JRL780 Assignment - II

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Drive Link for Models

1 Base Line Models

I have used ResNet18 and VGG16 as base models, employing Cross Entropy loss and the Adam optimizer with a learning rate of 0.0001 for both. Each model was trained for 25 epochs. Below are the baseline accuracies, losses, and testing results on the PCam dataset.

1.1 Training Accuracies and Losses

Table 1: Comparison of Training Accuracies and Losses at Different Epochs

Model	10th Epoch		20th Epoch		25th Epoch	
	Accuracy	Loss	Accuracy	Loss	Accuracy	Loss
ResNet18	99.42	0.0166	99.70	0.0087	99.75	0.0075
VGG16	99.27	0.0224	99.48	0.0173	99.60	0.0177

1.2 Validation Accuracies and Losses

Table 2: Comparison of Validation Accuracies and Losses at Different Epochs

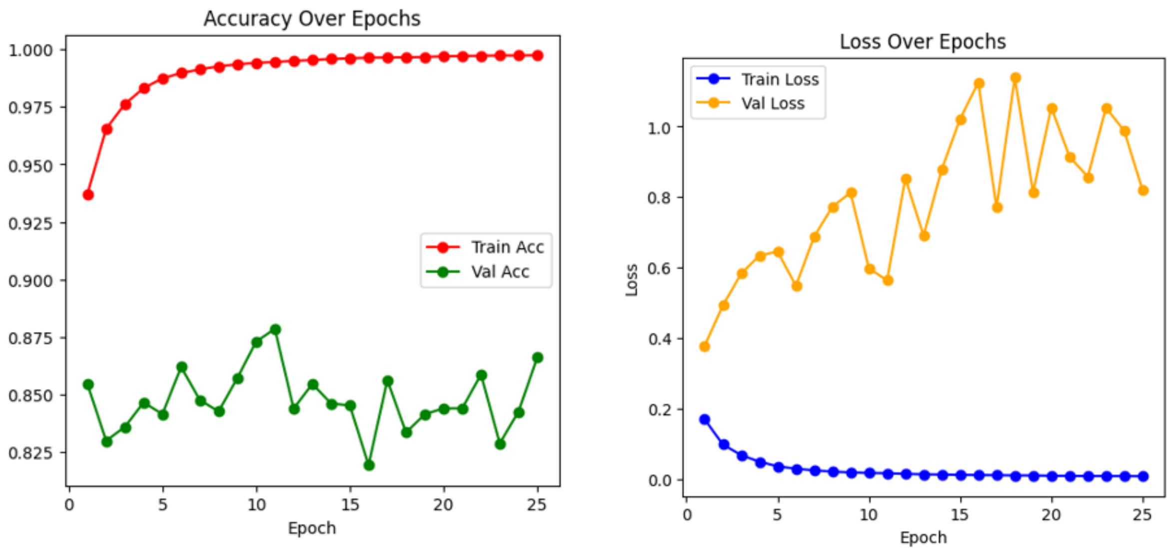
Model	10th Epoch		20th Epoch		25th Epoch	
	Accuracy	Loss	Accuracy	Loss	Accuracy	Loss
ResNet18	87.29	0.5979	84.38	1.0545	86.59	0.8204
VGG16	84.19	1.2249	79.16	1.9401	80.92	1.4010

1.3 Testing Results

Table 3: Testing Results: Accuracy, Precision, Recall, F1 Score

Model	Accuracy	Precision	Recall	F1 Score
ResNet18	82.85	0.9667	0.6802	0.7985
VGG16	80.07	0.9829	0.6118	0.7542

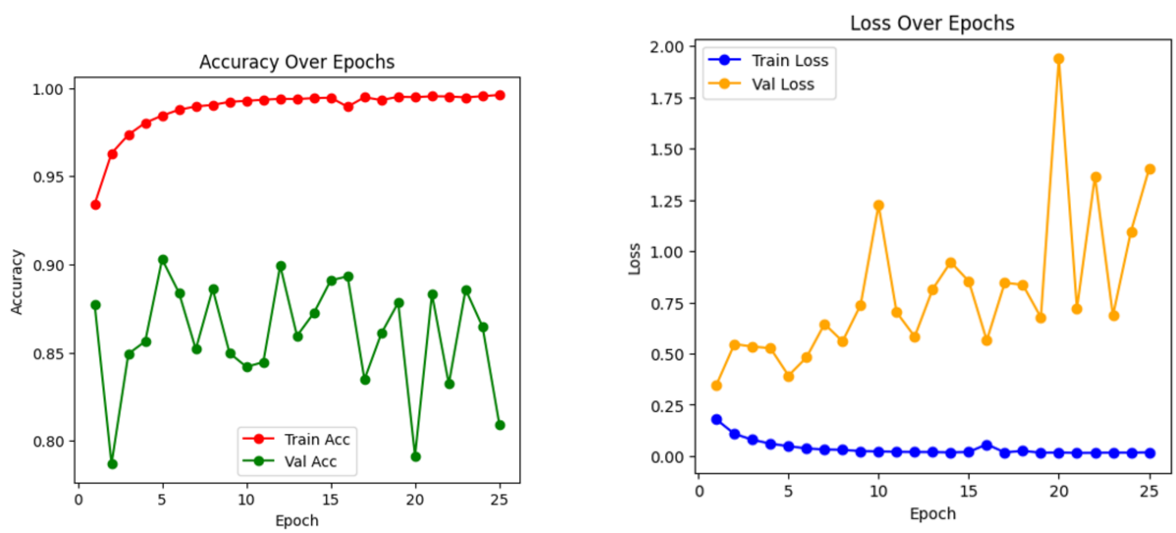
2 Training Performance Plots



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 1: Accuracy and Loss for ResNet18



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 2: Accuracy and Loss for VGG16

3 Part I: Ablation Studies

Considering the baseline models, I have analyzed the effect of each parameter.

ResNet Variations

1)Learning rates

Training and Validation Accuracies

Table 4: Training Accuracies for ResNet Variations

Learning Rate	10th Epoch	20th Epoch	25th Epoch
1e-2	96.77	98.41	98.70
1e-3	98.85	99.49	99.60
1e-4	99.52	99.71	99.75
1e-5	99.56	99.79	99.82

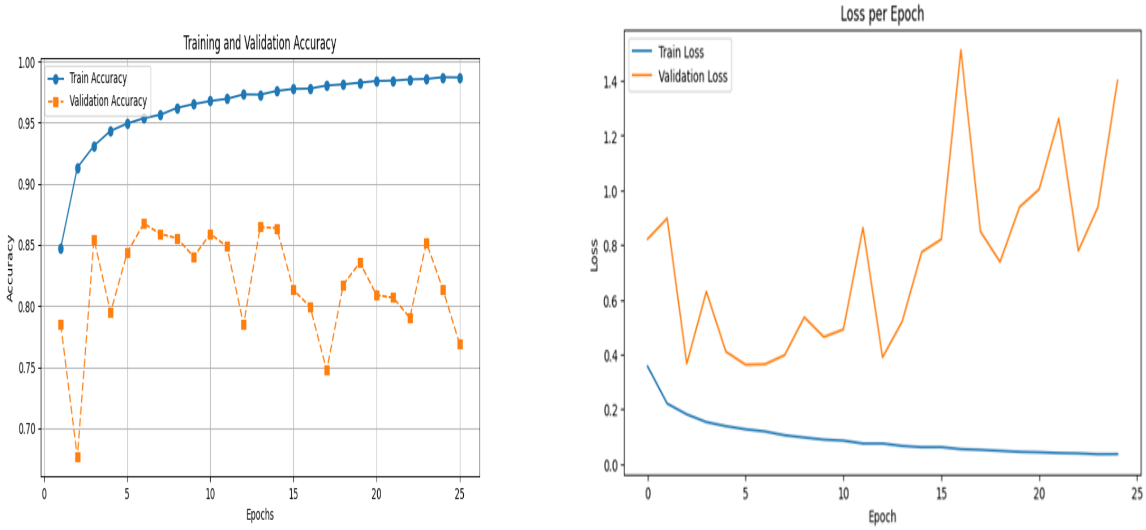
Table 5: Validation Accuracies for ResNet Variations

Learning Rate	10th Epoch	20th Epoch	25th Epoch
1e-2	85.90	80.89	76.88
1e-3	84.71	79.09	81.92
1e-4	86.92	84.61	86.22
1e-5	84.11	84.21	84.48

Testing Performance Metrics

Table 6: Testing Performance Metrics for ResNet Variations

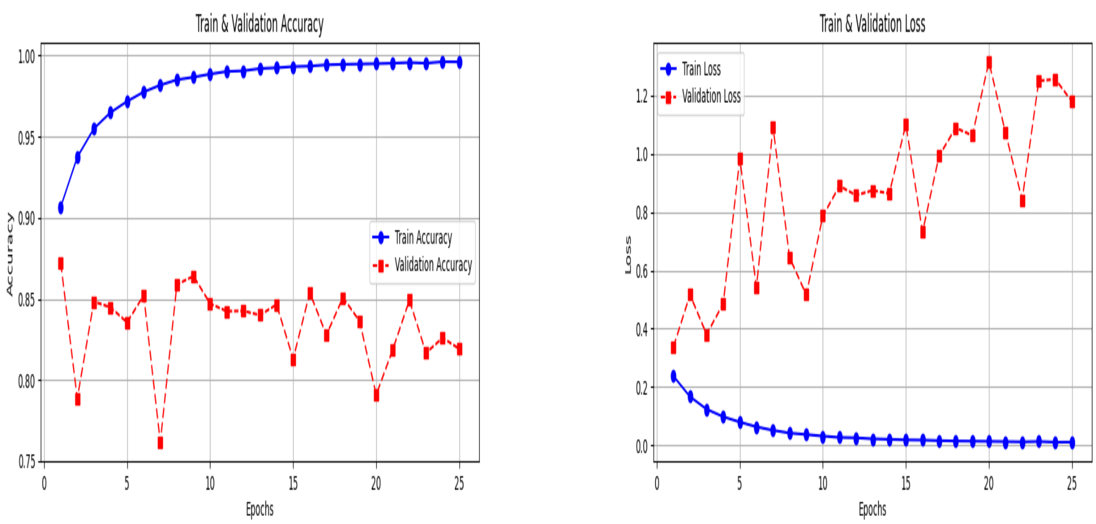
Learning Rate	Accuracy	Precision	Recall	F1-score
1e-2	75.12	0.9497	0.5303	0.6806
1e-3	79.46	0.9673	0.6096	0.7479
1e-4	82.85	0.9667	0.6802	0.7985
1e-5	80.82	0.9557	0.6461	0.771



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 3: Accuracy and Loss for ResNet18 LR=0.01



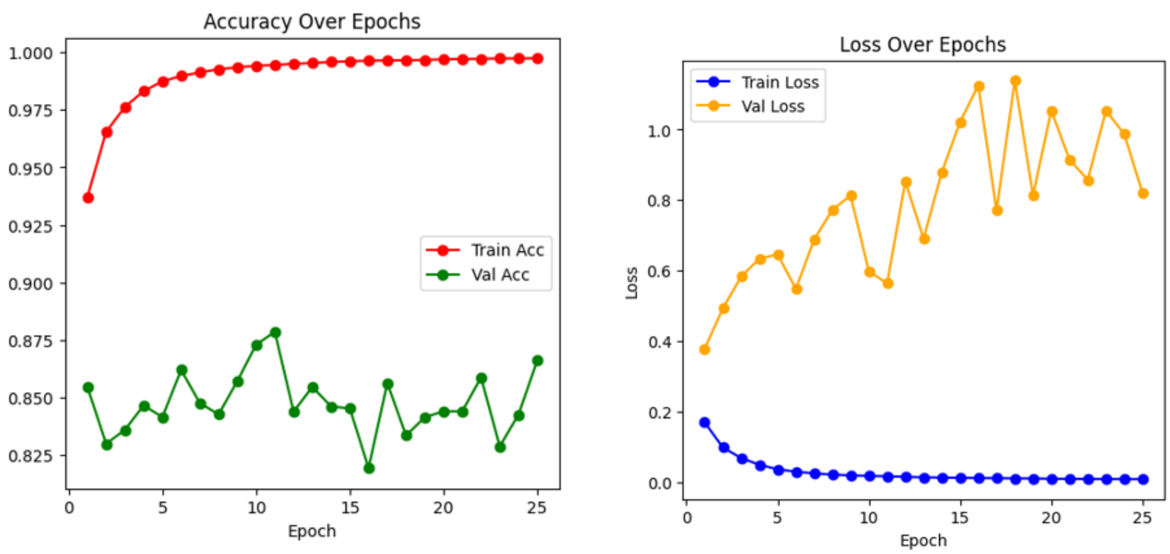
(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 4: Accuracy and Loss for ResNet18 LR=0.001

Observation:

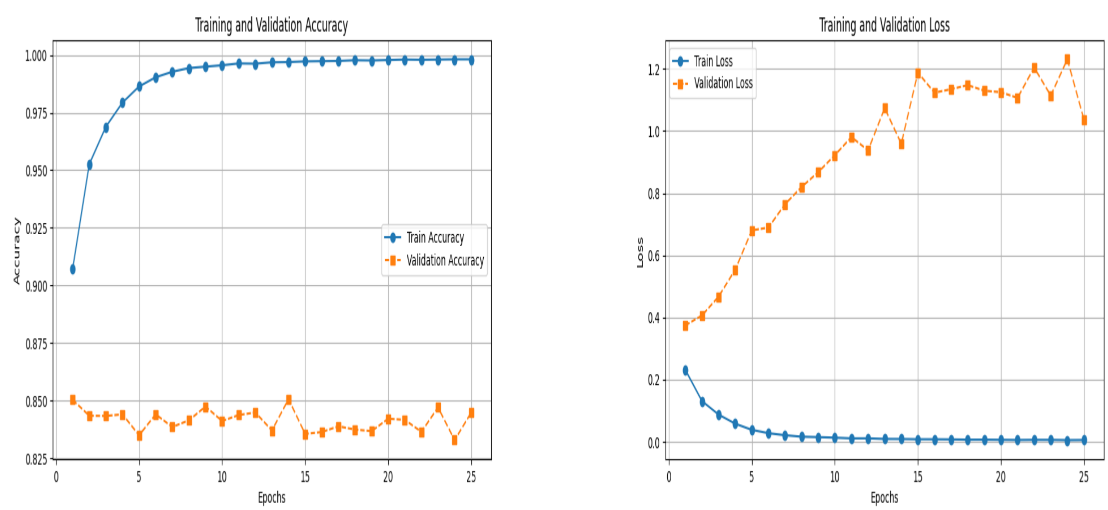
1.Higher learning rate like 1e-2 and 1e-3 may have caused instability or overshooting of local optimal minima,leading to poor convergence.
2.In the case of lower learning rate like 1e-5, the training might have been too slow,getting stuck in local minima or failing to learn meaningful features.
3.Learning rate 1e-4 provided the right balance,allowing stable and effective updates.



