Comparative Analysis of CNN Architectures for EuroSAT Image Classification for Land Use

Course: **Deep Learning and Reinforcement Learning**

Project Title: **Satellite Image Classification For Land Use**

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1. Project Objective

The primary goal of this project was to classify satellite images from the from the EuroSAT dataset into one of 10 distinct land use and land cover land cover categories.

1. **Model Implementation**

   Implement, train, and evaluate three different Convolutional Neural Neural Network (CNN) architectures.

2. **Architecture Comparison**

   Compare the performance of these models to determine the most the most effective architecture for this image classification task. task.

2. Methodology and Workflow

The project followed a structured machine learning workflow to ensure consistent and comparable results across models.

Dataset & Preprocessing

- EuroSAT (RGB) dataset, split into training and validation sets.
- Images resized (VGG16: 64x64, Custom CNN: 128x128, ResNet50: 224x224).
- Pixel values normalized; ResNet50 used specific preprocesed input. input.
- Custom CNN applied data augmentation (random flips, rotations).

Model Architectures & Training

- VGG16 & ResNet50: Pre-trained on ImageNet, custom classification heads classification heads added.
- Custom CNN: Built from scratch with Swish activation, Batch Normalization, and Dropout.
- All models compiled with Adam or RMSprop optimizer and appropriate appropriate loss function.
- Pre-trained models underwent two-phase training: initial frozen base, then fine-tuning.

3. Key Assumptions

Our analysis relies on several foundational assumptions regarding the dataset and the effectiveness of transfer learning.

Dataset Quality

The EuroSAT dataset is assumed to be clean, well-labeled, and representative of satellite imagery for land imagery for land cover classes.

Transfer Learning Effectiveness

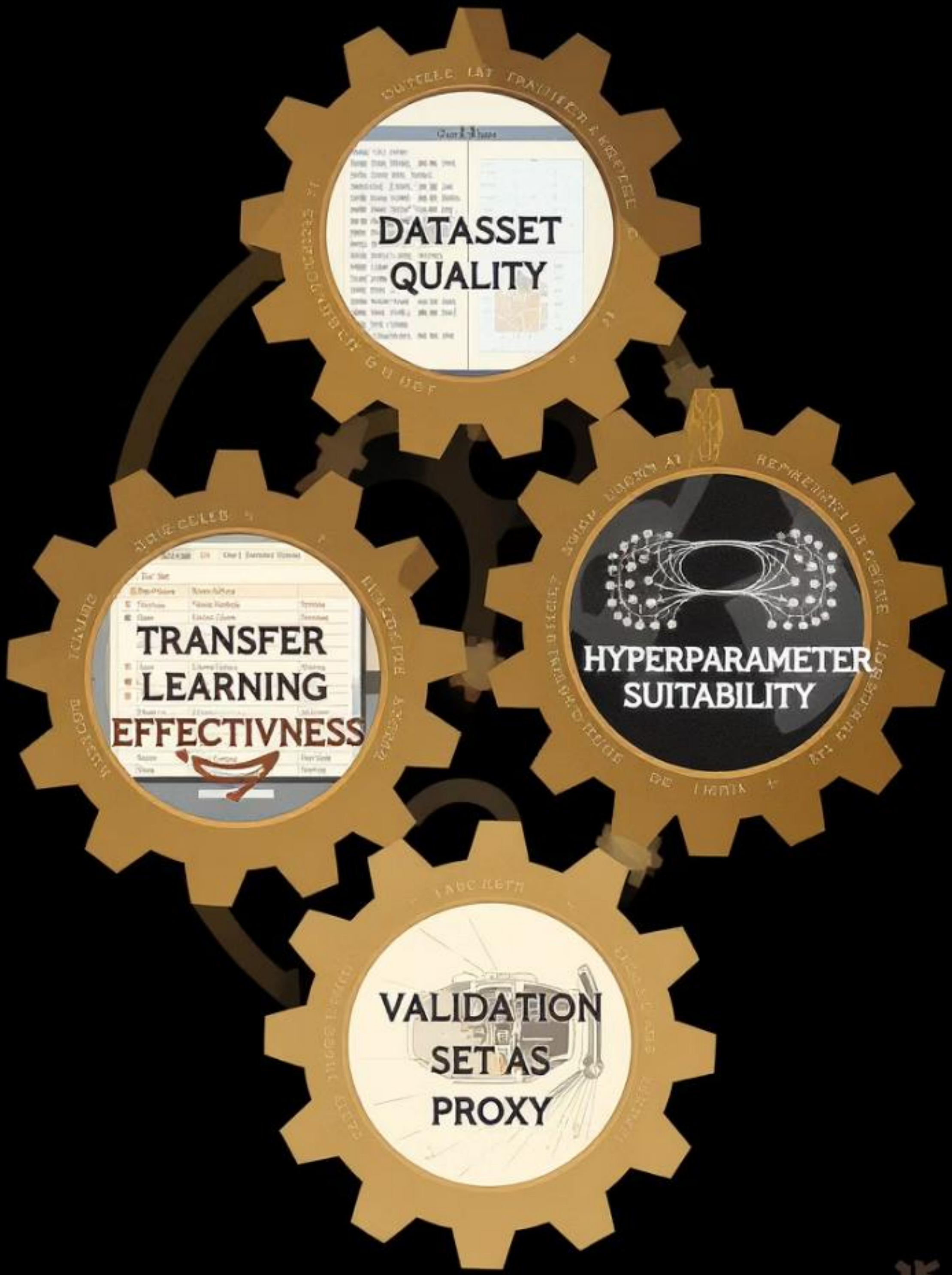
Features learned by VGG16 and ResNet50 on ImageNet are assumed to be transferable and beneficial for EuroSAT classification.

