SKIN DISEASES
DETECTION

Supervised by:

Dr. Yasser Abd El Hamid

Eng. Yasmine Mahmoud

Center:

Alexandria

TEAM MEMBERS

Raed Mohamed Badr	20-00898
Banoub Nagy Edwar	20-01025
Sherif Mohamed Waheed	20-01153
Mohamed Kamal Abdelaziz	20-01080
Rawda Abdelhadi Alkashef	20-00774
Rowan Abdelkader Mohamed	20-01472
Maryam Mohamed Abdelsamad	20-00120

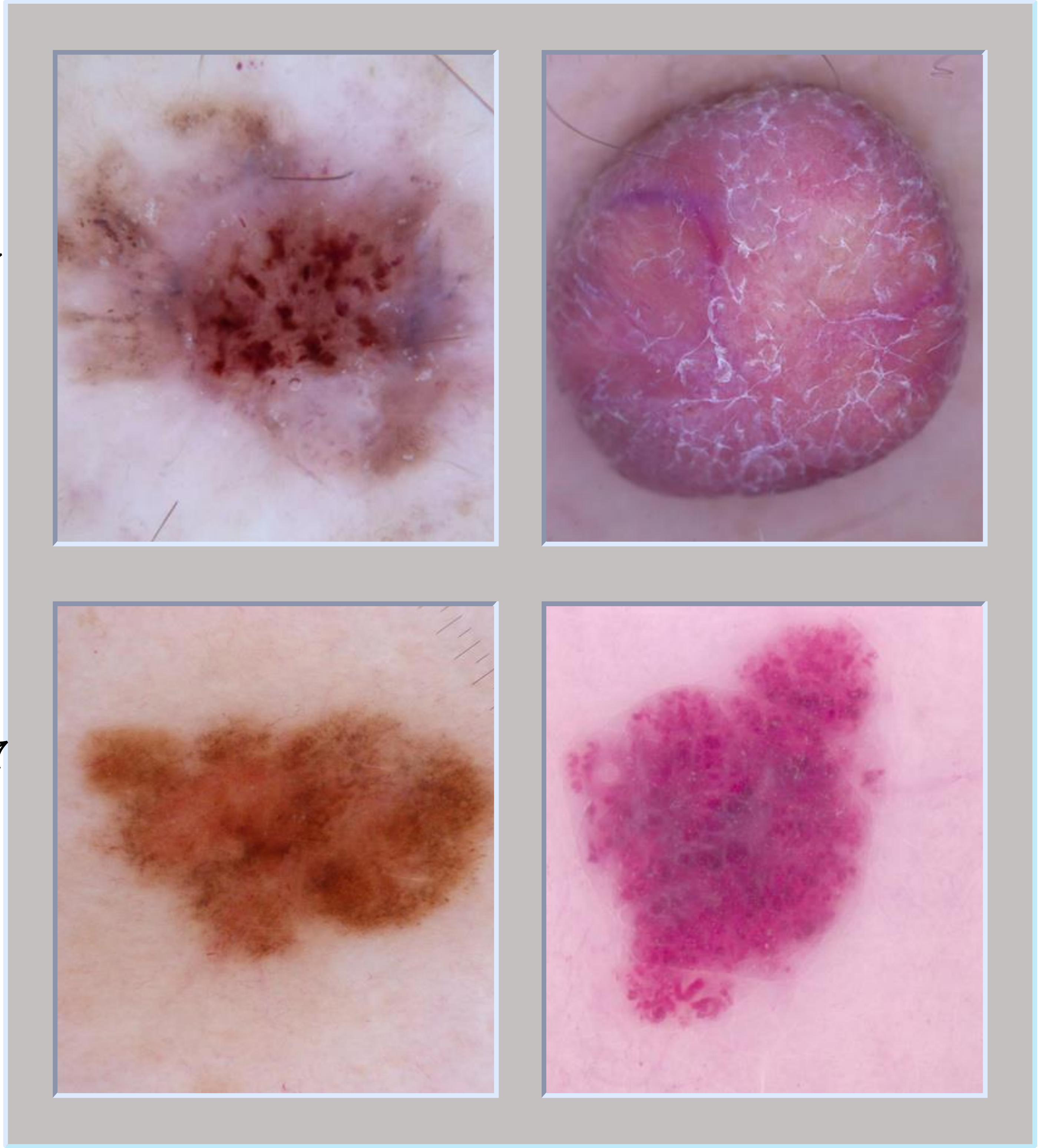
AGENDA

Introduction

Problem

Actinic keratosis

Dermatofibroma



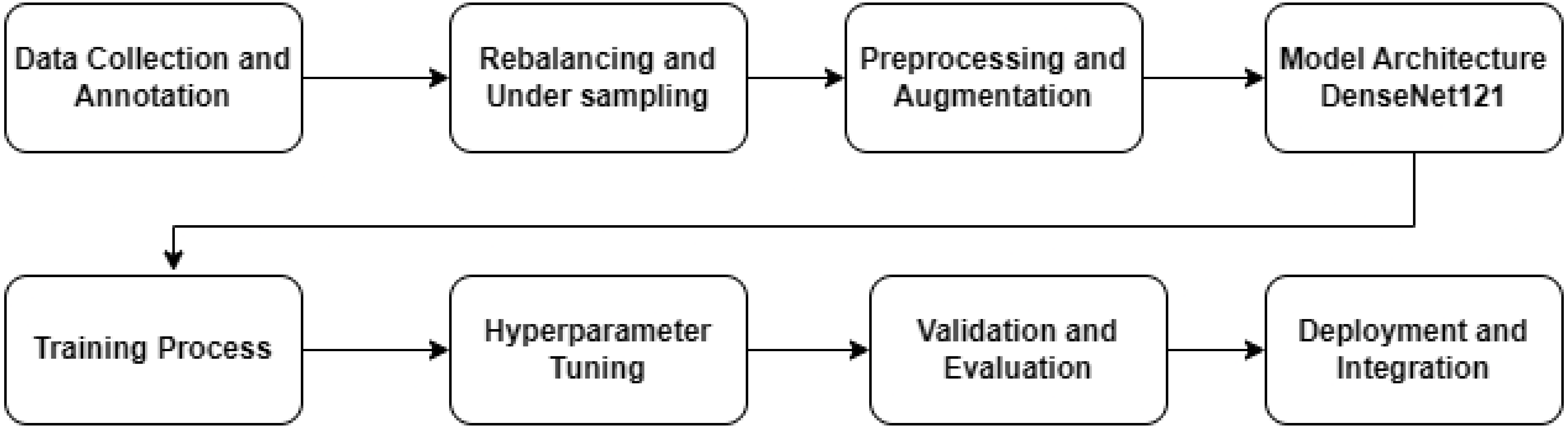
Melanocytic nevus

Vascular lesion

Objectives of Project:

- Exploring Appropriate Dataset
- Building DL Model
- Test and Enhance The Model
- Building Web App
- Hosting

How


Data Collection and Annotation
Rebalancing and Under sampling
Preprocessing and Augmentation
Model Architecture DenseNet121
Training Process
Hyperparameter Tuning
Validation and Evaluation
Deployment and Integration

Methodology

•We applied insights to address project-specific challenges and optimize our decision-making processes.

•A systematic survey was conducted, analyzing datasets in a structured order, highlighting strengths and weaknesses.

•Making exploration on the algorithms that helped us in emphasizing a methodical evaluation criteria.

•Arranging the results based on priorities in terms of highest accuracy to facilitate decision-making

Related Work

References of Skin Diseases with Deep Learning :

Paper	Year	Dataset	Accuracy
Classification of Skin Cancer with Deep Transfer Learning Method	2022	International Skin Imaging Collaboration (ISIC)	97.89%
Multi-Features Extraction Based on Deep Learning for Skin Lesion Classification	2022	ISIC 2019	(92.34% and 91.71%)
Early Detection of Skin Cancer Using Deep Learning Architectures	2019	ISIC-archive	88.20%

Datasets

Disease Name	ISIC 2019	HAM10000	PAD-UFES-20	ISIC 2017	Merge
Melanoma	4522	1113	52	521	6208
Melanocytic	12896	6705	244	0	19845
Basal cell	3323	514	845	0	4682
Actinic keratosis	867	327	730	0	1924
Benign keratosis	2624	1099	0	0	3723
Dermatofibroma	239	115	0	0	354
Vascular lesion	253	142	0	0	395
Squamos cell	629	0	192	0	821
Seborrheic keratosis	0	0	235	374	609
Benign nevi	0	0	0	1855	1855
Total	**23127**	**11711**	**5578**		**40416**
		17289			

Priority Criteria

ISIC 2019

1 2 3 4 25k

HAM 10000

1 2 3 4 10k

PAD-UFES-20

1 2 3 2.2k

ISIC 2017

1 2 2.7k

1. Availability
2. Aim to facilitate training neuron network
3. Suitable number of skin diseases.
4. Large number of images in each disease.

