Machine Learning Course Project

Acne Counting and Grading

Group 17

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Part 1. Background and Motivation

- **Acne**:

  A common chronic inflammatory skin disease, often found in teenagers.

- **Effects of acne on daliy life**:

  Acne is often associated with stress, staying up late, irregular diet and other bad habits, seriously affecting the appearance and quality of life of patients.

- **Treatment method**:

  Doctors need to precisely target acne for topical treatments or laser therapy, both of which require accurate localization of the acne.

Part 1. Background and Motivation

- **Why we need acne localization**?

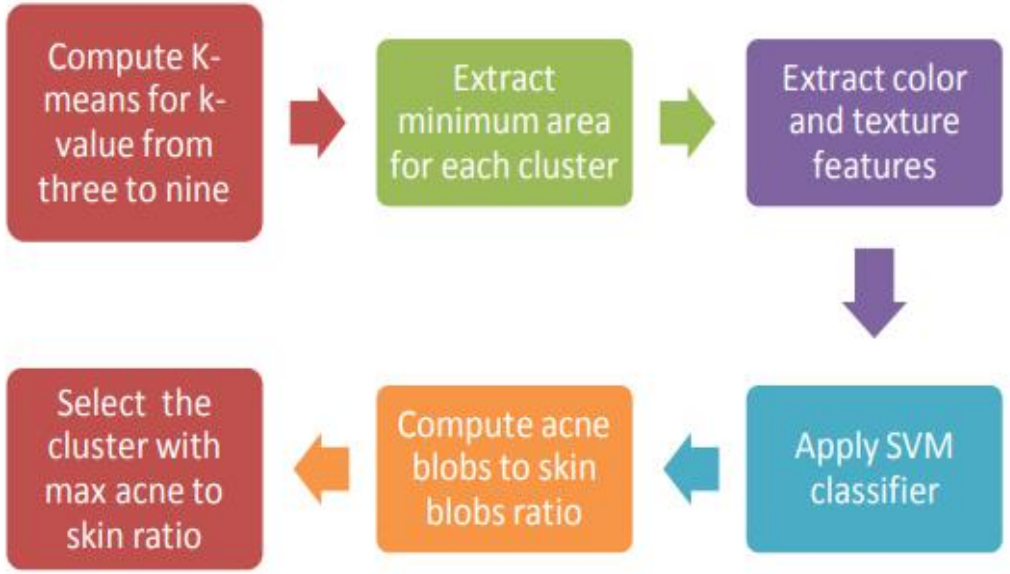
  In clinical practice, it is laborious for dermatologists to diagnose acne grade manually. The purpose of this project is to use the method of object detection in deep neural network to solve it.

- **Practical significance**:
  - Enhancing doctors' efficiency
  - Provide services to patients doctors
  - Offer more effective treatment guidance

Fig. 1. The example of four lesion (acne) images. From left to right: Comedone, Papule, Pustule, Nodule.

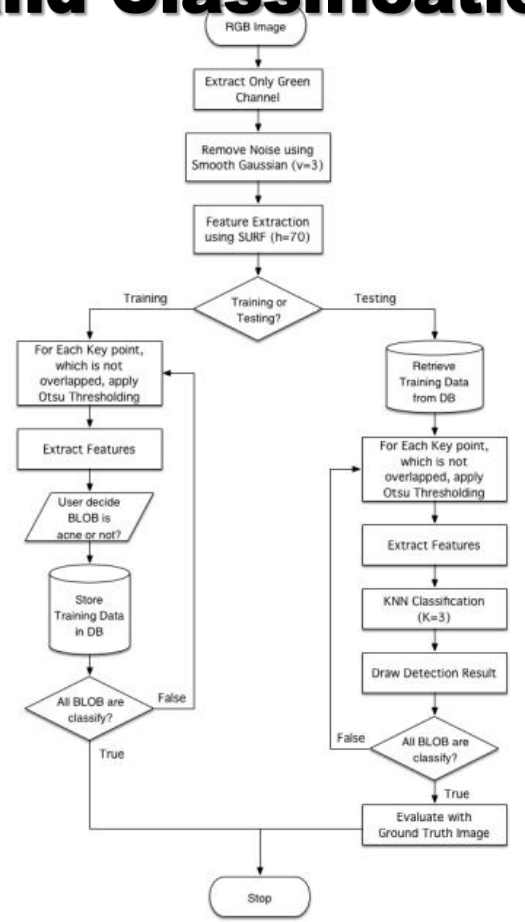
Part 2. Related Works: Acne Detection and Classification

