# IFT6759 - Advanced Projects in Machine Learning

## Analysis of Image Augmentation Methods on Different Types of Learning Problems

Alekhya Dronavalli
Krishna Maneesha Dendukuri
Prishruit Punia
Rakshit Shetty
Timothy Lee
Yassir Mamouni

# Background

Advantages of Data Augmentation:

- Acts as a regularizer and improve model generalization (reduce overfitting)
- Improve robustness of the model
- Address class imbalance issue
- Overcome data scarcity

**“Data-Driven and Informed Regularization Strategy that Artificially Increase the Number of Training Samples.”**

**(Shorten and Khoshgoftaar, 2019)**

# Motivation

- Current Literature has several data augmentation methods that are proposed to improve the model performance on various settings, models and types of datasets .

- Combining different advanced data augmentation techniques on small low quality datasets is a relatively unexplored/overlooked field

- Observe the effect of various data augmentation techniques independently and study the scenarios in which it helps.

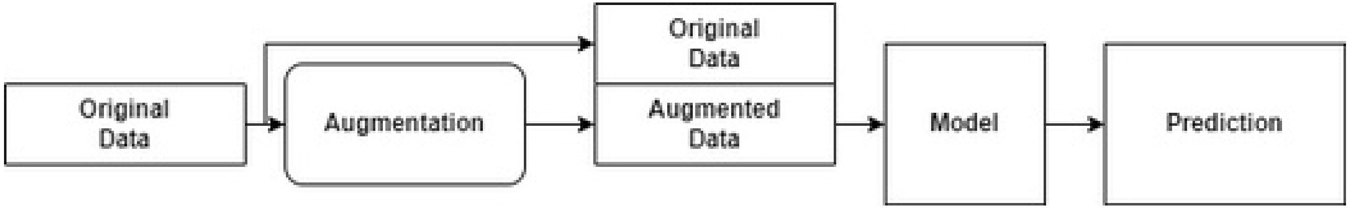
# Objective

- Our objective is to explore and compare individual data augmentation techniques and their combinations in Supervised and Semi-Supervised Settings.

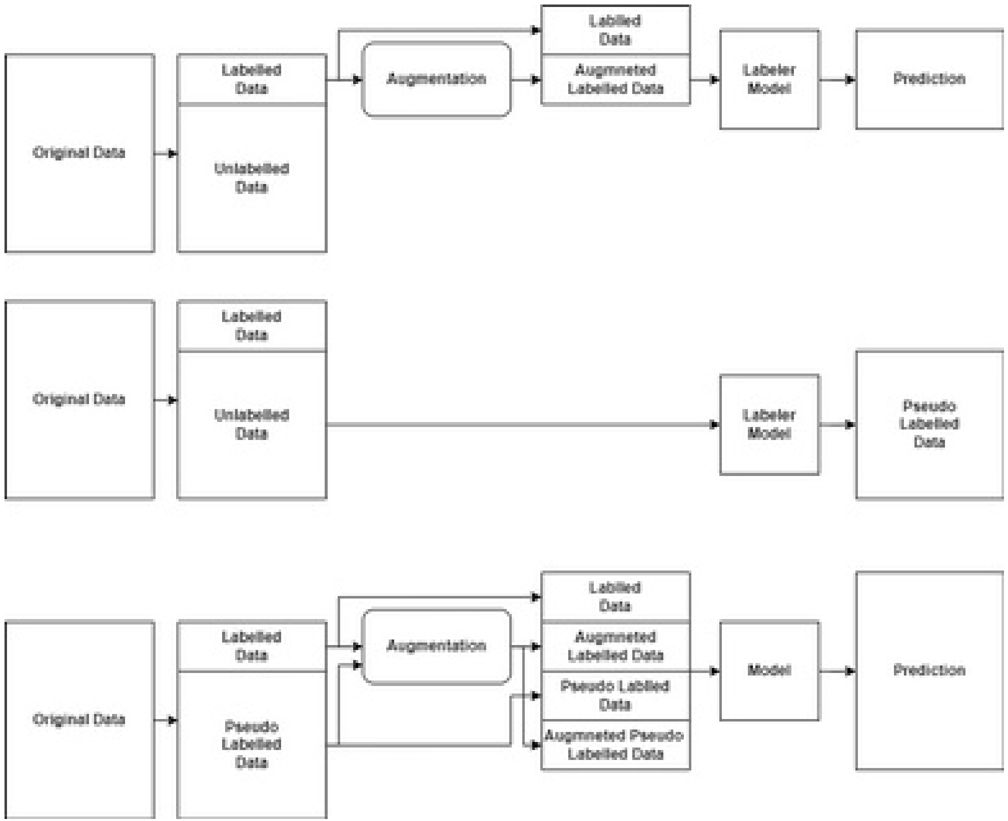
# Methodology

- Settings : Supervised Setting and Semi Supervised Setting
- Augmentation Techniques
- Network Architecture
- Dataset Details

