# WELCOME TO AI PRESENTATION

Submitted to,

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# INTRODUCTION

## Our Problem is-

- Gastric cancer is a leading cause of cancer-related deaths worldwide.
- Histopathology image classification is difficult due to complex tissue structures, similar patterns
- Manual diagnosis is slow, subjective, and prone to variability.

## It is important-

- Early, accurate detection improves treatment planning and survival rates.
- Deep learning-based automation supports pathologists with fast, consistent, and accurate diagnosis.
- AI enhances healthcare efficiency, especially in low-resource settings.

## Our Main Goal is-

- Develop and evaluate deep learning models using the GCHTID dataset (31,080 images).
- Apply pre-trained models (DenseNet201, EfficientNetV3, ResNet) with transfer learning.
- Design and test a custom CNN mode.
- Custom CNN with Custom Pooling
- Compare model performance to find the best approach.

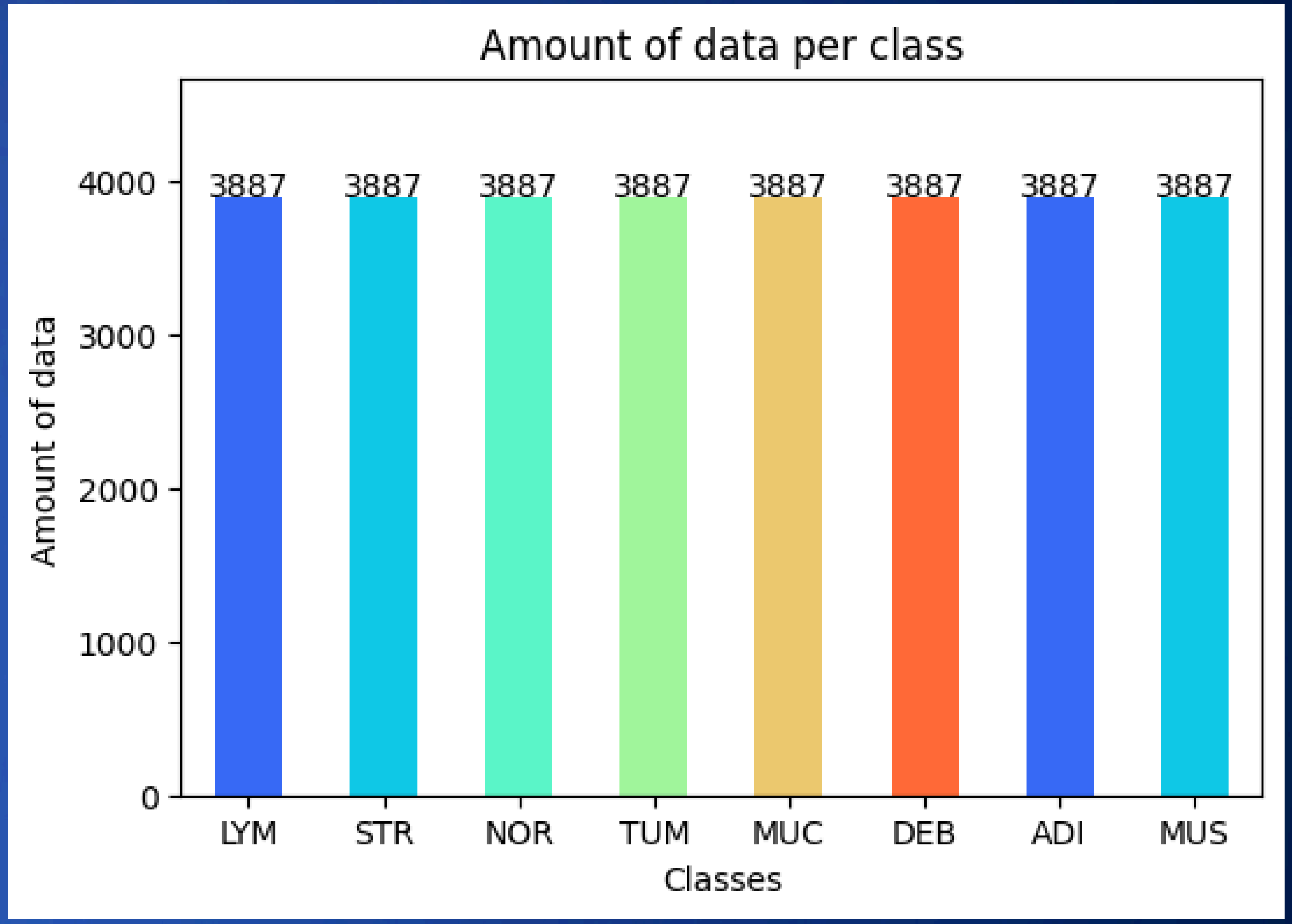
# LITERATURE REVIEW

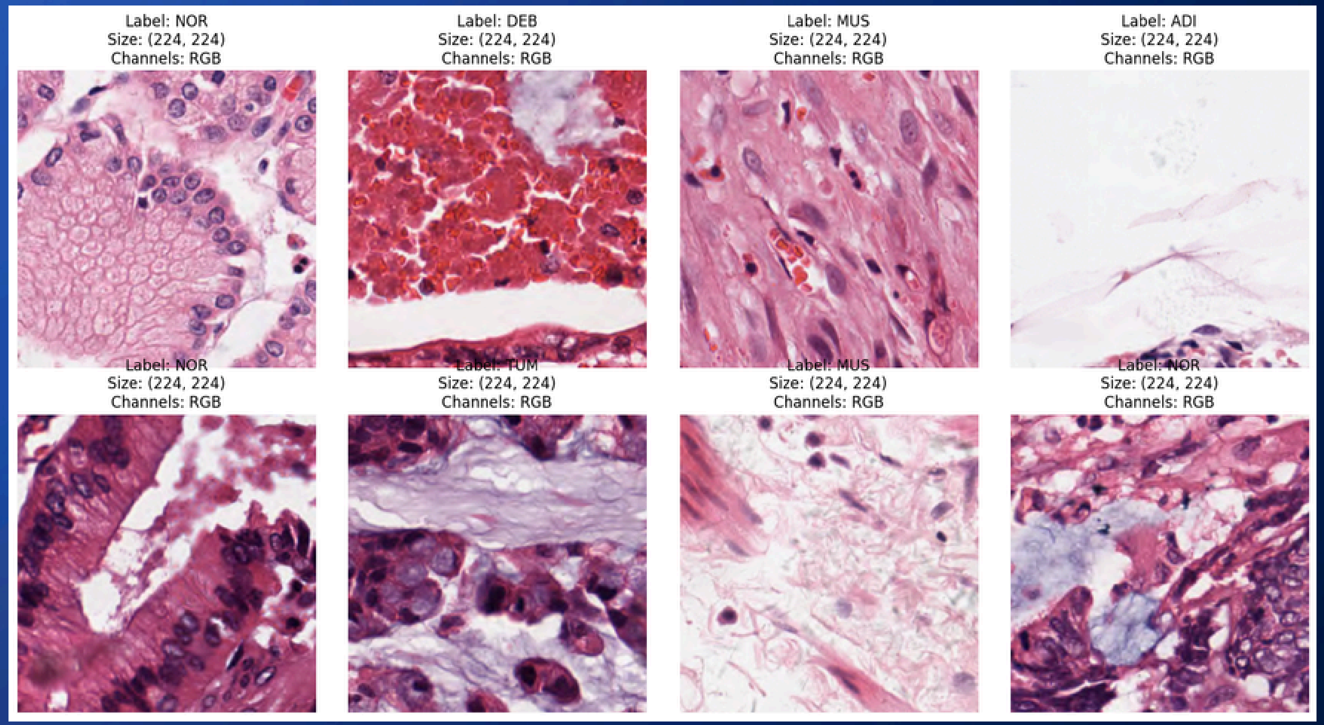
| Ref No | Method | Dataset & Source | Best Model | Accuracy | Advantages | Limitations |
|---|---|---|---|---|---|---|
| 1 | CNN (VGG, ResNet) | 13,584 Endoscopic Images | ResNet | 92.5% | High accuracy, supports rapid diagnosis | Misclassifies gastritis vs cancer; poor on blurred images |
| 2 | EfficientNet, DenseNet | 1200 WSIs (South Korea) | EfficientNet | 95% | Subclassification of gastric carcinoma subtypes | High computation; artifacts handling issue |
| 3 | ResNet | 2296 Endoscopic Images (Japan) | ResNet | 92% | Outperforms endoscopists; early detection | Weak on rare/complex cases |
| 4 | GoogLeNet (CNN) | 386 NBI Images (Tokyo Medical Univ) | GoogLeNet | 89% | Early-stage detection using NBI imaging | Single-center data; quality-dependent |
| 5 | VGG, ResNet | 1500 NBI Images | ResNet | 85% | Differentiates gastritis and cancer | Low diversity; misclassification in some cases |
| 6 | CNN + Autoencoder (Multimodal) | 500 WSIs + Gene (TCGA) | Custom Multimodal | 87.5% | Predicts survival risk; supports treatment planning | Low stain variation; hard to interpret |

| Ref No | Method | Dataset & Source | Best Model | Accuracy | Advantages | Limitations |
|---|---|---|---|---|---|---|
| 7 | ResNet-50+Supervised Contrastive | 4000+ Histopathology Images (Private) | ResNet-50 | 79% | Better feature separation; handles class imbalance | High computational cost; complex to interpret |
| 8 | CNN, ResNet-50 + Feature Fusion | Gastric-Histopath Dataset (10,000 images, Private) | Fusion Model | 82% | Sensitive to micro-structure changes | Manual feature fusion is time-consuming |
| 9 | Custom CNN (Diagnosis & Prognosis) | 2500 WSIs, China (Multi-Center, Private) | Custom CNN | >90% | Accurate diagnosis & prognosis prediction | Stain inconsistency; needs normalization |
| 10 | DeepRisk(MIL+Weak Supervision) | 1600 WSIs + Clinical Data, China (Private) | DeepRisk | 94% | Predicts therapy response; risk stratification | Needs validation on diverse datasets |
| 11 | DenseNet+Attention Mechanism | Gastric Histopathology Sub-Image, HCRF Dataset (Private) | Attention | 99.07% | High accuracy; interpretable framework | Small dataset; limited external validation |
| 12 | DenseNet (KimiaNet) | Kimia Path24 Dataset (Public, GitHub) | DenseNet | 88% | General histopathology classification | Not specific to gastric cancer; needs domain adaptation |