- **Conventional approaches**:
  suffer from noise and low accuracy



Digital Assessment of Facial Acne Vulgaris
(2014 I2MTC Proceedings)

Pipeline: Manual feature + SVM

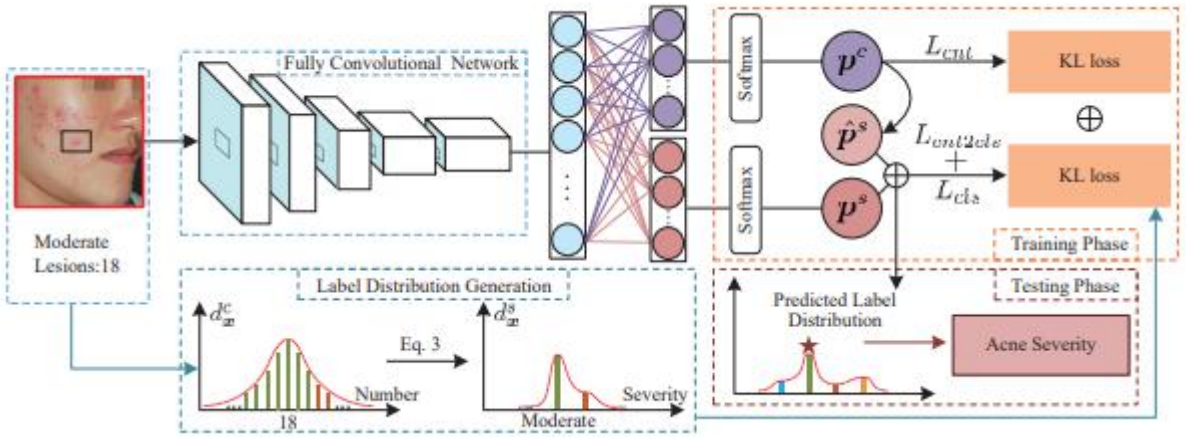


Acne Detection Using Speeded up Robust Features and Quantification Using K-Nearest Neighbors Algorithm (2014 ICCBS)

Pipeline: SURF + KNN

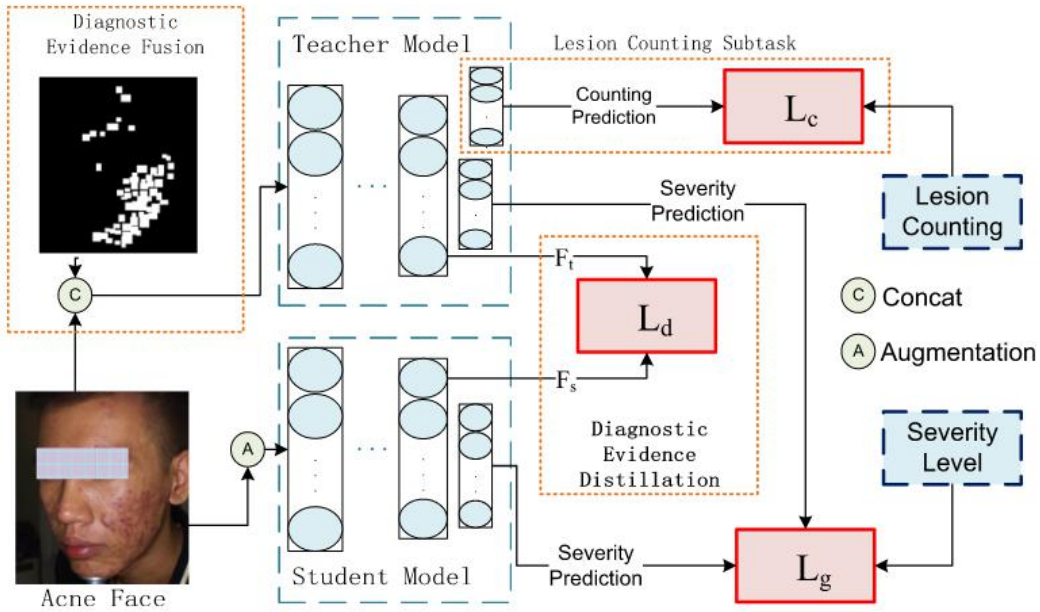
Part 2. Related Works: Acne Detection and Classification

- **Deep learning-based methods**:
  Regression, classification and segmentation tasks have many applications in medical image analysis.