# Setting - **Supervised Learning**

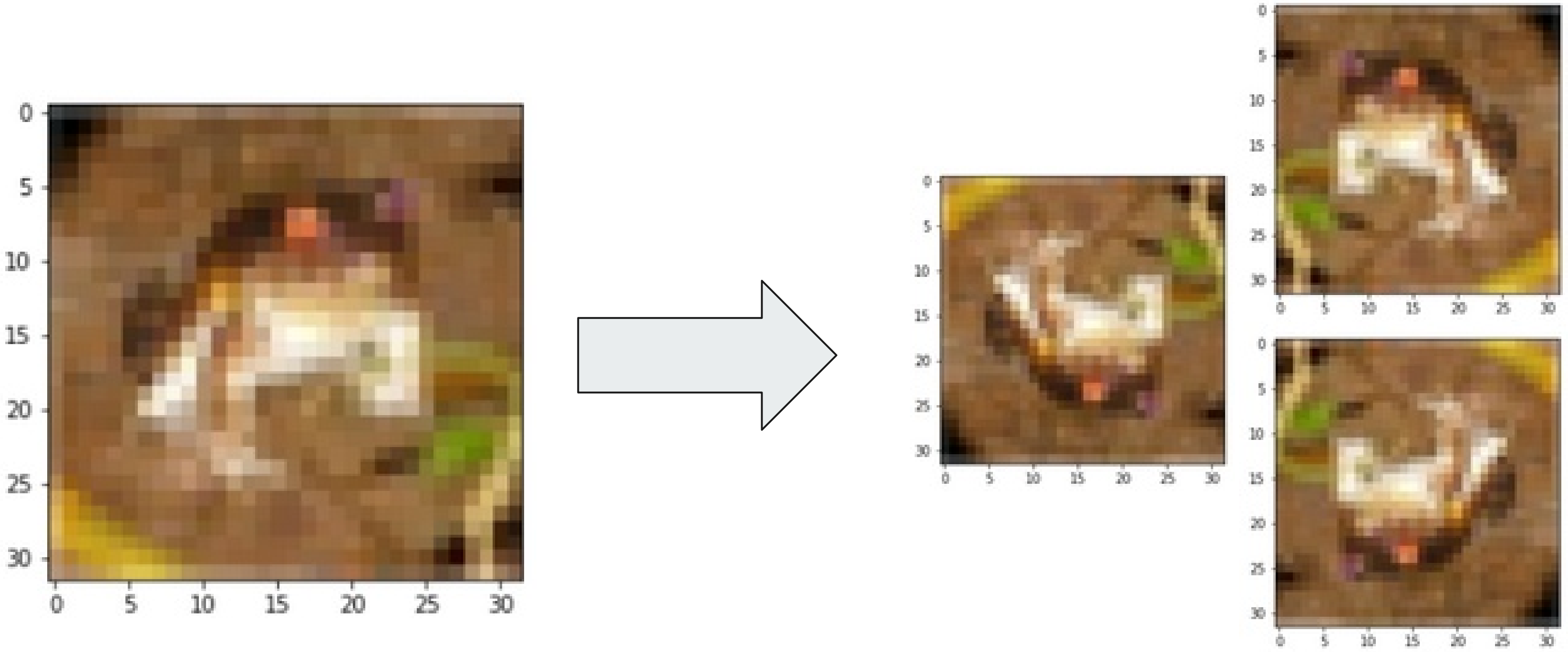


Setting - **Semi-Supervised Learning**



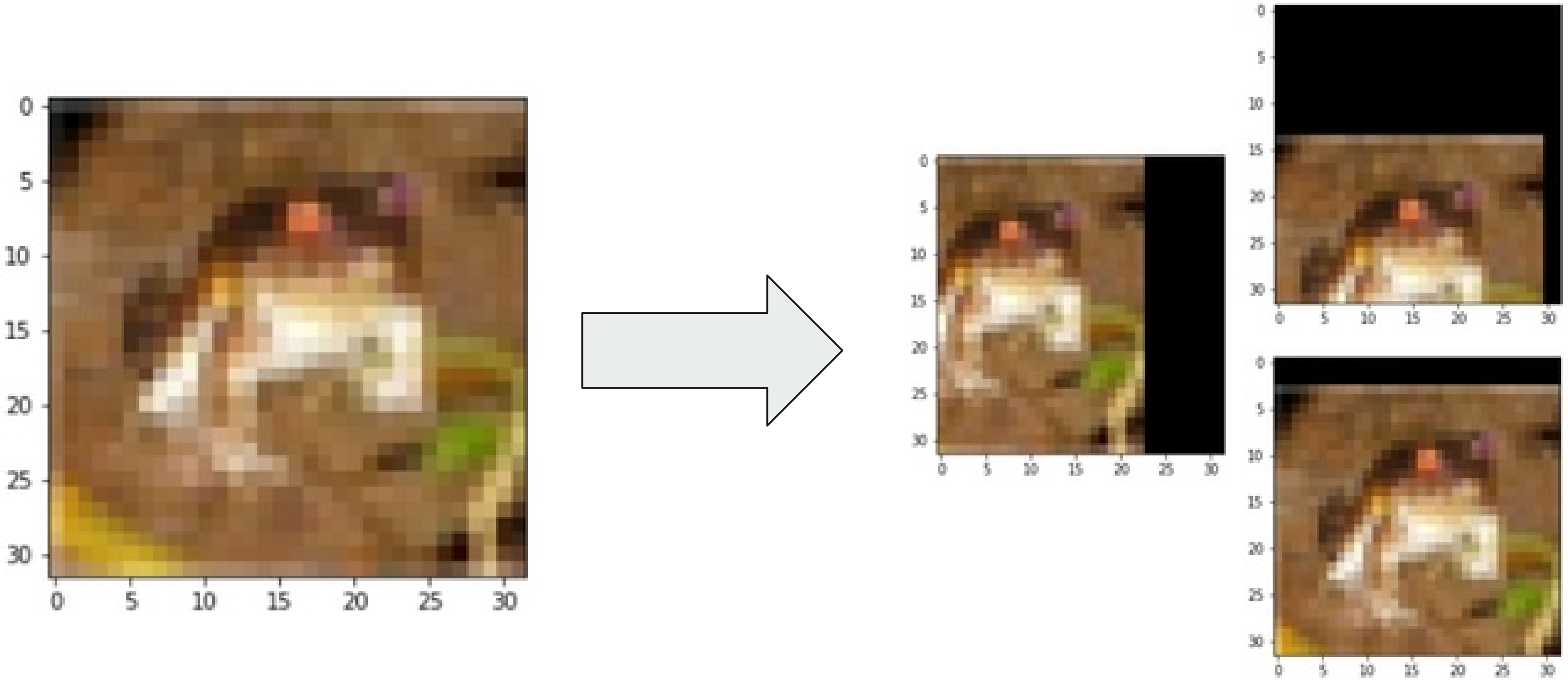
## Augmentation Techniques - **Horizontal and Vertical Flips**

