CS316

DETECTION OF RETINOPATHY OF PREMATURITY

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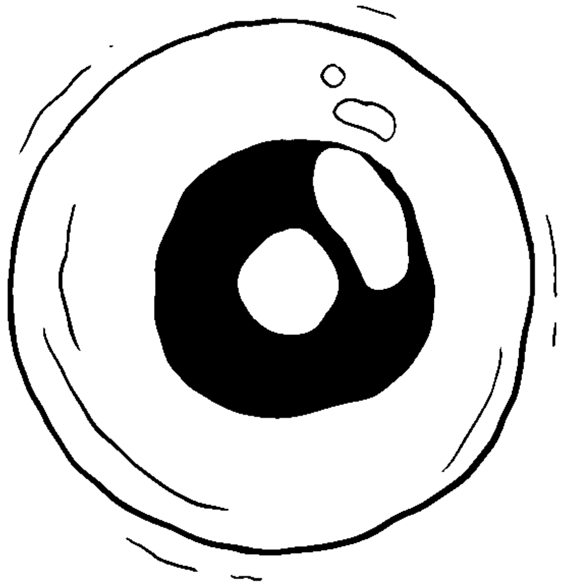
Research Question

Given a set of retinal images of a patient, classify the severity of ROP in the patient.



Purpose

CHALLENGES

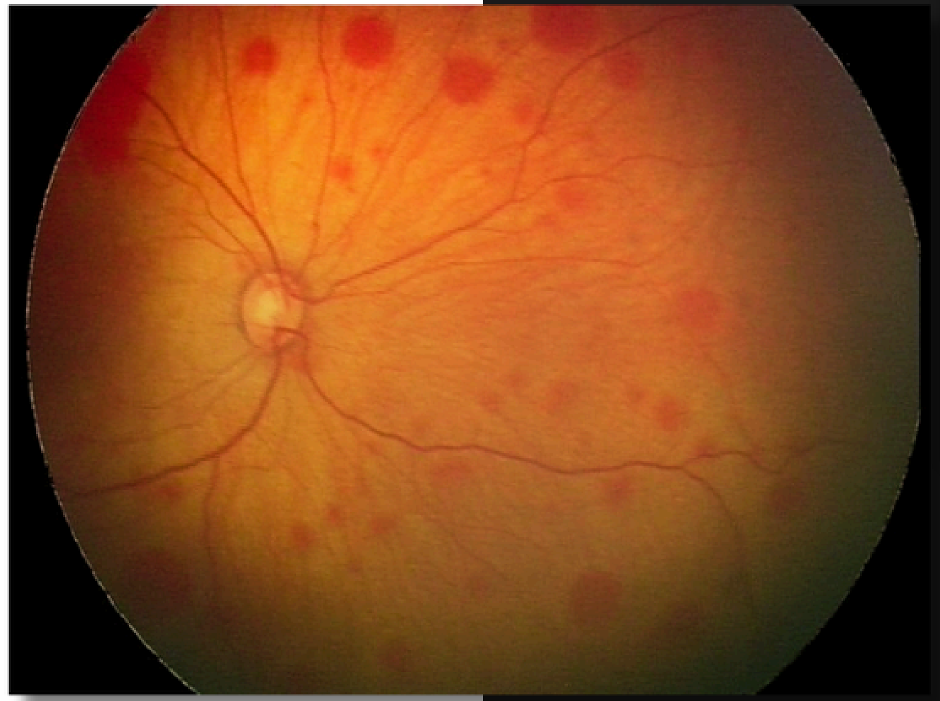
- Requires weekly/bi-weekly checks, causing infant distress (fluctuating heart rate, blood pressure, feeding intolerance, bradycardia).
- Overburdens medical staff, increasing time and cost.

BENEFITS

- Processes large volumes of images efficiently, enabling scalable and faster screening.
- Reduces manual effort, costs, and risks of misdiagnosis.

