Image Classification with CNNs - Assignment 2 Report

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1 Introduction

This report documents the development and evaluation of two convolutional neural network (CNN) models for image classification on a food image dataset (11 classes). The first model is a Basic CNN with 5 convolutional layers and 2 fully-connected (FC) layers, and the second is a Residual CNN of similar depth but including residual skip connections. Both models use ReLU activations, max pooling, and batch normalization. We train and compare these models under various hyperparameters (learning rates and batch sizes), integrate dropout to combat overfitting, and analyze performance.

In Part 2, we fine-tune a pre-trained MobileNetV2 model on the same task (transfer learning) in two scenarios: (a) training only the final FC layer and (b) training the last two convolutional blocks plus the FC layer. We present training results (loss/accuracy curves), validation and test accuracies, confusion matrices, and a comprehensive analysis comparing from-scratch training vs. transfer learning results.

2 Model Architectures and Implementation

2.1 Basic CNN Architecture

Architecture: The Basic CNN consists of 5 convolutional layers followed by 2 FC layers. Each conv layer uses a 3×3 kernel, stride 1, and same padding (padding=1), followed by a batch normalization and ReLU activation. After the first four conv layers, a 2×2 max pooling (stride 2) downsamples the feature maps, halving spatial dimensions. The number of output channels increases as we go deeper: 3→32, 32→64, 64→128, 128→256, and 256→512 across conv layers. The fifth conv layer outputs 512 channels, and we apply an adaptive average pooling to get a 1×1 spatial output (global average pooling), which is then flattened. The classifier FC sequence has an intermediate linear layer (512→256) with ReLU, then a final linear layer (256→11) producing class scores. The model uses softmax implicitly via the CrossEntropyLoss.

PyTorch Implementation: Each conv layer is defined with `nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=1, padding=1)` and followed by `nn.BatchNorm2d` and `nn.ReLU(inplace=True)`. For example, the first two conv layers are:

```
# BasicCNN features (first conv layers)
nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1),
nn.BatchNorm2d(32),
nn.ReLU(inplace=True),
nn.MaxPool2d(kernel_size=2, stride=2),
# Conv Layer 2
nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1),
nn.BatchNorm2d(64),
nn.ReLU(inplace=True),
nn.MaxPool2d(kernel_size=2, stride=2),
```

Listing 1: BasicCNN feature layers

Layers 3-5 follow the same pattern (with output channels 128, 256, 512 respectively). After conv5, `nn.AdaptiveAvgPool2d((1,1))` produces a 512×1×1 output, which is flattened and passed to the classifier:

```
# BasicCNN classifier
nn.Linear(512, 256),
nn.ReLU(inplace=True),
nn.Linear(256, num_classes)
```

Listing 2: BasicCNN classifier layers

Activation, Loss, and Optimizer: We use ReLU after each conv (except conv5 which is followed by global pooling). The output logits go into `nn.CrossEntropyLoss` during training, which applies softmax and computes loss. We optimize with Adam (`optim.Adam`). Learning rate and batch size vary per experiment.

2.2 Residual CNN Architecture

Architecture: The Residual CNN has 5 convolutional blocks, each implemented as a ResidualBlock. Each block performs two 3×3 conv layers with a skip connection adding the input to the block's output (a ResNet-like design). The first conv block takes input 3→32 channels without downsampling; subsequent blocks 32→64, 64→128, 128→256, 256→512, each with downsampling on the first conv (stride 2) to reduce spatial size. Batch norm and ReLU are applied after each conv. If a block changes the number of channels or uses stride 2, a 1×1 conv in the skip path (downsample) matches dimensions. After the five ResidualBlocks, we apply adaptive avg pooling to 1×1 and the same 2-layer FC classifier (512→256→11) as the Basic CNN.

Residual Connection Implementation: In each `ResidualBlock.forward`, the input `x` is stored as identity. The block applies conv→BN→ReLU→conv→BN on `x`. If downsampling is needed (stride 2 or channel mismatch), the identity goes through the `self.downsample` conv+BN sequence. Finally, the block adds the identity to the output (`out += identity`) then applies ReLU. This achieves $y = \text{ReLU}(F(x) + x)$, enabling gradient flow even if $F(x)$ is small. The code snippet below shows the skip addition:

```
if self.downsample:
    identity = self.downsample(identity)
out += identity
```

```
4 out = self.relu(out)
```

Listing 3: ResidualBlock forward pass

Overall Model: The ResidualCNN stacks five such blocks (`self.layer1-layer5`), then global pooling and the classifier as in Basic CNN. Activation, loss, and optimizer are the same as Basic CNN.