Apply horizontal flip, a vertical flip, or both at the same time with equal probability.



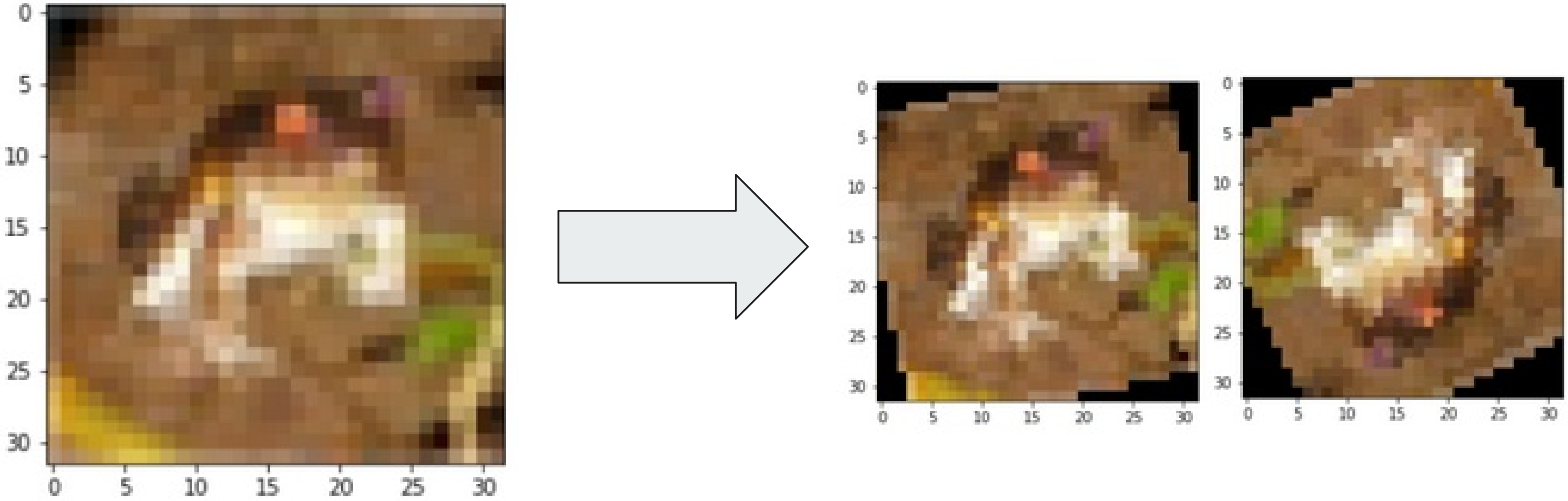
# Augmentation Techniques - **Horizontal and Vertical Translation**

Apply horizontal translation, a vertical translation, or both at the same time with equal probability.
The image is shifted by a pixel value between [-16, 16].