Dataset

- Our dataset consists of 6004 retinal images.
- These 6004 retinal images are taken from 188 infants, most of whom are premature infants.
- Retinal images were taken at University Hospital Ostrava, Czech Republic.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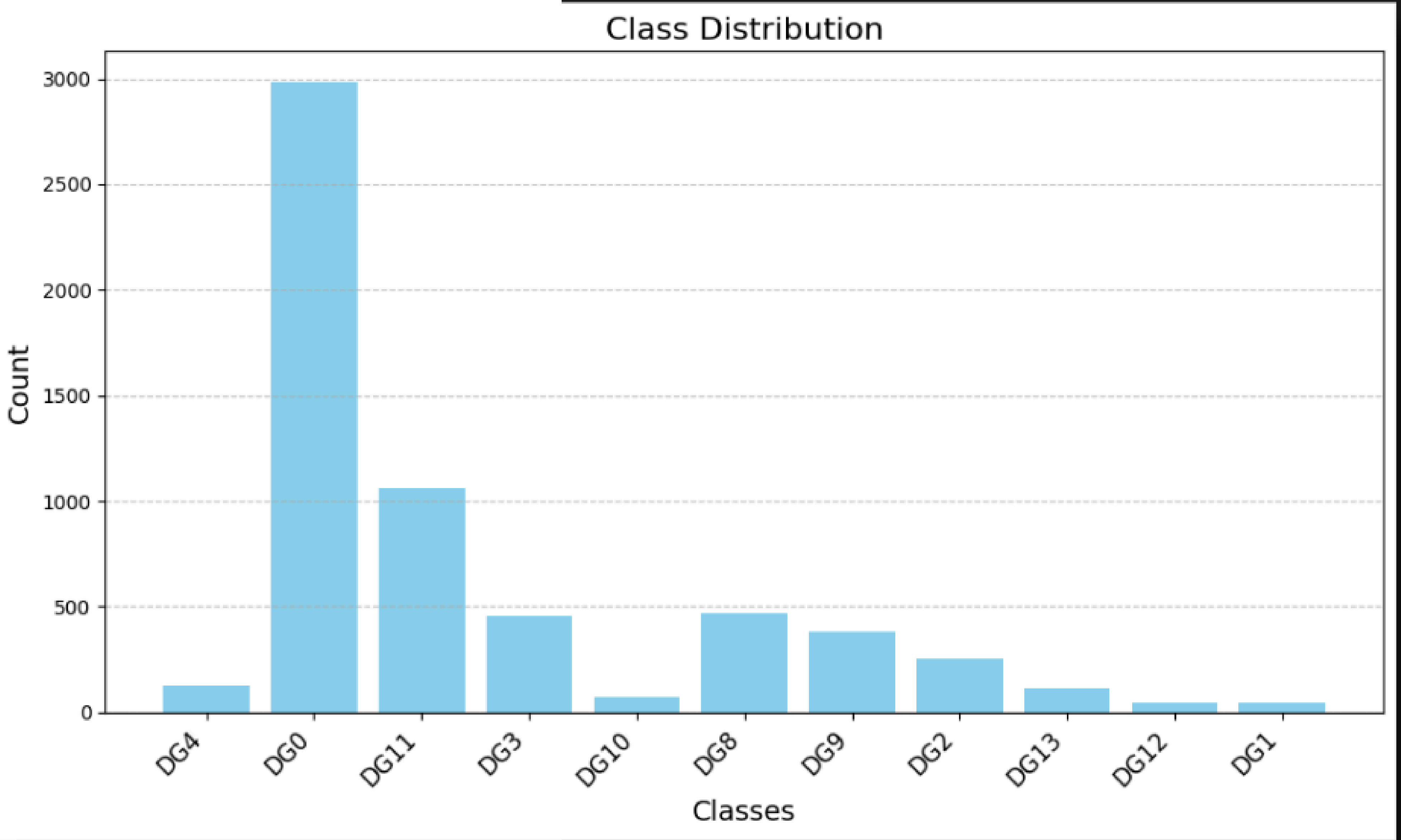


Diagnoses Codes

Diagnosis Code (DG)	ROP Stage
0	NO ROP
1	ROP 0
2	ROP 1
3	ROP 2
4	ROP 3
5	ROP 4A
6	ROP 4B
7 till 12	ROP 5 (+ additional elements)

- Our dataset consists of 6004 Each patient has multiple retinal images in multiple post conceptual ages.
