Eyal Ben Barouch - 318651494 Alon Fridental - 209370774

# Deep Learning Assignment 2 Report

## Siamese Neural Networks for One-shot Image Recognition

### Introduction

In this project, we implemented a Siamese network architecture inspired by the paper *"Siamese Neural Networks for One-shot Image Recognition"* to solve the task of verifying whether two faces are identical or not. The network uses two identical branches to extract features from the image pairs, compares them using the L1 distance, and predicts if they match. Along the way, we learned a lot about designing deep learning architectures, trying out different configurations, and understanding how things like data augmentation, regularization, and hyperparameters affect the results. It was a hands-on experience that taught us a lot about what works and what doesn't when training a model like this.

### Data Analysis - LFW - a

**Train Dataset Statistics:**

Total Examples: 2200

Positive Pairs: 1100

Negative Pairs: 1100

**Test Dataset Statistics:**

Total Examples: 1000

Positive Pairs: 500

Negative Pairs: 500

Image size: (250, 250)

Image mode: Gray Sclae

## Data loading

- Mount your drive.

```
from google.colab import drive
drive.mount('/content/drive')
```

- Save the zip file in my drive inside the folder names "DeepLearning".

```
# Path to the zip file
zip_data_set = '/content/drive/MyDrive/DeepLearning/lfwa.zip'
```

- Unzip it and allocate the complete dataset, train and test in accordense
  - Create a folder "lfw2".
  - Create a sub-folder called 'lfw2' inside 'lfwa' and copy all images there.
  - Create sub folder "train" and "test" and allocate accordingly to the train and test given, for example : "/content/lfw2/test/AJ_Lamas/AJ_Lamas_0001.jpg ".

**Data Preprocessing**

To enhance the robustness of the model and ensure consistency in input size and format, the following preprocessing steps were applied to all images:

- Resizing: All images were resized to a uniform dimension of 250x250 pixels. (Same as input)
- Data Augmentation:
  - Random Horizontal Flip: To introduce variability and simulate real-world conditions, images were flipped horizontally with a random probability.
  - Random Rotation: Images were randomly rotated within a range of ±10 degrees to account for slight orientation differences in real-world images.
- Normalization:
  - Images were normalized to have a mean of 0.5 and a standard deviation of 0.5 for each channel to standardize pixel intensity values.

**Initialization:**

While the paper suggests initializing weights with a normal distribution (mean=0, std=0.01), we found better results using Kaiming He initialization for convolutional layers (optimized for ReLU activations), Xavier Glorot initialization for fully connected layers (balanced for symmetric activations like Sigmoid), and initializing batch normalization layers with weights of 1.0 and biases of 0.0. This approach improved convergence, stabilized training, and maintained gradient flow, leading to significantly better performance in our tests.

**<u>HyperParameters</u>**:

We Used GridSearch to evaluate different hyperparameters and these showed the best results:

- **Validation Split**: 20% of the training data was used for validation.
- **Batch Size**: 64
- **Learning Rate**: 0.01
- **Momentum**: 0.9 (used for the SGD optimizer to accelerate convergence and stabilize updates)
- **Weight Decay**: 0.001 (L2 regularization to prevent overfitting)
- **Max Epochs**: 50
- **Early Stopping Patience**: 20 (training stops if validation performance does not improve for 20 consecutive epochs)
- **Seed**: 42 (for reproducibility of results)

## Model Architecture:

We experimented with two different architectures:

1. **Architecture Based on the Paper:**
   - Input size: 250x250
   - Detailed layer configuration:

| Layer | Input Size | Filters | Kernel | Max Pooling | Activation |
|---|---|---|---|---|---|
| 1 | 1x250x250 | 64 | 10x10 | Yes,Stride - 2 | Relu |
| 2 | 64x48x48 | 128 | 7x7 | Yes,Stride - 2 | Relu |
| 3 | 128x21x21 | 128 | 4x4 | Yes,Stride - 2 | Relu |
| 4 | 128x9x9 | 256 | 7x7 | No | Relu |
| 5 | 256x6x6 - FC Layer to 4096 Dims | - | - | - | Sigmoid |

This network represents the branch that processes each image pair independently before the final layer, where the L2 distance between their feature embeddings is computed to classify whether the images depict the same person or not. Another Approach we tried was to decrease the final output size from 4096 to 1024 , This didn't lead to significantly better performance on the test set.