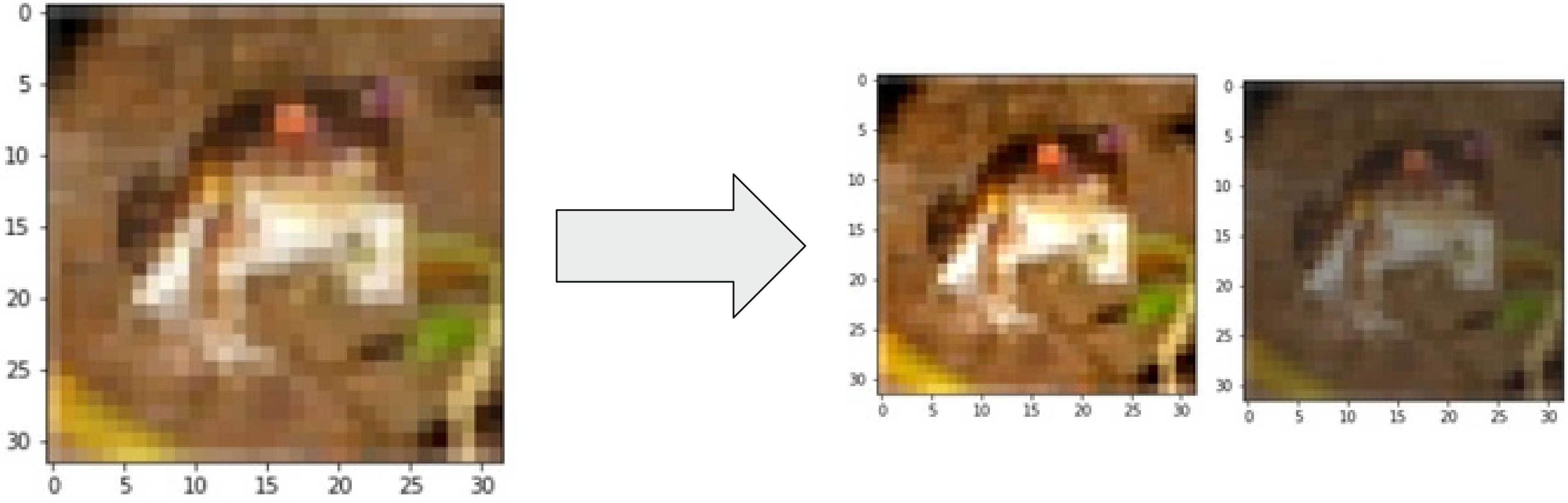
# Augmentation Techniques - **Rotations**

Apply rotation in the range of [-180, 180].



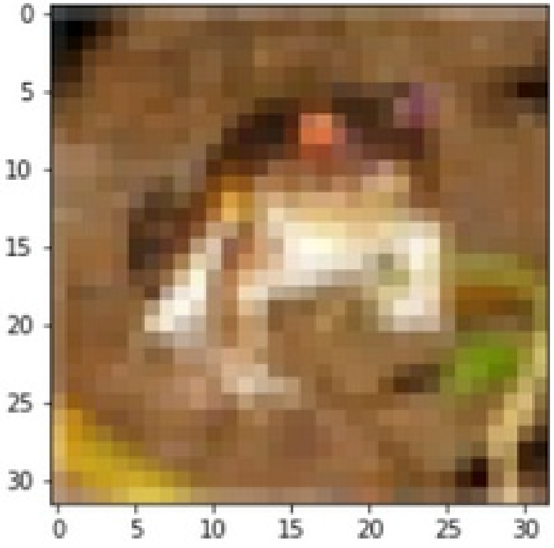
# Augmentation Techniques - **Contrast and brightness adjustment**

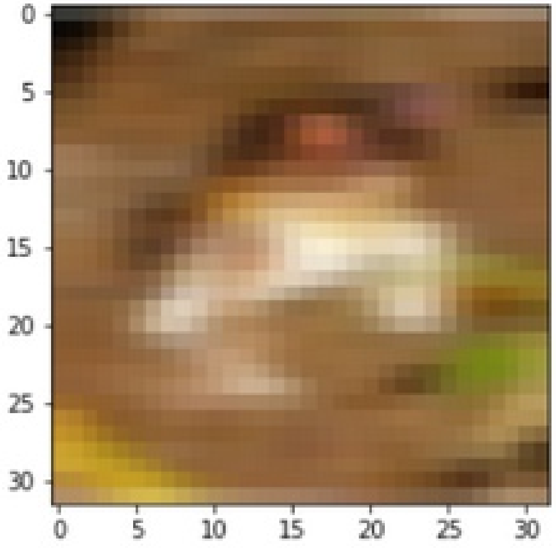
Apply contrast adjustment, brightness adjustment, or both at the same time with equal probability.
`contrast_factor` is selected to be in the range of [0.5, 1.5].
`brightness_factor` is selected to be in the range of [0.5, 1.5].



# Augmentation Techniques - **Gaussian blur**

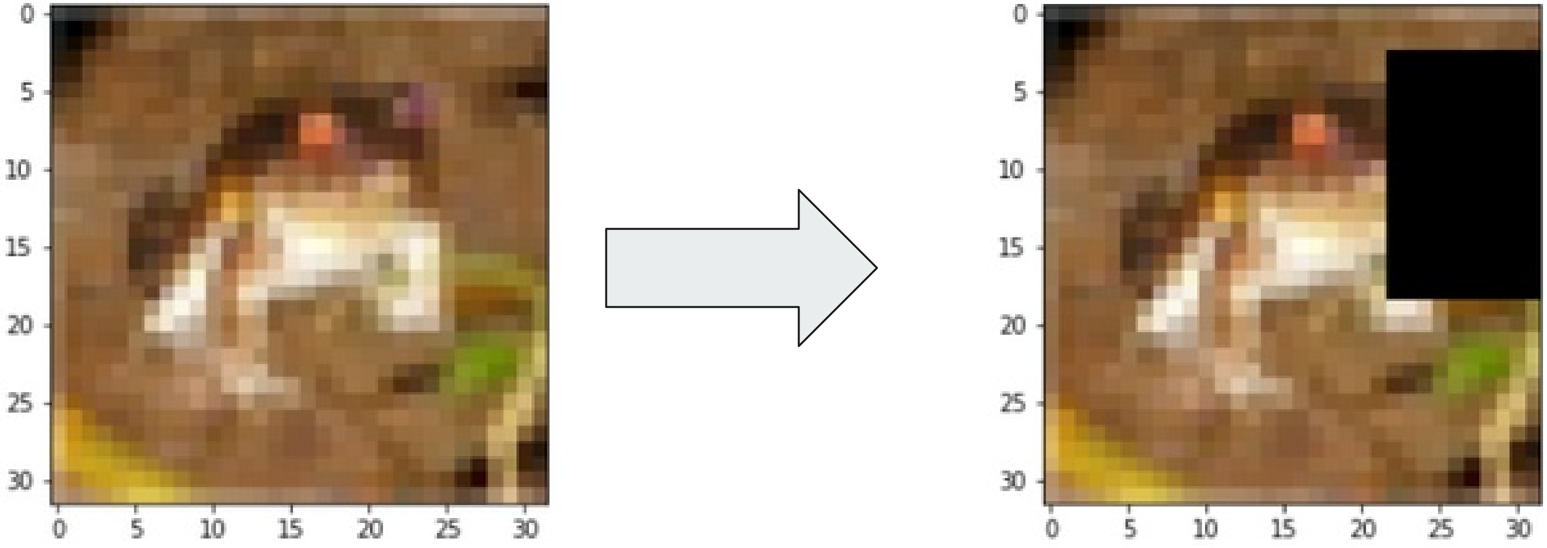
`kernel_size` is selected in the range of [1,16].