- Each image is in the format: Patient's ID_sex_gestational age_(GA)_birth_weight_(BW)_postconceptual_age_(PA)_diagnosis_code_(DG)_plusform_(PF)_device(D)__series_(S)_image number.jpg.
- Diagnosis Code (DG) will be used to detect and classify ROP into it’s stages.

Our models

Convolutional Neural Networks

We used the base model for CNNs with custom layers just like we did in labs.

Efficient-Net

Followed the approach of our CNN model.

Lightweight ResNet Model

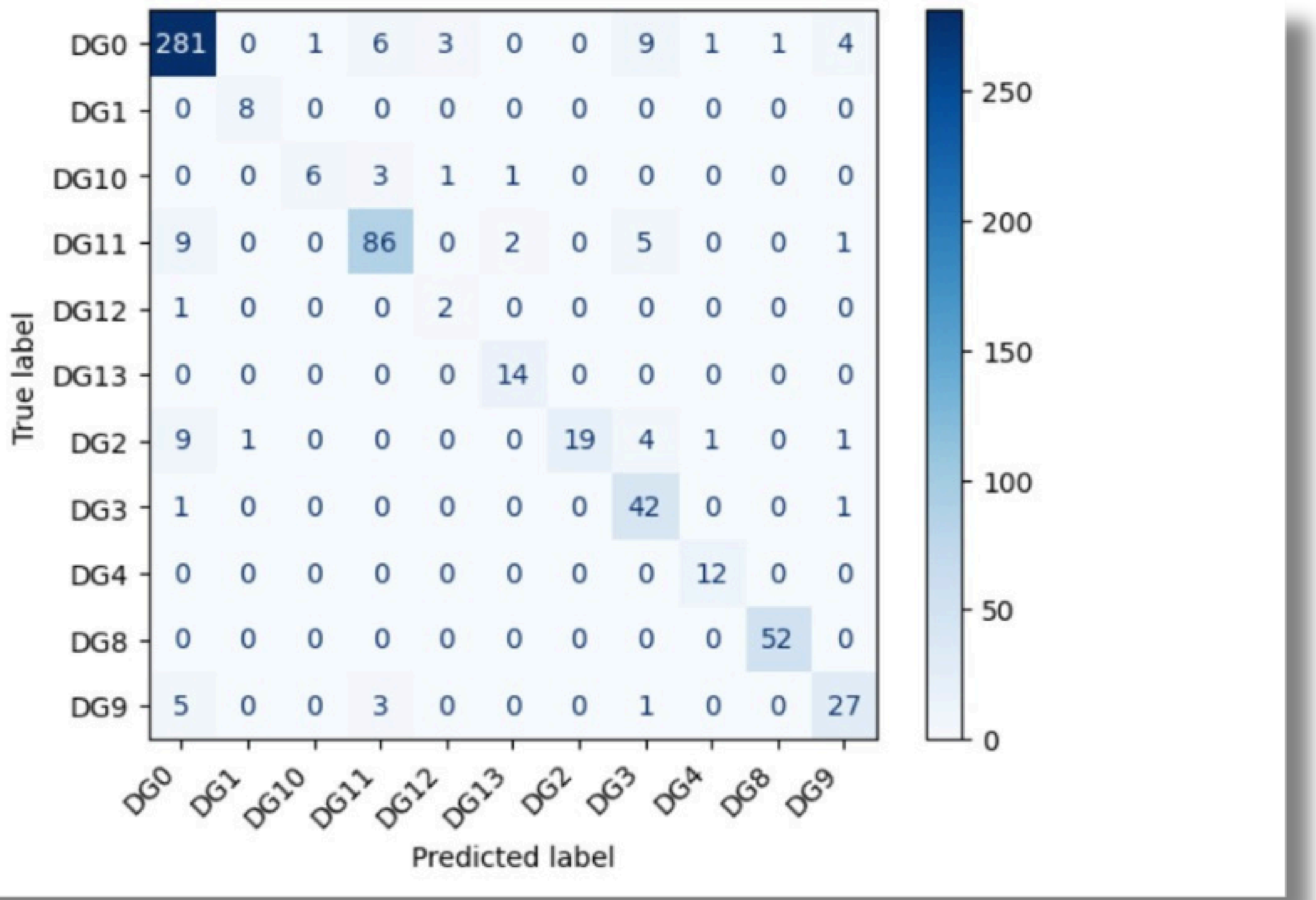
Followed the approach of our CNN model with res-net architecture.

