Project Report: Image Noise Distribution Matching

Course: Practical Machine Learning
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Group: 412

Best Accuracy: 90.178% (XGBoost)

Gemini 3 was used to assist in the structural organization and grammatical polishing of this report. All experimental data, model architectures and results were produced by the author.

1. Introduction

The objective of this project is to develop a machine learning solution capable of distinguishing between noise images coming from different distributions.

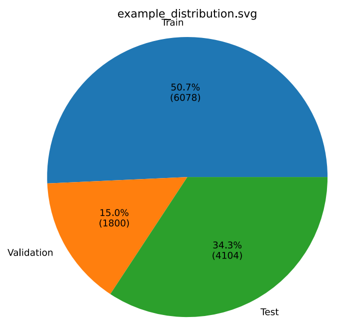
This report documents the end-to-end process, starting from exploratory data analysis and feature engineering, moving through the training of classical machine learning models based on statistical features, and concluding with a Deep Learning approach (CNN). The performance of these models is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and rank correlation coefficients (Spearman and Kendall) on a validation dataset.

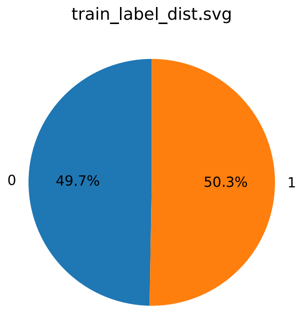
2. Data Analysis and Preprocessing

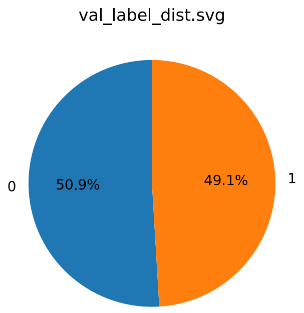
2.1 Dataset Overview

The dataset consists of a collection of images stored in `.npy` (numpy array) format, accompanied by CSV files containing labels for training, validation, and testing.

- **Train Set:** 6078 labeled pairs
- **Validation Set:** 1800 labeled pairs
- **Test Set:** 4104 unlabeled pairs







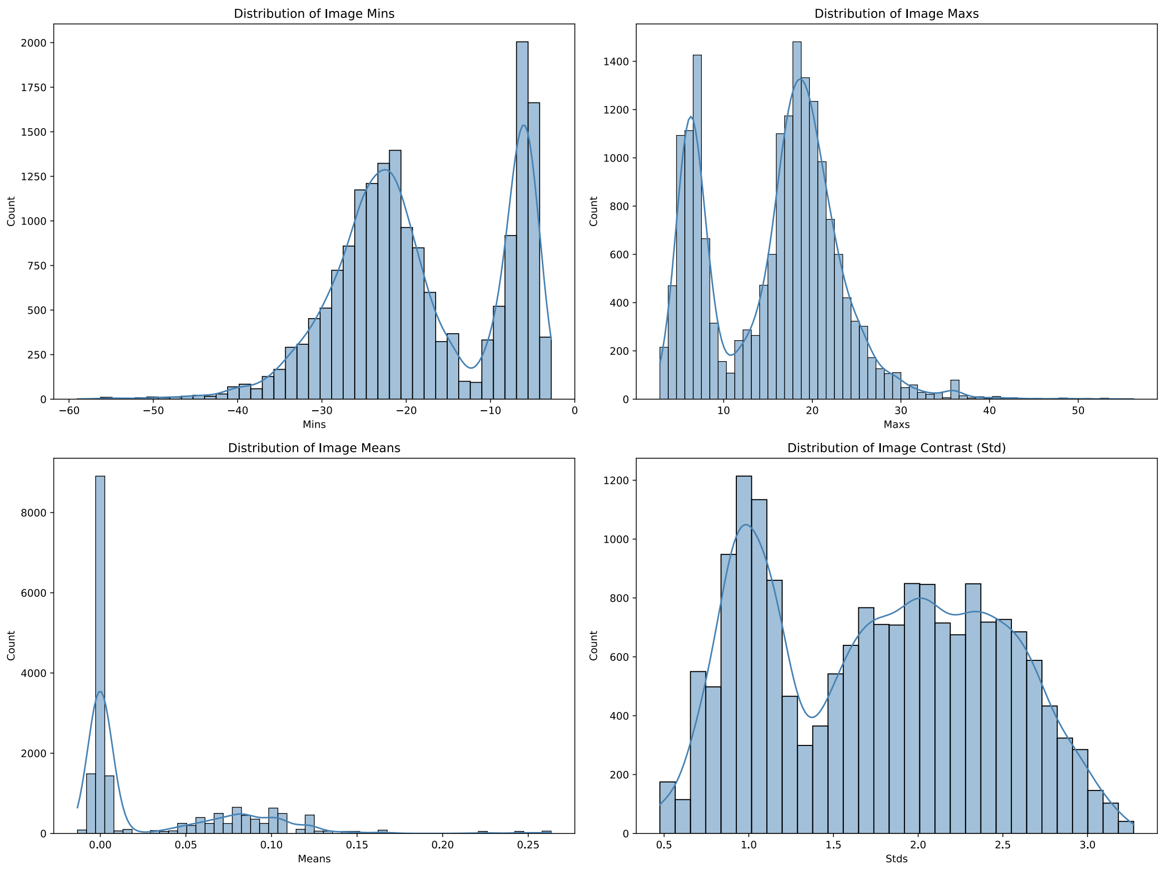
Initial analysis shows that the data is well-split. The labels are evenly distributed, so no further balancing is required.

