كلية الحاسبات والذكاء الإصطناعي
Faculty of Computers & Artificial Intelligence

Face Classification using Deep Learning and Neural Networks

Project No. (1)

Dataset: Labelled Faces in the Wild (LFW)
Models Used: Resnet, Xception, Densenet.

Submitted by:

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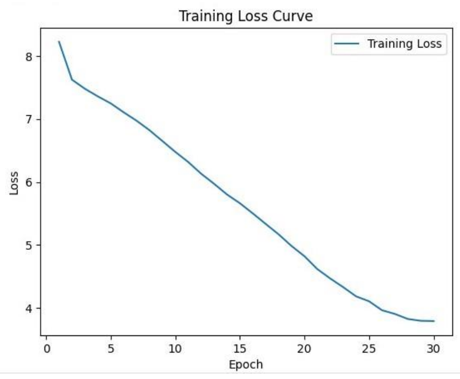
Introduction:

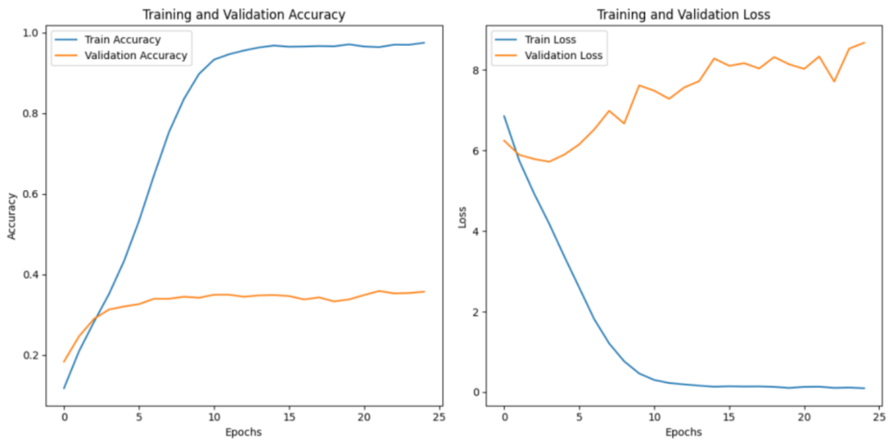
Our project aims to study a dataset of over 13,000 images of famous people (LFW) and learn and train on that data to be able to assign each image to the right person. We've used three different models to achieve this with minor differences in the results of each model. Here we compare each of the models' results using evaluation metrics and other visualized graphs.

Evaluation Metrics:

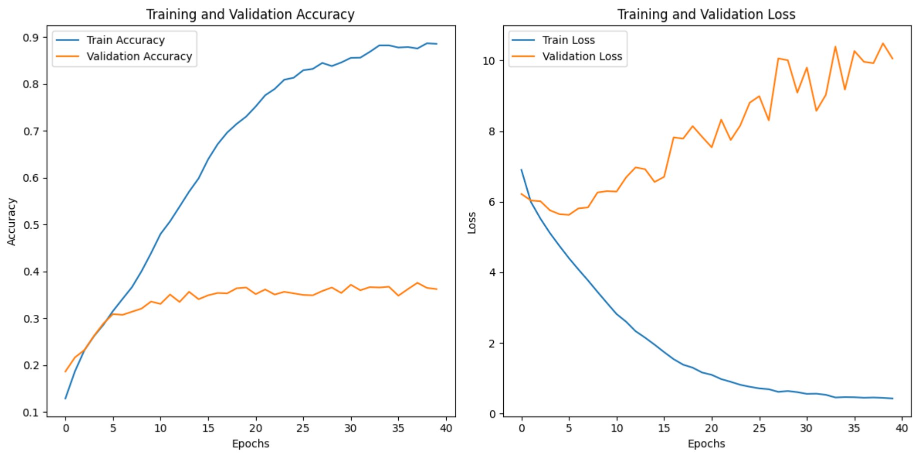
1. Resnet



2. Xception

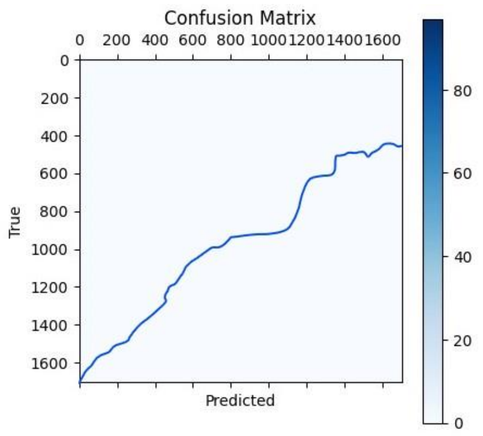


3. Densenet

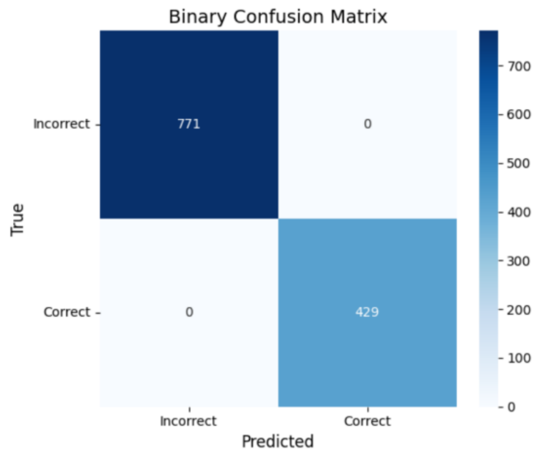


Confusion Matrix:

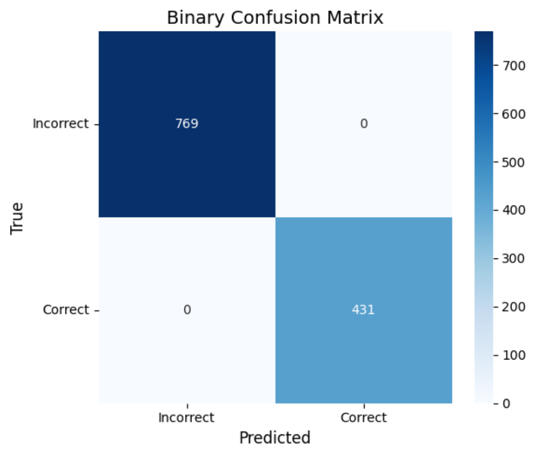
1. Resnet



2. Xception



3. Densenet

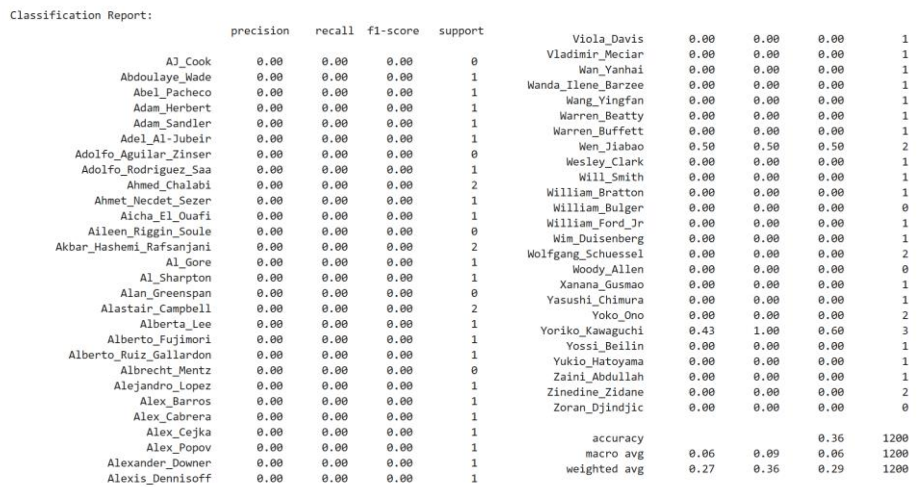


Classification Report:

1. Resnet

   Precision: 0.0381, Recall: 0.0756, F-Score: 0.0453

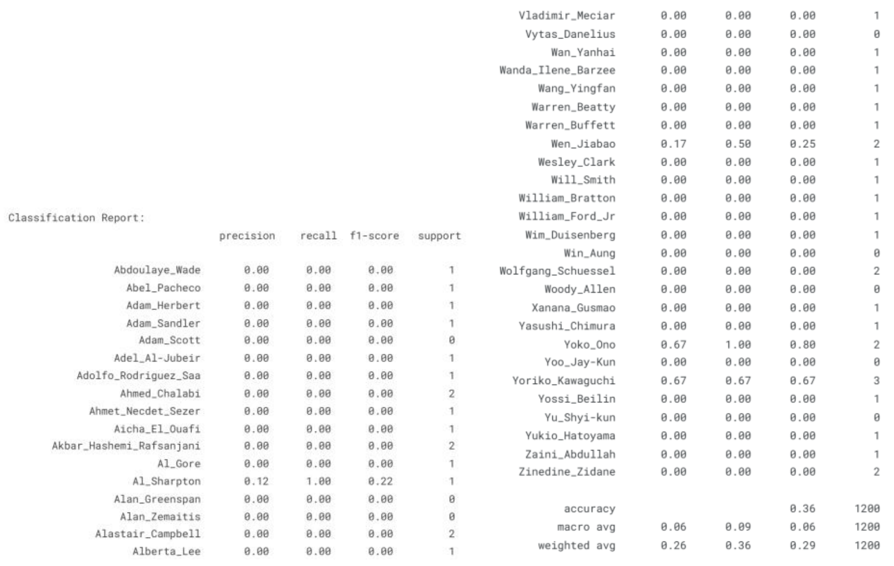
2. Xception



```
Classification Report:
                          precision    recall  f1-score   support

                  AJ_Cook       0.00      0.00      0.00         0
           Abdoulaye_Wade       0.00      0.00      0.00         1
             Abel_Pacheco       0.00      0.00      0.00         1
             Adam_Herbert       0.00      0.00      0.00         1
             Adam_Sandler       0.00      0.00      0.00         1
           Adel_Al-Jubeir       0.00      0.00      0.00         1
     Adolfo_Aguilar_Zinser       0.00      0.00      0.00         0
     Adolfo_Rodriguez_Saa       0.00      0.00      0.00         1
            Ahmed_Chalabi       0.00      0.00      0.00         2
       Ahmet_Necdet_Sezer       0.00      0.00      0.00         1
           Aicha_El_Ouafi       0.00      0.00      0.00         1
      Aileen_Riggin_Soule       0.00      0.00      0.00         0
  Akbar_Hashemi_Rafsanjani       0.00      0.00      0.00         2
                  Al_Gore       0.00      0.00      0.00         1
              Al_Sharpton       0.00      0.00      0.00         1
           Alan_Greenspan       0.00      0.00      0.00         0
        Alastair_Campbell       0.00      0.00      0.00         2
              Alberta_Lee       0.00      0.00      0.00         1
         Alberto_Fujimori       0.00      0.00      0.00         1
   Alberto_Ruiz_Gallardon       0.00      0.00      0.00         1
          Albrecht_Mentz       0.00      0.00      0.00         0
          Alejandro_Lopez       0.00      0.00      0.00         1
              Alex_Barros       0.00      0.00      0.00         1
             Alex_Cabrera       0.00      0.00      0.00         1
               Alex_Cejka       0.00      0.00      0.00         1
               Alex_Popov       0.00      0.00      0.00         1
         Alexander_Downer       0.00      0.00      0.00         1
        Alexis_Dennisoff       0.00      0.00      0.00         1
```

```
              Viola_Davis       0.00      0.00      0.00         1
         Vladimir_Meciar       0.00      0.00      0.00         1
               Wan_Yanhai       0.00      0.00      0.00         1
       Wanda_Ilene_Barzee       0.00      0.00      0.00         1
             Wang_Yingfan       0.00      0.00      0.00         1
           Warren_Beatty       0.00      0.00      0.00         1
          Warren_Buffett       0.00      0.00      0.00         1
               Wen_Jiabao       0.50      0.50      0.50         2
            Wesley_Clark       0.00      0.00      0.00         1
               Will_Smith       0.00      0.00      0.00         1
         William_Bratton       0.00      0.00      0.00         1
          William_Bulger       0.00      0.00      0.00         0
         William_Ford_Jr       0.00      0.00      0.00         1
          Wim_Duisenberg       0.00      0.00      0.00         1
       Wolfgang_Schuessel       0.00      0.00      0.00         2
              Woody_Allen       0.00      0.00      0.00         0
           Xanana_Gusmao       0.00      0.00      0.00         1
         Yasushi_Chimura       0.00      0.00      0.00         1
                 Yoko_Ono       0.00      0.00      0.00         2
         Yoriko_Kawaguchi       0.43      1.00      0.60         3
             Yossi_Beilin       0.00      0.00      0.00         1
          Yukio_Hatoyama       0.00      0.00      0.00         1
          Zaini_Abdullah       0.00      0.00      0.00         1
          Zinedine_Zidane       0.00      0.00      0.00         2
          Zoran_Djindjic       0.00      0.00      0.00         0

                 accuracy                           0.36      1200
                macro avg       0.06      0.09      0.06      1200
             weighted avg       0.27      0.36      0.29      1200
```

