Robust Image Classification with Gaussian Noise

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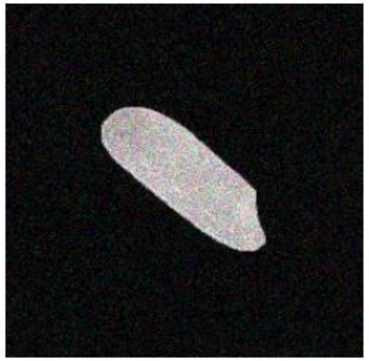
Problem Statement and Background Material

- CNN models like **VGG16** and **ResNet50** perform well on clean images.
- Their accuracy **drops significantly** in the presence of **Gaussian noise**, common in real-world settings.
- This affects critical applications in **agriculture, surveillance, autonomous systems, and healthcare**.
- The aim of this project is to improve the accuracy and reduce loss of these pretrained models.

- Background Material : The research paper 'Robust Convolutional Neural Network for Image Classification with Gaussian Noise. The dataset : The Rice Image Dataset .

Original

Noisy



Dataset Overview

Dataset: Rice Image Dataset with 75,000 high-resolution images of 5 rice varieties.

Subset: Used a manually processed subset of 2,000 images due to resource limits and 1000 images for modifications.

Arborio

Basmati

Ipsala

Jasmine

Karacadag

Proposed Solution

Data Augmentation	Batch Normalization
Denoising/Autoencoder	Regularization

Implementation Details

1. Data Processing
2. Train – Validation –Test Val Split
3. Initialization of Pretrained Model
4. Training of Pretrained Model
5. Evaluation using Accuracy and Loss Metrics using Cleaned Dataset
6. Computing Accuracy and Loss Metrics with Added Gaussian Noise in different levels.

Enhancement Details

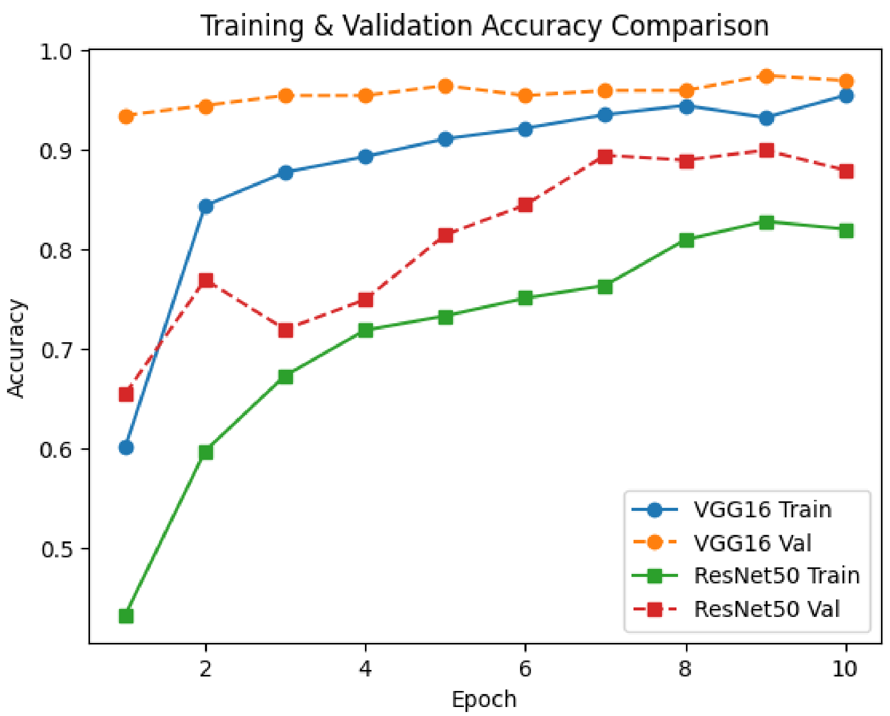
1. Data Processing
2. Train – Validation – Test Split
3. Designing of U-Net Auto Encoder
4. Training U-Net AutoEncoder with Gaussian Noise in Images
5. Data Augumentation Injection in Training Samples
6. Training Pretrained Models on Denoised Data & Augumented Data and L2-Regularization and Batch Normalization in Layers.
7. Evaluation of Performance