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 5: Accuracy and Loss for ResNet18 0.0001



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 6: Accuracy and Loss for ResNet18 LR=0.00001

2)Layers

Training and Validation Accuracies

Table 7: Training Accuracies for ResNet Variations

Model	10th Epoch	20th Epoch	25th Epoch
ResNet18	99.42	99.70	99.75
ResNet34	99.46	99.70	99.78
ResNet50	99.52	99.71	99.75

Table 8: Validation Accuracies for ResNet Variations

Model	10th Epoch	20th Epoch	25th Epoch
ResNet18	87.29	84.38	86.59
ResNet34	85.28	84.35	84.52
ResNet50	86.92	84.61	86.22

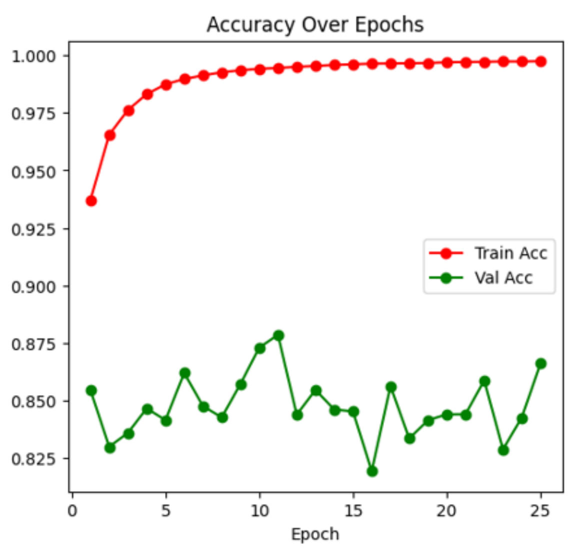
Testing Performance Metrics

Table 9: Testing Performance Metrics for ResNet Variations

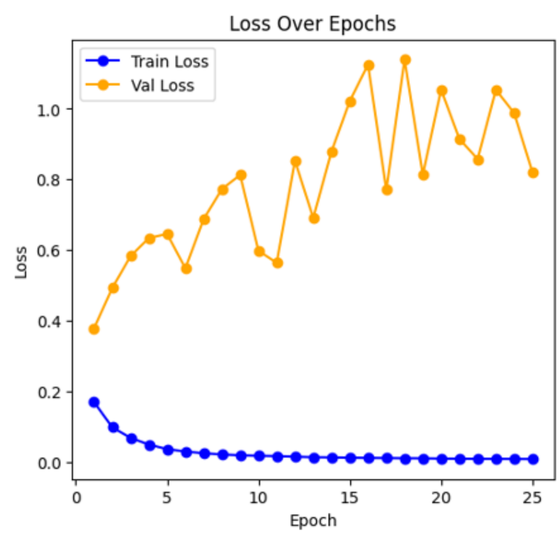
Model	Accuracy	Precision	Recall	F1-score
ResNet18	82.85	0.9667	0.6802	0.7985
ResNet34	83.15	0.9654	0.6876	0.8032
ResNet50	83.47	0.9714	0.6896	0.8066

Observation:

1.Resnet 34 and Resnet 50 achieved slightly better F1 scores than Resnet18,indicating that deeper networks extract more complex features.
2.Performance gain is marginal and also deeper models increase computational cost.

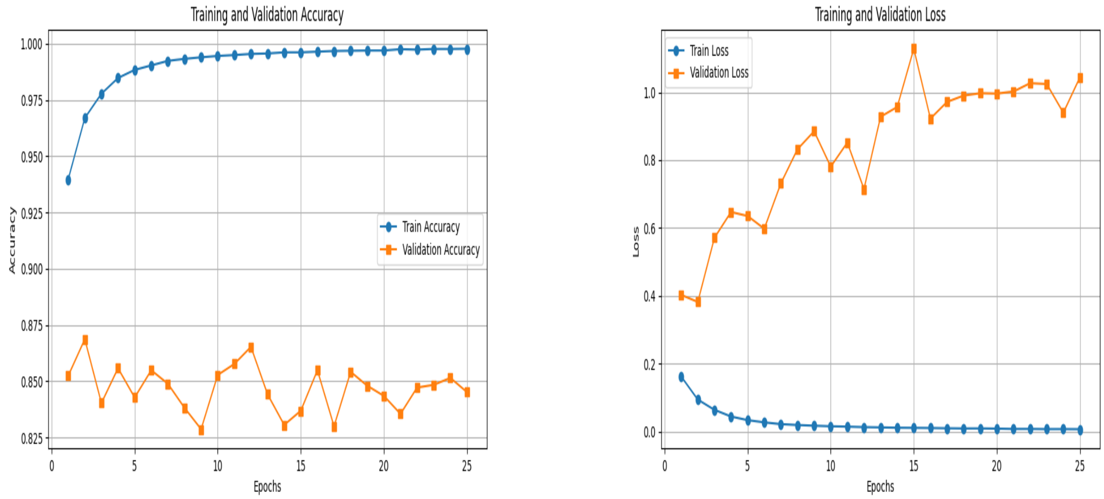


(a) Training Accuracy vs Epochs



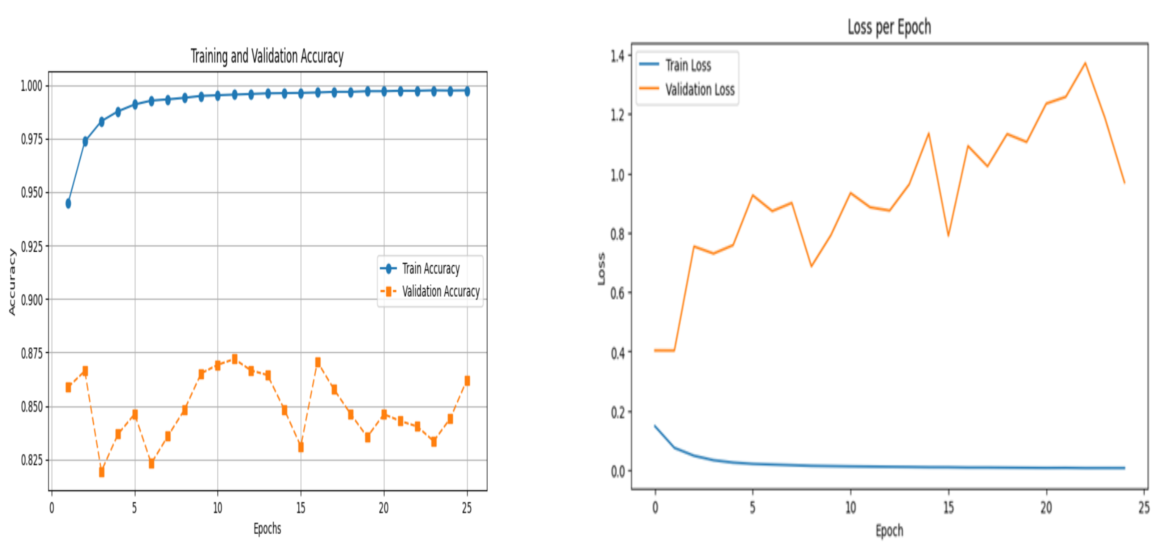
(b) Training Loss vs Epochs

Figure 7: Accuracy and Loss for ResNet18



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 8: Accuracy and Loss for ResNet34



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 9: Accuracy and Loss for ResNet50

3)Skip Connections

Training and Validation Accuracies

Table 10: Training and Validation Losses for ResNet Variations

ResNet18	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
No Skip	97.75	76.09	99.01	73.68	99.24	81.32
Skip	99.42	87.29	99.70	84.38	99.75	86.59

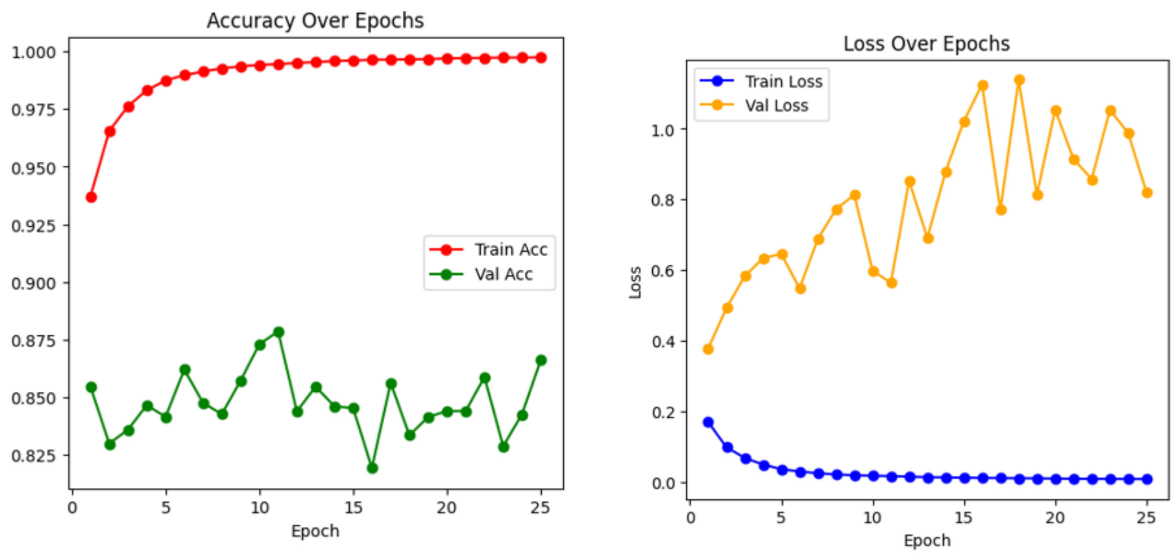
Testing Performance Metrics

Table 11: Testing Performance Metrics for ResNet Variations

ResNet18	Accuracy	Precision	Recall	F1-score
No Skip	76.21	0.9260	0.5696	0.7054
Skip	82.85	0.9667	0.6802	0.7985

Observation:

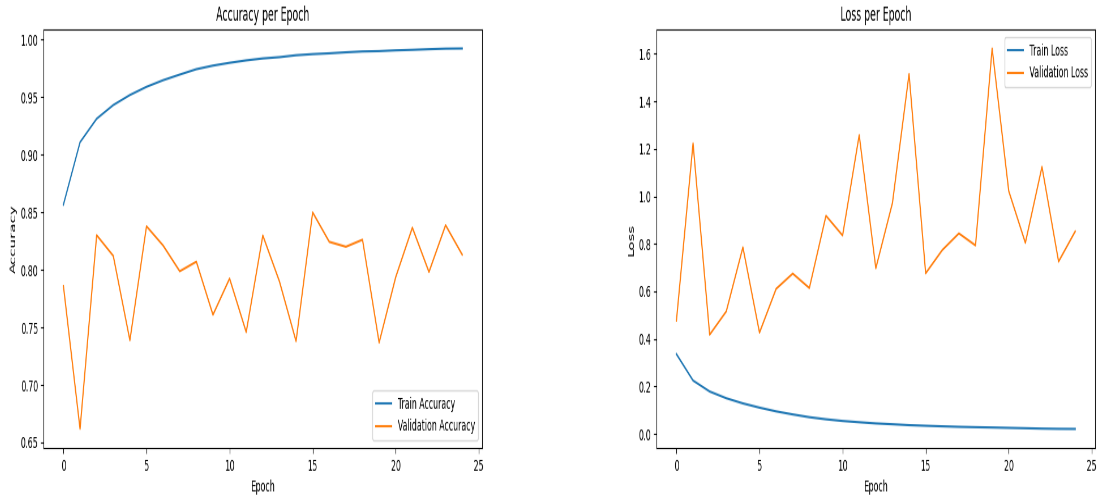
1.Removing skip connections led to lower accuracy,confirming their importance in stabilizing the deep network training.
2.Skip connections help to mitigate vanishing gradients allowing better feature learning and convergence.



