Comparative Analysis of Log, Linear, and JPG Images: Insights and Comparisons

Introduction:

In this study, we conduct a comprehensive comparison among Log, Linear, and JPG images utilizing a custom dataset. The dataset comprises images categorized across 10 classes, each possessing dimensions of 480 by 480 pixels. Intriguingly, our observations reveal that training models using the Log space facilitates a more effective learning of image features when compared to training with Linear and JPG images. This advantage is attributed to the inherent property of Log space to capture pixel ratios during the training process.

To substantiate this observation, a series of meticulous experiments were conducted to ascertain the optimal accuracy model among the three datasets. Furthermore, the robustness of these models was tested against adversarial images featuring random color alterations, diverse intensity adjustments, and a combination of both. The intent behind these tests was to validate the assertion that models trained on Log images also demonstrate superior performance when subjected to such adversarial scenarios.

Experiment Setup:

To train the model, we have selected DenseNet121 as the training architecture. Fig. 1 shows the standard DenseNet121 architecture.

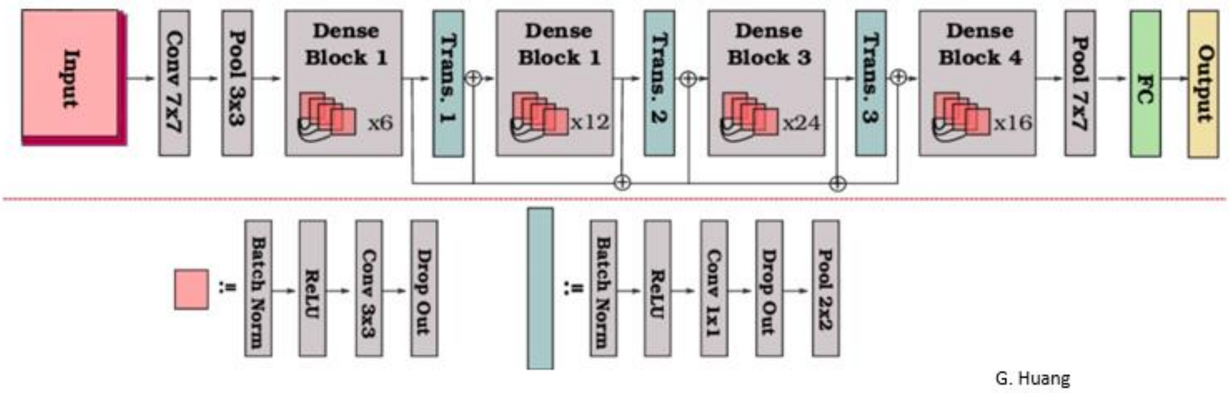

Fig. 1. DenseNet121 architecture

During our experimentation, we noticed that the model was exhibiting signs of overfitting to the dataset. To address this, we introduced a dropout layer with a dropout rate of 0.5, placed just before the fully connected (FC) layer. Following this modification, all subsequent experiments were conducted using the updated architecture incorporating the dropout layer.

For our experiments, we opted for two of the most promising optimizers, namely SGD and AdamW. Additionally, we employed two distinct learning rate scheduling strategies: Polynomial and Step learning rate schedulers.

Throughout the experiments, we systematically varied hyperparameters during training to explore and identify the optimal configuration for achieving peak performance on each dataset.

Analysis:

Our goal is to find the best performing model on each dataset and then validate their performance on adversarial images featuring random color alterations, diverse intensity adjustments, and a combination of both. We have selected 2 optimizers and 2 schedulers and thus each dataset is trained using 4 combinations and tuning the hyperparameters to get the best performance. Below results shows the best performance of each dataset with 4 combinations and the hyperparameters to achieve these results:

Optimizer: AdamW, Scheduler: Polynomial

Table 1. Best results on datasets with AdamW optimizer and Polynomial scheduler

Image Dataset	Learning Rate	Batch Size	Epsilon	Weight Decay	Epoch	Max. Train Accuracy	Max. Validation Accuracy	Test Accuracy			
								No Augmentation	Color Balance	Intensity Variation	Both
Log	0.005	4	0.1	0.03	100	98.92%	90.17%	91.94%	87.95%	91.75%	86.85%
Linear	0.005	4	0.1	0.01	100	99.69%	88.20%	90.10%	75.00%	89.90%	71.75%
JPG	0.005	4	0.1	0.01	100	99.92%	88.70%	90.50%	80.65%	89.85%	77.65%

Optimizer: AdamW, Scheduler: Step (Exponential)

Table 2. Best results on datasets with AdamW optimizer and Step scheduler

Image Dataset	Learning Rate	Batch Size	Epsilon	Weight Decay	Step Size	Gamma	Epoch	Max. Train Accuracy	Max. Validation Accuracy	Test Accuracy			
										No Augmentation	Color Balance	Intensity Variation	Both
Log	0.007	4	0.1	0.03	2	0.9	100	99.62%	88.58%	89.18%	81.55%	89.35%	78.80%
Linear	0.005	4	0.1	0.01	2	0.9	100	99.58%	85.10%	86.75%	66.85%	85.95%	62.35%
JPG	0.005	4	0.1	0.03	2	0.9	100	99.81%	87.40%	89.05%	76.05%	88.20%	71.75%

