Comparative Study and Optimization of SVD and CNN in Image Processing

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Abstract

Skin lesion image classification is pivotal for early dermatological diagnosis, yet traditional CNNs suffer from poor performance due to image noise and scarce annotated data.
This study proposes an SVD-enhanced CNN framework: SVD preprocesses ISIC 2019 images to suppress noise while preserving key lesion features. Combined with class weight optimization for data imbalance, it notably boosts skin lesion classification accuracy and robustness.

Introduction

Cutaneous malignancies (e.g., malignant melanoma) severely threaten human health, and early accurate diagnosis is critical for improving patients' survival rates. As a core of computer-aided diagnosis (CAD) systems, skin lesion image classification is indispensable for standardizing clinical screening and enhancing diagnostic efficiency, with datasets like ISIC 2019 providing large-scale annotated images for algorithm development.
Convolutional Neural Networks (CNNs) perform well in medical image recognition via robust feature extraction but have limitations in this task: image noise (e.g., hair artifacts) and scarce high-quality annotated data impair their ability to capture lesion features, leading to insufficient classification accuracy that fails to meet clinical needs.
Singular Value Decomposition (SVD) achieves signal-noise separation by preserving key feature-related components. Thus, this study proposes an SVD-enhanced CNN framework—integrating SVD into preprocessing to optimize input quality and combining class weight optimization to boost performance—with its accuracy validated on the ISIC 2019 dataset.

Summary & Outlook

Summary
This study examined EfficientNet-B7 in skin lesion classification with Singular Value Decomposition (SVD) preprocessing. ISIC 2019 experiments showed SVD notably improved performance: training/validation accuracy (85%/83% vs. 78%/75% without SVD), loss (0.6/0.7 vs. 0.6/0.8), AUC (0.98/0.96 vs. 0.96/0.94), and more balanced precision/recall (~0.8).
Outlook
Future work includes: optimizing SVD parameters for diverse lesions; combining SVD with other preprocessing methods; expanding datasets or using transfer learning for better generalization; and enhancing model interpretability to assist clinicians and facilitate clinical application.

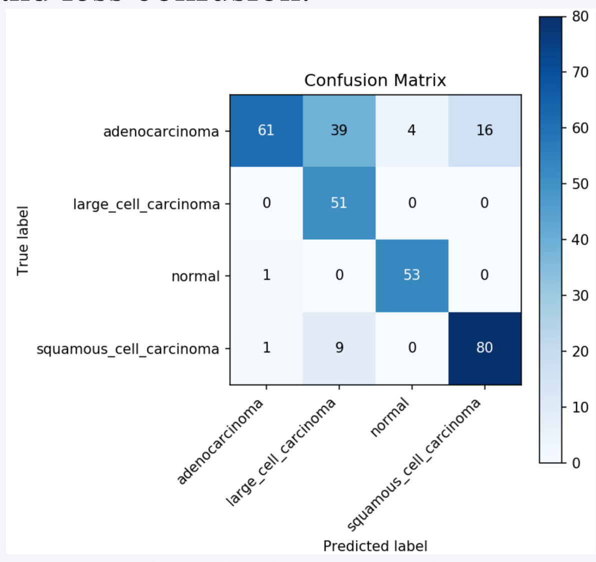
Methodology

Initial SVD Validation
We first validated SVD on a small 4-class lung histopathology dataset using a lightweight pipeline:

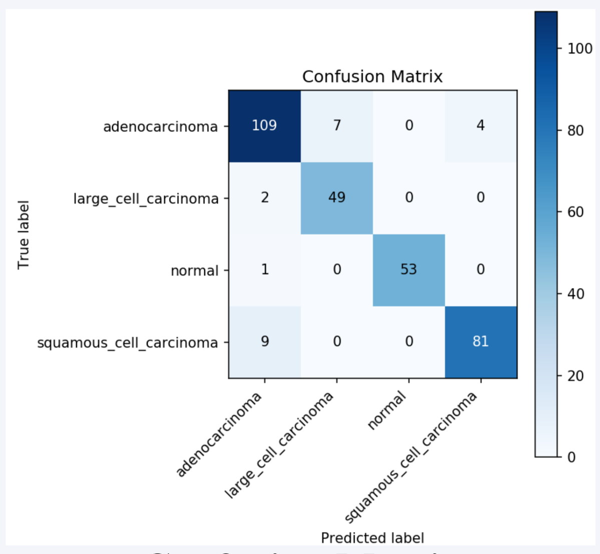
- Preprocessing: 224×224 images with standard augmentation, per-channel SVD (fixed k=50, 100, 150 or auto-k, τ=0.95), then normalization.
- Model: ResNet-18 trained with AdamW & early stopping.
- Result: SVD boosted test accuracy from 77.78% to >92%, with k=100, 150 being most stable.

