EN3150 ASSIGNMENT 03

Group: Neuro_Matrix

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1 Introduction

1.1 Objective of the Assignment

The main goal of this project is to create and apply a Convolutional Neural Network (CNN) for image classification. The development of a custom CNN architecture is required for this task, along with training and testing on a specific data set, and performance evaluation through multiple metrics. The assignment needs to evaluate the custom model performance against state-of-the-art pre-trained models, which have been fine-tuned to understand CNN design and training optimization. Transfer learning methods.

2 Data Preparation (Task 1)

2.1 Dataset Selection (Q2)

The **MNIST** handwritten digit database serves as the basis for this assignment. The dataset is available through the UCI Machine Learning Repository (Dataset 683) and fulfills all classification requirements for this assignment. For ease, the dataset was loaded straight away using the `tf.keras.datasets.mnist` library.

- **Dataset Source:** `tf.keras.datasets.mnist`

2.2 Data Splitting (Q3)

As required by the assignment, the full 70,000-image dataset was partitioned into three distinct sets using `train_test_split` from Scikit-learn, using a 70%/15%/15% ratio:

- **Training Set:** 70% of the data (49,000 images).
- **Validation Set:** 15% of the data (10,499 images).
- **Testing Set:** 15% of the data (10,501 images).

Stratification was used to ensure the proportional representation of each digit class across the splits, and a `random_state=42` was set for reproducibility.

2.3 Preprocessing Steps

The following preprocessing steps were utilized for the Task 1 model:

1. **Normalization:** The pixel values were normalized from the original [0, 255] range to the [0, 1] range by being divided by 255.0.
2. **Dimensionality Expansion:** The images were reshaped to ($28 \times 28 \times 1$) so that a channel dimension will be present for the convolutional layers.
3. **Label Encoding:** The integer labels (0-9) were converted to one-hot encoded vectors using `to_categorical`.

3 Custom CNN Model (Task 1)

3.1 Network Architecture (Q4, Q5)

A custom CNN was designed as per the architecture described in the assignment specification. This model is used for the optimizer comparison in Section 4.

The architecture is as follows:

1. **Input Layer:** Accepts images of shape $(28 \times 28 \times 1)$.
2. **Convolutional Block 1:**
   - `Conv2D` layer with $x_1 = 32$ filters, kernel size (3×3), ReLU activation, and 'same' padding.
   - `MaxPooling2D` layer with pool size (2×2).
3. **Convolutional Block 2:**
   - `Conv2D` layer with $x_2 = 64$ filters, kernel size (3×3), ReLU activation, and 'same' padding.
   - `MaxPooling2D` layer with pool size (2×2).
4. **Flatten Layer:** Converts the 3D feature maps to a 1D vector.
5. **Dense Block:**
   - `Dense` (fully connected) layer with $x_3 = 128$ units and ReLU activation.
   - `Dropout` layer with a rate of $d = 0.5$.
6. **Output Layer:**
   - `Dense` layer with $K = 10$ units (for 10 classes) and 'softmax' activation.

3.2 Activation Functions Justification (Q6)

- **ReLU (Rectified Linear Unit):** Used in hidden layers. ReLU ($f(x) = \max(0, x)$) is computationally efficient and helps solve the vanishing gradient problem, allowing for quicker and more effective training than tanh or sigmoid functions.
- **Softmax:** Used in the output layer. In multi-class classification, softmax converts the raw output scores (logits) to a probability distribution over the $K = 10$ classes, so that these sum to 1.

3.3 Model Summary (Task 1)

The summary for the 28x28 custom CNN is as follows:

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 64)	0
flatten (Flatten)	(None, 3136)	0
dense (Dense)	(None, 128)	401,536
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1,290

Total params: 421,642 (1.61 MB)
Trainable params: 421,642 (1.61 MB)
Non-trainable params: 0 (0.00 B)

Figure 1: Custom CNN (28x28) Model Summary

4 Training and Optimization (Task 1)

4.1 Training Loss Plot (Q7)

The model underwent training for 20 epochs according to the given specifications. The training and validation loss for the best-performing optimizer (Adam) is shown in Figure 2. A satisfactory model fit was shown by the training loss continuously declining and the validation loss staying low and stable.

