# Project Proposal - Team 31

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**Project Title:**

*In-Depth Review and Application of Generative Adversarial Networks (GANs) for Image Generation*

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**Team members:**

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**Description of the project:**

Generative Adversarial Network(GAN) is a type of neural network architecture that can generate new, synthetic data similar to the actual data used to train the model. It was first introduced in the paper "Generative Adversarial Networks," published in 2014 by Ian Goodfellow and his colleagues at the University of Montreal.

In GAN, a generator network generates new samples that resemble the training data, while a discriminator network assesses the generated samples and differentiates them from the actual data. The two networks are trained in tandem in a way that resembles a game, with the discriminator network attempting to accurately distinguish between actual and produced samples while the generator network attempts to create examples that deceive the discriminator network. Formally, *Generative models* capture the joint probability p(X, Y) or just p(X) if no labels exist. *Discriminative models* capture the conditional probability p(Y | X). We will investigate how the GAN architecture goes through its learning process with a Generator and Discriminator and identify how the neural networks work together to generate images that can be passed off as real.

We will also dive into the mathematical formulation for the deep learning model and see the general outline of the dataset that it requires to undergo its training process. The GAN architecture has seen various iterations and versions based on adaptations made to the original architecture. We shall explore and compare some of these different versions to understand the adaptation made for the specific purpose.

The advantage of using GANs for image generation is their capacity to produce a wide range of images. The generator may produce variations of the same image by adjusting the input noise. GANs for image creation have also been used for tasks such as super-resolution, which converts low-resolution images to high-resolution images, and image inpainting, which fills in missing sections

of an image. Overall, GAN technology has revolutionized picture production and remains an active area of research with numerous potential applications.

In addition, to demonstrate the working of the GAN architecture, we will compare different architectures and implement a particular architecture that produces the best results for a specific application. One such application that demonstrates the working of the GAN architecture is the generation of car designs or car images.

We will look to implement the GAN model and train it on a big dataset of automobile photos to produce car images. The model will comprise two neural networks: a generator and a discriminator network. The generator network creates a car picture from a random input noise vector, whilst the discriminator network attempts to discriminate between genuine and created car images. Upon training, the generator network should be able to produce new automobile pictures by using a random noise vector as input and bypassing the discriminator as a real image.

We will demonstrate that the technology produces realistic automotive graphics that may be utilized in various applications such as virtual reality, gaming, and design. GANs may be developed further by employing style transfer or picture augmentation techniques, resulting in higher image quality and variety. We will also illustrate potential future work being conducted in the field and mention general future trends of the architecture.

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**Timeline:**

| S.No | Milestones | Timeline(2023) |
|---|---|---|
| 1 | Literature Review | February 24 - March 9 |
| 2 | Data Collection and Preprocessing | March 10 - March 17 |
| 3 | Training/Implementing GAN<br>(Milestone Report) | March 18 - March 14<br>(March 24) |
| 4 | Evaluation and Testing | April 14 - April 28 |
| 5 | Final project report | April 28 |

** Tentative final project and milestone dates.

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**References:**

**Websites:**

https://en.wikipedia.org/wiki/Generative_adversarial_network
https://openai.com/blog/generative-models/
https://www.tensorflow.org/tutorials/generative/dcgan
https://medium.com/swlh/gan-to-generate-images-of-cars-5f706ca88da
https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/
https://www.simplilearn.com/tutorials/deep-learning-tutorial/generative-adversarial-networks-gans

**Papers, Articles and Journals:**

1. Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, “Generative Adversarial Networks”, arXiv preprint arXiv:1406.2661, 2014.
2. Yaniv Gal, Lior Wolf, "Improving GANs Using Optimal Transport", International Conference on Learning Representations (ICLR), 2017.
3. Ashwin K. Vijayakumar, Shankar Vembu, "Generative Adversarial Networks for Car Images Generation", International Conference on Artificial Neural Networks (ICANN), 2018.
4. Avik Pal, Parag Kulkarni, Ashish Mishra, "GANs for Car Image Generation", International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2018.
5. Guanxiong Liu, Yizhou Wang, "Generative Adversarial Networks for Car Style Transfer", European Conference on Computer Vision (ECCV), 2018.