Unused Datasets

DermNet

1. Num_images is very small
2. Aim to archive to medical.
3. lack of Organization.

Derm7pt

1. Num_images is very small.
2. Diseases don’t intersect with the majority of available diseases.

BCN20000

1. Unavailable independently.
2. Embedded with ISIC 2019.

PH2

1. Num_images is very small.
2. Diseases are very general.

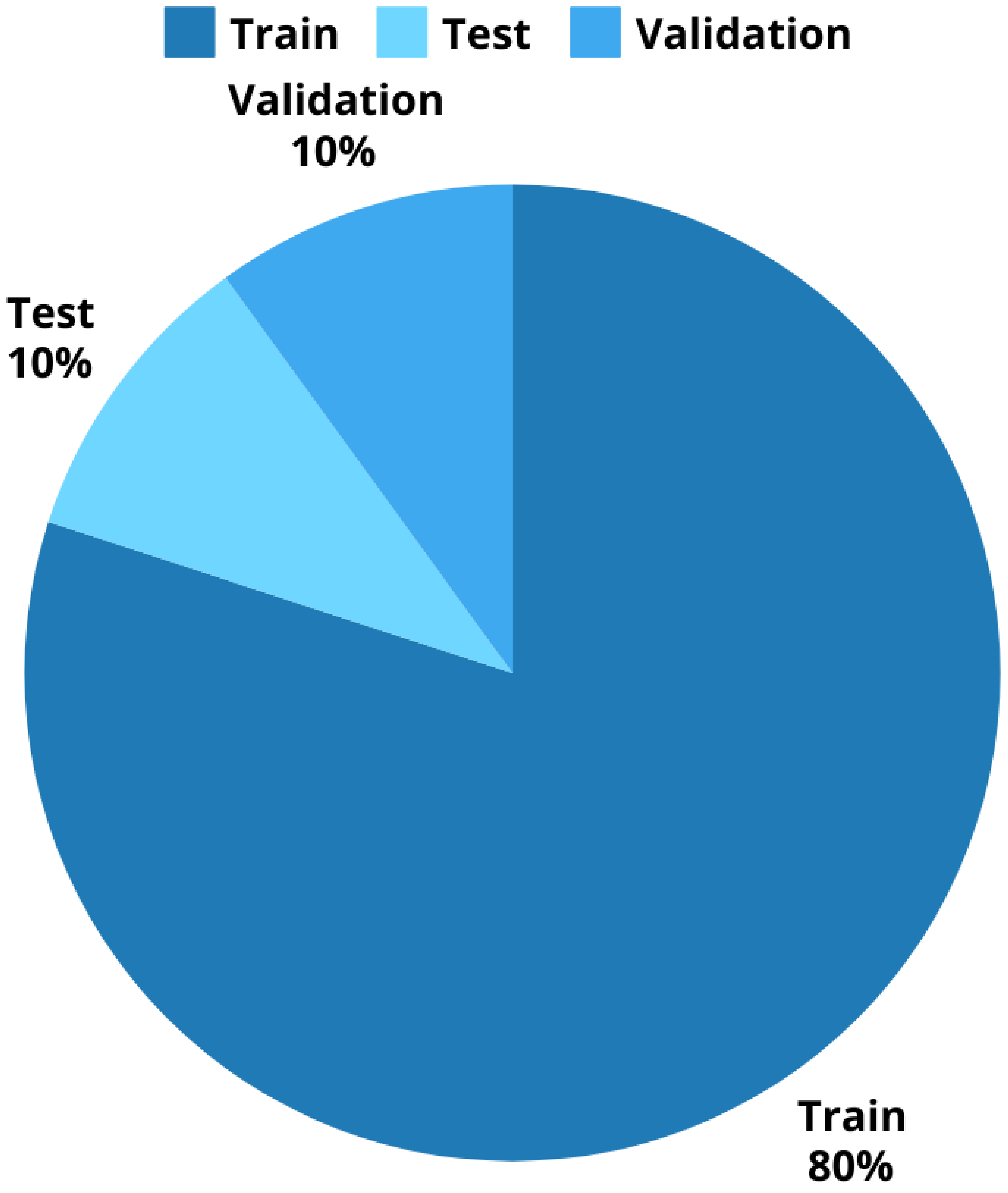
Dermofit

Unavailable

DataSet from :

kaggle

Isic 2019



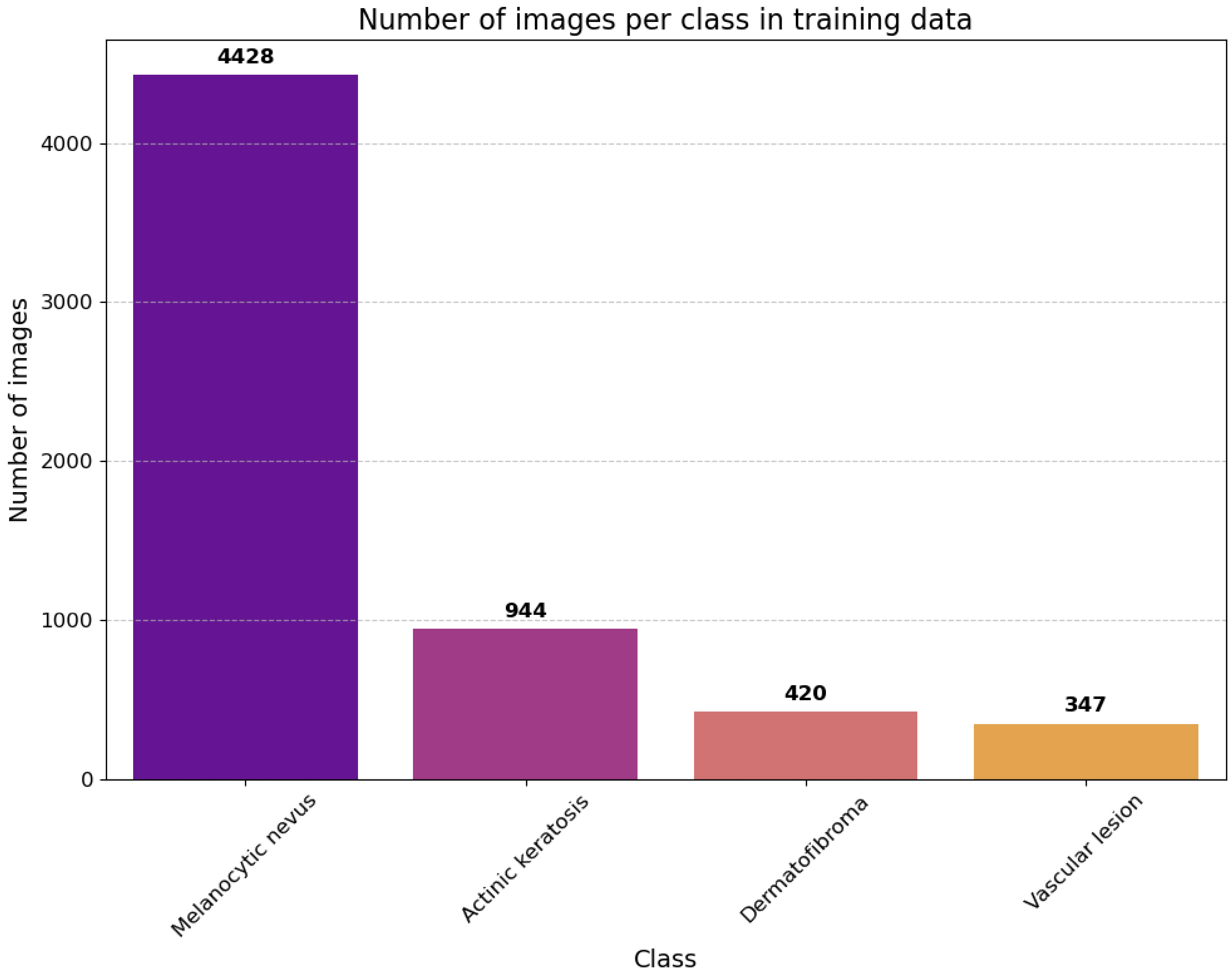
Preprocessing

Under sampling :

- An exaggerated increase for Melanocytic

- There are few remaining diseases

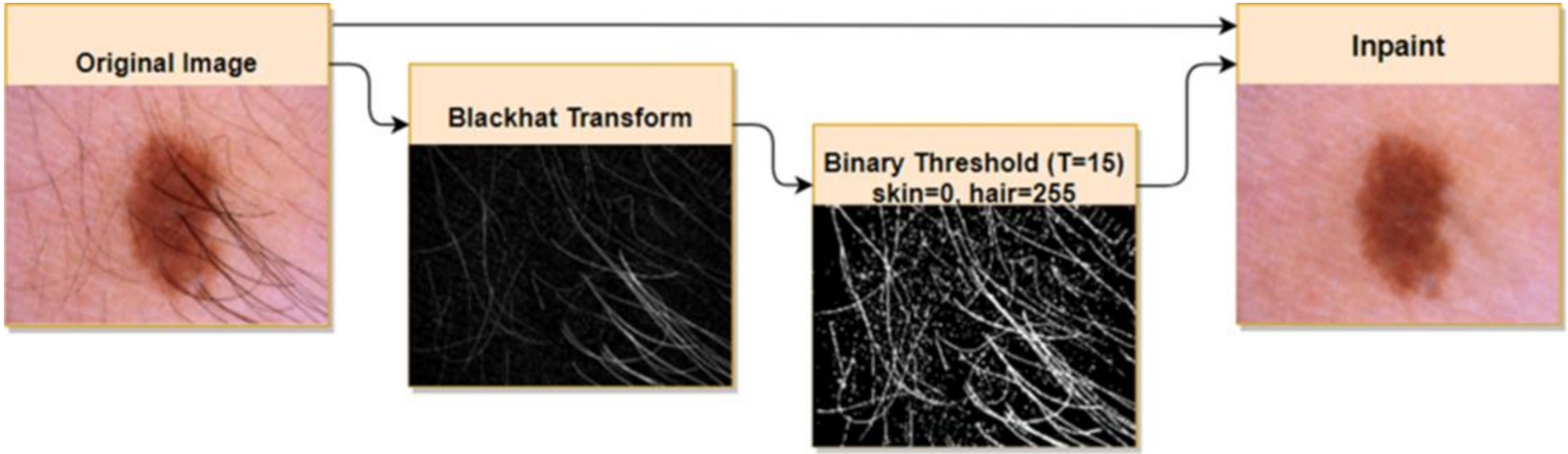
- Reduce Melanocytic From 11k to 4k



Data Augmentation

rescale	1.0/255
rotation range	40
width shift range	0.2
height shift range	0.2
shear range	0.2
zoom range	0.2
fill mode	nearest
horizontal flip	true
feature wise std normalization	true

Dull razor Algorithm



Grayscale Conversion

Gaussian Filtering

Hair Mask Creation

Morphological Operations

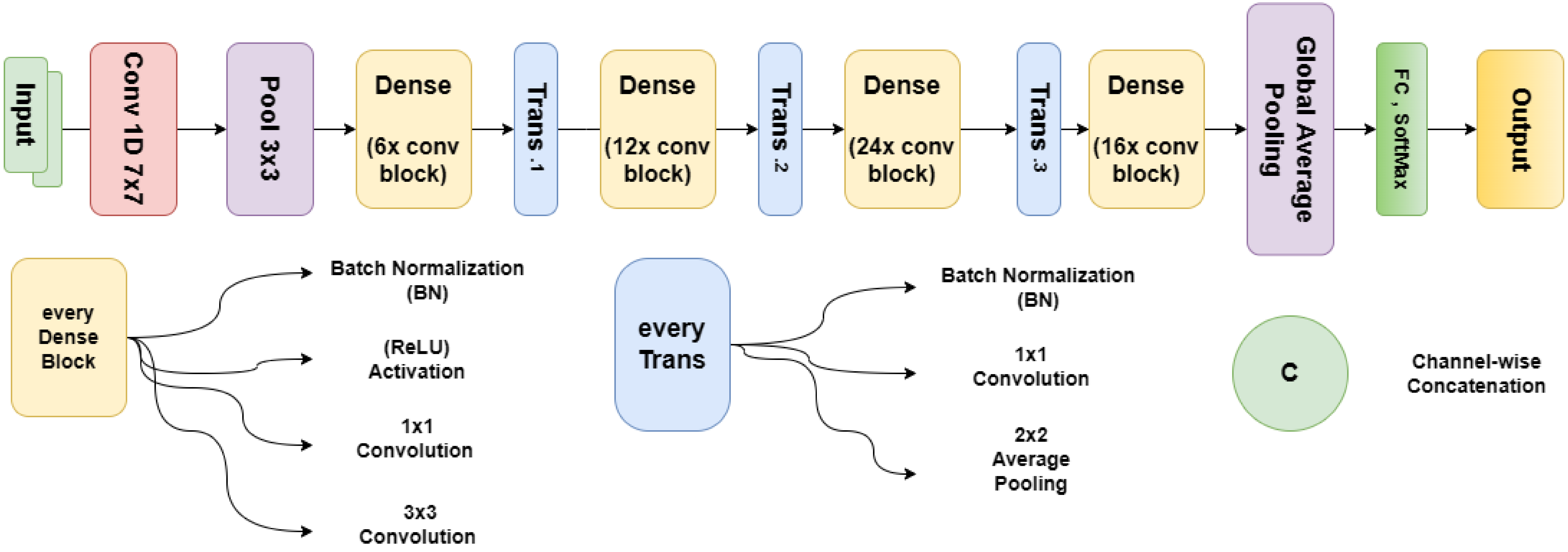
Inpainting (Interpolation)