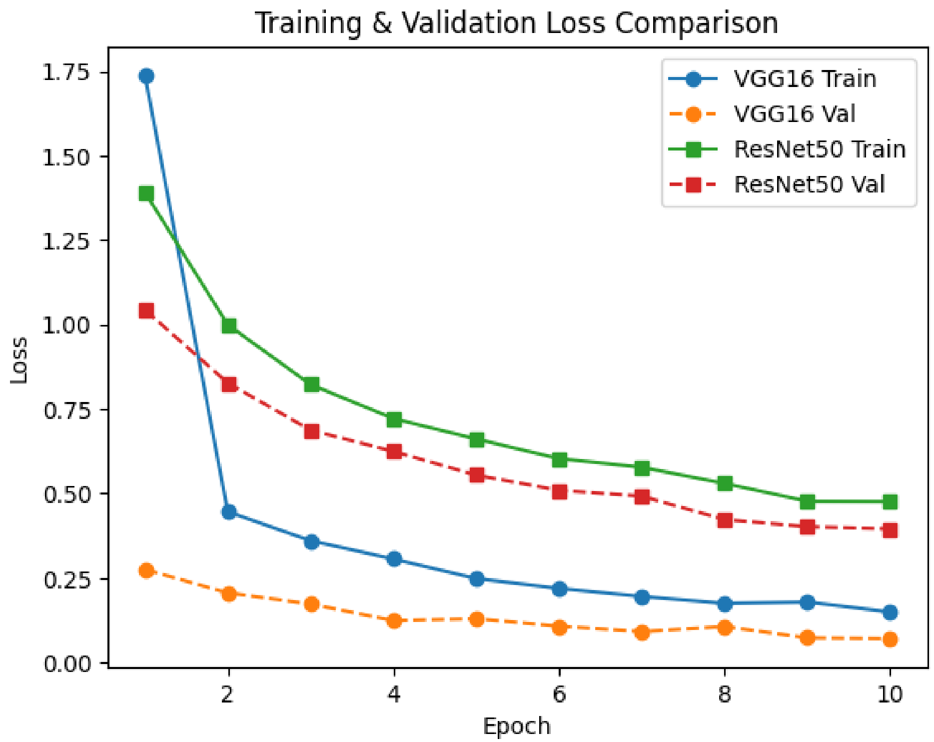
Implementation Details

2000 rice grain (resized to 224x224)

