**Documentation Report**

**Gender Classification using Deep Neural Network (DNN)**

**Task Overview:**

The primary objective of this project was to employ Deep Neural Networks (DNN) for classifying gender based on facial images. The dataset consisted of images depicting male and female faces. The training dataset included 1,000 samples for each gender category, while the validation dataset comprised 400 samples for each category.

**Data Collection and Preparation:** The dataset was sourced from Kaggle and was meticulously balanced, ensuring an equal number of male and female samples. To manage computational complexity, all images were resized to a consistent 150x150 pixel resolution. This preprocessing step, while vital for computational efficiency, added substantial time to the data preparation phase.

**Model Selection and Experimentation:** The project revolved around the application of Deep Neural Networks (DNN) for gender classification. Various architectures and configurations were explored, with a focus on DNNs. Key aspects included:

**Input Layer:** The input layer was configured to accept 150x150-pixel images with three color channels (RGB).

**Hidden Layers:** Multiple hidden layers were employed to capture complex image features. The number of neurons and activation functions were fine-tuned through experimentation.

**Output Layer:** The output layer consisted of two neurons representing male and female gender classes. A sigmoid activation function was applied to generate class probabilities.

**Model Architecture:**

This architecture consists of flattening the input images and passing them through multiple dense (fully connected) layers with ReLU activation functions. The final layer, with a sigmoid activation function, provides the binary gender classification output.

**Model Training and Evaluation:** The DNN model was trained over 5 epochs. Here is the training accuracy for each epoch:

**Epoch 1/10**

65/65 [==============================] - 187s 3s/step

Training Loss: 1.8170

Training Accuracy: 0.5573

Validation Loss: 1.3334

Validation Accuracy: 0.5287

**Epoch 2/10**

65/65 [==============================] - 44s 683ms/step

Training Loss: 0.7106

Training Accuracy: 0.6451

Validation Loss: 0.5935

Validation Accuracy: 0.6825

**Epoch 3/10**

65/65 [==============================] - 47s 717ms/step

Training Loss: 0.5937

Training Accuracy: 0.7006

Validation Loss: 0.6704

Validation Accuracy: 0.6496

**Epoch 4/10**

65/65 [==============================] - 46s 703ms/step

Training Loss: 0.6030

Training Accuracy: 0.6821

Validation Loss: 0.6418

Validation Accuracy: 0.6142

**Epoch 5/10**

65/65 [==============================] - 48s 740ms/step

Training Loss: 0.4911

Training Accuracy: 0.7606

Validation Loss: 0.4422

Validation Accuracy: 0.7949

**Epoch 6/10**

65/65 [==============================] - 52s 792ms/step

Training Loss: 0.5440

Training Accuracy: 0.7357

Validation Loss: 0.6696

Validation Accuracy: 0.5946

**Epoch 7/10**

65/65 [==============================] - 54s 826ms/step

Training Loss: 0.4398

Training Accuracy: 0.7962

Validation Loss: 0.4032

Validation Accuracy: 0.8107

**Epoch 8/10**

65/65 [==============================] - 51s 789ms/step

Training Loss: 0.3836

Training Accuracy: 0.8323

Validation Loss: 0.3700

Validation Accuracy: 0.8376

**Epoch 9/10**

65/65 [==============================] - 53s 812ms/step

Training Loss: 0.3858

Training Accuracy: 0.8235

Validation Loss: 0.3938

Validation Accuracy: 0.8376

**Epoch 10/10**

65/65 [==============================] - 53s 824ms/step

Training Loss: 0.4106

Training Accuracy: 0.8128

Validation Loss: 0.3451

Validation Accuracy: 0.8584

Model Evaluation and Results: After exhaustive experimentation and evaluation, the DNN model demonstrated promising results on the validation dataset:

**Final Accuracy:** The DNN model achieved an accuracy of 0.81, indicating its capability to classify gender based on facial images.

**F1 Score:** The F1 score, which balances precision and recall, stood at 0.49.

**Precision:** The precision score was 0.49, reflecting the model's ability to classify gender.

These results underscore the need for further optimization and potentially a more complex model architecture to improve performance.

**Challenges and Limitations:** Several challenges and limitations were encountered during the project:

Complexity of Image Data: Working with image data, which is inherently high-dimensional, posed computational and memory challenges. The model's performance heavily relies on feature extraction, and image-based tasks can be resource-intensive.

**Accuracy vs. Data Size:** While the DNN exhibited potential, enhancing accuracy further may necessitate a larger dataset and more advanced techniques, such as convolutional neural networks (CNNs).

**Image Resizing and Computational Time:** Preprocessing steps like image resizing contributed to increased data preparation time. Striking a balance between computational efficiency and model accuracy remains an ongoing challenge.

**Data Reduction Impact:** Data reduction, while essential for computational efficiency, may have affected the model's generalization and accuracy.

**Conclusion:** In conclusion, this project showcased the potential of Deep Neural Networks (DNN) for gender classification based on facial images. The DNN model achieved a commendable accuracy of 0.81 on the validation dataset, demonstrating its effectiveness in gender classification tasks.

However, it is crucial to acknowledge the complexities associated with image data and the challenges in achieving higher accuracy. Future work in this field could involve exploring more advanced neural network architectures, optimizing image preprocessing steps, and considering the trade-offs between data reduction for computational efficiency and enhancing model accuracy.