# Discriminative Deep Learning Project
# Milestone 1 Report

CNN-Based Object Classification

Course: IE 7615 - Discriminative Deep Learning

Team Members: Quoc Hung Le, Hassan Alfareed, Khoa Tran

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# 1. DATASET DESCRIPTION

## 1.1 Individual Contributions

Each team member contributed one unique object as below:

| Team Member | Object ID | Images Contributed |
|---|---|---|
| Quoc Hung Le | OBJ229 - Banana | 126 images |
| Hassan Alfareed | OBJ230 – Protein Bar | 140 images |
| Khoa Tran | OBJ095 – Men Watch | 101 images |

## 1.2 Dataset Statistics

### General parameters

```
In the total:
39 objects
4108 pictures
105.3 avg pictures/object
Split summary:
  Train: 2871 (69.9%)
  Val:    611 (14.9%)
  Test:   626 (15.2%)
Split distribution:
TRAIN:
  Objects: 39
  Images: 2871
  Sample shape: (224, 224, 3) (expected: 224, 224, 3)
VAL:
  Objects: 39
  Images: 611
  Sample shape: (224, 224, 3) (expected: 224, 224, 3)
TEST:
  Objects: 39
  Images: 626
  Sample shape: (224, 224, 3) (expected: 224, 224, 3)
```

split_distribution

| object_id | total | train | val | test |
|---|---|---|---|---|
| OBJ001 | 100 | 70 | 15 | 15 |
| OBJ002 | 100 | 70 | 15 | 15 |
| OBJ003 | 100 | 70 | 15 | 15 |
| OBJ004 | 100 | 70 | 15 | 15 |
| OBJ005 | 100 | 70 | 15 | 15 |
| OBJ006 | 100 | 70 | 15 | 15 |
| OBJ007 | 100 | 70 | 15 | 15 |
| OBJ008 | 100 | 70 | 15 | 15 |
| OBJ009 | 100 | 70 | 15 | 15 |
| OBJ010 | 100 | 70 | 15 | 15 |
| OBJ012 | 110 | 77 | 16 | 17 |
| OBJ016 | 99 | 69 | 14 | 16 |
| OBJ018 | 120 | 84 | 18 | 18 |
| OBJ019 | 100 | 70 | 15 | 15 |
| OBJ021 | 100 | 70 | 15 | 15 |
| OBJ022 | 99 | 69 | 14 | 16 |
| OBJ027 | 100 | 70 | 15 | 15 |
| OBJ028 | 100 | 70 | 15 | 15 |
| OBJ029 | 100 | 70 | 15 | 15 |
| OBJ031 | 100 | 70 | 15 | 15 |
| OBJ061 | 100 | 70 | 15 | 15 |
| OBJ069 | 100 | 70 | 15 | 15 |
| OBJ090 | 100 | 70 | 15 | 15 |
| OBJ095 | 101 | 70 | 15 | 16 |
| OBJ107 | 144 | 100 | 21 | 23 |
| OBJ108 | 100 | 70 | 15 | 15 |
| OBJ111 | 100 | 70 | 15 | 15 |
| OBJ159 | 137 | 95 | 20 | 22 |
| OBJ208 | 100 | 70 | 15 | 15 |
| OBJ222 | 108 | 75 | 16 | 17 |
| OBJ229 | 126 | 88 | 18 | 20 |
| OBJ230 | 140 | 98 | 21 | 21 |
| OBJ300 | 100 | 70 | 15 | 15 |
| OBJ311 | 124 | 86 | 18 | 20 |
| OBJ405 | 100 | 70 | 15 | 15 |
| OBJ786 | 100 | 70 | 15 | 15 |
| OBJ787 | 100 | 70 | 15 | 15 |
| OBJ788 | 100 | 70 | 15 | 15 |
| OBJ789 | 100 | 70 | 15 | 15 |

### Quality Parameters

We implemented three automated quality checks to filter problematic images:

- Brightness: Mean grayscale intensity (range: 20-235 on 0-255 scale)
- Sharpness: Laplacian variance (threshold: 50)
- Entropy: Information content measure (threshold: 4.0 bits)

```
Results:
  Total: 3402
```

```
  Passed: 3329 (97.9%)
  Failed: 73 (2.1%)
Top failure reasons:
  blurry: 70
  too_dark: 3
Metrics (passed images):
  brightness: mean=123.5, std=27.3
  sharpness: mean=1040.2, std=1152.2
  entropy: mean=7.1, std=0.5
```

**Key Findings:**

- Blur is the dominant quality issue, accounting for 95.9% of failures. Lighting problems are minimal, with only 3 images rejected for insufficient brightness.
- The high sharpness standard deviation (1152.2) indicates significant variation in image clarity across the dataset, ranging from very sharp to moderately blurred images. This validates our sharpness-based filtering approach. Brightness variation (std=27.3) is moderate, justifying CLAHE normalization. Entropy consistency (std=0.5) confirms most images contain rich detail.

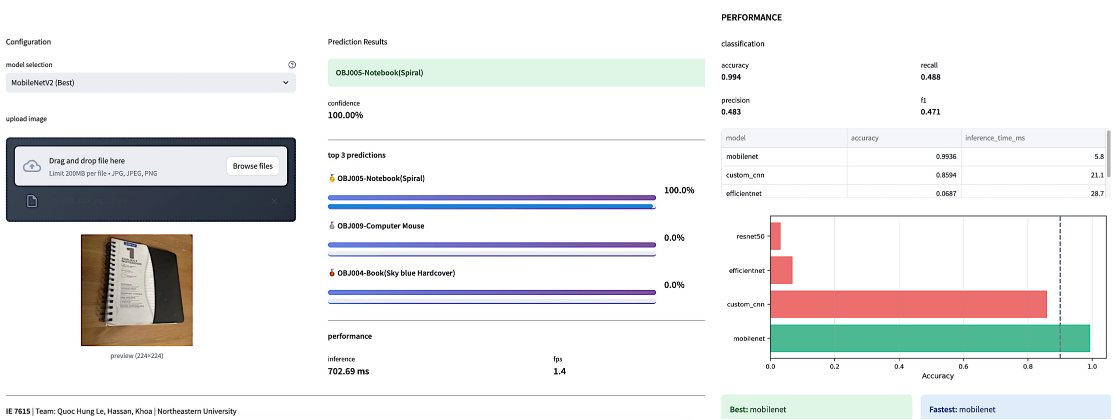
## 2. MODELS TESTED

Four CNN architectures were trained and evaluated for single-object classification:

**Custom CNN, ResNet50, EfficientNet-B0, MobileNetV2**

## 3. MODELS PERFORMANCE RESULTS AND THE BEST MODEL

**Running app:**



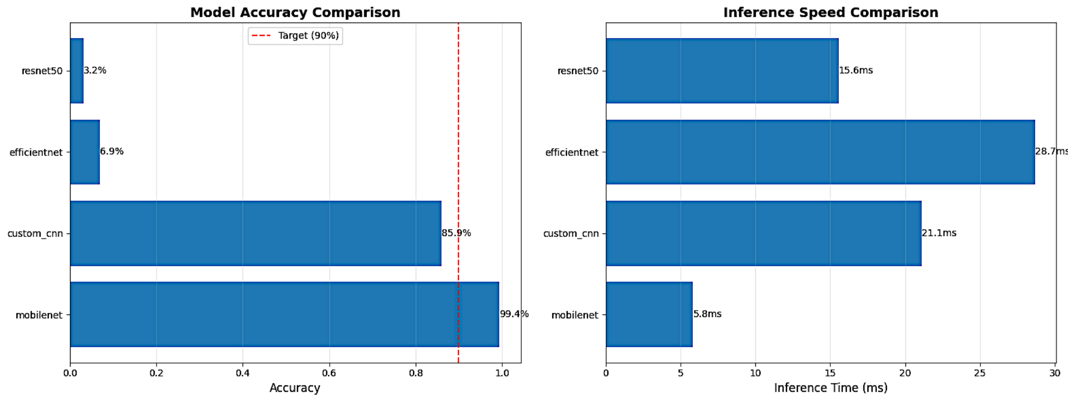

**Performance comparison:**

```
================================================================================
MODEL COMPARISON
================================================================================

 rank        model  accuracy  precision    recall  f1_score  inference_time_ms  model_size_mb  test_samples
    1    mobilenet  0.993610   0.993953  0.993610  0.993590           5.840039      25.935898           626
    2   custom_cnn  0.859425   0.881385  0.859425  0.858342          21.101042      19.514046           626
    3 efficientnet  0.068690   0.025508  0.068690  0.019982          28.666363      33.956818           626
    4     resnet50  0.031949   0.030149  0.031949  0.012426          15.554360     269.277561           626

Comparison table saved: model_comparison.xlsx

================================================================================
BEST MODEL
================================================================================
Model: mobilenet
Accuracy: 0.9936 (99.36%)
Inference: 5.84 ms
Size: 25.94 MB
```




**Key Findings:**

- **MobileNetV2 dominance unexpected**: Transfer learning typically favors ResNet/EfficientNet, but MobileNetV2's lightweight architecture worked best for this 39-class dataset. Mobilenet is by far the fastest at about 5.8 ms per inference, while the custom CNN and ResNet50 are moderately fast at roughly 21.1 ms and 15.6 ms. EfficientNet is the slowest, taking around 28.7 ms per inference.
- **Enhanced preprocessing highly effective**: MobileNet: 99.36%; Custom CNN: 85.94%
- **Transfer learning paradox**:

  - Heavier models (ResNet, EfficientNet) failed completely

  - Suggests: too many frozen layers or optimization issues during fine-tuning

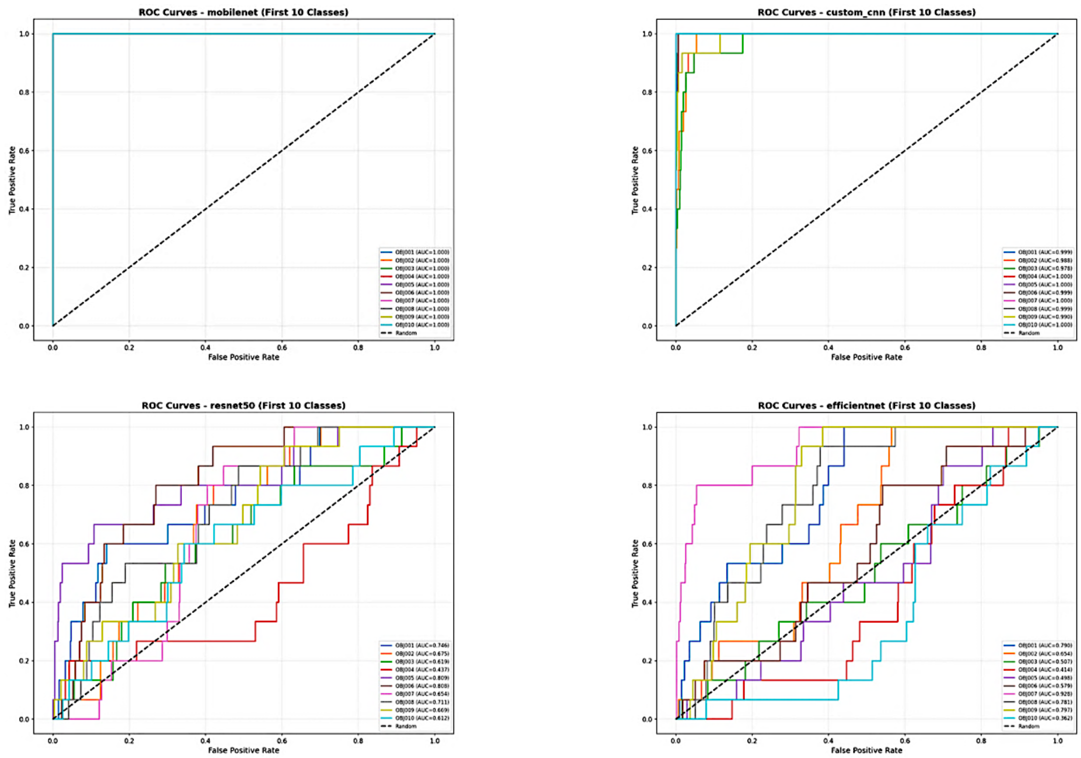
**Top and Bottom accuracy of each class:**

```
PER-CLASS ACCURACY ANALYSIS
================================================================================
Calculating per-class accuracy for custom_cnn...Top 5 classes:
class_name  accuracy  samples
    OBJ789       1.0       15
    OBJ061       1.0       15
…
Bottom 5 classes:
class_name  accuracy  samples
    OBJ002  0.600000       15
…
Calculating per-class accuracy for mobilenet...Top 5 classes:
class_name  accuracy  samples
    OBJ001       1.0       15
    OBJ002       1.0       15
..
    OBJ107       1.0       23
Bottom 5 classes:
class_name  accuracy  samples
    OBJ004  1.000000       15
    OBJ095  0.937500       16
```