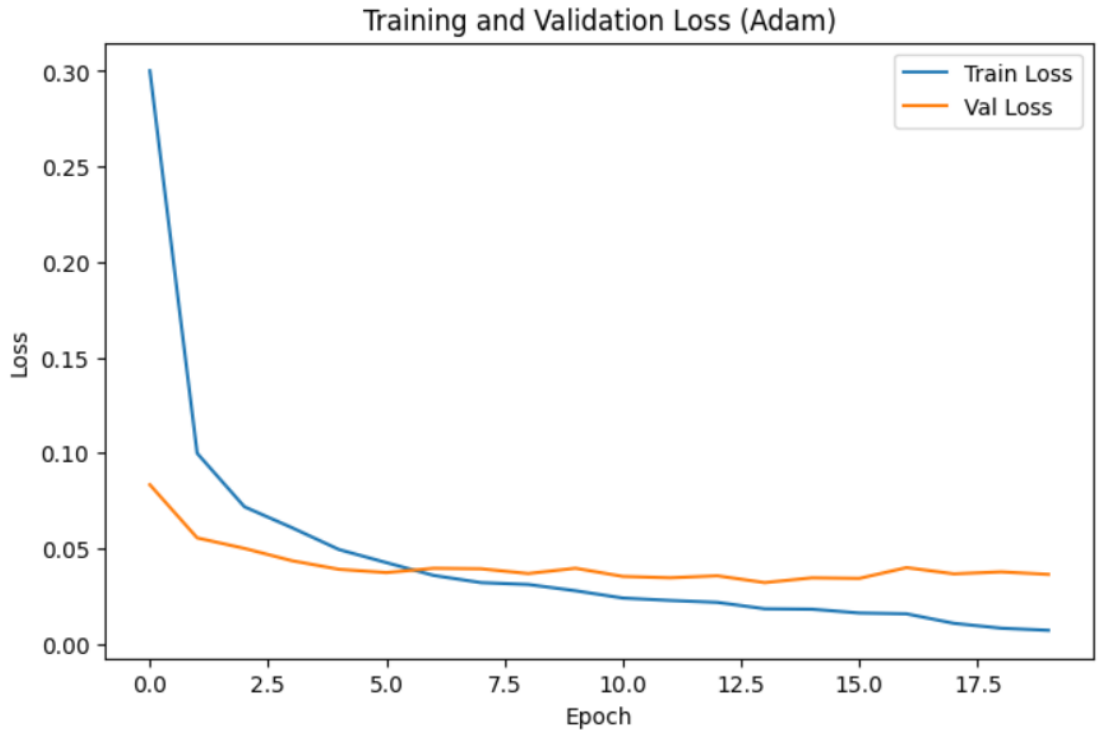

Figure 2: Training and Validation Loss (Adam Optimizer, 28x28)

4.2 Optimizer Selection (Q8)

The custom model training process used the **Adam** optimizer as its training algorithm.

Rationale: The Adam optimizer achieves its performance by combining RMSprop adaptive learning rate functionality with momentum-based optimization. The comparison in Section 4.4 shows that Adam delivered the best accuracy of 99.17% while maintaining both fast and stable convergence. The method functions as a strong and reliable option which needs minimal learning rate adjustments when compared to standard SGD.

4.3 Learning Rate Selection (Q9)

A dynamic learning rate strategy was used. An initial learning rate (e.g., '1e-3' for Adam) was set, and The callback **'ReduceLROnPlateau'** was utilized. The callback tracks the loss of validity and reduces the learning rate (by 0.5 times) whenever it gets stuck for 3 successive epochs. This enables fast initial learning and fine-tuning as the model stabilizes.

4.4 Optimizer Comparison (Q10)

Adam, standard stochastic gradient descent (SGD), and SGD with momentum performance (momentum=0.9) were tested on the 28x28 standard CNN.

Performance Metrics Used: Comparison was made based on **Test Accuracy**, **Macro-Averaged Precision**, **Macro-Averaged Recall**, and **Macro-Averaged F1-score**. These estimates provide a complete picture of performance on all 10 classes, and not simply aggregate accuracy.