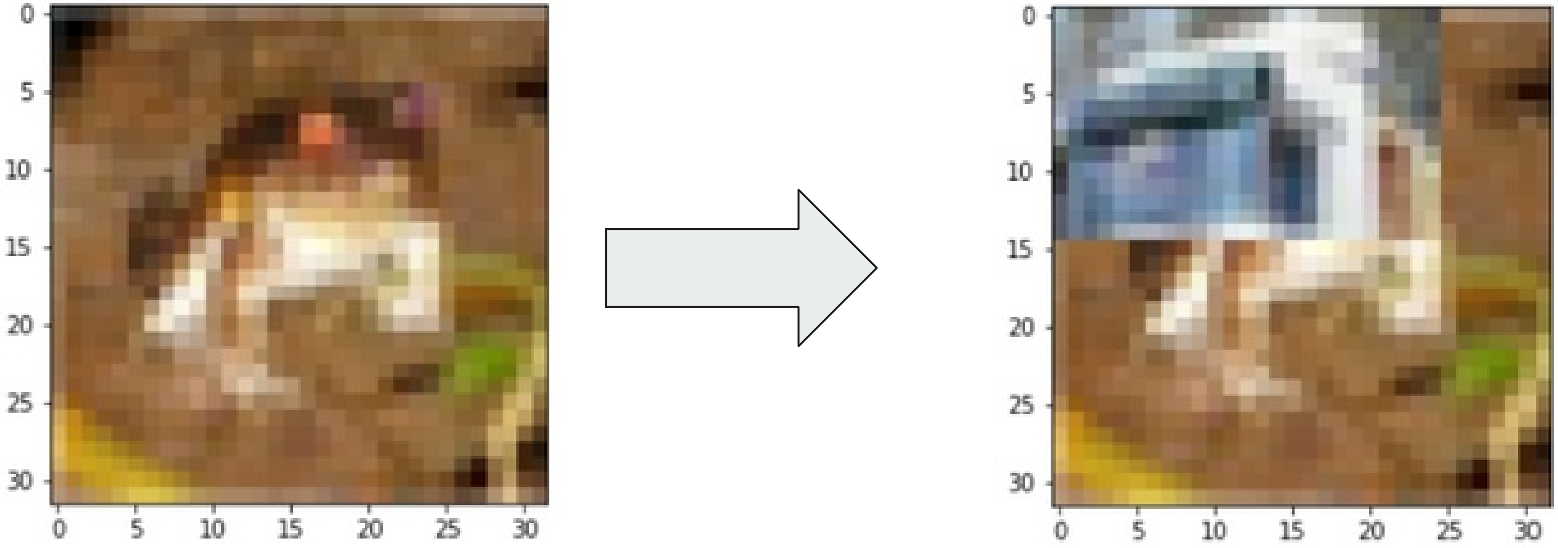
## Augmentation Techniques - **Cutout**

Apply a single rectangular mask to the image. The portion of the mask that lies outside the image is ignored.
Randomly select a pixel within the image, this pixel represents the center of the mask.
Select a value in the range of [1, 8], this value times 2 represents the width of the mask.
Select a value in the range of [1, 8], this value times 2 represents the height of the mask.