Hyper parameters

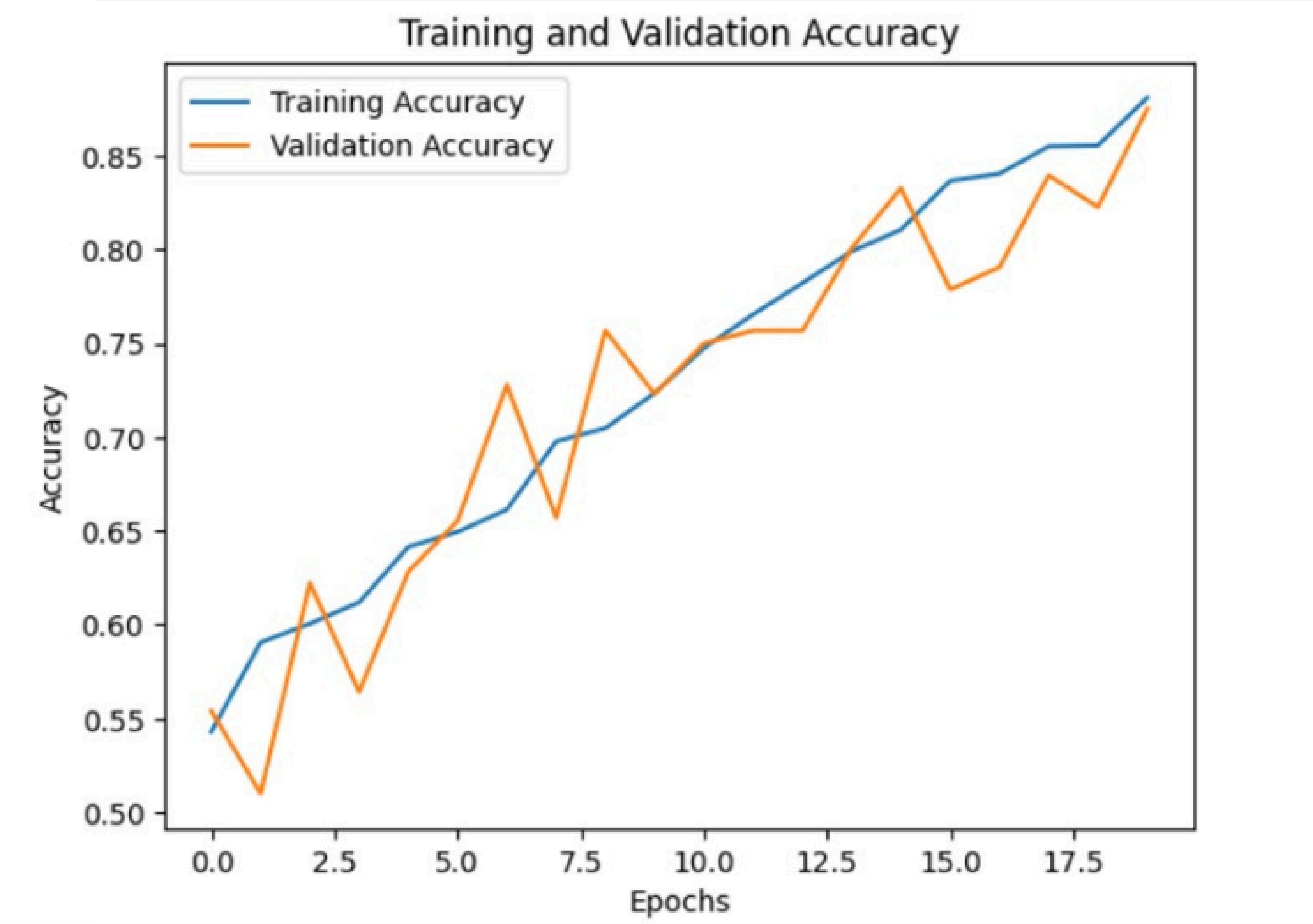
Hyperparameter	Value
Epochs	20
Batch size	16/32
Learning rate	0.001
Optimizer	Adam
Loss function	Sparse Categorical Cross entropy
Early stopping patience	5