Result Integration

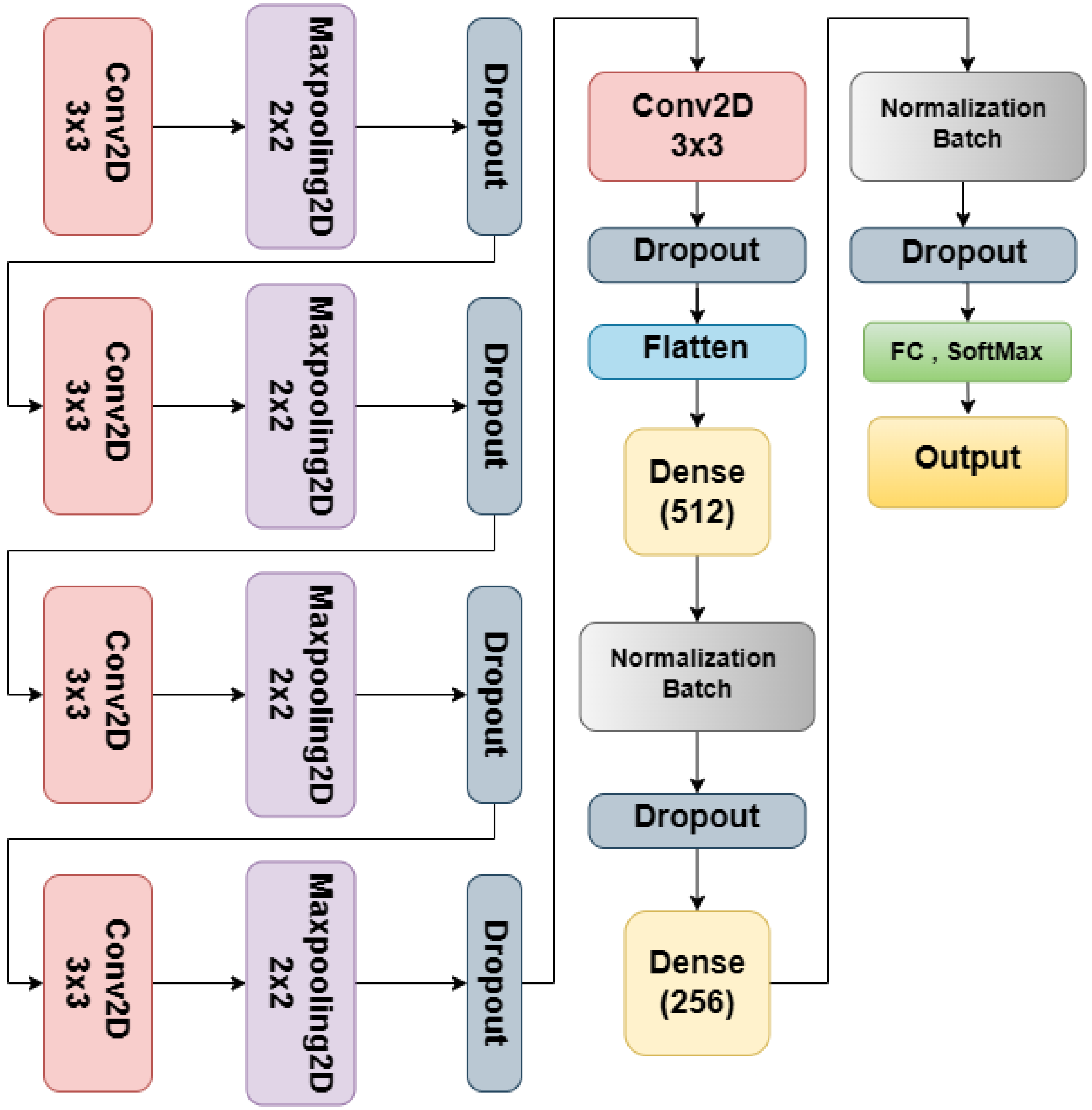
Proposed Final Model

Architecture of DenseNet121

The Base Model with pre-trained Dataset ImageNet



Custom Layers:



- Conv2D and Dense use activation Funcation Relu
- MaxPooling2D and Conv2D padding is same
- Dropout (0.5/0.3)

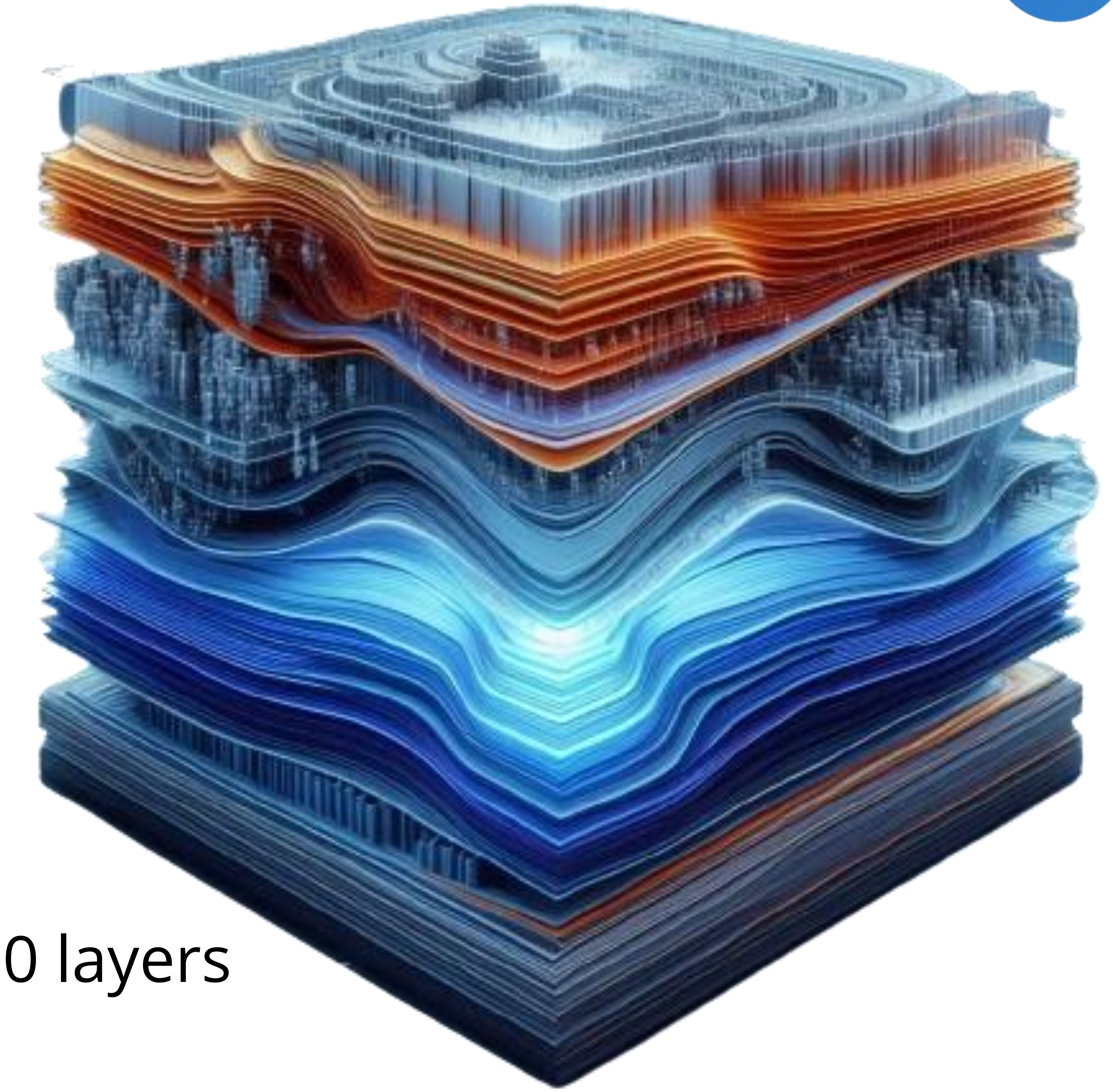
Freezing Layers:

the combination of freezing and selectively unfreezing layers is a key technique in transfer learning.