Summary Metrics

- **Mean:** 0.03
- **Standard Deviation:** 1.88
- **Range:** -59.0 (Min) to 56.25 (Max)

Key Observations

- **Min/Max Distributions:** The histograms for both Minimum and Maximum values show two clear peaks. This structure suggests these extreme values capture significant variance, indicating they could serve as features for the model.
- **Mean Distribution:** The global mean is approximately 0 (0.03). As shown in the "Distribution of Image Means," the data is heavily concentrated near zero with a long tail, showing no other discernible patterns.
- **Standard Deviation:** The standard deviation falls within the range of $[0, 3.5]$. Similar to the min/max values, the standard deviation histogram displays two peaks. This bimodal shape implies a potential correlation between the noise distribution and the image contrast (standard deviation).



2.3 Data Preprocessing

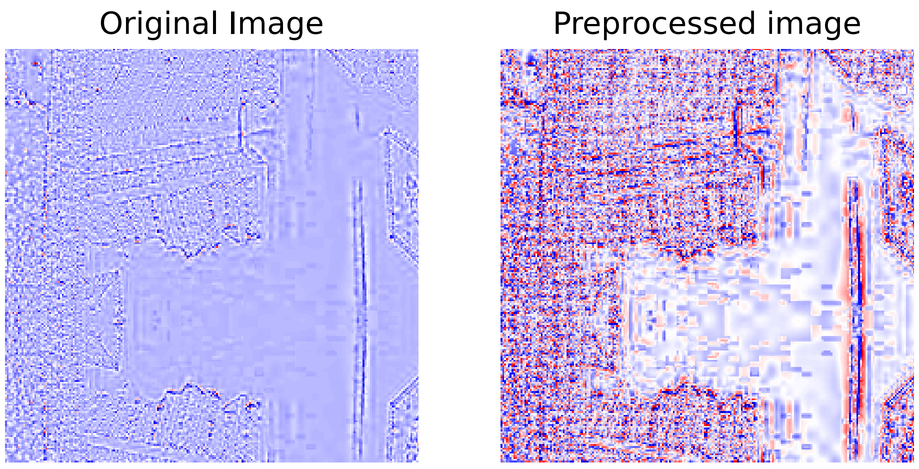
Images were loaded from the `samples` directory. Since the data is stored as raw numpy arrays, the following preprocessing steps were applied:

Symlog Transformation: As observed in the exploratory phase, the raw pixel values showed a high dynamic range. A symmetric logarithmic transformation (`symlog`) was applied to the raw data during the feature extraction phase to suppress outliers and make the distribution of pixel intensities more Gaussian-like.

$$f(x) = sign(x) \cdot \log_{10}(|x| + 1)$$

Metric	Before	After	Change
Mean	0.0006	0.0030	≈ 0 (Centering maintained)

Std Dev	2.2955	0.3885	**Decreased** (Variance reduced)
Min	-19.1250	-1.3037	Range Compressed
Max	25.3438	1.4207	Range Compressed
Kurtosis	6.4418	0.0513	**Drastic Drop** (Distribution flattened)
Skew	-0.0720	-0.0720	**Identical** (Symmetry preserved)
Entropy	4.0683	14.1598	**Increased** (Higher information density)



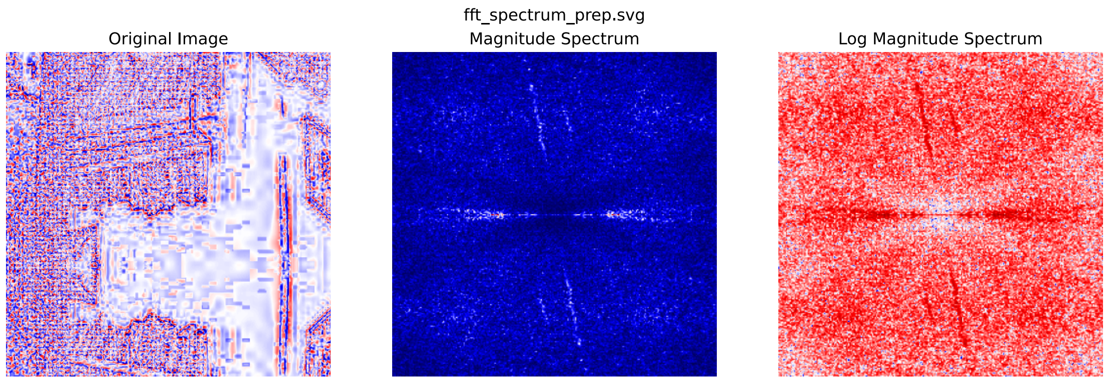
Preprocessing significantly enhances the visibility of underlying patterns.

