SCRUTINY OF DIVERSE IMAGE AUGMENTATION STRATEGIES FOR DEEP LEARNING

## Problem

Deep learning models have performed remarkably well when there is abundance of data and high computing power is available to estimate parameters present in the deep learning architectures. With the recent advances in deep learning, the size of networks have grown exponentially. Those networks require a large amount of data to train and state of the art gpus, among both of which 2nd is readily available but we often lack in data for example in cases of biomedical images where rarity of the diseases can be issue, on top of which we have to take care of patients privacy and requirements of medical experts for labelling the images, or fault detection as the likelihood of occurrence of such an event is very low. Even for transfer learning such image features, a certain amount of data is needed. And if variance in data is not sufficient enough then the generalisation ability of the deep learning CNN based model is challenged, thus it becomes very important to address this problem

## Solution

These obstacles have led researchers to perform wide experiments with image data augmentation techniques specially based on Generative Adversarial Networks, the positive advances of which can be applied to solve application issues related to medical images. A lot of existing studies on image data augmentation utilizes popular datasets like ImageNet, MNIST handwritten digit dataset, tiny-imagenet-200, MIT\_Adobe-5k-datset, Pascal VOC, Cifar-10, Cifar-100 datasets. Many of the above listed datasets can be classified as big data so researchers have drawn a subset of these datasets to simulate limited image datasets. Additionally while addressing the problem of data generation, we will also try to address data imbalance problems and test how data augmentation can be a potential solution.

## Value Proposition

To solve the problem of limited data I will try to find a data-space solution based on Image Augmentation. Under the umbrella of Image Augmentation various methods will be covered which will be responsible for enhancing the sizes and quality of training datasets such that better generalizable deep learning models can be built. I will try to cover Image data augmentation methods like geometric transformation, color space augmentations, kernel filters, mixing images, random erasing, feature space augmentation, adversarial training, generative adversarial networks, neural style transfer, and meta-learning. In my work I will talk about image augmentation methods, present developments and meta-level decisions required to implement those techniques. At the end I want to present how people can leverage data augmentation techniques to improve performance of deep learning models and how to expand limited datasets to utilize capabilities of big data learning