Preserve Learned Features

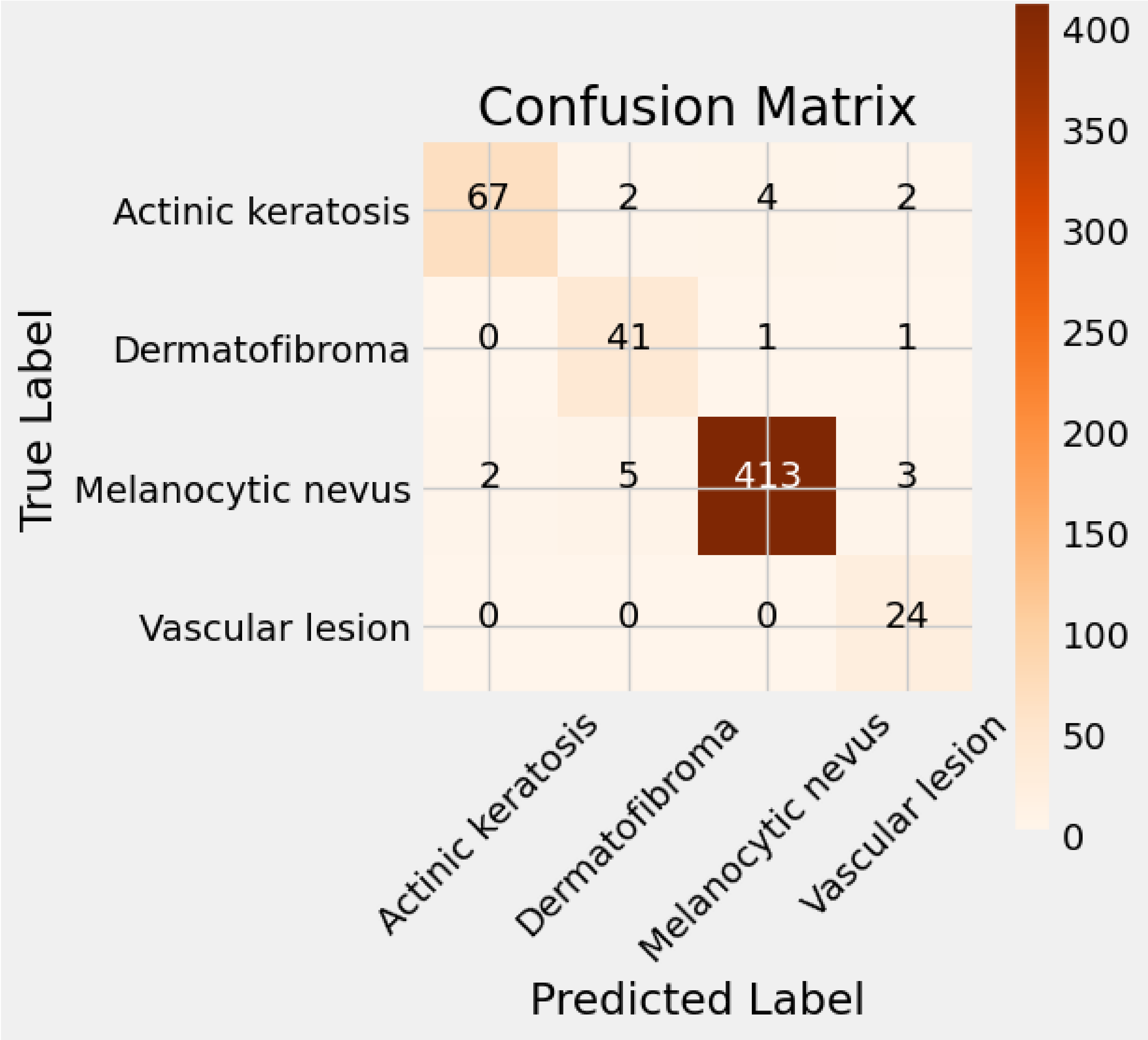
Adapt to New Task

Efficient Training



Unfreeze the top 30 layers

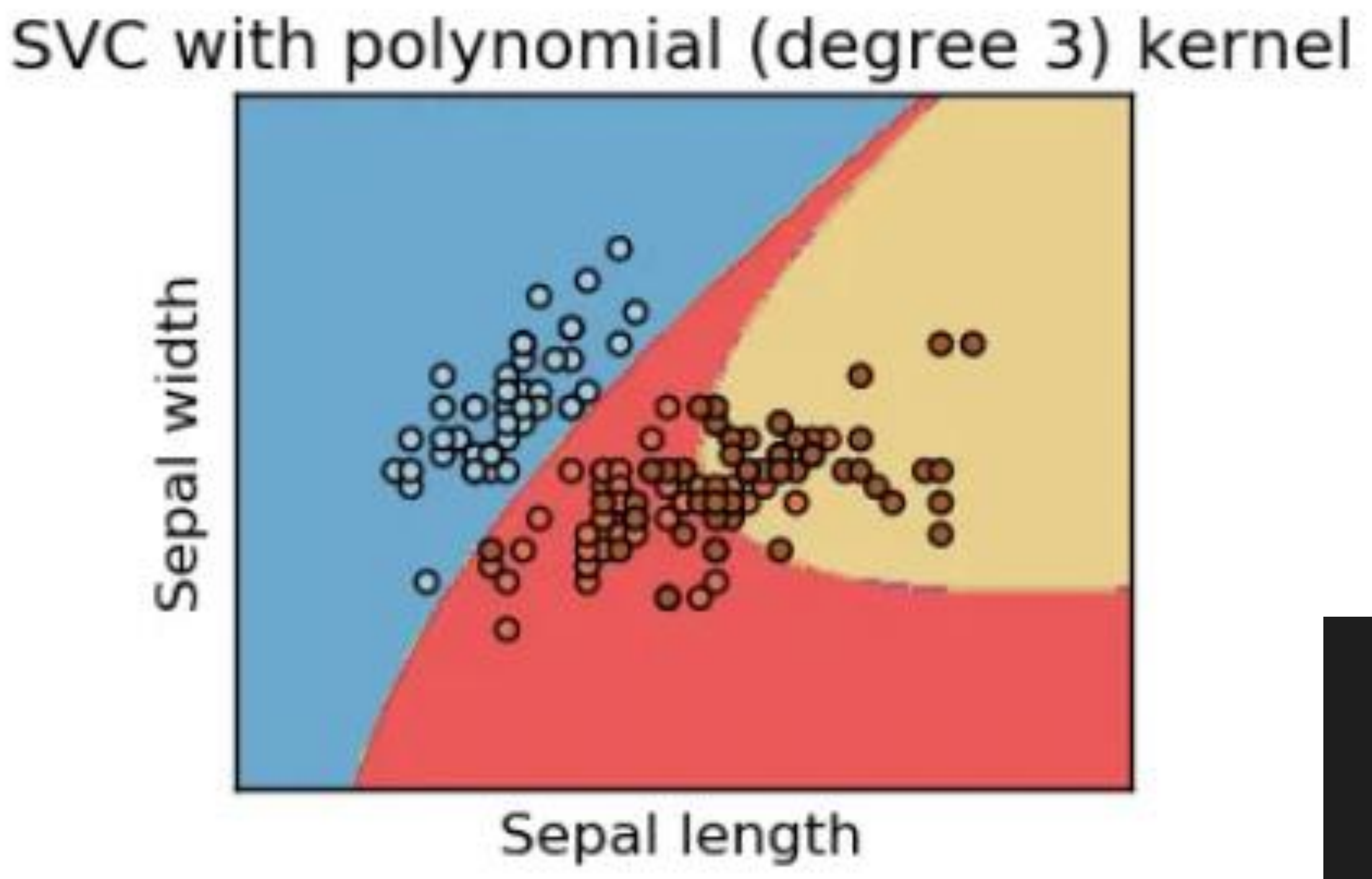
Confusion Matrix:



Classification Report:

	Precision	Recall	F1-Score	Support
Actinic keratosis	0.97	0.89	0.93	75
Dermatofibroma	0.85	0.95	0.9	43
Melanocytic nevus	0.99	0.98	0.98	423
Vascular lesion	0.8	1	0.89	24
Accuracy			0.96	565
Macro avg	0.9	0.96	0.93	565
Weighted avg	0.97	0.96	0.97	565

Svc Method :

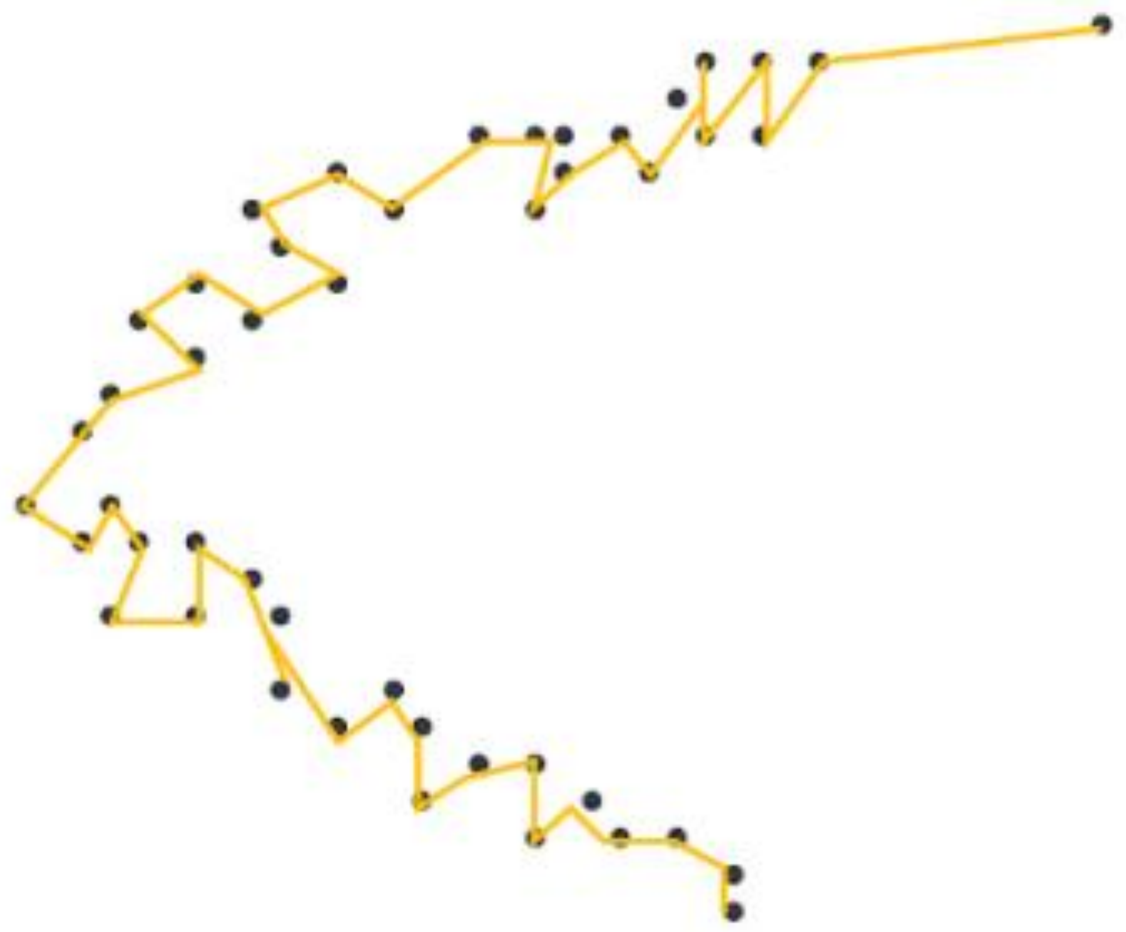



```python
test_features, test_labels = extract_features(model, test_generator)

svc_model = Pipeline([
    ('scaler', StandardScaler()),
    ('svc', SVC(kernel='poly', degree=3))
])
svc_model.fit(test_features, test_labels)
```