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 10: Accuracy and Loss for ResNet18 with skip connections



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 11: Accuracy and Loss for ResNet18 without skip connections

4)Loss Functions

Training and Validation Accuracies

Table 12: Training and Validation Losses for ResNet Variations

Loss Function	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
CEL	97.75	76.09	99.01	73.68	99.24	81.32
Focal	99.40	86.44	99.68	79.93	99.73	84.66

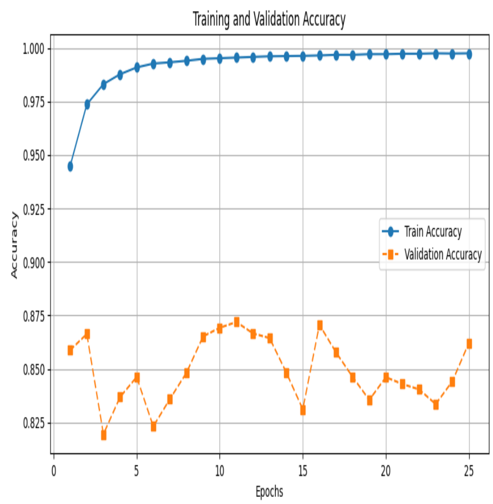
Testing Performance Metrics

Table 13: Testing Performance Metrics for ResNet Variations

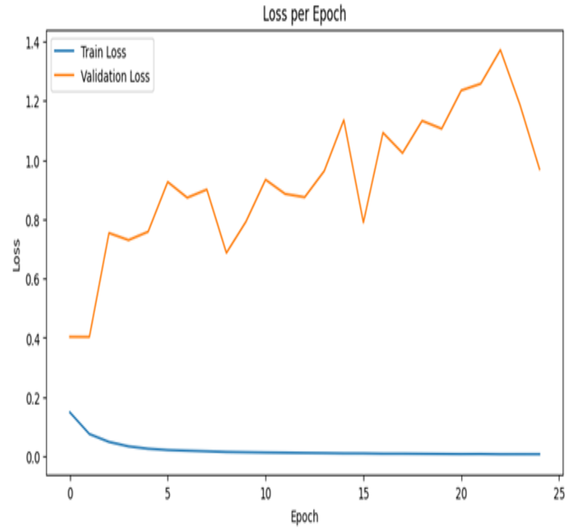
Loss Function	Accuracy	Precision	Recall	F1-score
CEL	82.85	0.9667	0.6802	0.7985
Focal	80.19	0.9575	0.6317	0.7612

Observation:

1.With Cross entropy loss,performace is better than Focal loss.
2.Focal loss is mainly designed for highly imbalanced dataset.It may have overly down weighted easy samples leading to suboptimal optimization and lower overall accuracy.

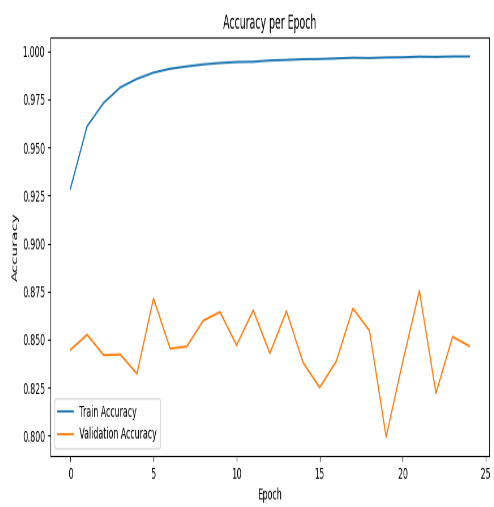


(a) Training Accuracy vs Epochs

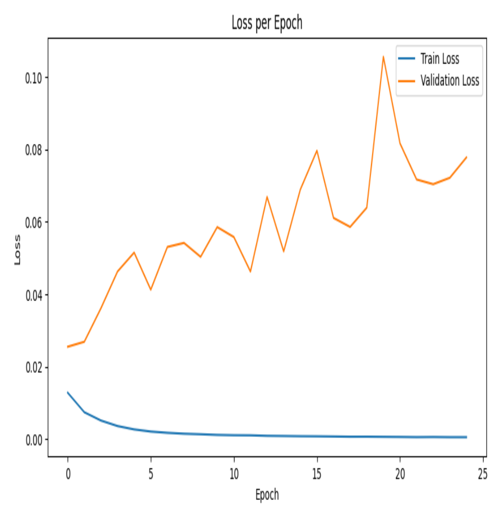


(b) Training Loss vs Epochs

Figure 12: Accuracy and Loss for ResNet18 Cross Entropy Loss



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 13: Accuracy and Loss for ResNet18 Focal Loss

5)Learning Rate Scheduling

Training and Validation Accuracies

Table 14: Training and Validation Losses for ResNet Variations

LR	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
SLR	99.42	87.29	99.98	85.73	99.98	85.39
Cosine	99.61	85.65	99.97	84.34	99.99	85.13

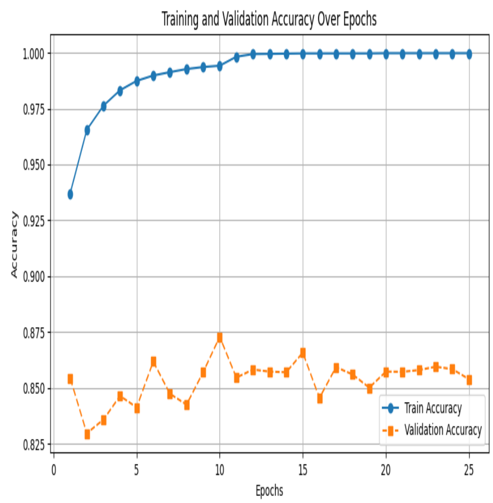
Testing Performance Metrics

Table 15: Testing Performance Metrics for ResNet Variations

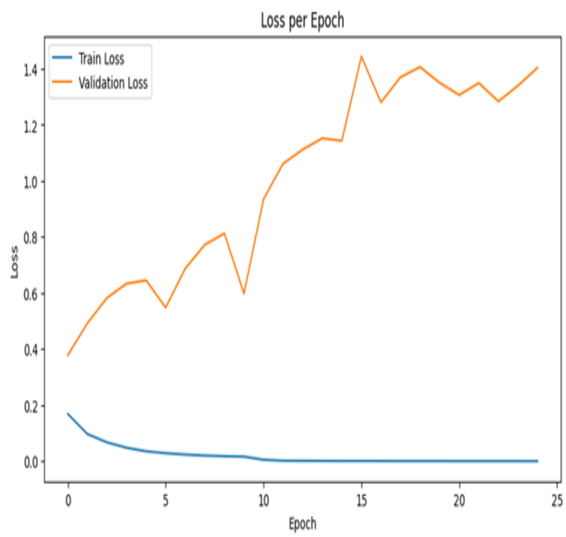
LR	Accuracy	Precision	Recall	F1-score
SLR	83.16	0.9713	0.6833	0.8022
Cosine	81.82	0.9721	0.6550	0.7826

Observation:

1.Step learning rate outperformed both cosine annealing and the baseline,indicating that scheduled stepwise reductions helped stabilize training.
2.Cosine annealing may have reduced the learning rate too aggressively,leading to suboptimal convergence compared to SLR.

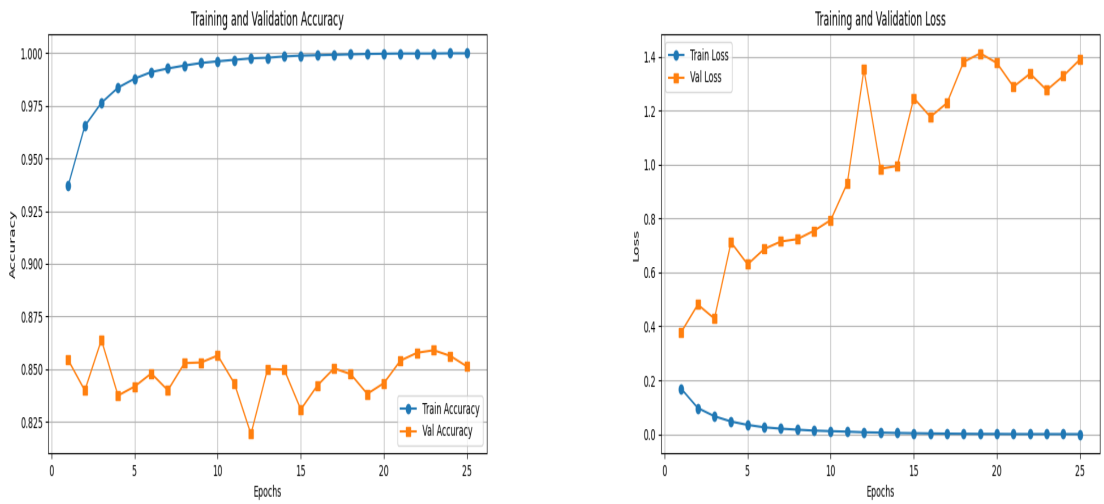


(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 14: Accuracy and Loss for ResNet18 Step Learning Rate



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 15: Accuracy and Loss for ResNet18 Cosine Annealing

6)Data Augmentation

Random horizontal/vertical flips,Rotation (±15),Color jittering.

Training and Validation Accuracies

Table 16: Training and Validation Losses for ResNet Variations

Data Aug	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
Yes	95.91	88.87	96.92	88.37	97.30	86.37
No	97.75	76.09	99.01	73.68	99.24	81.32

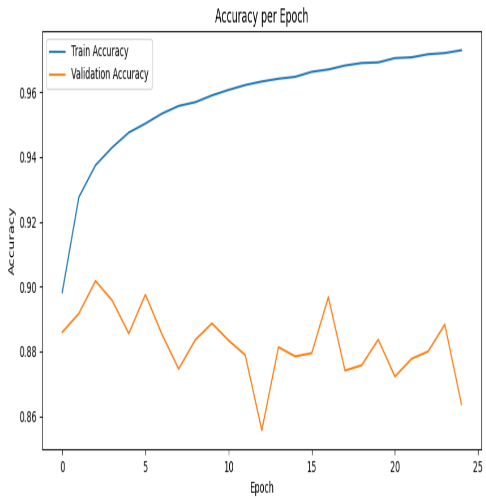
Testing Performance Metrics

Table 17: Testing Performance Metrics for ResNet Variations

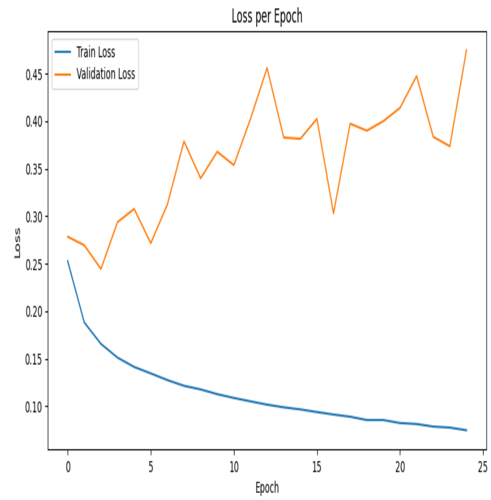
Data Aug	Accuracy	Precision	Recall	F1-score
Yes	84.05	0.9702	0.7024	0.8149
No	82.85	0.9667	0.6802	0.7985

Observation:

1.Data Augmentation improved model performance,indicating that increased data variability helped generalization.
2.Augmented training prevented overfitting,allowing the model to learn more robust features.
3.Without augmentation,the model had lower accuracy,likely due to limited diversity in the training data.

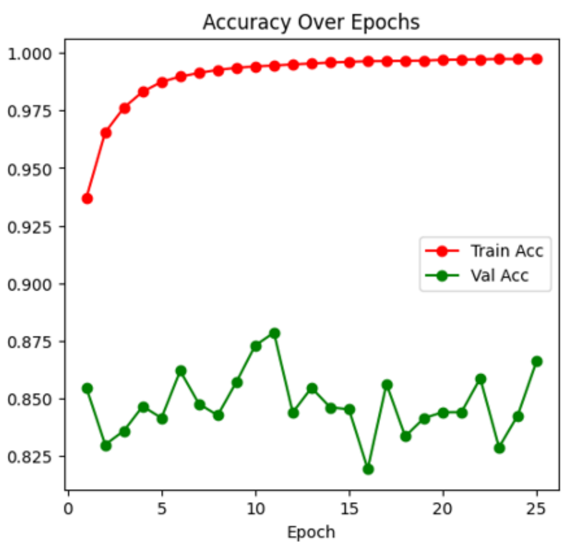


(a) Training Accuracy vs Epochs

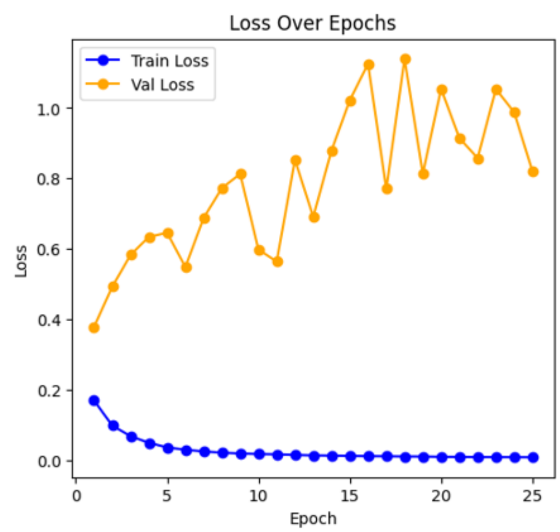


(b) Training Loss vs Epochs

Figure 16: Accuracy and Loss for ResNet18 with Data Augmentation



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 17: Accuracy and Loss for ResNet18 without Data Augmentation

7)Optimizer

Training and Validation Accuracies

Table 18: Training and Validation Losses for ResNet Variations

	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
Adam	97.75	76.09	99.01	73.68	99.24	81.32
SGD	97.71	83.68	99.46	83.31	99.65	83.38