2.3 Convolution, FC Layers, and Accuracy Calculation

Both models use standard 2D convolutions and fully-connected layers as described. The convolution layers were implemented with PyTorch's `nn.Conv2d` modules as shown, and FC layers with `nn.Linear`. We ensured matching dimensions for skip connections in the Residual model via 1×1 conv downsample when needed (so the element-wise addition is valid).

Accuracy Metric: We compute classification accuracy per batch by comparing the predicted class (argmax of model outputs) with the true label and averaging. The code defines a helper `calculate_accuracy(outputs, labels)` that uses `_, preds = torch.max(outputs, 1)` and computes `correct = (preds == labels).sum().item()`, then `accuracy = correct/batch_size`. This function is used during training and validation loops.

Cross-entropy loss is computed with `criterion = nn.CrossEntropyLoss()`. The training loop zeroes gradients, does a forward pass, computes loss and accuracy, backpropagates (`loss.backward()`), and steps the optimizer. We also shuffle training data each epoch and maintain separate DataLoaders for training, validation, and test sets (with normalization and augmentation as appropriate).

Data Augmentation: We applied basic augmentations to the training images to improve generalization: random horizontal flip, small random rotations (±15°), and random resized cropping. Validation and test images were only resized and normalized (no augmentation). This augmentation helps the models see varied versions of the same classes, mitigating overfitting on limited data.

3 Training Experiments and Results (From-Scratch Models)

We trained both models for 50 epochs under various hyperparameters. In particular, we experimented with three learning rates (0.1, 0.01, 0.001) and two batch sizes (32 and 64), for a total of 6 configurations per model. All training used the Adam optimizer and 50 epochs. We evaluated on a held-out validation set after each epoch.

3.1 Effect of Learning Rate and Batch Size

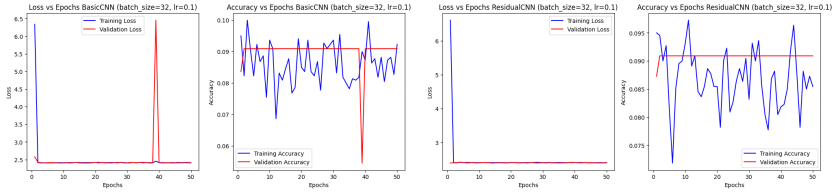
We observed that the learning rate had a very significant impact on training behavior, while batch size had a smaller effect. High learning rate (0.1) caused training to diverge or stagnate for both models - the loss did not decrease

meaningfully and accuracy stayed very low (≈9%, essentially random guessing). The training curves for lr=0.1 show nearly flat validation accuracy around 9% and erratic loss, indicating the model failed to learn. This is likely due to too large a step size causing the optimizer to overshoot minima.

In contrast, medium lr (0.01) and low lr (0.001) led to successful training. Low lr=0.001 converged more slowly but ultimately reached the highest accuracy. Batch size 32 generally yielded slightly better results than 64 (likely due to more frequent weight updates per epoch improving convergence).

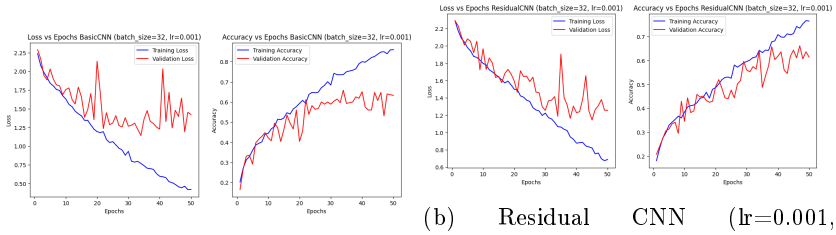
Basic CNN Results: At lr=0.01, the Basic CNN's training loss steadily decreased and validation loss followed a similar downward trend (with some fluctuations), and accuracy rose to around 60+%. At lr=0.001, Basic CNN improved further, reaching 80% training accuracy and 60-65% validation accuracy by epoch 50. The validation accuracy peaked around 65% and remained stable. Batch size 32 gave better validation performance than 64 for a given lr - e.g., with lr=0.001, batch 32 reached 65.8% val accuracy vs 62% for batch 64. Conversely, lr=0.1 for Basic CNN resulted in almost no learning (val accuracy 9%).