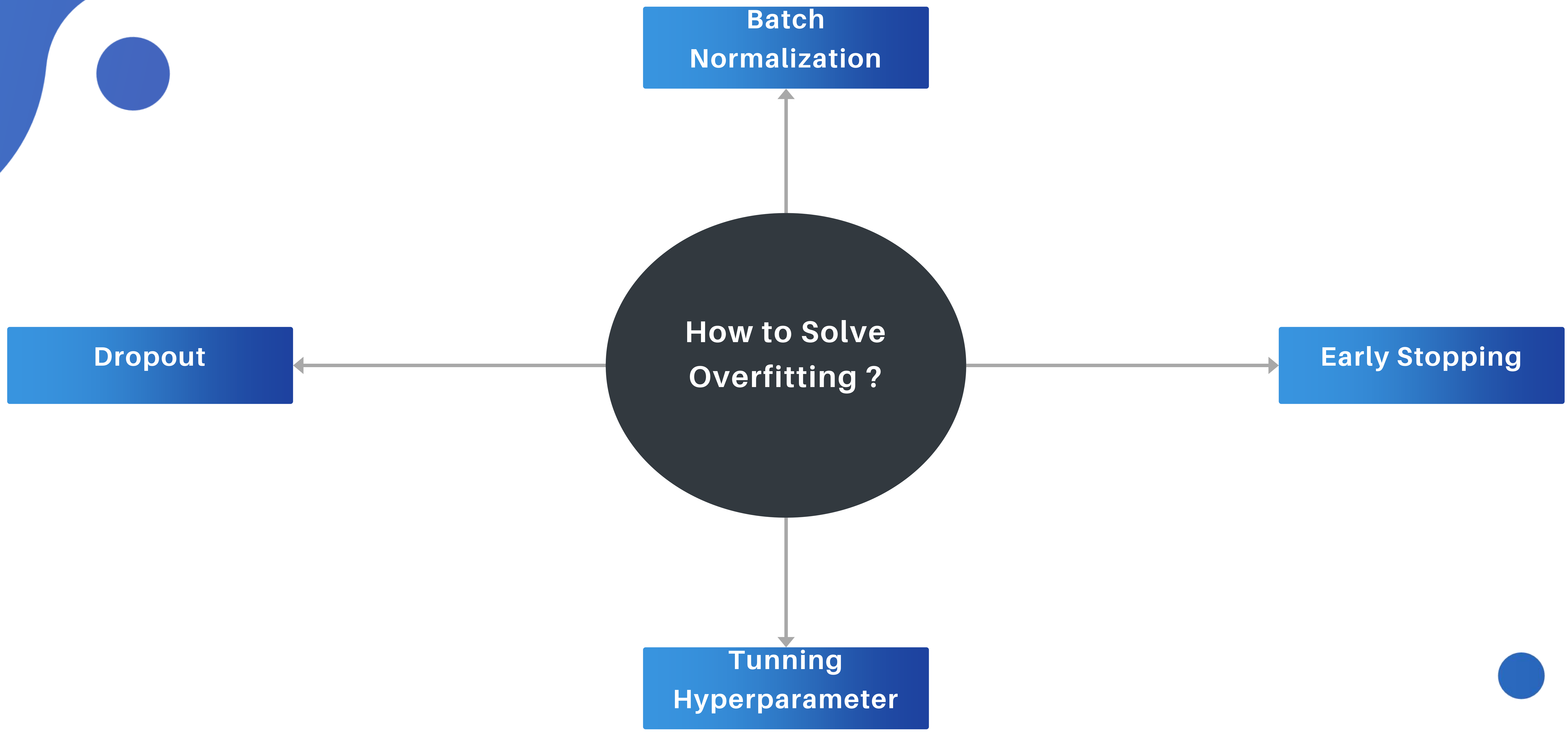
What is Overfitting?

Overfitting is a modeling error in machine learning and statistics where a model is too complex and fails to generalize to new data.

It occurs when a model is too tailored to the training data, memorizing it instead of learning true patterns, resulting in poor performance on test data or real-world applications.



Overfit

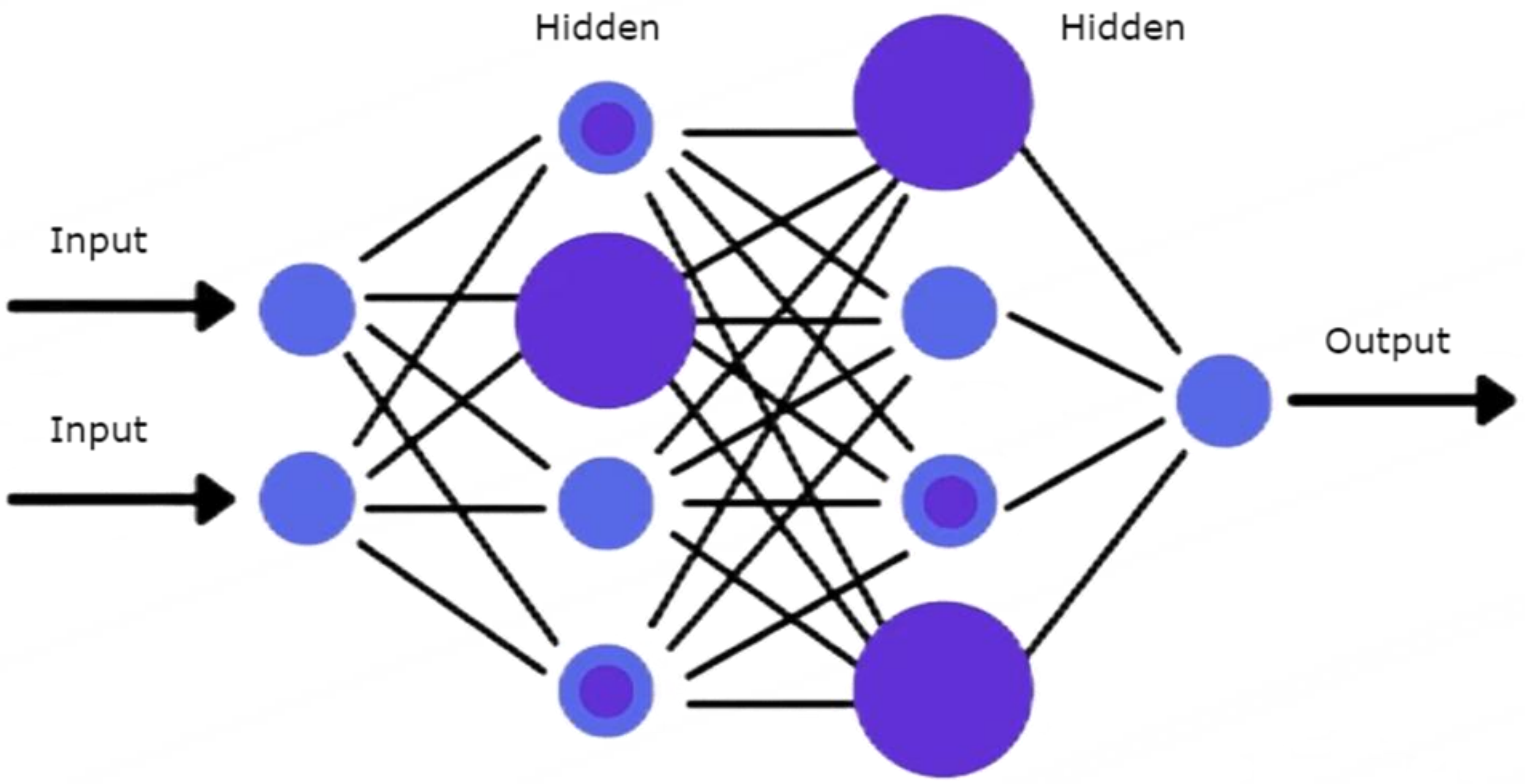

Batch Normalization
Dropout
How to Solve Overfitting ?
Early Stopping
Tunning Hyperparameter

Hyperparameter :

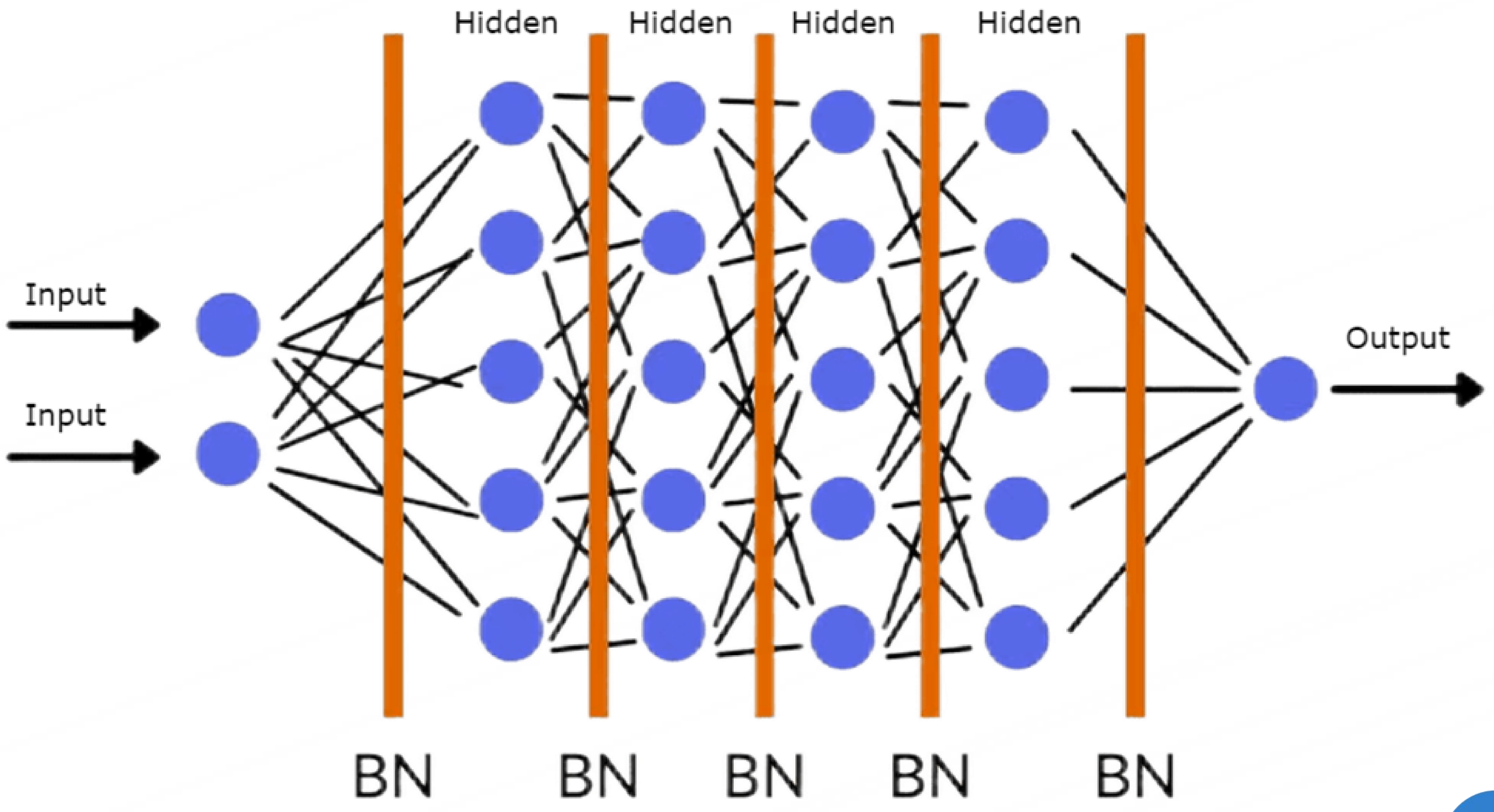
loss function	categorical_crossentropy
activation function	Relu
dropout rates	0.5 | 0.3
epochs	100
batch size	100
image size	224 x 224
learning rate	0.001