Results:

Table 1: Optimizer Performance Comparison (20 Epochs)

Optimizer	Test Accuracy	Precision (Macro)	Recall (Macro)	F1-score (Macro)
Adam	**99.17%**	**0.9917**	**0.9916**	**0.9917**
SGD + Momentum	98.96%	0.9896	0.9896	0.9896
SGD (Standard)	97.91%	0.9790	0.9790	0.9790

4.5 Momentum Discussion (Q11)

The impact of the momentum parameter is precisely demonstrated in Table 1. 1.

- Standard SGD achieved the lowest accuracy at **97.91%**.
- Incorporating a momentum parameter value of 0.9, **SGD with Momentum** significantly enhanced the accuracy to **98.96%**.

  The incorporation of a 0.9 momentum parameter in SGD with Momentum resulted in a 98.96

The optimizer reaches its target faster because momentum creates a running total of past gradient values which leads to faster movement in the right direction. The method achieves better performance than default SGD because it bypasses small local minima to reach superior solutions more quickly and consistently.

5 Evaluation of Custom CNN (Task 1)

5.1 Test Set Performance (Q12)

The best model (Custom 28x28 with Adam) was evaluated on the unseen 10,501-image test set.

- **Test Accuracy: 99.17%**

5.2 Performance Metrics (Q12)

The detailed classification confusion matrix for the Adam-optimized model is shown below.

