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UG FINAL YEAR DISSERTATION REPORT

Interpretable Seagull classification

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I hereby declare that this dissertation is all my own work, except as indicated in the text:

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Acknowledgement

Abstract

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(Simonyan and Zisserman, 2014)

1.0.1 Theoretical Background

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The pre-trained VGG16 model was adapted for our binary classification task through targeted modifications to the final classification layer. The implementation approach follows best practices for fine-grained bird classification established in recent research on transfer learning for avian species identification (**??**). Specifically, the original 1000-class classifier was replaced with a custom binary classification head while preserving the feature extraction capabilities of the convolutional base. The model modification strategy followed this approach:

1.1 Data Preprocessing and Augmentation Strategy

1.1.1 Image Preprocessing

Images were preprocessed using a consistent pipeline to ensure compatibility with the VGG16 architecture. All images were resized to 224×224 pixels to match VGG16's expected input dimensions. Following resize operations, pixel values were normalized using ImageNet mean values [0.485, 0.456, 0.406] and standard deviations [0.229, 0.224, 0.225]. This normalization strategy ensures input distributions match those seen during pre-training, facilitating effective transfer learning.

1.1.2 Training Augmentation

A comprehensive data augmentation strategy was implemented to enhance model generalization capabilities and mitigate overfitting (**?**). The augmentation pipeline for training incorporated multiple techniques designed to preserve critical taxonomic features while introducing beneficial variability:

Geometric Transformations:

- Random horizontal flips (probability 0.5)
- Random vertical flips (probability 0.3)

- Small rotations ($\pm$10 degrees)
- Minor affine transformations (translations up to 5%)
- Random resized crops (scale 0.95-1.0 of original size)

Color and Appearance Transformations:

- Brightness, contrast, and saturation adjustments ($\pm$10%)
- Sharpness enhancement (factor 1.2, probability 0.3)

This augmentation strategy was carefully calibrated to maintain the integrity of critical morphological features (particularly wingtip patterns) while simulating natural variations in viewing conditions. The relatively conservative parameter choices reflect the importance of preserving diagnostic features in fine-grained classification tasks (**?**).

1.1.3 Validation and Testing Preprocessing

For validation and testing phases, a simplified transformation pipeline was employed, consisting only of resizing to 224$\times$224 pixels, tensor conversion, and normalization. This approach ensures consistent evaluation conditions while maintaining the statistical properties expected by the pre-trained model.

1.2 Training Methodology

1.2.1 Dataset Organization and Splitting

The dataset was organized using the ImageFolder structure, with a 95:5 split between training and validation sets. This configuration provided substantial training data while maintaining a sufficient validation set for hyperparameter tuning and model selection. A separate test set was maintained for final performance evaluation.

1.2.2 Loss Function and Optimization

Cross-entropy loss was selected as the objective function for this binary classification task, providing appropriate gradients for optimization. This loss function effectively quantifies the discrepancy between predicted class probabilities and ground truth labels.

The AdamW optimizer (**?**) was employed with carefully tuned hyperparameters to facilitate effective model training:

- Learning rate: 0.0001 (relatively low to enable stable fine-tuning)
- Weight decay: 0.001 (for L2 regularization to prevent overfitting)

This optimization configuration balances the need for fine-grained weight adjustments with regularization to maintain generalization capacity.

1.2.3 Learning Rate Scheduling and Training Stabilization

An adaptive learning rate schedule was implemented using ReduceLROnPlateau with a patience factor of 3 epochs and a reduction factor of 0.1 (**?**). This approach automatically reduces the learning rate when validation performance plateaus, enabling finer weight adjustments as the model approaches optimal parameters.

To enhance training stability, gradient clipping was applied with a maximum norm of 2.0. This technique prevents exploding gradients by constraining the magnitude of parameter updates, which is particularly valuable when fine-tuning deep architectures like VGG16.

1.2.4 Batch Processing and Training Duration

The model was trained with a batch size of 16, striking a balance between computational efficiency and effective mini-batch gradient estimation. Training was configured to run for a maximum of 30 epochs with early stopping based on validation performance, ensuring optimal model selection while avoiding overfitting.

Model checkpoints were saved after each epoch, preserving the best-performing model configurations for subsequent evaluation and deployment.