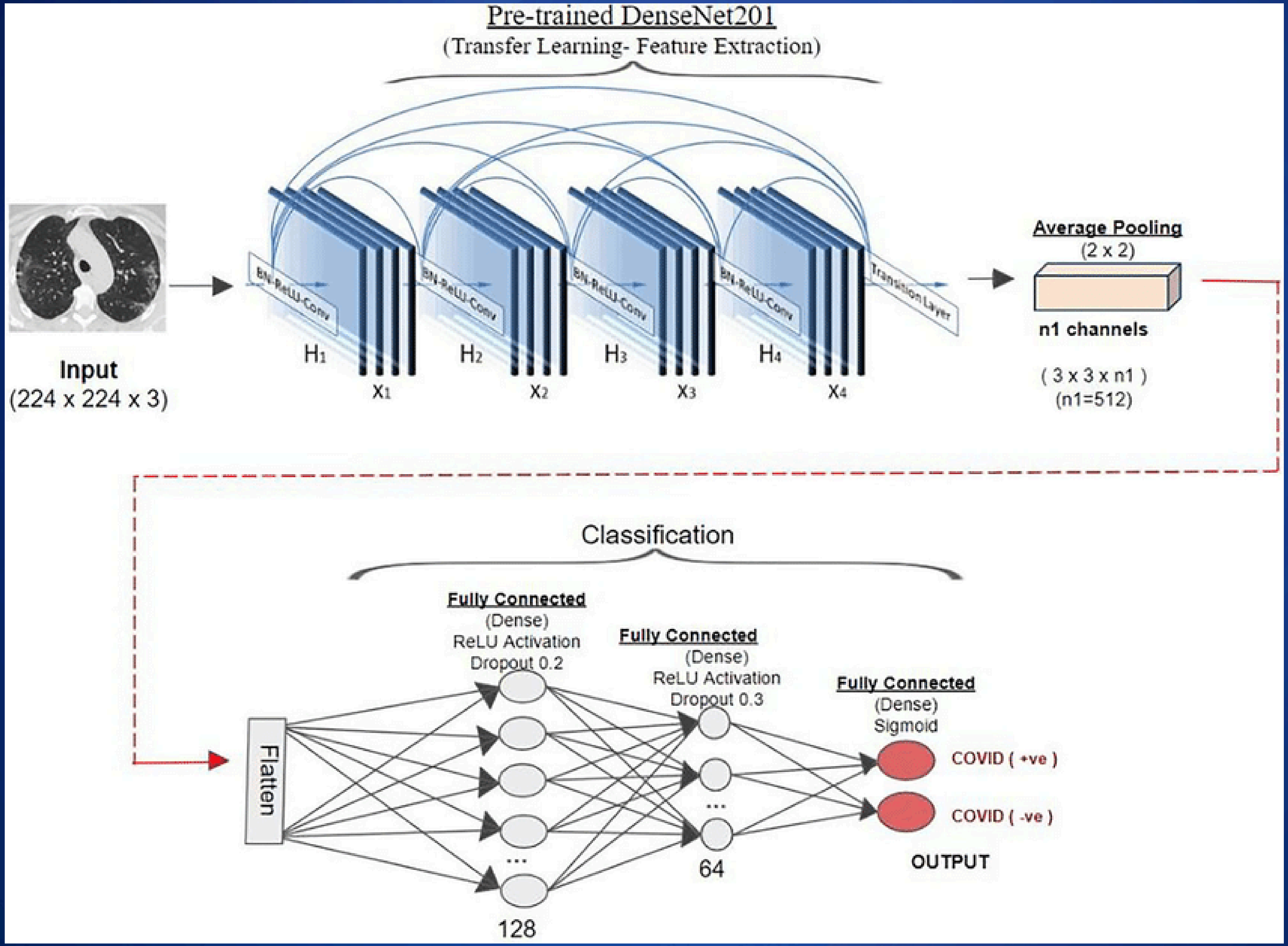
# DATASET DISCRIPTION

| Class | Label | Sample Count |
|---|---|---|
| ADI | 0 | 3887 |
| DEB | 1 | 3887 |
| LYM | 2 | 3887 |
| MUC | 3 | 3887 |
| MUS | 4 | 3887 |
| NOR | 5 | 3887 |
| STR | 6 | 3887 |
| TUM | 7 | 3887 |