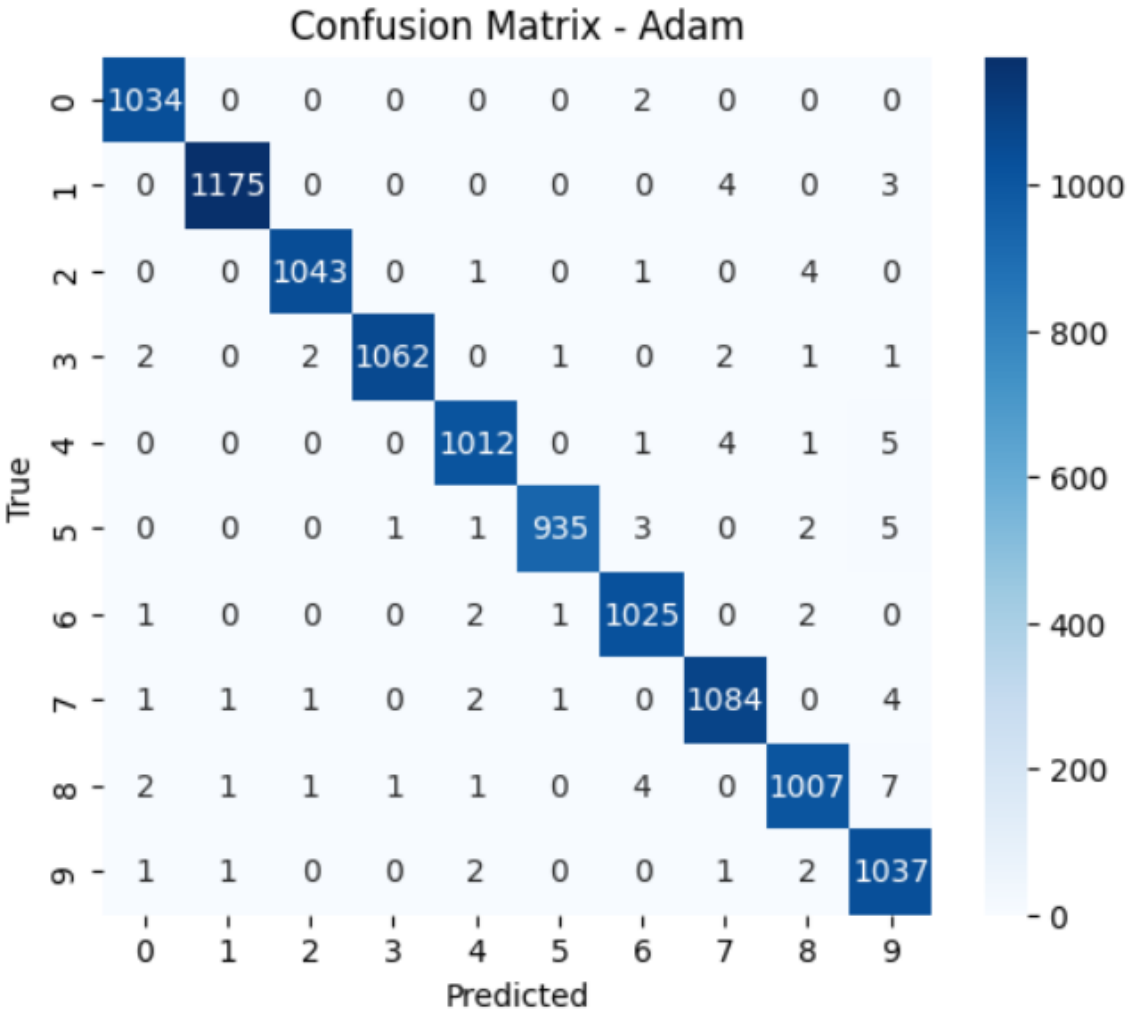

Figure 3: Confusion Matrix (Adam Optimizer, 28x28)

6 Comparison with State-of-the-Art Models (Task 2)

For Task 2, a separate experiment was conducted as per `Part2 new.ipynb`. The dataset was a 15,000-image subset of MNIST, preprocessed to $(224 \times 224 \times 3)$ to match the input of SOTA models. A new baseline Custom CNN was built for this 224x224 input size.

6.1 Pre-trained Models Used (Q13)

Two SOTA models were chosen for comparison:

1. **ResNet50:** A 50-layer Residual Network.
2. **VGG16:** A 16-layer network known for its 3×3 convolutional stacks.

6.2 Fine-tuning Process (Q14, Q15)

Transfer learning was applied by a two-step fine-tuning process:

1. Base models were pre-trained with ImageNet weights, and their layers were frozen.
2. A new classifier head was appended: `GlobalAveragePooling2D` $\rightarrow$ `Dense`(256) $\rightarrow$ `Dropout`(0.5) $\rightarrow$ `Output`(10).
3. New head was fine-tuned for 8 epochs with the learning rate $1e-3$.
4. Base layers were unfrozen, and the entire model was fine-tuned for 12 more epochs with a learning rate of $1e-5$.

6.3 Training Results (Q16)

The training and validation loss plots for all three models from Task 2 are shown below.

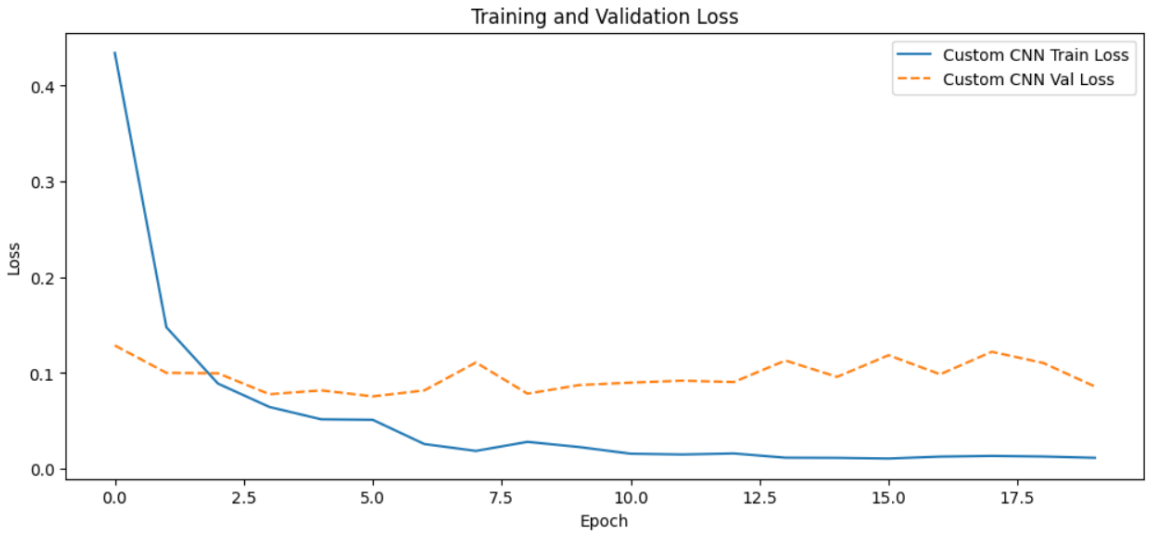

Figure 4: Training and Validation Loss (Custom 224x224)