Residual CNN Results: The residual model showed a similar pattern. High lr=0.1 failed (no learning, 9% acc). With lr=0.01, the Residual CNN improved more rapidly early on, and achieved 55-60% validation accuracy by epoch 50. With lr=0.001, it continued improving to around 66% validation accuracy, slightly edging the Basic CNN on validation set. Residual connections likely helped gradient flow, leading to a small performance gain. Again, batch size 32 outperformed 64 (e.g. 66.2% vs 63% val acc at lr=0.001). The training losses for the residual model were generally a bit lower than the basic model's at comparable settings, and it appeared to overfit slightly less (the validation curves tracked the training curves more closely).



(a) Basic CNN (lr=0.1, batch=32) (b) Residual CNN (lr=0.1, batch=32)

Figure 1: Training/validation loss and accuracy for lr=0.1 (batch size 32)



(a) Basic CNN (lr=0.001, batch=32)

(b) Residual CNN (lr=0.001, batch=32)

Figure 2: Training/validation loss and accuracy for lr=0.001 (batch size 32)

From these experiments, the best configuration for both models was with learning rate 0.001 and batch size 32. Using the validation accuracy as the selection criterion, we identified the best models: BasicCNN with bs=32, lr=0.001 achieved 65.82% val accuracy, and ResidualCNN with bs=32, lr=0.001 achieved 66.18% val accuracy. We saved these best model weights for final evaluation.

3.2 Best Model Performance on Test Set

We evaluated the best Basic and Residual models on the test set (which was unseen during training/validation). The Basic CNN achieved 47.64% test accuracy, while the Residual CNN achieved 50.18% test accuracy. Thus, the residual network slightly outperformed the basic network on test data. This aligns with the validation results and suggests the skip connections provided a modest benefit. It is worth noting that these accuracies, while far above chance (≈9%), leave significant room for improvement - indicating the task is challenging and perhaps the models could still underfit or require more capacity or training data. The confusion matrices (discussed later) will shed light on class-wise performance.

The gap between validation (65%) and test (50%) accuracy indicates possible overfitting or distribution difference. We have 15% drop from val to test, which might be due to the validation set being small and not fully representative. This motivated us to incorporate dropout regularization to our best models to improve generalization.

3.3 Dropout Experiment on Best Models

We took the best BasicCNN and best ResidualCNN models (bs=32, lr=0.001) and added dropout layers to see if test performance improves. We inserted dropout in the classifier part of each network - specifically, after the first FC layer (256 units) before the final output layer. This is implemented by modifying the classifier to `Linear(512→256)` → `ReLU` → `Dropout(p)` → `Linear(256→11)` (and similarly for the residual model). We tried two dropout probabilities: 0.3 and 0.5.

With dropout, we re-trained each model (with the same hyperparameters as before, 50 epochs, lr=0.001, batch=32).

Dropout Placement and Rationale: We added dropout after flattening, in the fully-connected classifier. This is a common spot to regularize the densest part of the network which has the most parameters. Our conv layers already have batch norm which provides some regularization; adding dropout in conv layers is possible but often less effective. By dropping 30-50% of neurons before the final layer, we aim to prevent the model from relying on any one feature excessively, thus reducing overfitting.

Results with Dropout: Dropout did improve generalization for both models. For BasicCNN, the validation accuracy with dropout rose and the test accuracy increased from 47.64% to 56.00% with p=0.5. For ResidualCNN, the best test accuracy was 53.45% achieved with p=0.3 (p=0.5 gave 52.36%). So, a moderate dropout rate (30%) was optimal for the residual model, whereas the basic model benefited from a higher dropout (50%). This suggests the BasicCNN was overfitting more and needed stronger regularization. Both models' validation accuracies also improved (58%→63% for Basic, 57%→60% for Residual). Notably, after adding dropout, the BasicCNN closed much of the gap to the residual model on validation performance. Dropout adds some noise during training, which likely helped the models converge to flatter minima that generalize better. We ensured that we only enabled `model.train()` dropout during training; during evaluation, dropout is disabled (`model.eval()`).