3. Densenet

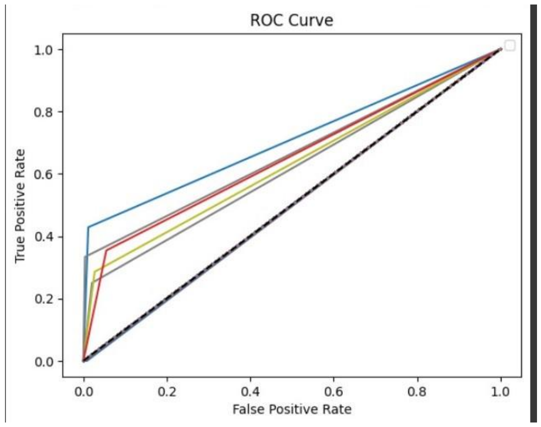


```
Classification Report:
                          precision    recall  f1-score   support

           Abdoulaye_Wade       0.00      0.00      0.00         1
             Abel_Pacheco       0.00      0.00      0.00         1
             Adam_Herbert       0.00      0.00      0.00         1
             Adam_Sandler       0.00      0.00      0.00         1
               Adam_Scott       0.00      0.00      0.00         0
           Adel_Al-Jubeir       0.00      0.00      0.00         1
     Adolfo_Rodriguez_Saa       0.00      0.00      0.00         1
            Ahmed_Chalabi       0.00      0.00      0.00         2
       Ahmet_Necdet_Sezer       0.00      0.00      0.00         1
           Aicha_El_Ouafi       0.00      0.00      0.00         1
  Akbar_Hashemi_Rafsanjani       0.00      0.00      0.00         2
                  Al_Gore       0.00      0.00      0.00         1
              Al_Sharpton       0.12      1.00      0.22         1
           Alan_Greenspan       0.00      0.00      0.00         0
            Alan_Zemaitis       0.00      0.00      0.00         0
        Alastair_Campbell       0.00      0.00      0.00         2
              Alberta_Lee       0.00      0.00      0.00         1
```

