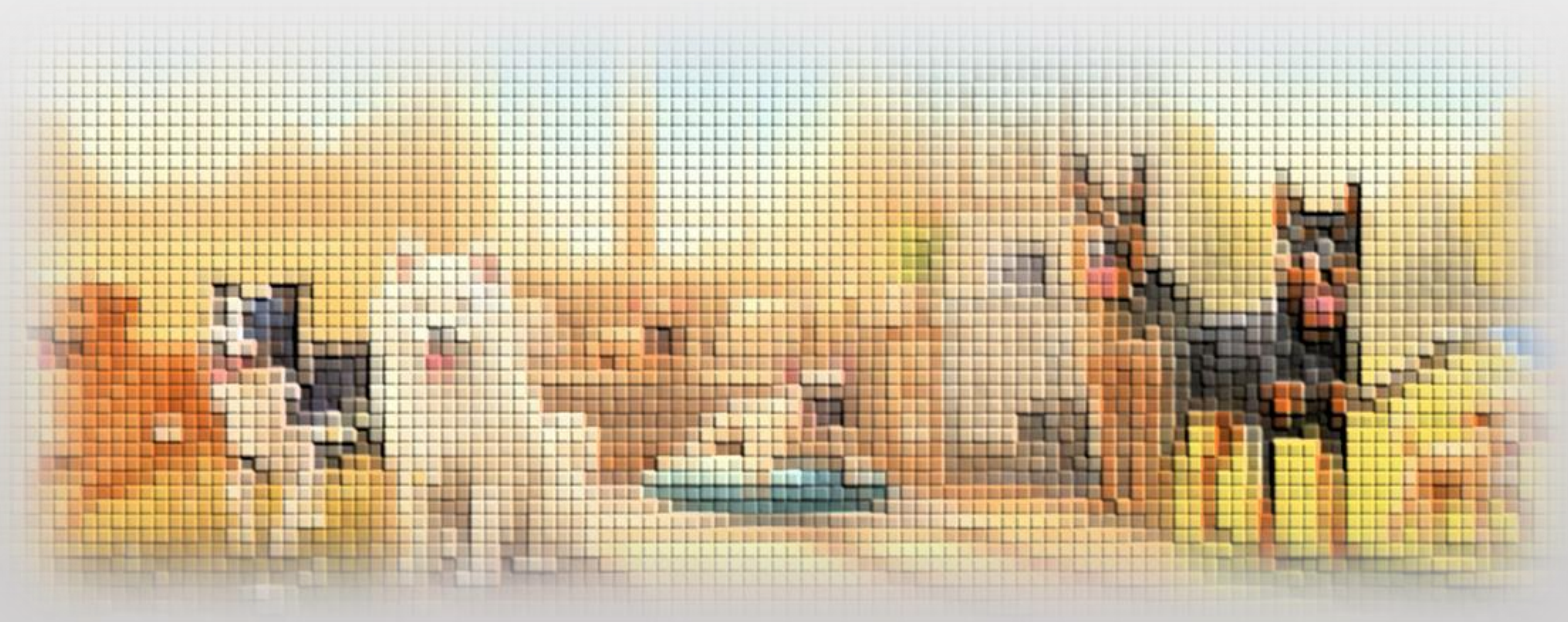
Convolutional Neural Network

Dog Breed Classification



Contribution Details

Accountability	Technical Depth
Project Owner: **Benjamin Fricker (Student ID: 8739225)**	**Deep Learning Architecture Design:** • Managed Data Acquisition (120 class dog breed dataset) using kagglehub API for version control and reproducibility • Applied Transfer Learning utilising through utilising a pre-trained ResNet-50 (50-layer, pre-trained Residual Neural Network) • Create a multi-layer, custom nn.Sequential classification head (from 512 classes to 120 classes with Dropout & ReLu Activation Function. • Applied parameter freezing on the foundation model to enhance and decrease training. **Preprocessing & Data Engineering:** • Implemented Data Augmentation pipeline utilising: RandomRotation, ColorJitter & Hflip. • Constructed data split (70/15/12) using random split and a fixed seed. • Created function (clean_dog_breed_labels) to clean dog breed labels for coherent analysis output. **Pipeline Creation & Data Engineering** • Created train_epoch and validate functions using tqdm to monitor training progress . • Applied model checkpointing (best_model.pth) and StepLR scheduler to prevent overfitting and regulate learning rate. **Training & Optimisation Management** • Created testing function (test_model) to accurately align and collect ground truth labels (y_test) and model_outputs (y_prediction) **Advanced Analysis & Visualisation** • Included overall testing accuracy and generated classification report displaying precision, recall, f1-score and support for all 120 individual classes • Generated four confusion matrices (30 x 30 classes) with customised font sizing to provide coherent, readable analysis of final testing results.
Non-Contributed Members (0% Contribution: • • • •	