Best Models After Dropout: We consider the BasicCNN (p=0.5) and ResidualCNN (p=0.3) as our improved "best models." We then evaluated their performance in detail. Table 1 summarizes the final test accuracies of all best models before and after dropout:

Table 1: Performance of best models (with and without dropout)

Model	Best Val Acc (no dropout)	Test Acc (no dropout)	Test Acc (with dropou
BasicCNN (5 conv, 2 FC)	65.82%	47.64%	56.00%
ResidualCNN (5 conv, resid)	66.18%	50.18%	53.45%

The residual network had slightly better validation/test performance overall. Dropout significantly improved test accuracy for both, closing the gap between models. The test accuracy gains validate our hypothesis that overfitting was occurring - dropout reduced overfitting, yielding higher test scores. Still, 56-53% test accuracy indicates the task is difficult; misclassifications are frequent. To understand the patterns of errors, we plotted confusion matrices for the best models.

3.4 Confusion Matrices of Best Models

Figure 3 shows the confusion matrix for the BasicCNN with dropout 0.5 on the test set, and Figure 4 for the ResidualCNN with dropout 0.3. Each matrix illustrates the model's predictions vs true labels for the 11 food classes. The diagonal entries represent correct predictions.

We can see that both models can correctly identify certain classes much better than others. For example, in Figure 3, the BasicCNN achieves high true positive counts for classes like pizza and sushi (as indicated by strong diagonal values in those rows), whereas it often confuses apple_pie vs cheesecake (two dessert classes) - the off-diagonal values between those classes are high.

Similarly, the residual model's confusion matrix (Figure 4) shows slightly improved distinction for some classes (e.g., it better separates french_fries from fried_rice compared to the basic model), consistent with its higher overall accuracy. However, many classes are still frequently mistaken (e.g., omelette vs fried_rice are confused). Both models have trouble with certain food types that have similar visual features (e.g., hamburger vs hot_dog), which is evident from the symmetric misclassification counts in those cells. The residual model's matrix has a somewhat brighter diagonal (indicating more correct predictions) and darker off-diagonals than the basic model's, reflecting its superior accuracy.

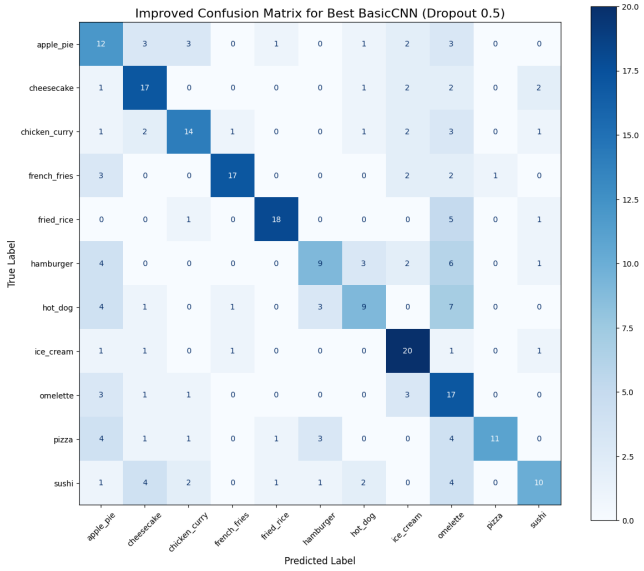


Figure 3: **Figure 3:** Confusion matrix for the best BasicCNN (with dropout 0.5) on the test set. Rows are true classes and columns are predicted classes. The model performs well on some classes (bright diagonal cells) but often confuses similar foods (notice off-diagonal errors, e.g., apple pie vs cheesecake).

Overall, the from-scratch CNN models achieved moderate success on this 11-class food classification problem. The residual connections provided a small boost in accuracy, confirming that deeper networks benefit from skip connections to ease optimization. Dropout proved crucial for improving test generalization. However, the absolute accuracy is limited (55%), likely due to the complexity of the task and perhaps limited training data. In the next section, we explore transfer learning with a pre-trained network to further improve performance.