Batch Normalization

Batch normalization is a deep neural network training technique that reduces internal covariate shift by normalizing inputs to a mean of zero and variance of one.



During Batch Normalization



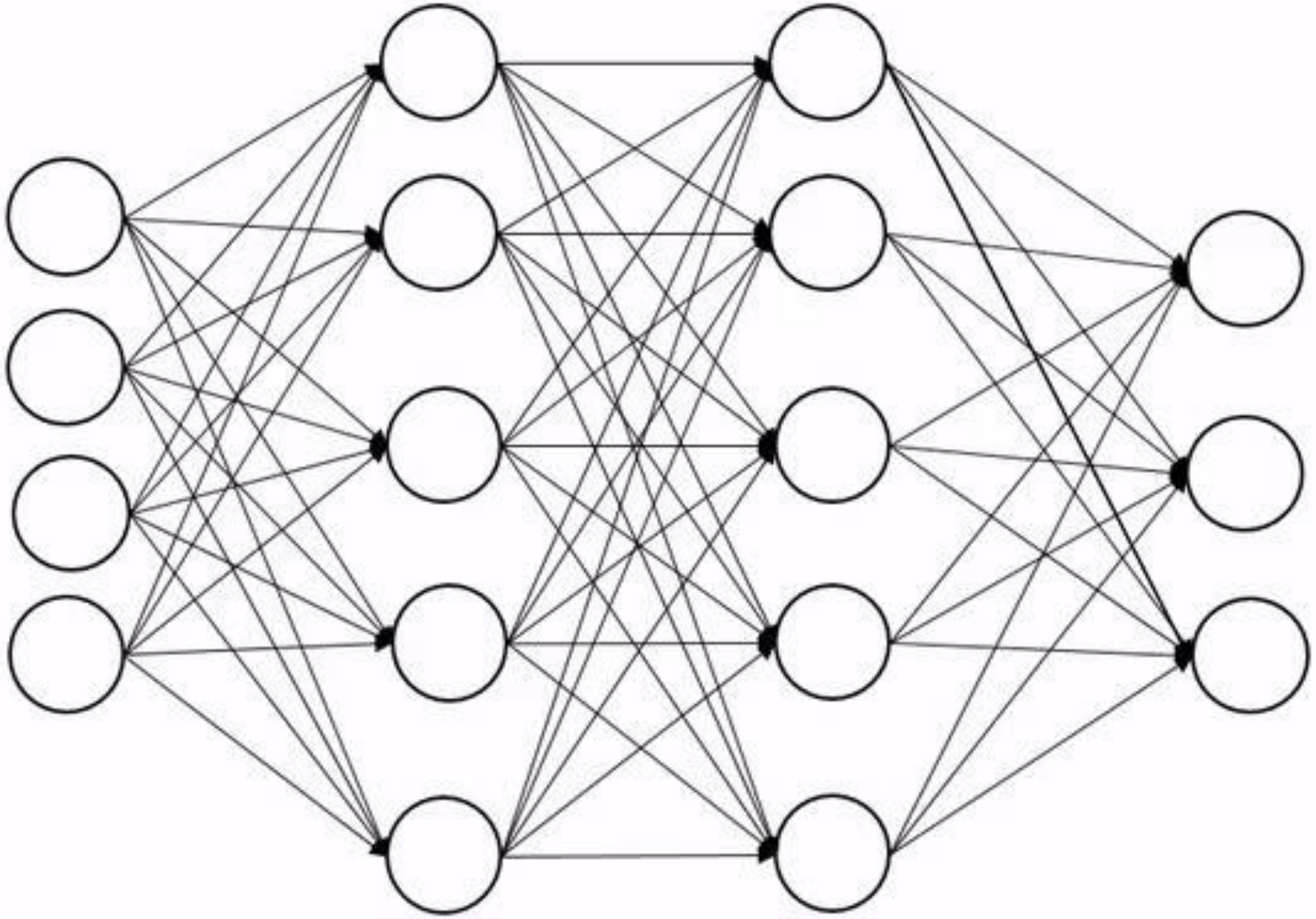
Dropout

Randomly Disable Neurons:

By randomly ignoring neurons during training

During training, the remaining neurons are scaled up to maintain expected output values, such as multiplying the output of the remaining neurons by 2 if half are dropped out.

Dropout



Early Stopping

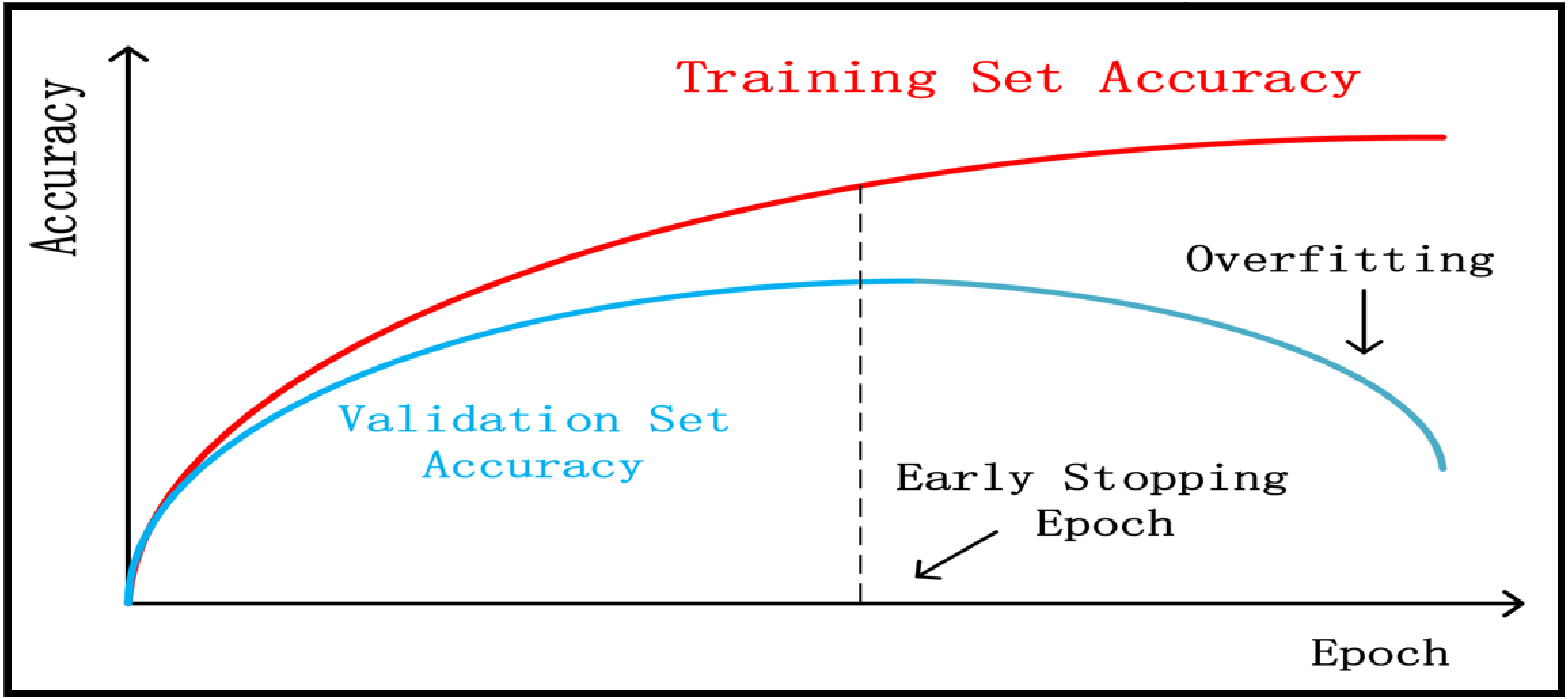
Method to avoid overfitting.

Early stopping involves terminating training shortly once the validation error is at its lowest level.