Joint Acne Image Grading and Counting via Label Distribution Learning (2019 ICCV)

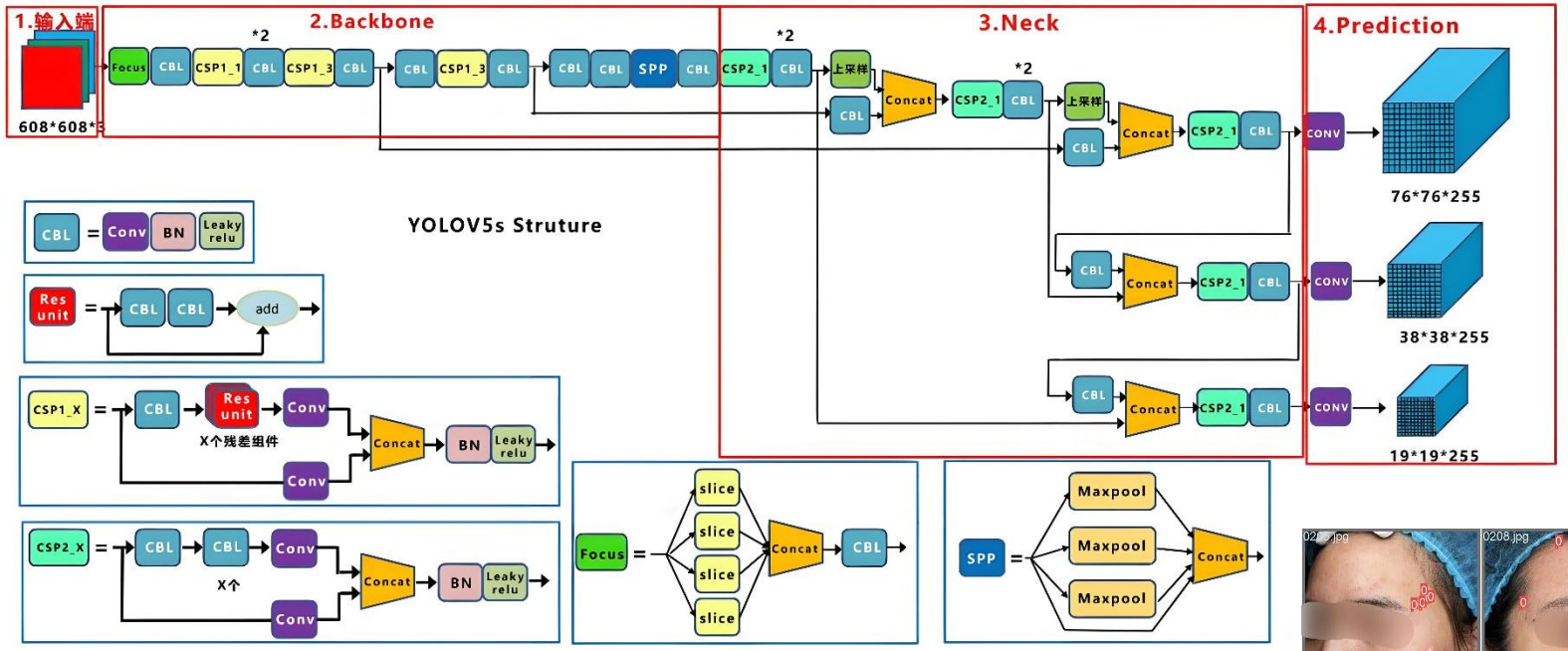
Pipeline: Counting Distribution Severity Distribution in ResNet Backbone Generating Label Distribution