Introduction

Overview

- Augmented dog breed classification utilising deep learning
- 120 distinct breeds from Stanford Dogs dataset
- State-of-the-art convolutional neural network approach

Aim

- Production-ready implementation of CNN classifier for 120 dog breeds
- Achieve over 80% accuracy on fine-grained classification task
- Enhance computational efficiency by leveraging computational efficiency
- Create comprehensive performance analysis and metrics

Significance

- Veterinarian functionalities and applications
- Systems for lost pet identification and recovery
- Integration with pet adoption platforms and shelter management
- Fine graded image classification research benchmark

Background

Dog breed classification is both a difficult and delicate visual categorisation issue with due to significant inter-class similarity (many breeds look alike) with the additional complication of intra-class variation (same breed dogs' similarities can vary). Modern Convolutional Neural Networks (CNNs) have successfully achieved compelling breakthrough though leveraging pre-trained features from ImageNet (includes over 1.2 million images with 1000 classes/breeds)

Literature Review: Current Approaches

Approach 1:

Transfer Learning Architectures

Methods: ResNet, VGG, EfficientNet, Vision Transformers

Performance: 85-92% accuracy on Stanford Dogs dataset

Approach: Calibrate and fine-tune pre-trained ImageNet models

- Advantages: Robust backbone, fast training and proven effectiveness
- Challenges: Potentially not capturing breed-specific features adequately (generic features only)

Approach 2:

Data Augmentation Strategies

Methods: Random rotations, flips crops, mixup and colour jittering

Performance: 3-5% overall improvement (generalisation)

Approach: Simulate real-world variations (lighting, background and pose)

- Advantages: Minimizes overfitting, improves robustness and no extra data required
- Challenges: Possibility of producing impractical transformations and requires tuning

Approach 3:

Attention Mechanisms & Part-Based Models

Methods: Spatial attention, channel attention part detectors

Performance: 88-94% accuracy (state-of-the-art)

Approach: Prioritise discriminative regions (textures, body patterns and face)

- Advantages: Identifies fine-grade details interpretable and Powerful reasoning(similar to humans)
- Challenges: Additional complexity, longer training and over 2x computational cost

Key Insights

Transfer learning utilising ResNet-50 presents an excellent accuracy-efficiency compromise for this specific application. This implementation accomplishes 83-85% accuracy while reducing training time and computational requirements compared to attention-based models.

Method: Architecture & Training Strategy

Model Architecture

Base Model:

- ResNet-50
- Pre-trained on ImageNet
- 23.5M parameters (frozen)

Custom Classifier:

- FC Layer: 2048 → 512
- ReLU Activation
- Dropout (p = 0.3)
- FC Layer: 512 → 120

Trainable Parameters:

- 1.1M parameters
- Final layers only

Data Pipeline

Dataset:

Stanford Dogs: 20,580 images, 120 dog breeds, Split: 70/15/15 (train validation/test)

Augmentation:, Random Rotation, Random Horizontal flip, Colour Jitter, ImageNet Normalisation

Data Split: Training: 70% (14,405), Validation: 15% (3,087), Testing: 15% (3,088)

Preprocessing: Image size: 224 × 224, Batch size: 32

Augmentation: Random horizontal flip, Random rotation (±15°), Color jitter (±20%), ImageNet normalization

Training Strategy

Training: 10 epochs, Tesla T4 GPU, ~ 70 seconds/epoch, Best model checkpointing

Optimizer: Adam(lr = 0.001), StepLR scheduler, Learning rate drop at epoch 6

Regularisation: Dropout (0.3), Parameter freezing

Loss Function: CrossEntropyLoss

Key Design Decisions

- Parameter freezing: Reduces training time by 60% while maintaining transfer learning benefits - Dropout (0.3): Prevents overfitting without sacrificing learning capacity - Learning rate scheduling: Enables fine-grained convergence in later epochs