Hyperparameter Suitability

Selected hyperparameters (e.g., learning rates, batch size) are assumed to be reasonably effective for model convergence.

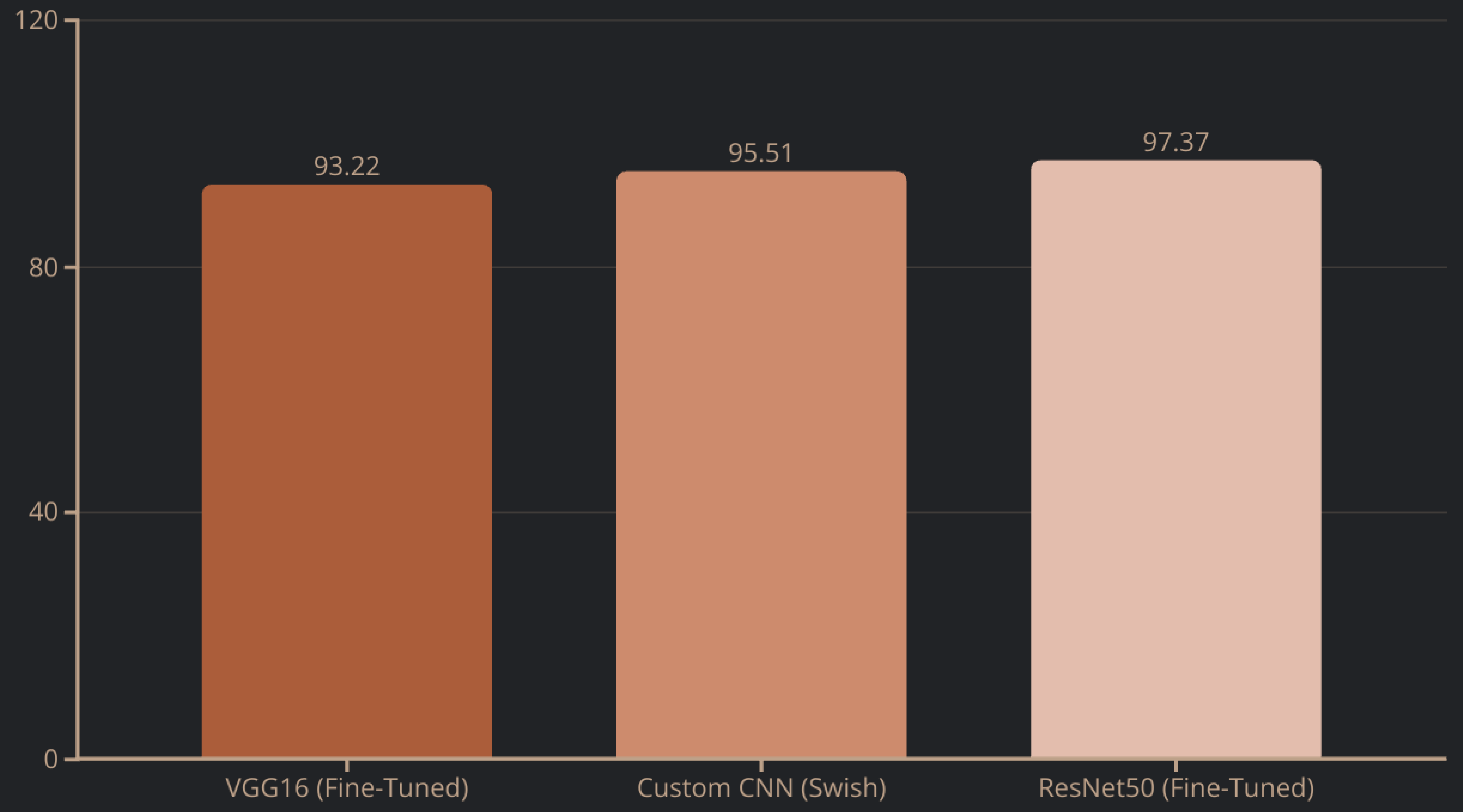
Validation Set as Proxy

Validation set performance is assumed to reliably indicate the model's generalization ability to unseen data.



4. Model Evaluation and Analysis

The models were primarily evaluated based on their validation accuracy, revealing a clear performance hierarchy.



The bar chart illustrates the peak validation accuracy achieved by each model. ResNet50 consistently outperformed the others, followed closely by the Custom CNN, and then VGG16.

4. Model Evaluation and Analysis (Continued)

A deeper dive into the performance of each model reveals their strengths and weaknesses in the EuroSAT classification task. classification task.

ResNet50 (Top Performer)

Achieved the highest validation accuracy (97.04%) and a test accuracy accuracy of 97.15%. Its deep architecture and residual connections connections enabled it to learn highly highly complex and discriminative features, making it the superior model. model.

Custom CNN (with Swish)

Delivered a strong performance with with 95.74% validation accuracy and and test accuracy 95.13%, outperforming the older VGG16. This This demonstrates that a well-designed designed custom model with modern modern components like Swish activation and data augmentation can can be highly effective.

VGG16

Showed significant improvement from from initial training (86.76%) to fine-fine-tuned state (93.11%). While effective, its shallower, more straightforward architecture was outperformed by both the custom model and the more advanced ResNet50.

5. Project Summary and Outcomes

This project successfully implemented and rigorously compared three different CNN models for classifying EuroSAT satellite imagery.

Primary Outcome