3. Feature Engineering

3.1 Magnitude Spectrum

We developed a diagnostic tool to evaluate image frequency content before and after preprocessing. The pipeline consists of the following steps:

- **Transformation:** Utilized `numpy.fft.fft2` to compute the discrete Fourier transform, converting images from spatial pixels to frequency components.
- **Centralization:** Applied `fftshift` to move the zero-frequency component to the center of the image for standard visualization.
- **Logarithmic Scaling:** Implemented a log-transformation to attenuate dominant low-frequency energy, thereby revealing high-frequency textures and potential scanning artifacts.
- **Normalization:** Rescaled all spectral magnitudes to $[0, 1]$ to ensure consistent contrast across different samples.
- **Comparison:** The analysis was generated for both raw and `symlog`-transformed images to verify that preprocessing preserves essential structural information while handling noise.



3.2 Radial Profile

To simplify the complex information found in the 2D frequency maps, we implemented a **Radial Profile Analysis**. This technique reduces the 2D spectrum into a clear 1D line graph, making it easier to identify trends and anomalies.

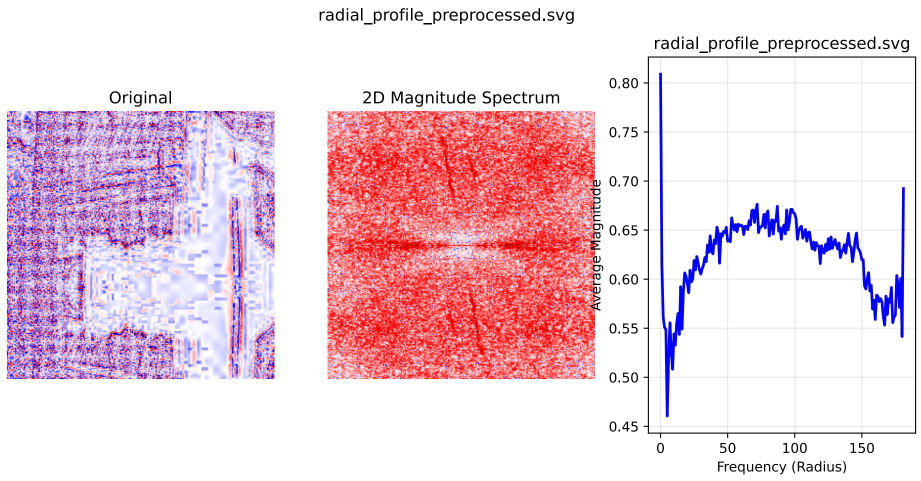
The Algorithm (Radial Averaging) The process can be visualized as drawing a series of expanding, concentric rings around the center of the spectrum (the DC component).

1. **Distance Calculation:** For every pixel in the frequency map, the algorithm calculates its distance from the center.

2. **Averaging:** It then calculates the average brightness (magnitude) of all pixels located within each ring.
3. **Result:** This produces a single plot showing the **Average Magnitude** versus **Frequency (Radius)**.

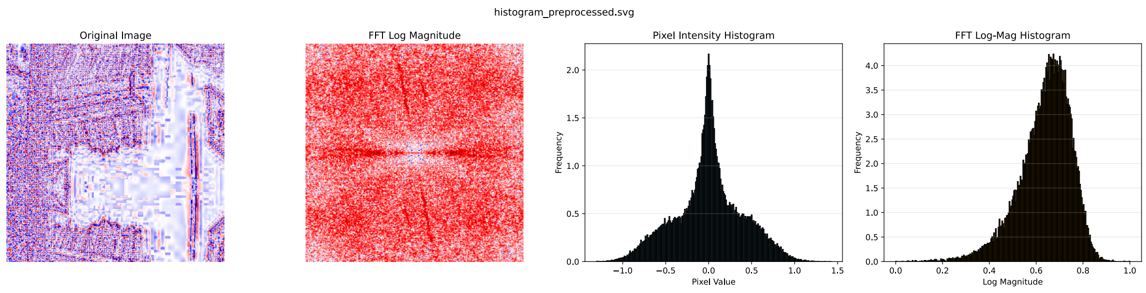
Interpretation This 1D profile allows for immediate visual diagnosis:

- **Natural Decay:** In healthy images, the line should drop smoothly as frequency increases (following a natural power law).
- **Artifact Detection:** Sudden spikes or bumps in the line indicate specific, repetitive noise frequencies that might not be obvious in the 2D image.



3.3 Pixel Value Histogram

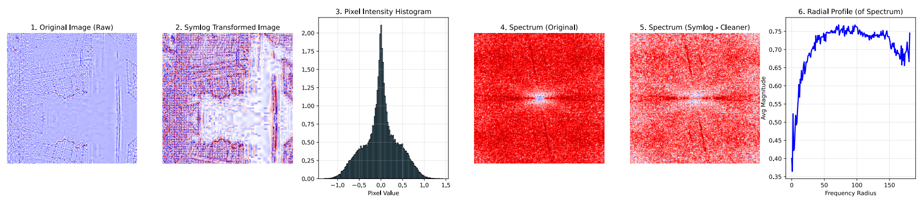
To reduce the complex spatial data into a one-dimensional statistical summary, we calculated pixel intensity histograms using 128 bins.



3.4 Full Feature Set Visualization

Simple values: mean, standard deviation, min pixel value, max pixel value, kurtosiss,skewness, entropy

More complex features: pixel value histogram, spectrum, radial profile



4. XGBoost

An **XGBoost Classifier** was selected for the learning task due to its efficiency with tabular data and ability to model non-linear interactions.