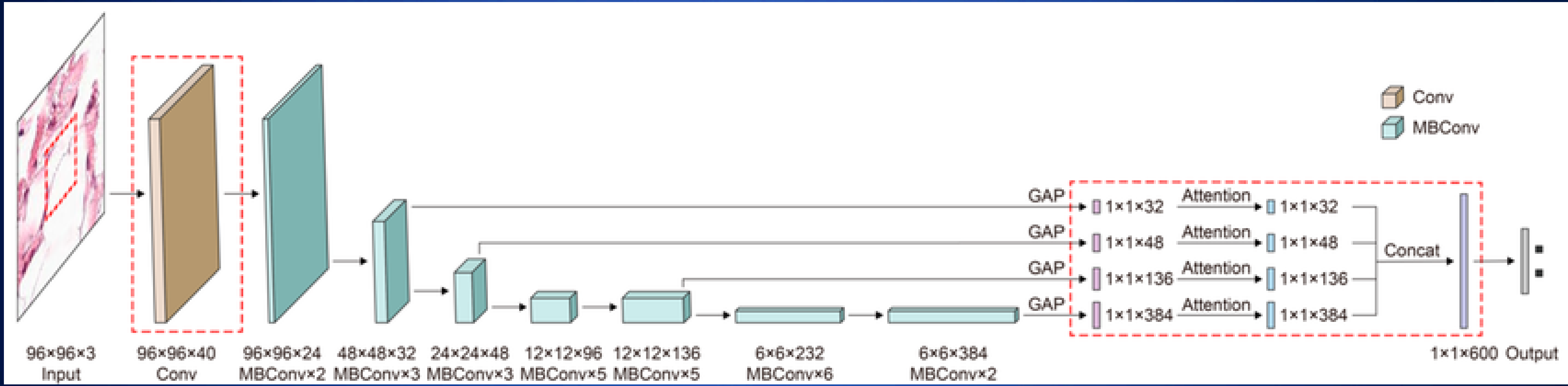


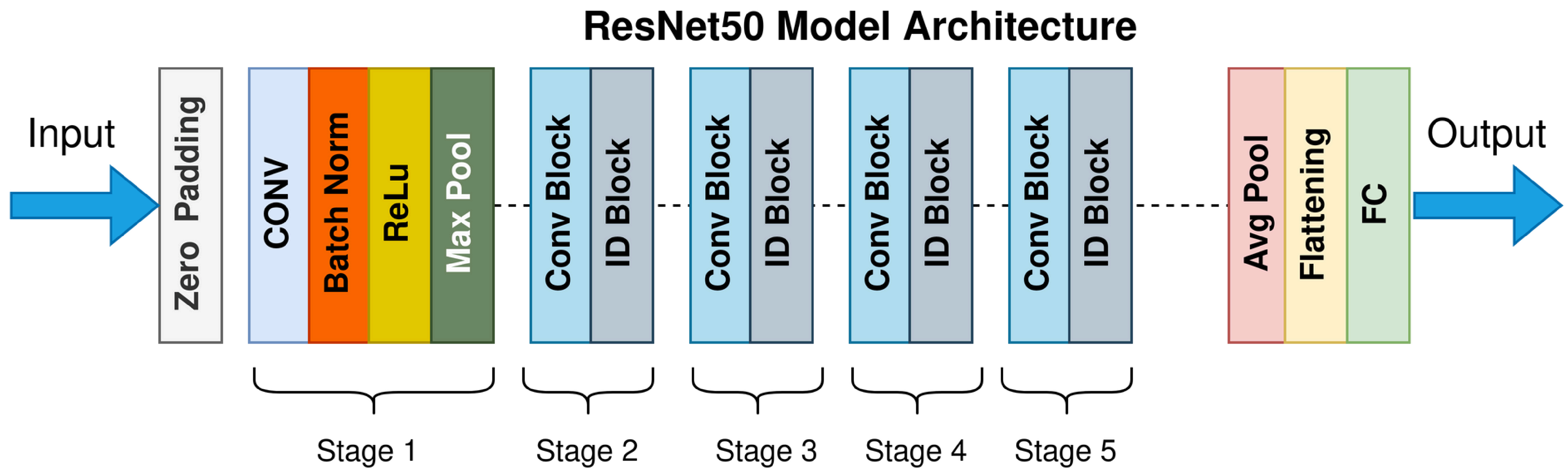
# DENSENET201



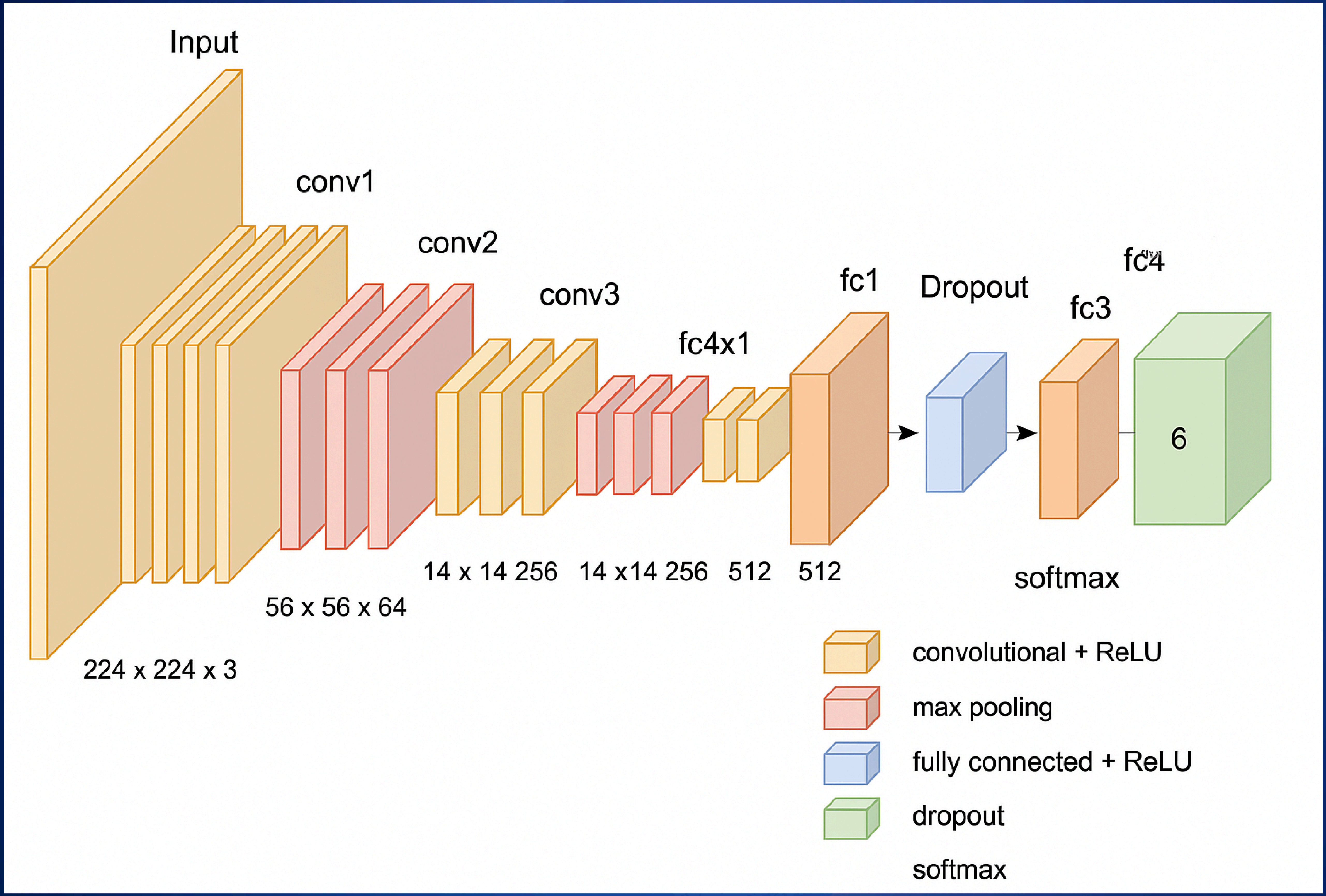
# EFFICIENTNETB3



# RESNET50

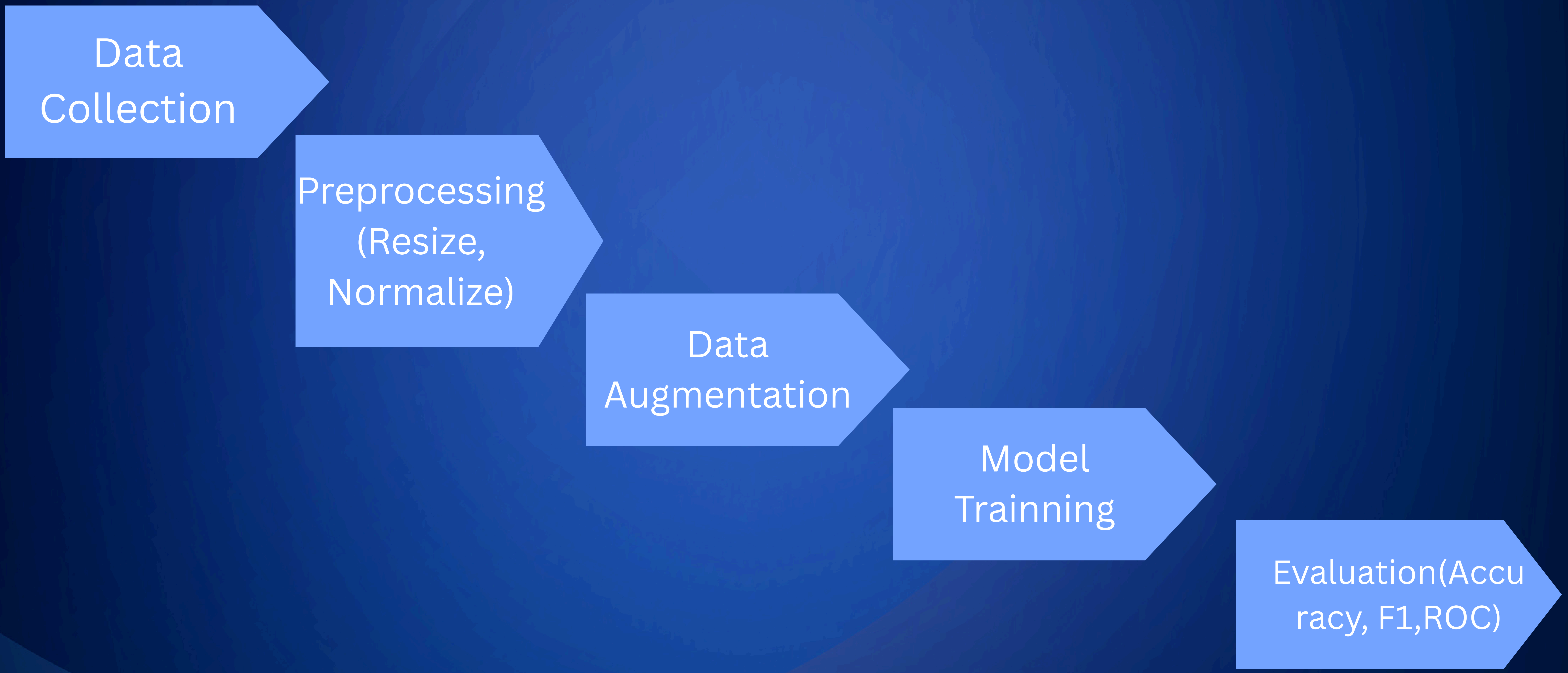

ResNet50 Model Architecture
Input
Zero Padding
CONV
Batch Norm
ReLu
Max Pool
Conv Block
ID Block
Conv Block
ID Block
Conv Block
ID Block
Conv Block
ID Block
Avg Pool
Flattening
FC
Output
Stage 1
Stage 2
Stage 3
Stage 4
Stage 5

# CUSTOM CNN


Input
conv1
conv2
conv3
fc4x1
fc1
Dropout
fc3
fc4
6
224 x 224 x 3
56 x 56 x 64
14 x 14 256
14 x14 256
512
512
softmax
convolutional + ReLU
max pooling
fully connected + ReLU
dropout
softmax

# STUDY PLAN

## Flow Diagram

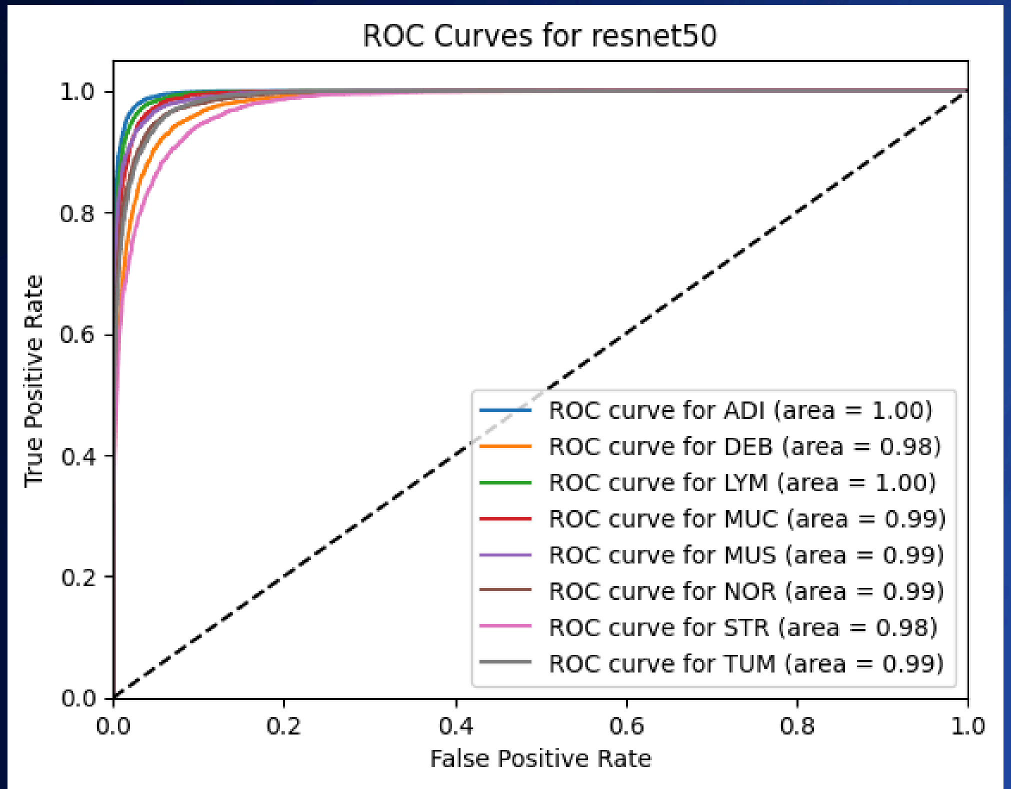


# PERFORMANCE TABLE

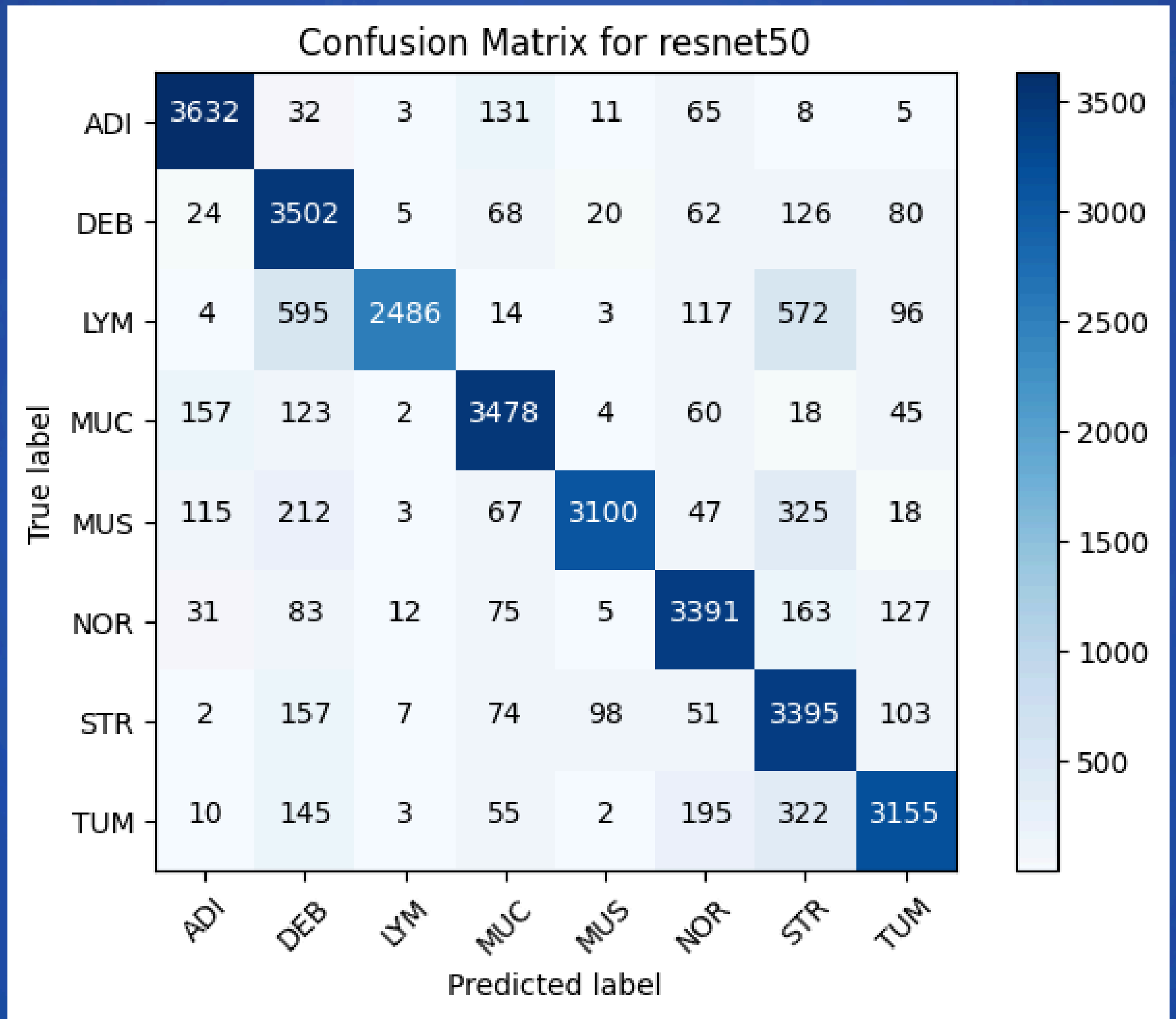
| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| **Custom CNN** | **100%** | **100%** | **100%** | **100%** |
| Densenet201 | 98% | 98% | 98% | 98% |
| EfficientNetB3 | 94% | 94% | 94% | 94% |
| Resnet50 | 84% | 86% | 84% | 84% |
| **Custom Pooling** | **100%** | **100%** | **100%** | **100%** |