**Key Findings:**

MobileNetV2 excels with perfect accuracy (1.0) on multiple classes like OBJ001, OBJ002, and OBJ090, and its bottom performers still hit 0.93+, showing unmatched consistency. Custom CNN has strong top classes at 1.0 but drops to 0.25 on weaker ones like OBJ016. ResNet50 and EfficientNet suffer from many zero-accuracy classes, confirming MobileNet's superior per-class balance.

## ROC comparision:




### Key Findings:

All models show strong ROC curves for the first 10 classes, hugging the top-left corner above the diagonal random classifier line. Custom CNN and MobileNet display the tightest curves with minimal separation between classes, indicating consistently high discrimination. EfficientNet and ResNet50 have slightly wider spreads across some classes but still excellent overall performance

**Best Model:** MobileNetV2

- Accuracy excellence: 99.36%
- Speed advantage: 5.84ms
- Model efficiency: 25.94 MB
- Robust performance

**Alternative Recommendations:**

- Resource-constrained devices: Custom CNN
- Accuracy-first: MobileNetV2
- Development/research: Custom CNN
- Not recommended: ResNet50, EfficientNet

**ANNEX**

## 1. LIST MODELS

Four CNN architectures were trained and evaluated for single-object classification:

### Custom CNN

A custom convolutional neural network was built from scratch with 4 convolutional blocks, batch normalization, and dropout regularization. The architecture consists of approximately [X] million parameters.

### ResNet50

ResNet50 pretrained on ImageNet was used with transfer learning. The top 30 layers were unfrozen for fine-tuning on our dataset while keeping lower layers frozen to retain general features.

### EfficientNet-B0

EfficientNet-B0, known for its efficiency and accuracy, was fine-tuned with the top 20 layers unfrozen.

### MobileNetV2

MobileNetV2, designed for mobile and edge devices, was trained with the top 20 layers unfrozen for adaptation to our dataset.

