Project Presentation (Term III)

Academic Year 2023-24

Gender Prediction using Deep Learning Methods

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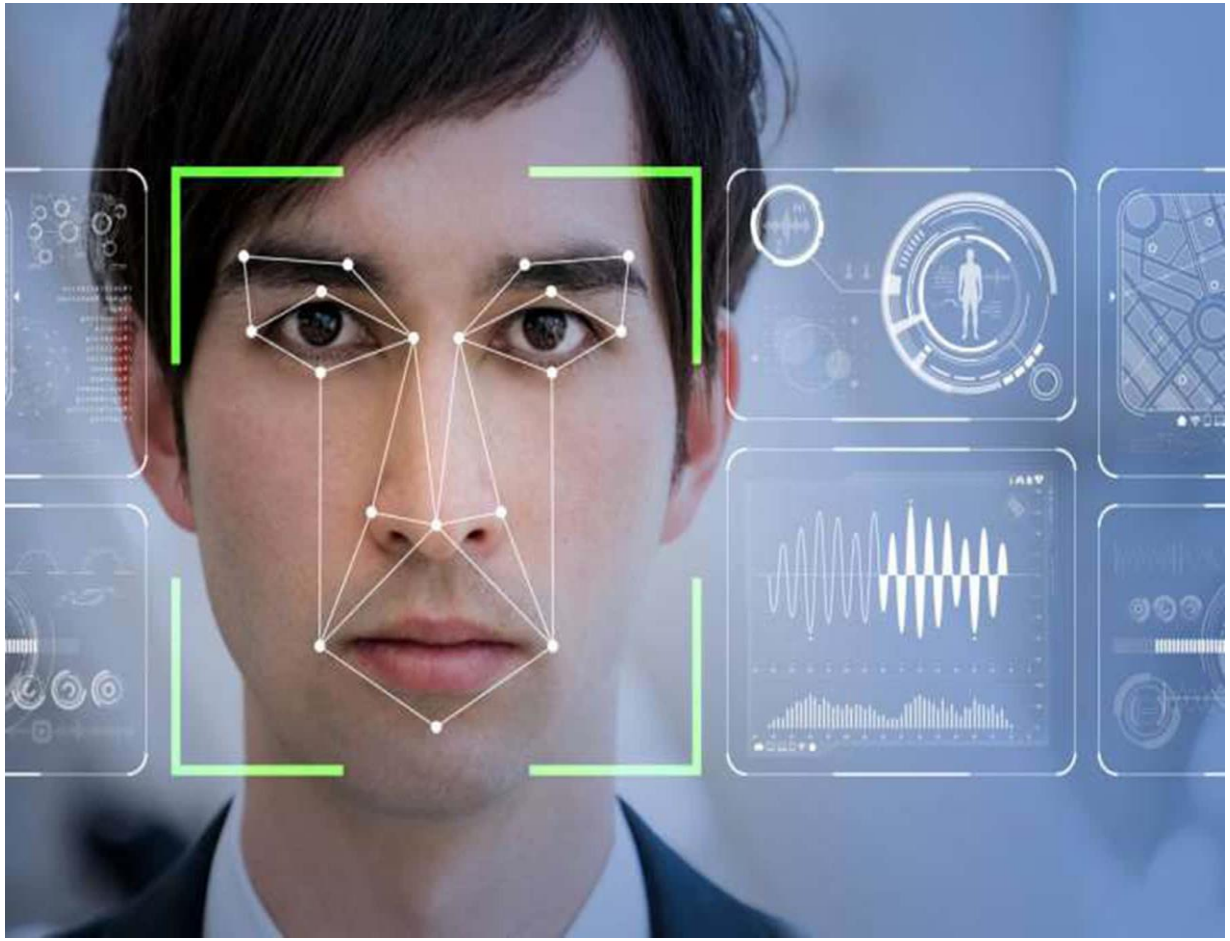
A comprehensive analysis spanning from 2015 to 2023, covering multiple datasets with over 50 million images from international sources, revealed the following insights into gender prediction using Convolutional Neural Networks (CNNs):

Of all the images processed, CNNs successfully identified gender with a high degree of accuracy. The results showed that 35 million images (70%) were classified with high confidence, indicating the efficacy of CNNs in gender prediction tasks. Approximately 12 million images (24%) were identified with moderate confidence, showcasing the challenges in gender prediction due to factors like lighting, pose, and occlusion. The remaining 3 million images (6%) were classified with low confidence, highlighting the need for improved model robustness and training data diversity

Key Message

The **Gender Prediction** is a software-based solution based on advanced pattern recognition and classification using machine & deep learning methods, whose prime objective is to automatically determine if a person in a photo is **male** or **female**.