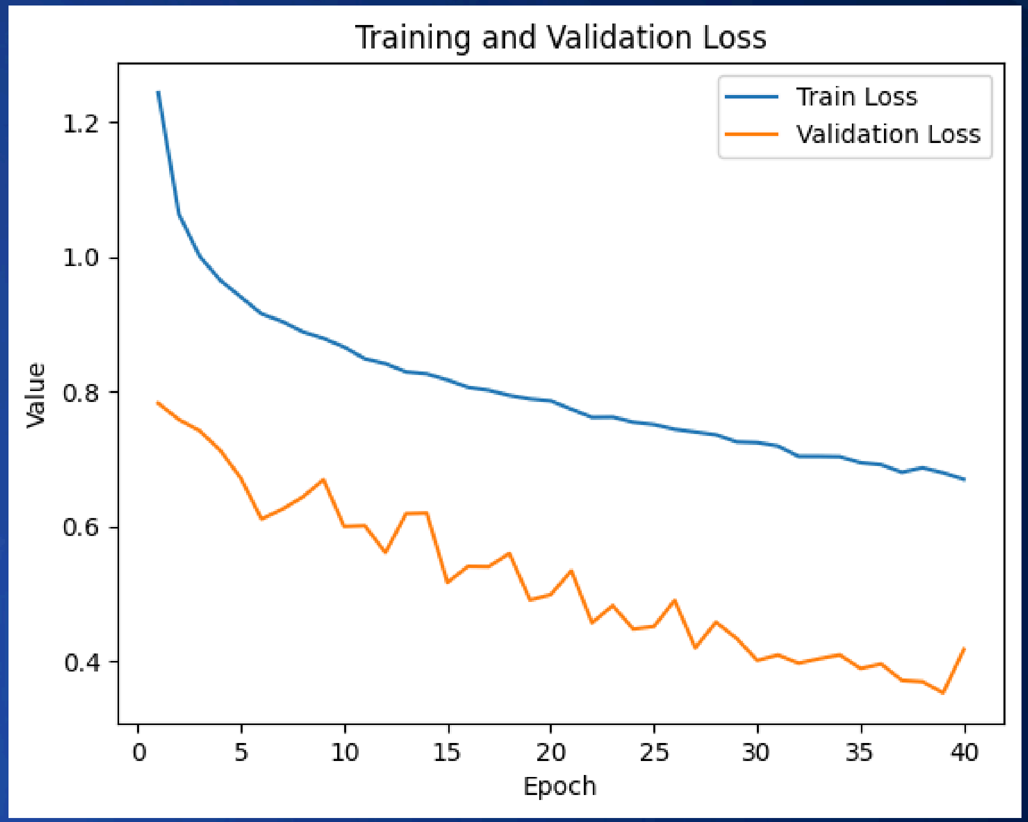
# RESNET50

## ROC CURVE

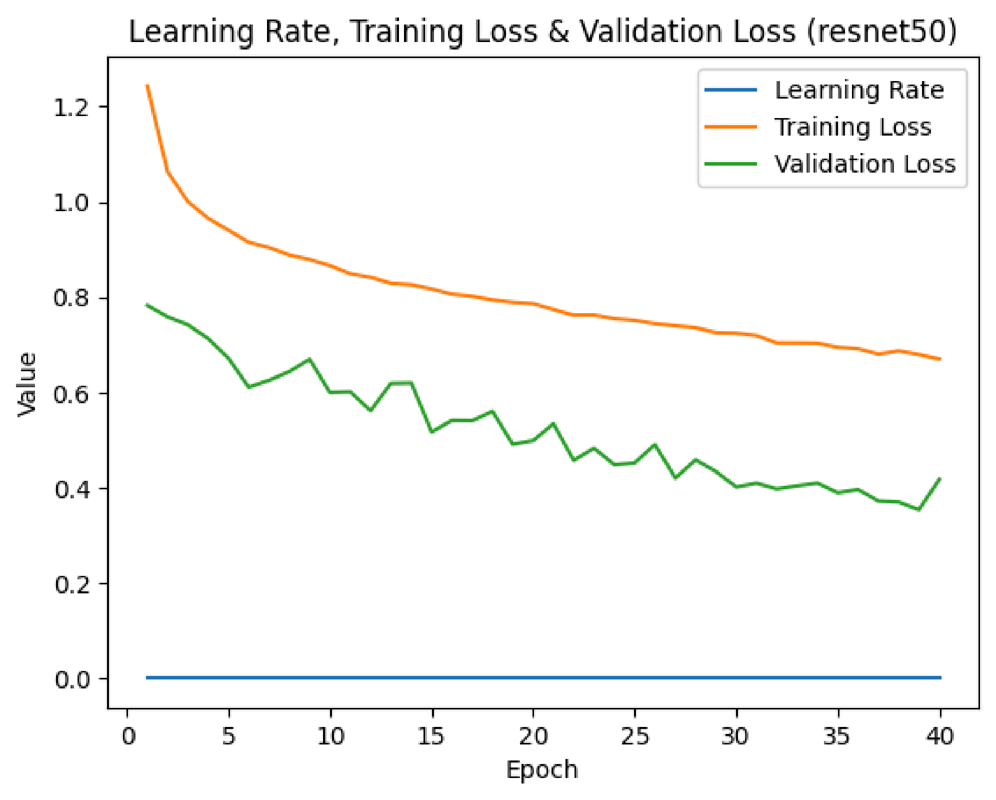



## Confusiion Matrix

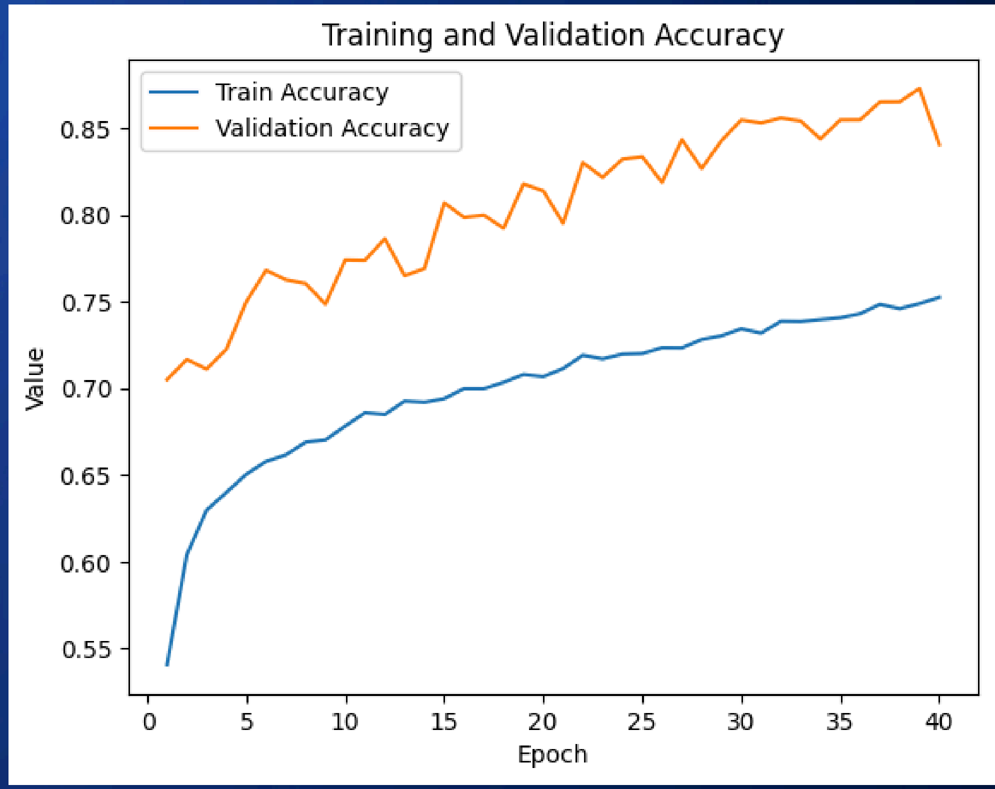



## Learning Rate

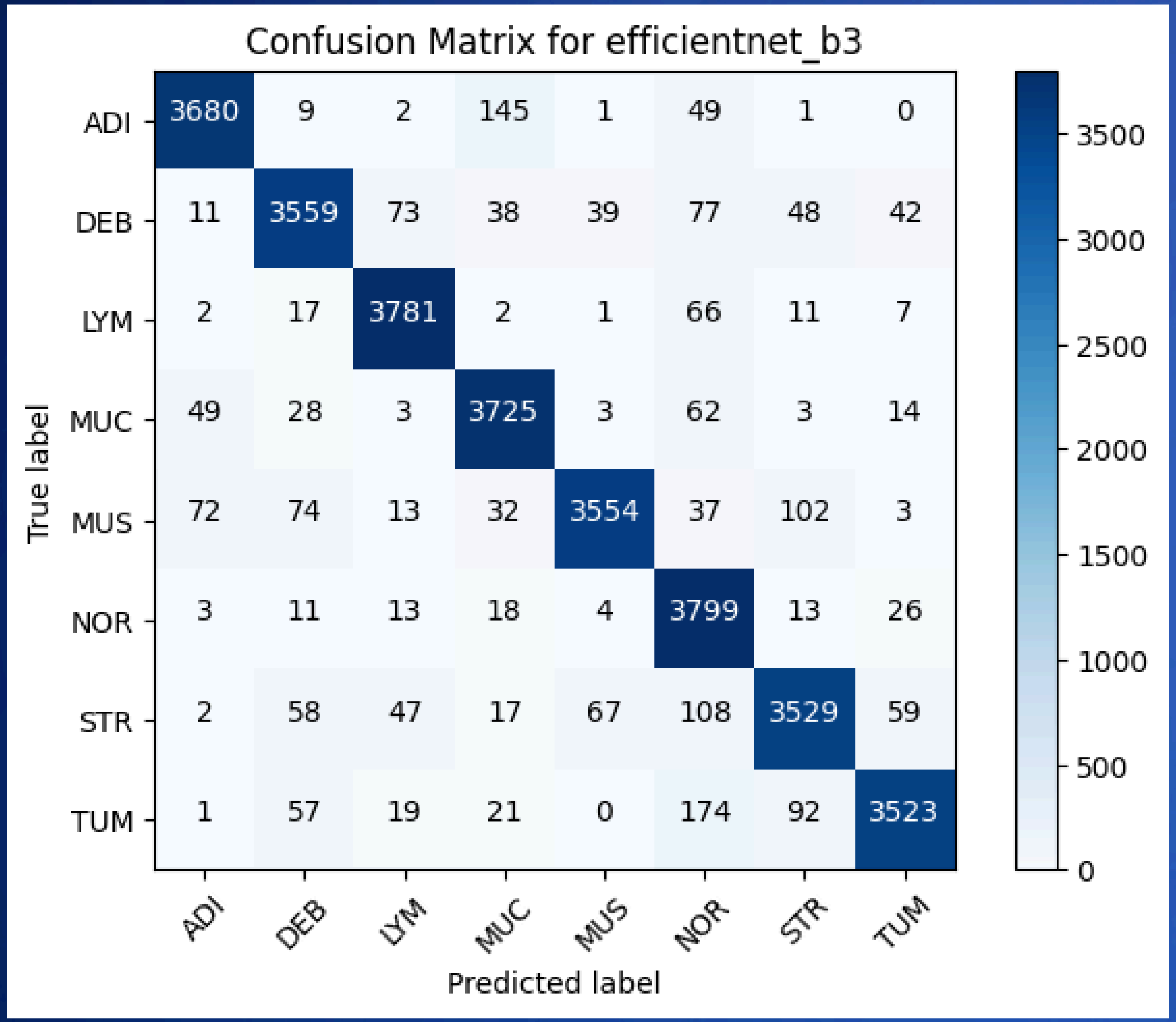



## Accuracy

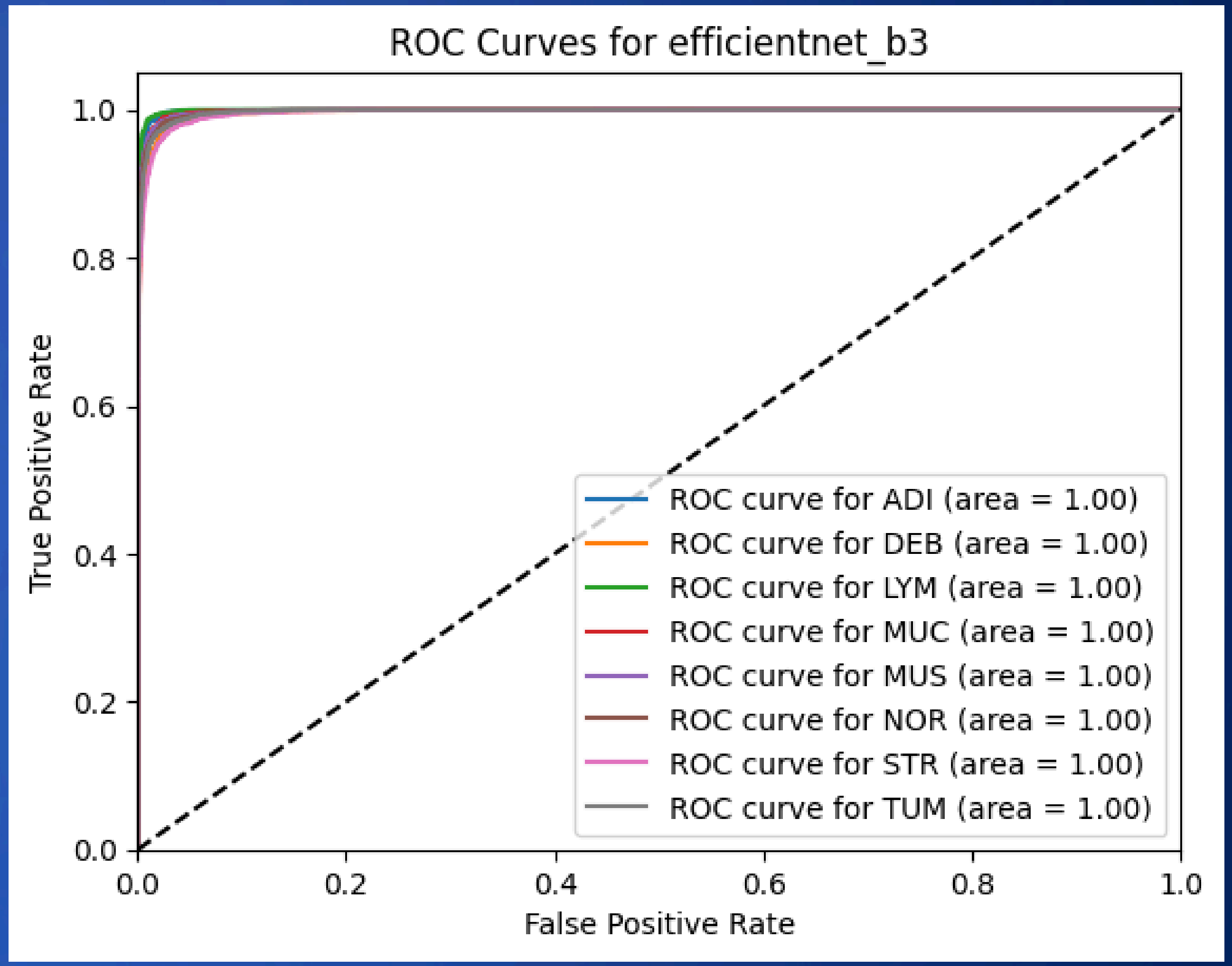


# EFFICIENTNET_B3

## Confusion Matrix

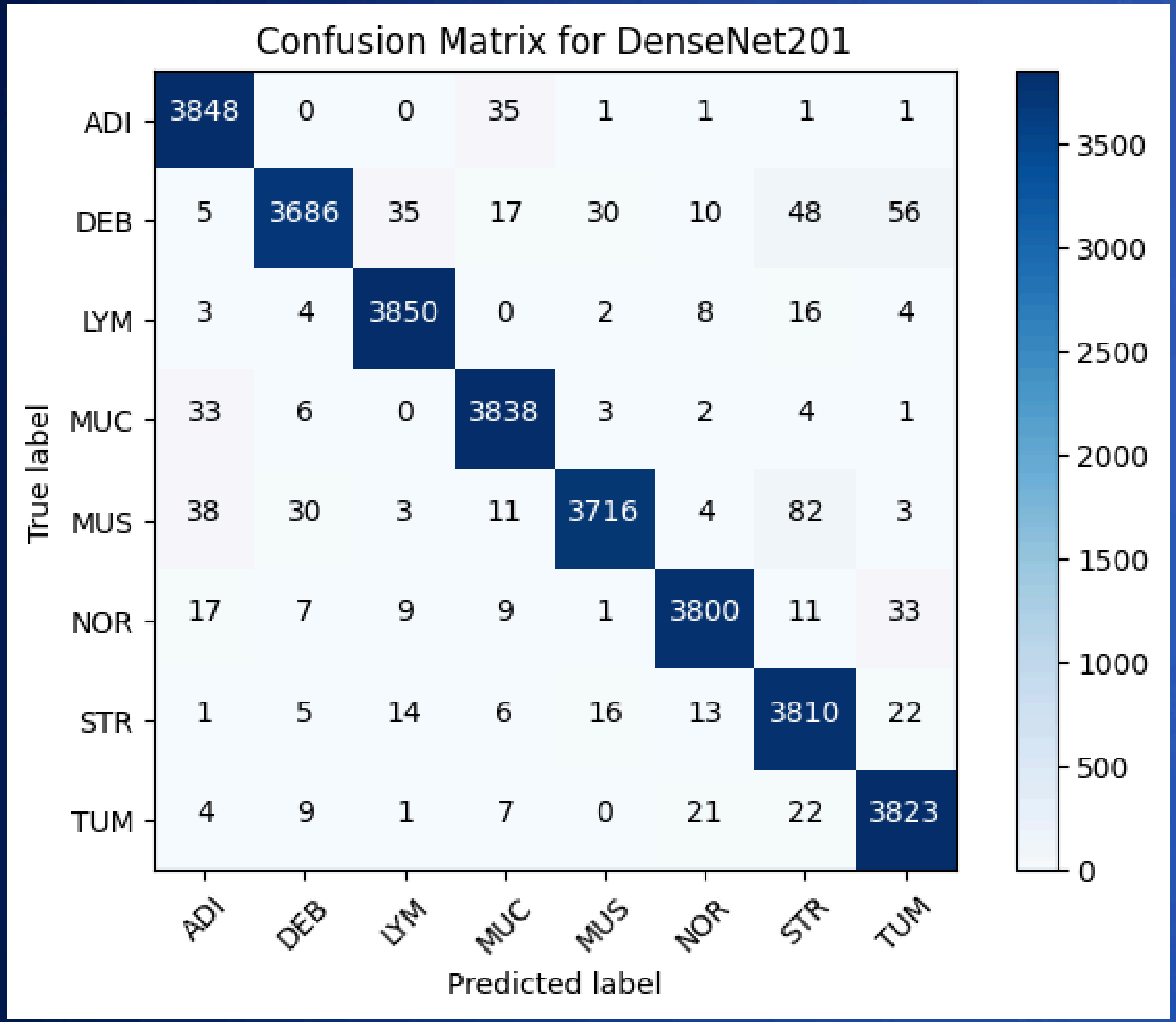



## ROC CURVE

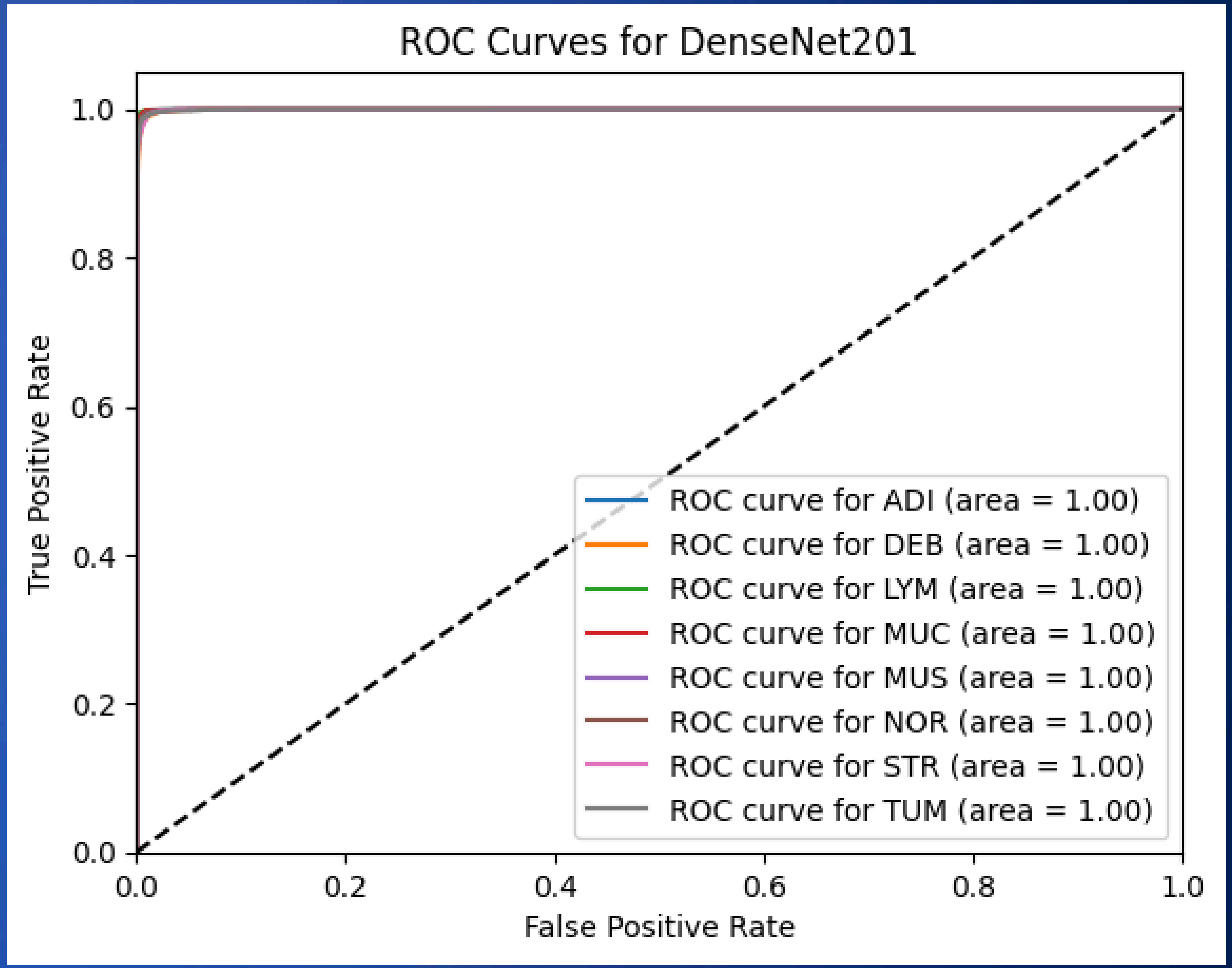


# DENSENET201

## Confusion Matrix

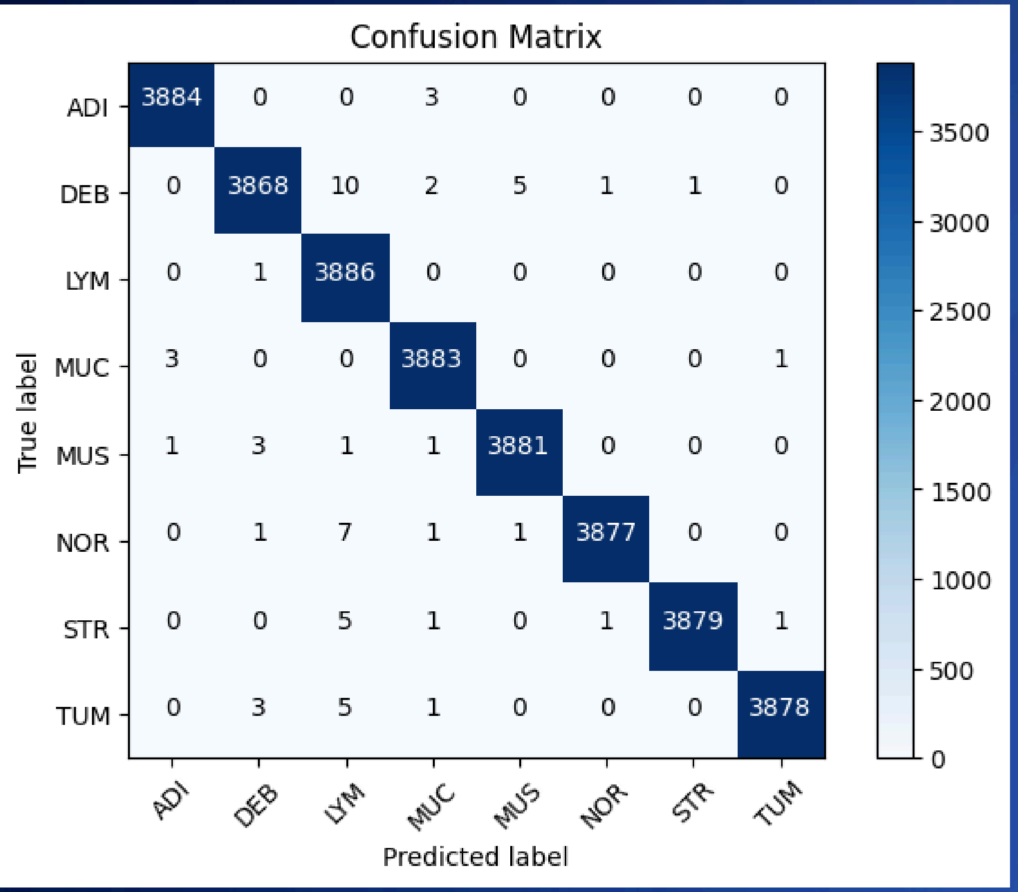



## ROC CURVE

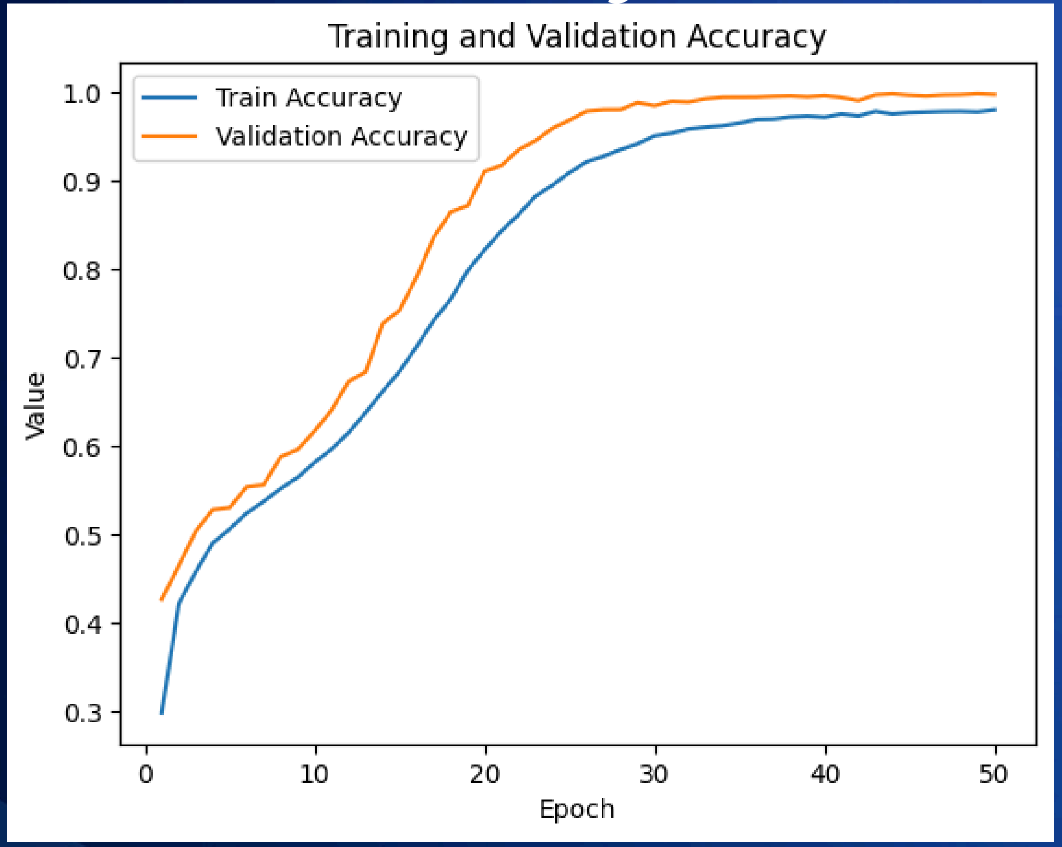