## 2. **Simplified Architecture:**

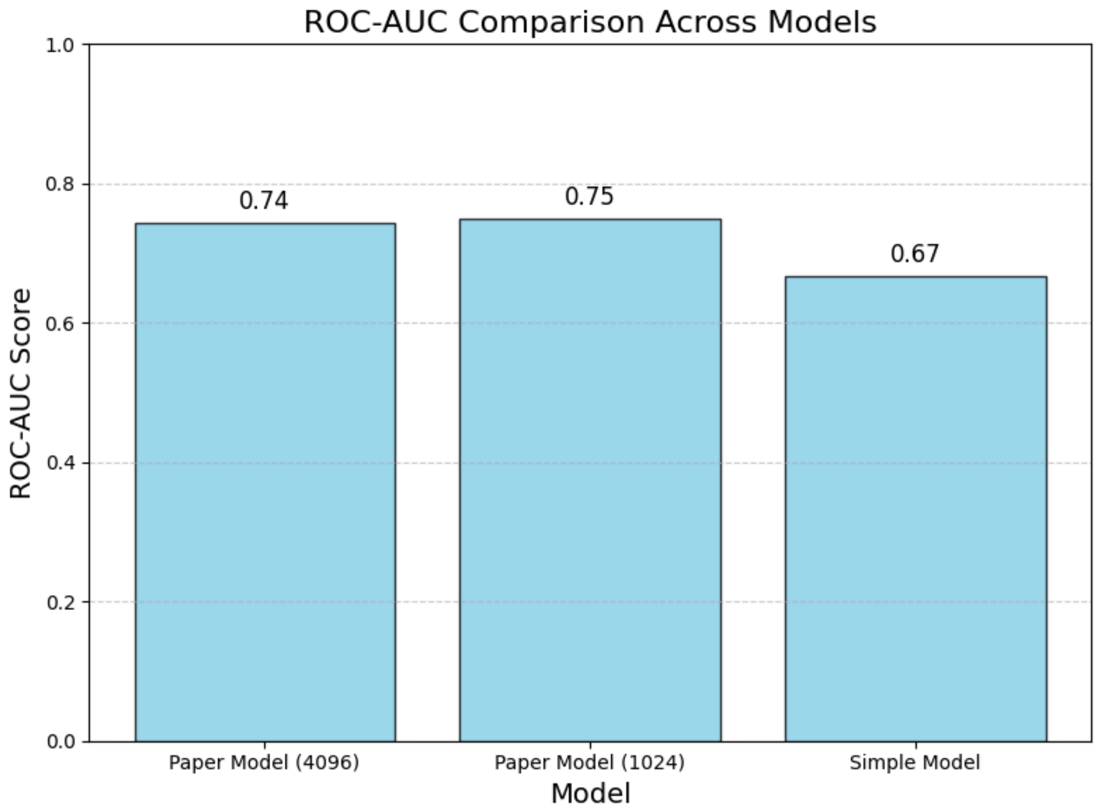
After training our paper-based network, we observed that it overfitted quickly, leading us to believe that the architecture was too complex for the task. To address this, we designed a simpler network to experiment and determine if a less complex model would perform better.

| **Layer** | **Input Size** | **Filters** | **Kernel** | **Max Pooling** | **Activation** |
|---|---|---|---|---|---|
| 1 | 1x250x250 | 32 | 5x5 | Yes,Stride - 2 | Relu |
| 2 | 32x62x62 | 64 | 3x3 | Yes,Stride - 2 | Relu |
| 3 | 64x15x15 | 128 | 3x3 | Yes,Stride - 2 | Relu |
| 4 | 128x4x4 FC Layer to 1024 Flattened | - | - | No | Relu |