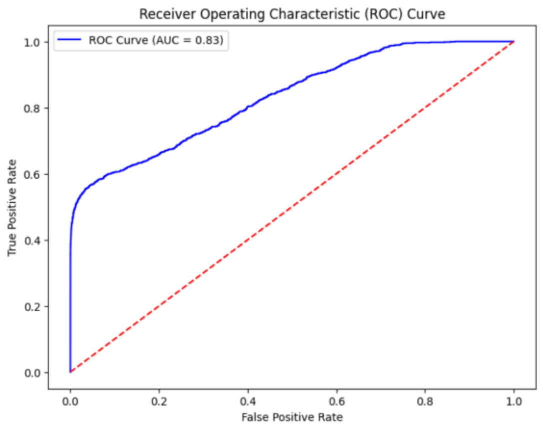
```
         Vladimir_Meciar       0.00      0.00      0.00         1
          Vytas_Danelius       0.00      0.00      0.00         0
               Wan_Yanhai       0.00      0.00      0.00         1
       Wanda_Ilene_Barzee       0.00      0.00      0.00         1
             Wang_Yingfan       0.00      0.00      0.00         1
           Warren_Beatty       0.00      0.00      0.00         1
          Warren_Buffett       0.00      0.00      0.00         1
               Wen_Jiabao       0.17      0.50      0.25         2
            Wesley_Clark       0.00      0.00      0.00         1
               Will_Smith       0.00      0.00      0.00         1
         William_Bratton       0.00      0.00      0.00         1
         William_Ford_Jr       0.00      0.00      0.00         1
          Wim_Duisenberg       0.00      0.00      0.00         1
                 Win_Aung       0.00      0.00      0.00         0
       Wolfgang_Schuessel       0.00      0.00      0.00         2
              Woody_Allen       0.00      0.00      0.00         0
           Xanana_Gusmao       0.00      0.00      0.00         1
         Yasushi_Chimura       0.00      0.00      0.00         1
                 Yoko_Ono       0.67      1.00      0.80         2
             Yoo_Jay-Kun       0.00      0.00      0.00         0
         Yoriko_Kawaguchi       0.67      0.67      0.67         3
             Yossi_Beilin       0.00      0.00      0.00         1
              Yu_Shyi-kun       0.00      0.00      0.00         0
          Yukio_Hatoyama       0.00      0.00      0.00         1
          Zaini_Abdullah       0.00      0.00      0.00         1
          Zinedine_Zidane       0.00      0.00      0.00         2

                 accuracy                           0.36      1200
                macro avg       0.06      0.09      0.06      1200
             weighted avg       0.26      0.36      0.29      1200
```

ROC/AUC Curve:

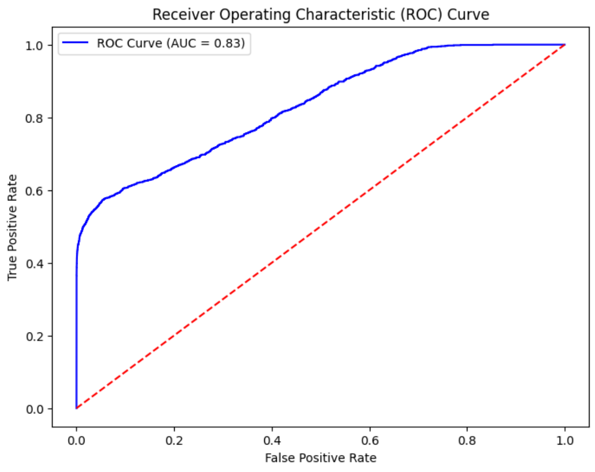
1. Resnet



2. Xception



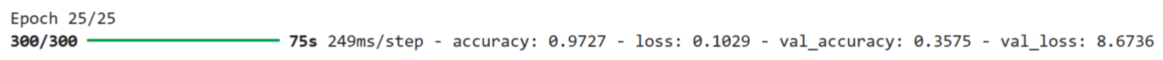
3. Densenet



Accuracy:

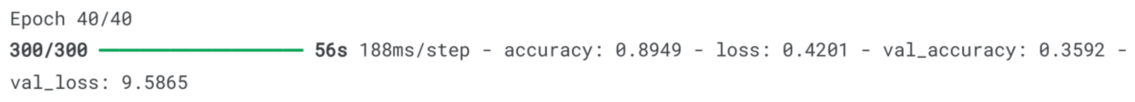
1. Resnet
   Accuracy on Test Data: 0.0756

2. Xception



```
Epoch 25/25
300/300 ━━━━━━━━━━━━━━━━━━━━ 75s 249ms/step - accuracy: 0.9727 - loss: 0.1029 - val_accuracy: 0.3575 - val_loss: 8.6736
```

3. Densenet



```
Epoch 40/40
300/300 ━━━━━━━━━━━━━━━━━━━━ 56s 188ms/step - accuracy: 0.8949 - loss: 0.4201 - val_accuracy: 0.3592 -
val_loss: 9.5865
```

1. ResNet (Residual Network)

Pros:

- **Deep Networks:** ResNet's residual connections make it possible to train very deep networks (up to hundreds of layers) without vanishing gradient issues.
- **Strong Feature Learning:** It excels at learning both low-level and high-level features, making it ideal for **image classification** and object detection.
- **Stable Training:** Skip connections ensure better gradient flow, making training stable for deep architectures.
- **Wide Adoption:** It is a widely used, well-tested architecture with pre-trained models readily available.

