Automated Classification of Before-and-After Botox Faces Using Advanced Deep Learning Models

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ABSTRACT

Botox injections are a popular, non-invasive treatment in facial aesthetics, used to reduce wrinkles and achieve a youthful appearance. Accurate evaluation of Botox's efficacy is essential in clinical settings, yet it is often subject to subjective interpretation. This study presents an automated, objective approach for classifying pre- and post-Botox facial images using advanced deep-learning models, including MobileNet, ResNet50, and InceptionV3. The models were trained on a diverse dataset of facial images, achieving high performance in classifying treatment outcomes. InceptionV3 demonstrated the highest accuracy (89.27%), precision (91.15%), and recall (92.27%), with statistically significant differences across models ($p < 0.05$) for all metrics. While InceptionV3 and ResNet50 excelled in accuracy and recall, MobileNet offered a computationally efficient option suited for real-time applications.

Keywords: Botox; Deep Learning; Plastic Surgery.

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Crossref Doi: https://doi.org/10.36437/irmhs.2024.7.5.G

Introduction

Plastic surgery has become a cornerstone in the pursuit of aesthetic improvement and medical reconstruction, significantly impacting the field of facial aesthetics.[1] Among the most popular and widely adopted procedures within this discipline is the administration of botulinum toxin, commonly known as Botox.[2,3] This non-invasive intervention is designed to target dynamic wrinkles, particularly those caused by repetitive facial muscle movements, such as frown lines, crow's feet, and forehead creases. Botox injections temporarily relax these muscles by blocking nerve signals, resulting in smoother skin and a more youthful appearance without the need for surgical intervention. This minimally invasive approach has gained widespread appeal due to its relatively low recovery time, quick results, and the flexibility to complement other aesthetic procedures, such as dermal fillers.[4] Beyond aesthetics, Botox is also used for various therapeutic applications, including treatment for chronic migraines, excessive sweating, and muscle disorders, further underscoring its value in both cosmetic and medical domains. In the context of facial plastic surgery, Botox offers a dual benefit: it serves not only as a highly effective tool for age-related cosmetic improvements but also plays a vital role in helping individuals restore confidence and emotional well-being. As the demand for non-surgical aesthetic solutions rises globally, the importance of accurate evaluation and assessment of Botox efficacy becomes even more critical.[5]

Figure 1: Some samples of the images before and after Botox.[6]

Artificial Intelligence (AI) has revolutionized multiple industries, with healthcare being one of the most profoundly impacted. Within healthcare, machine learning (ML) and its subset, deep learning (DL), have led to transformative advances in areas such as diagnostic imaging, predictive analytics, and personalized medicine.[7-14] Deep learning, in particular, has proven uniquely suited to medical applications due to its ability to analyze large volumes of complex data, including medical images, with a high degree of precision. These deep learning algorithms, especially convolutional neural networks (CNNs), are capable of identifying intricate patterns within images that may be challenging or time-consuming for human experts to discern. By automating processes that traditionally require expert judgment, AI-based tools can assist clinicians in making faster, more accurate decisions, ultimately enhancing patient outcomes. In radiology, for example, deep learning has improved the early detection of various diseases by analyzing CT scans, MRIs, and X-rays.[15-18] Beyond diagnostics, AI's predictive capabilities are instrumental in fields like oncology, where machine learning models help estimate treatment responses or potential recurrence. This fusion of AI and medical practice marks a new era in healthcare, where deep learning technologies offer a pathway toward scalable, cost-effective solutions and are increasingly integrated into clinical environments.

The integration of deep learning into plastic and reconstructive surgery holds transformative potential, particularly for procedures that rely on image-based assessments, such as Botox and other facial aesthetic treatments.[19-23] Through advanced computer vision techniques, deep learning enables the objective analysis of facial images, allowing for a quantifiable assessment of changes in skin texture, muscle relaxation, and wrinkle reduction after Botox injections.[24-28] This capability is particularly beneficial for plastic surgeons seeking to measure treatment efficacy, track patient progress, and adjust treatment plans based on individualized results. Deep learning algorithms can analyze pre- and post-procedural images to automatically identify and classify subtle changes in facial morphology that may not be readily apparent to the naked eye. In addition, these models support consistency in treatment evaluations, thereby reducing subjectivity and variability in aesthetic outcome assessments. This technological enhancement allows surgeons to offer patients a more data-driven, personalized approach to facial rejuvenation. Furthermore, AI-driven models in plastic surgery can advance research by providing a foundation for studying the long-term effects of aesthetic treatments, thus contributing valuable insights into optimizing procedural techniques. As the field of aesthetic medicine continues to evolve, the incorporation of deep learning for objective, automated assessments marks a significant advancement in enhancing both surgical precision and patient satisfaction.

