_5…
max_pooling2d_4 (MaxPooling2D)	(None, 75, 75, 32)	0	activation_5[0][0]
dropout_5 (Dropout)	(None, 75, 75, 32)	0	max_pooling2d_4[0][0]
conv2d_5 (Conv2D)	(None, 75, 75, 64)	18,496	dropout_5[0][0]
batch_normalization_6 (BatchNormalization)	(None, 75, 75, 64)	256	conv2d_5[0][0]
activation_6 (Activation)	(None, 75, 75, 64)	0	batch_normalization_6…
max_pooling2d_5 (MaxPooling2D)	(None, 37, 37, 64)	0	activation_6[0][0]
dropout_6 (Dropout)	(None, 37, 37, 64)	0	max_pooling2d_5[0][0]
conv2d_6 (Conv2D)	(None, 37, 37, 128)	73,856	dropout_6[0][0]
batch_normalization_7 (BatchNormalization)	(None, 37, 37, 128)	512	conv2d_6[0][0]
activation_7 (Activation)	(None, 37, 37, 128)	0	batch_normalization_7…
max_pooling2d_6 (MaxPooling2D)	(None, 18, 18, 128)	0	activation_7[0][0]
dropout_7 (Dropout)	(None, 18, 18, 128)	0	max_pooling2d_6[0][0]
conv2d_7 (Conv2D)	(None, 18, 18, 256)	295,168	dropout_7[0][0]
batch_normalization_8 (BatchNormalization)	(None, 18, 18, 256)	1,024	conv2d_7[0][0]
activation_8 (Activation)	(None, 18, 18, 256)	0	batch_normalization_8…
max_pooling2d_7 (MaxPooling2D)	(None, 9, 9, 256)	0	activation_8[0][0]
dropout_8 (Dropout)	(None, 9, 9, 256)	0	max_pooling2d_7[0][0]
flatten_4 (Flatten)	(None, 180000)	0	dropout_5[0][0]
flatten_5 (Flatten)	(None, 87616)	0	dropout_6[0][0]
flatten_6 (Flatten)	(None, 41472)	0	dropout_7[0][0]
flatten_7 (Flatten)	(None, 20736)	0	dropout_8[0][0]
concatenate_1 (Concatenate)	(None, 329824)	0	flatten_4[0][0], flatten_5[0][0], flatten_6[0][0], flatten_7[0][0]
dense_2 (Dense)	(None, 128)	42,217,600	concatenate_1[0][0]
batch_normalization_9 (BatchNormalization)	(None, 128)	512	dense_2[0][0]
activation_9 (Activation)	(None, 128)	0	batch_normalization_9…
dropout_9 (Dropout)	(None, 128)	0	activation_9[0][0]
dense_3 (Dense)	(None, 1)	129	dropout_9[0][0]

Total params: 42,608,579 (162.54 MB)
Trainable params: 42,607,361 (162.53 MB)
Non-trainable params: 1,216 (4.75 KB)
Optimizer params: 2 (12.00 B)

Figure 3 Architectural Summary of the Cascaded Convolutional Neural Network

The type of each layer, its output shape, and the number of parameters have all been accounted for. Such an in-depth overview summarizes the multi-stage feature extraction, from the first convolution operation to the dense layers where classification eventually takes place. The process starts with convolutional layers to extract low-level features like edges and textures. Such are interspersed with pooling operations that compress spatial dimensions while retaining critical features. As the process continues, deeper layers deal with more complex forms, which allow for the most accurate identification of facial asymmetry. A fully connected dense layer at the end assembles features into one output signal classified as either paralyzed or not paralyzed.