1.3 Evaluation Metrics and Performance

The model's performance was assessed using multiple complementary metrics to ensure robust evaluation:

- Accuracy: Percentage of correctly classified images
- Precision: Proportion of true positive predictions among all positive predictions
- Recall: Proportion of true positives identified among all actual positives
- F1-Score: Harmonic mean of precision and recall

The final VGG16 model achieved exceptional performance with 98.80% validation accuracy and 100% test accuracy, demonstrating its effectiveness in distinguishing between the two gull species based on the refined dataset. This performance exceeds typical benchmarks for fine-grained bird classification tasks (**?**), highlighting the effectiveness of the implemented architecture, data preparation strategy, and training methodology.

A confusion matrix analysis confirmed the model's strong classification performance across both classes, with minimal misclassifications. This indicates the model successfully learned the discriminative morphological features necessary for distinguishing between Glaucous-winged and Slaty-backed Gulls.

1.4 VGG-16 Architecture

1.4.1 Theoretical Foundation

VGG-16 is a convolutional neural network architecture developed by Simonyan and Zisserman (2014) at the Visual Geometry Group (VGG) at Oxford, consisting of 16 weight layers including 13 convolutional layers followed by 3 fully connected layers. The architecture is characterized by its simplicity and depth, using small 3×3 convolutional filters stacked in increasing depth, followed by max pooling layers here. With approximately 138 million parameters, VGG-16 provides a strong foundation for feature extraction in computer vision tasks.

The primary advantage of employing VGG-16 for transfer learning in fine-grained classification tasks is its hierarchical feature representation capability, which enables the capture of both low-level features (edges, textures) and high-level semantic features here. Pre-trained on the ImageNet dataset containing over 1.2 million images across 1,000 classes, VGG-16 offers robust initialization weights that facilitate effective knowledge transfer to domain-specific tasks with limited training data here.

VGG-16 has demonstrated superior performance in fine-grained classification tasks compared to conventional techniques. Recent studies show that VGG-16 with logistic regression achieved 97.14% accuracy on specialized datasets like Leaf12, significantly outperforming traditional approaches that combined color channel statistics, texture features, and classic classifiers which only reached 82.38% accuracy here. For our specific task of gull species classification, the hierarchical feature representation capabilities of VGG-16 proved particularly effective at capturing the subtle differences in wing patterns and morphological features that distinguish between the target species.

1.4.2 Model Adaptation for Fine-Grained Classification

For our specific fine-grained binary classification task with limited data and class imbalance, the VGG-16 architecture was adapted through a targeted modification strategy:

The implementation follows best practices for transfer learning in fine-grained classification here. Specifically:

- The pre-trained VGG-16 model was loaded with ImageNet weights.
- The feature extraction layers (convolutional base) were preserved to maintain the rich hierarchical representations learned from ImageNet.
- The original 1000-class classifier was replaced with a custom binary classification head consisting of:
  - A dropout layer with a rate of 0.4 to reduce overfitting, a critical consideration given our limited dataset here.
  - A fully-connected layer mapping from the original 4096 features to 2 output classes.

This approach aligns with successful methodologies in avian species classification using VGG-16 as demonstrated by Brown et al. (2018), where fine-tuning the architecture by modifying the final classification layer enabled the model to retain general feature recognition capabilities while adapting to species-specific visual characteristics here.

2 Addressing Class Imbalance

Our dataset exhibited significant class imbalance, which can degrade model performance by biasing predictions toward the majority class here. To mitigate this challenge, we implemented multiple complementary strategies:

2.1 Class-Weighted Loss Function

We employed a class-weighted cross-entropy loss function, assigning higher importance to samples from the minority class:

This approach follows the inverse frequency weighting method described by Cui et al. (2019) here, which adjusts the contribution of each class to the loss function inversely proportional to its frequency in the training set.

2.2 Weighted Random Sampling

To ensure balanced mini-batches during training, we implemented weighted random sampling:

This technique oversamples the minority class and undersamples the majority class, effectively balancing the class distribution in each training batch here. The implementation uses PyTorch's WeightedRandomSampler with replacement, ensuring that minority class samples appear more frequently during training.

2.3 Class-Specific Data Augmentation

We implemented differential data augmentation strategies for majority and minority classes:

For the minority class, we applied more aggressive augmentation techniques, including wider rotation ranges (30° vs. 15°), stronger color jittering, and random resized crops. This approach, inspired by Shorten and Khoshgoftaar (2019) here, effectively expands the minority class representation in the feature space, helping to balance the effective class distribution while maintaining the integrity of class-discriminative features.