Efficient Net Results

Confusion Matrix

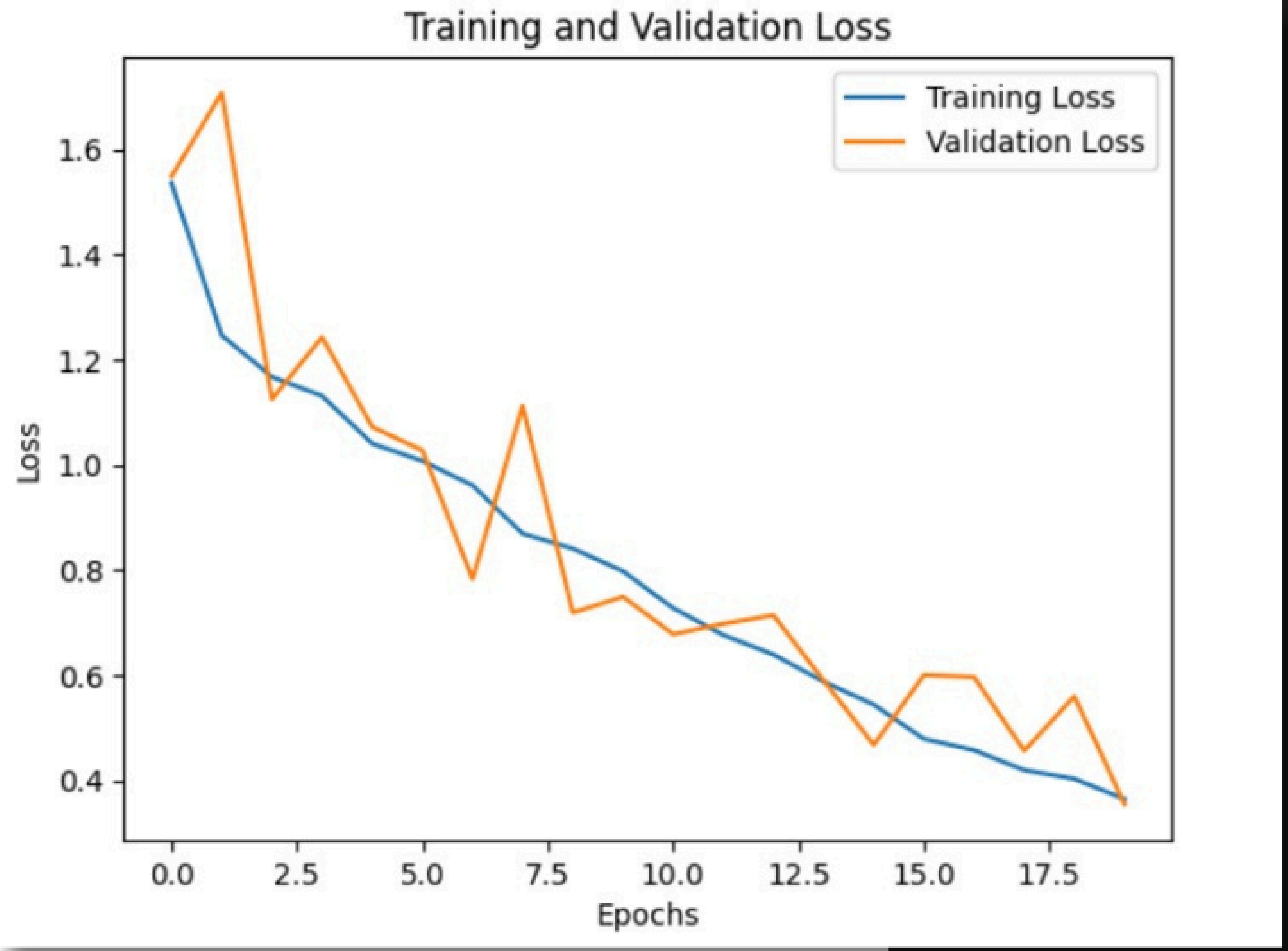


Accuracy



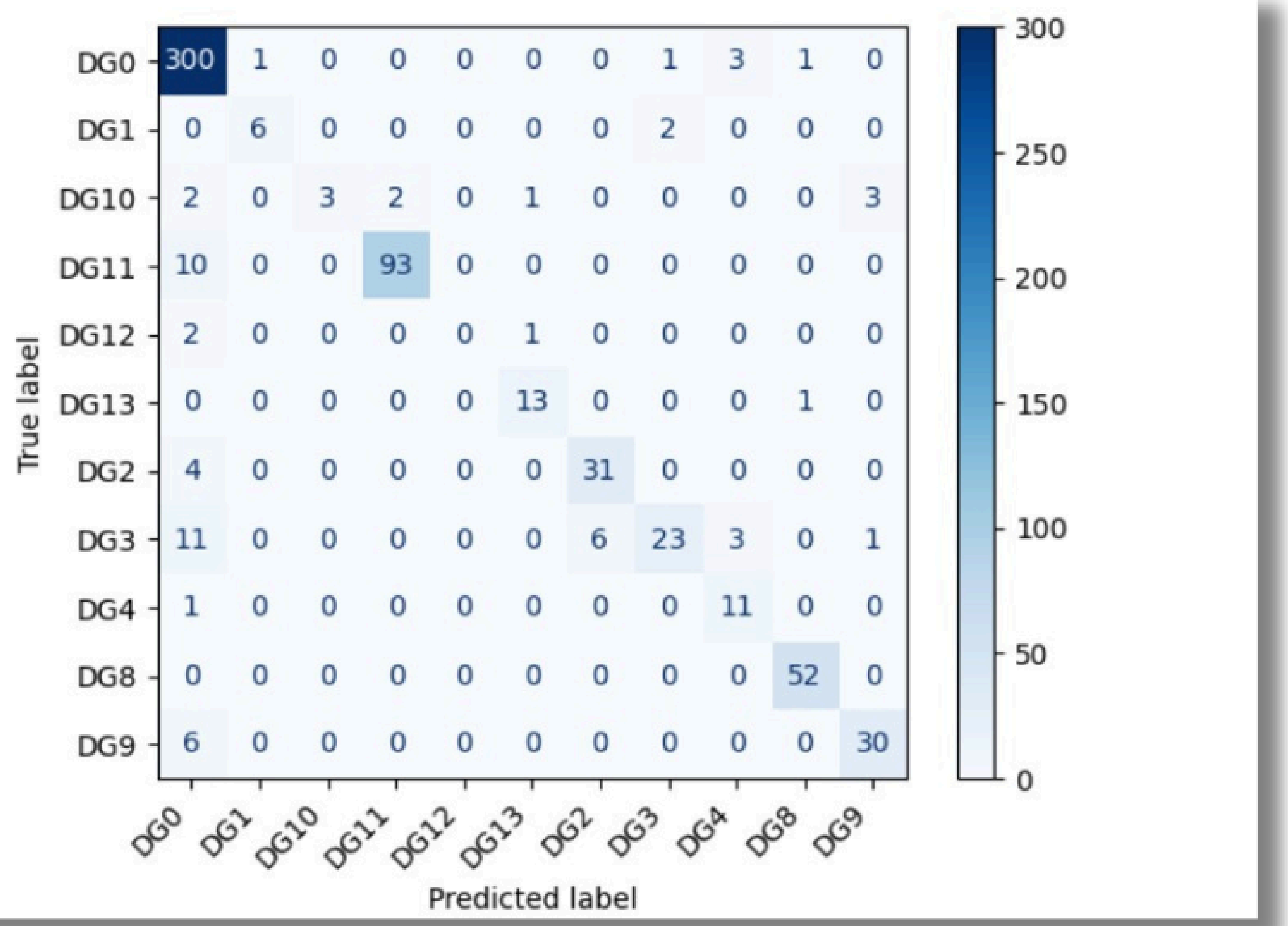
Efficient Net Results

Loss



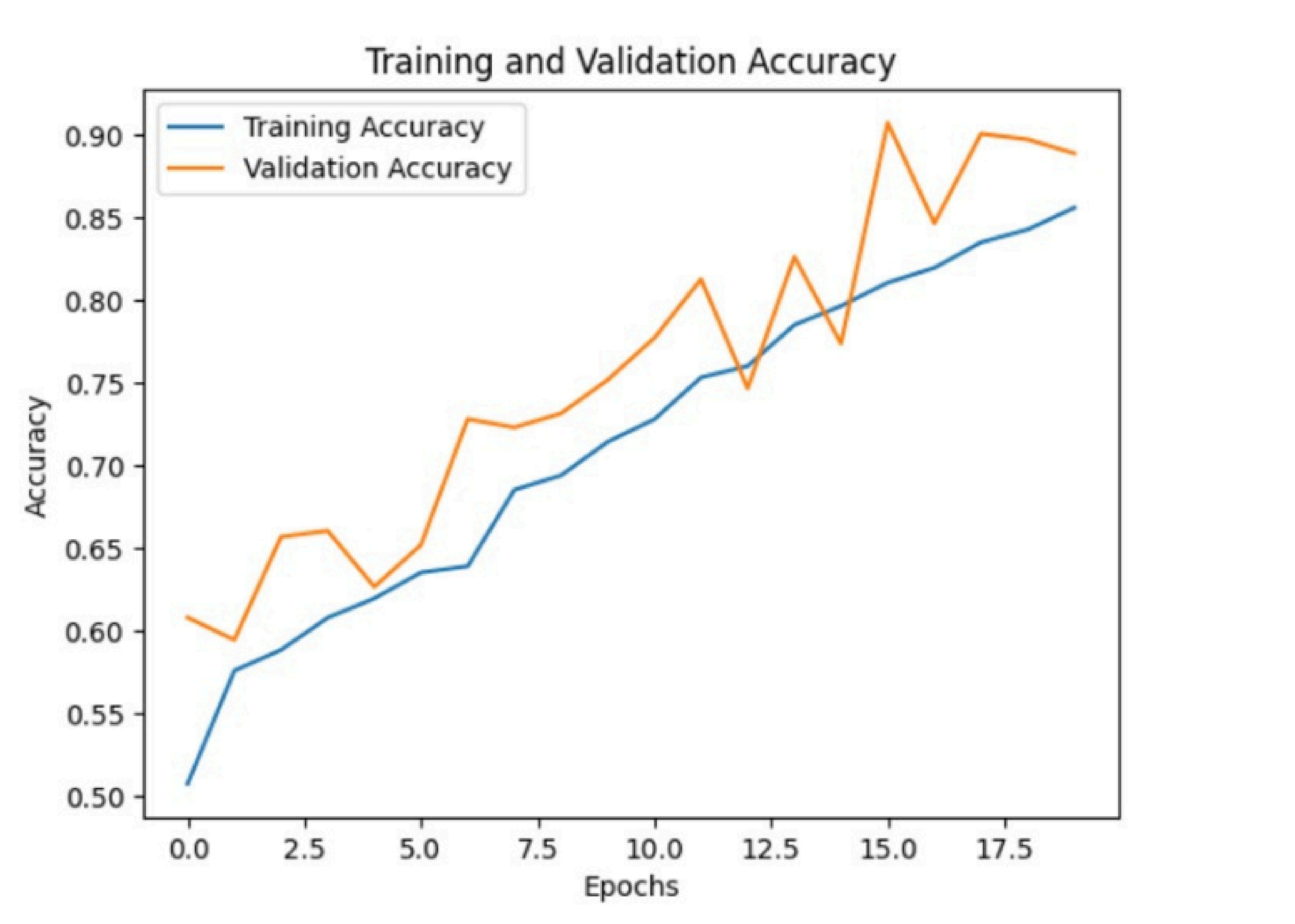
Res Net Results

Confusion Matrix



	DG0	DG1	DG10	DG11	DG12	DG13	DG2	DG3	DG4	DG8	DG9
DG0	300	1	0	0	0	0	0	1	3	1	0
DG1	0	6	0	0	0	0	0	2	0	0	0
DG10	2	0	3	2	0	1	0	0	0	0	3
DG11	10	0	0	93	0	0	0	0	0	0	0
DG12	2	0	0	0	0	1	0	0	0	0	0
DG13	0	0	0	0	0	13	0	0	0	1	0
DG2	4	0	0	0	0	0	31	0	0	0	0
DG3	11	0	0	0	0	0	6	23	3	0	1
DG4	1	0	0	0	0	0	0	0	11	0	0
DG8	0	0	0	0	0	0	0	0	0	52	0
DG9	6	0	0	0	0	0	0	0	0	0	30