6. Results and Discussions

The proposed cascaded CNN framework achieves great progress toward the effective detection and classification of facial paralysis. Such an architecture yielded as high as 99.86% accuracy in comparison to classical methodologies and previously established CNN architectures. Precision, recall, and F1-score also performed on an equally commendable level, reporting 99.63%, 100.00%, and 99.81% correct predictions, respectively, showing a balanced performance across all evaluation metrics. We report accuracy, recall, f1 score, and precision for training and testing. Precision measures the number of samples where a sample falls outside the total sample. Precision measures the ability of the model to avoid errors in negative classes (non-paralysis classes) and Recall is the ability of the model to find all good models (class paralysis). Precision and Recall are defined accordingly.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Where TP is the true positive, FP is the false positive, and FN is the false negative. F1-score is the weighted average of precision and recall and gives the holistic measure of performance.

$$\text{F1 Score} = \frac{Precision * Recall}{2 * Precision + Recall}$$

Comparative analysis with baselines establishes the efficacy of the cascaded CNN architecture. Notably, single-stage CNNs, with an accuracy of 92%, have been reported by Chen et al. (2020) to highlight the benefits of the cascaded approach [1]. Similarly, the hybrid methods proposed by Wang et al. (2020), combining CNNs with SVMs, offer accuracy still at 90% but are highly complex and less scalable [4]. Therefore, whole discussions above expose how the proposed system is superior to traditional approaches in terms of performance. The visualizations of intermediate layers explain how the features are refined as they are fed to the cascaded network. Coarse feature extraction is involved at the primary step, emphasizing facial geometry and general symmetry. Progressing through the networks will emphasize a more detailed analysis of unevenness in localized areas like the eyes, mouth, and cheeks. For instance, the second-stage filters could identify mouth curvature deviations or eyelid asymmetries, both of which are critical clues in diagnosing facial paralysis [7]. Finally, the aggregation stage takes care of combining these features so that a holistic and accurate classification of the severity of facial paralysis can be executed. Moreover, the cross-validation results obtained from experiments across varied data set families proved the framework's robustness. The model was tested with images from different backgrounds and environmental conditions which showed it always derived consistent performance from many external testing datasets, reinforcing its generalizability. Further reinforcement of such a framework comes from its robust training, which incorporated data augmentation techniques: for example, horizontal flipping, rotation, or adding Gaussian noise, targeting some of the variability you can expect in the real world. operation to the dense layers where classification eventually takes place. The process starts with convolutional layers to extract low-level features like edges and textures. Such are interspersed with pooling operations that compress spatial dimensions while retaining critical features. As the process continues, deeper layers deal with more complex

6.1. Training and Validation Accuracy

Figure 4 shows the evolution of training and validation accuracy throughout epochs.

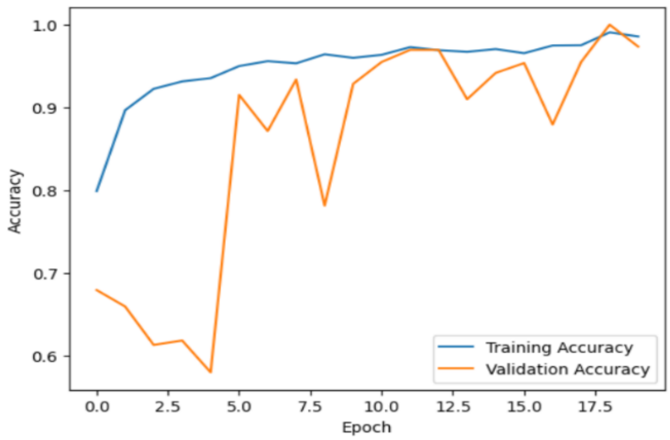

Figure 4 Accuracy of Training Versus Validation Over Epochs

6.2. Training and Validation Loss

Figure 5 shows the training and validation loss over epochs.

