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SVHN Dataset Classification Using VGG-like Neural Network

Summarizing the approach, findings, and analyses of the implementation

Overview of Implementation Methodology

SVHN Dataset Classification Using VGG-like Neural Network

Data Processing

Utilized the SVHN dataset with augmentation techniques to enhance model generalization.

Model Architecture

Designed a VGG-like neural network with multiple convolutional layers and fully connected layers.

Training Procedures

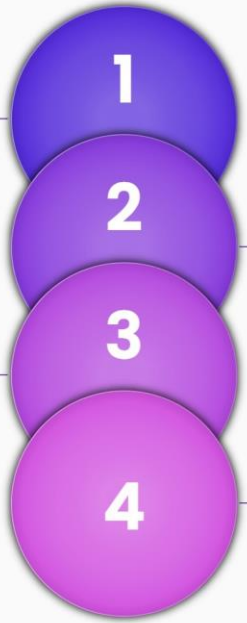
Employed various optimizers, learning rates, and batch sizes to optimize training.

Evaluation Methods

Leveraged multiple metrics including accuracy, test loss, and ROC AUC scores for comprehensive evaluation.

Data Processing Techniques

Applying Data Augmentation Techniques for SVHN Dataset



Rotation

Images were randomly rotated within a 30-degree limit to improve model robustness.

Random Resized Crop

Cropped images were resized to 32x32 pixels, scaled between 0.8 to 1.0 for consistency.

Aspect Ratio Change

Alterations to aspect ratios ranged from 0.75 to 1.33, generating diverse image forms.

Normalization

Applied mean and standard deviation normalization specific to the SVHN dataset for accurate scaling.

Model Architecture Breakdown

Detailed Overview of Neural Network Structure

Convolutional Layers organized into three blocks

These layers are crucial for feature extraction, structured to optimize learning.

Block 1: 2 layers with 8 and 16 filters

The first block effectively captures low-level features through its dual filter approach.

Block 2: 2 layers, each with 32 filters

This block focuses on capturing more complex patterns with increased filter depth.

Block 3: 2 layers, also with 32 filters

Similar to Block 2, it further refines the features extracted, ensuring robust learning.

Fully Connected Layers after flattening

These layers integrate the features learned from the convolutional blocks for final classification.

Layer 1: 256 units with ReLU activation and 20% dropout

This layer enhances model capacity while mitigating overfitting through dropout.

Layer 2: 10 units for classification corresponding to the 10 classes in SVHN dataset

The final layer outputs the probabilities for each class in the dataset, enabling accurate predictions.

Training Settings Overview

1 Optimizers

Both Adam and SGD were utilized to assess performance.

2 Learning Rates

Tested rates of 0.001 and 0.0001 for optimal performance.

3 Batch Sizes

Evaluated with sizes of 32 and 64 to find the best fit.

4 Epochs

Models were trained across 10 and 20 epochs to ensure robustness.

5 Loss Function

Cross-entropy loss was employed for training to measure performance.

Evaluation Techniques and Metrics

Key metrics for assessing model performance in SVHN classification

Accuracy

Evaluated to determine correct classifications, indicating overall model performance.

Test Loss

Measured to assess model accuracy, providing insights into prediction errors.

ROC AUC Scores

Both macro and micro scores calculated using a one-vs-rest strategy for multi-class classification.

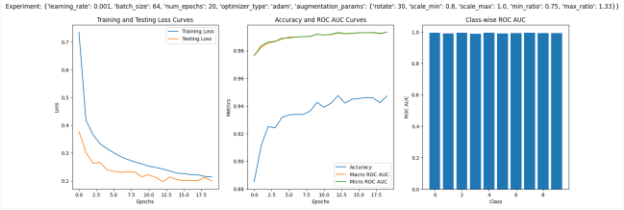
Quantitative Results Summary

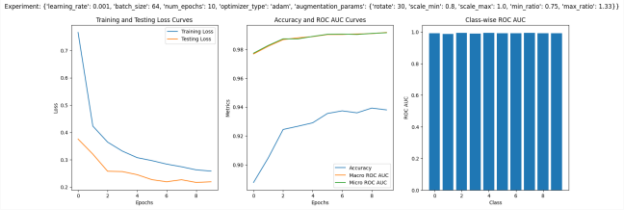
Loss, Accuracy and ROC AUC Scores using different configurations

