NEURAL SYSTEMS - COURSEWORK

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INTRODUCTION

- This project focuses on classifying clothing images from the Fashion MNIST dataset.
- Our main goal is to understand how different neural network architectures ANN and CNN perform on the same task.
- We also aim to see how improving these models can boost accuracy and reduce validation loss.
- By comparing both models, we can better understand the impact of architectural choices in deep learning.

PURPOSE OF THE PROJECT

- The purpose of this project is to improve both ANN and CNN models and observe how these improvements affect their performance.
  We build a baseline version of each model, then an improved version with architectural and training changes.
  The results are evaluated based on accuracy and validation loss.
  Overall, we want to demonstrate how proper tuning can increase generalization and model stability.

DATA PREPARATION & HANDLING

```
# Mount Google Drive
drive.mount('/content/drive')

# Dataset path
data_path = '/content/drive/MyDrive/Coursework-NS/fashion_mnist_cnn_ann_data.npz'

# Load data from the npz file
with np.load(data_path) as data:
    x_train_cnn = data['x_train_cnn']
    y_train = data['y_train']
    x_test_cnn = data['x_test_cnn']
    y_test = data['y_test']
    x_val_cnn = data['x_val_cnn']
    y_val = data['y_val']
    x_train_ann = data['x_train_ann']
    x_val_ann = data['x_val_ann']
    x_test_ann = data['x_test_ann']


# Normalize to [0,1] - This was already done when the .npz was created,
# but including it here as a safeguard and for clarity
x_train_cnn = x_train_cnn.astype('float32') / 255.0
x_val_cnn = x_val_cnn.astype('float32') / 255.0
x_test_cnn = x_test_cnn.astype('float32') / 255.0
x_train_ann = x_train_ann.astype('float32') / 255.0
x_val_ann = x_val_ann.astype('float32') / 255.0
x_test_ann = x_test_ann.astype('float32') / 255.0

print('Train shape (CNN):', x_train_cnn.shape)
print('Val shape (CNN):', x_val_cnn.shape)
print('Test shape (CNN):', x_test_cnn.shape)
print('Train shape (ANN flattened):', x_train_ann.shape)
print('Val shape (ANN flattened):', x_val_ann.shape)
print('Test shape (ANN flattened):', x_test_ann.shape)

# Class names for plotting
class_names = ['T-shirt/top','Trouser','Pullover','Dress','Coat','Sandal','Shirt','Sneaker',
```

- We used the Fashion MNIST dataset, which contains 70,000 grayscale images of clothing items in 10 categories.
  The data was split into training, validation, and test sets.
  Each image was normalized so that pixel values range from 0 to 1.
  We also applied data augmentation techniques such as random flipping, rotation, and zooming to make the model more robust.
  Finally, we visualized both the original and the augmented images to confirm that the transformations looked realistic.

BASELINE ANN MODEL

```python
def build_ann(input_shape=(28*28,), num_classes=10):
    model = models.Sequential([
        layers.Input(shape=input_shape),
        layers.Dense(512, activation='relu'),
        layers.Dropout(0.3),
        layers.Dense(256, activation='relu'),
        layers.Dropout(0.3),
        layers.Dense(128, activation='relu'),
        layers.Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model
```

- The baseline Artificial Neural Network consists of multiple fully connected dense layers with ReLU activation and a softmax output.
  It was trained using the Adam optimizer and categorical cross-entropy loss.
  Although the model learned quickly, it showed signs of overfitting during validation.
  The accuracy reached around 85–88%, which is good but not optimal for image classification.

IMPROVED ANN MODEL

```python
def build_ann_improved(input_shape=(28*28,), num_classes=10):
    model = models.Sequential([
        Input(shape=input_shape),
        layers.Dense(1024, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.4),
        layers.Dense(512, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.4),
        layers.Dense(256, activation='relu'),
        layers.Dense(num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=optimizers.Nadam(learning_rate=1e-3),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )
    return model
```

- To improve the ANN, we added dropout layers to reduce overfitting and batch normalization to stabilize learning.
  We also tuned the number of neurons in each layer to find a better balance between performance and complexity.
  These improvements helped the validation accuracy rise and made the loss curve smoother.
  The model became more generalizable and less sensitive to training noise.