Fine-tuned ResNet50 model was the most effective solution, achieving the highest validation (97.04%) and test (97.15%) accuracies.

Architecture Matters

The advanced residual structure of ResNet50 provided a clear performance advantage.

Custom Models Compete

Custom CNN's success shows a tailored architecture can outperform older pre-trained models like VGG16.

Transfer Learning Power

Both pre-trained models demonstrated the value of leveraging features from ImageNet.

6. Future Improvements and Extensions

To further enhance the model's performance and explore new avenues, several improvements and extensions are recommended.

Explore Advanced Architectures

Test more recent and powerful pre-trained models like EfficientNet, InceptionV3, or Vision Vision Transformer (ViT) for higher accuracy.

Systematic Hyperparameter Tuning

Employ automated tuning techniques (Grid Search, Bayesian Optimization) to find optimal optimal hyperparameters for each model.

Advanced Data Augmentation

Implement sophisticated data augmentation strategies tailored for satellite imagery (e.g., imagery (e.g., random brightness/contrast, elastic distortions).

Model Ensembling

Combine predictions from top-performing models (ResNet50 and Custom CNN) using CNN) using ensemble methods for a more robust final model.

7. Reflections and Learning Outcomes

This project provided invaluable practical experience and deepened our understanding of deep learning for image classification.

Technical Skills Acquired

- Practical experience in transfer learning and fine-tuning.
- Mastered TensorFlow and Keras for model building and training.
- Effective use of Keras callbacks (EarlyStopping, ReduceLROnPlateau).

Key Conceptual Takeaways

- Deeper appreciation for CNN architectural differences and their impact.
- Recognized the immense practical advantage of pre-trained models. models.
- Learned to critically analyze training/validation curves for model diagnosis.