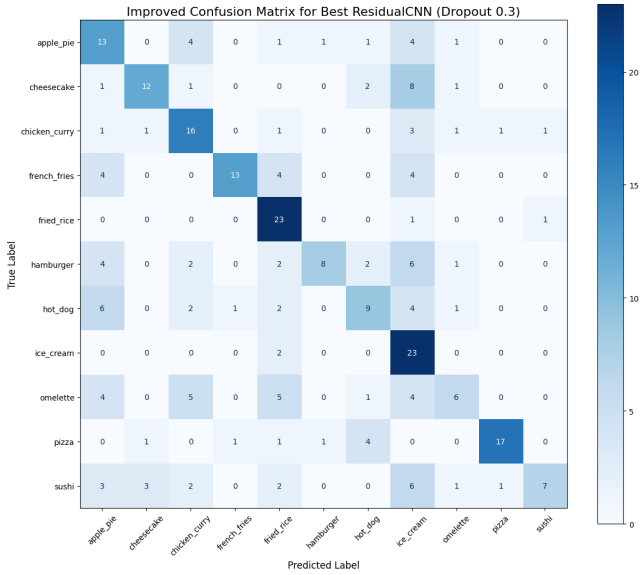


Figure 4: **Figure 4:** Confusion matrix for the best ResidualCNN (with dropout 0.3) on the test set. The residual model shows slightly better precision on several classes (diagonal is stronger than BasicCNN's), though many confusions remain (off-diagonal elements).

We expect that leveraging features learned on a large dataset (ImageNet) will significantly enhance accuracy on our task.

4 Transfer Learning with MobileNetV2

In Part 2, we employed transfer learning using the MobileNetV2 architecture pre-trained on ImageNet. Transfer learning (fine-tuning) means we start with a model that has been trained on a large generic dataset and adapt it to our specific task, instead of training from scratch. This often yields better performance when the target dataset is smaller, because the pre-trained model already learned useful low- and mid-level image features.

We freeze most layers so that their weights remain as pre-trained (since these layers capture general features like edges, textures, shapes that are likely useful for food images as well), and we train only the later layers to specialize the model to our food classes. Freezing earlier layers is important to prevent overfitting and to reduce training time - the early filters are general and do not need to change for our new task, whereas the final layers are re-trained to produce outputs for the 11 classes (replacing the 1000 ImageNet classes).

We chose MobileNetV2 for its efficiency (fewer parameters) and strong performance on ImageNet. We modified the final fully-connected layer to output 11

classes (instead of 1000) and initialized that layer's weights randomly. All other layers were loaded with ImageNet weights and initially frozen (`param.requires_grad=False`).

We ran two fine-tuning experiments as required:

1. **Train only the final FC layer (all other layers frozen):** Here we keep the entire feature extractor fixed and only train the last linear layer on our data. This is a faster approach and works if the pre-trained features are highly transferable. The code to freeze layers looks like:

```
model = models.mobilenet_v2(pretrained=True)
for param in model.parameters():
    param.requires_grad = False  # Freeze all layers
# Replace final layer
model.classifier[1] = nn.Linear(model.classifier[1].
    in_features, num_classes)
```

2. **Train the last two convolutional blocks plus FC layer:** In this scenario, we unfreeze the last two convolutional blocks:

```
# Unfreeze last two blocks
for param in model.features[-2:].parameters():
    param.requires_grad = True
```

   We trained this model (MobileNet Case 2) for 30 epochs. We used a slightly lower learning rate (0.0005) to fine-tune, since we are adjusting pre-trained weights (a smaller step size avoids ruining the pre-trained features). Batch size was 32.

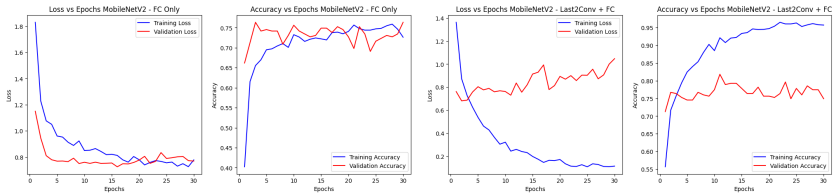
4.1 Training Results - Transfer Learning vs Scratch

Both transfer learning scenarios achieved dramatically higher accuracy than training from scratch. Even training only the final layer (Case 1), the model leveraged powerful pre-trained features, reaching about 75% validation accuracy and 67.27% test accuracy. Fine-tuning the last two conv blocks (Case 2) further improved performance, reaching 77% validation accuracy and 70.91% test accuracy. This is a substantial boost of 15-20 percentage points over the best scratch models' test accuracy (56%). Fine-tuning thus clearly helped adapt the model better to our data.