BASELINE CNN MODEL

```python
def build_cnn(input_shape=(28,28,1), num_classes=10):
    model = models.Sequential([
        layers.Input(shape=input_shape),
        data_augmentation,  # Apply data augmentation after the input layer
        layers.Conv2D(32, (3,3), activation='relu', padding='same'),
        layers.MaxPooling2D((2,2)),
        layers.Conv2D(64, (3,3), activation='relu', padding='same'),
        layers.MaxPooling2D((2,2)),
        layers.Flatten(),
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.4),
        layers.Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model
```

- The baseline Convolutional Neural Network includes convolutional layers for feature extraction, pooling layers for downsampling, and dense layers for classification.
  This model performed better than the ANN from the start, because CNNs can detect spatial patterns such as edges and textures.
  The baseline CNN achieved around 90% accuracy but still had a visible validation gap, meaning some overfitting remained.

IMPROVED CNN MODEL

- We enhanced the CNN by adding more convolutional layers and batch normalization after each block.
  Dropout layers were included to further reduce overfitting.
  We also increased the number of filters to allow the model to learn more complex visual features.
  With these changes, the improved CNN achieved higher accuracy—around 92–94%—and significantly reduced validation loss.

```python
# Streamlined CNN model
def build_cnn_improved(input_shape=(28, 28, 1), num_classes=10):
    model = models.Sequential([
        layers.Input(shape=input_shape),
        aug,

        layers.Conv2D(32, (3, 3), padding='same', activation='relu'),
        layers.BatchNormalization(),
        layers.Conv2D(32, (3, 3), padding='same', activation='relu'),
        layers.MaxPooling2D((2, 2)),

        layers.Conv2D(64, (3, 3), padding='same', activation='relu'),
        layers.BatchNormalization(),
        layers.Conv2D(64, (3, 3), padding='same', activation='relu'),
        layers.MaxPooling2D((2, 2)),

        layers.Flatten(),
        layers.Dense(256, activation='relu'),
        layers.BatchNormalization(),
        layers.Dropout(0.5),
        layers.Dense(num_classes, activation='softmax')
    ])

    model.compile(
        optimizer=optimizers.Adam(learning_rate=1e-3),
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )
    return model
```

WHAT WE CHANGED AND WHY

- **Batch Normalization:** reduces internal covariate shift, helps stabilize and accelerate training.
- **Dropout:** regularization to reduce overfitting.
- **More filters / deeper CNN:** gives the model more capacity to learn complex patterns.
- **Data augmentation:** makes the model robust to transformations and reduces overfitting.
- **Optimizer & LR scheduling:** Nadam/Adam and ReduceLROnPlateau help find better minima and adapt learning.
- **EarlyStopping:** prevents overfitting by stopping training when validation stops improving.

