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## Title: Increasing Rosacea Awareness Among Population Using Deep Learning and Statistical Approaches

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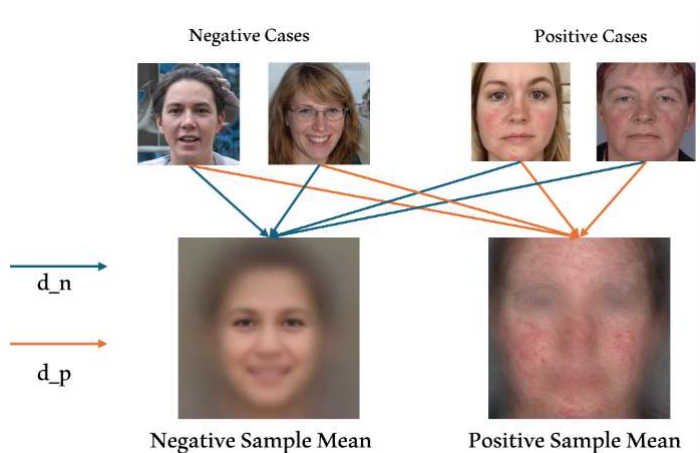


# Introduction

- Rosacea Overview and Symptoms
- Importance of Early Detection
- Challenges with Deep Learning:
  - Data Scarcity
  - Data Privacy
  - Overfitting
  - Explainability
- Our study:
  - one deep learning method
  - one statistical approach

# Method

- Deep learning:
  - ResNet-18 pretrained on ImageNet
- Statistical method:



## Algorithm 1 Automatic Rosacea Detection Using PCA

```

1: procedure ARDUP( $X_{neg}, X_{pos}, \bar{x}_{neg}, \bar{x}_{pos}, x, r$ )
2:    $U_{neg}, S_{neg}, V_{neg}^T = \text{SVD}(X_{neg})$ 
3:    $U_{pos}, S_{pos}, V_{pos}^T = \text{SVD}(X_{pos})$  //pca on training data
4:    $\bar{U}_{neg} \leftarrow U_{neg}[:, r], \bar{U}_{pos} \leftarrow U_{pos}[:, r]$  //get r principal components
5:    $\bar{x}_{neg} \leftarrow \bar{x}_{neg} \cdot \bar{U}_{neg}, \bar{x}_{pos} \leftarrow \bar{x}_{pos} \cdot \bar{U}_{pos}$  //projection to principal components'
   space
6:   if  $\|x \cdot \bar{U}_{neg} - \bar{x}_{neg}\|^2 \leq \|x \cdot \bar{U}_{pos} - \bar{x}_{pos}\|^2$  then //compare projected distance
7:     return 0
8:   else
9:     return 1
    
```

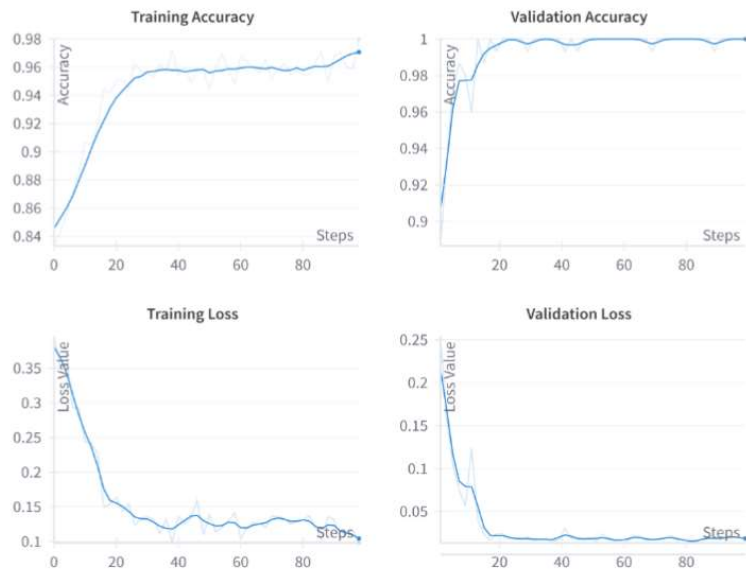
# Experiment

- Dataset:
  - Training Dataset
    - 250 generated rosacea
    - 500 generated normal
  - Validation Dataset
    - 50 generated rosacea
    - 100 generated normal
  - Test Dataset
    - 50 real rosacea
    - 150 real normal



**Fig. 1.** The first column shows the mean images of the two datasets from the rosacea negative and positive classes, respectively. The remaining five columns display five random example images from the two datasets corresponding to the normal people and those with rosacea, respectively.

# Experiment



**Fig. 2.** The training/validation loss and accuracy of the ResNet-18.

**Table 1.** Confusion matrix for the deep learning method on the test set

	Predicted Rosacea	Predicted Not Rosacea
Rosacea	29	21
Not Rosacea	0	150

**Table 2.** The automatic rosacea detection performance on the validation data set of the proposed deep learning and the statistical approaches, respectively.

	Accuracy	Precision	Recall	F1 Score
ResNet-18	1.00	1.00	1.00	1.00
Stats Method with PCA	0.90	0.77	0.96	0.86

**Table 3.** The confusion matrix for the statistical method on the test data set with PCA

	Predicted Rosacea	Predicted Not Rosacea
Rosacea	44	6
Not Rosacea	15	135

**Table 4.** The automatic rosacea detection performance on the test data set using the proposed deep learning and the statistical approaches, respectively.

	Accuracy	Precision	Recall	F1 Score
ResNet-18	<b>0.895</b>	<b>1.00</b>	0.58	0.73
Stats Method with PCA	<b>0.895</b>	0.75	<b>0.88</b>	<b>0.81</b>

# Conclusion

- Deep Learning Method:**

- Achieves high accuracy but suffers from overfitting.
- Limited generalizability to real-world data, leading to missed detections.
- Lacks explainability, which is essential for clinical acceptance.

- Statistical Method with PCA:**

- Achieve better recall rates, identifying rosacea cases more effectively.
- Provide interpretability by measuring the distance metric from the sample mean.

## Q & A