Many variables are used in early stops :

monitor= 'loss'
mode= 'min'
patience= 10
min_delta= 0.001

Early Stopping



Experiments

Results of Exprements: 2 April

epochs	10
Input size	224,224
Reduce lr	no
Dropout	0.3 | 0.5
Unfreeze Layers	30 top layer from base
early_stop	no

Test acc	0.860
Test Loss	0.717

Results of Exprements: 3 May

epochs	15
Input size	250,250
Reduce lr	yes (factor=0.1,patience = 15)
Dropout	0.5 | 0.5
Unfreeze Layers	top 30 layer
early_stop	no

Test acc	0.914
Test Loss	0.422

Results of Exprements: 15 April after using SVC method

epochs	100
Input size	224,224
Reduce lr	no
Dropout	0.5 | 0.3
Unfreeze Layers	30 from top
early_stop	(monitor='loss', mode='min',patience=10)

Test acc	0.959
Test Loss	0.137

Cubic SVM Test acc	0.9
Cubic SVM Test Loss	0.09999

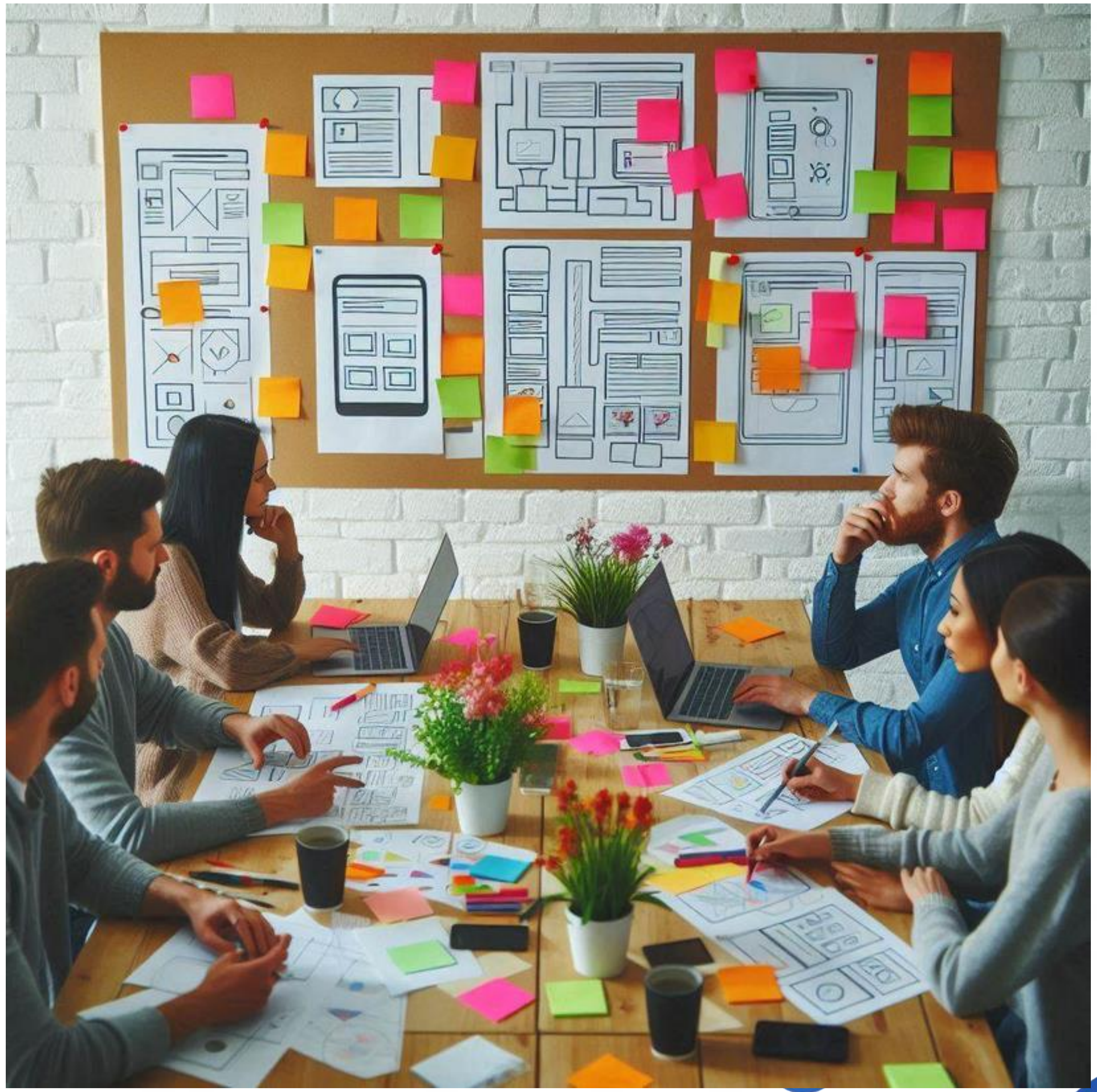
Results of Exprements: 30 April after reduce Melanocytic to 4k

epochs	100
Input size	224,224
Reduce lr	no
Dropout	0.5 | 0.3
Unfreeze Layers	30 from top
early_stop	(monitor='loss', mode='min',patience=10)

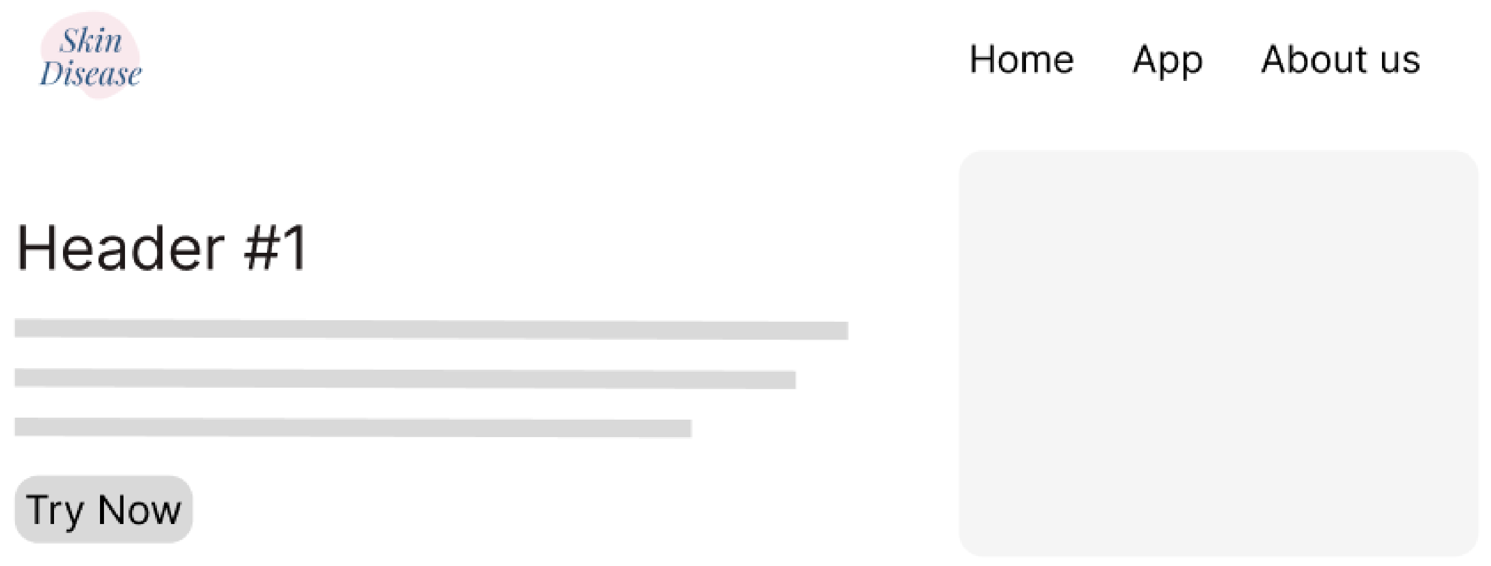
Test acc	0.964
Test Loss	0.127

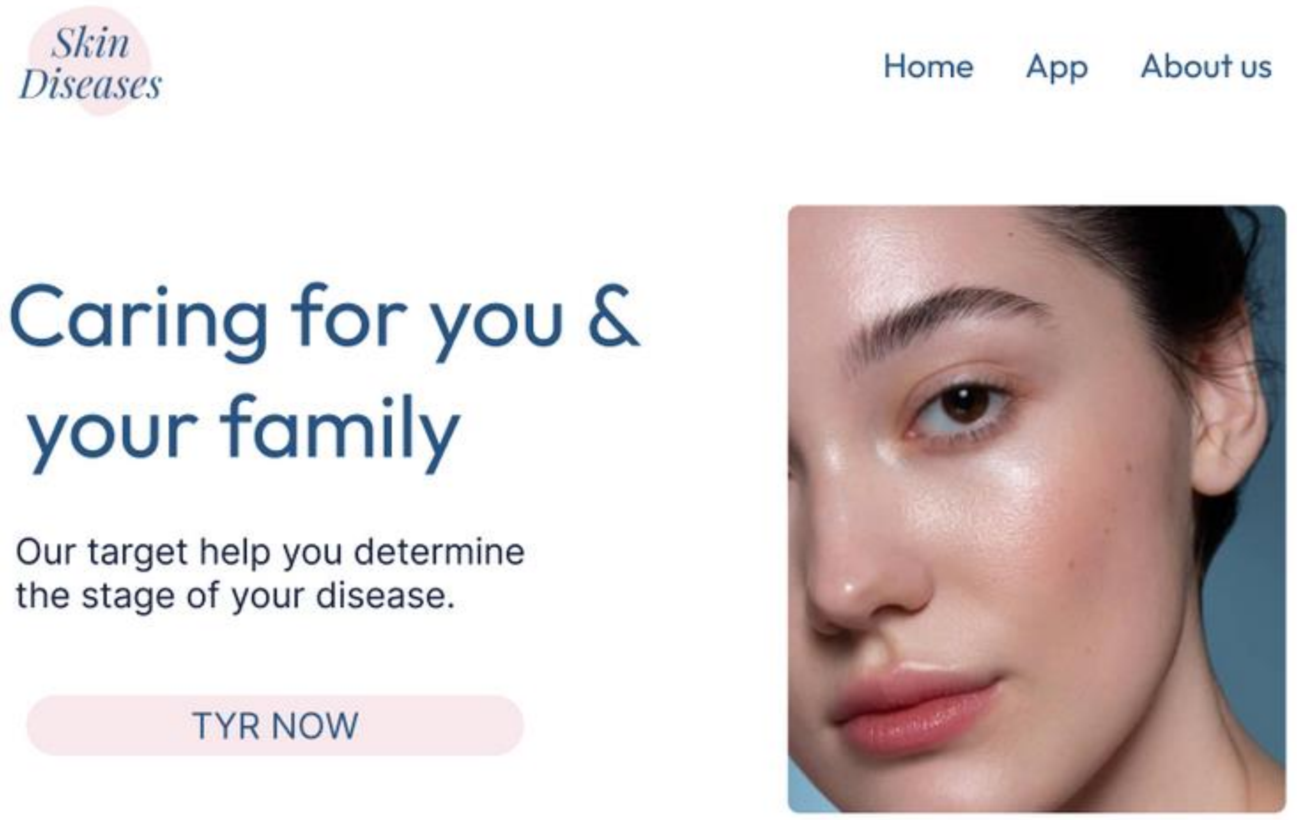
Cubic SVM Test acc	0.99
Cubic SVM Test Loss	0.010000

Web Application



UI/UX





[Full design in Figma]

Application Stack

Front-end	Back-end	Webserver	Cloud Platform
React	Flask	Nginx	Digital Ocean

Data flow

- API Requests
  - Fetch data from backend API
  - Handle responses and errors
- State Managment
  - Update components based on state changes