# CUSTOM CNN

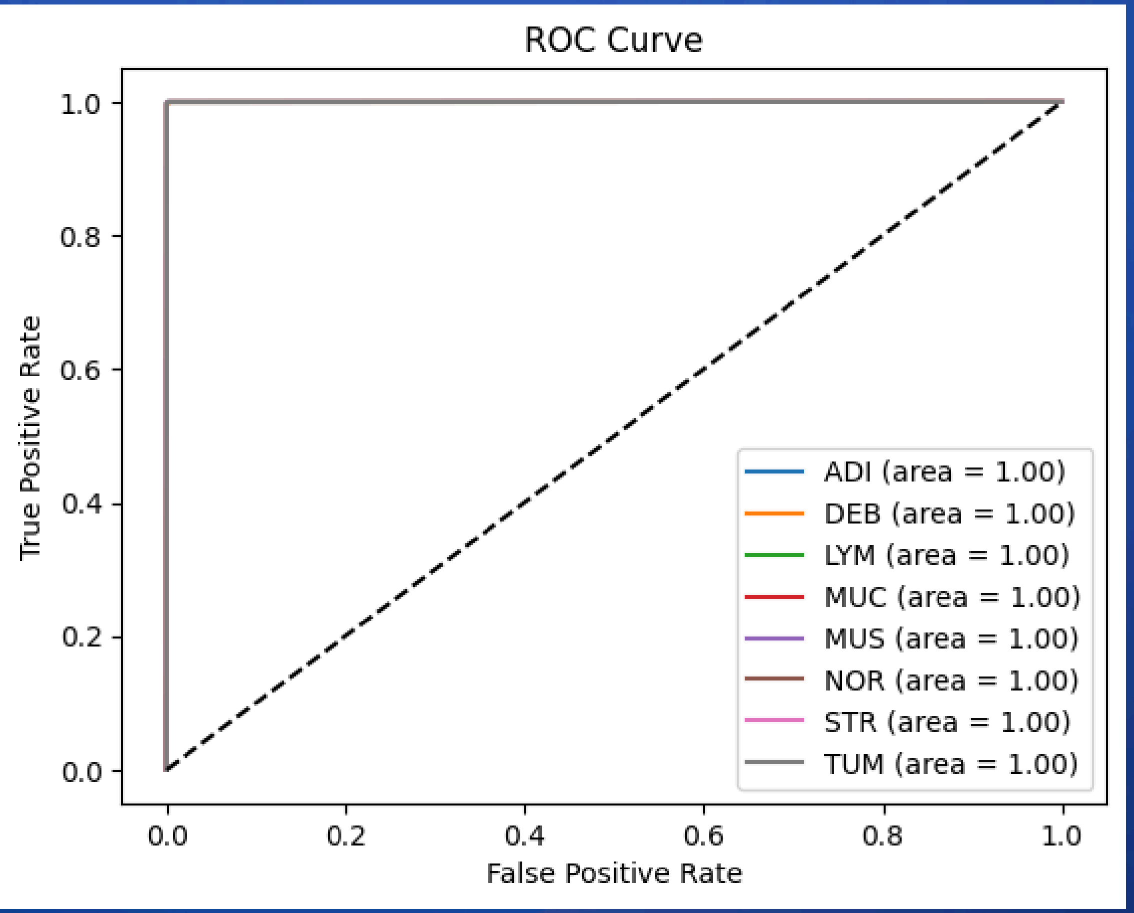
## Confusion Matrix



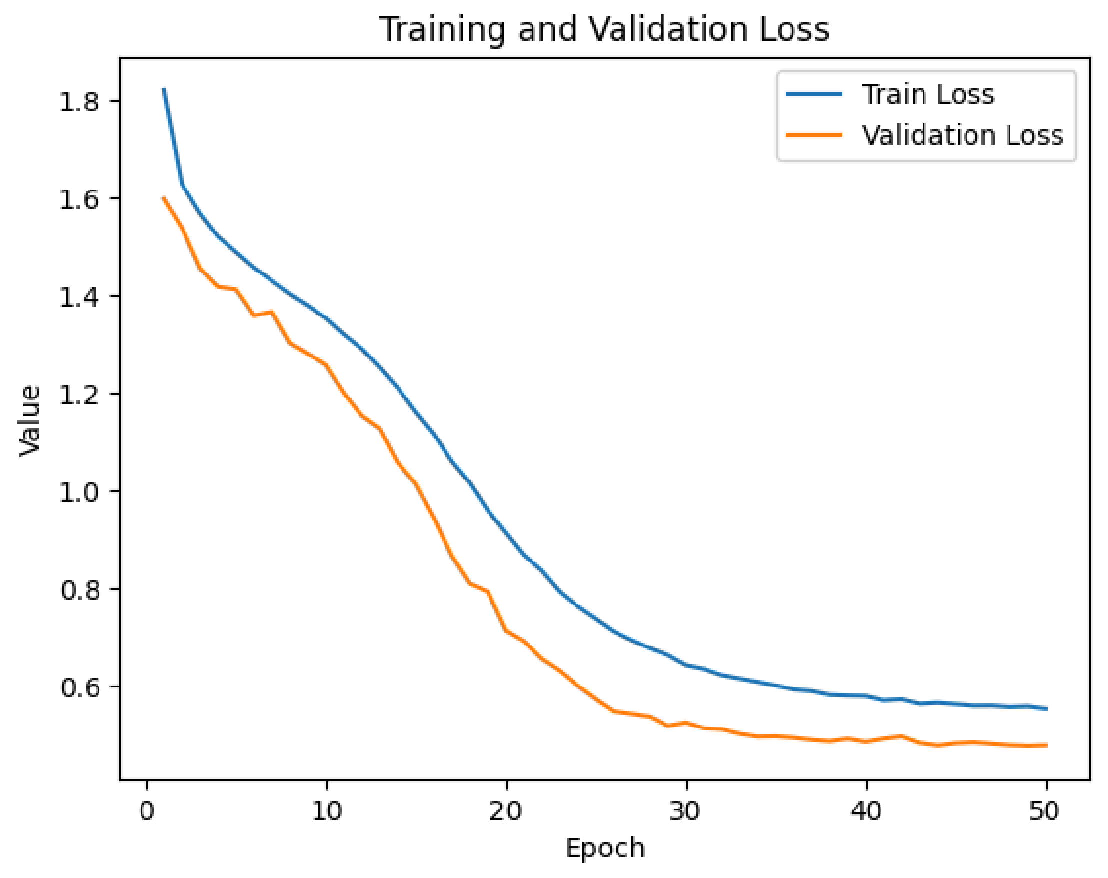

## Accuracy




## ROC CURVE

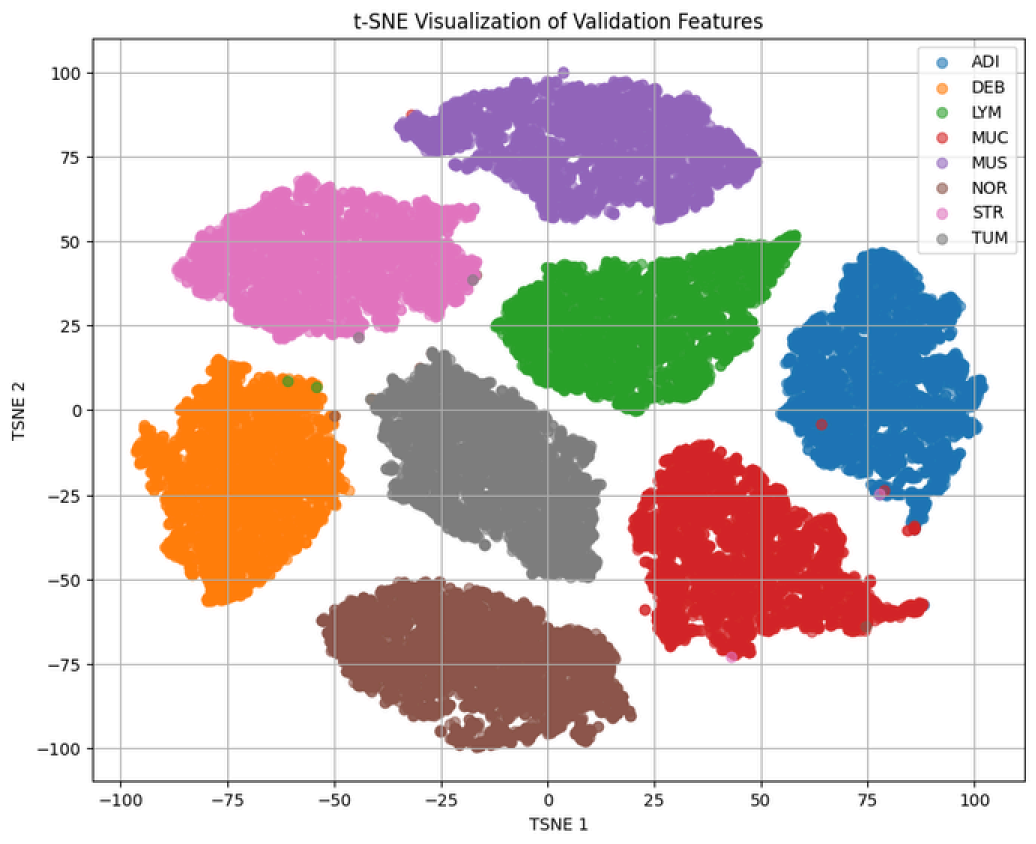



## Loss

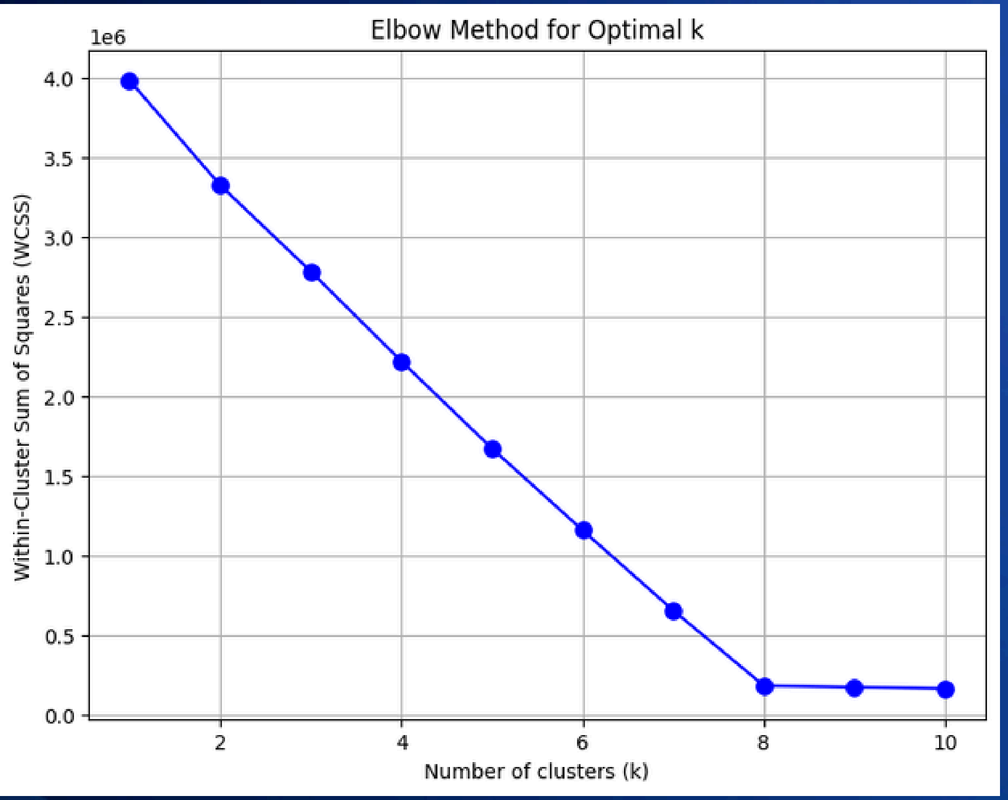


# CUSTOM CNN VISUALIZATION

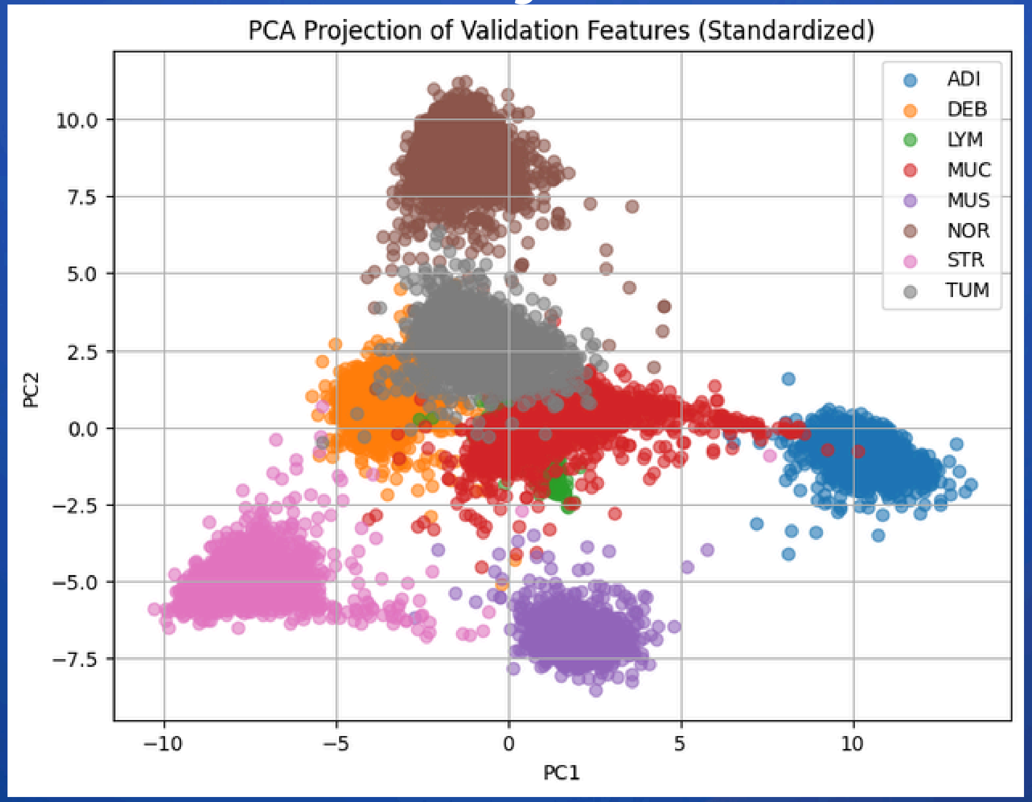
## T-SNE



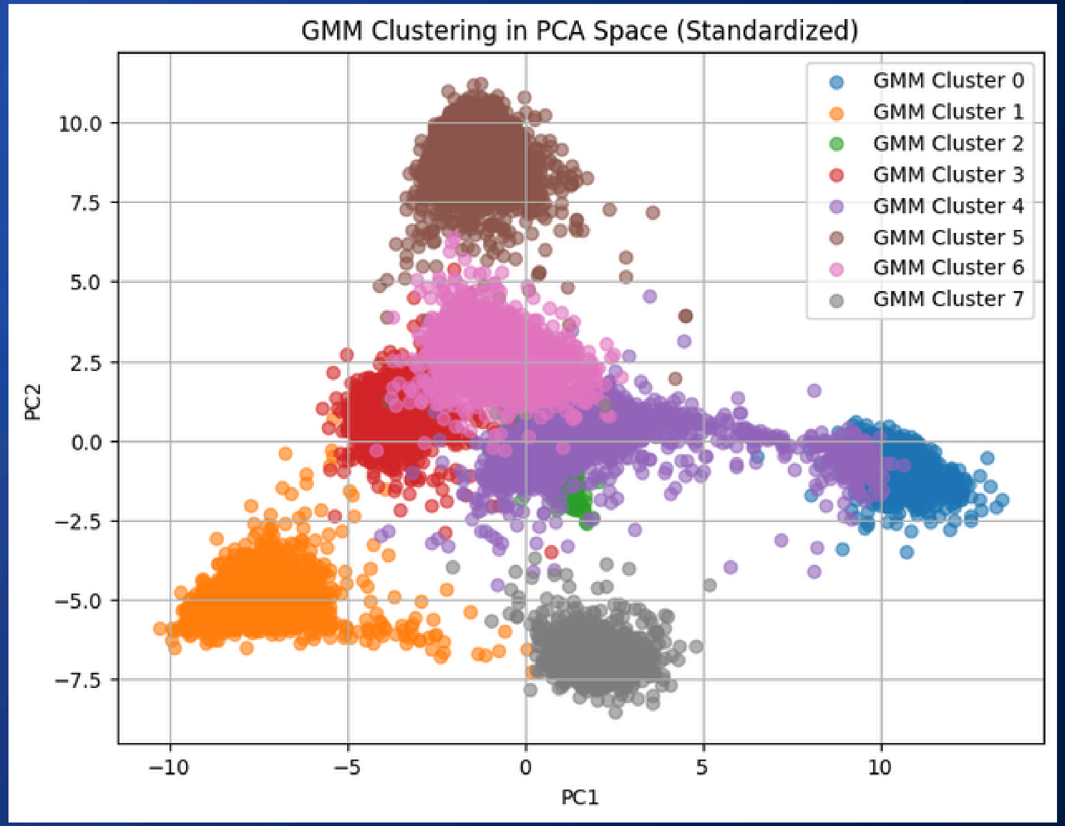

## Elbow




## PCA Projection

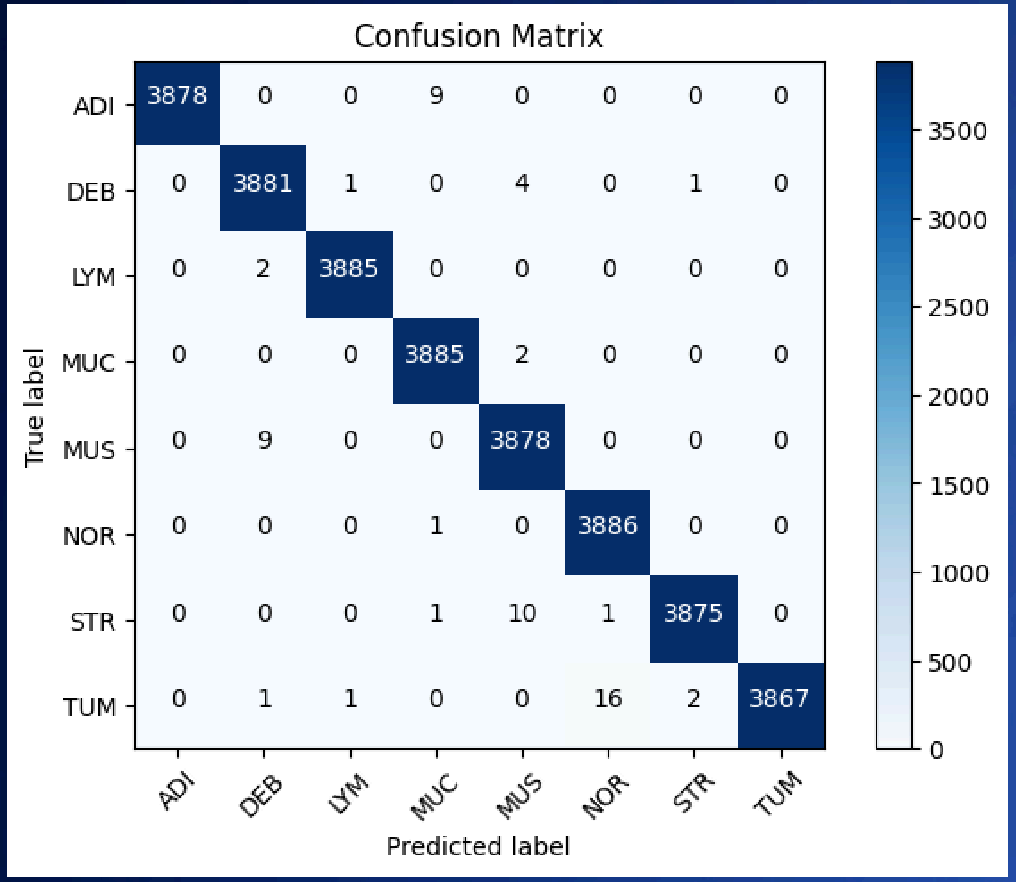



## GMM Clustering

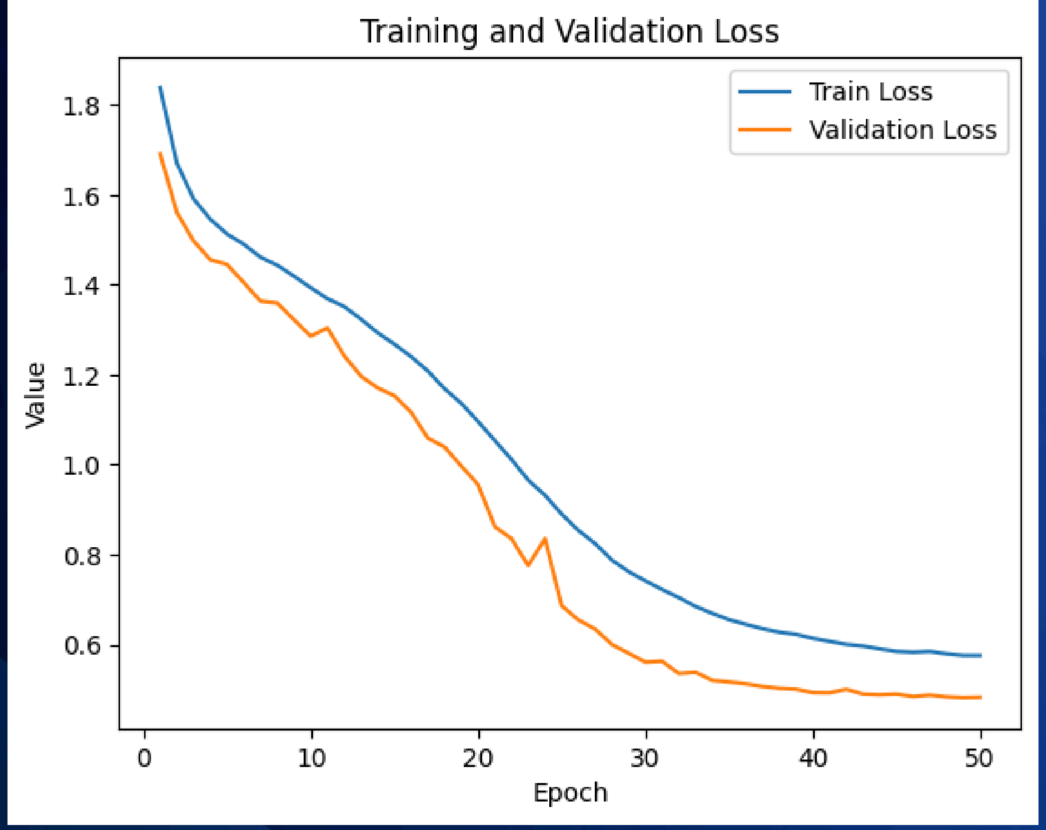


# CUSTOM CNN WITH CUSTOM POOLING

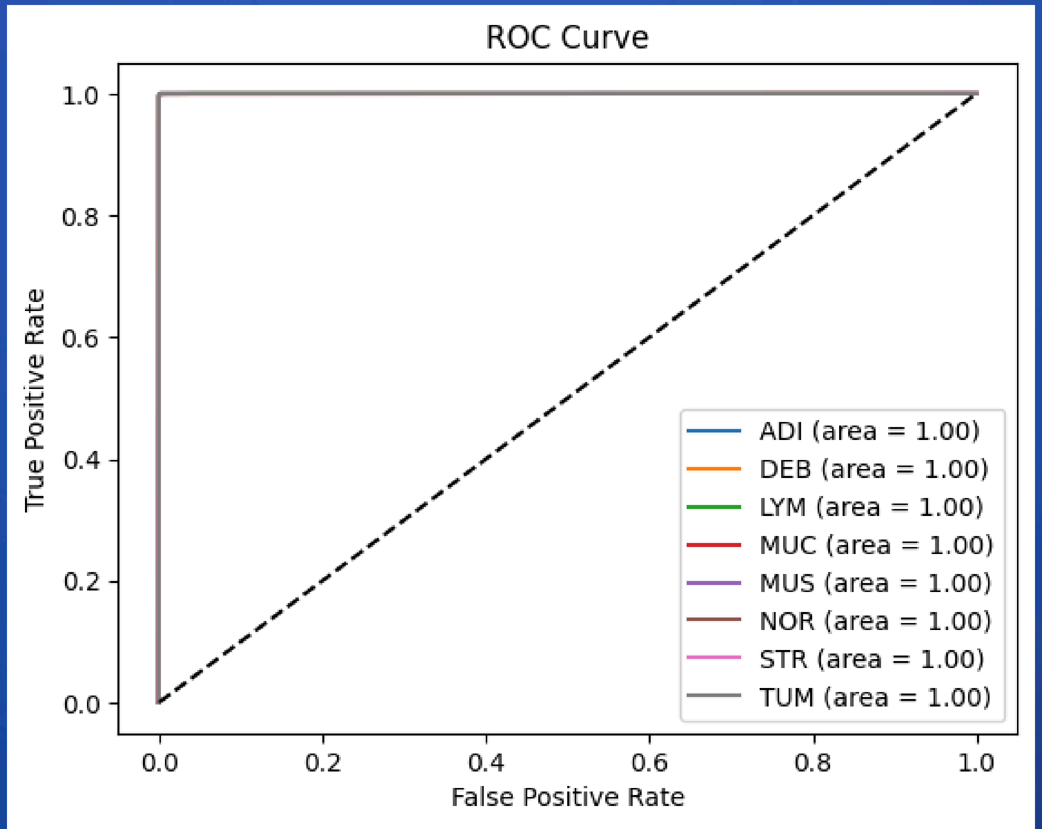