3 Data Preprocessing and Augmentation

3.1 Image Preprocessing

All images were preprocessed through a standardized pipeline to ensure compatibility with the VGG-16 architecture:

Images were resized to 224×224 pixels to match VGG-16's expected input dimensions. Pixel values were normalized using ImageNet mean values [0.485, 0.456, 0.406] and standard deviations [0.229, 0.224, 0.225], ensuring input distributions aligned with those seen during pre-training here.

3.2 Training Augmentation Strategy

For the base training augmentation, we implemented a comprehensive strategy including:

This augmentation pipeline incorporated:

- Geometric transformations: random horizontal flips and rotations to introduce positional variance.
- Color space transformations: brightness, contrast, and saturation adjustments to simulate varying lighting conditions.

These techniques enhance model robustness to natural variations in image appearance, reducing overfitting and improving generalization capability here.

3.3 Optimization Strategy

We employed the AdamW optimizer, an extension of Adam that incorporates decoupled weight decay regularization:

This configuration used:

- A conservative learning rate of 0.0001, appropriate for fine-tuning pre-trained models.
- Weight decay of 0.001 to provide L2 regularization, countering overfitting tendencies here.

3.4 Learning Rate Scheduling

An adaptive learning rate schedule was implemented using ReduceLROnPlateau:

This approach automatically reduces the learning rate by a factor of 0.1 when validation performance plateaus for 3 consecutive epochs, allowing for finer weight adjustments as training progresses here. This technique is particularly valuable for fine-tuning deep architectures where navigating the loss landscape requires progressively smaller step sizes.

3.5 Gradient Clipping

To enhance training stability, we applied gradient clipping with a maximum norm of 2.0:

This technique prevents exploding gradients by constraining parameter update magnitudes, particularly important when fine-tuning deep networks with varying gradient scales across layers here.

3.6 Model Evaluation and Selection

We implemented a comprehensive evaluation strategy using multiple complementary metrics:

The model was evaluated using:

- Standard accuracy.
- Balanced accuracy (accounting for class imbalance).
- Matthews Correlation Coefficient (MCC) - a reliable metric for imbalanced classification.
- Area Under the ROC Curve (ROC-AUC).
- Average Precision (AP).

Model selection was based on ROC-AUC, which provides a threshold-independent assessment of classification performance across different operating points, making it particularly suitable for imbalanced datasets here.

3.7 Reproducibility Considerations

To ensure experimental reproducibility, we implemented random seed fixing for all stochastic components:

This approach aligns with best practices in machine learning experimentation, where controlling randomness is essential for reliable hyper-parameter tuning, performance assessment, and research reproducibility here.

4 Implementation Details

The model was implemented using PyTorch, with training conducted on NVIDIA GPU hardware. Training progressed for up to 30 epochs with early stopping based on validation ROC-AUC to prevent overfitting. Batch processing used a size of 16-32 (varied between implementations), balancing computational efficiency with gradient estimation quality.

Visualization tools including confusion matrices, ROC curves, and precision-recall curves were integrated into the evaluation pipeline to provide comprehensive assessment of model performance beyond scalar metrics. The model's effectiveness in fine-grained classification tasks has been further demonstrated in recent studies, with VGG-16 based architectures achieving significant improvements over conventional approaches in similar classification problems here.

5 Vision Transformer (ViT) Architecture

5.1 Theoretical Framework

Vision Transformers (ViT) represent a paradigm shift in computer vision, applying the self-attention mechanism from transformer models—originally developed for natural language processing—to image classification tasks. First introduced by (**?**), ViT processes images by dividing them into a sequence of fixed-size patches, which are then linearly embedded and processed through transformer encoder blocks.

Unlike CNNs that build hierarchical representations through local convolutional operations, ViT applies self-attention mechanisms to capture global relationships between image patches. This allows the model to attend to long-range dependencies within the image, potentially capturing more holistic patterns. As demonstrated by research from (**?**), these attention mechanisms enable transformers to excel at detecting subtle features in biomedical images by focusing on the most discriminative regions.

The standard ViT architecture consists of:

- Patch embedding layer that converts image patches to token embeddings
- Position embedding to provide spatial information
- Multiple transformer encoder blocks with multi-head self-attention
- Layer normalization and MLP blocks within each transformer layer
- A classification head for prediction

This architecture's capacity to model global relationships makes it particularly promising for fine-grained classification tasks where relationships between distant parts of an image (e.g., wing patterns in relation to head features) may be important for accurate classification (**?**).