Cons:

- **Higher Computational Cost:** ResNet models, especially deeper ones (e.g., ResNet-101), require more computations and memory.
- **Parameter Redundancy:** ResNet does not reuse features as efficiently as DenseNet, leading to slightly larger models.

Advantages for Specific Tasks:

- **Large Datasets:** ResNet is advantageous when trained on large datasets (e.g., ImageNet) due to its depth and residual learning.
- **General-purpose Classification Tasks:** ResNet performs well on image classification, detection, and segmentation tasks where deeper features are beneficial.

2. Xception

Pros:

- **Efficient Convolutions:** Xception uses *depthwise separable convolutions* that reduce the number of parameters and computations compared to traditional convolutions.
- **Lightweight and Fast:** It achieves high performance while being computationally efficient, making it suitable for tasks requiring faster inference (e.g., mobile devices).
- **Comparable Accuracy:** Despite its lightweight design, Xception achieves performance comparable to ResNet on many image classification benchmarks.

Cons:

- **Not as Deep:** Xception is not as deep as ResNet (limited to ~50 layers), which can limit its ability to capture very complex features in large datasets.
- **Requires Tuning:** Fine-tuning Xception may require more careful adjustments due to its unique convolutional design.

Advantages for Specific Tasks:

- **Medium-Sized Datasets:** Xception is ideal for datasets where efficiency and speed matter, such as real-time applications.

- **Mobile/Edge Devices:** Its lightweight architecture makes it suitable for deployment in resource-constrained environments.

3. DenseNet

Pros:

- **Feature Reuse:** DenseNet's dense connectivity ensures that each layer reuses features from all previous layers, leading to better gradient flow and feature efficiency.
- **Parameter Efficiency:** DenseNet requires fewer parameters compared to ResNet while achieving similar or better accuracy.
- **Better Generalization:** Feature reuse reduces overfitting, making DenseNet better for small to medium-sized datasets.
- **Gradient Flow:** Dense connections help prevent vanishing gradient issues in deep networks.

Cons:

- **Computational Bottlenecks:** DenseNet can become computationally expensive for very large datasets because concatenating feature maps increases memory usage.
- **Training Speed:** DenseNet models are slower to train compared to ResNet and Xception due to the dense connections.

Advantages for Specific Tasks:

- **Small and Medium Datasets:** DenseNet performs exceptionally well on datasets with limited data, where feature reuse improves generalization.
- **Dense Prediction Tasks:** For tasks like segmentation or other spatial predictions, DenseNet's feature reuse enhances performance.

Comparison Table

Criteria	**ResNet**	**Xception**	**DenseNet**
Architecture Type	Residual Connections	Depthwise Separable Convolutions	Dense Connectivity
Parameter Efficiency	Medium	High (fewer parameters)	Very High
Computational Cost	High for deep versions	Lower than ResNet	Moderate to High (dense connections)
Training Speed	Faster than DenseNet	Fast and Efficient	Slower due to feature concatenation
Gradient Flow	Good due to skip connections	Standard	Excellent due to dense connections
Feature Reuse	Limited	Limited	High
Best For	Large-scale datasets, deep tasks	Medium datasets, real-time tasks	Small/medium datasets, generalization
Inference Efficiency	Moderate	Very High	Moderate

Choosing the Best Model

1. **ResNet** is suitable when:
   - You have **large-scale datasets** (like ImageNet).
   - You need deep models for tasks like **image classification** and **detection** where high-level features matter.
   - You have sufficient computational resources.

2. **Xception** is advantageous when:
    - You require a **lightweight and efficient model** for **real-time tasks** or mobile/edge devices.
    - You are working with medium-sized datasets where computational cost matters.
    - Deployment speed is a critical factor.
3. **DenseNet** is ideal when:
    - You have **small to medium datasets**, where feature reuse improves generalization.
    - You are solving tasks like **dense segmentation** where feature reuse is essential.
    - Memory efficiency in terms of parameters is a priority.

Xception would be the best choice due to its efficiency and performance. For larger datasets, ResNet would be preferred due to its ability to handle deeper networks. For smaller datasets, DenseNet would generalize better by reusing features effectively