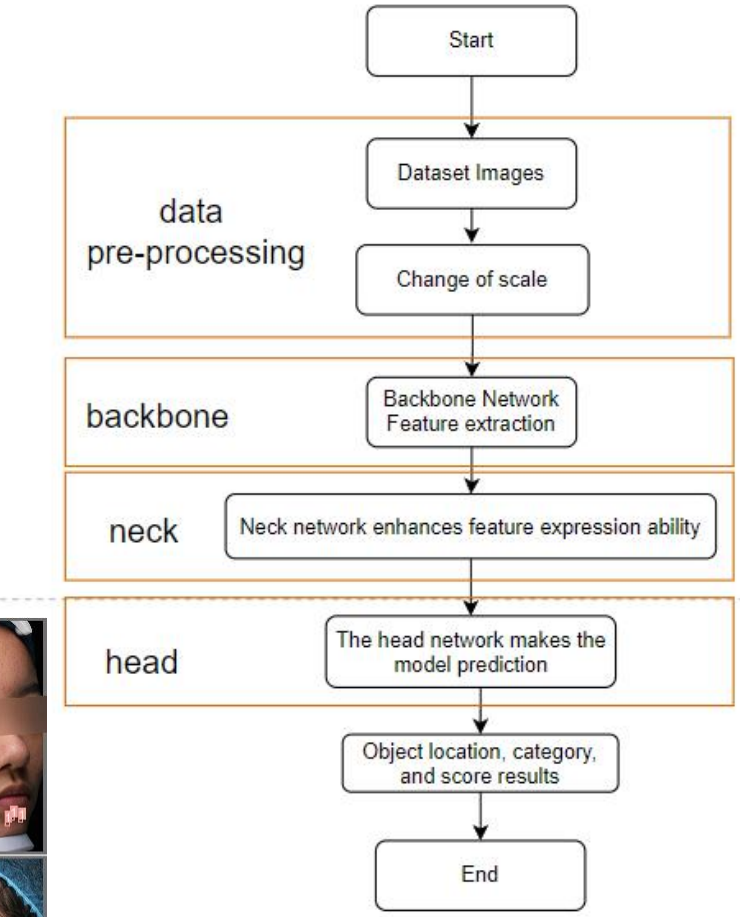


DED: Diagnostic Evidence Distillation for acne severity grading on face images (2023 Expert Systems With Applications EI)

Pipeline: knowledge distillation framework incorporates with joint learning for the teachernetwork

Part 2 Related Works : Object Detection





Why didn't Yolo perform very well?

- The target features are not obvious.
- Dense distribution leads to confusion.
- Complex background.

Part 3. Dataset Development

- Training and Validation Dataset: ACNE04 (80%)
- Test Dataset: ACNE04 (20%)
- 5-fold Cross-validation

Name	images	size	classes(including background)
ACNE04	1457	3112×3456	5
CelebAMask-HQ	30000	512×512	4
Flickr-Faces-HQ	1572	224×224	-
Nestlé Skin Health	4700	224×224	5
ACNE-Shanghai	322(309 selected)	3456×5184	5

Tab.1 information about 5 acne datasets

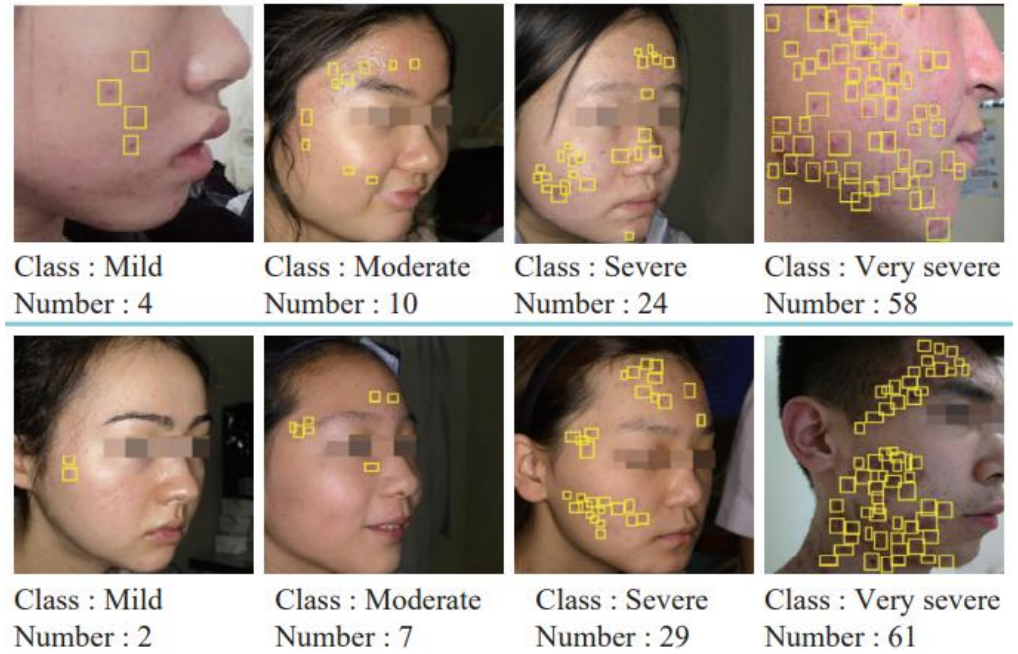
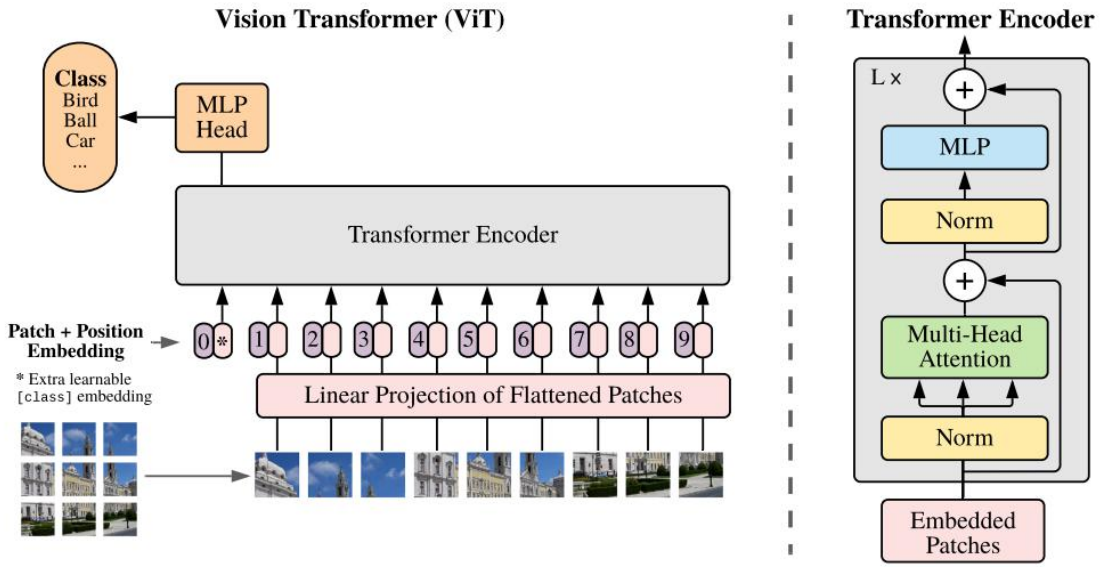