Confusion Matrix
We use the confusion matrix to visualize the test results to show which categories are mistakenly identified as which categories.
The rows represent the true categories, the columns represent the predicted categories, and the diagonal cells represent correct predictions, while the non-diagonal cells represent incorrect predictions.

The absence of SVD shows obvious non-diagonal cells, indicating more confusion between categories.
When using SVD (with k fixed at 100), the diagonal becomes stronger, the non-diagonal cells shrink, suggesting higher accuracy for each category and less confusion.



Confusion Matrix without SVD



Confusion Matrix with k=100 SVD

Large-Scale Evaluation (ISIC 2019 Skin Lesion Dataset)

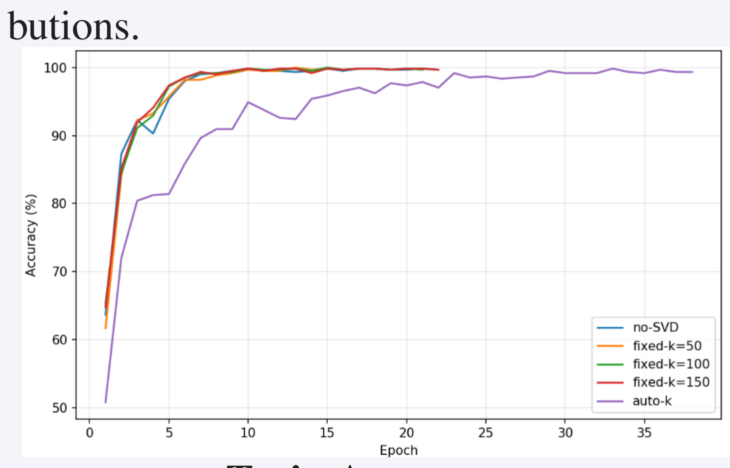
Preprocessing
- Color Handling: $BGR \to RGB$, LAB split; CLAHE (clip=3.0, grid=8×8) on L channel + bilateral filtering (kernel=9, σ=75).
- Standardization: Resize to 384×384, normalize [0,1].
- Cache: NumPy arrays stored for reuse.

SVD Processing
Using PyTorch, the model based on EfficientNet-B7 has two parts:
- Convert $RGB \to 3 \times 384 \times 384$, apply per-channel SVD (k=60), reconstruct, and revert to $384 \times 384 \times 3$.

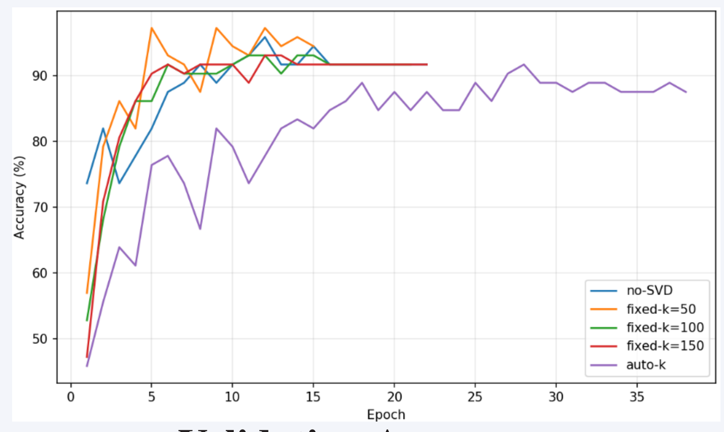
Model
- Backbone: EfficientNet-B7 (ImageNet pretrained), adaptive pooling→2560D features.
- Head: 4-layer FC ($2560 \to 1024 \to 512 \to 256 \to 7$) with SiLU, BatchNorm1d, Dropout(0.5).

Training
- Loss: Weighted cross-entropy (rare classes $\times$2–5).
- Optimizer: AdamW (lr=2e-5, wd=1e-5).
- Training: Gradient accumulation (batch=8→32), dual schedulers (cosine + plateau), mixed precision, early stopping (15-epoch patience).