5.2 Standard Vision Transformer Implementation

My standard ViT implementation utilized the pre-trained 'vit_base_patch16_224' model from the TIMM library, which features a patch size of 16×16 pixels and was trained on the ImageNet dataset. The model adaptation process included:

- Loading the pre-trained ViT model with frozen weights
- Extracting the embedding dimension from the original model (768 features)
- Replacing the classification head with a binary classifier for our gull species task

- Maintaining the self-attention mechanisms and transformer blocks

This approach leverages the powerful feature extraction capabilities of ViT while customizing the final classification stage for our specific task. The implementation follows best practices established by (**?**) for adapting vision transformers to specialized classification tasks.

5.3 Enhanced Vision Transformer with Custom Attention

To further improve the model's ability to focus on taxonomically relevant features, we developed an Enhanced Vision Transformer (EnhancedViT) that incorporates a custom attention mechanism specifically designed for fine-grained classification tasks.

The key innovation in this implementation is an attention-based pooling layer that computes importance scores for each patch token, enabling the model to focus on the most discriminative regions of the input image. This approach draws inspiration from the work of (**?**), who demonstrated that specialized attention mechanisms in vision transformers can significantly improve fine-grained classification by emphasizing taxonomically relevant features.

The enhanced ViT architecture extends the standard implementation with:

- A custom attention layer that computes importance scores for each token
- An attention-weighted aggregation step that prioritizes informative regions
- A multi-layer perceptron classifier with dropout regularization
- Layer normalization for improved training stability

The attention mechanism was implemented as:

This approach allows the model to dynamically focus on the most relevant parts of the image for classification, such as distinctive wingtip patterns or other morphological features that differentiate between gull species (**?**).

5.4 Data Processing and Augmentation

Both ViT implementations used standardized preprocessing and augmentation pipelines:

- Resize operations to 224$\times$224 pixels (the standard input size for ViT models)
- Normalization with mean [0.5, 0.5, 0.5] and standard deviation [0.5, 0.5, 0.5]

- Augmentation techniques including:
  - Random horizontal flipping
  - Random rotation ($\pm$15 degrees)
  - Color jittering (brightness, contrast, saturation)

The input normalization values specifically used [0.5, 0.5, 0.5] rather than ImageNet statistics, following recommendations from(**?**) for transfer learning with vision transformers.

5.5 Training Methodology

The training approach for both ViT variants included:

- AdamW optimizer with learning rate 0.0001 and weight decay 1e-4
- Learning rate scheduling with ReduceLROnPlateau (patience=3, factor=0.1)
- Batch size of 16 to balance computational efficiency and training stability
- Training for 20 epochs with early stopping based on validation performance

For the EnhancedViT, we employed additional training refinements:

- Layer-wise learning rate decay to fine-tune different components at appropriate rates
- Dropout regularization (p=0.3) in the custom classification head
- Checkpoint saving to preserve the best-performing model configuration

Both models were trained on the refined high-quality dataset (Stage 3), with an 80:20 split between training and validation sets to ensure robust performance evaluation during development.

Inception v3 Architecture

Theoretical Background

Inception v3, developed by Szegedy et al. (2016), represents a sophisticated CNN architecture designed to efficiently capture multi-scale features through parallel convolution pathways with varied kernel sizes. The key innovation in Inception architectures is the utilization of ”Inception modules” that process the same input tensor through multiple convolutional paths with different receptive fields, and then concatenate the results.

This enables the network to capture both fine-grained local patterns and broader contextual information simultaneously ([Szegedy et al., 2016](https://arxiv.org/abs/1512.00567)).

Inception v3 builds upon earlier versions with several important architectural improvements:

- Factorized convolutions to reduce computational complexity - Spatial factorization into asymmetric convolutions (e.g., 1×n followed by n×1) - Auxiliary classifiers that inject additional gradient signals during training - Batch normalization for improved training stability and faster convergence - Label smoothing regularization to prevent overconfidence

These design elements collectively enable Inception v3 to achieve high accuracy while maintaining computational efficiency. As demonstrated by Huang et al. (2019), Inception architectures are particularly effective for tasks requiring multi-scale feature extraction, such as discriminating between visually similar biological specimens ([Huang et al., 2019](https://ieeexplore.ieee.org/document/8803812)).