Libraries

- axois
- react-dropzone
- react-slideshow

Tools

- eslint for code linting
- Vite for module managmenet

Flask

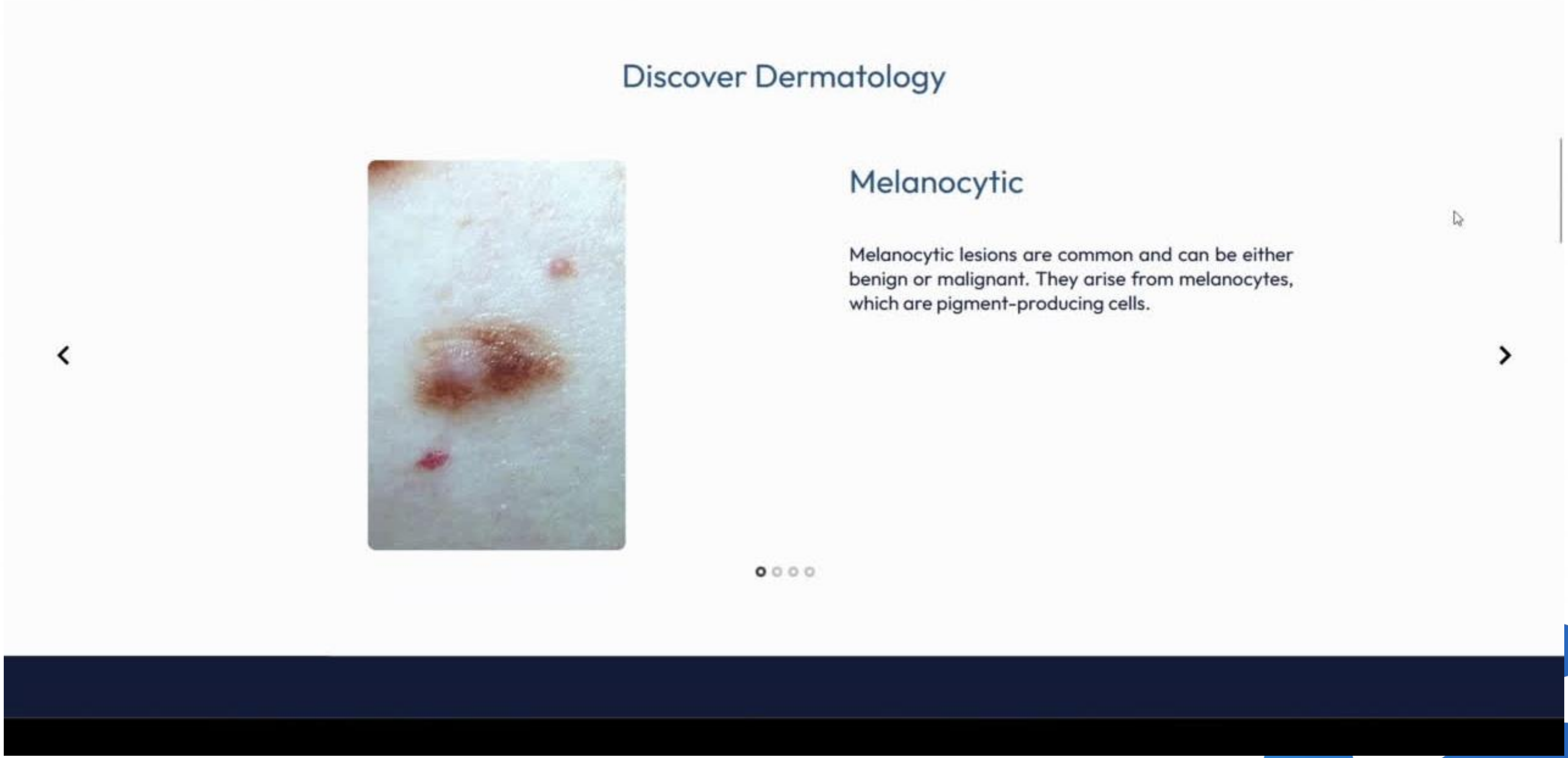
API Endpoint

AI implementation

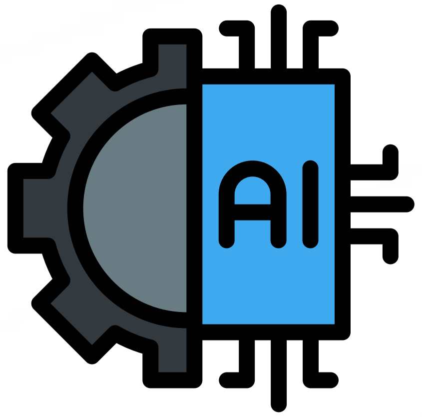
Server response

```python
@app.route('/upload', methods=['POST'])
def predict():
    if 'file' not in request.files:
        return jsonify({'error': 'No file'}), 400

    file = request.files['file']
    img_data = file.read()

    img = image.load_img(io.BytesIO(img_data), target_size=(224, 224))
    img = image.img_to_array(img)
    img = np.expand_dims(img, axis=0)
    img /= 255.0
    prediction = model.predict(img)
    predicted_class = np.argmax(prediction, axis=-1)
    label = class_labels[predicted_class[0]]
    print(label)

    return jsonify({'prediction': label})
```

Demo

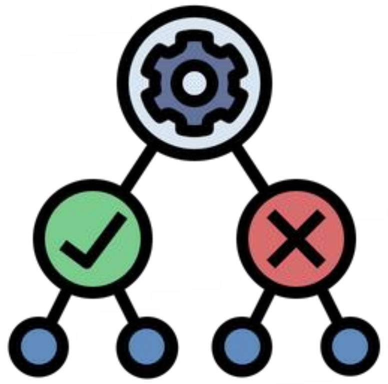

Discover Dermatology
Melanocytic
Melanocytic lesions are common and can be either benign or malignant. They arise from melanocytes, which are pigment-producing cells.

Computational time



Training model

4 hour,
26 minutes,
and 40
seconds



Testing model

32
second

Testing Web App

About 5 seconds

Future plans & Conclusion

Conclusion

- The DenseNet-121 algorithm was chosen due to its proven ability to capture intricate features and efficiently manage complex image data.
- The integration of a Cubic SVM classifier further enhanced the accuracy, achieving a test accuracy of 0.99 in the best experimental setup.
- Effectively resolved the project's several challenges.
- Create a successful Web application that will allow us to sell it with additional work and marketing.

Future Plans

What we hope to achieve :

Expanding service

Increasing the number of dermatologists on the web Application and expanding the service regions .

Add User Profile

Keep track of their personal data, medical history, and previous diagnoses .

Categorize Users Groups

Creating 2 categories of users by dividing membership into patients and doctors

Future Plans

What we hope to achieve :

contribution

We aim to publish a comprehensive research paper on our skin disease classification accuracy rate of 0.99, presenting new results in dermatological diagnostics.

References

[1] Skin Cancer MNIST: HAM10000, Kaggle, (2018, September 20). https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000

[2] International Skin Imaging Collaboration. (n.d.), ISIC, https://www.isic-archive.com/

[3] Pacheco, A. G. C., Lima, G. R., Salomão, A. S., Krohling, B. A., Biral, I. P., De Angelo, G. G., Alves, F. C. R., Esgario, J. G. M., Simora, A. C., Castro, P. B. C., Rodrigues, F. B., Frasson, P., Krohling, R. A., Knidel, H., Santos, M. C. S., Santo, R. B. D. E., Macedo, T. L. S. G., Canuto, T. R. P., & De Barros, L. F. S. PAD-UFES-20: A skin lesion dataset composed of patient data and clinical images collected from smartphones. Data in Brief, 32, 106221,(2020), https://doi.org/10.1016/j.dib.2020.106221

[4] Combalia, M. BCN20000: Dermoscopic lesions in the wild, arXiv.org, (2019, August 6), https://arxiv.org/abs/1908.02288

[5] Dr Ian Coulson. DermNet. (2021). https://dermnetnz.org/

[6] Mendonca, T., Ferreira, P. M., Marques, J. S., Marcal, A. R. S., & Rozeira, J. PH2 - A dermoscopic image database for research and benchmarking. 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), (2013), https://doi.org/10.1109/embc.2013.6610779

[7] ADDI - Automatic computer-based Diagnosis system for Dermoscopy Images, (2013), https://www.fc.up.pt/addi/ph2%20database.html

[8] Rees, Aldridge, Fisher, Ballerini, A Color and Texture Based Hierarchical K-NN Approach to the Classification of Non-melanoma Skin Lesions, Color Medical Image Analysis, Lecture Notes in Computational Vision and Biomechanics 6 (M. E. Celebi, G. Schaefer (eds.)), (2013) https://licensing.edinburgh-innovations.ed.ac.uk/product/dermofitimage-library

[9] Mendes, D. B. Skin lesions classification using convolutional neural networks in clinical images. arXiv.org, (2018, December 6), https://arxiv.org/abs/1812.02316

[10] Demir, A., Yilmaz, F., & Kose, O. Early detection of skin cancer using deep learning architectures: resnet-101 and inception-v3, TIPTEKNO 2019, https://doi.org/10.1109/tiptekno47231.2019.8972045

[11] Al-Saedi, D. K. A., & Savaş, S. Classification of Skin Cancer with Deep Transfer Learning Method, Computer Science, (2022), https://doi.org/10.53070/bbd.1172782

[12] Rehman, M. Z. U., Ahmed, F., Alsuhibany, S. A., Jamal, S. S., Ali, M. Z., & Ahmad, J. Classification of skin cancer lesions using explainable deep learning, Sensors, 22(18), 6915, (2022),
https://doi.org/10.3390/s22186915

[13] Chaturvedi, S. S., Gupta, K., & Prasad, P. S. Skin lesion analyser: An efficient Seven-Way multi-class skin cancer classification using MobileNet, In Advances in intelligent systems and computing (pp. 165–176),(2020), https://doi.org/10.1007/978-981-15-3383-9_15

[14] Srinivasu, P. N., SivaSai, J. G., Ijaz, M. F., Bhoi, A. K., Kim, W., & Kang, J. J. Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM, Sensors, 21(8), 2852, (2021), https://doi.org/10.3390/s21082852.

[15] Kaya, V., & Akgül, İ. Classification of skin cancer using VGGNet model structures. Gümüşhane Üniversitesi Fen Bilimleri Enstitüsü Dergisi, (2022), https://doi.org/10.17714/gumusfenbil.1069894

[16] Pai, V. R., Pai, S. G., Suhasi, P. M., & Rekha, P. M. Identification and Classification of Skin Diseases using Deep Learning Techniques, Research Square (Research Square), (2023), https://doi.org/10.21203/rs.3.rs-2628782/v1.
https://arxiv.org/pdf/1512.03385.pdf

THANK'S FOR WATCHING