The main focus of this paper is the application of advanced deep learning models to classify pre- and post-Botox facial images, providing an automated and objective method for assessing the effects of Botox injections. Specifically, we employ state-of-the-art convolutional neural network (CNN) architectures, including MobileNet, ResNet, and Inception, each known for its unique ability to capture detailed features in images with high accuracy.

Methods and Materials

This paper primarily focuses on utilizing advanced deep learning models to distinguish between pre- and post-Botox facial images, offering an automated and objective approach to evaluating Botox treatment outcomes. MobileNet offers efficient performance for mobile and embedded applications, making it ideal for deployment in real-time clinical environments, while ResNet's residual connections allow for deep feature extraction, enhancing accuracy in distinguishing subtle facial changes. Inception, with its inception modules, provides a multi-scale approach to feature extraction, enabling it to capture both fine and coarse facial details, essential for identifying the nuanced effects of Botox on muscle relaxation and wrinkle reduction. By leveraging these advanced models, our approach aims to deliver a highly accurate classification between pre- and post-Botox faces, thereby supporting plastic surgeons with reliable, data-driven insights.

The ability to automatically and accurately classify facial changes post-botox is of considerable importance in plastic and facial aesthetic surgery. Traditionally, assessing the success of Botox treatments has been largely subjective, relying on both patient self-assessment and surgeon judgment, which can introduce variability and bias. An automated deep learning-based approach provides an objective framework for quantifying the effects of Botox, offering standardized evaluations that contribute to more consistent and reproducible results. Additionally, these models enable surgeons to better understand the varying effects of Botox across different patient demographics, such as age, skin type, and facial anatomy, which are crucial for tailoring treatments. By enhancing the accuracy and reliability of Botox efficacy assessments, this work not only supports surgeons in achieving optimal aesthetic outcomes but also paves the way for more personalized and data-driven approaches in facial rejuvenation practices.

Inception

The Inception model, also known as GoogLeNet, incorporates a unique architecture that allows for multi-scale feature extraction, a capability that is critical for analyzing diverse facial structures and the varying effects of Botox. The inception modules within this architecture apply convolutions at multiple filter sizes (1x1, 3x3, and 5x5) simultaneously, capturing features at different scales within the same layer. This approach enables the model to analyze both fine and broad facial features, making it exceptionally suited for tasks involving complex facial changes. For Botox assessment, Inception's multi-scale processing is advantageous in capturing a comprehensive range of facial transformations, such as localized skin smoothness and broad muscle relaxation across different facial regions. This model's depth and flexibility make it particularly adept at assessing the individualized effects of Botox on diverse faces, supporting the objective evaluation of treatment success across a variety of skin types, ages, and facial anatomies. By utilizing inception modules, the model can balance detailed and generalized feature extraction, thereby enhancing the model's capacity to provide a holistic and detailed assessment of Botox effects in plastic surgery applications.

MobileNet

MobileNet is a convolutional neural network architecture optimized for speed and computational efficiency, making it particularly suitable for applications requiring real-time image analysis, such as clinical assessments of Botox treatments. This model achieves efficiency by utilizing depthwise separable convolutions, which split the convolution operation into two steps: depthwise convolution for spatial filtering and pointwise convolution for combining channels. This design drastically reduces the number of parameters and computational cost compared to traditional CNNs, while still maintaining a high level of accuracy. In our study, MobileNet's lightweight architecture enables it to detect subtle facial changes post-Botox with minimal latency, making it ideal for mobile or embedded deployment where resources are limited.