4.1. Feature Extraction Pipeline

To capture the distinct characteristics of each image, a dedicated feature extraction function (`get_feature_vector`) was implemented. This function aggregates multiple features to create comprehensive input for the model.

The input consists of the concatenation of the following features:

- Statistics of the original image
- Statistics of the preprocessed image
- Pixel value histogram
- Radial Profile

4.2. Pairwise Dataset Construction

The core of the classification task involves comparing two images to determine their relationship (labeled in the dataset). The `build_dataset` function generates the training data by combining the feature vectors of two images (f_1 and f_2) using interaction terms:

> **Feature Combination Strategy:** To ensure the model captures both the individual properties of the images and the relationship between them, the final input vector is constructed by concatenating:
>
> - The raw features of both images (f_1, f_2)
> - The absolute difference ($|f_1 - f_2|$) to measure distance/divergence.
> - The element-wise product ($f_1 \cdot f_2$) to capture interaction and correlation.

4.3 Manual Tuning

After some manual testing, this was the best performing model configuration:

- **Preprocessing:** All input features are normalized using `StandardScaler` to ensure zero mean and unit variance, facilitating stable convergence.
- **Hyperparameters:** The model is configured with 1000 estimators, a learning rate of 0.05, and a maximum depth of 6 to balance model complexity and generalization.
- **Optimization:** Training utilizes **early stopping** (patience of 200 rounds) based on the validation set performance to prevent overfitting.

This model achieved the following results:

- **Validation Accuracy: 70.5%**
- **Validation AUC: 0.79**

4.4 Grid Search Hyperparameter Tuning

To optimize the model's performance and mitigate overfitting, we employed a Grid Search strategy. This method systematically explores a defined combination of hyperparameters to identify the configuration that yields the best evaluation metric.

Tuned Parameters The following hyperparameters were selected for tuning to balance model complexity and generalization capabilities:

- **learning_rate:** It is tuned to ensure the model converges efficiently without overshooting the optimal solution.
- **max_depth:** It si tuned toapture complex non-linear patterns while restricting the tree's depth to prevent overfitting.
- **min_child_weight:** It is tuned to control the algorithm's conservatism, ensuring the model does not learn highly specific patterns representing noise.
- **subsample:** It is tuned to introduce randomness (row subsampling), which helps reduce variance and prevent overfitting.
- **colsample_bytree:** It is tuned to ensure feature diversity and prevent the model from relying too heavily on a subset of dominant features.

Search Space Configuration
The Grid Search was executed over the following parameter space (72 configurations):

Hyperparameter	Values Tested
learning_rate	`0.01`, `0.05`, `0.1`
max_depth	`4`, `6`, `8`
min_child_weight	`1`, `5`
subsample	`0.6`, `0.8`
colsample_bytree	`0.7`, `1.0`

Static Configuration To ensure computational efficiency during the extensive search process, specific parameters were held constant across all runs. Notably, `early_stopping_rounds` was set to 50 to prune non-improving iterations quickly.

- **n_estimators:** 1000
- **early_stopping_rounds:** 50
- **n_jobs:** -1 (Utilizing all available processors)
- **eval_metric:** 'logloss'
- **random_state:** 42 (For reproducibility)

Grid Search Results

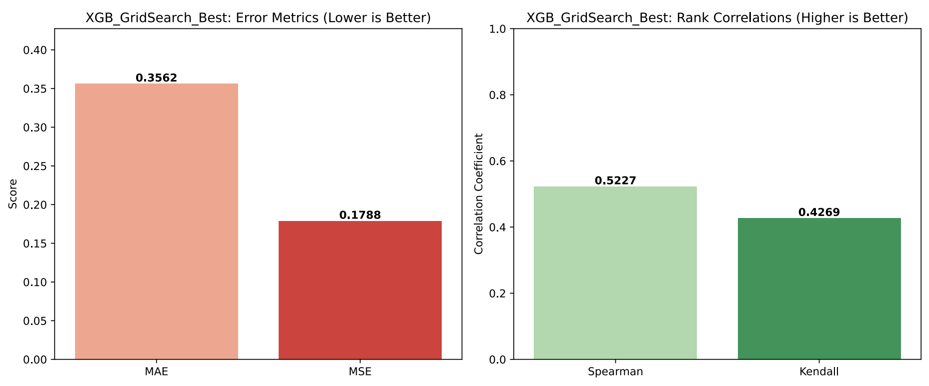
Iter	ColSamp	LR	Depth	Child_W	Sub	Accuracy	AUC
1	0.7	0.01	4	1	0.6	0.6794	0.7581
2	0.7	0.01	4	1	0.8	0.6906	0.7646
3	0.7	0.01	4	5	0.6	0.6856	0.7584
4	0.7	0.01	4	5	0.8	0.6906	0.7634
5	0.7	0.01	6	1	0.6	0.7000	0.7845
6	0.7	0.01	6	1	0.8	0.7133	0.7931
7	0.7	0.01	6	5	0.6	0.6967	0.7809
8	0.7	0.01	6	5	0.8	0.7044	0.7838
9	0.7	0.01	8	1	0.6	0.7128	0.7964
10	**0.7**	**0.01**	**8**	**1**	**0.8**	**0.7122**	**0.8005**
11	0.7	0.01	8	5	0.6	0.7067	0.7942
12	0.7	0.01	8	5	0.8	0.7139	0.7935
13	0.7	0.05	4	1	0.6	0.6989	0.7781
14	0.7	0.05	4	1	0.8	0.6889	0.7768
15	0.7	0.05	4	5	0.6	0.6983	0.7658
16	0.7	0.05	4	5	0.8	0.6978	0.7796
17	0.7	0.05	6	1	0.6	0.7044	0.7821
18	0.7	0.05	6	1	0.8	0.7094	0.7923
19	0.7	0.05	6	5	0.6	0.7000	0.7771
20	0.7	0.05	6	5	0.8	0.7033	0.7900
21	0.7	0.05	8	1	0.6	0.6950	0.7814
22	0.7	0.05	8	1	0.8	0.7106	0.7900