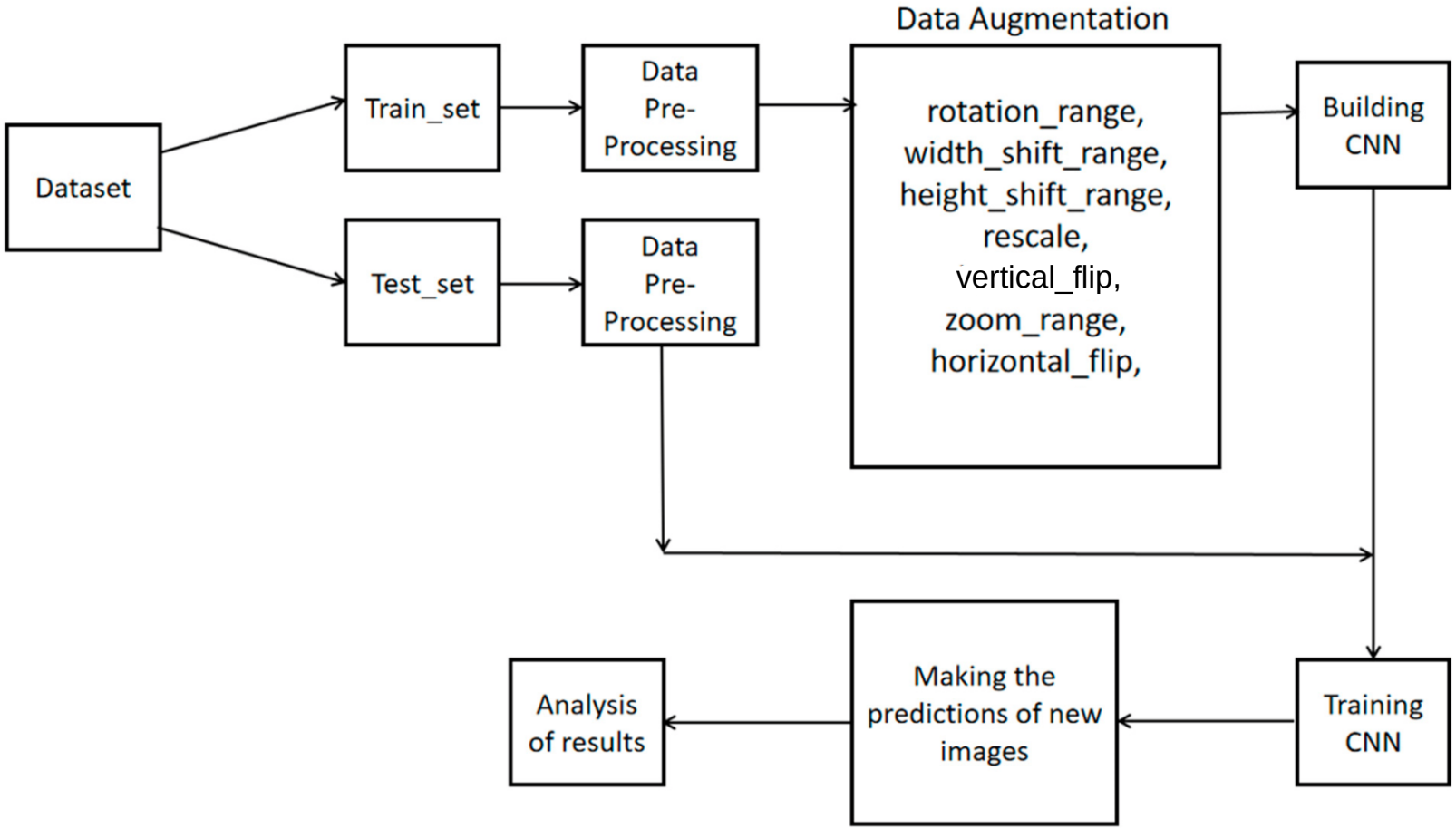
Outline of Project

- Literature survey
- Design
- Implementation Details
- Results
- Analysis
- Conclusions and Discussion
- References