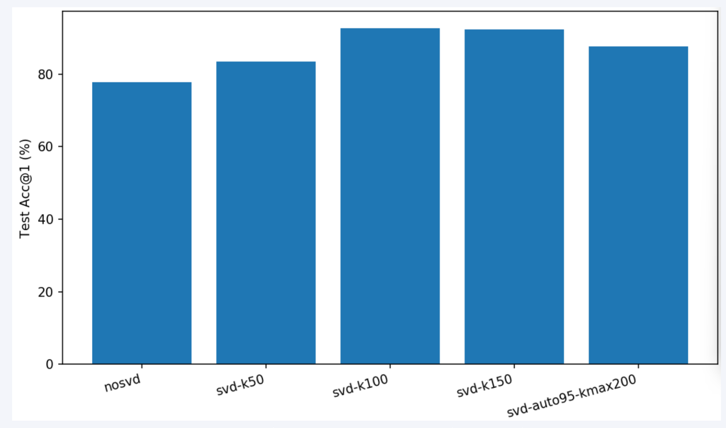
Metrics
Accuracy, AUC, Precision, and Recall. Test outputs include probabilities and class distributions.



Train Accuracy

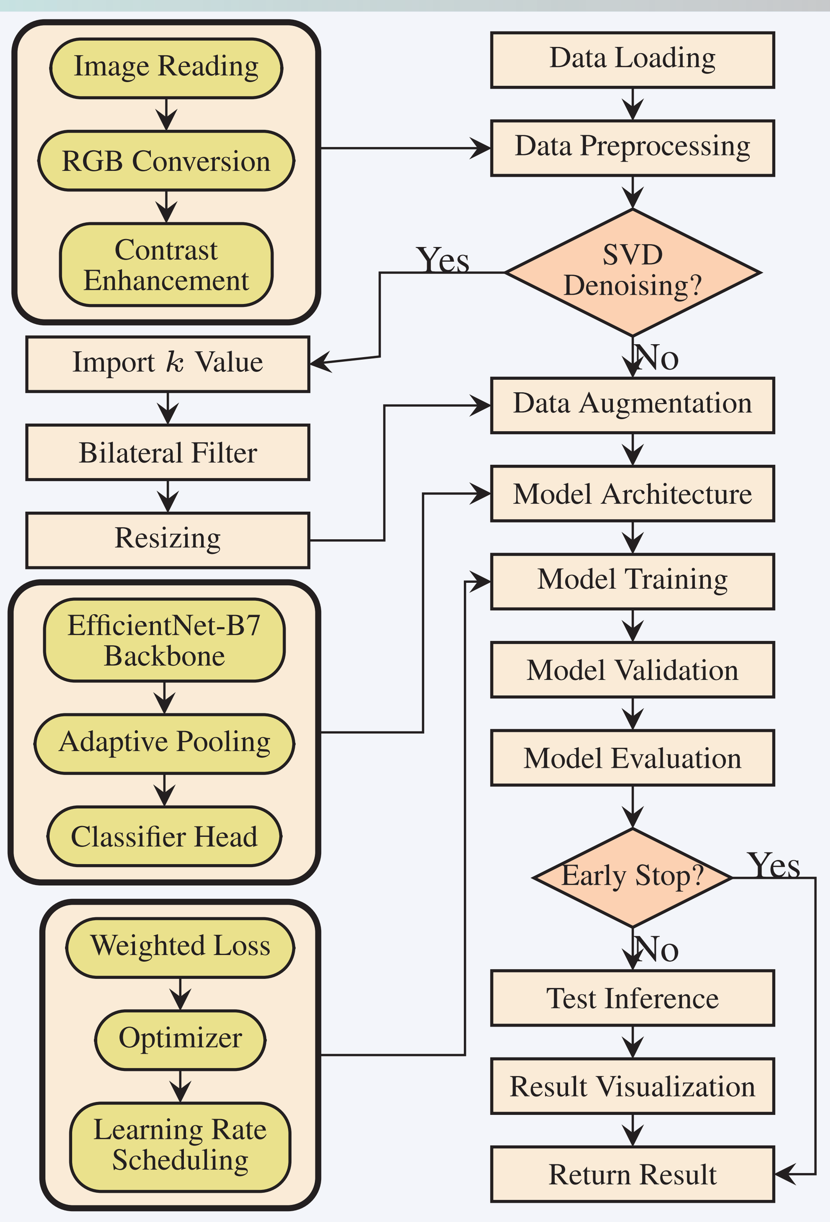


Validation Accuracy



Test Accuracy (Bar)