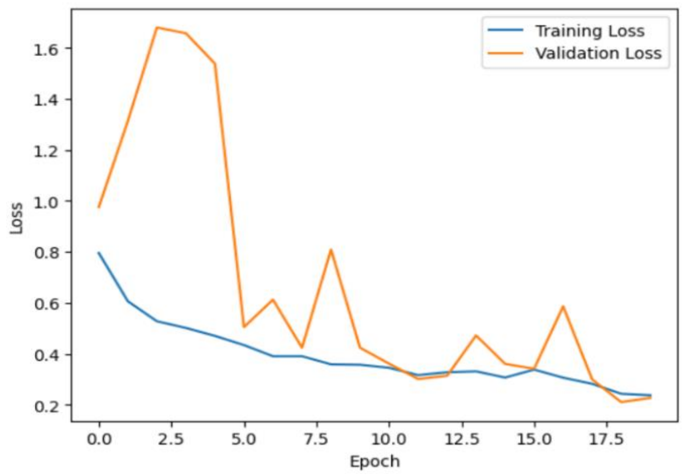

Figure 5 Training Versus Validation Loss Over Epochs

6.3. Detailed Analysis of Metrics

The model was validated by performing qualitative analysis and using the quantitative metric in determining whether the facial images classify into "Paralyzed" or "Not Paralyzed." The cascaded CNN was shown to be successful in recognizing asymmetries in the face as signs of paralysis, as well as successfully identifying cases that had not been affected by the paralysis. Examples of results from the classification are shown in Placeholder for Images. For "Paralyzed" cases, these include features like hazy closure of the eyes, drooping corners of the

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https://doi.org/10.47392/IRJAEH.2025.0134

mouth, and uneven lines of eyebrows. These features are consistent with clinical features of facial paralysis and do indicate the CNN's subtle localization and discrimination of deviations. In the cases labeled "Not Paralyzed", the network demonstrated a high capacity for recognizing symmetric existing facial particulate faces from a noisy background with an acceptable level of variability for a broad illumination range. This is a good indicator of the way the different working mechanisms will interact with ideal imaging data sets while recognizing what's nonideal. Also, the extracted feature maps from intermediate layers accelerated the understanding of the cascaded CNN's hierarchical processing. Low-level and early processing should describe general information such as the general shape of the face, while deeper processing extracts detail in all kinds of local asymmetries of different facial landmarks. These results prove that the arrangement in cascaded architecture works well in integrating the global and the local representation. The results of classification illustrate the feasibility of employing the cascaded CNN for early detection of facial paralysis, demonstrating that the model generalizes well across the different categories of patients and different conditions. Future work will focus on the deployment of the CNN in actual clinical environments to further validate the model's performance and use, shown in Figure 6 & 7.

Figure 6 CCNN Model prediction on images as Paralyzed or Non-Paralyzed

Figure 7 CCNN Model prediction on images as Paralyzed or Non-Paralyzed

6.4. Comparison with Previous Research

As shown in Table 2, our model performs better than several current methods in the literature.

Table 2 Comparison with Previous Research

Study	Accuracy
Chen et al. [1]	92%
Wang et al. [4]	90%
Silva et al. [5]	89%
Our Model	99.86%

6.5. Upcoming Projects

By adding more datasets and optimizing the model architecture to lower misclassification rates in difficult situations, future research could concentrate on enhancing the model's generalizability even further.

Conclusion

It can be seen that the proposed framework is a log of good promise in effectively detecting early signs of facial paralysis, overcoming the hindrances associated with traditional diagnostic systems. With respect to a multi-stage approach that has a hierarchical end system, the model adequately extracts features on a global scale as well as features on a localized scale for the discrimination of facial asymmetry, with any aspect being the origin of paralysis. A performance of accuracy 99.86, precision 99.63, recall 100, and F1-score 99.81 are just a few data that show there is a chance for this framework to take the lead in this field of medical technology. The combined cascade has also emphasized the strength of feature learning through cascade layers, which aid in identifying slight facial asymmetries. Future work includes real-time integration, a bigger dataset, and ultimately clinical evaluation trials to make the solution more generalizable. The findings put forth this framework as a promissory next step toward advanced early diagnostic methods and tailoring a better patient outcome in a medical scenario.

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International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
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https://doi.org/10.47392/IRJAEH.2025.0134

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