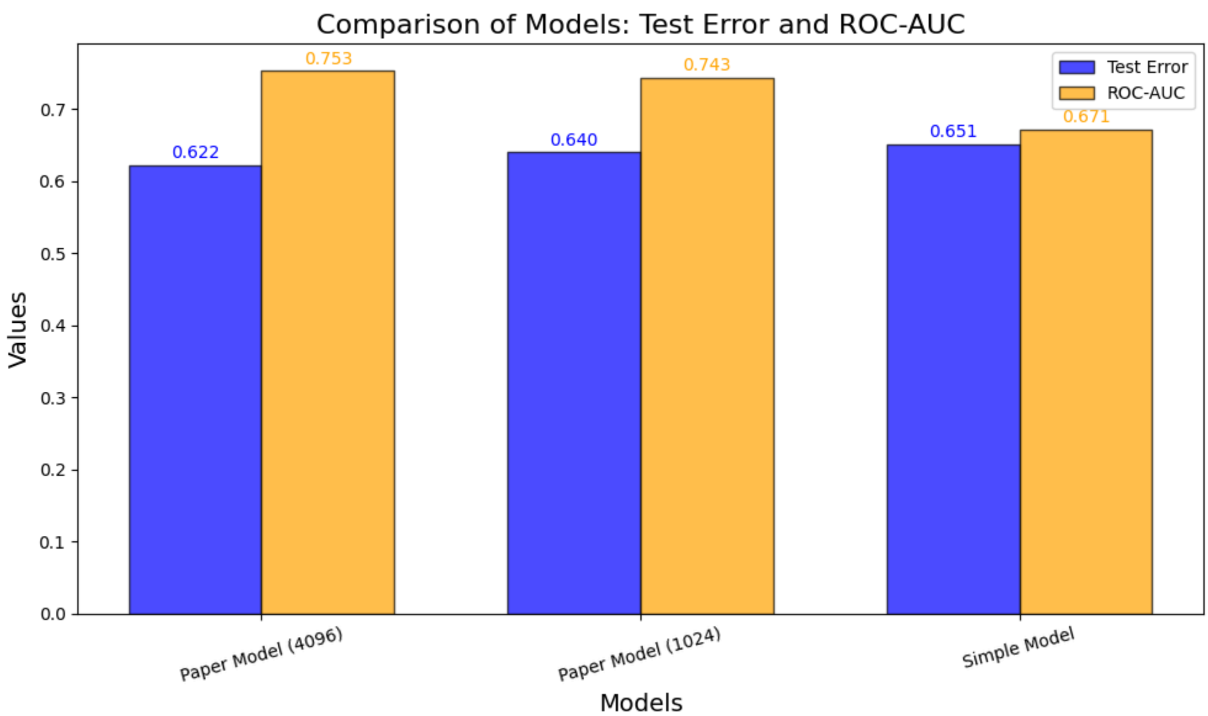
We designed the simplified architecture to address the overfitting observed in the paper-based network, which we believed was too complex for the dataset. By reducing the number of filters, using smaller kernels (5x5, 3x3), and lowering the fully connected layer size from 4096 to 1024, we significantly reduced the number of parameters. This simpler design focuses on extracting essential features while minimizing the risk of overfitting. Dropout (0.3) and batch normalization were added to further improve generalization, making the model more suitable for the limited dataset size.