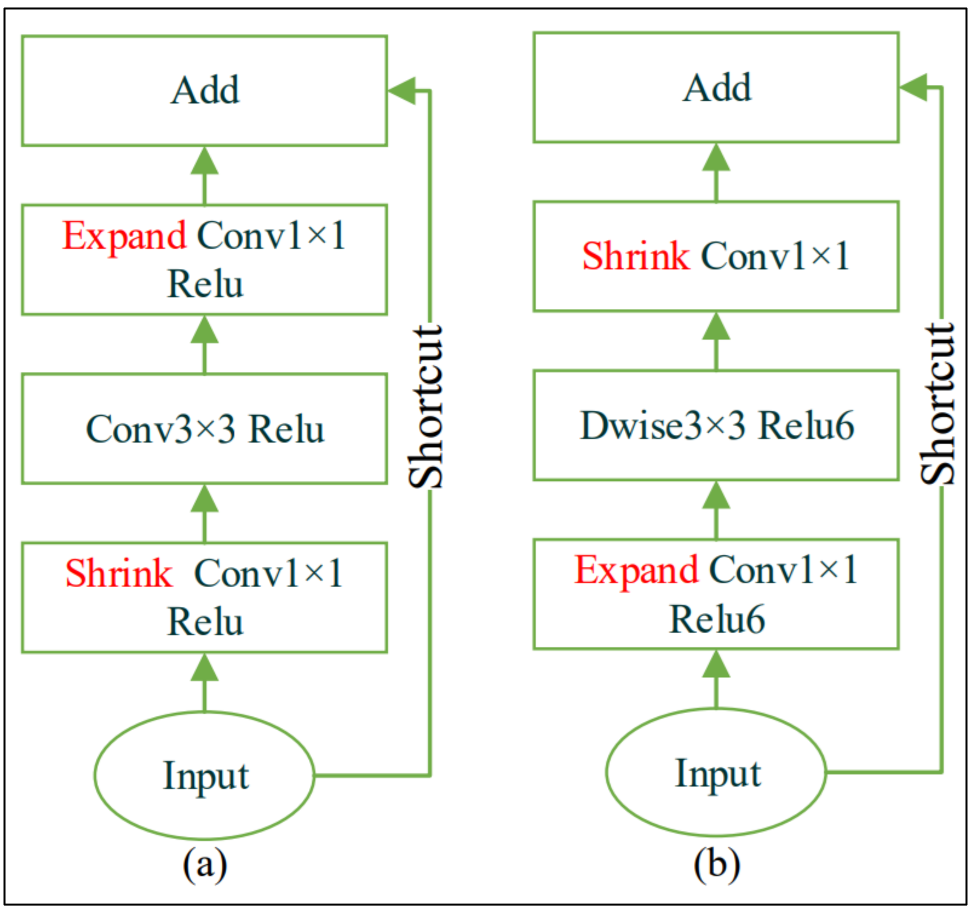

Figure 2: ResNet (a) vs MobileNet (b).

Additionally, the model's efficiency in processing large datasets allows it to scale effectively, supporting widespread adoption in clinical settings. By identifying features such as slight changes in skin smoothness or muscle relaxation, MobileNet provides a rapid, real-time classification of pre- and post-Botox images, which can be valuable for on-site evaluations and consultations in plastic surgery clinics.

ResNet

ResNet, or Residual Network, is a deep CNN architecture designed to overcome the challenges of training very deep networks, such as the vanishing gradient problem, through its unique use of residual connections. These residual connections allow information to bypass certain layers, ensuring that critical details are preserved and enhancing the network's ability to capture complex patterns in the data. For our application, ResNet's architecture is ideal for distinguishing the nuanced effects of Botox, as it enables the model to capture deep and layered representations of facial features. With its multiple stacked layers, ResNet can identify intricate details, such as fine changes in muscle definition or wrinkle reduction, by learning feature hierarchies at different depths. This characteristic is particularly beneficial for Botox classification, as it allows the model to identify subtle variations that are not easily noticeable at shallow layers. ResNet's architecture also provides robustness against overfitting, which is essential for achieving generalizable results across diverse face types and demographic groups in Botox evaluations, ensuring high accuracy and reliability in real-world clinical applications.