## Confusion Matriix



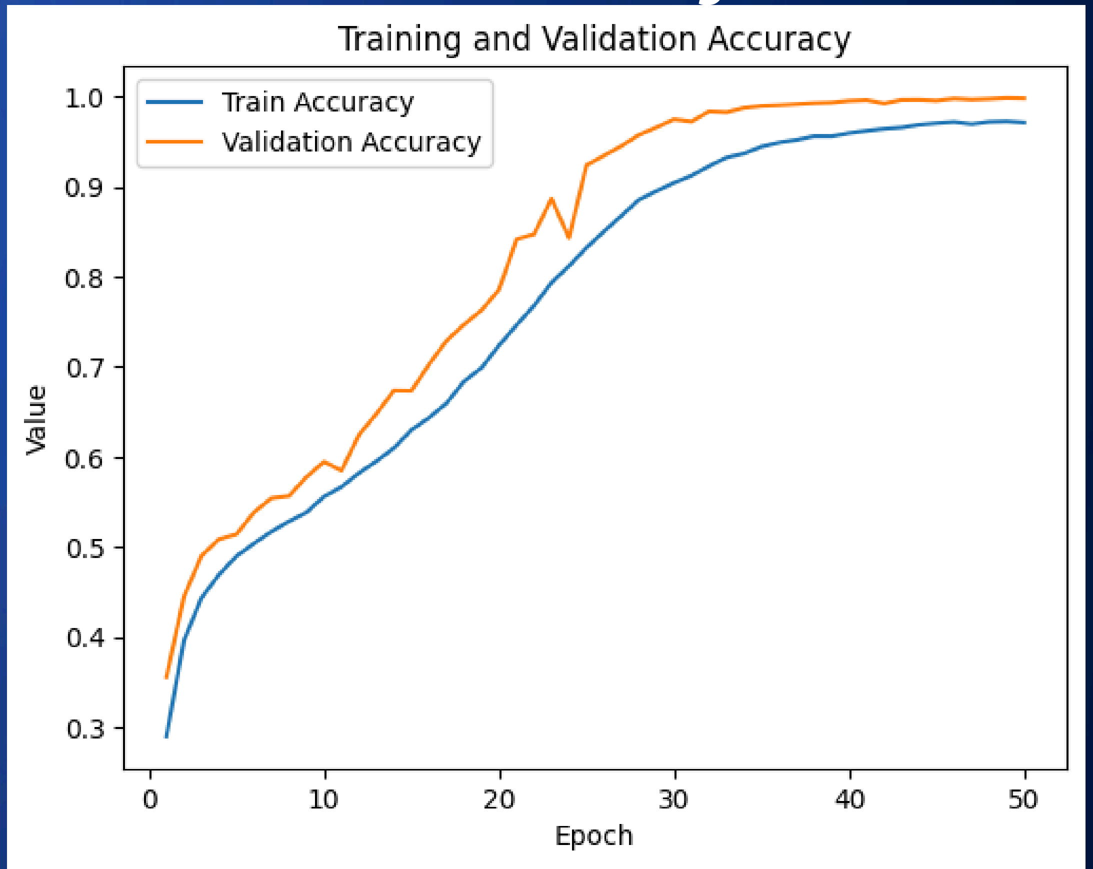

## Loss




## ROC CURVE



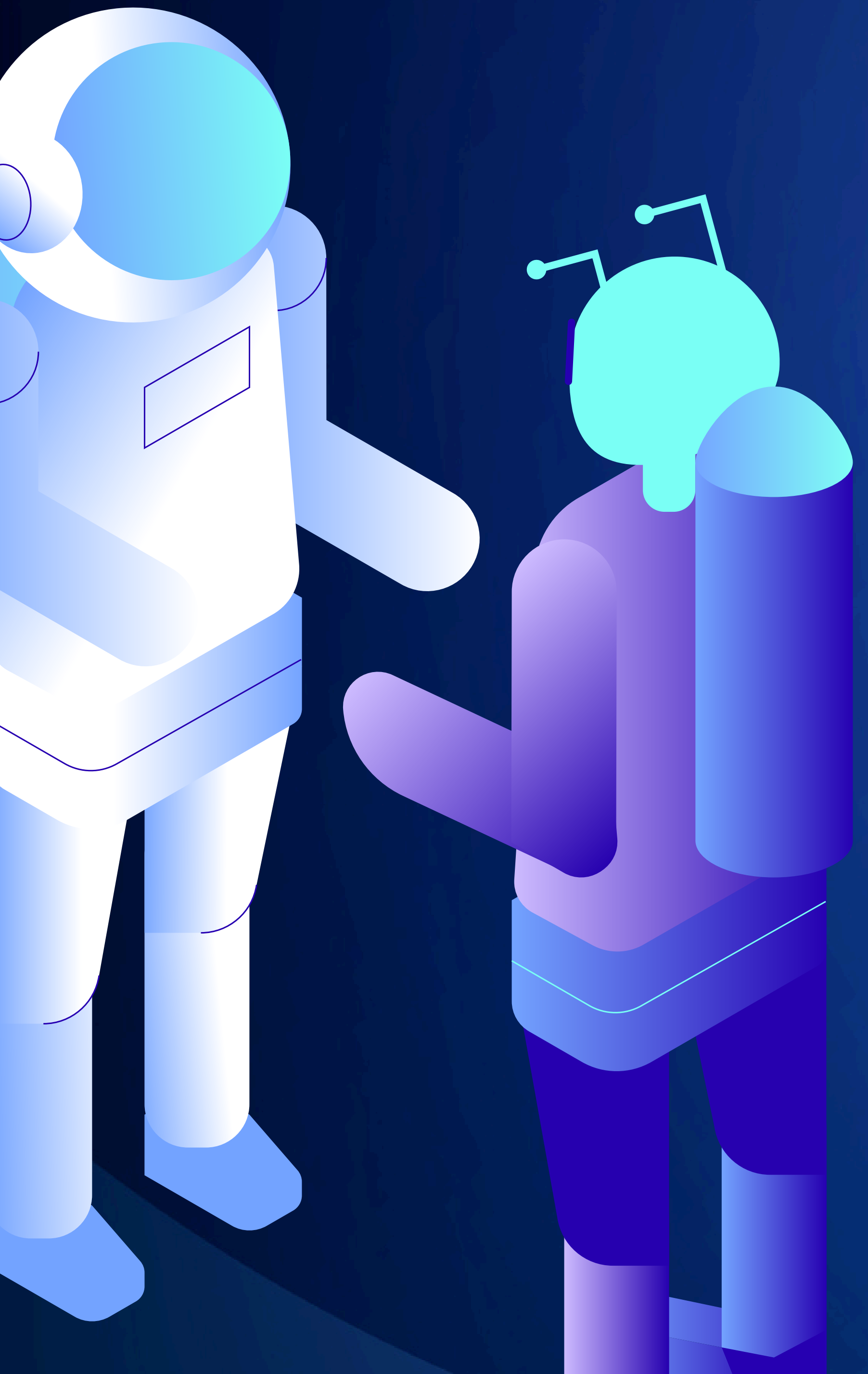

## Accuracy



# DISCUSSION & COMPARISON

- No work on this dataset found for comparison

**Our Work**



| Aspects | Details |
|---|---|
| Dataset | Gastric Cancer Histopathology Tissue Image Dataset (GCHTID) – 31,096 images from Harbin Medical University |
| Pretrain models | EfficientNetB3 (efficient and accurate), ResNet (deep and stable), DenseNet (dense connections for rich features) |
| Customs | Two custom architectures designed .Special pooling layers used to improve feature extraction . |
| Outcome | Strong classification performance on a novel, diverse dataset ; foundation for future gastric cancer AI research |

# CONCLUSION

- Custom CNN and Custom Pooling models achieved perfect accuracy (100%), outperforming pre-trained models.
- DenseNet201 (98%) and EfficientNetB3 (94%) showed strong performance, validating their medical imaging effectiveness.
- Results highlight the efficiency, accuracy, and scalability of the proposed models for gastric cancer detection.
- The approach supports reliable and automated diagnosis, suitable for real-world clinical use.

# FUTURE WORK

- Expand dataset size using multi-center collaborations for better generalization.
- Enhance image preprocessing with advanced stain normalization and augmentation.
- Explore cutting-edge architectures like Vision Transformers for improved accuracy.
- Optimize models for faster inference and lower computational cost.
- Integrate explainable AI techniques to increase clinical trust and transparency.
- Conduct extensive validation in real clinical environments to ensure robustness.

# REFERENCES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THANK YOU