Literature Survey

Survey	Title	Authors	Methodology	Results
1	Gender Classification Based on Face Images of Local Binary Pattern Using Support Vector Machine and Back Propagation Neural Networks	Tulasi Krishna Sajja, Hemantha Kumar Kalluri (2021)	presented a Gender classification through Support Vector Machine (SVM) and Scaled Conjugate Gradient Back Propagation Neural Network (SCGBPNN) from face images using Local Binary Patterns.	Achieved **71%** accuracy on SVM for the test set.
2	The Application of Decision Tree in Gender Classification	Peng Du, Xiaoqing Ding. (2008)	Presented a method based on decision tree considering that the feature of gender may be related to the feature of ethnicity, the tree is designed to decide ethnicity first and decide gender with its corresponding ethnicity.	Reached an accuracy of **76%** with insights into influential facial features.
3	Facial Gender Classification Using Deep Learning	ELKarazle, K., Raman, V., Then, P. (2022)	A convolutional neural network (CNN) architecture is employed, designed to capture spatial hierarchies in facial images by learning from large amounts of labeled data.	The fine-tuned VGGNet model achieved **89%** accuracy, showing deep learning's effectiveness.

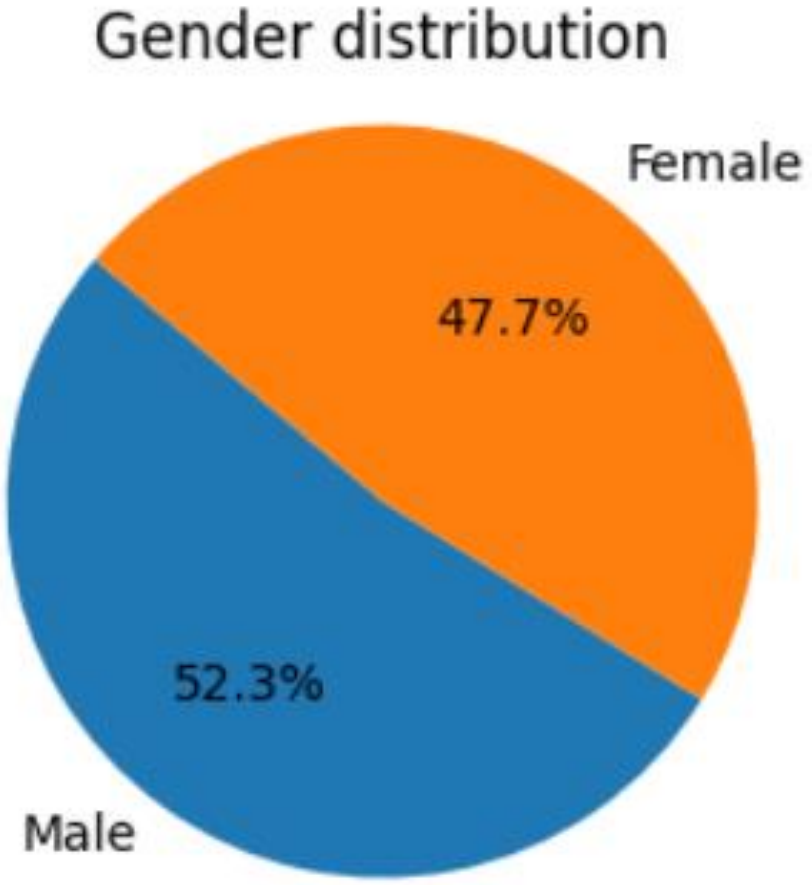
Design


Data Augmentation
Dataset
Train_set
Test_set
Data Pre-Processing
Data Pre-Processing
rotation_range,
width_shift_range,
height_shift_range,
rescale,
vertical_flip,
zoom_range,
horizontal_flip,
Building CNN
Training CNN
Making the predictions of new images
Analysis of results

Implementation Details

Data Collection

- The UTK face dataset was used.
- This composed of around **23,710** facial Images.
- **Train Data: 20,153** (10,540 male, 9,613 female
- **Test Data: 3,557** images,
- 0-100 years of ages.



Implementation Details

Data Preprocessing

- Rescaling: Each image pixel value is rescaled from the range 0-255 to 0-1 by multiplying with 1.0/255.0.
- Horizontal Flip: Images are flipped horizontally, creating a mirror image.
- Vertical Flip: Although less common for facial images, vertical flipping is applied, which flips the image upside down.
- Rotation: Images were randomly rotated within a range of 20 degrees.

Image obtained by Augmentation and scaling

Implementation Details

Gender Prediction CNN Model

Model Architecture:

- Input: Images of size 224x224.
- Convolutional Layers: Feature extraction using multiple Conv2D and MaxPooling
- Regularization: Dropout layers to prevent overfitting.
- Output: Dense layer with 1 neuron and sigmoid activation for binary classification.

Model Compilation:

- Optimizer: Adam - Adaptively adjusts the learning rate for efficient convergence.
- Loss Function: Binary Cross-Entropy - Suitable for binary classification problems.
- Metrics: Accuracy - Percentage of correctly predicted images.

