In this project, I assessed the performance of two neural network types—Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN)—on the Labeled Faces in the Wild (LFW) dataset. The aim was to identify which model offers superior accuracy in face recognition.

Dataset:

I utilized the LFW dataset, particularly the deep-funneled version, which aligns and centers faces to boost face recognition algorithms' effectiveness. This dataset includes 13,233 images of 5,749 individuals, but I concentrated on those with at least 50 images for consistency. Labeled Faces in the Wild (LFW) is a database of face photographs designed for studying the problem of unconstrained face recognition. This database was created and maintained by researchers at the University of Massachusetts, Amherst (specific references are in Acknowledgments section). 13,233 images of 5,749 people were detected and centered by the Viola Jones face detector and collected from the web. 1,680 of the people pictured have two or more distinct photos in the dataset. The original database contains four different sets of LFW images and also three different types of "aligned" images. According to the researchers, deep-funneled images produced superior results for most face verification algorithms compared to the other image types. Hence, the dataset uploaded here is the deep-funneled version.

Models and Preprocessing:

Deep Neural Network (DNN):

Architecture: The DNN had several dense layers, with each successive layer having more neurons. ReLU activation functions were used to introduce non-linearity.

Preprocessing: I applied Min-Max scaling to normalize pixel values between 0 and 1, speeding up convergence during training.

Training: The model was trained using the Adam optimizer with a learning rate of 0.001. Performance was measured in terms of accuracy.

Convolutional Neural Network (CNN):

Architecture: The CNN included layers like Conv2D for feature extraction, MaxPooling2D for dimensionality reduction, and Dropout to prevent overfitting. Dense layers at the end performed classification.

Preprocessing: Similar to the DNN, Min-Max scaling was used, and data was reshaped to fit CNN's input requirements (height, width, channels).

Training: The CNN was trained using the Adam optimizer, with early stopping to avoid overfitting if the validation loss plateaued.

Key Techniques and Choices

Learning Rate Adjustment: Crucial for ensuring both models converge effectively.

Filter Size in CNN: Smaller filters captured finer details, essential for face recognition.

Early Stopping: Used for the CNN to save resources and prevent overfitting.

Results and Analysis

Performance: The CNN outperformed the DNN, achieving a test accuracy of 82.69% compared to the DNN's 56.59%. This underscores CNNs' effectiveness in image data handling, thanks to their ability to capture spatial hierarchies.

Analysis of Results: The CNN's architectural advantages for image processing, particularly convolutional layers, led to its superior performance.

Conclusion

This analysis underscores CNNs' strength in image-based recognition tasks compared to traditional DNNs. Model choice and parameter tuning significantly impact performance in complex image data tasks.