EAI 6020: AI System Technologies

Week 6:
FACE AGING USING Cycle-GAN
(Cycle-Generative adversarial networks)

Submitted To:
Prof. Siddharth Rout, Faculty Lecturer

Submitted By:
Abhilash Dikshit
Murtaza Vora
Gunjan Paladiya

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Northeastern University, Vancouver, BC,Canada
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I. Abstract:

The study explores the potential of using CycleGAN for age progression, a technique that aesthetically renders facial images to simulate the effect of aging. Different datasets and components of datasets were examined, and various techniques like hyperparameter tuning, fine-tuning, and transfer learning were employed to expedite the training process. The performance of the models was evaluated both quantitatively and qualitatively.

II. Introduction:

- **Purpose:** Age progression is essential for various applications, including entertainment and forensic science.
- **Challenges:** The complexity arises from variations in facial expressions, photographic settings, and the diverse physical environments people grow up in.
- **Solution:** A deep learning model based on CycleGAN is proposed to generate aging effects without the need for paired data.

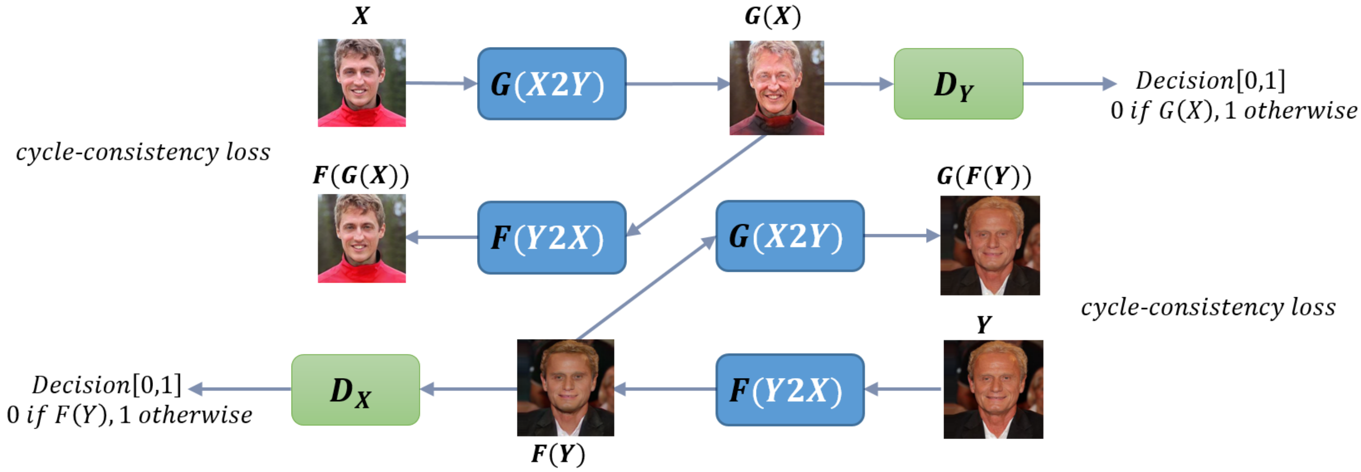
III. Related Work:

- **Historical Approaches:** Earlier methods focused on specific facial features, while recent works adopted more holistic approaches.
- **Advancements:** Generative Adversarial Nets (GANs) have shown promise due to their simplicity, implementation ease, and less stringent training requirements.