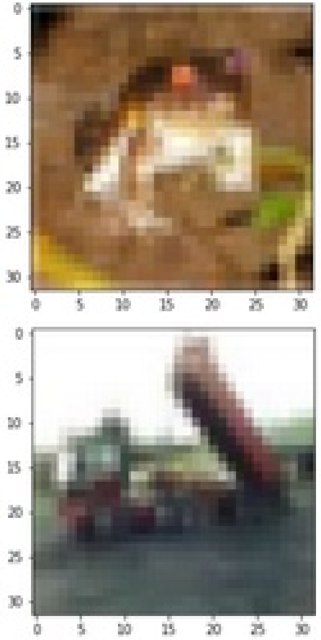
## Augmentation Techniques - **Cutmix**

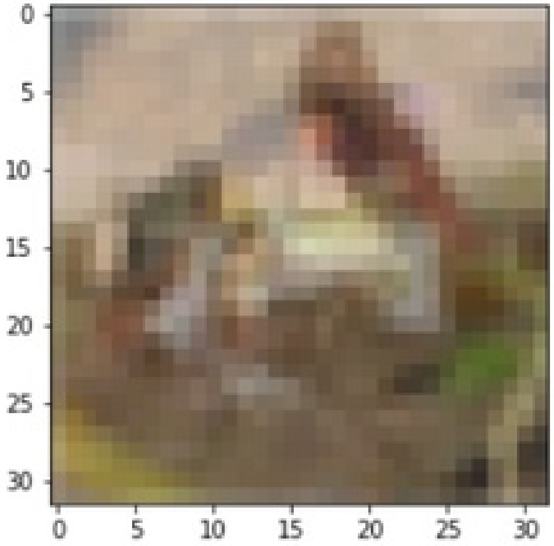
Apply a single rectangular mask to the image. The portion of the mask that lies outside the image is ignored. Fill the masked area with pixels located at the same area from another randomly selected image. The final label is adjusted based on the patch size.
Randomly select a pixel within the image, this pixel represents the center of the mask.
Select a value in the range of [1, 8], this value times 2 represents the width of the mask.
Select a value in the range of [1, 8], this value times 2 represents the height of the mask.



## Augmentation Techniques - **Mixup**

Select a random image and overlay the two images. A strength parameter is used to adjust the pixel values of the two images. The final label is adjusted based on the patch size.
The strength parameter is selected in the range of [0, 1].

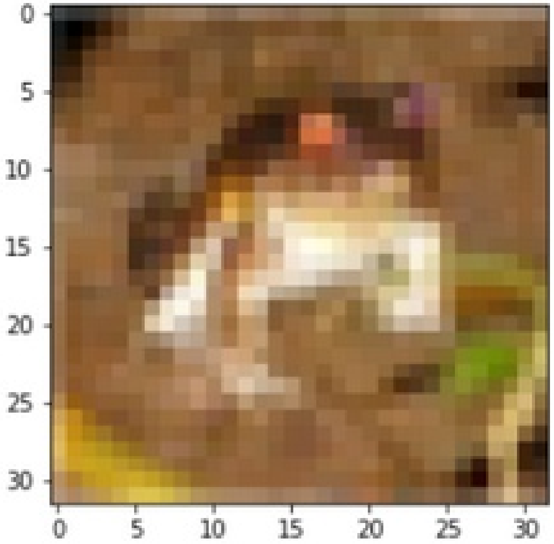


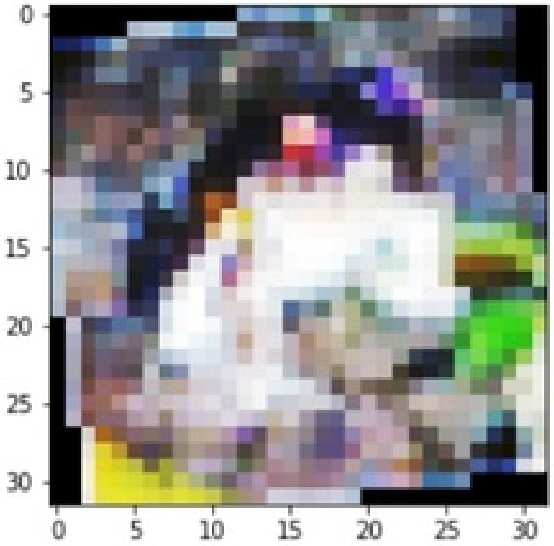


## Augmentation Techniques - **RandAugment**

Automatic augmentation methods that randomly selects a set of augmentations from their reservoir and applies the augmentation to the original image following a strength value.

| | | | | | | |
|---|---|---|---|---|---|---|
| Identity | Auto Contrast | Equalize | Rotate | Solarize | Color | Posterize |
| Contrast | Brightness | Sharpness | Shear-X | Shear-Y | Translate-X | Translate-Y |

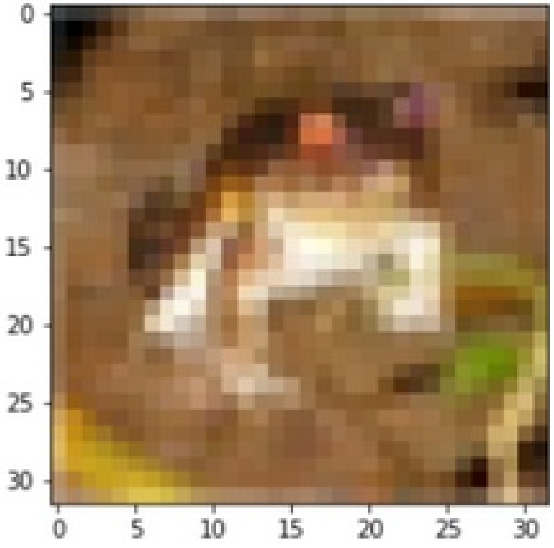


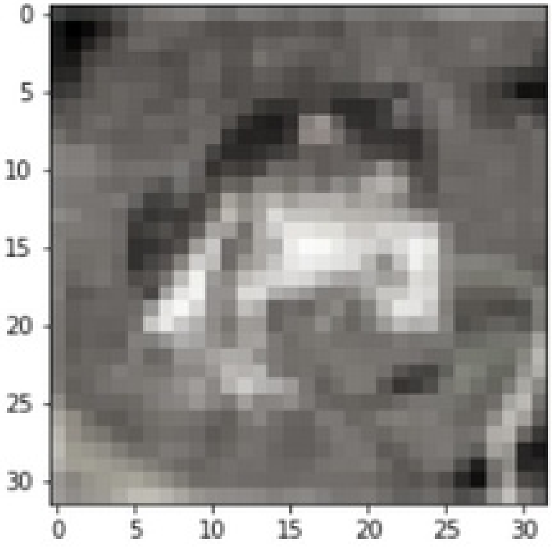



## Augmentation Techniques - **TrivalAugment**

Automatic augmentation methods that randomly selects a set of augmentations from their reservoir and applies the augmentation to the original image following a strength value.