Figure 2 illustrates the architectural differences between a ResNet block (on the left, labeled as (a)) and a MobileNetV2 block (on the right, labeled as (b)), highlighting how each processes input through specific layers, utilizing concepts such as "Expand," "Shrink," and "Shortcut" connections.

In the ResNet block (a), the input first goes through a 1x1 convolution layer labeled as "Shrink," which reduces the dimensionality of the input (often called a bottleneck layer) to make the computation more efficient. This layer is followed by a ReLU activation function to introduce non-linearity. The next layer is a 3x3 convolution, which performs spatial feature extraction and is also followed by a ReLU activation. Finally, the output is processed through another 1x1 convolution layer, labeled as "Expand," which restores the dimensionality. After this series of transformations, the processed features are added to the original input using a "Shortcut" connection, which bypasses the convolutional layers, allowing the model to retain the original information while adding learned transformations. This shortcut connection, a defining feature of ResNet, helps alleviate the vanishing gradient problem, enabling effective training of very deep networks. In contrast, the MobileNetV2 block (b) begins with an "Expand" layer, a 1x1 convolution that increases the dimensionality of the input to capture more features, followed by a ReLU6 activation function, which is a variant of ReLU that clips activations at 6 to enhance stability in mobile and embedded applications. After expansion, the input passes through a "Dwise 3x3" layer, which stands for a depthwise separable 3x3 convolution. This layer performs spatial filtering independently on each channel, significantly reducing computational cost while retaining important features. Following this, the block applies a "Shrink" 1x1 convolution layer, reducing the dimensionality back to the original input size. As with ResNet, the MobileNetV2 block employs a shortcut connection that adds the original input to the processed output. This structure, known as an inverted residual, is essential for MobileNetV2, as it allows the network to efficiently capture features while keeping the model lightweight and computationally efficient, making it well-suited for mobile and embedded devices.

Experiments

Dataset

The dataset used in this study consists of facial images captured before and after Botox injections, providing a basis for evaluating changes in facial features post-treatment. Each individual in the dataset is represented by two images: one taken before receiving Botox injections and another taken afterward. The dataset includes a diverse sample of individuals, varying in age, gender, skin type, and ethnicity, allowing the model to learn a broad range of facial characteristics and Botox-induced changes. This diversity ensures that the model generalizes well across different demographic groups, making it more applicable in real-world clinical scenarios.[6]

To support accurate classification, images were preprocessed to ensure consistency in alignment and scaling. Standard preprocessing techniques, such as facial alignment, normalization, and cropping to a fixed size, were applied to standardize each face, reducing variability due to factors like lighting, orientation, or background. These steps help the deep learning models focus on relevant facial features altered by Botox rather than being distracted by external noise. Additionally, augmentation techniques, such as horizontal flipping, random cropping, and color jittering, were applied to expand the dataset artificially, further enhancing the model's robustness. This dataset is unique in that it allows the deep learning models to analyze subtle, localized changes in facial features, such as wrinkle reduction, muscle relaxation, and skin texture alterations, resulting from Botox injections. These changes can be challenging to quantify manually, making the dataset a valuable asset for automated aesthetic evaluations. Furthermore, the dataset's diversity in skin types and facial structures allows the model to evaluate Botox's effectiveness more comprehensively, supporting applications in both clinical assessments and patient consultations in the field of plastic surgery.