Dataset: 70% train, 20% val, 10% test

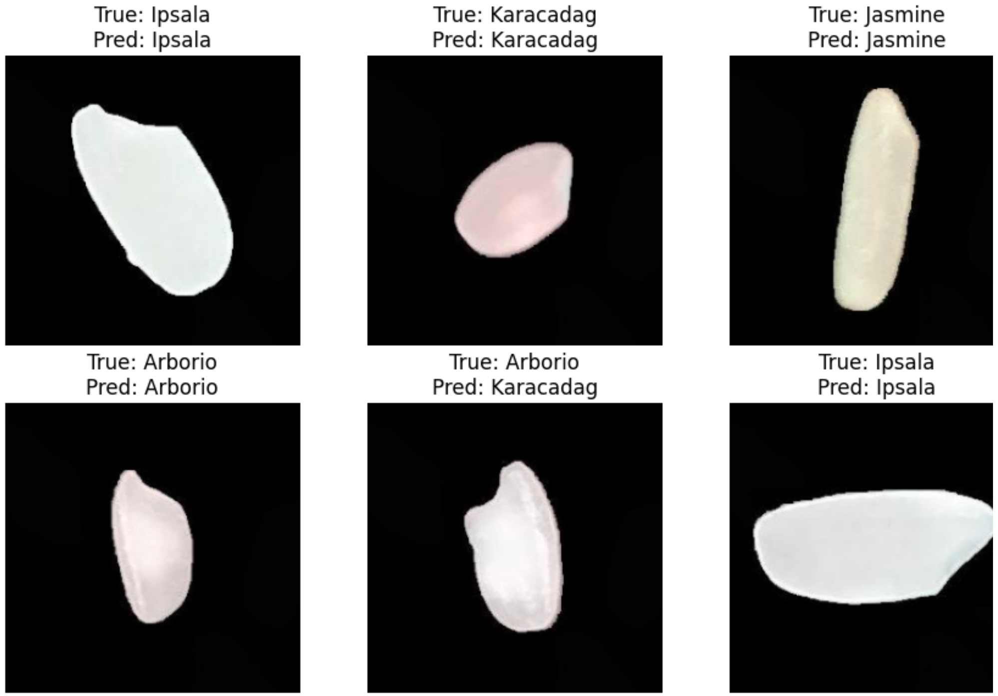
Pretrained VGG16 &ResNet50



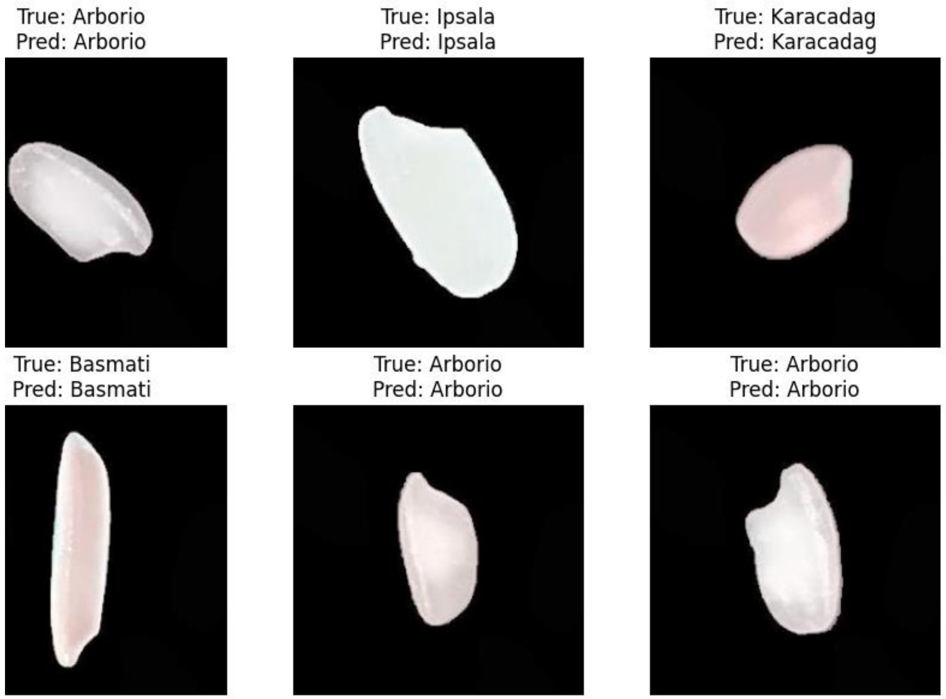


Implementation Details

VGG16 - MODEL



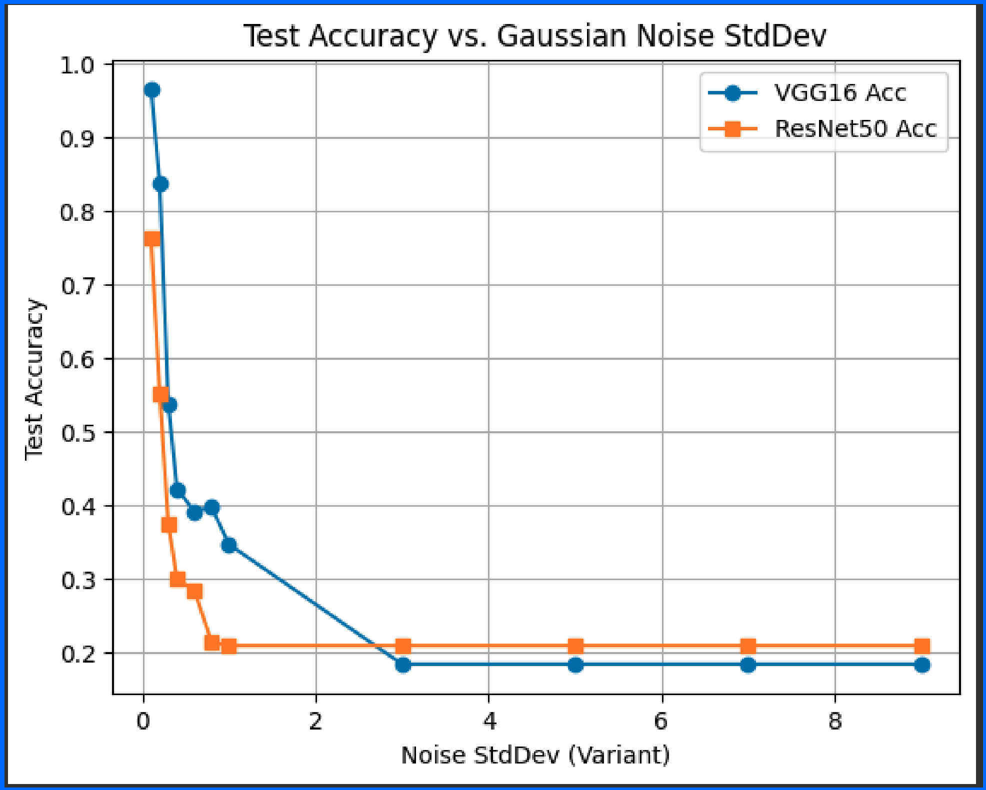
RESNET50 - MODEL

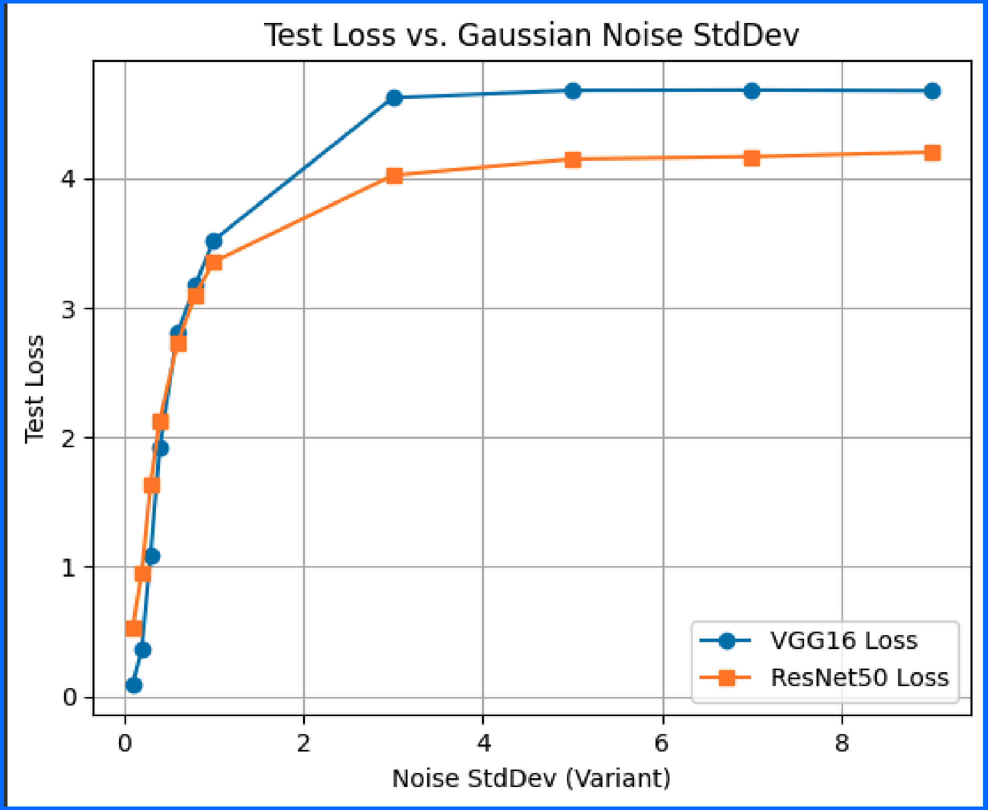