Network Structure of Methodology



Core Background Knowledge

What is SVD
SVD (Singular Value Decomposition) is a matrix factorization method in linear algebra used to decompose any matrix (whether square or not) into the product of three specific matrices. The mathematical form is:

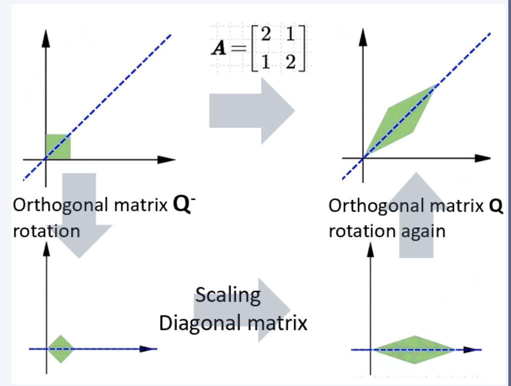
$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{\mathsf{T}}$$

$\mathbf{A}$: An $m \times n$ real or complex matrix.
$\mathbf{U}$: An $m \times m$ orthogonal matrix, known as the *left singular vectors matrix*.
$\mathbf{\Sigma}$: An $m \times n$ diagonal matrix where the non-negative real numbers on its diagonal are called *singular values*.
$\mathbf{V}^{\mathsf{T}}$: The transpose of $\mathbf{V}$. $\mathbf{V}^{\mathsf{T}} = \mathbf{V}^{-1}$
$\mathbf{V}$ is an $n \times n$ orthogonal matrix known as the *right singular vectors matrix*.

The algebraic principles of SVD
In essence, the process consists of a rotation, followed by a scaling operation, and then another rotation.

$$\begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 3 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

As shown in the figure, SVD can effectively achieve data compression in image processing.
By retaining the top k largest singular values, we can approximate the original matrix with significantly reduced data, leading to substantial storage savings.