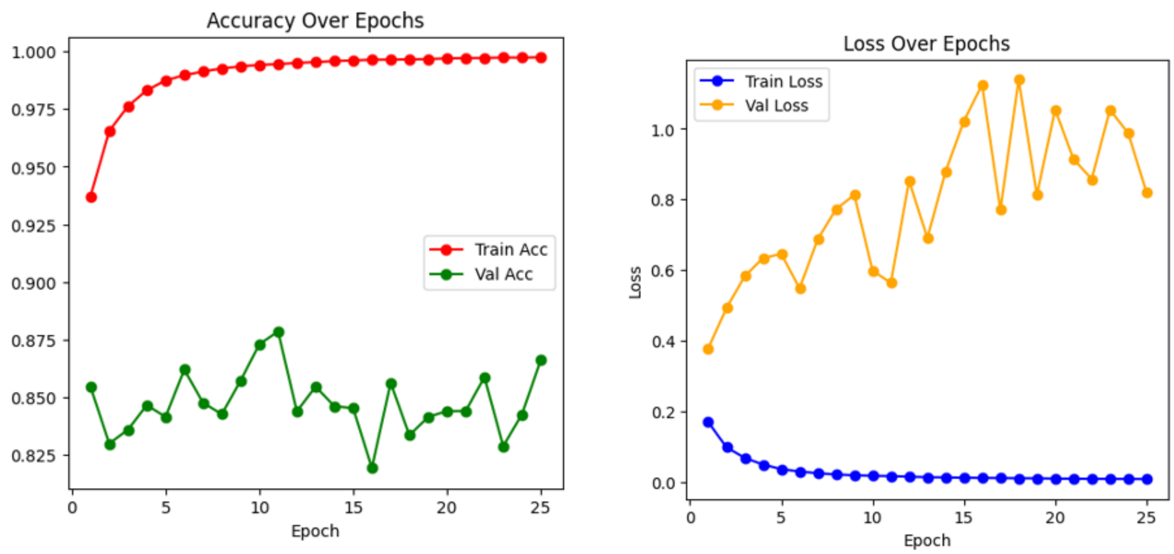
Testing Performance Metrics

Table 19: Testing Performance Metrics for ResNet Variations

	Accuracy	Precision	Recall	F1-score
Adam	82.85	0.9667	0.6802	0.7985
SGD	78.72	0.9510	0.6054	0.7398

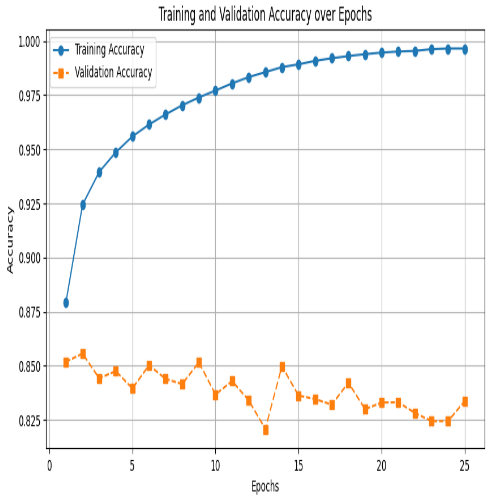
Observation:

1.Adam outperformed SGD,suggesting that its adaptive learning rate helped in faster and more stable convergence.
2.SGD may have required finetuning of hyperparameters,such as momentum and learning rate scheduling,to achieve competitive performance.

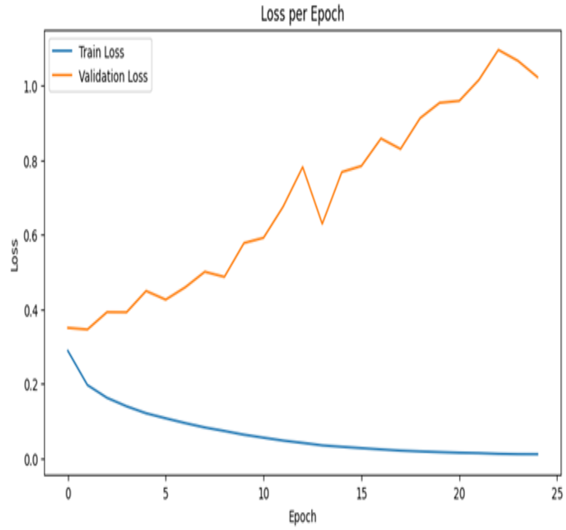


(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 18: Accuracy and Loss for ResNet18 Adam Optimizer



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

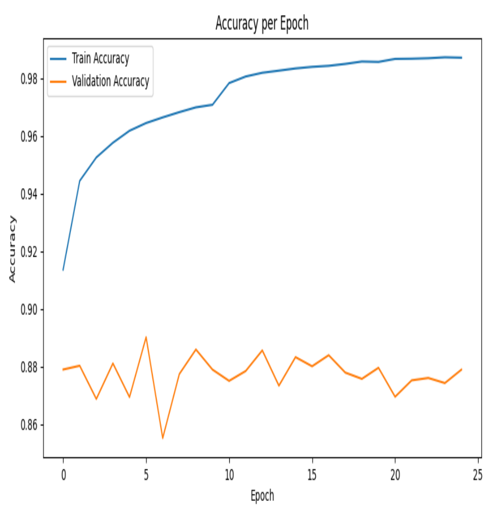
Figure 19: Accuracy and Loss for ResNet18 SGD

Best Model from Resnet

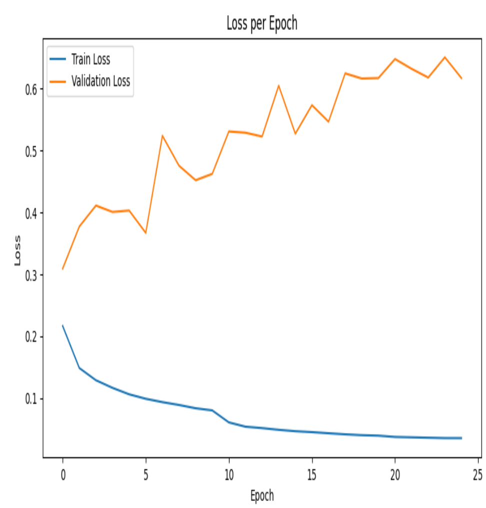
Model=ResNet50,Learning Rate=0.0001, Step Learning Rate,Cross Entropy Loss,Adam Optimizer,Data Augmentation.(All the best parameters taken from each ablation study)
*But choosing learning rate as 0.00001 gave better F1 score.

Table 20: Testing Performance Metrics for ResNet Variations

	Accuracy	Precision	Recall	F1-score
LR=0.0001	84.63	0.9726	0.7126	0.8226
LR=0.00001	86.04	0.9663	0.7468	0.8425

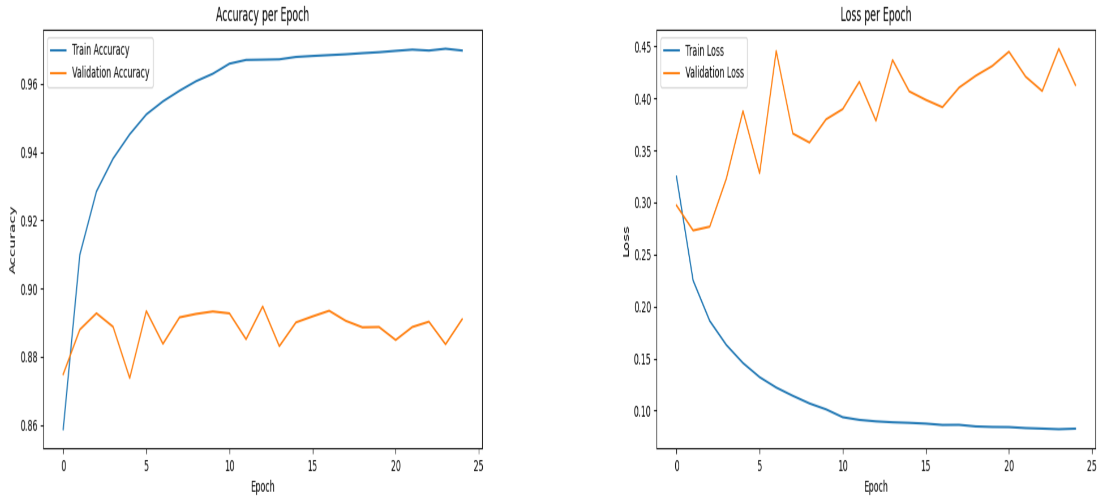


(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 20: Accuracy and Loss for ResNet18 with LR=0.0001



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 21: Accuracy and Loss for ResNet18 with LR=0.00001

VGGNet Variations

1)Learning rates

Training and Validation Accuracies

Table 21: Training Accuracies for VGGNet Variations

Learning Rate	10th Epoch	20th Epoch	25th Epoch
1e-2	50.08	49.92	49.99
1e-3	49.89	49.98	49.73
1e-4	99.27	99.48	99.60
1e-5	99.59	99.77	99.82

Table 22: Validation Accuracies for VGGNet Variations

Learning Rate	10th Epoch	20th Epoch	25th Epoch
1e-2	50.05	49.95	49.95
1e-3	50.05	49.95	49.95
1e-4	84.19	79.16	80.92
1e-5	87.23	86.36	87.04

Testing Performance Metrics

Table 23: Testing Performance Metrics for VGGNet Variations

Learning Rate	Accuracy	Precision	Recall	F1-score
1e-2	49.98	0.4998	1.0000	0.6665
1e-3	49.98	0.4998	1.0000	0.6665
1e-4	80.07	0.9829	0.6118	0.7542
1e-5	85.46	0.9692	0.7324	0.8343

Observation:

1.1e-5 achieved the best performance,indicating that a lower learning rate helped in stable convergence.
2.1e-4 performed slightly worse than 1e-5.
3.1e-3 and 1e-2 resulted in poor performance(around 50 percent accuracy),likely due to unstable updates and divergence.

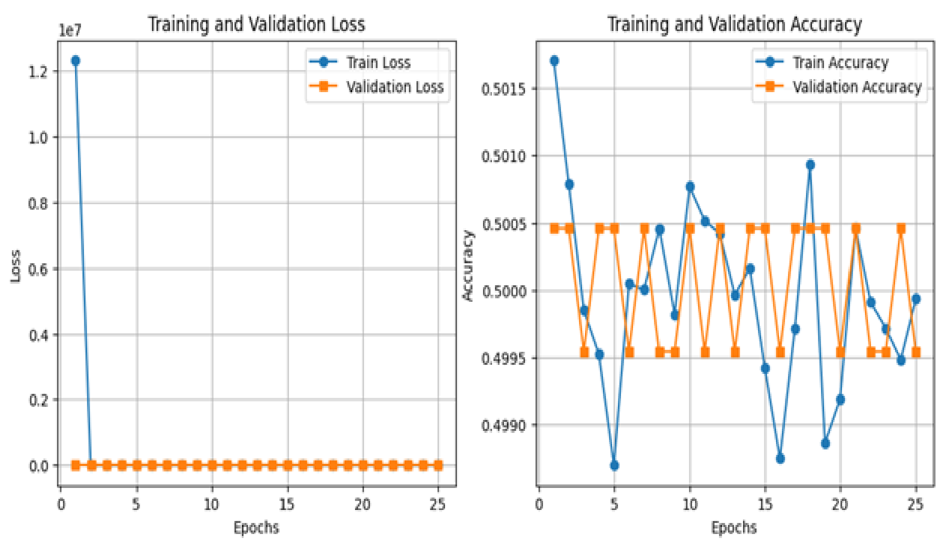


Figure 22: Loss and Accuracy for VGGNet16 LR=0.01

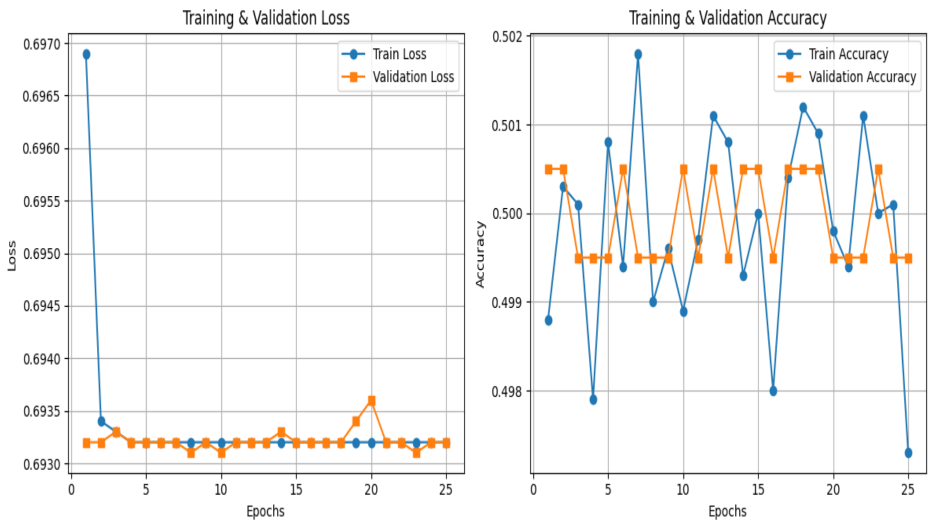
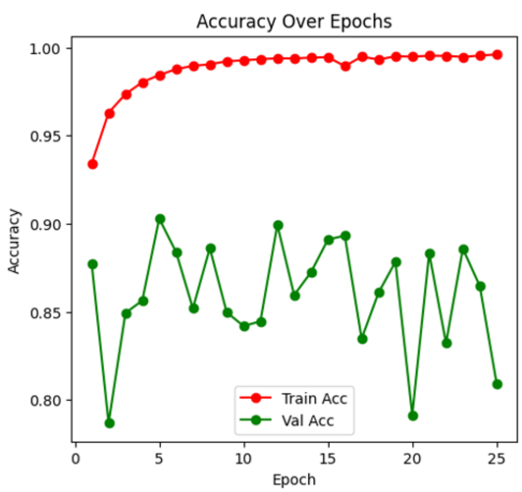
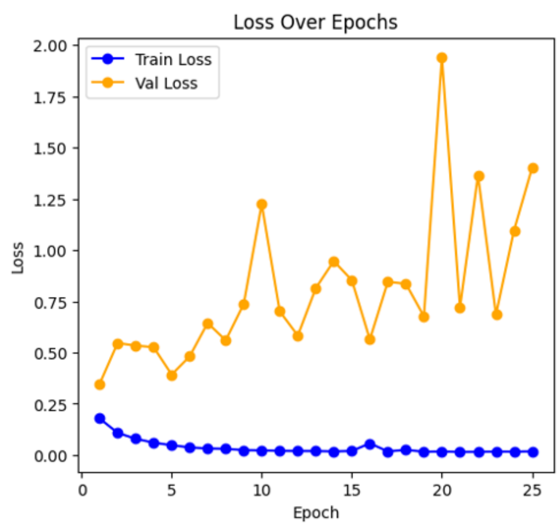