Comparative Analysis of the Gaussian Noise on the Pretrained Models

variant	VGG16 Test Loss	ResNet50 Test Loss	VGG16 Test Accuracy	ResNet50 Test Accuracy
0.1	0.091384	0.526133	0.9650	0.7625
0.2	0.362854	0.955461	0.8375	0.5525
0.3	1.086346	1.636482	0.5375	0.3750
0.4	1.913560	2.127842	0.4225	0.3000
0.6	2.810026	2.728065	0.3925	0.2850
0.8	3.175332	3.100902	0.3975	0.2150
1.0	3.518163	3.352969	0.3475	0.2100
3.0	4.620660	4.020796	0.1850	0.2100
5.0	4.677307	4.146552	0.1850	0.2100
7.0	4.679777	4.164486	0.1850	0.2100
9.0	4.674774	4.199956	0.1850	0.2100

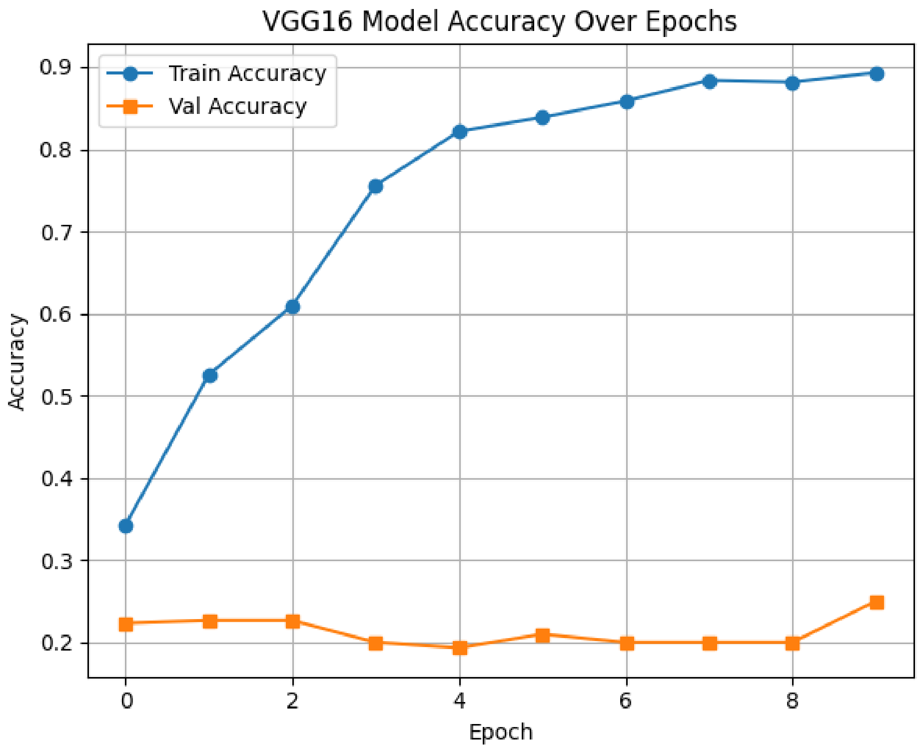
Comparative Analysis of the Gaussian Noise on the Pretrained Models