| | | | | | | |
|---|---|---|---|---|---|---|
| Identity | Auto Contrast | Equalize | Rotate | Solarize | Color | Posterize |
| Contrast | Brightness | Sharpness | Shear-X | Shear-Y | Translate-X | Translate-Y |



# Augmentation Techniques - **Configuration Table**

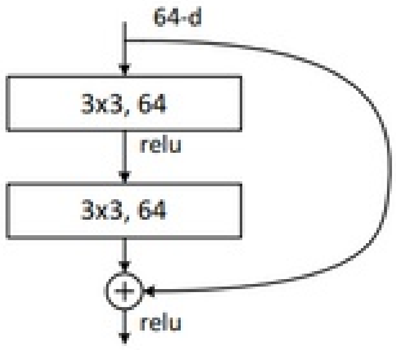
| ID | Method |
|---|---|
| A1 | Horizontal and vertical flips |
| A2 | Horizontal and vertical translation |
| A3 | Rotations |
| A4 | Contrast and brightness adjustment |
| A5 | Gaussian blur |
| A6 | Cutout |
| A7 | Cutmix |
| A8 | Mixup |
| A9 | RandAugment |
| A10 | TrivalAugment |

| | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 | A9 | A10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Config0 | - | - | - | - | - | - | - | - | - | - |
| Config1 | 100 | - | - | - | - | - | - | - | - | - |
| Config2 | - | 100 | - | - | - | - | - | - | - | - |
| Config3 | - | - | 100 | - | - | - | - | - | - | - |
| Config4 | - | - | - | 100 | - | - | - | - | - | - |
| Config5 | - | - | - | - | 100 | - | - | - | - | - |
| Config6 | - | - | - | - | - | 100 | - | - | - | - |
| Config7 | - | - | - | - | - | - | 100 | - | - | - |
| Config8 | - | - | - | - | - | - | - | 100 | - | - |
| Config9 | - | - | - | - | - | - | - | - | 100 | - |
| Config10 | - | - | - | - | - | - | - | - | - | 100 |
| Config11 | 20 | 20 | 20 | 20 | 20 | - | - | - | - | - |
| Config12 | - | - | - | - | - | 20 | 80 | - | - | - |
| Config13 | - | - | - | - | - | 50 | 50 | - | - | - |
| Config14 | - | - | - | - | - | 80 | 20 | - | - | - |
| Config15 | - | - | - | - | - | 20 | - | 80 | - | - |
| Config16 | - | - | - | - | - | 50 | - | 50 | - | - |
| Config17 | - | - | - | - | - | 80 | - | 20 | - | - |
| Config18 | - | - | - | - | - | - | 20 | 80 | - | - |
| Config19 | - | - | - | - | - | - | 50 | 50 | - | - |
| Config20 | - | - | - | - | - | - | 80 | 20 | - | - |
| Config21 | - | - | - | - | - | 20 | 20 | 60 | - | - |
| Config22 | - | - | - | - | - | 20 | 40 | 40 | - | - |
| Config23 | - | - | - | - | - | 20 | 60 | 20 | - | - |
| Config24 | - | - | - | - | - | 40 | 20 | 40 | - | - |
| Config25 | - | - | - | - | - | 40 | 40 | 20 | - | - |
| Config26 | - | - | - | - | - | 60 | 20 | 20 | - | - |

## Network Architecture - **Resnet 20**

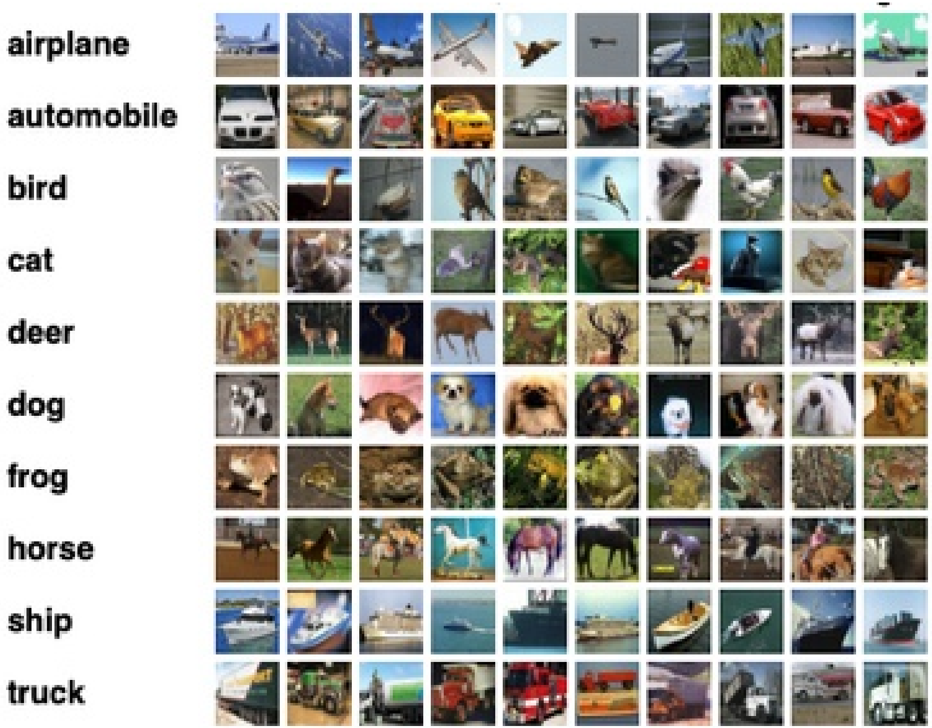
- We use Resnet-20 for Cifar 10 dataset as proposed in section 4.2 of the paper Deep Residual Learning for Image Recognition , which is different from the Resnet-18 model used to train on Imagenet.