Model Adaptation for Binary Gull Classification

Our implementation adapted the pre-trained Inception v3 model for fine-grained gull species classification using the following approach:

The implementation involved:

1. Loading the pre-trained Inception v3 model with ImageNet weights 2. Extracting the feature dimension from the original classifier (2048 features) 3. Replacing the final classifier with a custom sequence: - Dropout layer (p=0.5) for regularization to mitigate overfitting - Linear layer mapping 2048 features to 2 output classes

This approach leverages transfer learning, where knowledge acquired from large-scale image classification on ImageNet is transferred to our specific domain of gull species classification ([Tan et al., 2018](https://arxiv.org/abs/1805.08974)).

A distinctive aspect of our Inception v3 implementation was the utilization of auxiliary outputs during training. Inception v3's auxiliary classifier, which branches off from an intermediate layer, provides an additional gradient path during backpropagation. This approach helps combat the vanishing gradient problem and provides regularization ([Szegedy et al., 2016](https://arxiv.org/abs/1512.00567)).

The loss function was modified to incorporate both the main output and the auxiliary output during training:

The auxiliary loss weight (0.3) was selected based on empirical optimization and aligns with recommendations in the literature for fine-tuning Inception architectures ([He et al., 2019](https://arxiv.org/abs/1902.04103)).

Advanced Training Techniques

The Inception v3 implementation incorporated several advanced training techniques

to optimize performance:

Mixed-Precision Training

We employed PyTorch's Automatic Mixed Precision (AMP) to accelerate computation while maintaining numerical stability ([Micikevicius et al., 2018](https://arxiv.org/abs/1710.03740)):

This technique allows the use of float16 precision where appropriate, which reduces memory usage and increases computational speed, especially beneficial when training on GPU-constrained environments like Google Colab.

Gradient Clipping

To prevent explosive gradients and stabilize training, we implemented gradient clipping with a maximum norm of 2.0 ([Pascanu et al., 2013](https://arxiv.org/abs/1211.5063)):

This ensures that gradient updates remain within a reasonable magnitude, preventing destabilizing parameter updates that can occur in deep networks.

Hyperparameter Optimization

Our implementation utilized precisely tuned hyperparameters for the AdamW optimizer:

Learning Rate Scheduling

We implemented an adaptive learning rate schedule using ReduceLROnPlateau:

This approach automatically reduces the learning rate by a factor of 0.1 when validation performance plateaus for 3 consecutive epochs, allowing for finer weight adjustments as training progresses ([Smith, 2017](https://arxiv.org/abs/1506.01186)).

- Resize operations to 299×299 pixels (the standard input size for Inception v3)

The larger input resolution (299×299 vs 224×224 used by VGG16) provides the Inception architecture with more detailed information, potentially beneficial for capturing the subtle wing pattern differences between gull species ([Xie et al., 2020](https://arxiv.org/abs/1911.090

This approach ensures that results can be replicated in future experiments, a critical aspect of rigorous scientific methodology ([Bouthillier et al., 2019](https://arxiv.org/abs/1902.02476)).

6 ResNet50 Architecture

6.1 Theoretical Background

Residual Networks (ResNet) represent a significant innovation in deep neural network architecture, introduced by He et al. to address the degradation problem that occurs

when training very deep networks. The key innovation in ResNet is the introduction of skip connections or ”shortcut connections” that bypass one or more layers, allowing gradients to flow more easily through the network during backpropagation (**?**). This design enables the training of much deeper networks than was previously feasible, with ResNet-50 containing 50 layers organized in residual blocks.

ResNet-50 architecture consists of five stages, each containing multiple residual blocks. Each residual block contains a ”shortcut” that skips over the main path and rejoins it later, allowing the network to learn residual functions with reference to the layer inputs rather than learning unreferenced functions (**??**). This approach enables ResNet to achieve high performance on image classification tasks while mitigating the vanishing gradient problem common in very deep networks.

The architecture's ability to effectively extract hierarchical features through its deep structure makes it particularly well-suited for fine-grained classification tasks where subtle differences must be detected. As noted by Ghani et al., ResNet architectures have demonstrated strong performance in avian classification tasks due to their capacity to learn discriminative features at multiple scales and levels of abstraction (**?**).

6.2 Model Adaptation for Gull Species Classification

For our gull classification task, we adapted the pre-trained ResNet-50 model using a focused transfer learning approach. The model was initialized with weights pre-trained on the ImageNet dataset, providing a strong foundation of general visual features. The adaptation process involved:

1. Loading the pre-trained ResNet-50 model with ImageNet weights
2. Preserving the convolutional backbone to maintain feature extraction capabilities
3. Replacing the final fully connected layer (classifier) with a custom sequence:
    (a) Dropout layer with probability 0.5 to reduce overfitting
    (b) Linear layer mapping from 2048 features to 2 output classes

This adaptation strategy preserved ResNet-50's powerful feature extraction capabilities while customizing the classification head for our binary task. The relatively high dropout rate (0.5) was implemented to address potential overfitting, which is particularly important given the visual similarities between the target species and the limited size of our specialized dataset (**?**).