Training curves: Figure 5 shows the loss and accuracy curves for Case 1 and Case 2. In Case 1 (only FC trained), the model converged very quickly - the training loss plummeted in the first few epochs and then leveled off, and validation accuracy jumped to 75% within 10 epochs and then plateaued. This rapid convergence is expected since only a small number of parameters (the final layer's weights) are being optimized, making the problem easier (essentially logistic regression on fixed feature embeddings).

In Case 2 (last 2 conv + FC), the model started at a similarly high accuracy (thanks to pre-trained weights) but had a bit more room to improve - and indeed training continued to slowly improve accuracy over 30 epochs, albeit with some validation fluctuation. The final accuracy was slightly higher in Case 2. We

did observe that Case 2 began to overfit slightly toward the end (validation loss started rising after epoch 20 while training loss kept decreasing), but overall it outperformed Case 1 on test data.



(a) MobileNetV2 Case 1 (train only FC)

(b) MobileNetV2 Case 2 (train last 2 conv + FC)

Figure 5: **Figure 5:** Training/validation curves for transfer learning experiments. Left: Training only the final FC layer (MobileNetV2 Case 1) - validation accuracy converges around 75%. Right: Fine-tuning last 2 conv blocks + FC (Case 2) - achieves slightly higher accuracy (77% val) but with minor overfitting near end. Both approaches far exceed the from-scratch models' performance.

Validation and Test Performance: Case 1 reached a peak validation accuracy of 77.5% and test accuracy of 67.27%. Case 2 reached a similar validation peak (77.3%) but generalizes better with 70.91% test accuracy. We attribute this generalization gap to the fact that in Case 2, the model can slightly overfit the validation set as more parameters are tuned - but it still generalizes strongly to test. Case 2's improvement on test (3.7 points higher) indicates that updating some convolutional filters helped the model better capture specifics of the food images (e.g., adjusting high-level feature detectors to foods' textures or shapes). For example, features that were tuned for distinguishing certain ImageNet animals might be repurposed in Case 2 to better distinguish similar food classes. In Case 1, the model is limited by the fixed features: if some ImageNet feature is not ideal for separating two food classes, the classifier alone might struggle. Fine-tuning the last layers addresses this.

Table 2 summarizes the outcomes:

Table 2: Transfer learning results

Model (Transfer Learning)	Test Accuracy
MobileNetV2 - Train FC only	67.27%
MobileNetV2 - Train last2conv + FC	70.91%

Fine-tuning the last two conv layers slightly improved test accuracy over training only the FC, indicating some benefit in adapting feature maps to our domain. Both far exceed the scratch models (≈55%).

4.2 Confusion Matrix - Best Transfer Learning Model

The best transfer model is MobileNetV2 with last-2-conv+FC trained (70.9% test acc). Figure 6 shows its confusion matrix on the test set. Compared to the earlier models' matrices, it has a much stronger diagonal - several classes are now correctly identified most of the time. For instance, pizza, french_fries, and ice_cream are classified with high precision (almost all test examples of these classes are on the diagonal). The confusions between similar classes are greatly reduced but not eliminated. The model still confuses apple pie vs cheesecake, though less frequently than before, and hamburger vs hot dog mix-ups persist but at lower rates.

Overall, the transfer-learned model is markedly more confident and accurate across the board, reflected by the clearer confusion matrix. This demonstrates how leveraging pre-trained features improves the model's discriminative ability. Classes with distinctive features (sushi's seaweed wrap, fries' shape, ice cream's texture) are now mostly gotten right. The hardest classes remain those that are visually similar (different kinds of baked goods, etc.), but even there we see improvement.