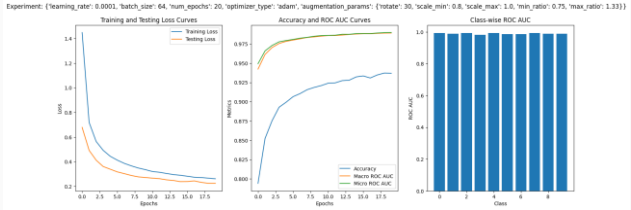
Learning Rate	Batch Size	Num Epochs	Optimizer	Rotate	Scale Min	Scale Max	Min Ratio	Max Ratio	Final Train Loss	Final Test Loss	Final Accuracy	Final Macro ROC AUC	Final Micro ROC AUC
0.001	64	20	adam	30	0.8	1.0	0.75	1.33	0.214062	0.200033	0.947219	0.993327	0.993328
0.0001	64	20	adam	30	0.8	1.0	0.75	1.33	0.262110	0.225124	0.936924	0.989040	0.989621
0.001	32	20	adam	30	0.8	1.0	0.75	1.33	0.217262	0.206273	0.945106	0.994471	0.994571
0.001	64	10	adam	30	0.8	1.0	0.75	1.33	0.258487	0.219250	0.937999	0.991799	0.991578
0.001	64	20	sgd	30	0.8	1.0	0.75	1.33	0.246013	0.211248	0.940727	0.987761	0.988416
0.001	64	20	adam	15	0.9	1.0	0.85	1.23	0.150420	0.210503	0.945644	0.993036	0.993205

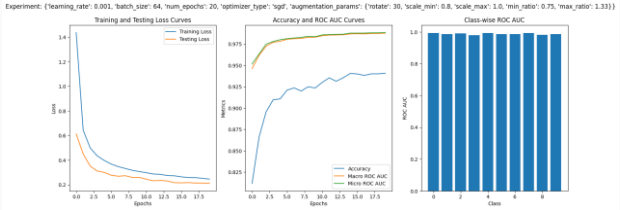
Visualizing Model Performance

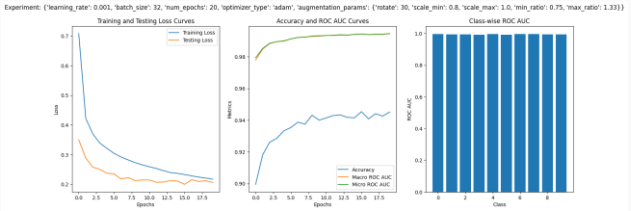
Loss, Accuracy and ROC AUC Scores using different configurations

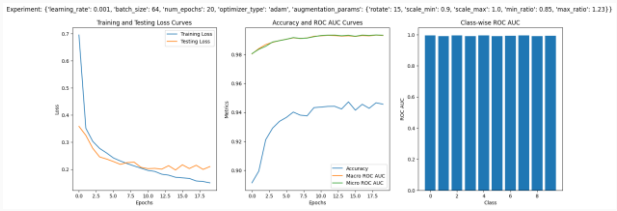












Discussion of Key Findings

Key aspects of SVHN Dataset Classification using VGG-like Neural Network

Learning Rate Impact

A learning rate of 0.001 consistently yielded better results than 0.0001, indicating its importance in model training.

Batch Size Effect

A batch size of 64 outperformed 32, providing more stable gradients and improving convergence.

Optimizer Efficiency

The Adam optimizer's adaptive learning rate capabilities significantly improved model performance over SGD, leading to faster training.

Data Augmentation

Optimal augmentation strategies enhanced model generalization without excessive distortion, improving robustness.