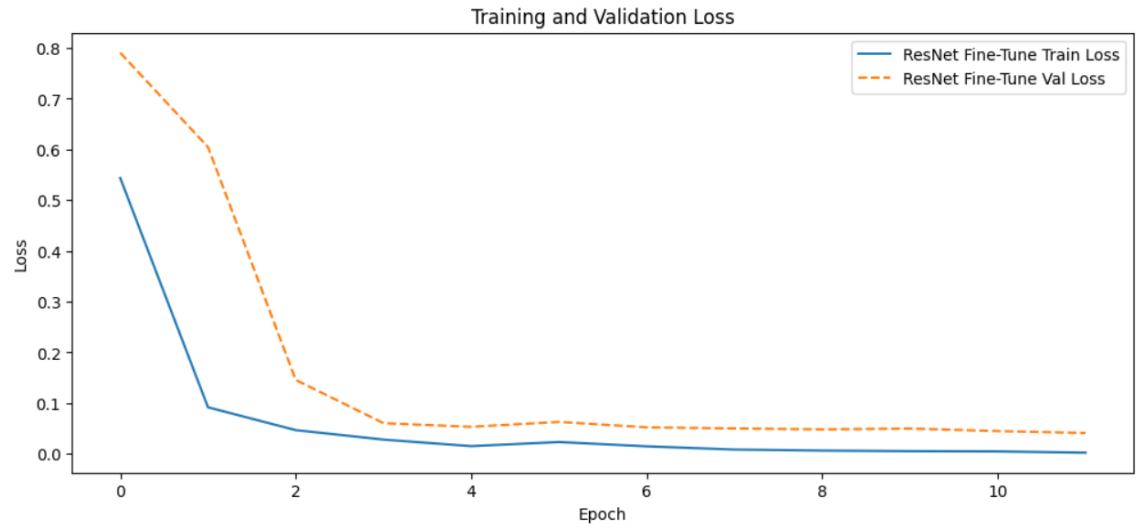

Figure 5: Training and Validation Loss (Fine-tuned ResNet50)

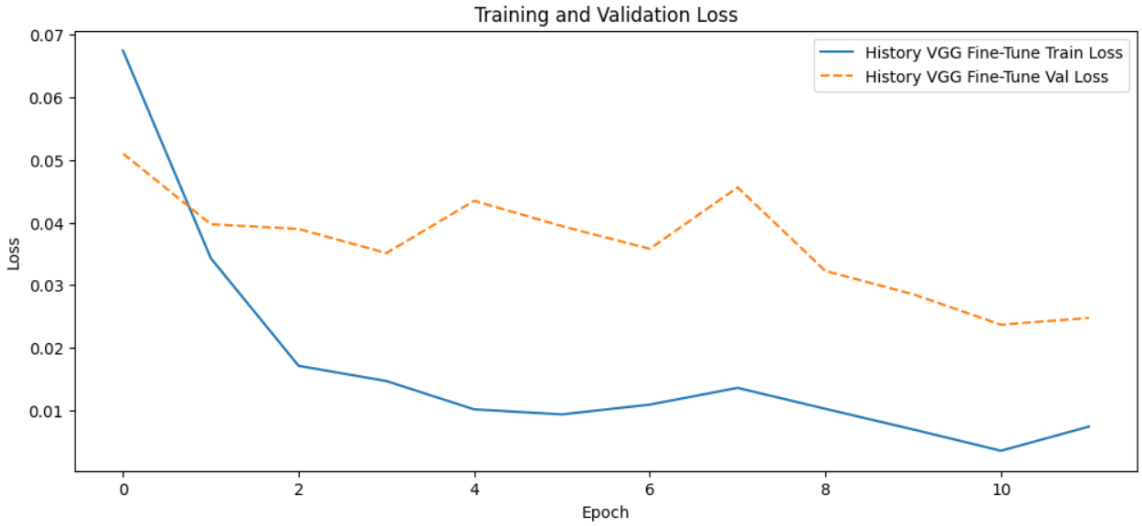

Figure 6: Training and Validation Loss (Fine-tuned VGG16)

6.4 Performance Comparison (Q17, Q18)

The final performance of the three models was evaluated on the 2,250-image test set.