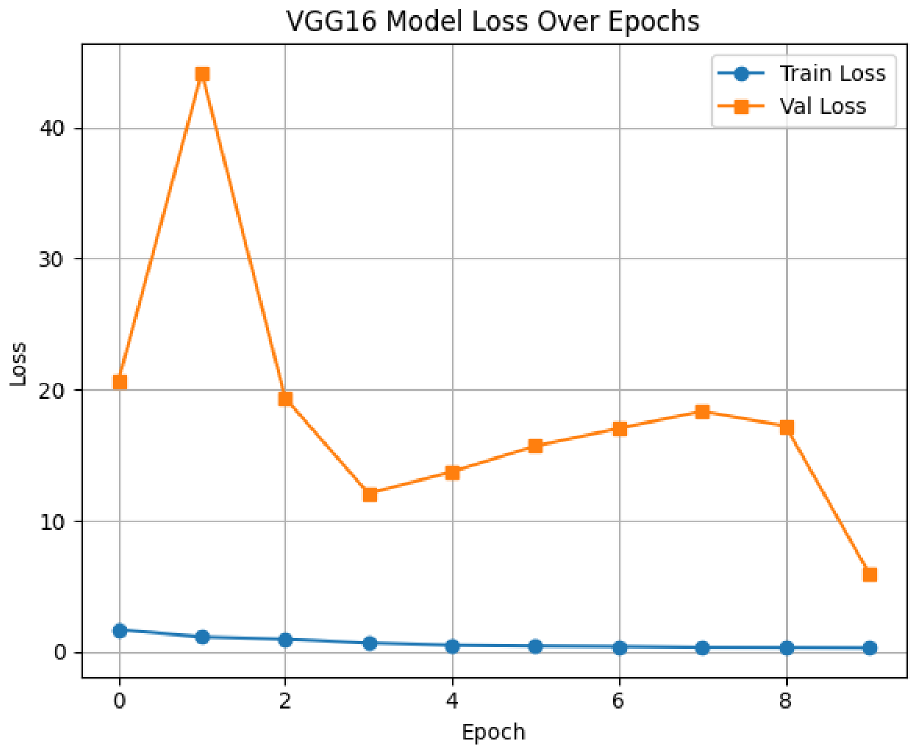




Enhancement Details

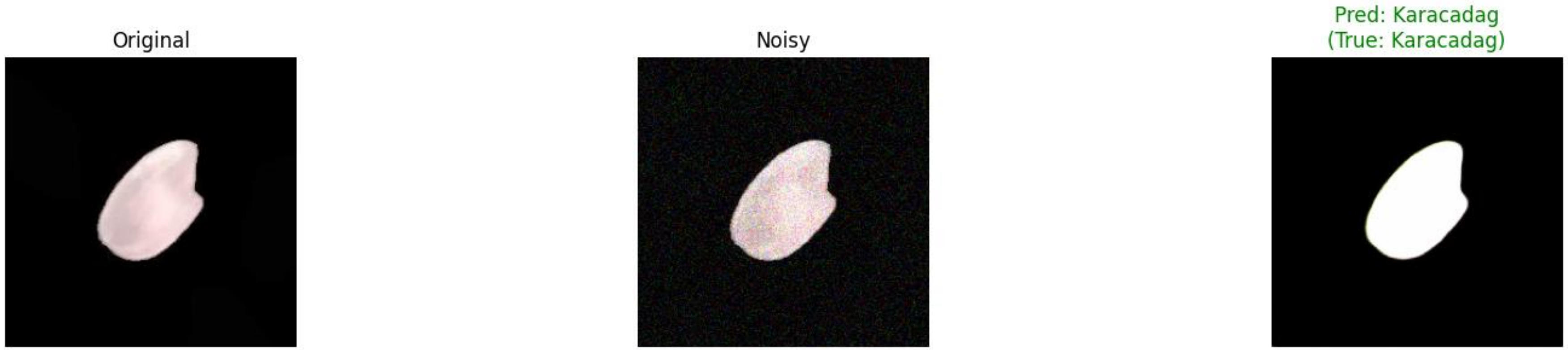
1000 rice grain (resized to 224x224) → Dataset: 70% train, 20% val, 10% test → Train U-net Autoencoder → Data Augmentation with Noise → Combine Denoised and Augmented Data → Retrain CNN with L2 and Batch Norm