6.3 Image Preprocessing and Enhancement

A distinctive aspect of our ResNet-50 implementation was the incorporation of image sharpening as a preprocessing step. This approach was motivated by research from

Zhou et al. showing that enhancing edge definition can improve the detection of subtle morphological features in avian classification tasks (**?**). The image enhancement process applied a 3×3 sharpening kernel through a custom preprocessing function:

This technique enhanced the visibility of critical diagnostic features like wingtip patterns while preserving the overall image content. To ensure consistency, image sharpening was applied across both training and evaluation pipelines (**?**).

6.4 Data Augmentation Strategy

The data augmentation pipeline for ResNet-50 was structured to enhance model robustness while preserving class-discriminative features:

- Resize operations (300×300 pixels) followed by sharpening
- Random horizontal flipping to simulate viewpoint variation
- Random rotation (±15 degrees) to account for flight angle variability
- Color jittering (brightness, contrast, saturation adjusted by ±20%)
- Random cropping with padding to vary focus regions

For validation and testing, a more conservative approach was employed with resizing, center cropping (256×256 pixels), and the same sharpening preprocessing to maintain feature clarity without introducing variability (**?**).

6.5 Training Approach and Optimization

The ResNet-50 model was trained using the following methodological approach:

- Adam optimizer with learning rate 0.001 and weight decay 1e-4 for regularization
- Adaptive learning rate scheduling using ReduceLROnPlateau with patience=3
- Early stopping with patience=5 to prevent overfitting
- Batch size of 16 for efficient GPU utilization

The implementation of early stopping was particularly valuable for the ResNet model, as it helped prevent overfitting to the training data while ensuring the model retained its generalization capabilities. As demonstrated by Huang et al., early stopping acts as an effective regularization technique for deep networks when working with specialized datasets of limited size (**?**).

7 Custom CNN with Squeeze-and-Excitation Blocks

7.1 Architectural Innovation

To complement the transfer learning approach with pre-trained models, we developed a custom CNN architecture specifically designed for our gull classification task. The architecture incorporates Squeeze-and-Excitation (SE) blocks, an attention mechanism introduced by Hu et al. (2018) that adaptively recalibrates channel-wise feature responses by explicitly modeling interdependencies between channels.

The SE mechanism enhances standard convolutional operations by adding two operations:

- A ”squeeze” operation that aggregates feature maps across spatial dimensions to produce a channel descriptor
- An ”excitation” operation that produces per-channel modulation weights

This channel-wise attention mechanism allows the network to emphasize informative features and suppress less useful ones, improving the representational power of the network. As demonstrated by Hu et al. (2018), the SE mechanism yields significant performance improvements while adding minimal computational overhead.

Our custom CNN implementation follows this architectural pattern:

7.2 Addressing Class Imbalance

An important methodological consideration in our custom CNN implementation was addressing potential class imbalance in the dataset. To ensure balanced learning despite the uneven distribution of examples between classes, we implemented a weighted sampling approach based on class frequencies.

The implementation calculated inverse class weights to prioritize examples from underrepresented classes:

This approach ensures that the model receives a balanced distribution of examples during training, preventing bias toward the majority class. The effectiveness of this technique for handling class imbalance has been demonstrated in fine-grained classification research by Buda et al. (2018), who showed that sampling strategies can significantly improve model performance on imbalanced datasets.

7.3 Training Methodology

The custom CNN was trained using the following approach:

- Adam optimizer with learning rate 0.001 and weight decay 0.0005
- Cosine Annealing learning rate scheduler for cyclical learning rate adjustment
- Cross-entropy loss function
- Batch size of 32 (larger than the pre-trained models due to lower memory requirements)
- Training for 20 epochs with checkpoint saving for best-performing models

The use of Cosine Annealing for learning rate scheduling represents a different approach compared to the ReduceLROnPlateau used with the pre-trained models. This scheduler cyclically varies the learning rate between a maximum and minimum value following a cosine function, helping the model escape local minima and potentially converge to better solutions. This approach aligns with research by Loshchilov and Hutter (2017) demonstrating the effectiveness of cyclical learning rates for CNN training.

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