Fig. 4. Examples in the ACNE04 dataset. The numbers undereach image denote the ground-truth severity and lesion number.

Part 4.1 Model Selection : ViT



An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale (ICLR 2021)

Model overview: We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder

- **Advantages**
  Global relationship modeling can enlarge the receptive field of image and obtain more context information

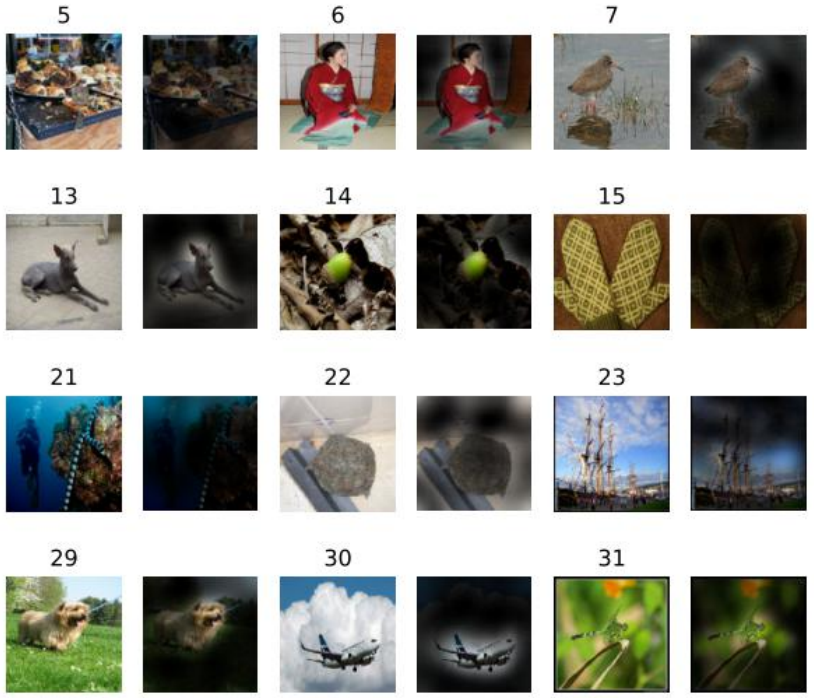
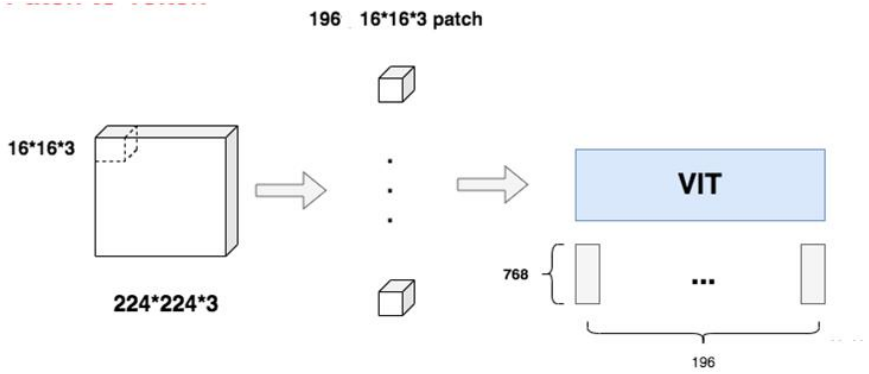