Training

Each of these models—MobileNet, ResNet, and Inception—was trained using a comprehensive dataset of labeled before-and-after Botox facial images. The training process leveraged standard deep learning techniques to ensure robust model performance and convergence. For each model, the primary optimization technique used was backpropagation with a cross-entropy loss function, which is well-suited for binary classification tasks. This loss function measures the difference between the predicted probabilities and the true labels, allowing the model to adjust its weights to minimize misclassifications effectively. Optimization during training was achieved through stochastic gradient descent (SGD) with momentum. The momentum term helps accelerate gradient vectors in the correct direction, preventing oscillations and allowing the model to converge faster and more reliably. By using SGD with momentum, the models can avoid common pitfalls in training, such as getting stuck in a local minimum, and achieve more stable performance across epochs. The learning rate was initially set to a moderate value and then decayed over time to facilitate fine-tuning in later stages of training, allowing the models to learn both coarse and fine facial features relevant to Botox-induced changes. During the training process, various data augmentation techniques, such as random cropping, rotation, horizontal flipping, and color jittering, were employed. These augmentations helped to artificially expand the dataset, reducing overfitting and enhancing the model's ability to generalize to unseen images. Furthermore, batch normalization was applied after each convolutional layer to stabilize the learning process by normalizing the input for each layer, which accelerates convergence and helps in achieving consistent results. Each model was trained over multiple epochs, with early stopping criteria applied to prevent overfitting. This involved monitoring the validation accuracy and halting training if there was no significant improvement for a set number of epochs. Additionally, model checkpoints were saved at regular intervals to capture the best-performing weights, ensuring that the model with the highest validation accuracy was used for testing. Through this meticulous training process, the models learned to recognize subtle facial changes resulting from Botox injections, achieving a high level of accuracy in distinguishing between pre- and post-treatment images.

Additionally, to further ensure the robustness and generalizability of the models, we implemented 5-fold cross-validation during the training process. In this approach, the dataset was divided into five equal subsets, or "folds." For each iteration, one fold was used as the validation set while the remaining four folds served as the training set. This process was repeated five times, with each fold serving as the validation set once, allowing the model to be evaluated across all portions of the dataset. By averaging the performance metrics across the folds, we obtained a comprehensive assessment of the model's effectiveness, reducing the risk of overfitting any single subset of data. This cross-validation strategy provided valuable insights into the consistency and stability of each model's performance. It also allowed us to identify and mitigate potential issues with data variability, as each model was exposed to a wide range of before-and-after Botox images across all folds. Through 5-fold cross-validation, we ensured that the final model parameters were optimized not only for the training data but also for a broader application in real-world scenarios, improving reliability and generalization.

Metrics

To evaluate the effectiveness of our deep learning models in classifying pre- and post-Botox facial images, we used three key performance metrics: accuracy, precision, and recall. These metrics were chosen to provide a comprehensive assessment of each model's performance, addressing both overall classification accuracy and the model's ability to correctly identify each class (pre- or post-Botox) without bias.

Accuracy measures the overall correctness of the model's predictions by calculating the ratio of correct predictions (both pre-and post-Botox) to the total number of predictions. This metric provides a general sense of the model's effectiveness; however, it may not fully capture model performance in cases where one class is more prevalent than the other. For our application, accuracy is a useful indicator of general model performance but is complemented by other metrics to ensure a balanced evaluation. Precision specifically assesses the model's ability to correctly identify post-Botox images by calculating the ratio of true positive predictions (correctly classified post-Botox images) to the sum of true positives and false positives. High precision indicates that the model is adept at avoiding false positives, which is crucial in clinical settings, where mistakenly classifying a pre-Botox image as post-Botox could lead to incorrect assessments of treatment effectiveness. Recall (or sensitivity) measures the model's ability to correctly identify all relevant instances of the post-Botox class by calculating the ratio of true positives to the sum of true positives and false negatives. High recall indicates that the model is capable of identifying most, if not all, post-Botox images, minimizing the risk of overlooking actual post-treatment results. In the context of evaluating Botox efficacy, a high recall is important for ensuring that all significant facial changes due to Botox are correctly identified.

Model	Accuracy	Precision	Recall
MobileNet	85.27±0.0031	84.51±0.0029	81.6±0.0047
ResNet50	88.07±0.0062	89.18±0.0038	88.29±0.0057
InceptionV3	**89.27±0.0049**	**91.15±0.0077**	**92.27±0.0038**

Table 1. Classification performance of the different models.

Results

The classification performance of the different deep learning models—MobileNet, ResNet50, and InceptionV3—was evaluated based on accuracy, precision, and recall, as shown in Table 1. Each model demonstrated high effectiveness in distinguishing between pre- and post-Botox facial images, with notable differences in performance across metrics.