23	0.7	0.05	8	5	0.6	0.7017	0.7809
24	0.7	0.05	8	5	0.8	0.7078	0.7869
25	0.7	0.1	4	1	0.6	0.6850	0.7675
26	0.7	0.1	4	1	0.8	0.6950	0.7748
27	0.7	0.1	4	5	0.6	0.6894	0.7627
28	0.7	0.1	4	5	0.8	0.6972	0.7694
29	0.7	0.1	6	1	0.6	0.7006	0.7837
30	0.7	0.1	6	1	0.8	0.6928	0.7740
31	0.7	0.1	6	5	0.6	0.6889	0.7677
32	0.7	0.1	6	5	0.8	0.6922	0.7795
33	0.7	0.1	8	1	0.6	0.6967	0.7722
34	0.7	0.1	8	1	0.8	0.7033	0.7895
35	0.7	0.1	8	5	0.6	0.6978	0.7752
36	0.7	0.1	8	5	0.8	0.6911	0.7797
37	1.0	0.01	4	1	0.6	0.6839	0.7613
38	1.0	0.01	4	1	0.8	0.6911	0.7638
39	1.0	0.01	4	5	0.6	0.6794	0.7587
40	1.0	0.01	4	5	0.8	0.6894	0.7645
41	1.0	0.01	6	1	0.6	0.7022	0.7849
42	1.0	0.01	6	1	0.8	0.7094	0.7898
43	1.0	0.01	6	5	0.6	0.7000	0.7805
44	1.0	0.01	6	5	0.8	0.7072	0.7850
45	1.0	0.01	8	1	0.6	0.7078	0.7936
46	1.0	0.01	8	1	0.8	0.7133	0.7995
47	1.0	0.01	8	5	0.6	0.7083	0.7897
48	1.0	0.01	8	5	0.8	0.7133	0.7923
49	1.0	0.05	4	1	0.6	0.6922	0.7752
50	1.0	0.05	4	1	0.8	0.7061	0.7847
51	1.0	0.05	4	5	0.6	0.6950	0.7706

52	1.0	0.05	4	5	0.8	0.6983	0.7763
53	1.0	0.05	6	1	0.6	0.6833	0.7733
54	1.0	0.05	6	1	0.8	0.7083	0.7932
55	1.0	0.05	6	5	0.6	0.6900	0.7724
56	1.0	0.05	6	5	0.8	0.7094	0.7908
57	1.0	0.05	8	1	0.6	0.6950	0.7836
58	1.0	0.05	8	1	0.8	0.6967	0.7857
59	1.0	0.05	8	5	0.6	0.6967	0.7783
60	1.0	0.05	8	5	0.8	0.7083	0.7894
61	1.0	0.1	4	1	0.6	0.6811	0.7479
62	1.0	0.1	4	1	0.8	0.6922	0.7667
63	1.0	0.1	4	5	0.6	0.6894	0.7661
64	1.0	0.1	4	5	0.8	0.7022	0.7823
65	1.0	0.1	6	1	0.6	0.6950	0.7814
66	1.0	0.1	6	1	0.8	0.6944	0.7767
67	1.0	0.1	6	5	0.6	0.6778	0.7628
68	1.0	0.1	6	5	0.8	0.6922	0.7747
69	1.0	0.1	8	1	0.6	0.6994	0.7830
70	1.0	0.1	8	1	0.8	0.6944	0.7765
71	1.0	0.1	8	5	0.6	0.6861	0.7672
72	1.0	0.1	8	5	0.8	0.7056	0.7854

Best Model Results

- **Accuracy**: 71.22%
- **AUC**: 0.8005
- **Public Test Accuracy**: 77.11%



5. Siamese Network

The core of our approach utilizes a Siamese Neural Network architecture. Unlike traditional classification models, this network consists of two identical sub-networks that share the same weights and parameters. The primary objective is to learn a similarity function by mapping input pairs into a common feature space. During the forward pass, two distinct images are processed by the shared sub-networks to produce feature vectors. The network then computes the distance between these vectors to determine the degree of similarity, outputting a probability score indicating whether the inputs belong to the same class.