## Experiments Comparison:

## Max Epochs - 15

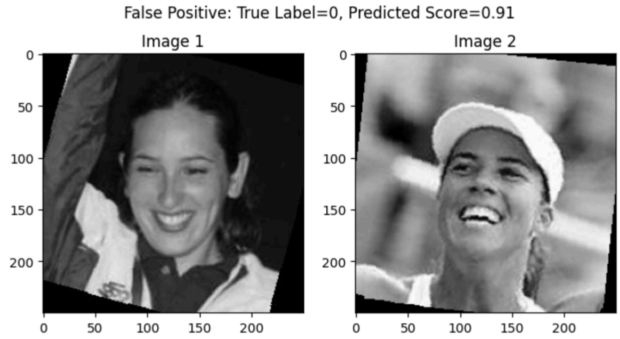


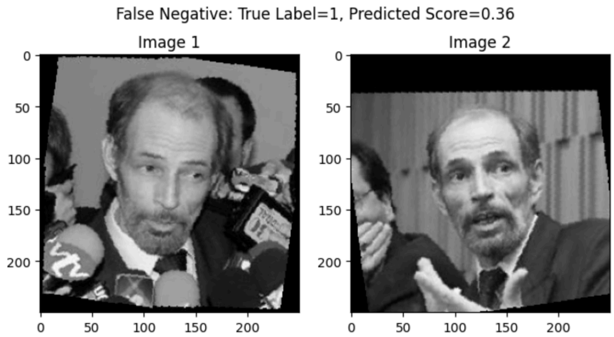

## Max Epochs - 50:



# Error Analysis

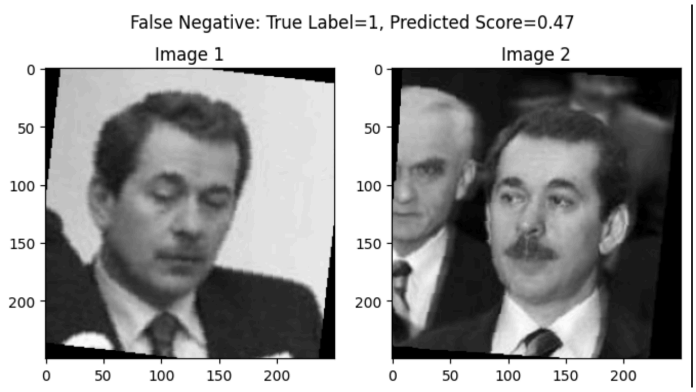
## Paper Model:

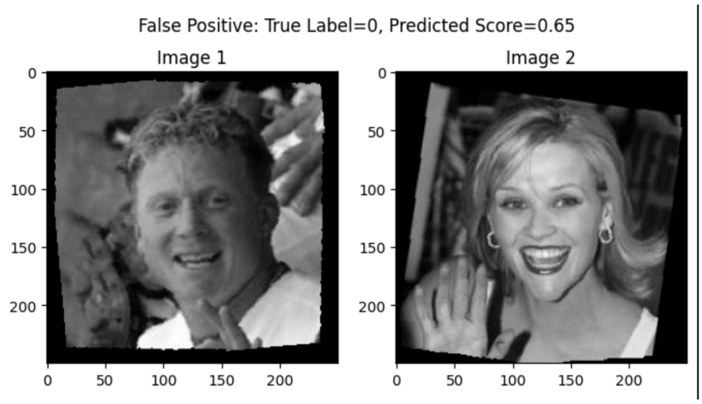



As we can see, the Paper model made some acceptable errors, such as misclassifications where even a human might struggle (e.g., a score of 0.91). It also faced challenges in recognizing similarities between images of the same person taken from different angles, which is a common limitation of convolutional neural networks (CNNs).

## **Simple Model:**




The simplified model, while reducing overfitting, made some more severe misclassifications, likely due to its inability to capture essential details in the images, as it lacked the complexity needed to identify subtle yet critical features.

## Conclusion

From our experiments, the Paper Model (4096) performed better overall in terms of ROC-AUC and test error, effectively capturing essential features in the data. However, it suffered from significant overfitting due to its complexity and large number of parameters. The Simplified Model was designed to reduce overfitting by lowering complexity, but, to our surprise, it also exhibited overfitting, likely due to insufficient capacity to .generalize across the dataset

Key lessons learned include the importance of balancing model complexity with the dataset size and exploring additional strategies to address overfitting, such as stronger regularization, further data augmentation, or modifying the training process. Future research should investigate intermediate architectures, pretrained models, or advanced techniques like attention mechanisms to improve performance and .generalization