IV. Dataset and Features:

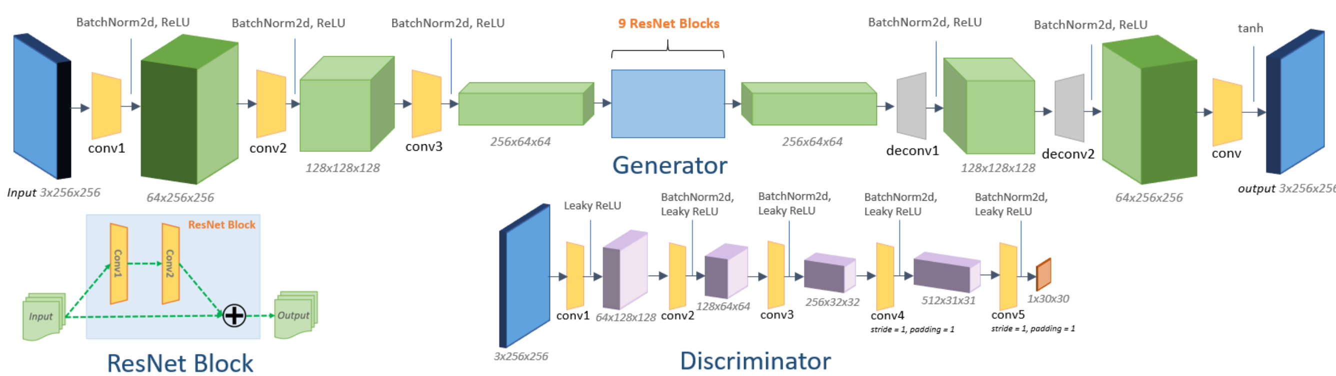
- Datasets Explored:
  - IMDB-WIKI: 500k+ face images with age and gender labels.
  - Cross-Age Celebrity Dataset (CACD): 163k+ images of 2,000 celebrities.
- Data Processing:
  - IMDB-WIKI: Only Wikipedia's 62k images were used after filtering.

- **CACD:** 2,200 images were randomly selected for each age group.



V. Methods and Implementations:

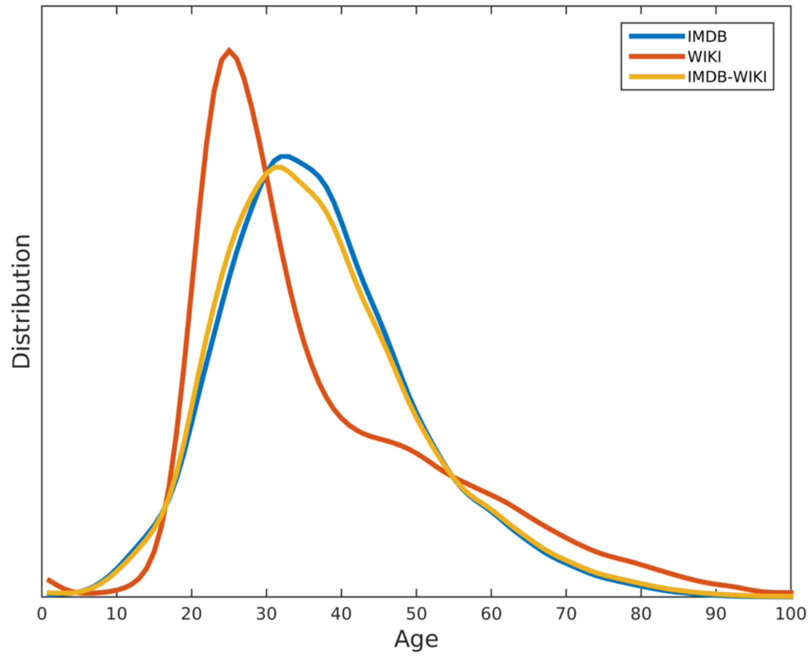
- **Model Structure:** CycleGAN consists of two generators (G, F) and two discriminators (DX, DY).
- **Implementation:**
    - Generators: Encoder, Transformer (9 ResNet Blocks), Decoder.
    - Discriminator: 5 down sampling layers.
- **Objective:** Minimize the adversarial losses and cycle consistency losses to ensure meaningful mappings between domains.



VI. Experiments and Results:

- **Data Source Analysis:**
    - IMDB-WIKI outperformed CACD significantly, likely due to the professional

settings of CACD images.