Figure 23: Loss and Accuracy for VGGNet16 LR=0.01



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 24: Accuracy and Loss for VGGNet16 0.0001

Figure 25: Accuracy and Loss for VGGNet16 LR=0.00001

2)Layers

Training and Validation Accuracies

Table 24: Training Accuracies for VGGNet Variations

Model	10th Epoch	20th Epoch	25th Epoch
VGGNet11	99.12	99.42	99.66
VGGNet13	99.25	99.57	99.63
VGGNet16	99.27	99.48	99.60
VGGNet19	97.90	99.47	99.68

Table 25: Validation Accuracies for VGGNet Variations

Model	10th Epoch	20th Epoch	25th Epoch
VGGNet11	86.28	86.02	86.18
VGGNet13	87.09	85.48	87.89
VGGNet16	84.19	79.16	80.92
VGGNet19	88.43	86.15	86.21

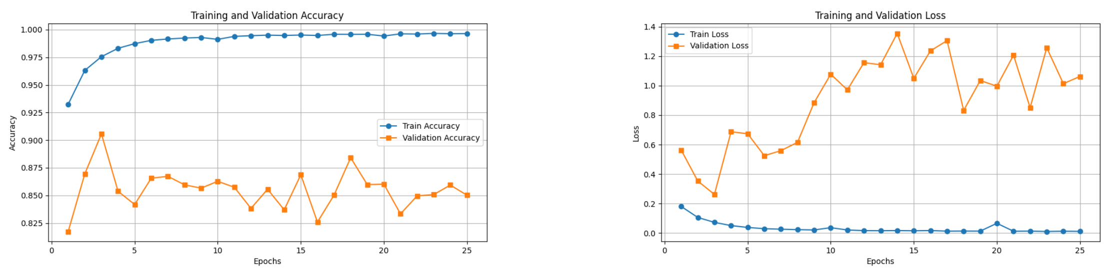
Testing Performance Metrics

Table 26: Testing Performance Metrics for VGGNet Variations

Model	Accuracy	Precision	Recall	F1-score
VGGNet11	86.34	0.9480	0.7688	0.8491
VGGNet13	87.97	0.9271	0.8241	0.8726
VGGNet16	80.07	0.9829	0.6118	0.7542
VGGNet19	84.18	0.9662	0.7082	0.8173

Observation:

1.VGG13 achieved the highest accuracy,suggesting that its architecture provides an optimal balance of depth and feature extraction.
2.VGG11,VGG16,VGG19 performed slightly worse, indicating that either too few or too many layers may not be ideal for this dataset.
3.Excesssively deep networks like VGG19 may introduce redundancy,while shallower ones like VGG11 may lack sufficient feature extraction capacity.



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 26: Accuracy and Loss for VGGNet11

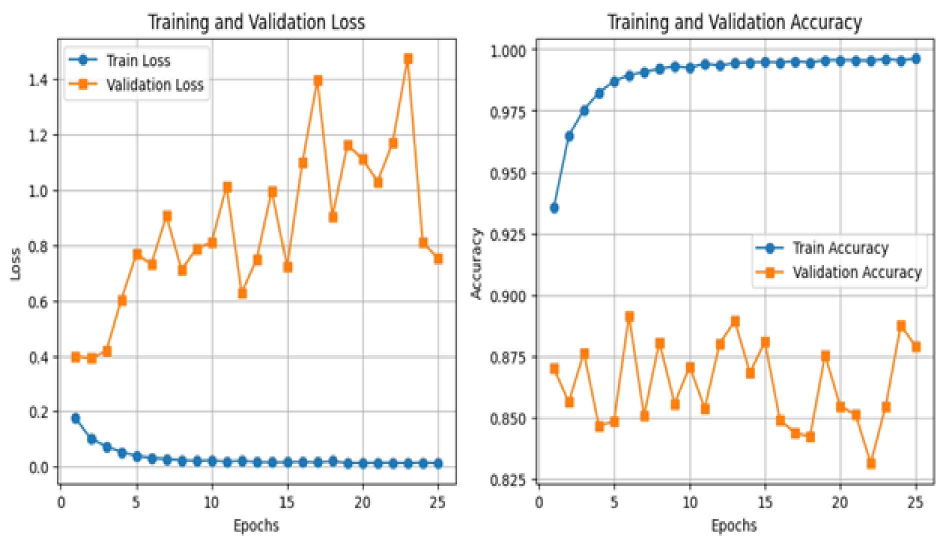
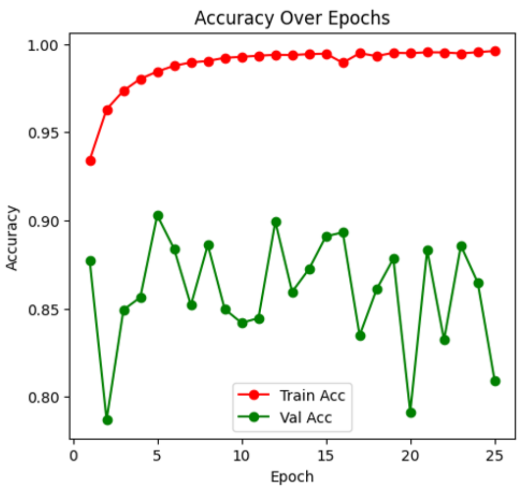
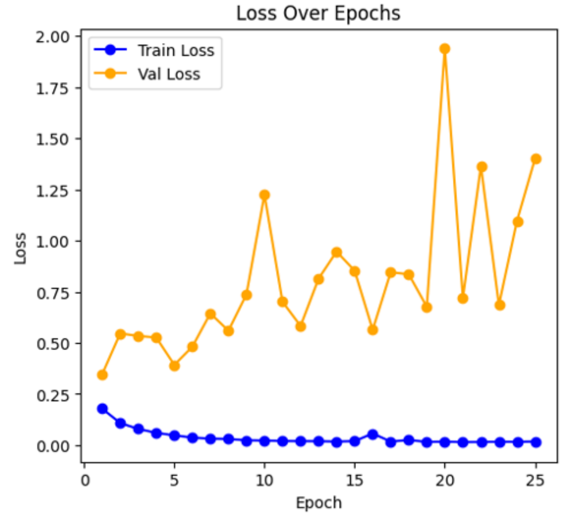


Figure 27: Accuracy and Loss for VGGNet13

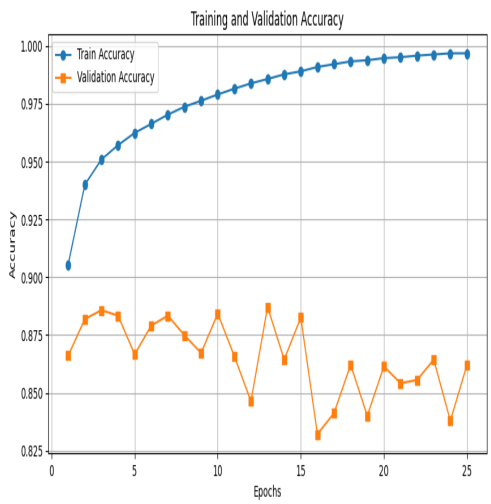


(a) Training Accuracy vs Epochs

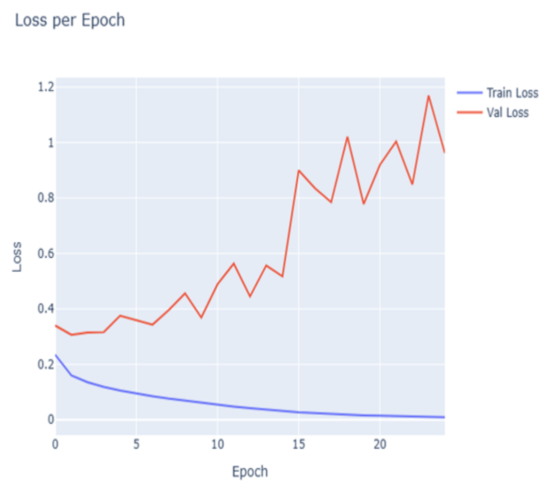


(b) Training Loss vs Epochs

Figure 28: Accuracy and Loss for VGGNet16



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 29: Accuracy and Loss for VGGNet19

3)Loss Functions

Training and Validation Accuracies

Table 27: Training and Validation Losses for VGGNet Variations

Loss Function	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
CEL	99.27	84.19	99.48	79.16	99.60	80.92
Focal	99.06	84.52	99.36	87.52	99.34	82.64

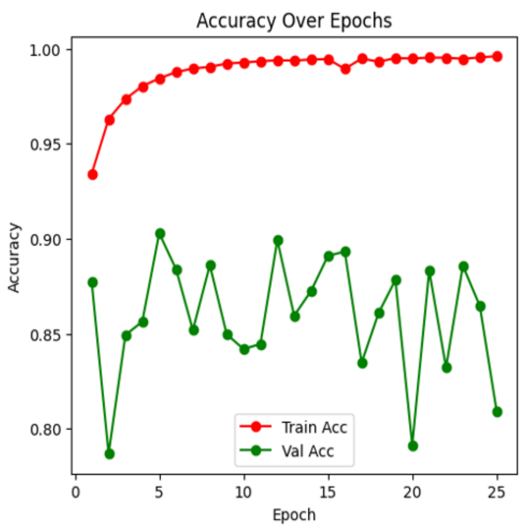
Testing Performance Metrics

Table 28: Testing Performance Metrics for VGGNet Variations

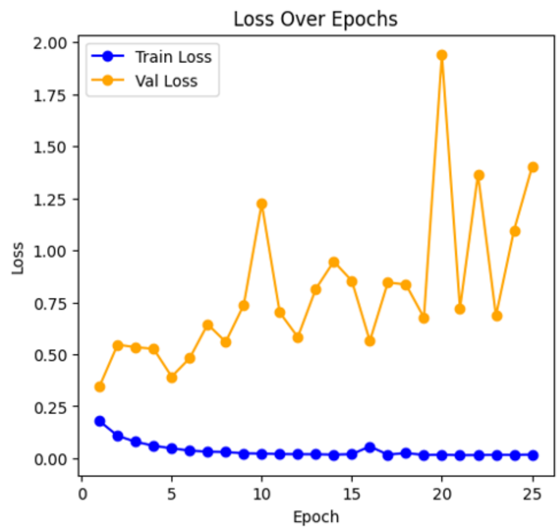
Loss Function	Accuracy	Precision	Recall	F1-score
CEL	80.07	0.9829	0.6118	0.7542
Focal	80.95	0.9776	0.6334	0.7688

Observation:

1.With Cross entropy loss,performace is better than Focal loss.
2.Focal loss is mainly designed for highly imbalanced dataset.It may have overly down weighted easy samples leading to suboptimal optimization and lower overall accuracy.