5.1 Feature Extraction Pipeline

To prepare the raw data for the network, we implemented two distinct preprocessing strategies to enhance feature perceptibility:

- **Option 1: SymLog Transformation** We apply a Symmetric Logarithmic (SymLog) transformation to the raw images.
- **Option 2: Magnitude Spectrum and SymLog Tranformation** This pipeline extends the first option by computing the magnitude spectrum of the SymLog-transformed images and concatenating the two.

5.2 Data Augmentation

To mitigate overfitting and improve the model's generalization capabilities, the following geometric transformations are applied during training:

- **Horizontal/Vertical Flipping**
- **90-Degree Rotation**

5.3 Model Architecture

The architecture is designed to handle 256×256 single-channel inputs. It utilizes a Convolutional Neural Network (CNN) as the feature extractor, followed by an L1 distance calculation and a fully connected classifier head.

Table: Detailed Layer Configuration

Layer / Block	Input Shape (C, H, W)	Operation / Components	Output Shape (C, H, W)
Input	$(in\_channels, 256, 256)$	Input Image	$(in\_channels, 256, 256)$
Conv Block 1	$(in\_channels, 256, 256)$	Conv2d(32) $\rightarrow$ ReLU $\rightarrow$ BN $\rightarrow$ MaxPool(2)	$(32, 128, 128)$
Conv Block 2	$(32, 128, 128)$	Conv2d(64) $\rightarrow$ ReLU $\rightarrow$ BN $\rightarrow$ MaxPool(2)	$(64, 64, 64)$
Conv Block 3	$(64, 64, 64)$	Conv2d(128) $\rightarrow$ ReLU $\rightarrow$ BN $\rightarrow$ MaxPool(2)	$(128, 32, 32)$
Conv Block 4	$(128, 32, 32)$	Conv2d(256) $\rightarrow$ ReLU $\rightarrow$ BN $\rightarrow$ MaxPool(2)	$(256, 16, 16)$
Conv Block 5	$(256, 16, 16)$	Conv2d(512) $\rightarrow$ ReLU $\rightarrow$ BN $\rightarrow$ MaxPool(2)	$(512, 8, 8)$
Conv Block 6	$(512, 8, 8)$	Conv2d(512) $\rightarrow$ ReLU $\rightarrow$ BN $\rightarrow$ MaxPool(2)	$(512, 4, 4)$
Flatten	$(512, 4, 4)$	`view(batch, -1)`	$Vector : 8192$
Distance	$Vector : 8192$	L1 Distance (`abs(feat1 - feat2)`)	$Vector : 8192$
FC Layer 1	8192	Linear(512) $\rightarrow$ ReLU $\rightarrow$ Dropout(0.5)	$Vector : 512$
FC Layer 2	512	Linear(256) $\rightarrow$ ReLU $\rightarrow$ Dropout(0.5)	$Vector : 256$
Output Layer	256	Linear(1) $\rightarrow$ Sigmoid	$Scalar : 1$

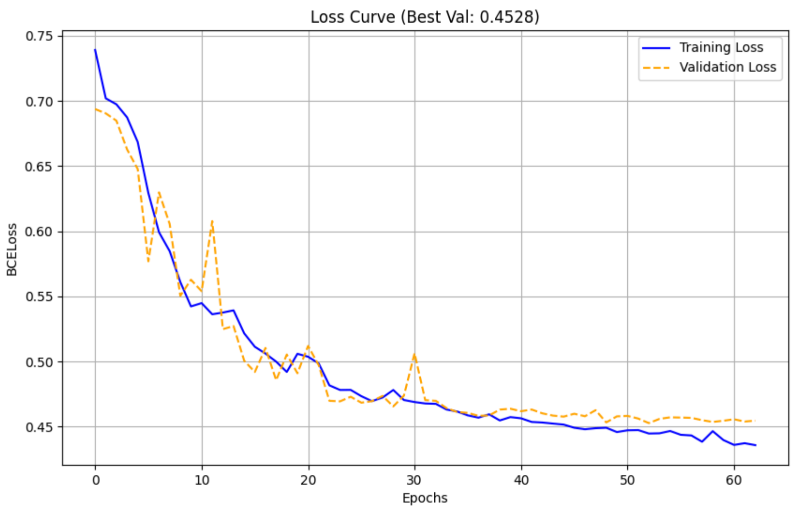
5.3 Manual Tuning

> SymLog transformed images

Experimental Setup The `SiameseNetwork` was trained on 256×256 grayscale inputs using the Adam optimizer (initial $\alpha = 2 \times 10^{-4}$, weight decay 10^{-4}) and Binary Cross Entropy loss. The batch size was set to 128 distributed across GPUs. To prevent overfitting, a `ReduceLROnPlateau` scheduler (factor 0.5, patience 3) and early stopping (patience 10) were employed.