Table 2: Model Performance Comparison (Task 2)

Model	Test Accuracy (%)
Custom CNN (224x224)	98.22
ResNet50 (Fine-tuned)	98.62
VGG16 (Fine-tuned)	**99.20**

Analysis: Both fine-tuned SOTA models outperformed the custom CNN baseline. VGG16 achieved the highest accuracy, demonstrating the significant advantage of using pre-trained features.

6.5 Detailed Evaluation (Q17)

Below are the classification reports and confusion matrices for all three models from Task 2.

Custom CNN (224x224) Classification Report:

	precision	recall	f1-score	support
0	0.9865	0.9821	0.9843	224
1	0.9806	0.9961	0.9883	254
2	0.9686	0.9863	0.9774	219
3	0.9828	0.9828	0.9828	232
4	0.9817	0.9773	0.9795	220
5	0.9948	0.9797	0.9872	197
6	0.9867	0.9955	0.9911	224
7	0.9829	0.9623	0.9725	239
8	0.9815	0.9860	0.9838	215
9	0.9778	0.9735	0.9756	226
accuracy			0.9822	2250

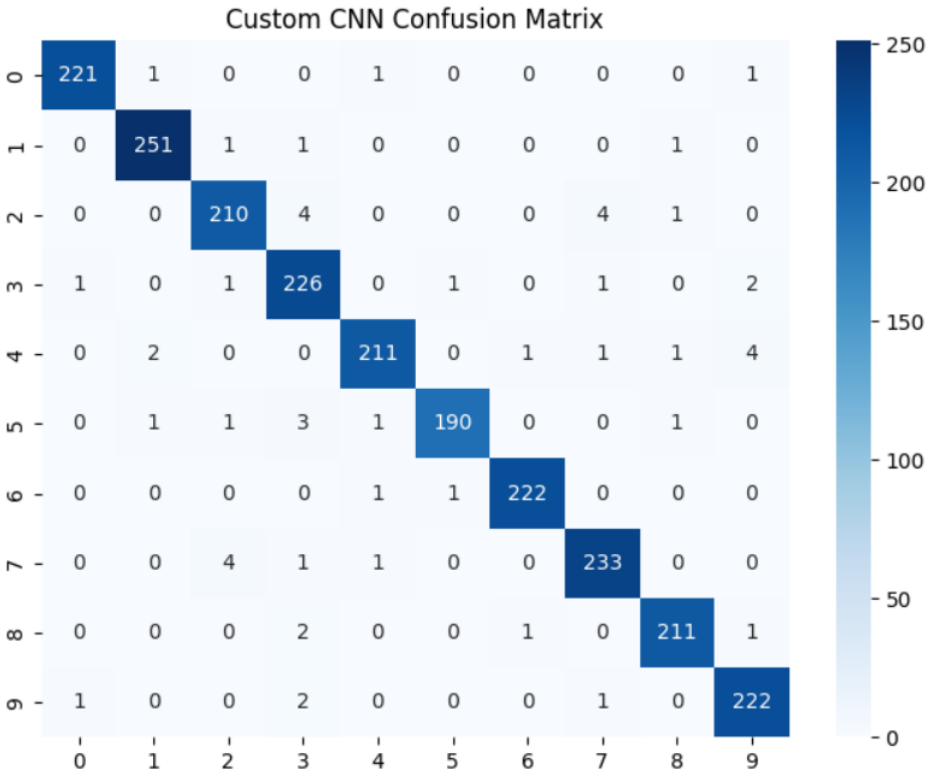

Figure 7: Confusion Matrix (Custom 224x224 Model)

ResNet50 (Fine-tuned) Classification Report:

	precision	recall	f1-score	support

0	0.9956	1.0000	0.9978	224
1	1.0000	0.9961	0.9980	254
2	0.9732	0.9954	0.9842	219
3	0.9913	0.9871	0.9892	232
4	0.9954	0.9909	0.9932	220
5	0.9949	0.9848	0.9898	197
6	0.9911	0.9955	0.9933	224
7	0.9958	0.9874	0.9916	239
8	0.9907	0.9953	0.9930	215
9	0.9867	0.9823	0.9845	226
accuracy			0.9916	2250