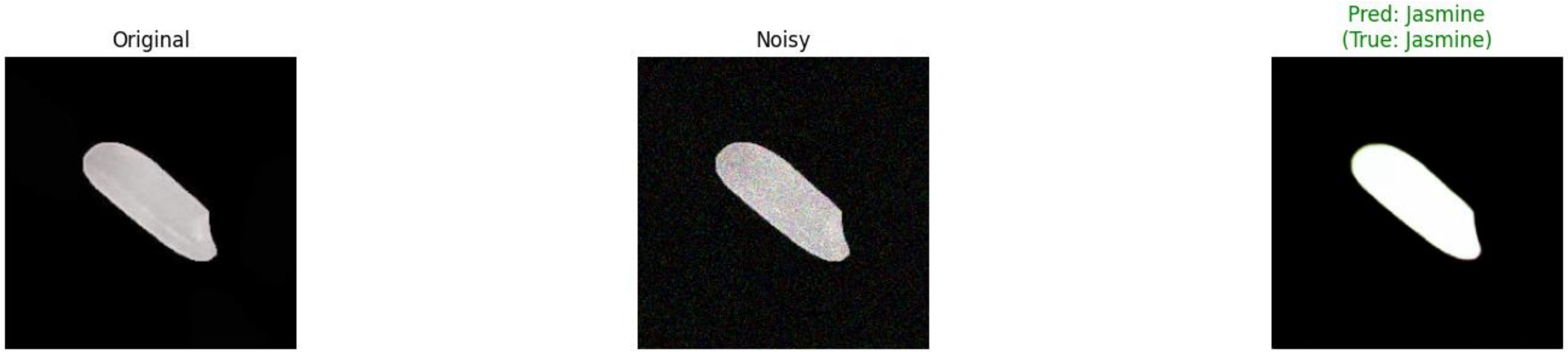


Enhancement Details

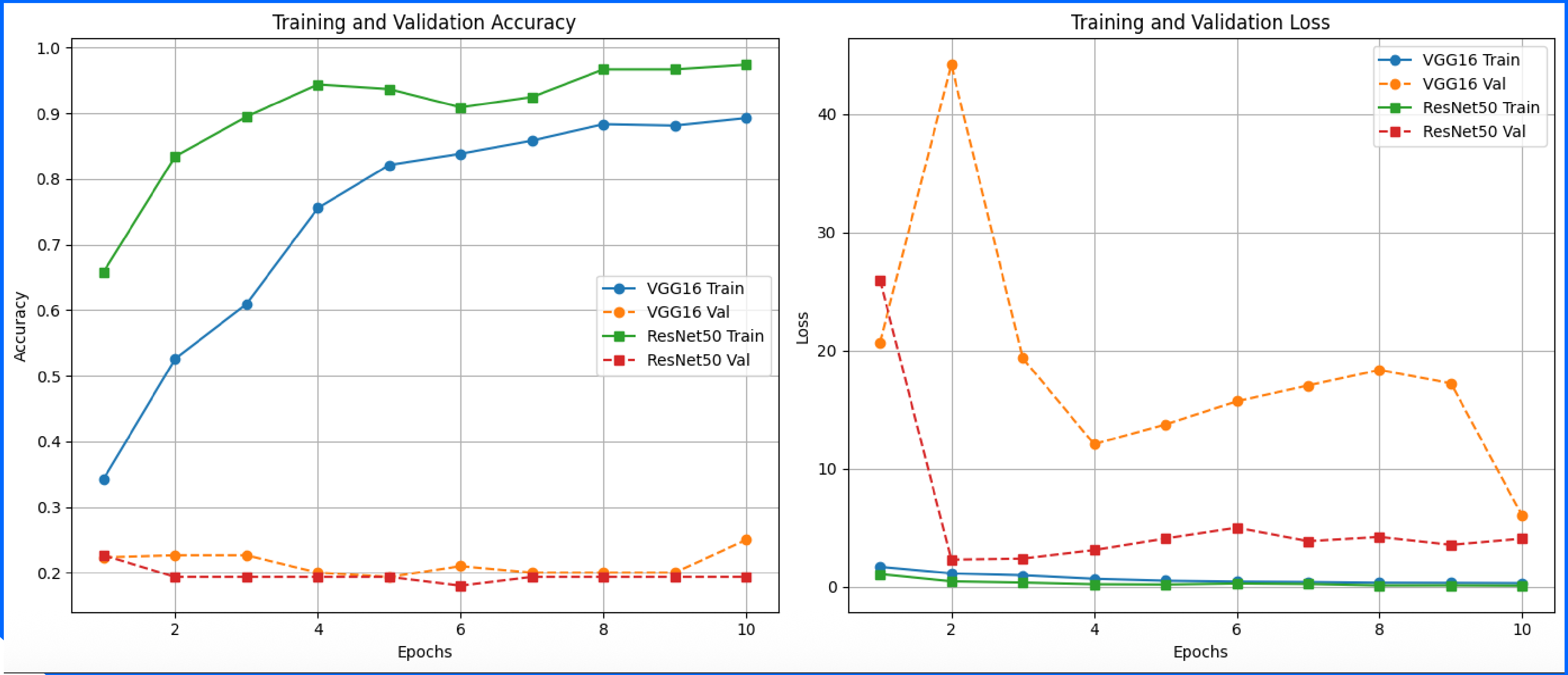
VGG16: Visual Comparison of Classification Result on Denoised Test Images