Results Training halted at epoch 63 upon triggering early stopping. The model achieved its lowest validation loss at **Epoch 53**, which was selected as the final model state:

- **Best Validation Loss: 0.4528**
- **Validation Accuracy: 75.7%**
- **Training Accuracy: 74.5%**
- **Public Test Results: 69.24%**

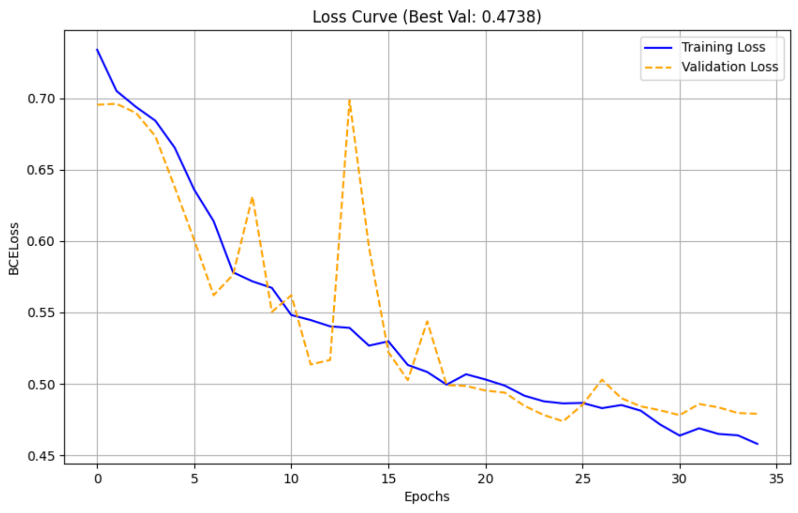


Magnitude Spectrum and SymLog Tranformation

Experimental Setup The `SiameseNetwork` was trained on $2-channel 256 \times 256$ inputs using the Adam optimizer (initial $\alpha = 2 \times 10^{-4}$) and Binary Cross Entropy loss. The batch size was set to 128 distributed across 2 GPUs. To prevent overfitting, a `ReduceLROnPlateau` scheduler (factor 0.5, patience 3) and early stopping (patience 10) were employed.

Results Training halted at **Epoch 35** upon triggering early stopping. The model achieved its lowest validation loss at **Epoch 25**, which was selected as the final model state:

- **Best Validation Loss: 0.4738**
- **Validation Accuracy: 75.2%**
- **Training Accuracy: 72.4%**
- **Public Test Results: 68.83%**



6. XGBoost with more features

6.1 Feature Definitions

- **Mean:** The average pixel intensity; used to determine the overall brightness of the image.
- **Standard Deviation:** The spread of pixel values; used to measure the global contrast level.
- **Minimum/Maximum:** The lowest and highest pixel values; used to define the dynamic range.
- **Skewness:** The measure of histogram asymmetry; used to see if pixels lean toward high or low values.
- **Kurtosis:** The measure of "tailedness" in the distribution; used to identify the presence of outliers or noise.
- **Shannon Entropy:** A measure of information uncertainty; used to quantify the overall complexity of the image.
- **Permutation Entropy:** A measure of order and complexity in pixel sequences; used to detect non-linear patterns.
- **GLCM Contrast:** The local variation in the image; used to highlight sharp intensity transitions.
- **GLCM Correlation:** How a pixel relates to its neighbor; used to identify linear structures or patterns.
- **GLCM Homogeneity:** The closeness of pixel distribution; used to measure the smoothness of textures.

- **GLCM Energy:** The sum of squared elements; used to identify uniformity and order in the image.
- **GLCM Dissimilarity:** Similar to contrast but grows linearly; used to measure the distance between pixel intensities.
- **LBP Histogram:** A distribution of local binary patterns; used to identify micro-structures like edges, spots, and corners.
- **LBP Smoothness/Uniformity:** Aggregated LBP values; used to distinguish between complex textures and flat, "smooth" areas.
- **HF (High-Frequency) Energy:** The power in the outer edges of the Fourier spectrum; used to detect fine details and noise.
- **LF (Low-Frequency) Power:** The power near the center of the Fourier spectrum; used to capture broad shapes and gradients.
- **Spectral Centroid:** The "center of mass" of the frequency spectrum; used to see if the image is dominated by blur or detail.
- **Spectral Slope:** The rate of decay in the power spectrum; used to distinguish between natural and artificial textures.
- Distance Metrics (Image Similarity)
    - L1 Distance (Manhattan): The sum of absolute differences between corresponding pixels; used to measure direct pixel-wise divergence without over-penalizing large outliers.
    - L2 Distance (Euclidean): The square root of the sum of squared differences; used as a standard measure of geometric distance between two images in vector space.
    - Cosine Distance: A measure of the angular difference between two image vectors; used to determine similarity based on orientation rather than magnitude (useful for lighting variations).
    - FID-like Distance (Frechet Inception Distance): A simplified version comparing the mean and variance of image distributions; used to quantify how similar the "statistical signature" of one image is to another.

For each image we have precomputed these features and, in order to create the input for the model, we concatenated

- image_1_features
- image_2_features
- absolute difference of the two feature lists
- distance metrics

Graph Trick

It is possible to create new training samples from the existing data by using the following two properties:

- if images A and B are from the same distribution and images B and C are from the same distribution, then we can infer that A and C are from the same distribution
- similarly, if images A and B are from the same distribution and images B and C are from different distributions, then we can deduce that A and C are from different distributions

This increases the number of examples:

- train: from 6078 to 8415 examples
- validation: from 1800 to 1998 examples
- both train and validation: from 7878 to 11817 examples

6.2 Grid Search

A grid search was performed across 27 combinations of hyperparameters to optimize the model's performance. The evaluation focused on **Validation Accuracy** and **AUC**.