Fig.5 Attention maps

Part 4.1 Model Selection : ViT

- **Stage 1: Embedding**
  - Patch Embedding $x_p E \in \mathbb{R}^{N \times D}$

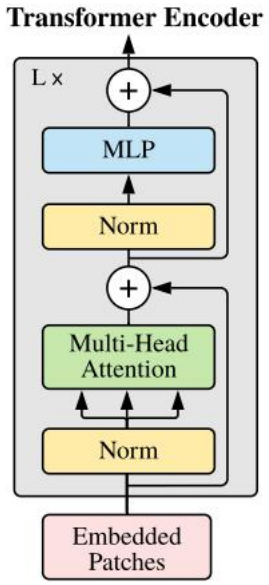


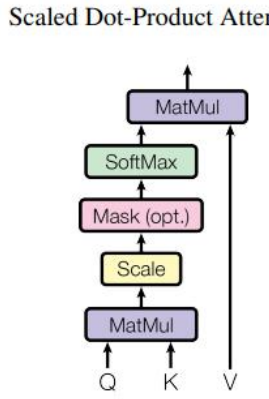
  - Class Embedding (Learnable Embedding) x_{cls}
  - Position Embedding $\mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D}$

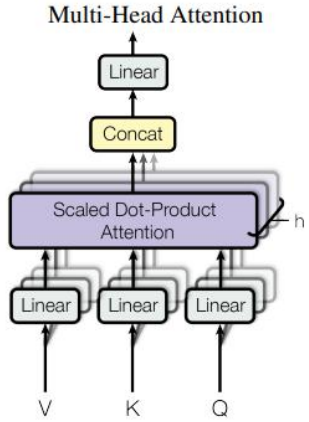
Final Input:

$$x_0 = [x_{cls}; x_p^1 E; x_p^2 E; \ldots; x_p^N E] + E_{pos}, \quad x_0 \in \mathbb{R}^{(N+1) \times D}$$

- **Stage 2: Transformer Encoder**





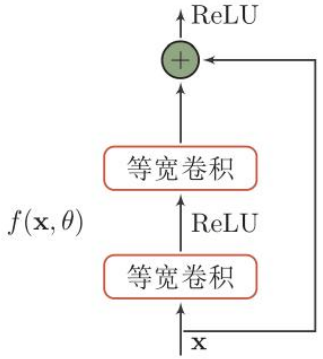


The Transformer encoder consists of alternating multi-head self-attention layers (MSA) and multi-layer perceptron blocks (MLP). Apply Layer Norm before each block and Residual Connection after each block

Part 4.2 Model Selection : ResNet

$$h(\mathbf{x}) = \underbrace{\mathbf{x}}_{\text{恒等函数}} + \underbrace{\big(h(\mathbf{x}) - \mathbf{x}\big)}_{\text{残差函数}}$$

$f(\mathbf{x}, \theta)$



Deep Residual Learning for Image Recognition
ILSVRC & COCO 2015 (nndl-book)

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig.6 Framework of ResNet layers

Advantages:

- avoid loss in information transmission.
- transmit the input information to the output to protect the integrity of the information.
- simplify the learning goal and difficulty.