Accuracy

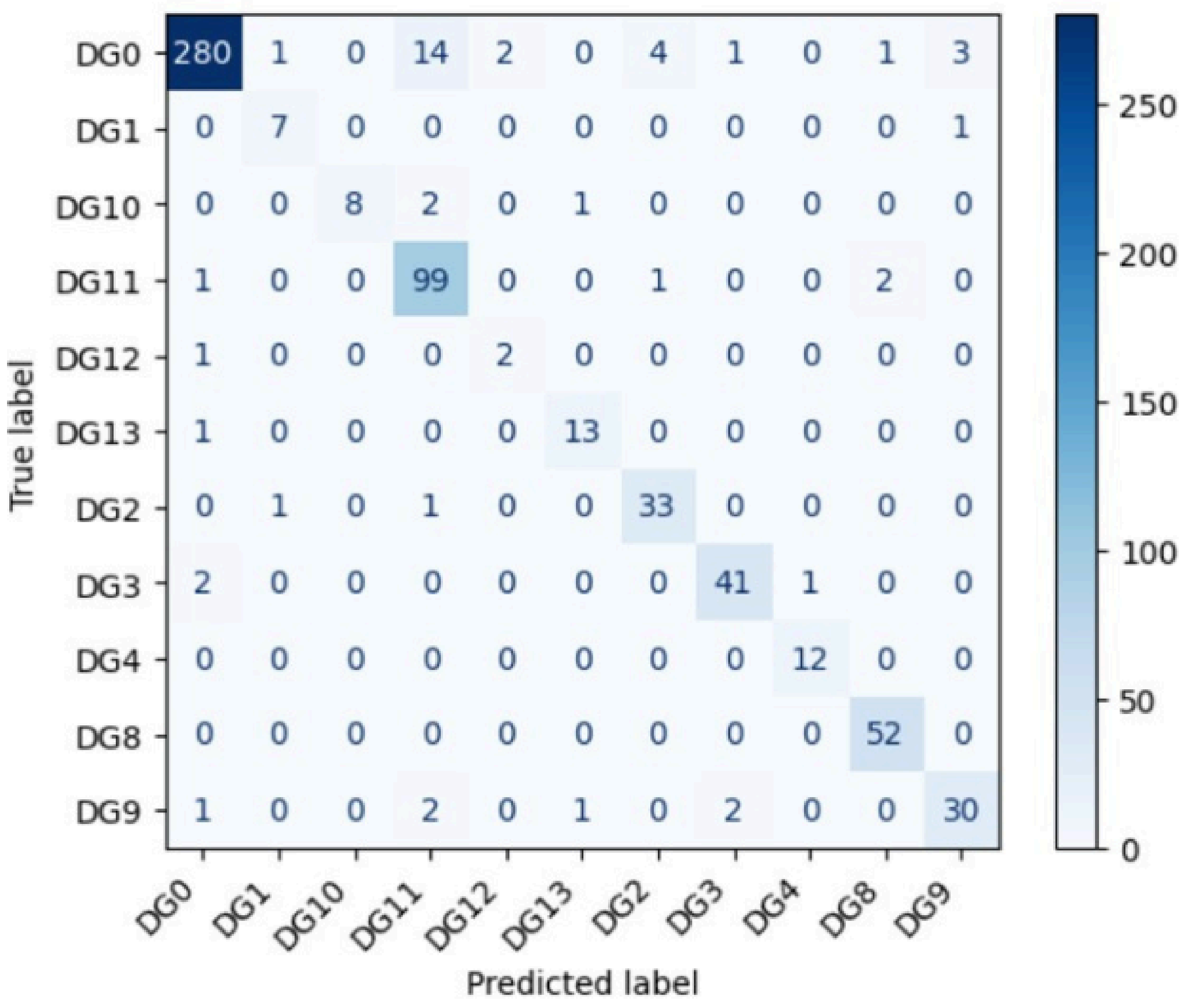


Res Net Results

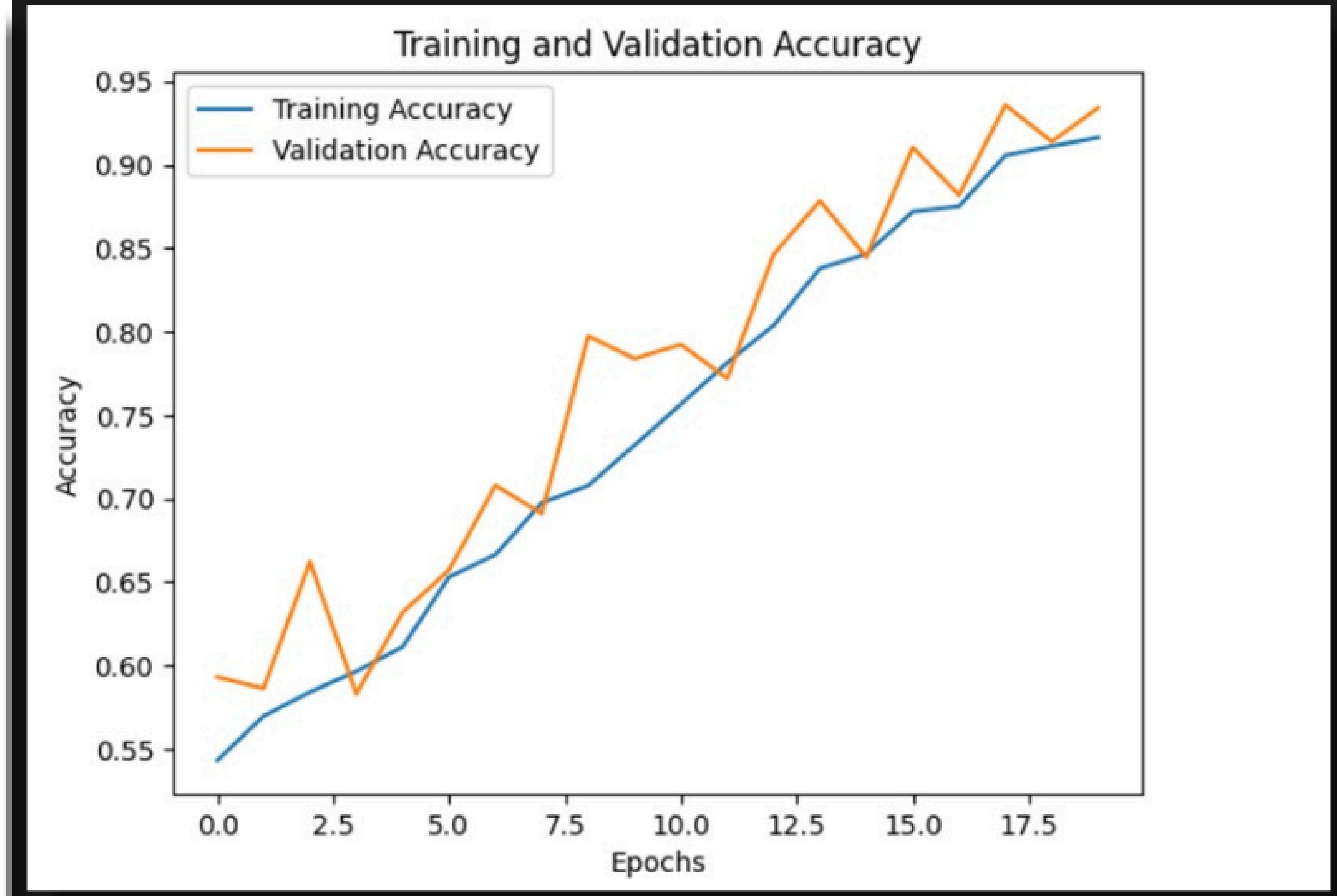
Loss

CNN Results

Confusion Matrix



Accuracy



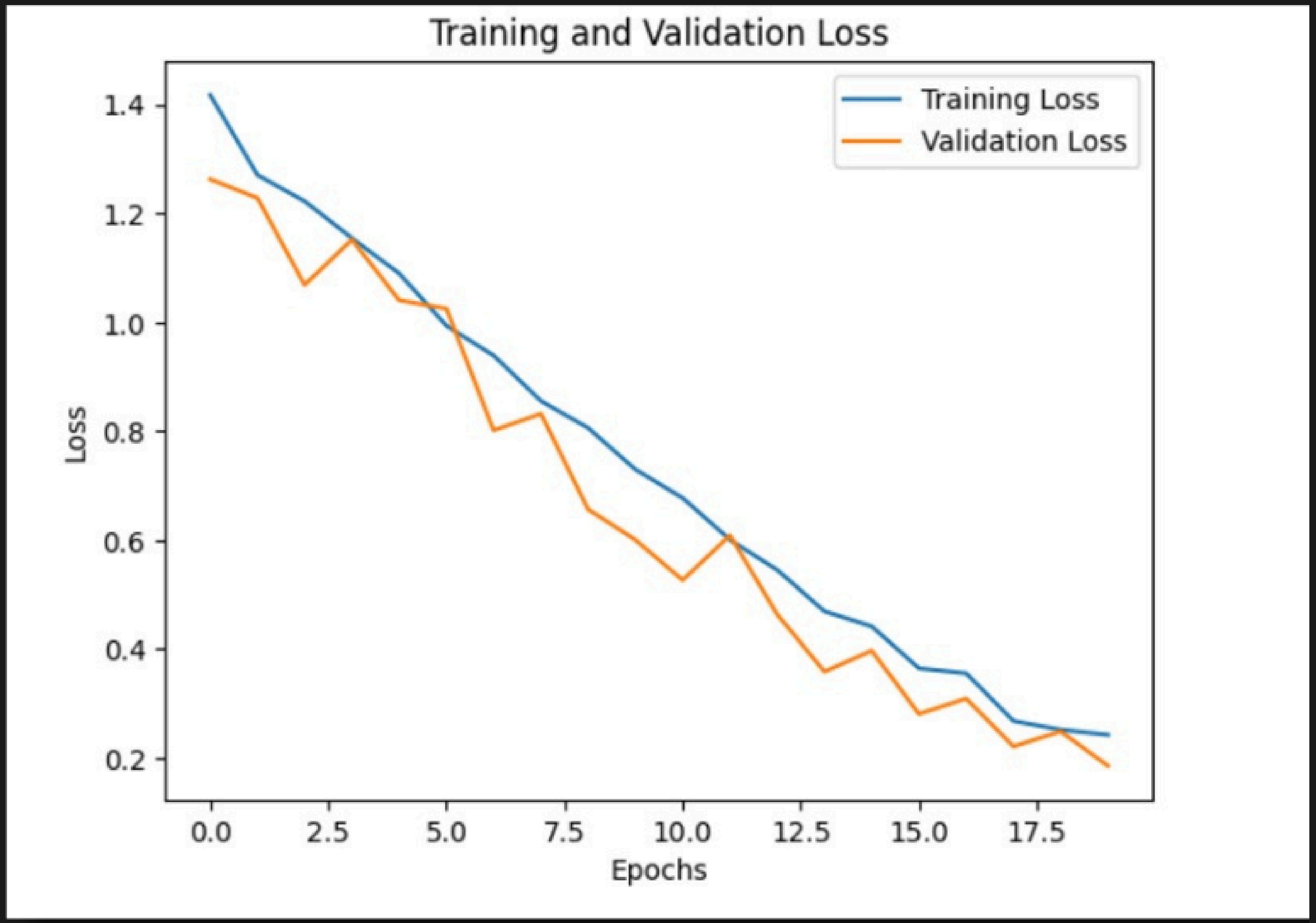
CNN Results

Model Summary

Layer (type)	Output Shape	Param #
resizing_2 (Resizing)	(None, 256, 256, 3)	0
rescaling_2 (Rescaling)	(None, 256, 256, 3)	0
conv2d_4 (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d_4 (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_5 (Conv2D)	(None, 125, 125, 64)	18,496
max_pooling2d_5 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_6 (Conv2D)	(None, 60, 60, 64)	36,928
max_pooling2d_6 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_7 (Conv2D)	(None, 28, 28, 64)	36,928
max_pooling2d_7 (MaxPooling2D)	(None, 14, 14, 64)	0
flatten_1 (Flatten)	(None, 12544)	0
dense_2 (Dense)	(None, 64)	802,880
dense_3 (Dense)	(None, 11)	715

Total params: 896,845 (3.42 MB)
Trainable params: 896,843 (3.42 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 2 (12.00 B)

Loss



Final Results

MODELS	Accuracy	Loss
CNN	94.07%	0.17
Lightweight ResNet Model	90.06%	0.29
EfficientNet	90.03%	0.26

Comparision

Our Results:

Model	Accuracy	Loss	Dataset Size
CNN	94.07%	0.17	6,004 images
ResNet	90.06%	0.29	6,004 images
EfficientNet	90.03%	0.26	6,004 images

Literature Review:

Model	Type/Usage	Accuracy	Dataset Size
ResNet	OC-Net (Identifies ROP)	53.8%	7,033 images
	SE-Net (Classifies Severity)	46.6%	7,033 images
Inception-CNN	General ROP Detection	97.3%	7,000 images
VGG19	Severity Classification	98.8%	7,000 images
SVM + Deep Learning	Combines Image and Clinical Data	95%	7,000 images

Future Milestones

1. Implement more robust augmentation techniques.
2. Develop explainable AI tools for clinical adoption.
3. Test the model on external datasets to validate generalizability.

Data Augmentation:

- Geometric, color, noise Augmentations
- larger dataset
- Mixup- Blend multiple images to increase generalization.

- Incorporation of Clinical Data
- Clinical Decision Support System (CDSS)

- External Validation
- Fine-tuning
- Ensemble Learning: Use predictions from multiple models (ResNet, EfficientNet, CNN) and apply majority voting or weighted averaging.

Q & A

Thank you.

References

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