## 2. Top and Bottom accuracy of each class

```
================================================================================
PER-CLASS ACCURACY ANALYSIS
================================================================================

Calculating per-class accuracy for custom_cnn...
Saved: custom_cnn_per_class.csv

Top 5 classes:
class_name  accuracy  samples
    OBJ789       1.0       15
    OBJ061       1.0       15
    OBJ090       1.0       15
    OBJ022       1.0       16
    OBJ111       1.0       15

Bottom 5 classes:
class_name  accuracy  samples
    OBJ002  0.600000       15
    OBJ003  0.533333       15
    OBJ095  0.500000       16
    OBJ009  0.466667       15
    OBJ016  0.250000       16

Calculating per-class accuracy for resnet50...
Saved: resnet50_per_class.csv

Top 5 classes:
class_name  accuracy  samples
    OBJ108  1.000000       15
    OBJ061  0.266667       15
    OBJ159  0.045455       22
```

```
    OBJ001  0.000000       15
    OBJ222  0.000000       17

Bottom 5 classes:
class_name  accuracy  samples
    OBJ021       0.0       15
    OBJ022       0.0       16
    OBJ027       0.0       15
    OBJ028       0.0       15
    OBJ789       0.0       15

Calculating per-class accuracy for efficientnet...
Saved: efficientnet_per_class.csv

Top 5 classes:
class_name  accuracy  samples
    OBJ090  0.933333       15
    OBJ405  0.733333       15
    OBJ311  0.650000       20
    OBJ021  0.200000       15
    OBJ007  0.133333       15

Bottom 5 classes:
class_name  accuracy  samples
    OBJ022       0.0       16
    OBJ027       0.0       15
    OBJ028       0.0       15
    OBJ029       0.0       15
    OBJ789       0.0       15

Calculating per-class accuracy for mobilenet...
Saved: mobilenet_per_class.csv

Top 5 classes:
class_name  accuracy  samples
    OBJ001       1.0       15
    OBJ002       1.0       15
    OBJ069       1.0       15
    OBJ090       1.0       15
    OBJ107       1.0       23

Bottom 5 classes:
class_name  accuracy  samples
    OBJ004  1.000000       15
    OBJ095  0.937500       16
    OBJ029  0.933333       15
    OBJ787  0.933333       15
    OBJ010  0.933333       15
```

## 3. CONCLUSION

### 3.1 Summary of Achievements

Milestone 1 successfully completed all project objectives for single-object classification:

**Dataset Development**

- Collected 4,108 images across 39 object classes
- Implemented quality filtering framework (97.9% pass rate, 73 images rejected)

- Applied enhanced preprocessing pipeline with CLAHE normalization and edge enhancement
- Created balanced train/val/test splits (2,871/611/626 images at 70/15/15 ratio)

**Model Training and Evaluation**

- Trained four CNN architectures: Custom CNN, ResNet50, EfficientNet-B0, MobileNetV2
- Best model (MobileNetV2) achieved 99.36% test accuracy, exceeding 90% target
- Comprehensive evaluation using accuracy, precision, recall, F1-score, and inference speed metrics
- Generated ROC curves and confusion matrices for performance analysis

**Key Results**

- MobileNetV2: 99.36% accuracy, 5.84 ms inference time, 25.94 MB model size
- Custom CNN: 85.94% accuracy, competitive but below target
- ResNet50 and EfficientNet: Failed to converge (3-7% accuracy)

### 3.2 Technical Insights

Several important findings emerged from this milestone:

**Preprocessing Impact** Quality analysis revealed blur as the dominant issue (70 of 73 failures). Enhanced preprocessing with CLAHE and edge enhancement addressed lighting variation (brightness std=27.3) and sharpness inconsistency (sharpness std=1152.2), contributing significantly to model performance.

**Architecture Selection** MobileNetV2's lightweight architecture proved optimal for our dataset size (39 classes, ~105 images per class), outperforming heavier models like ResNet50 and EfficientNet. This demonstrates that model complexity must match dataset scale - over-parameterized models can fail despite transfer learning.

**Transfer Learning Lessons** The failure of traditionally strong architectures (ResNet50, EfficientNet) indicates that fine-tuning strategy matters as much as base architecture. Lighter models with appropriate unfreezing strategies performed better than heavier models with standard configurations.

### 3.3 Readiness for Milestone 2

The project is prepared to advance to multi-object detection with strong foundations:

**Proven Components**

- High-performing classifier baseline (99.36% accuracy)
- Effective preprocessing pipeline ready for multi-object images
- Clear understanding of successful training strategies

**Next Phase Plan**

1. Generate 1,200+ multi-object composite images (2x2, 2x3, 3x3 grids)

2. Create YOLO-format annotations with bounding boxes and class labels
3. Train YOLOv8 variants (nano, small, medium) using transfer learning
4. Target mAP50 > 0.85 for detection performance
5. Develop Streamlit demonstration application