Part 4.3 Our Idea : FusedModel (ViT+Resnet)

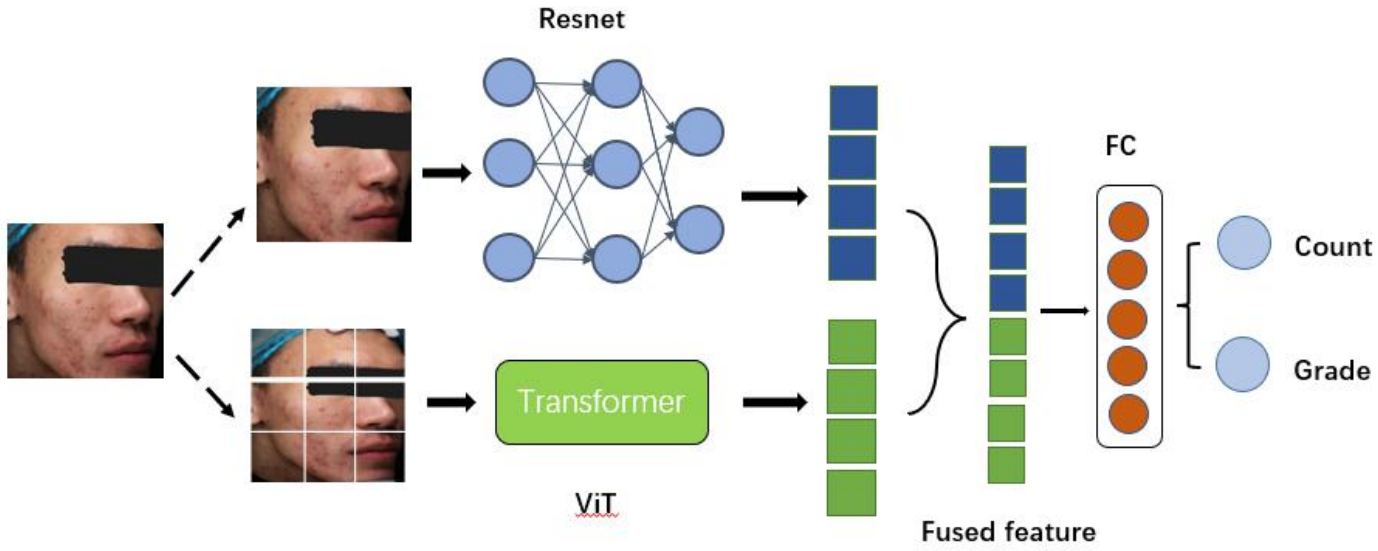


Fig. 7 Model proposed by us. Using the idea of feature fusion, the features extracted from Resnet and Vit models are spliced and then passed through the fully connected layer

Advantages:

- Resnet allows the network to train deeper and learn more complex expressions.
- ViT is good at processing global information

Some Possible Shortcomings:

- The mode and degree of feature fusion is somewhat simple.
- The training curve is not very smooth.

Part 4.4 Loss Function and Optimization

- Firstly, we choose L2-norm as loss function:

$$L_{cou} = \sum_{i=1}^{n} (x_{cou}^{(i)} - y_{cou}^{(i)})^2$$

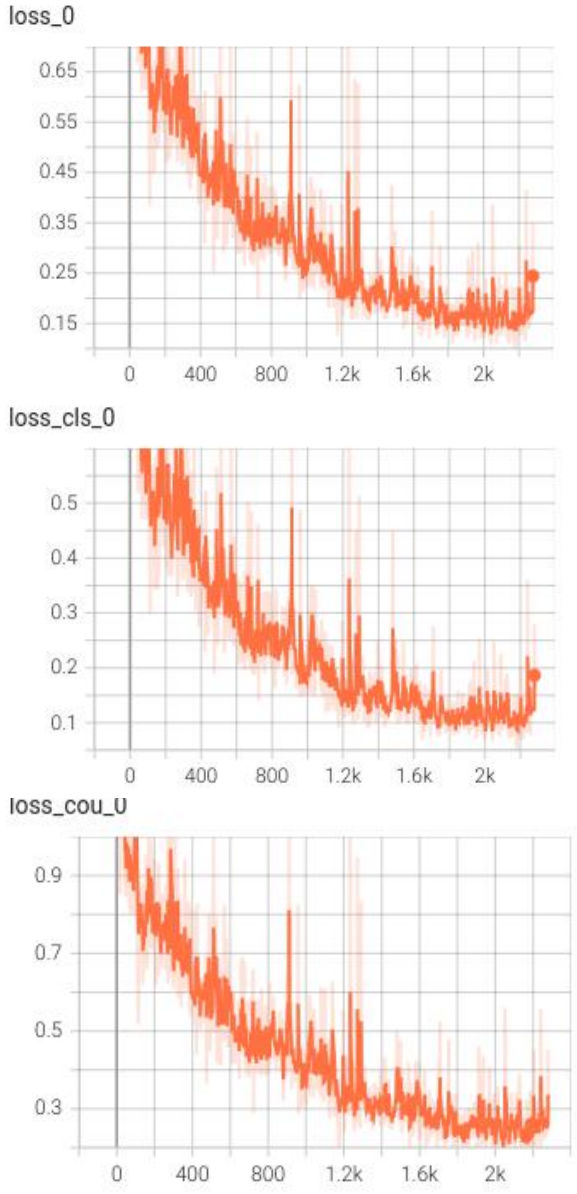
- **Add Kullback-Leibler Divergence:**

$$D_{KL}(P \,||\, Q) = \sum_{x} P(x)\, log\, \frac{P(x)}{Q(x)}$$

$$L_{cls} = \sum_{i=1}^{n} D_{KL}(x_{cou}^{(i)} - y_{cou}^{(i)})$$

$$Loss = \alpha\, L_{cou} + (1 - \alpha)\, L_{cls}$$

Optimizer: Adam



Part 5. Experiment Result

SE: Sensitivity (Recall), SP: Specificity, YI=SE+SP−1

	Precision	SE	SP	YI	MAE	MSE
class0	0.7863	0.8932	0.8677	0.7609	1.0680	1.6010
class1	0.8000	0.7874	0.8485	0.6359	2.8425	3.6121
class2	0.7692	0.5556	0.9766	0.5321	9.1111	13.7477
class3	0.8750	0.8077	0.9887	0.7964	7.0769	12.8333
avg / total	0.8076	0.7610	0.9204	0.6813	3.3664	6.6742

Tab.2 Prediction of FusedModel (KL-Loss) on acne counting

	Precision	SE	SP	YI
class0	0.8108	0.8738	0.8889	0.7627
class1	0.7923	0.8110	0.8364	0.6474
class2	0.7407	0.5556	0.9727	0.5282
class3	0.8750	0.8077	0.9887	0.7964
avg / total	0.8047	0.7620	0.9217	0.6837

Tab.3 Prediction of FusedModel (KL-Loss) on acne grading

Name	Value
learning rate	1e-4
num of epoch	120
batch size	64
sigma	3
alpha	0.6

Tab.4 HyperParameter Setting

Part 5. Comparison of Results

	Counting		Grading	
	AVG_ACC	AVG_PRE	AVG_ACC	AVG_PRE
ViT	0.5342	0.5090	0.5137	0.5342
ResNet	0.6615	0.6678	0.6712	0.6680
FusedModel (Ours)	**0.7979**	**0.8076**	**0.8014**	**0.8047**

Tab.5 Comparison of experimental results of different models

Conclusion:

- The experiment proves that our method is effective.
- In the future, we will try to integrate more abundant ways to make the advantages of the two models play a greater role

Part 6. References

- [CCID Dataset] Quattrini A, Boër C, Leidi T, Paydar R. A Deep Learning-Based Facial Acne Classification System. Clin Cosmet Investig Dermatol. 2022;15:851-857 https://doi.org/10.2147/CCID.S360450
- [ACNE04 Dataset] Wu, Xiaoping, Ni, Wen, Jie, Liang, Lai, Yu-Kun, Cheng, Dongyu, She, Ming-Ming, & Yang, Jufeng. (2019). Joint Acne Image Grading and Counting via Label Distribution Learning. In *IEEE International Conference on Computer Vision*.
- [Nestlé Skin Health Dataset] https://github.com/microsoft/nestle-acne-assessment
- [Flickr-Faces-HQ Dataset] https://github.com/HuynhThanhQuan/skin-detective

Part 6. References

- Islam, Md Baharul, Masum Shah Junayed, Arezoo Sadeghzadeh, Nipa Anjum, Afsana Ahsan, A. F. M. Shahen Shah. (2023). Acne Vulgaris Detection and Classification: A Dual Integrated Deep CNN Model.
- Lin, Yi, Jingchi Jiang, Dongxin Chen, Zhaoyang Ma, Yi Guan, Xiguang Liu, Haiyan You, Jing Yang. DED: Diagnostic Evidence Distillation for Acne Severity Grading on Face Images. Expert Systems with Applications 228 (2023): 120312.

Thanks