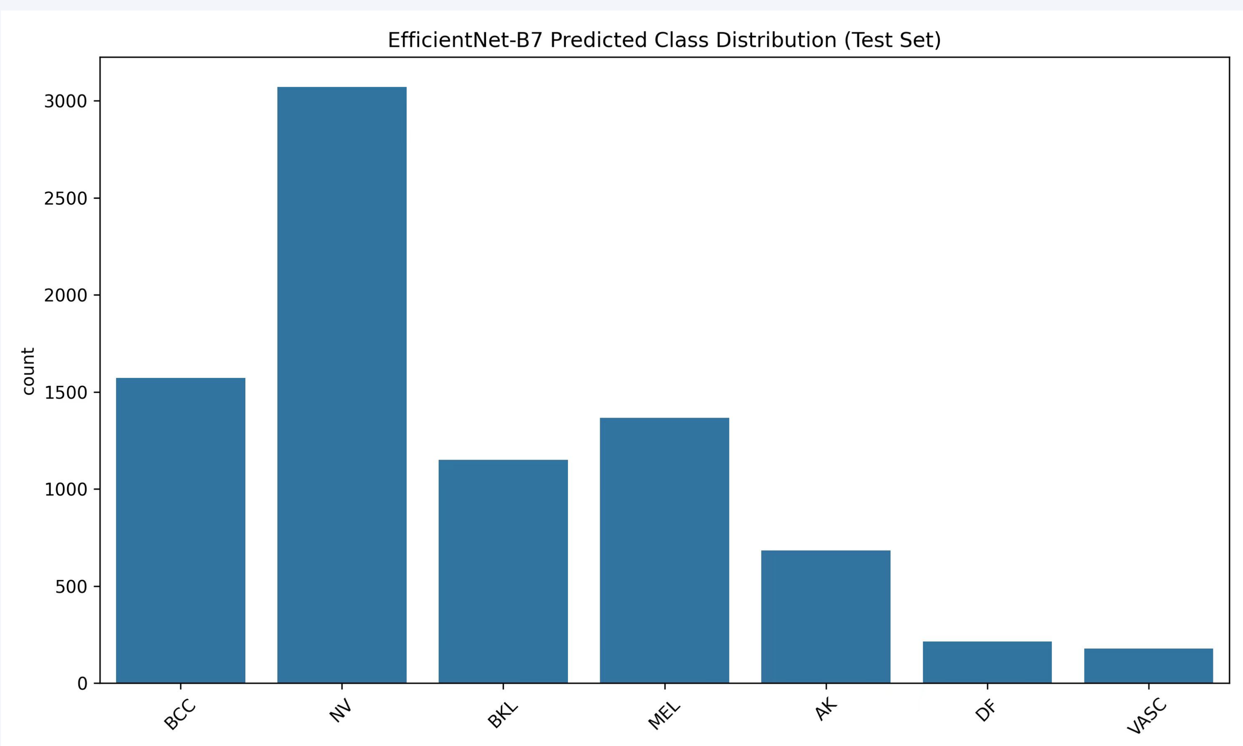


Applications of SVD in Image Processing

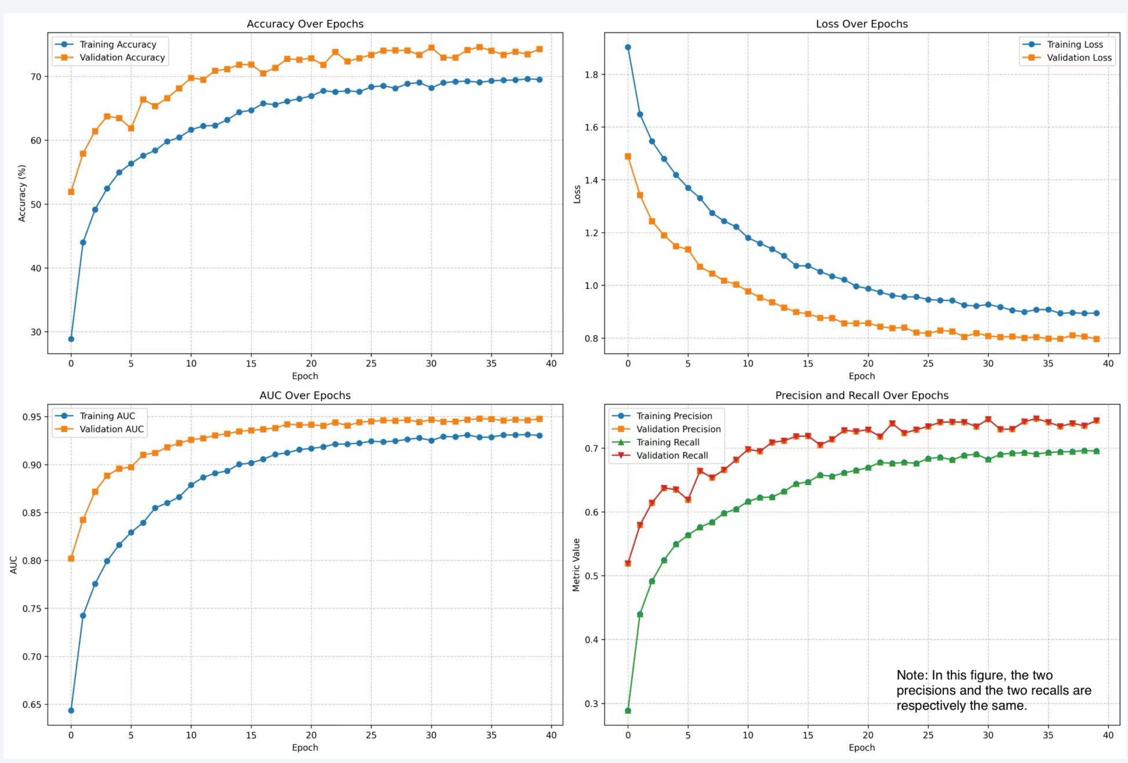
$$\boldsymbol{IM} = \boldsymbol{PSQ}^{\mathsf{T}} = (\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_n) \begin{bmatrix} s_1 & 0 & 0 & 0 \\ 0 & s_2 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & s_n \end{bmatrix} \begin{bmatrix} \boldsymbol{q}_1^{\mathsf{T}} \\ \boldsymbol{q}_2^{\mathsf{T}} \\ \vdots \\ \boldsymbol{q}_n^{\mathsf{T}} \end{bmatrix} \quad (s_1 > s_2 > s_3 > \cdots > s_n > 0)$$

$$\boldsymbol{IM} = s_1 \boldsymbol{p}_1 \boldsymbol{q}_1^{\mathsf{T}} + s_2 \boldsymbol{p}_2 \boldsymbol{q}_2^{\mathsf{T}} + s_3 \boldsymbol{p}_3 \boldsymbol{q}_3^{\mathsf{T}} + \cdots + s_n \boldsymbol{p}_n \boldsymbol{q}_n^{\mathsf{T}} = \boldsymbol{T}_1 + \boldsymbol{T}_2 + \boldsymbol{T}_3 + \cdots + \boldsymbol{T}_n$$