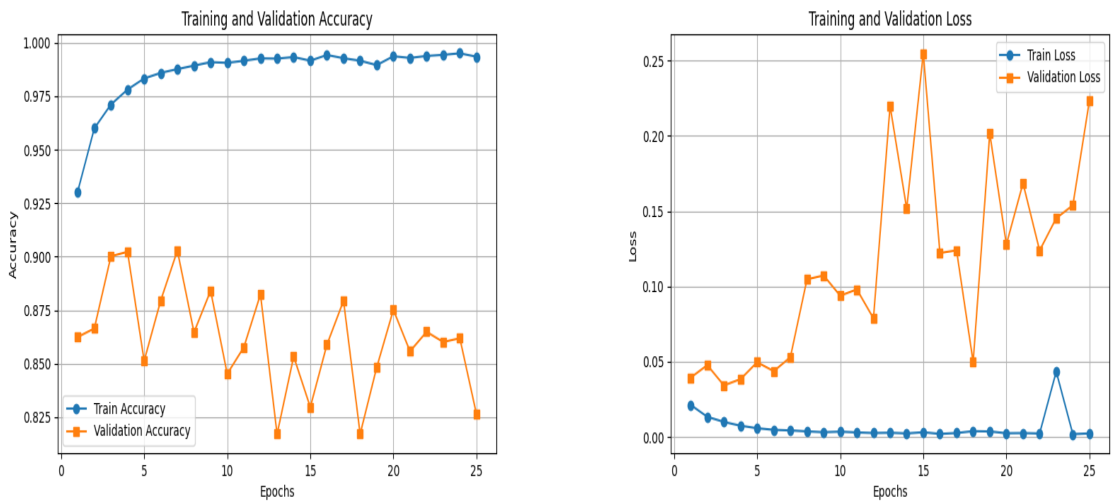


(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 30: Accuracy and Loss for VGGNet16 Cross Entropy Loss



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 31: Accuracy and Loss for VGGNet16 Focal Loss

4)Learning Rate Scheduling

Training and Validation Accuracies

Table 29: Training and Validation Losses for VGGNet Variations

LR	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
SLR	99.23	87.97	99.98	86.36	1	86.32
Cosine	99.44	85.02	99.97	84.82	99.99	86.29

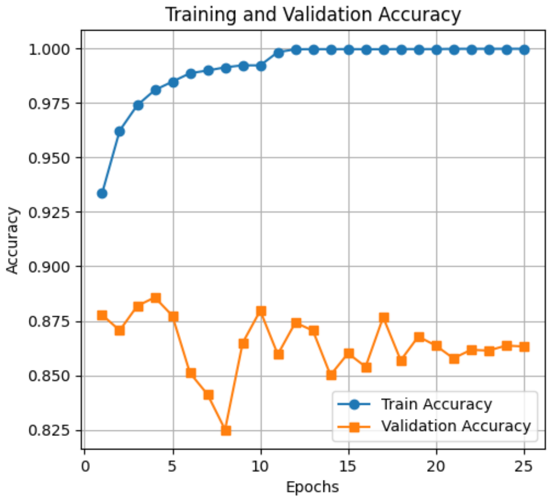
Testing Performance Metrics

Table 30: Testing Performance Metrics for VGGNet Variations

LR	Accuracy	Precision	Recall	F1-score
SLR	83.46	0.9740	0.6875	0.8060
Cosine	83.55	0.9789	0.6857	0.8064

Observation:

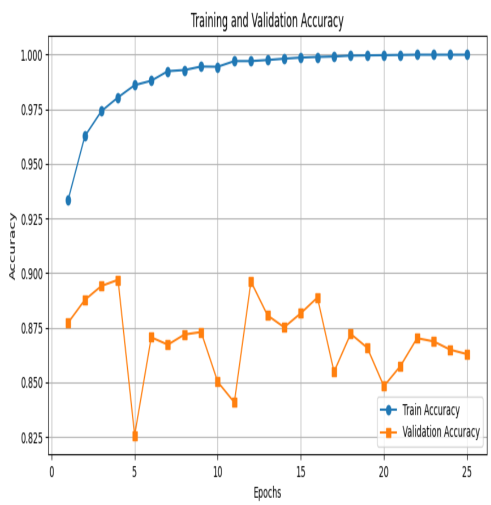
1.Cosine Annealing gave slightly better performane than SLR.
2.Cosine Annealing's smooth decay may have helped refine the model's learning process more effectively than SLR's abrupt changes.
3.The small difference suggests that both scheduling methods are viable,with cosine annealing providing a slight edge in performance.



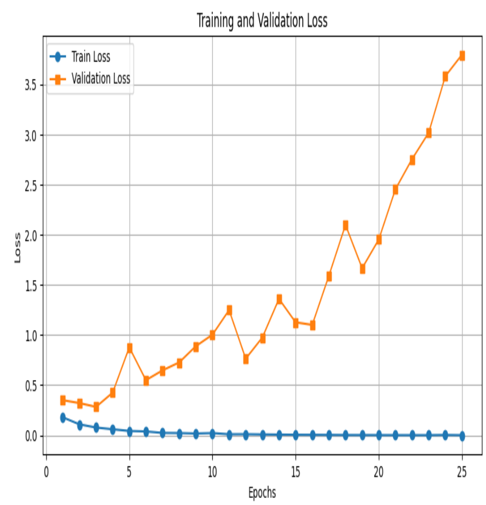
(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 32: Accuracy and Loss for VGGNet16 Step Learning Rate



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 33: Accuracy and Loss for VGGNet16 Cosine Annealing

5)Data Augmentation

Random horizontal/vertical flips,Rotation (±15),Color jittering.

Training and Validation Accuracies

Table 31: Training and Validation Losses for VGGNet Variations

Data Aug	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
Yes	95.96	89.76	96.58	90.06	96.62	90.31
No	99.27	84.19	99.48	79.16	99.60	80.92

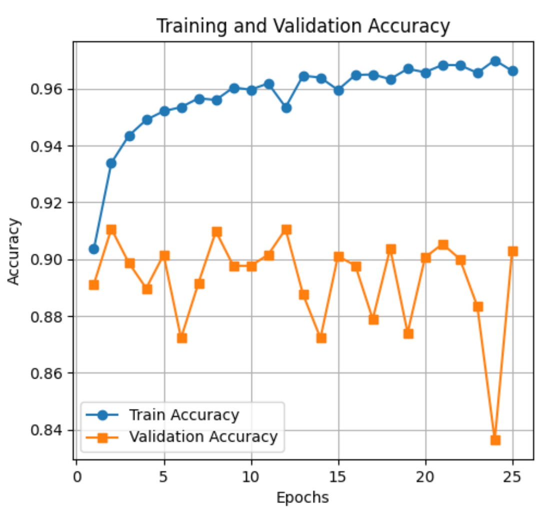
Testing Performance Metrics

Table 32: Testing Performance Metrics for VGGNet Variations

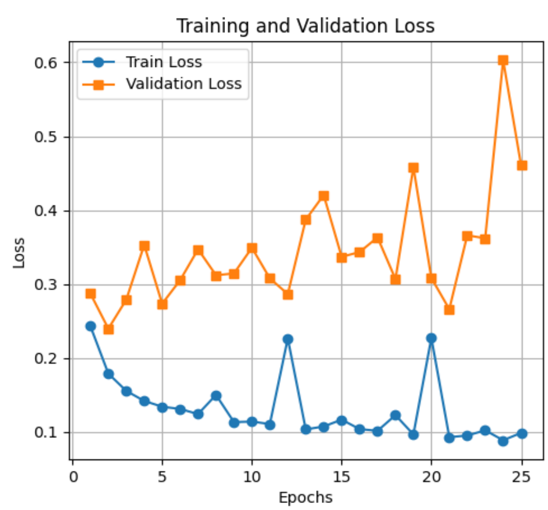
Data Aug	Accuracy	Precision	Recall	F1-score
Yes	90.28	0.9634	0.8374	0.8960
No	80.07	0.9829	0.6118	0.7542

Observation:

1.Data Augmentation improved model performance,indicating that increased data variability helped generalization.
2.Augmented training prevented overfitting,allowing the model to learn more robust features.
3.Without augmentation, the model had lower accuracy,likely due to limited diversity in the training data.

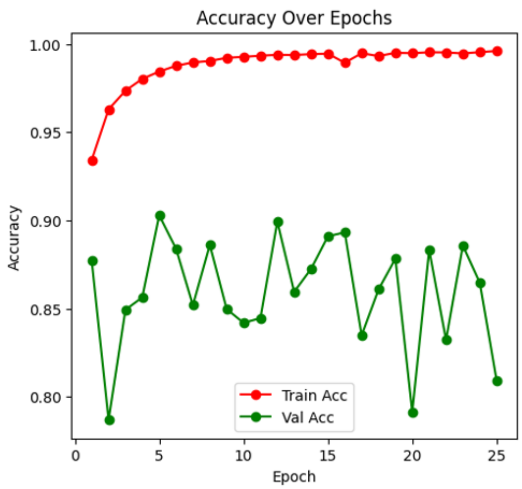


(a) Training Accuracy vs Epochs

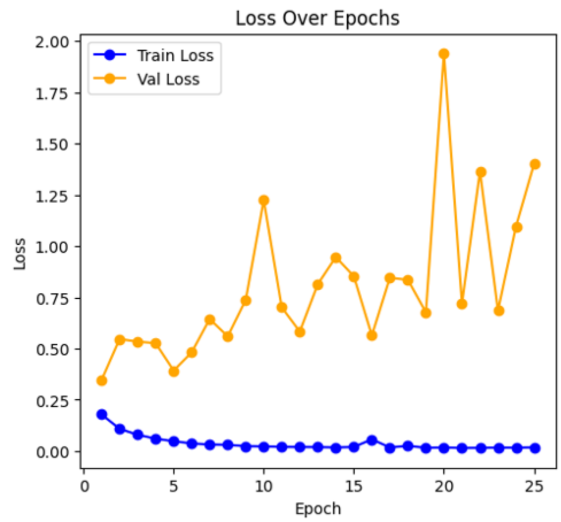


(b) Training Loss vs Epochs

Figure 34: Accuracy and Loss for VGGNet16 with Data Augmentation



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 35: Accuracy and Loss for VGGNet16 without Data Augmentation

6)Optimizer

Training and Validation Accuracies

Table 33: Training and Validation Losses for VGGNet Variations

	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
Adam	99.27	84.19	99.48	79.16	99.60	80.92
SGD	97.87	85.44	99.47	85.60	99.59	83.67

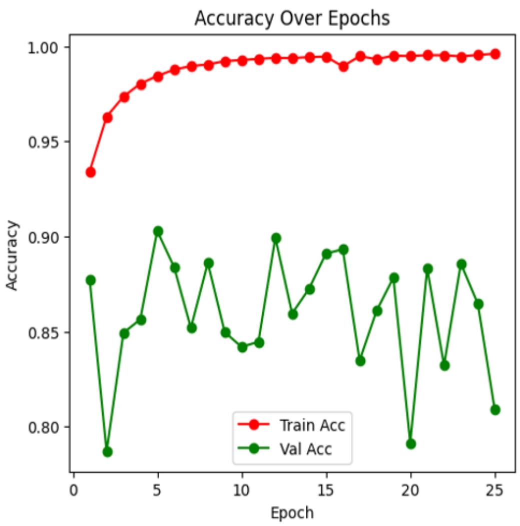
Testing Performance Metrics

Table 34: Testing Performance Metrics for VGGNet Variations

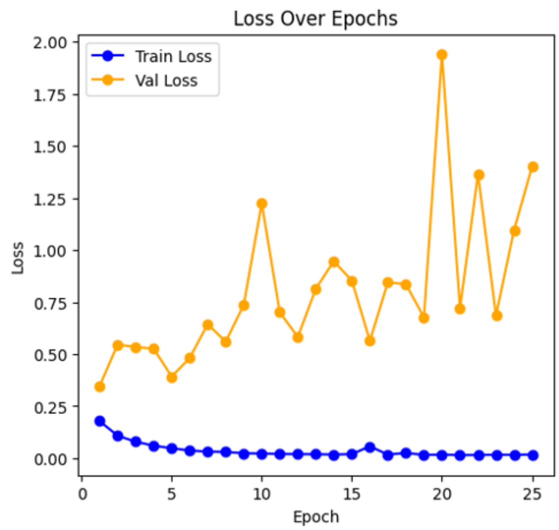
	Accuracy	Precision	Recall	F1-score
Adam	80.07	0.9829	0.6118	0.7542
SGD	82.16	0.9714	0.6626	0.7878

Observation:

1.SGD gave better results than Adam,likely because it generalizes well and avoids overfitting.
2.Adam might have adapted too aggressively,leading to suboptimal convergence.
3.SGD with the given momentum value, helped the model to learn more effectively over time.

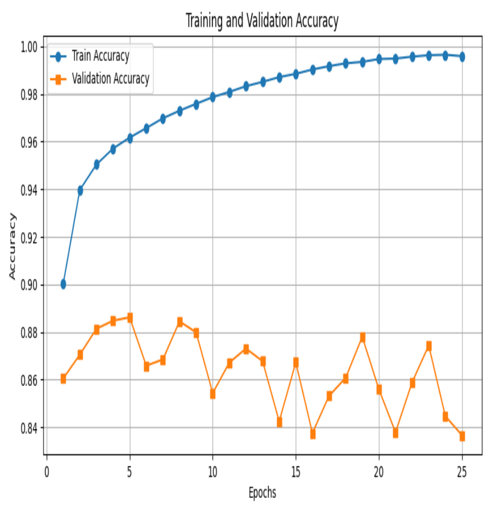


(a) Training Accuracy vs Epochs

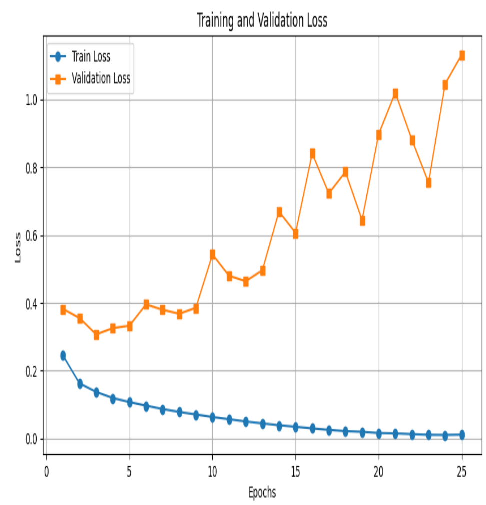


(b) Training Loss vs Epochs

Figure 36: Accuracy and Loss for VGGNet16 Adam Optimizer



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 37: Accuracy and Loss for VGGNet16 SGD

Best Model from VGGnet

Model=VGG13,Learning Rate=0.00001, Cosine Annealing,Focal Loss,SGD,Data Augmentation.(All the best parameters taken from each ablation study)
*But VGG16 with just data augmentation gave better performance.