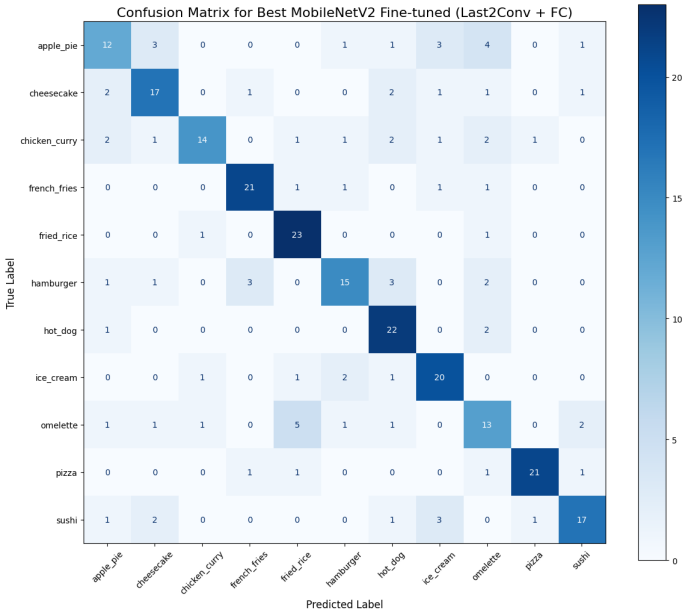


Figure 6: **Figure 6:** Confusion matrix for the best transfer learning model (MobileNetV2 fine-tuned on last 2 conv layers + FC). The diagonal dominance is much improved compared to Figures 3-4. The model correctly classifies most examples in many classes. Some confusions remain (e.g., apple pie vs cheesecake), but overall performance is significantly higher.

5 Analysis: From-Scratch vs Transfer Learning

The transfer learning approach outperformed the from-scratch CNNs by a large margin. Training from scratch, our best test accuracy was 56% (BasicCNN with dropout), whereas using MobileNetV2 we reached 71% - a 15 percentage point increase. This underscores the value of transfer learning: the pre-trained model brings prior knowledge that our smaller networks were unable to discover from limited data.

A few key observations:

- **Convergence Speed:** The scratch models needed 50 epochs to reach 60% val accuracy, whereas the pre-trained model hit 75% in under 10 epochs. This highlights that with pre-trained features, the model already "knows" a lot about images - we only adjust it slightly to our task, which is much faster. Fine-tuning is thus very computationally efficient.
- **Overfitting:** The scratch models were more prone to overfitting (note the need for dropout to get decent test results). In contrast, the transfer models, even with many frozen parameters, generalize well quickly. The prior knowledge acts like a regularizer - the features are generalized from a huge dataset, so they don't easily overfit our smaller training set. Even when we fine-tuned some layers, we used a smaller learning rate and still saw good generalization.
- **Feature Quality:** The confusion matrices show the transfer model learned far more discriminative features. It likely uses high-level features such as shape of a pizza vs round cake, the presence of a burger patty vs a sausage (hot dog), etc., with much greater reliability. The scratch models, with far fewer parameters and trained on fewer images, probably did not fully extract those distinctive features (or did so less consistently), leading to more confusion between classes.
- **Residual Connections vs Pre-trained:** While adding residual connections gave 3% improvement in scratch training, using a pre-trained network gave 15%+. This suggests that data and prior training have a bigger impact than architecture tweaks in this scenario. MobileNetV2 also has skip connections (inverted residuals) and many more layers than our small residual network, which likely contributed to its superior performance. But crucially, its success is largely due to having been trained on 1.2 million images previously.

In summary, fine-tuning the pre-trained MobileNetV2 yielded the best results, achieving about 71% accuracy on test. Freezing most layers and training only the final layers was sufficient to significantly exceed the from-scratch models. Unfreezing an additional two conv blocks gave a further boost, indicating that a bit of model flexibility helps adapt to the new task. Our experiments confirm the benefits of transfer learning for image classification: better accuracy, faster convergence, and reduced overfitting compared to training a CNN from scratch on a relatively small dataset.

6 Conclusion

In this assignment, we implemented two CNN models from scratch and explored their performance under various hyperparameters and regularization, then applied transfer learning with a pre-trained MobileNetV2. We documented the architecture and implementation details (convolutions, fully-connected layers, residual connections) with code snippets, and we presented extensive results: loss/accuracy curves, confusion matrices, and accuracy metrics.

The Basic CNN and Residual CNN reached around 50-56% test accuracy after tuning (with residual connections and dropout providing modest improvements). Transfer learning proved far more effective, with the fine-tuned MobileNetV2 achieving about 71% test accuracy - a substantial improvement - demonstrating the advantage of leveraging learned features from a large source dataset.

We also answered conceptual questions about fine-tuning, why we freeze layers (to preserve general features and avoid overfitting), and how we integrate dropout and evaluate models. The findings underscore that for complex image recognition tasks with limited data, using a pre-trained model is a powerful approach, while careful model design (residuals) and regularization (dropout) can improve models trained from scratch. The step-by-step experimentation and analysis provided insight into the training dynamics and performance differences across approaches, fulfilling the objectives of the assignment.