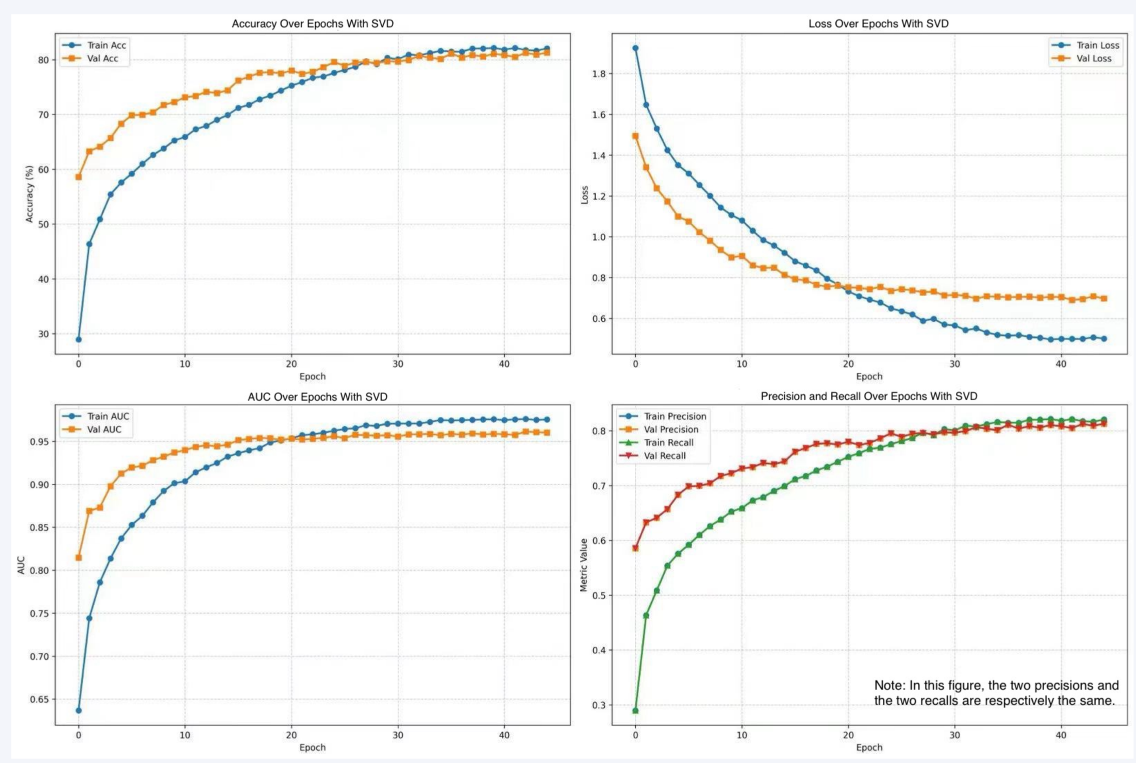
Results



Class Distribution



Without SVD



With SVD

Selected References

[1] H. Chen, X. Li, K.-H. Chan, Y. Sun, R. Wang, Q. Gao, T. Tong, and T. Tan, "Image harmonization and de-harmonization based on singular value decomposition (svd) in medical domain," *Quantitative Imaging in Medicine and Surgery*, vol. 15, no. 8, pp. 7062–7079, 2025. [Online]. Available: https://qims.amegroups.org/article/view/140131

[2] A. Bilal, A. Imran, T. I. Baig, X. Liu, H. Long, A. Alzahrani, and M. Shafiq, "Improved support vector machine based on cnn-svd for vision-threatening diabetic retinopathy detection and classification," *PLOS ONE*, vol. 19, no. 1, p. e0295951, 2024. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0295951

[3] M. S. Hossain, N. Basak, M. A. Mollah, M. Nahiduzzaman, M. Ahsan, and J. Haider, "Ensemble-based multiclass lung cancer classification using hybrid cnn-svd feature extraction and selection method," *PLOS ONE*, vol. 20, no. 3, p. e0318219, 2025. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0318219

[4] M. A. J. Mitchell, S. Sanvito, and L. Jones, "Rapid eigenpatch utility classifier for image denoising," *Scientific Reports*, vol. 15, p. 16626, 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-96859-x

Contact Information

Project QR Code

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