Table 35: Testing Performance Metrics for ResNet Variations

	Accuracy	Precision	Recall	F1-score
VGG13 with best parameters	87.66	0.9084	0.8376	0.8716
VGG16 with Data Augmentation	90.28	0.9634	0.8374	0.8960

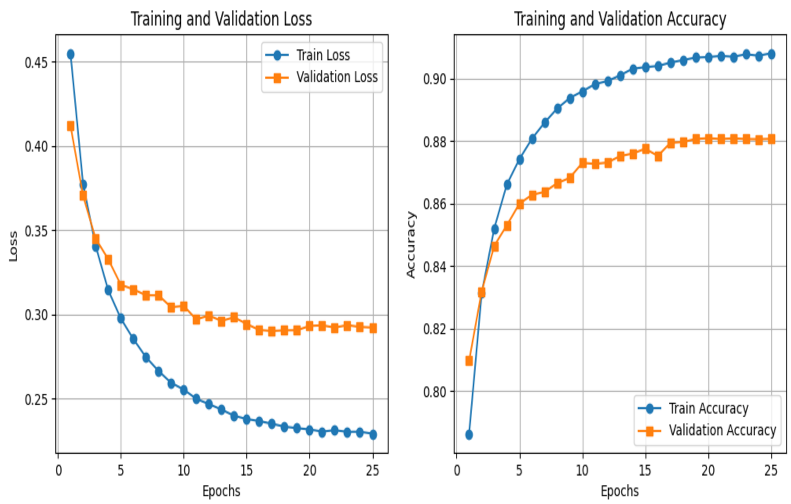


Figure 38: Accuracy and Loss for VGGNet13 with best parameters

4 Custom Architecture

I have used CustomNet employing Cross Entropy loss and the Adam optimizer with a learning rate of 0.0001 as base model.

4.1 Training Accuracies and Losses

Table 36: Training and Validation Losses for CustomNet Variations

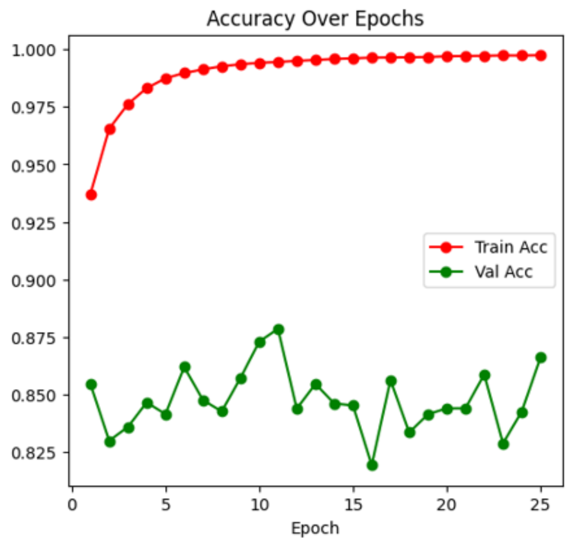
	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
CustomNet	97.90	79.33	99.01	79.01	99.24	81.23

4.2 Testing Results

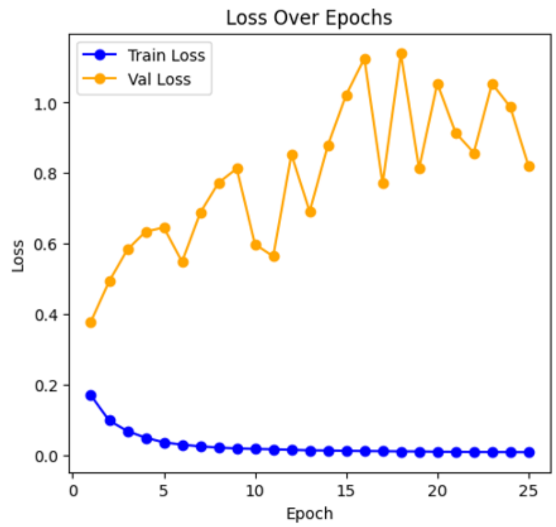
Table 37: Testing Results: Accuracy, Precision, Recall, F1 Score

Model	Accuracy	Precision	Recall	F1 Score
CustomNet	80.41	0.9429	0.6472	0.7675

5 Training Performance Plots



(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 39: Accuracy and Loss for CustomNet

CustomNet Ablation Studies

Considering the baseline models, I have analyzed the effect of each parameter.

CustomNet Variations

1)Learning rates

Training and Validation Accuracies

Table 38: Training Accuracies for CustomNet Variations

Learning Rate	10th Epoch	20th Epoch	25th Epoch
1e-2	96.47	97.70	50.00
1e-3	98.18	99.12	99.33
1e-4	97.90	99.01	99.24
1e-5	92.28	94.56	95.36

Table 39: Validation Accuracies for CustomNet Variations

Learning Rate	10th Epoch	20th Epoch	25th Epoch
1e-2	79.83	50.05	50.05
1e-3	82.63	81.49	82.34
1e-4	79.33	79.01	81.23
1e-5	78.88	81.24	84.34

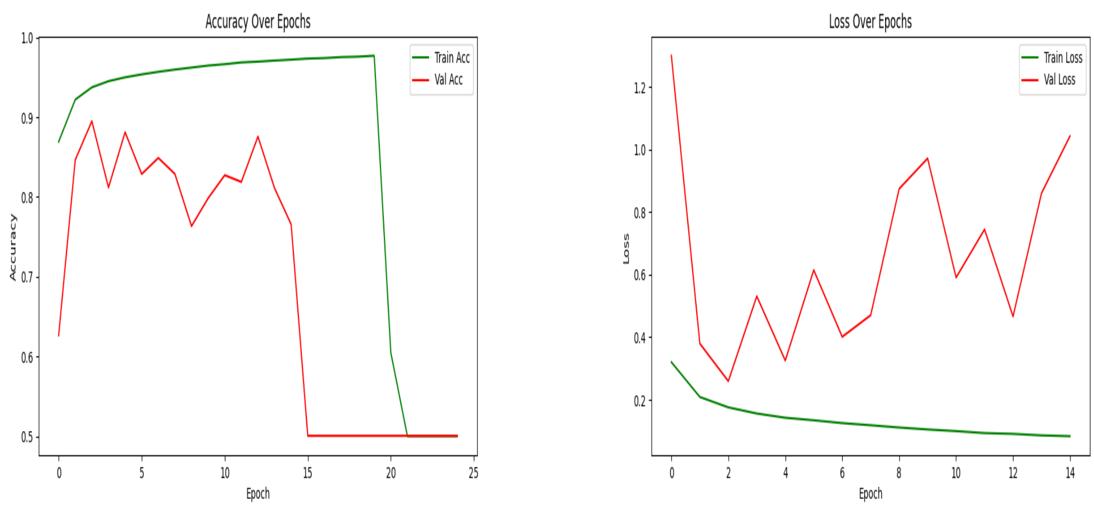
Testing Performance Metrics

Table 40: Testing Performance Metrics for CustomNet Variations

Learning Rate	Accuracy	Precision	Recall	F1-score
1e-2	50.02	0.00	0.00	0.00
1e-3	82.11	0.9718	0.6613	0.7870
1e-4	80.41	0.9429	0.6472	0.7675
1e-5	80.52	0.8931	0.6932	0.7806

Observation:

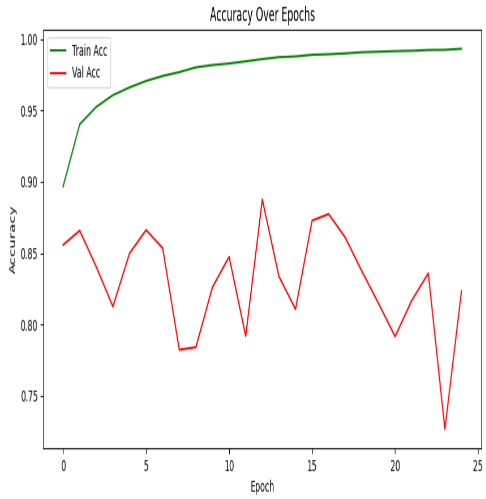
1.Best Learning Rate: 1e-3 achieved optimal performance, balancing convergence speed and stability.
2.High LR Issues: 1e-2 may have caused instability and poor generalization.
3.Low LR Drawbacks: 1e-4 and 1e-5 may have led to slow convergence and suboptimal results.



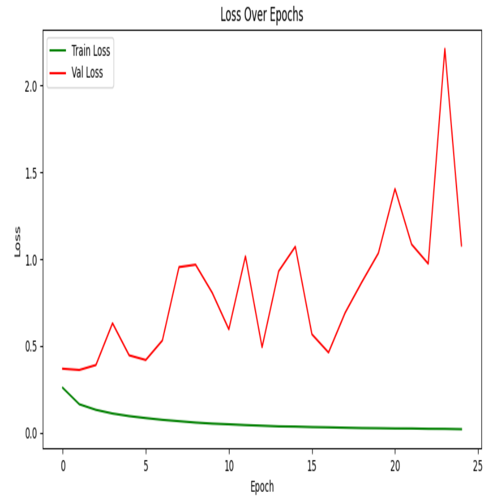
(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 40: Accuracy and Loss for CustomNet LR=0.01

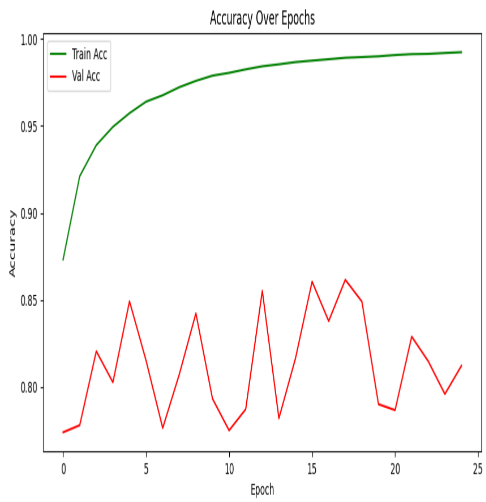


(a) Training Accuracy vs Epochs

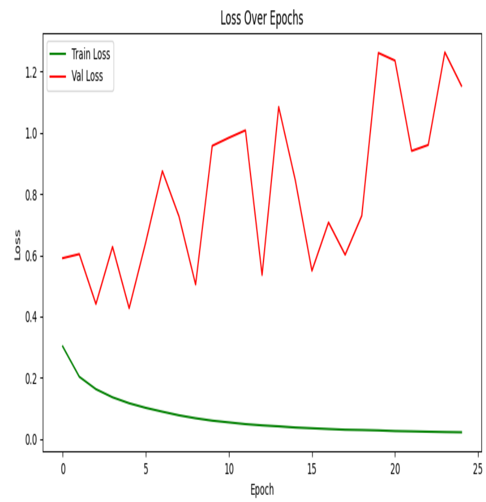


(b) Training Loss vs Epochs

Figure 41: Accuracy and Loss for CustomNet LR=0.001

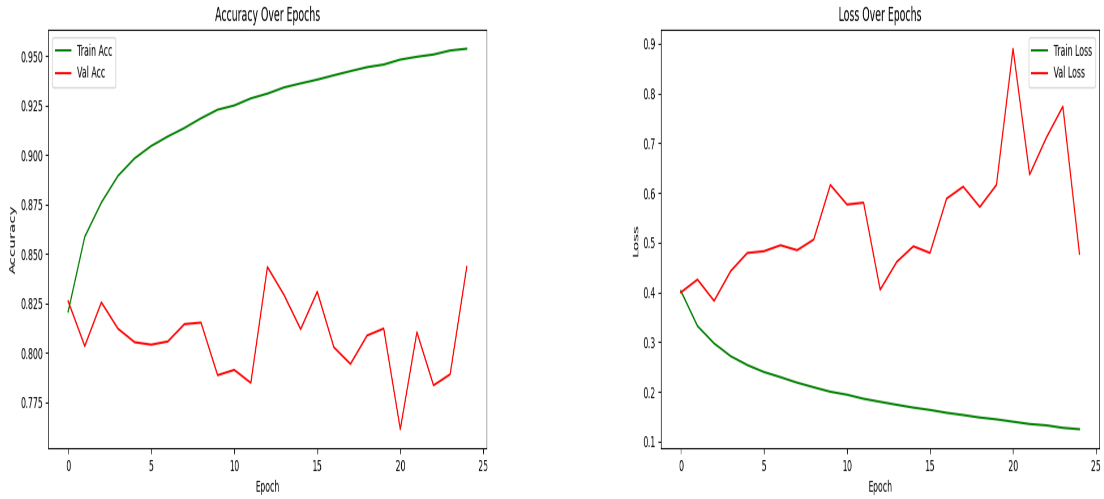


(a) Training Accuracy vs Epochs



(b) Training Loss vs Epochs

Figure 42: Accuracy and Loss for CustomNet 0.0001



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 43: Accuracy and Loss for CustomNet LR=0.00001

2)Data Augmentation

Random horizontal/vertical flips,Rotation (± 15),Color jittering.