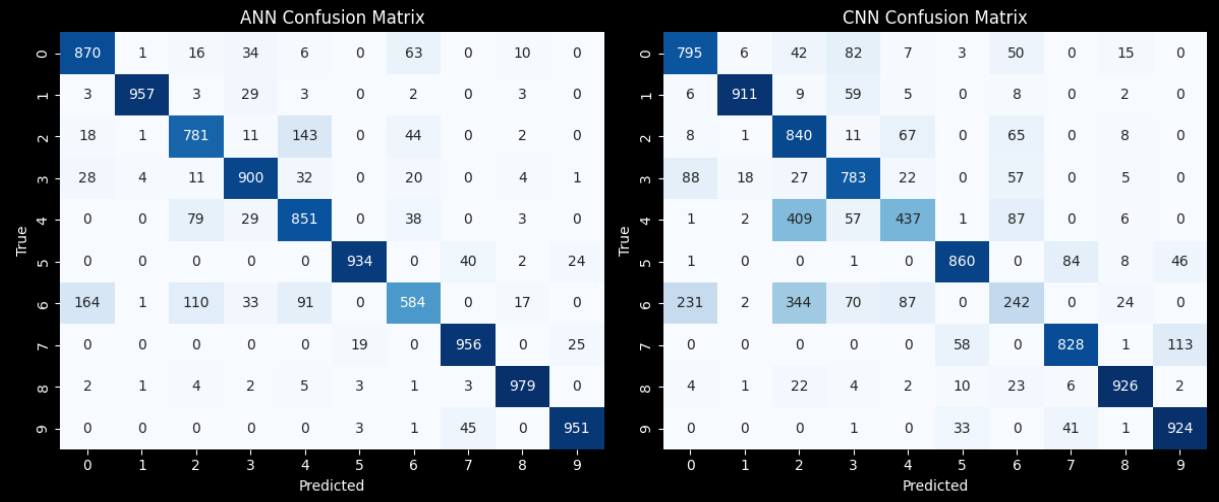
EVALUATION METRICS

Classification report – CNN:

	precision	recall	f1-score	support
T-shirt/top	0.70	0.80	0.75	1000
Trouser	0.97	0.91	0.94	1000
Pullover	0.50	0.84	0.62	1000
Dress	0.73	0.78	0.76	1000
Coat	0.70	0.44	0.54	1000
Sandal	0.89	0.86	0.88	1000
Shirt	0.45	0.24	0.32	1000
Sneaker	0.86	0.83	0.85	1000
Bag	0.93	0.93	0.93	1000
Ankle boot	0.85	0.92	0.89	1000
accuracy			0.75	10000
macro avg	0.76	0.75	0.75	10000
weighted avg	0.76	0.75	0.75	10000

Classification report – ANN:

	precision	recall	f1-score	support
T-shirt/top	0.80	0.87	0.83	1000
Trouser	0.99	0.96	0.97	1000
Pullover	0.78	0.78	0.78	1000
Dress	0.87	0.90	0.88	1000
Coat	0.75	0.85	0.80	1000
Sandal	0.97	0.93	0.95	1000
Shirt	0.78	0.58	0.67	1000
Sneaker	0.92	0.96	0.94	1000
Bag	0.96	0.98	0.97	1000
Ankle boot	0.95	0.95	0.95	1000
accuracy			0.88	10000
macro avg	0.88	0.88	0.87	10000
weighted avg	0.88	0.88	0.87	10000