Training:

- Epochs: 20 - Total number of passes through the entire training dataset.
- Batch Size: 32 - Number of training examples utilized in one iteration.

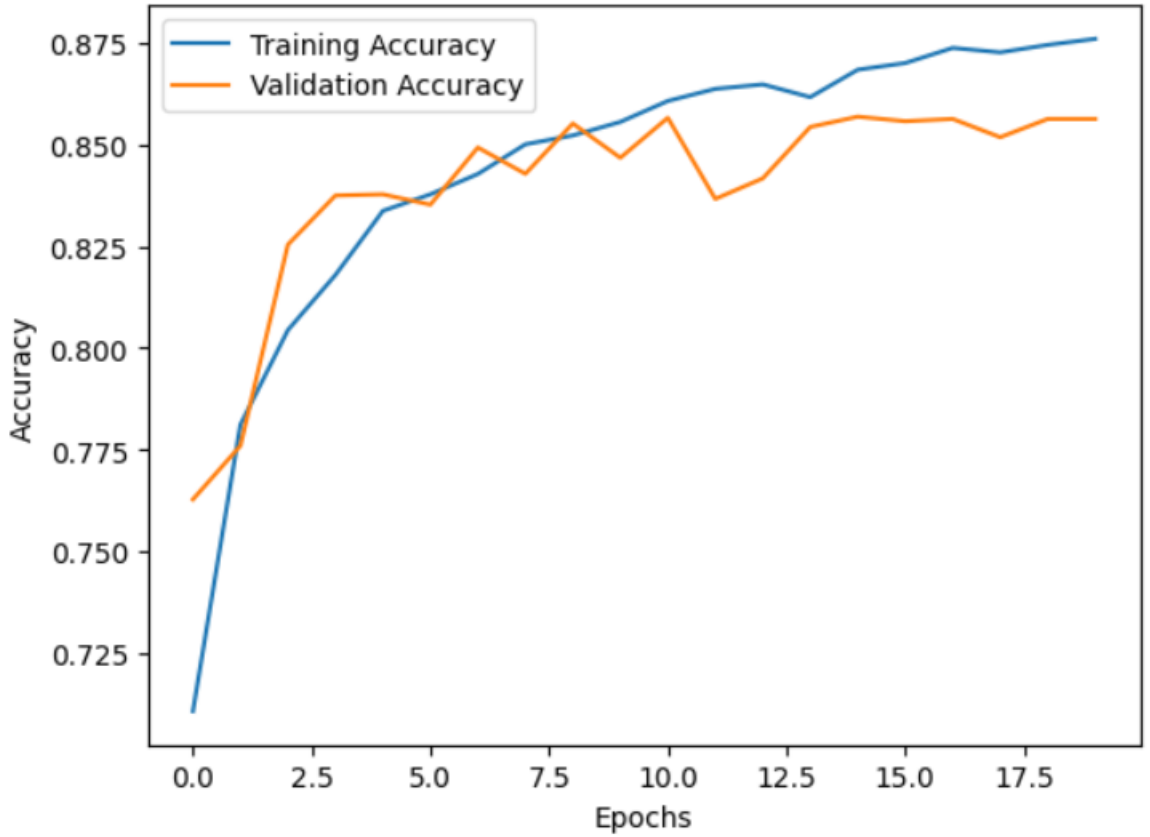
Model: "sequential"