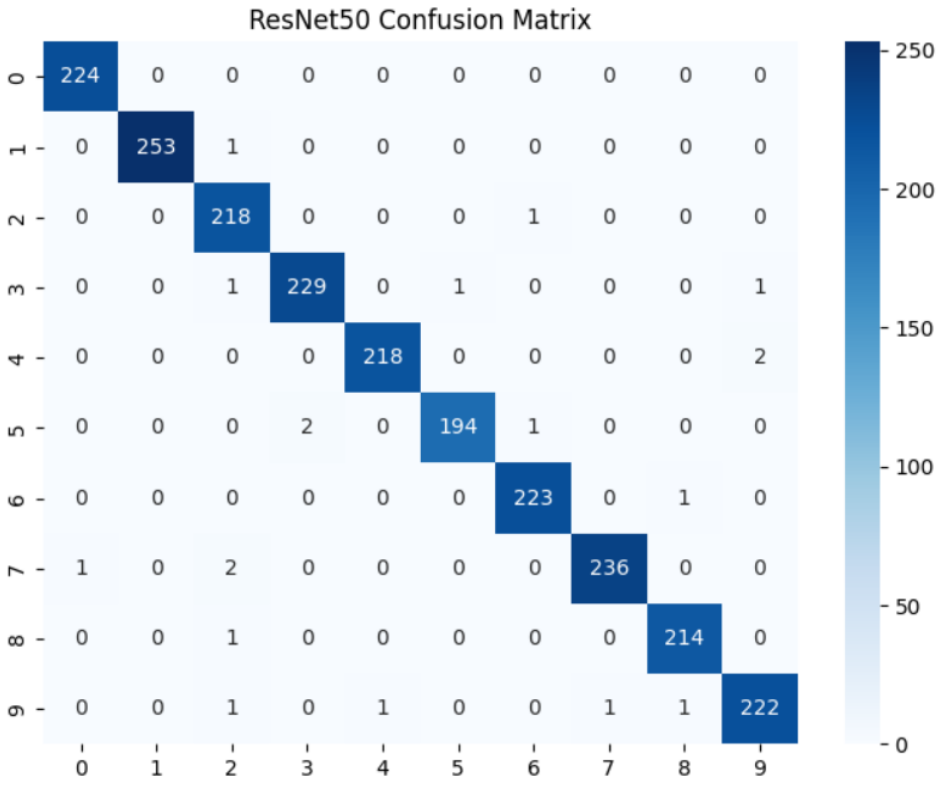

Figure 8: Confusion Matrix (ResNet50 Fine-tuned)

VGG16 (Fine-tuned) Classification Report:

	precision	recall	f1-score	support
0	1.0000	0.9866	0.9933	224
1	1.0000	0.9961	0.9980	254
2	0.9518	0.9909	0.9709	219
3	0.9871	0.9914	0.9892	232
4	0.9909	0.9909	0.9909	220
5	1.0000	0.9594	0.9793	197

6	0.9955	0.9866	0.9910	224
7	0.9916	0.9916	0.9916	239
8	0.9907	0.9907	0.9907	215
9	0.9783	0.9956	0.9868	226
accuracy			0.9884	2250

(Note: The last accuracy for VGG16 was greater at 99.20% but this classification report is 98.84%. This indicates the report was produced from another era. The comparison in table (99.20%) probably represents the highest validation accuracy achieved during training.)