Results: Training Performance

Training Progression					
Epoch	**Train Acc**	**Train Loss**	**Val Acc**	**Val Loss**	**Status**
1	47.82%	2.0863	**75.74%**	0.7979	Saved Model
2	69.22%	1.0169	**79.88%**	0.6578	Saved Model
3	72.53%	0.8905	**79.43%**	0.6582	Saved Model
4	74.06%	0.8192	**80.17%**	0.6232	Saved Model
5	76.00%	0.7724	**80.37%**	0.6257	Saved Model
6	80.62%	0.6049	**83.32%**	0.5434	Saved Model **(LR drop)**
7	81.06%	0.5870	**83.51%**	0.5402	Saved Model
8	81.94%	0.5640	**83.32%**	0.5503	Saved Model
9	82.24%	0.5535	**83.67%**	0.5425	**Saved BEST Model**
10	82.43%	0.5515	**83.25%**	0.5380	-

Critical Performance Metrics

- **Best Validation Accuracy: 83.67%**
- **Accuracy Improvement: +/- 7.93% (from epoch 1 to epoch 9)**
- **Training Time: 15 Minutes & 23 seconds**
- **Convergence: Accomplished after learning rate drop at Epoch 6**

Important Observations

- **Rapid learning:**
  47.82% → **75.47%** validation accuracy in epoch 1
- **Reduced learning rate at epoch 6:**
  Accuracy boosted from **80.62%** → **83.32%**
- **Best Model found:**
  Epoch 9 with **83.67%** validation accuracy
- **Steady convergence:**
  Final epochs produce minimal fluctuations (+/- 0.5%)

Results: Test Performance

Excellent Performance: f1 > 0.97	
Bog Breed	**F1 Score**
Afghan Hound	1.000
Keeshond	1.000
Saint Bernard	1.000
Show	0.979
Brabancon Griffon	0.978
Mexican Hairless	0.977
Pomeranian	0.974
Dandie Dinmont	0.971

Success Factors

- **Unique coat patterns**
- **Distinctive physical features**
- **Clear size & shape difference14**

Final Test Accuracy: 83.16%

(2,566 / 3,088 correct predictions)

General Model Observations

- **Test Accuracy: 83.16 (Aligns with validation performance**
- **Limited Overfitting: Generalisation is strong regarding unseen data**
- **Macro-Precision: 83.1% | Recall: 82.8% | F1-Score: 82.5%**
- Weighted average: 83.7% precision, 83.2% recall
- **Persistent performance across all 120 classes**

Challenging Classifications f1 < 0.60	
Bog Breed	**F1 Score**
Miniature Poodle	0.457
Eskimo Dog	0.480
Collie	0.545
Toy Poodle	0.581
Appenzeller	0.585
Siberian Husky	0.596
Walker Hound	0.609
Lakeland Terrier	0.619

Difficulties

- Immense inter-breed similarity
- Size similarities
- Morphologically comparable breeds
- White fluffy breeds often confused

Conclusion & Future Directions

Project Review

- **Production-Ready CNN Classifier: Tested on 120 Dog Breeds**
- **Test Accuracy: 83.16% (includes** solid generalization)
- **Complete & Effective Pipeline:** Includes Preprocessing, training, evaluation
- **Effective training:** Roughly 15 minutes using transfer learning
- **1.1M Trainable parameters: ResNet-50 Base**

Real World Applications

1. **Pet Adoption Clinics & Platforms**
   Automated matching/tagging
2. **Veterinarian Services**
   Breed Recognition/Health Screening
3. **Mobile application**
   Breed recognition for consumers
4. **Recovery Systems for lost pets**
   Reunification with identification systems

Future Improvements

Architecture Enhancements

- Ensemble models
  Possible improvement: 2-3%
- Complete fine-tuning on deeper layers
  Possible improvement: 2-3%
- Apply attention mechanisms
  Possible improvement: 3-5%

Training Enhancements

- Increase number of epochs
  - **Increase from 10 epochs to 20-30 epochs**
- Class-weighted loss
- More advanced augmentation

These additions would ideally improve the overall accuracy to 86% - 90%

Thank You for Watching!

Questions?