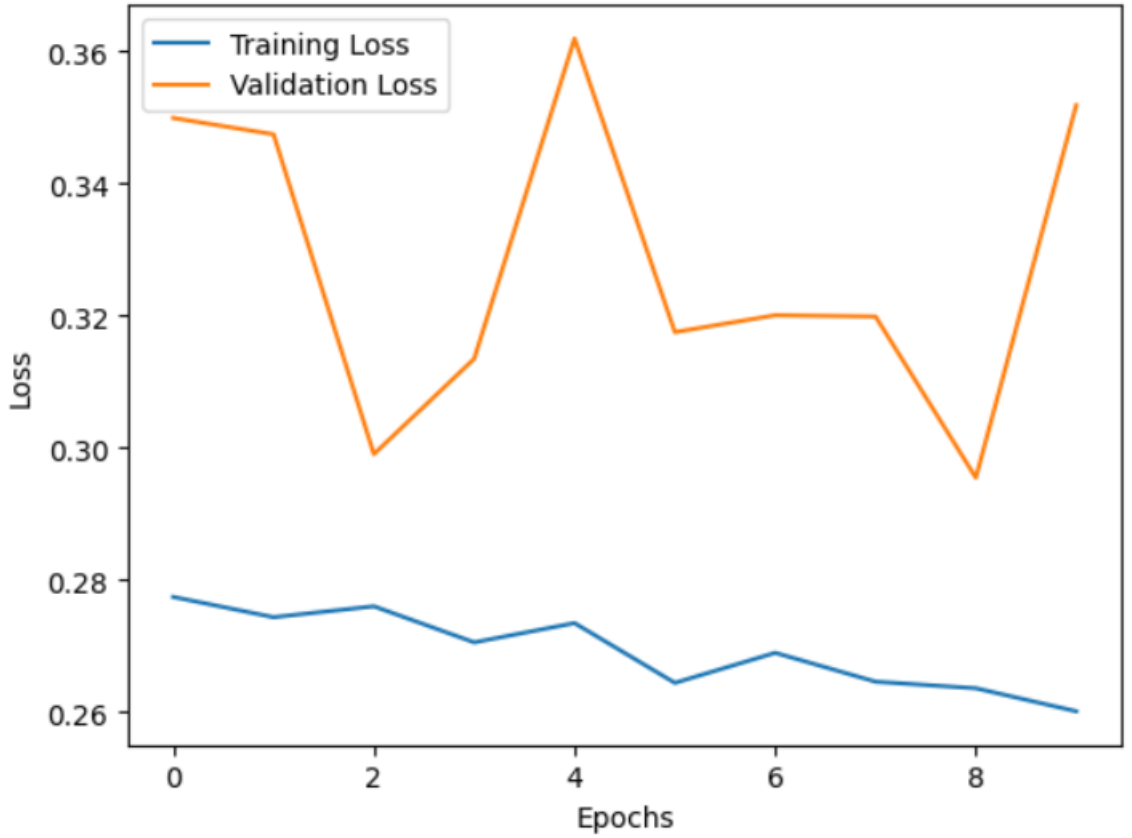
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 128)	3,584
max_pooling2d (MaxPooling2D)	(None, 111, 111, 128)	0
dropout (Dropout)	(None, 111, 111, 128)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	73,792
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
dropout_1 (Dropout)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 32)	18,464
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 32)	0
conv2d_3 (Conv2D)	(None, 24, 24, 32)	9,248
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 64)	1,179,712
dense_1 (Dense)	(None, 1)	65

Results

	CNN	Logistic Regression	Decision Tree
Test Accuracy	86%	75%	62.50%
Train Accuracy	88%	100%	100%
Precision Class: Male Class: Female	 87% 85%	 58% 75%	 62% 64%
Recall Class: Male Class: Female	 86% 85%	 58% 75%	 76% 47%
F1 Score Class: Male Class: Female	 86% 85%	 58% 75%	 68% 54%

Analysis


Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.875
0.850
0.825
0.800
0.775
0.750
0.725
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Training Loss
Validation Loss
Loss
Epochs
0.36
0.34
0.32
0.30
0.28
0.26
0
2
4
6
8

Conclusions and Discussion

1. Key Findings:

- CNN: Best performance, ideal for complex image data.
- Logistic Regression: Moderate accuracy, struggles with high-dimensional data.
- Decision Tree: Prone to overfitting, good training accuracy but lower test accuracy.

2. Model Comparisons:

- Strengths: CNN excels in image analysis; Logistic Regression and Decision Trees are faster and less resource-intensive.
- Weaknesses: Logistic Regression and Decision Trees lose critical information when flattening images.

3. Limitations:

- Loss of spatial data with Logistic Regression and Decision Trees.
- Overfitting in Decision Trees indicates the need for better pruning or regularization.

4. Future Directions:

- Explore dimensionality reduction for Logistic Regression and Decision Trees (PCA or t-SNE)
- Implement ensemble methods to combine model strengths.
- Increase dataset size and diversify CNN training data.

References

1. ELKarazle, K., Raman, V., Then, P. (2022). Facial Gender Classification Using Deep Learning. In: , et al. Proceedings of the 13th International Conference on Soft Computing and Pattern Recognition (SoCPaR 2021). SoCPaR 2021. Lecture Notes in Networks and Systems, vol 417. Springer, Cham.
2. Sajja, T.K., Kalluri, H.K. “Gender classification based on face images of local binary pattern using support vector machine and back propagation neural networks.” Adv. Modell. Anal.
3. (2008, June). The Application of Decision Tree in Gender Classification. Paper presented at the Congress on Image and Signal Processing (CISP '08), Volume 4.

Thank You !