Optimizer: SGD, Scheduler: Polynomial

Table 3. Best results on datasets with SGD optimizer and Polynomial scheduler

Image Dataset	Learning Rate	Batch Size	Momentum	Weight Decay	Epoch	Max. Train Accuracy	Max. Validation Accuracy	Test Accuracy			
								No Augmentation	Color Balance	Intensity Variation	Both
Log	0.01	4	0	0.01	100	99.66%	87.98%	90.79%	85.05%	90.30%	81.65%
Linear	0.01	4	0	0.01	100	99.54%	89.50%	91.60%	84.65%	91.40%	81.95%
JPG	0.005	4	0	0.01	100	99.79%	88.30%	91.35%	84.65%	91.00%	81.00%

Optimizer: SGD, Scheduler: Step (Exponential)

Table 4. Best results on datasets with SGD optimizer and Step scheduler

Image Dataset	Learning Rate	Batch Size	Momentum	Weight Decay	Step Size	Gamma	Epoch	Max. Train Accuracy	Max. Validation Accuracy	Test Accuracy			
										No Augmentation	Color Balance	Intensity Variation	Both
Log	0.001	4	0.9	0.01	2	0.9	100	99.93%	87.09%	88.28%	77.70%	88.35%	72.75%
Linear	0.001	4	0.9	0.01	2	0.9	100	99.88%	89.20%	90.65%	80.95%	90.00%	77.90%
JPG	0.001	4	0.9	0.01	2	0.9	100	99.92%	88.10%	90.55%	77.25%	89.75%	71.35%

After analysing various test results, best performing model is selected for each image dataset. Below is the comparison of performance of best models.

Table 5. Best results on datasets among all trials

Image Dataset	Max. Train Accuracy	Max. Validation Accuracy	Test Accuracy			
			No Augmentation	Color Balance	Intensity Variation	Both
Log	98.92%	90.17%	91.94%	87.95%	91.75%	86.85%
Linear	99.54%	89.50%	91.60%	84.65%	91.40%	81.95%
JPG	99.79%	88.30%	91.35%	84.65%	91.00%	81.00%

Among the experiments conducted, the logarithmic (Log) data exhibited superior performance when coupled with the AdamW optimizer and the Polynomial learning rate scheduler. This setup involved a learning rate of 0.005 and a weight decay of 0.03. On the other hand, the Linear and JPG data yielded their best results when employing the SGD optimizer along with the Polynomial learning rate scheduler with same weight decay of 0.01.

The model trained on Log images shows 3% and 6% better performance on the adversarial images of random color and combination of random color and intensity respectively . Also, on the original dataset (with no augmentation), Log images shows marginal better performance.

This indicates that training the Log images is different from the Linear and JPG images. Hence, Log images captures data differently which can also be seen in training plots. The Log plot shows least overfitting and continuous training without saturation unlike Linear JPG plots. Fig. 2 shows the training plots for each dataset.

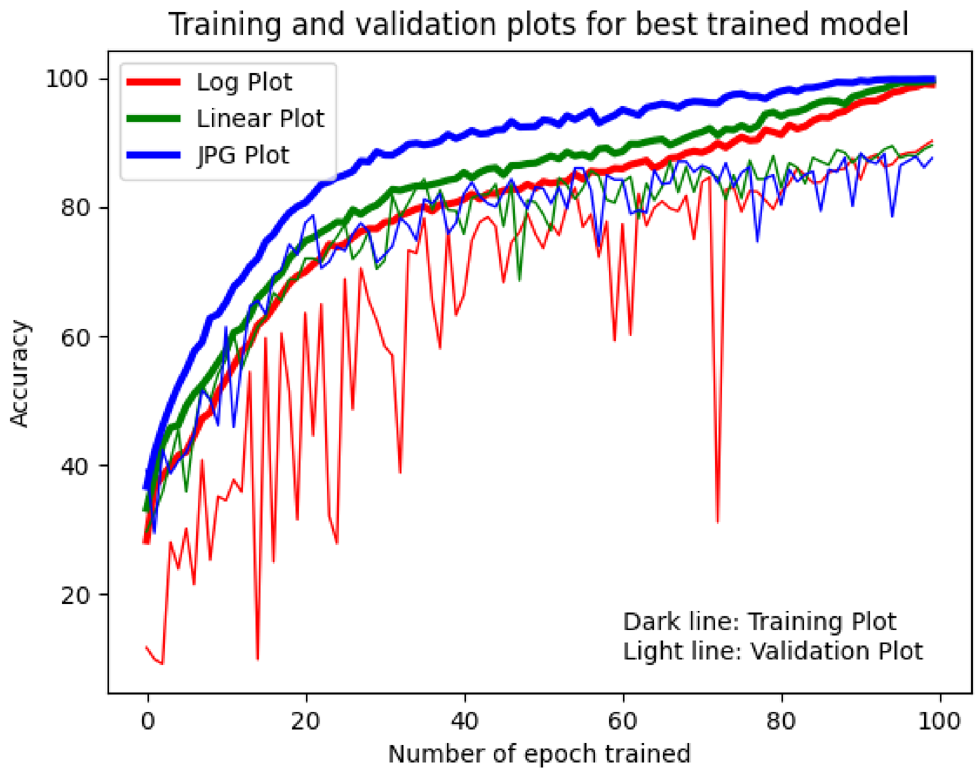

Fig. 2. Training and Validation plots for best performing models on each dataset

Conclusion:

The aforementioned outcomes validate that the model trained using Log images not only excels with the original images but also demonstrates superior performance when subjected to adversarial images. Due to the distinctive nature of Log images in capturing data, the training parameters for Log images inherently vary from those applied to the linear and JPG images.

In conclusion, it has been established that leveraging the Log space for training models proves advantageous, contributing to the enhanced robustness of the trained models.