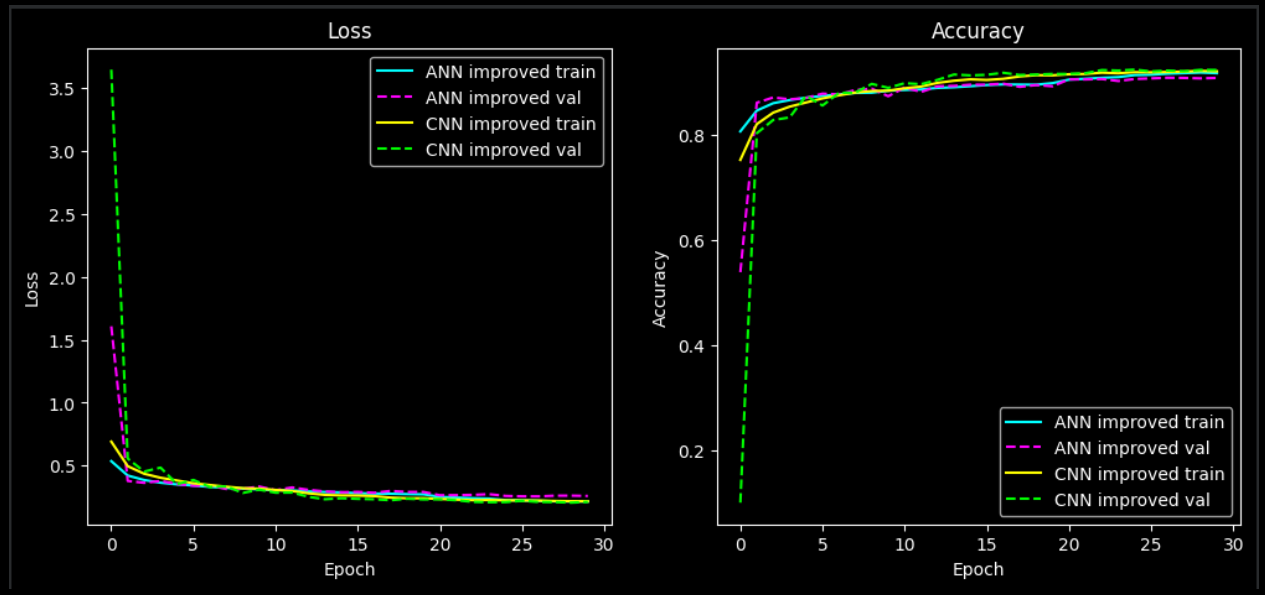


- We used several metrics to evaluate model performance.
  Accuracy measures how many predictions were correct.
  Loss shows how far the model's predictions are from the true labels.
  We also used a confusion matrix to visualize class-level accuracy and a classification report for precision, recall, and F1-score.
  These metrics helped us understand not only how accurate the models were, but also where they struggled.

RESULTS & GRAPH COMPARISON

Both models showed clear improvement after optimization.
Training and validation curves became more stable and consistent.
The improved CNN achieved the best results overall, with higher accuracy and lower validation loss than the ANN.
Graph comparisons show smoother convergence and reduced overfitting for both improved models.
This demonstrates that our architectural and training changes were effective.

	model	test_loss	test_acc	val_acc
0	ANN baseline	0.348721	0.8763	0.889500
1	CNN baseline	0.626060	0.7546	0.767833
2	ANN improved	0.301697	0.8958	0.907833
3	CNN improved	0.243799	0.9159	0.923000



DISCUSSION & INTERPRETATION

- From our results, CNNs clearly outperformed ANNs on image data because they can automatically capture spatial relationships.
  The improvements we made helped both models generalize better to unseen data.
  Batch normalization and dropout were the most effective modifications.
  Data augmentation also played an important role in stabilizing validation results and preventing overfitting.
  Overall, these experiments confirm that small structural changes can make a big difference.

OPTIMIZATION AND MODEL EVALUATION

- Throughout this project, we tested various optimization strategies, tuned hyperparameters, and compared multiple architectures to achieve the best possible accuracy.
  We experimented with different optimizers such as RMSprop and SGD, but Adam consistently produced the best results.
  After several improvements, both the ANN and CNN models reached strong performance levels. Further enhancements would likely require a more complex dataset or pretrained models beyond our current scope.
  In conclusion, careful tuning and regularization significantly improved model performance and generalization, making CNN the most effective model for this task.

CONCLUSION

- Throughout this project, we tested various optimization strategies, tuned hyperparameters, and compared multiple architectures to achieve the best possible accuracy.
  We experimented with different optimizers such as RMSprop and SGD, but Adam consistently produced the best results.
  After several improvements, both the ANN and CNN models reached strong performance levels. Further enhancements would likely require a more complex dataset or pretrained models beyond our current scope.
  In conclusion, careful tuning and regularization significantly improved model performance and generalization, making CNN the most effective model for this task.

Generating New Fashion MNIST Images with WGAN-GP

This code implements a **Wasserstein Generative Adversarial Network with Gradient Penalty (WGAN-GP)** to create new images that resemble the Fashion MNIST dataset.

Key Components:

•**Generator:** Takes random noise and transforms it into synthetic images using transposed convolutions.

•**Critic (Discriminator):** Evaluates the "realness" of images (both real and generated) and provides a score, not a probability.

- **Loss Functions:**
- **Critic Loss:** Encourages the critic to give higher scores to real images and lower scores to fake images.
- **Generator Loss:** Encourages the generator to produce images that receive higher scores from the critic.

•**Gradient Penalty:** A regularization technique applied to the critic to ensure stable training and prevent mode collapse.

•**Training Process:** The generator and critic are trained in an adversarial manner, with the critic typically trained more frequently than the generator in each step.

Outcome:

After training, the generator can produce novel images that capture the visual characteristics of the Fashion MNIST dataset.

THANK YOU FOR LISTENING!