Project Report: Supermarket Product Classification Using CNN

Project Title: Supermarket Product Classification Using Convolutional Neural Networks (CNN)
Course Name: C-417
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1. Introduction

Supermarket product classification is a crucial task in modern retail. It involves automatically identifying product categories (e.g., snacks, beverages, dairy, canned goods) from digital images. Automation in retail increasingly relies on computer vision techniques for faster, more accurate product recognition.

This project develops a **Deep Learning model using Transfer Learning with MobileNetV2** to classify supermarket items. MobileNetV2 is particularly effective due to its pre-trained convolutional layers that extract rich visual features, reducing the need for massive datasets and extensive training.

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2. Significance and Applications

2.1 Significance

- **Efficiency:** Reduces checkout time by automating product recognition.
- **Inventory Accuracy:** Enables real-time stock monitoring.
- **Customer Experience:** Facilitates “grab-and-go” shopping experiences with automated checkout.

2.2 Real-World Applications

1. **Self-Checkout Systems:** Automatic product identification without scanning barcodes.
2. **Smart Shopping Carts:** Cameras recognize items as they are added to the cart.
3. **Automated Inventory Management:** Robots detect misplaced or missing items on shelves.
4. **Retail Analytics:** Analyzes product placement, shelf share, and sales trends.

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3. Dataset Documentation

3.1 Data Source

The dataset was obtained from the University of Freiburg dataset, consisting of images representing various supermarket categories.

3.2 Dataset Statistics

- **Total Images:** 5000
- **Number of Classes:** 4 main categories (Beverage, Canned / Preserved, Pantry & Dry Goods, Snack / Confectionery)
- **Image Dimensions:** Resized to 224×224 pixels (RGB)

3.3 Data Split

- **Training Set (70%)** – used to train the model
- **Validation Set (15%)** – used to tune hyperparameters and monitor overfitting
- **Test Set (15%)** – for final evaluation

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4. Methodology

4.1 Data Preprocessing

- **Resizing:** All images resized to 224×224×3 (required by MobileNetV2)
- **Normalization:** Pixel values scaled to [-1, 1] using `preprocess_input`
- **Data Augmentation:** Includes random rotation, horizontal flip, zoom, and brightness adjustments

4.2 CNN Architecture (Transfer Learning with MobileNetV2)

The model leverages **MobileNetV2 pre-trained on ImageNet** with a custom dense head:

- **Base Model:** MobileNetV2 (frozen initially to retain pre-trained weights)
- **Global Average Pooling:** Reduces spatial dimensions to a single feature vector
- **Dense Layers:** Two fully connected layers with 128 and 64 neurons, ReLU activation
- **Dropout:** 30% to prevent overfitting
- **Output Layer:** Dense layer with 4 neurons and Softmax activation for 4 categories

(Include a diagram of the MobileNetV2 + Dense head architecture here)

4.3 Training Configuration

- **Optimizer:** Adam
- **Loss Function:** Categorical Cross-Entropy
- **Batch Size:** 16
- **Epochs:** 10 initial training + 10 fine-tuning
- **Callbacks:** EarlyStopping, ModelCheckpoint, ReduceLROnPlateau
- **Fine-Tuning:** Last 20 layers of MobileNetV2 unfrozen, learning rate reduced to 1e-5

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5. Evaluation Results

5.1 Model Performance

- **Test Accuracy:** [≈ 73.98%]
- **Test Loss:** [~0.6472]

5.2 Visualizations

Figure 1: Training & Validation Accuracy and Loss Curves
(Insert plot of accuracy and loss)
Comment: Curves show stable convergence, indicating good generalization.

Figure 2: Confusion Matrix
(Insert confusion matrix image)
Comment: The model performs well on [beverage], with occasional confusion between [canned] and [pantry and dry food].

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6. Discussion and Challenges

6.1 Challenges

1. **Packaging Similarity:** Some products across categories share similar packaging colors.
2. **Occlusions:** Partially visible items were harder to classify.
3. **Lighting Conditions:** Reflections created noise in the images.

6.2 Potential Improvements

- **Transfer Learning:** Already used MobileNetV2, but larger pre-trained models like ResNet50 could further improve accuracy.
- **Object Detection:** Detect multiple items per image using YOLO or SSD for shelf-level classification.

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7. Conclusion

The project successfully developed a MobileNetV2-based CNN for supermarket product classification. The system demonstrates the feasibility of deep learning in retail automation and shows strong potential for self-checkout and inventory management.

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8. References

1. University of Freiburg, Freiburg Groceries Dataset – Dataset Link