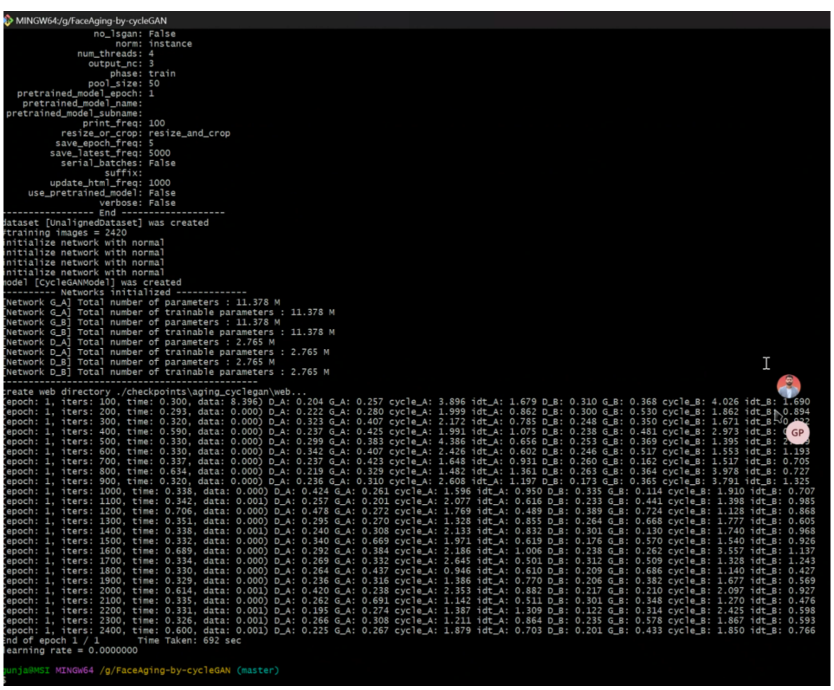


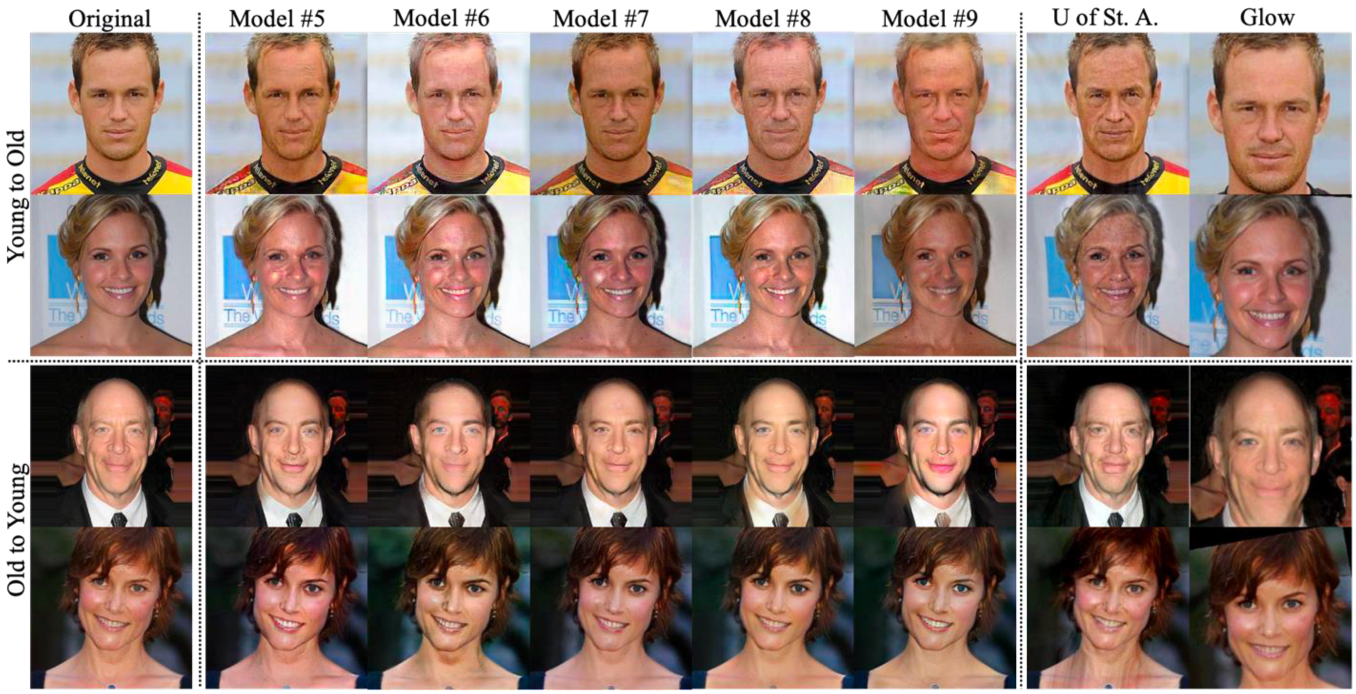
- Data Composition Analysis:

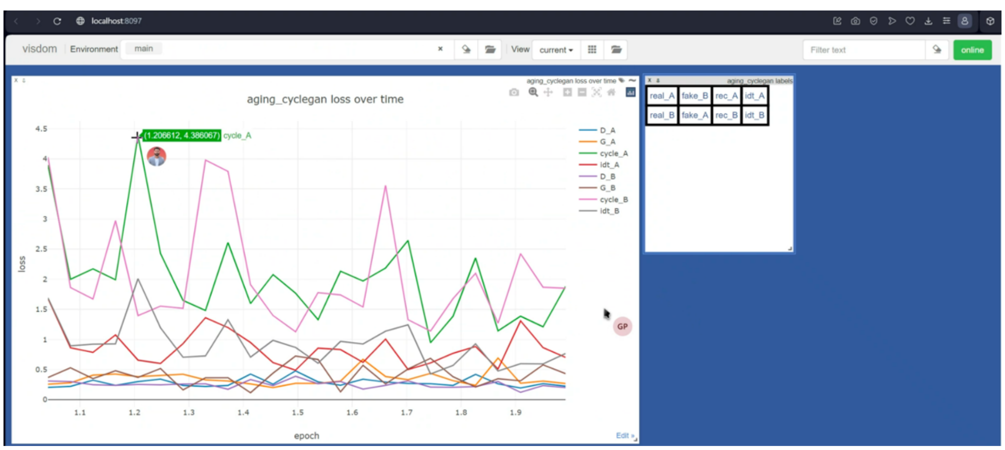
- Gender separation improved performance and eliminated gender-biased traits.

- Speed-up Techniques:

- Hyperparameter tuning, transfer learning, and fine-tuning were explored to reduce training time without compromising quality.







#	Source	Mix	Epochs	Preloaded?	Freeze until	G Size	Max	Avg	10+	15+	20+
0	CACD	All	200	N/A	N/A	9 blocks	25.8	6.7	22%	5.5%	1.7%
1	WIKI	All	200	N/A	N/A	9 blocks	31.2	8.8	37%	14%	5.8%
2	WIKI	Female	200	N/A	N/A	9 blocks	19.5	4.6	7.1%	2.5%	0.0%
3	WIKI	Male	200	N/A	N/A	9 blocks	27.3	10.3	50%	19%	5.1%
4	WIKI	Male	200	N/A	N/A	6 blocks	N/A	N/A	N/A	N/A	N/A
5	WIKI	All	200	horse2zebra	8th block	9 blocks	27.4	11.0	55%	20%	6.3%
6	WIKI	All	200	summer2winter	8th block	9 blocks	25.0	8.9	36%	10%	1.7%
7	WIKI	All	200	monet2photo	8th block	9 blocks	20.1	6.6	15%	2.5%	0.4%
8	WIKI	Male	100	horse2zebra	N/A	9 blocks	25.8	9.9	46%	12%	1.3%
9	WIKI	Male	100	Model #2	N/A	9 blocks	32.8	10.3	51%	18%	6.0%

VII. Conclusion:

In conclusion, the AgingGAN study successfully demonstrated the potential of CycleGAN in generating quality age progression images, addressing a challenging task in the realm of deep learning and computer vision. Through meticulous exploration of datasets, the study found that the IMDB-WIKI dataset outperformed the Cross-Age Celebrity Dataset (CACD), likely due to differences in image settings and professional photography. Additionally, gender-specific data composition proved crucial in enhancing model performance and eliminating gender-biased traits in the generated images. Various techniques, including hyperparameter tuning, transfer learning, and fine-tuning, were explored to expedite the training process without compromising the quality of the aging effects. However, attempts to reduce the size of the generator network proved futile, highlighting the intricate balance between model complexity and performance. Overall, the study offers valuable insights into the optimization of age progression models and underscores the importance of dataset selection and composition in achieving desirable outcomes.

VIII. References:

- Face aging with conditional generative adversarial networks. (2017, September 1). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/8296650

- Ai, N. (2022, April 7). GAN for Face Aging problem | Neurond AI | Medium. Medium. https://neurondai.medium.com/what-does-your-face-look-like-in-the-next-few-years-gans-for-face-aging-problems-8568299adfd

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- Jiechen. (n.d.). GitHub - jiechen2358/FaceAging-by-cycleGAN. GitHub. https://github.com/jiechen2358/FaceAging-by-cycleGAN/tree/master?tab=readme-ov-file