ResNet50: Visual Comparison of Classification Result on Denoised Test Images



Comparative Analysis of VGG16 and ResNet50 Performance



Results of Enhancement of Pretrained Models

	Noise STD	VGG16 Accuracy	VGG16 Loss	ResNet50 Accuracy	ResNet50 Loss
0	0.1	0.226667	5.992749	0.186667	4.068499
1	0.2	0.226667	5.999738	0.186667	4.067178
2	0.3	0.226667	6.002430	0.186667	4.064760
3	0.4	0.226667	6.006944	0.186667	4.062486
4	0.6	0.226667	6.029735	0.186667	4.056258
5	0.8	0.226667	6.072902	0.186667	4.049523
6	1.0	0.226667	6.113657	0.186667	4.044754
7	3.0	0.226667	35.416714	0.186667	4.011008
8	5.0	0.226667	53.483273	0.186667	3.982598
9	7.0	0.226667	54.116001	0.186667	3.966863
10	9.0	0.226667	53.119251	0.186667	3.959598

Final Model Performance Summary:

	Model	Train Accuracy	Validation Accuracy	Train Loss	Validation Loss	Test Accuracy	Test Loss
0	VGG16	0.892857	0.250000	0.297924	5.992175	0.226667	5.992578
1	ResNet50	0.974286	0.193333	0.088148	4.074579	0.186667	5.991834

Analysis & Limitations

- **Effectiveness of Denoising**

  The U-Net-based autoencoder successfully improved the quality of noisy images, leading to better classification performance, especially under moderate Gaussian noise.

- **Robustness Through Combined Training**

  Training the models on a mix of clean, noisy, and denoised images improved generalization and made the classifiers more resilient to real-world input distortions.

- **Noise Sensitivity Insight**

  Evaluation across varying noise levels showed that both VGG16 and ResNet50 experience sharp accuracy drops beyond a certain noise threshold (std ≥ 3.0), highlighting the need for denoising.

Model Comparison

While both models performed well under clean conditions, ResNet50 demonstrated slightly better robustness at higher noise levels compared to VGG16, likely due to its deeper architecture.

- **Limited GPU Availability :**

Training deep models like VGG16, ResNet50, and the U-Net autoencoder was time-consuming and restricted by hardware limitations, affecting model tuning and experimentation speed.

- Overfitting on Small Dataset:

Due to the relatively small size of the Rice Image Dataset, the models tended to overfit, especially without strong regularization or data augmentation.

- Performance

Drop at High Noise Levels .While the models handled low to moderate Gaussian noise well, their accuracy still declined significantly at high noise levels (std ≥ 5.0), showing the limits of even the denoised pipeline.

References

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Thank you