Top Performing Iterations

The following table summarizes the top 5 configurations based on the highest AUC scores:

Iteration	Colsample Bytree	Learning Rate	Max Depth	Accuracy	AUC
5 (Best)	**0.5**	**0.02**	**8**	**0.8308**	**0.9109**
6	0.5	0.02	10	0.8292	0.9092
8	0.5	0.03	8	0.8233	0.9090
17	0.6	0.03	8	0.8308	0.9086
9	0.5	0.03	10	0.8294	0.9086

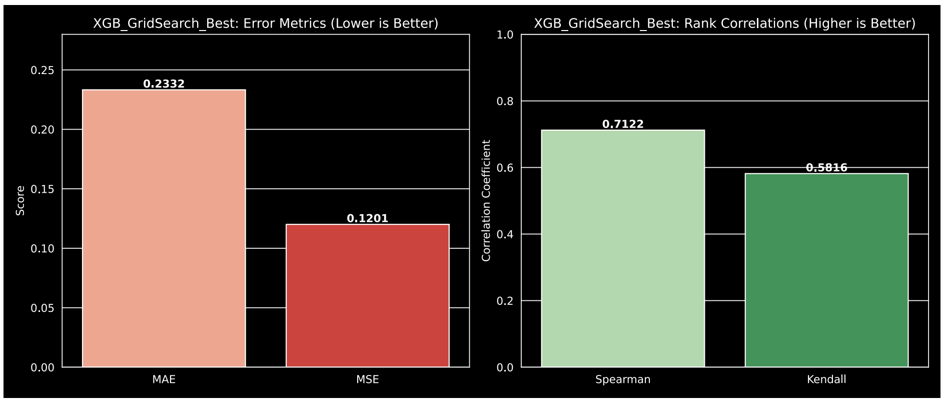
Final Optimized Parameters

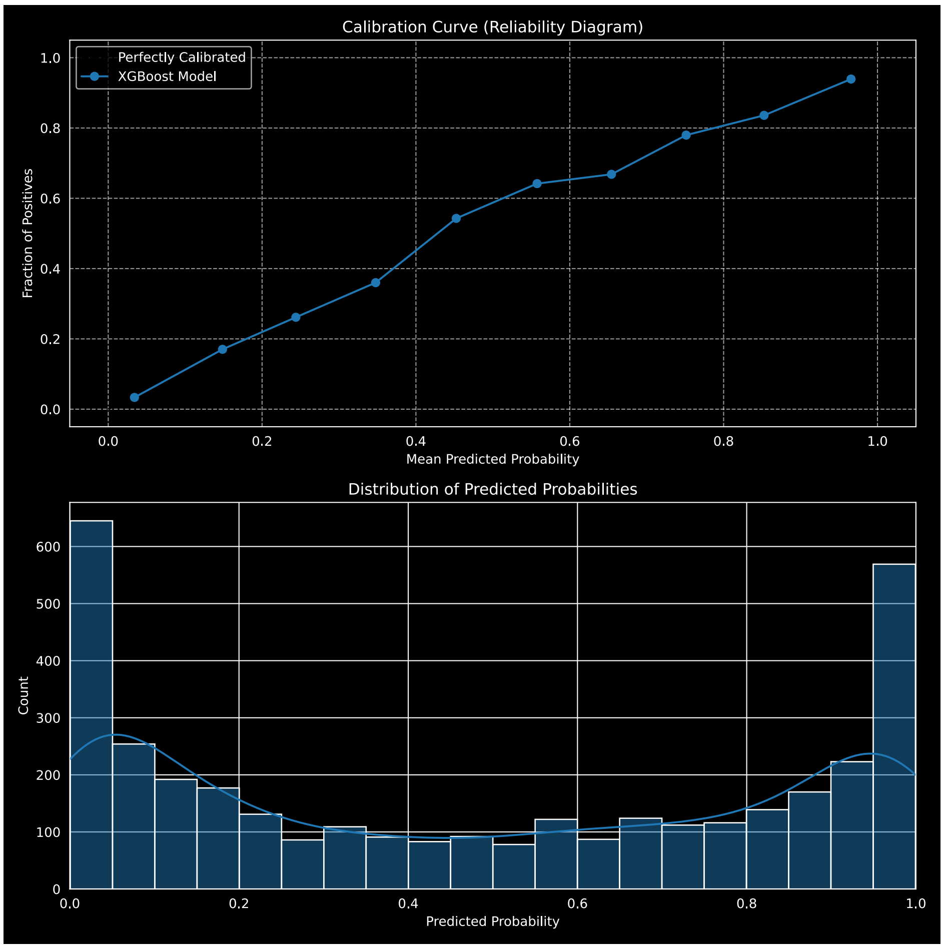
Based on the grid search results, the following parameters were selected for the final model:

- **Learning Rate:** 0.02
- **Max Depth:** 8
- **Colsample Bytree:** 0.5
- **Subsample:** 0.5
- **Min Child Weight:** 1
- **Trees (n_estimators):** 1000 (with early stopping at 955)

Final Performance: Accuracy of **83.08%** and AUC of **0.9109**.

Result Analysis





Final Results

For the official submission, the model has been trained using both train and validation datasets, using the graph trick and the same parameters as previously. This model achieves **90.178%** accuracy on the public test dataset.