Training and Validation Accuracies

Table 41: Training and Validation Losses for CustomNet Variations

Data Aug	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
Yes	94.90	88.72	96.04	87.27	96.42	89.98
No	97.90	79.33	99.01	79.01	99.24	81.23

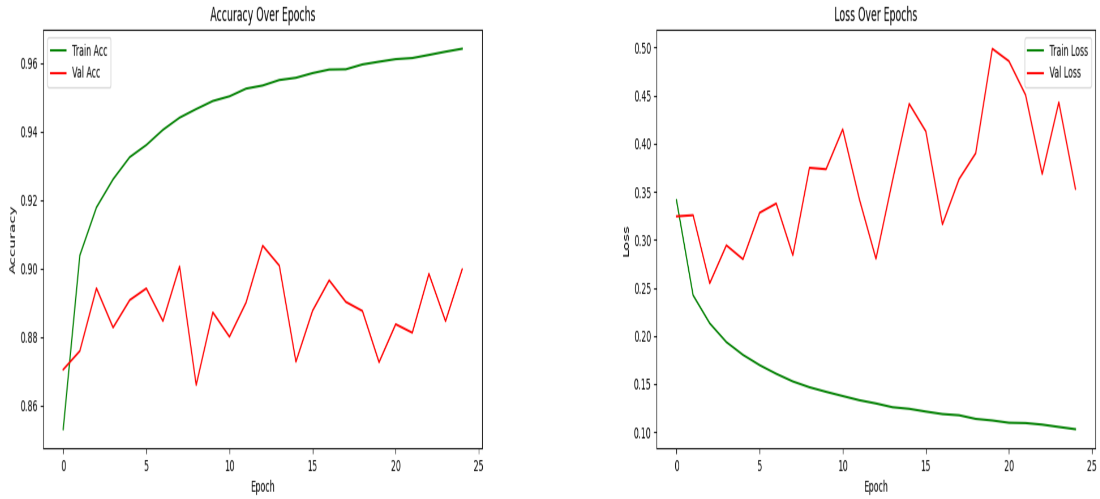
Testing Performance Metrics

Table 42: Testing Performance Metrics for CustomNet Variations

Data Aug	Accuracy	Precision	Recall	F1-score
Yes	87.22	0.9719	0.7665	0.8571
No	80.41	0.9429	0.6472	0.7675

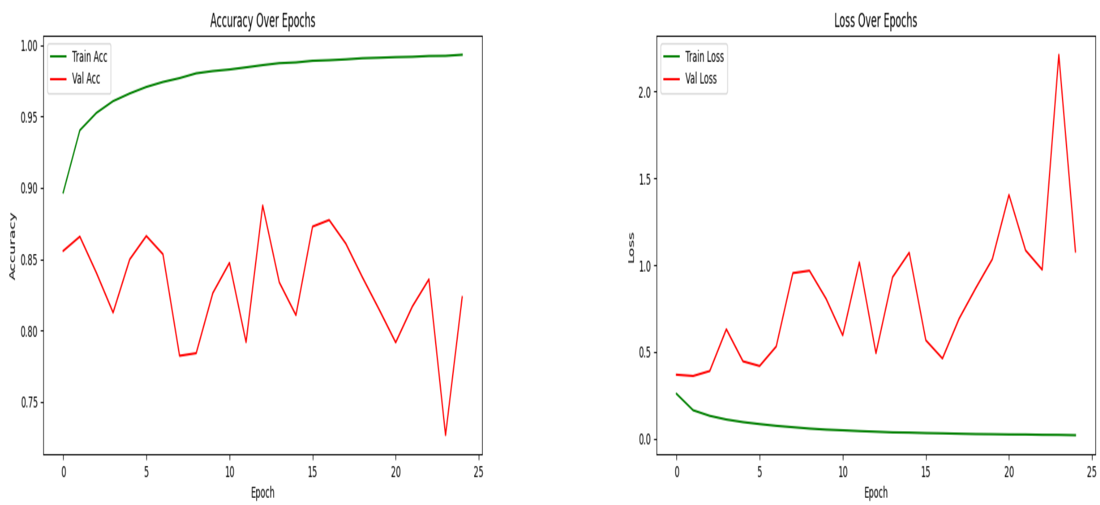
Observation:

1.Data Augmentation improved model performance,indicating that increased data variability helped generalization.
2.Augmented training prevented overfitting,allowing the model to learn more robust features.
3.Without augmentation, the model had lower accuracy,likely due to limited diversity in the training data.



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 44: Accuracy and Loss for CustomNet with Data Augmentation



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 45: Accuracy and Loss for CustomNet without Data Augmentation

3)Optimizer

Training and Validation Accuracies

Table 43: Training and Validation Losses for CustomNet Variations

	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
Adam	97.90	79.33	99.01	79.01	99.24	81.23
SGD	96.05	83.11	97.83	85.03	98.38	83.78

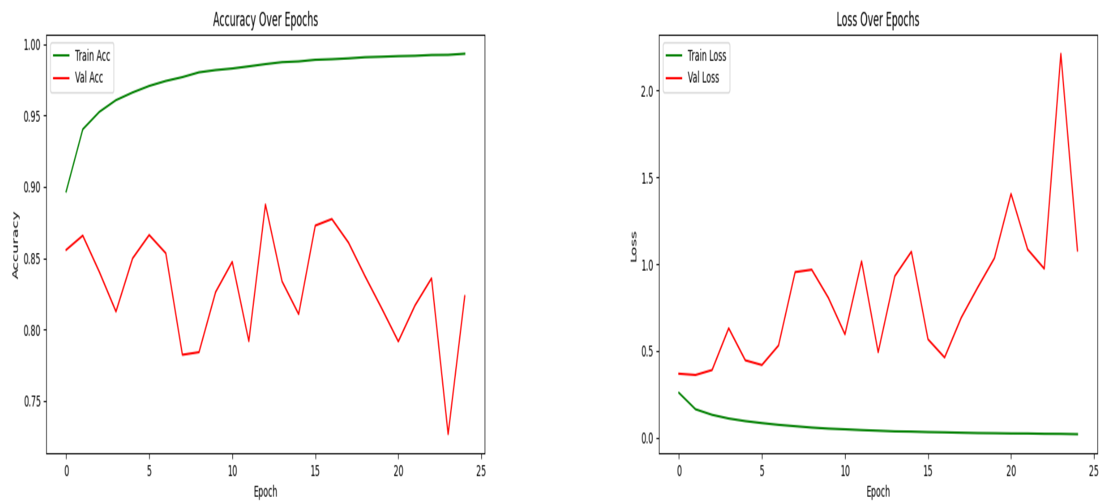
Testing Performance Metrics

Table 44: Testing Performance Metrics for CustomNet Variations

	Accuracy	Precision	Recall	F1-score
Adam	80.41	0.9429	0.6472	0.7675
SGD	81.51	0.9424	0.6711	0.7840

Observation:

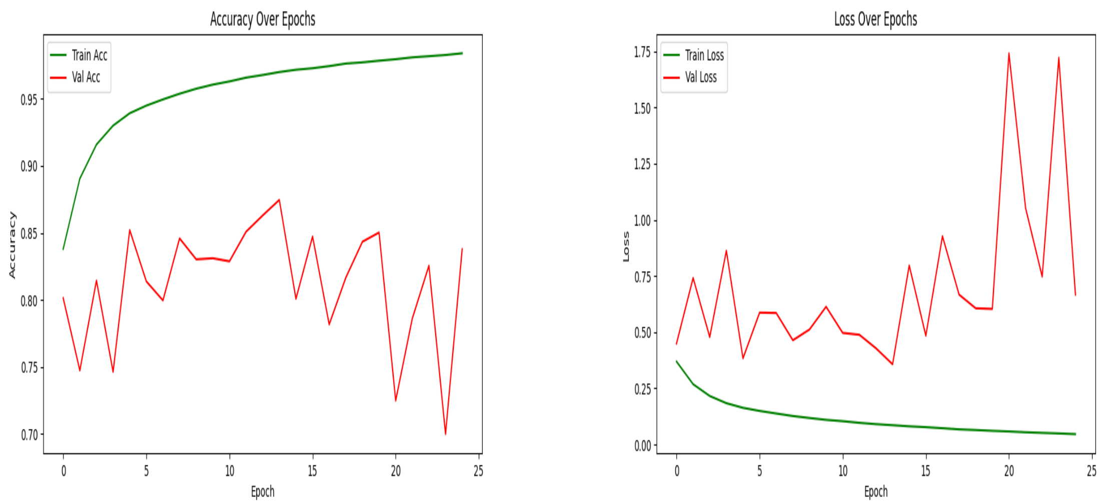
1.SGD gave better results than Adam,likely because it generalizes well and avoids overfitting.
2.Adam might have adapted too aggressively,leading to suboptimal convergence.
3.SGD with the given momentum value, helped the model to learn more effectively over time.



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 46: Accuracy and Loss for CustomNet Adam Optimizer



(a) Training Accuracy vs Epochs (b) Training Loss vs Epochs

Figure 47: Accuracy and Loss for CustomNet SGD

Best Model from CustomNet

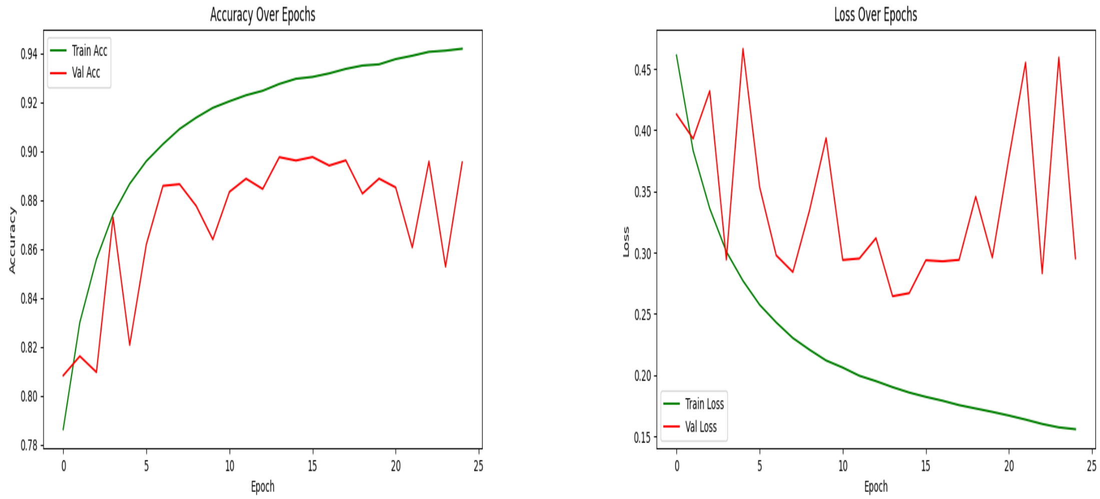
Learning Rate=0.001 ,Binary Cross Entropy Loss,SGD Optimizer,Data Augmentation.(All the best parameters taken from each ablation study)

Table 45: Training and Validation Losses for CustomNet Variations

	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
CustomNet	91.77	86.39	93.55	88.88	94.18	89.54

Table 46: Best model

	Accuracy	Precision	Recall	F1-score
CustomNet	87.52	0.9611	0.7818	0.8623



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 48: Accuracy and Loss for CustomNet with SGD and data augmentation.

Part-3:Improving CustomNet Model

After ablation studies of the given Custom architecture and previous Resnet and VGG observations,I have choosed some of the best performing parameters and techniques to optimize the model performance.Also I have tried with different combinations to improve Customnet model.

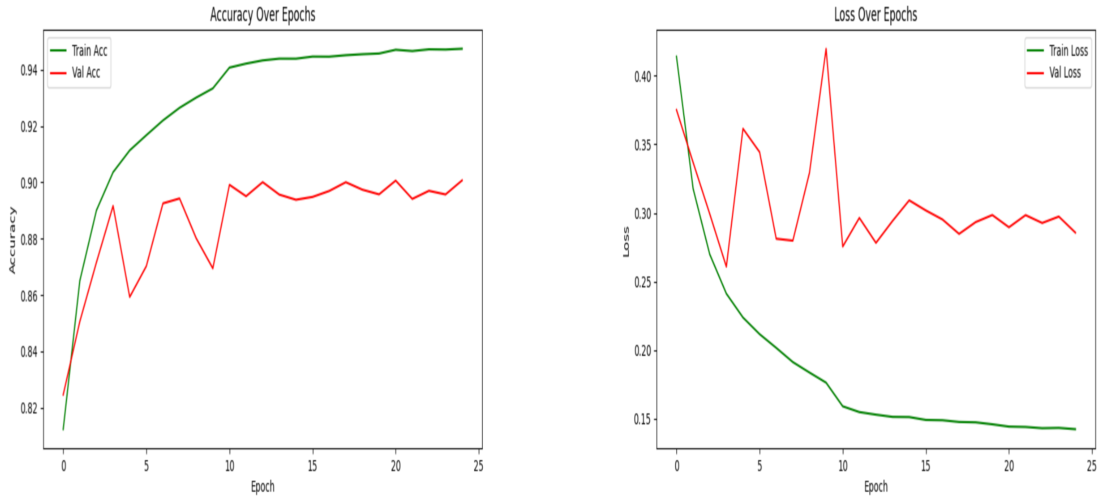
1.LR=0.0001
2.Adam Optimizer
3.Binary Cross Entropy Loss
4.Step Learning Rate
5.Data Augmentation

Table 47: Training and Validation Losses for CustomNet Variations

	10th Epoch		20th Epoch		25th Epoch	
	Train	Val	Train	Val	Train	Val
CustomNet	91.77	86.39	93.55	88.88	94.18	89.54
Improved CustomNet	93.34	86.95	94.57	89.58	94.74	90.07

Table 48: Best model

	Accuracy	Precision	Recall	F1-score
CustomNet	87.52	0.9611	0.7818	0.8623
Improved CustomNet	88.17	0.9560	0.8000	0.8711



(a) Training Accuracy vs Epochs

(b) Training Loss vs Epochs

Figure 49: Accuracy and Loss over epochs for Improved CustomNet

Conclusion:

After the ablation studies in Part-I,Part-II and in the process of improving the CustomNet model, the best performing model with highest accuracy and F1 score,I obtained is VGG16 with Data Augmentation.The accuracy achieved with this model is 90.28 percent.