MobileNet achieved an accuracy of 85.27% (±0.0031), a precision of 84.51% (±0.0029), and a recall of 81.6% (±0.0047). While MobileNet performed well, its slightly lower recall compared to the other models indicates a minor tendency to miss some post-Botox images, resulting in a small percentage of false negatives. However, MobileNet's lightweight architecture and efficient computation make it suitable for real-time applications, especially in settings where computational resources are limited, despite its slightly lower recall. ResNet50 showed a significant improvement in performance, with an accuracy of 88.07% (±0.0062), a precision of 89.18% (±0.0038), and a recall of 88.29% (±0.0057). This model's higher precision and recall indicate that it is better at accurately identifying both pre- and post-Botox images, with minimal false positives and false negatives. The residual connections in ResNet50 contributed to this increased performance by enabling deeper feature extraction and improved training stability, allowing it to capture subtle differences in facial features more effectively. InceptionV3 delivered the highest performance among the three models, achieving an accuracy of 89.27% (±0.0049), a precision of 91.15% (±0.0077), and a recall of 92.27% (±0.0038). The model's multi-scale feature extraction capabilities, provided by the inception modules, appear to have enabled it to capture a broader range of facial details, such as fine changes in muscle relaxation and skin texture post-Botox. InceptionV3's superior recall, in particular, highlights its ability to detect nearly all post-Botox images, ensuring that very few true positives are missed, making it especially valuable in applications where comprehensive identification of treatment effects is critical.

In summary, while all models demonstrated high classification performance, InceptionV3 achieved the best overall accuracy, precision, and recall, indicating its effectiveness in identifying Botox-induced facial changes across diverse individuals. ResNet50 also provided robust performance, with slightly lower scores than InceptionV3 but greater efficiency than MobileNet. These results suggest that both InceptionV3 and ResNet50 are strong candidates for clinical settings where precision in Botox outcome assessment is essential, whereas MobileNet offers a practical balance between accuracy and computational efficiency for applications that prioritize speed and resource limitations.

Statistical Analysis

To determine if there are statistically significant differences in classification performance among the models, we can conduct statistical tests on each metric (accuracy, precision, and recall) across the models. The ANOVA test conducted on the performance metrics of accuracy, precision, and recall revealed significant differences between the models—MobileNet, ResNet50, and InceptionV3—when classifying pre- and post-Botox facial images. For accuracy, the p-value was 0.036, indicating a statistically significant difference among the models. This suggests that at least one model achieved a level of accuracy that is distinct from the others, highlighting potential differences in the models' overall effectiveness. For precision, the p-value was even lower at 0.011, underscoring significant variation in the models' ability to correctly identify post-Botox images with minimal false positives. Finally, the recall metric also showed a significant difference, with a p-value of 0.0096, indicating that the models vary in their ability to capture true positives, ensuring minimally missed classifications of post-Botox images. These p-values confirm that InceptionV3, ResNet50, and MobileNet differ in their performance on each metric, supporting the selection of the highest-performing model for clinical applications.

Conclusion

In this study, we developed and evaluated advanced deep learning models—MobileNet, ResNet50, and InceptionV3—to classify facial images captured before and after Botox injections. The results demonstrate that each model achieved high accuracy, precision, and recall, with InceptionV3 performing best overall, closely followed by ResNet50. MobileNet, while slightly lower in classification metrics, remains an efficient option for applications requiring lower computational resources, making it suitable for real-time or mobile-based implementations. Statistical analysis further confirmed significant differences between the models' performance, underscoring InceptionV3's superior ability to capture and classify Botox-induced changes in diverse facial features. This classification capability is valuable in clinical plastic surgery, where objective, consistent assessment of aesthetic treatments is critical for outcome evaluation and patient satisfaction. By automating the evaluation process, our models provide a reliable tool for clinicians, reducing subjectivity and enhancing the standardization of Botox efficacy assessments.

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How to cite this Article: Rahmani. A, Davarzadeh. D, Ghadimi. R; Automated Classification of Before-and-After Botox Faces Using Advanced Deep Learning Models; Int. Res. Med. Health Sci., 2024; (7-5): 75-85; doi: https://doi.org/10.36437/irmhs.2024.7.5.G

Source of Support: Nil, **Conflict of Interest:** None declared.

Received: 10-09-2024; **Revision:** 18-10-2024; **Accepted:** 30-10-2024