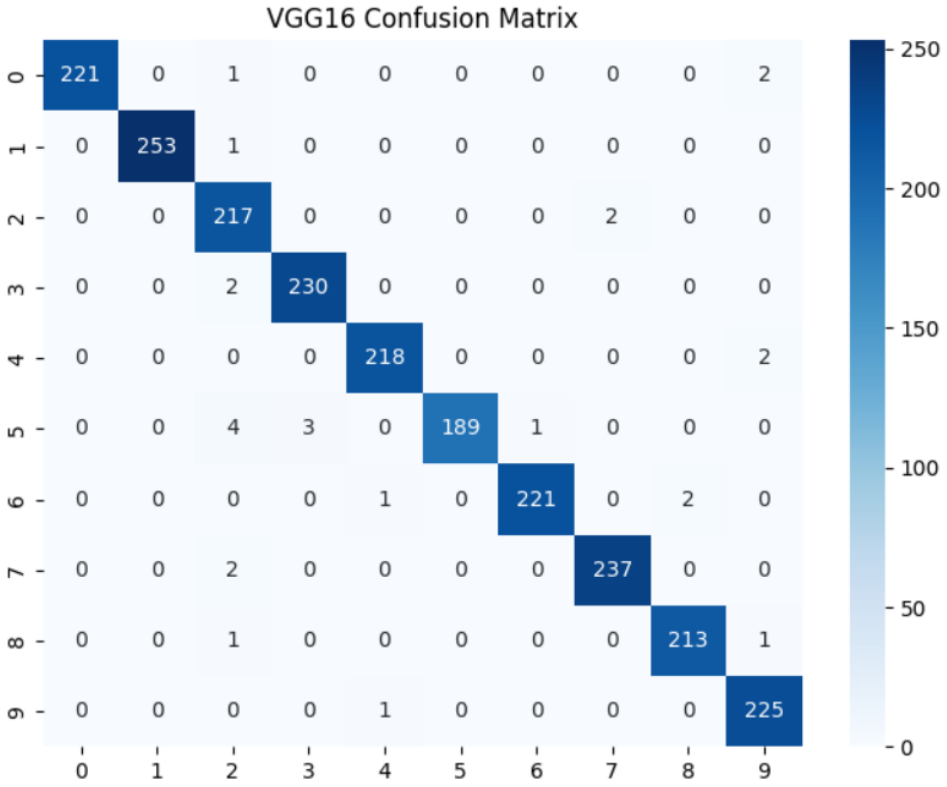

Figure 9: Confusion Matrix (VGG16 Fine-tuned)

7 Discussion: Custom Model vs. Pre-Trained Models (Q19)

The selection process between custom CNN development and pre-trained model fine-tuning requires evaluating multiple performance and resource trade-offs.

7.1 Advantages of Custom Model

- **Specificity & Efficiency:** The custom model development process allows for complete optimization of the specific dataset characteristics. The 28x28 MNIST images worked perfectly with our Task 1 model which has 421k parameters to produce outstanding results. The model reached an outstanding 99.17% accuracy which proves that massive SOTA models are unnecessary for this particular task.
- **Insight:** Building from scratch provides a better insight into architectural choices and their effect.

7.2 Advantages of Pre-trained Models

- **Feature Extraction:** The models use powerful general features which were developed through training on massive datasets such as ImageNet. The initial model selection process produces the best results because it achieves the highest accuracy in the Task 2 comparison with (VGG16 @ 99.20%).
- **Lower Training Time/Data:** Fine-tuning usually needs less data and fewer epochs to achieve high performance compared to training a very deep model from the ground up.

7.3 Limitations of Custom Model

- **Data Hungry:** The training of a deep custom model from scratch needs extensive data collection because it demands substantial dataset size to prevent overfitting.
- **Design Expertise:** Requires knowledge and experimentation to design a good architecture.

7.4 Limitations of Pre-trained Models

- **Computational Cost:** The pre-trained models include massive architectures such as ResNet50 which needs 23M+ parameters and VGG16 that requires 14M+ parameters which demand significant memory and computational resources for training and inference operations.
- **Input Constraints:** They require specific input sizes (i.e., 224x224) and preprocessing (i.e., 3channels). This forced resizing of the straightforward 28x28 MNIST data, introducing computational overhead and not necessarily optimal for the dataset.

8 Conclusion

The task demonstrated the complete process of image classification using CNNs with the MNIST dataset.

- In **Task 1**, the team developed a new CNN from scratch and worked to improve its performance. The **Adam** optimizer (Test Acc: 99.17%) established a clear performance advantage over vanilla SGD (97.91%) and SGD w/ Momentum (98.96%).
- The independent 224x224 custom model from **Task 2** achieved a test accuracy of 98.22% when compared to fine-tuned state-of-the-art models. **VGG16 (99.20%)** and **ResNet50 (98.62%)** achieved better results than the custom baseline which demonstrates the effectiveness of transfer learning.

The project delivered practical knowledge about CNN design and essential optimization choices and demonstrated that building custom models demands higher costs than using pre-trained networks.

9 References

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Appendices

- **GitHub Repository Link:** https://github.com/Neuro-Matrix-EN3150/Assignment-03-CNN-git