- Uniqueness to other networks of its time: Residual Mapping which is achieved by shortcut connections for feed forward NNs to train deeper networks.



## Dataset - CIFAR 10

- Contains 32x32 colour images of 10 classes.
- Total 6,000 images per class.
- Training set contains 50,000 images
- Test set contains 10,000 images.
- It is a small, low resolution but well balanced dataset.



# Questions Explored in the Study

- Which data augmentation technique individually performs best in Supervised and Semi-supervised settings ?

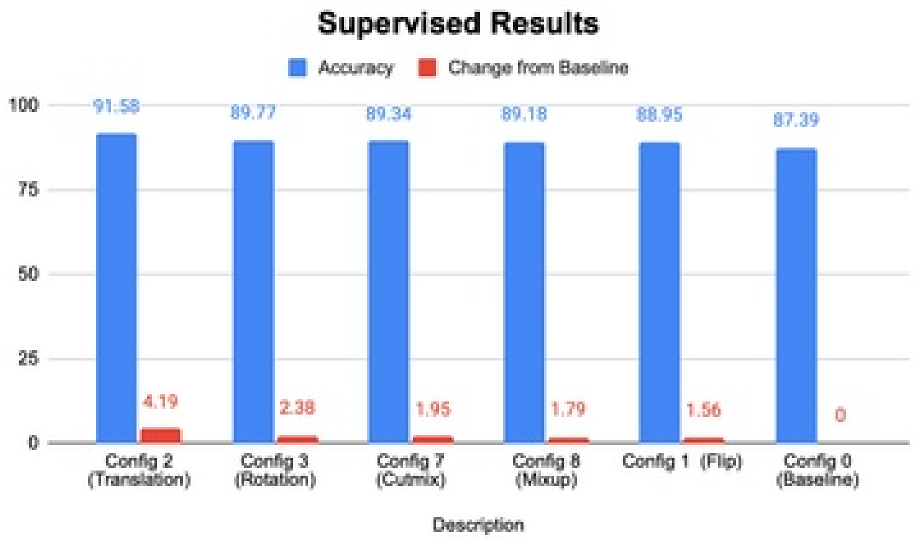
- Do combinations of these techniques outperform the best individual techniques ?

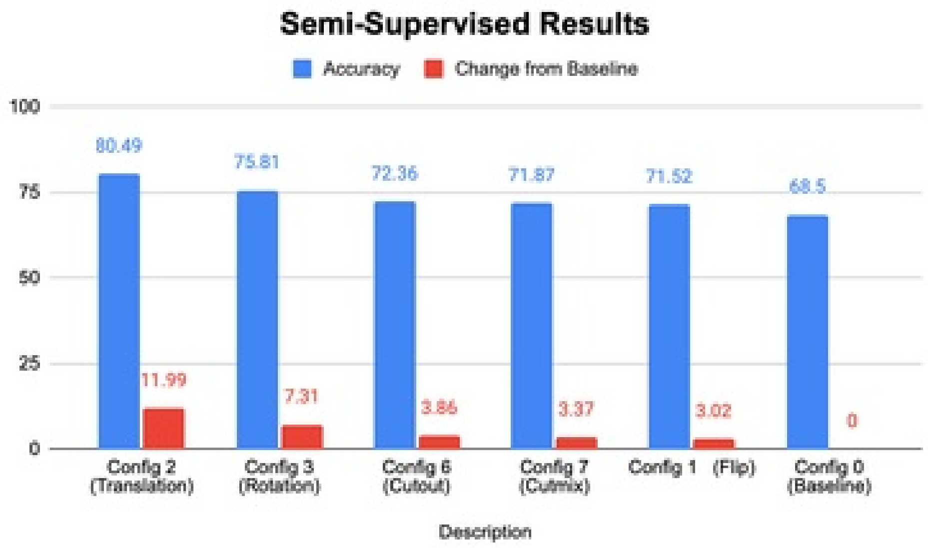
- How does the performance of a technique change when we move from supervised to semi-supervised setting ?

- How does the combination perform when compared with their individual techniques, do they complement each other ?

- Are certain techniques biased towards some specific classes in terms of performance improvement.

## **Result** - Top 5 Individual Data Augmentation Techniques



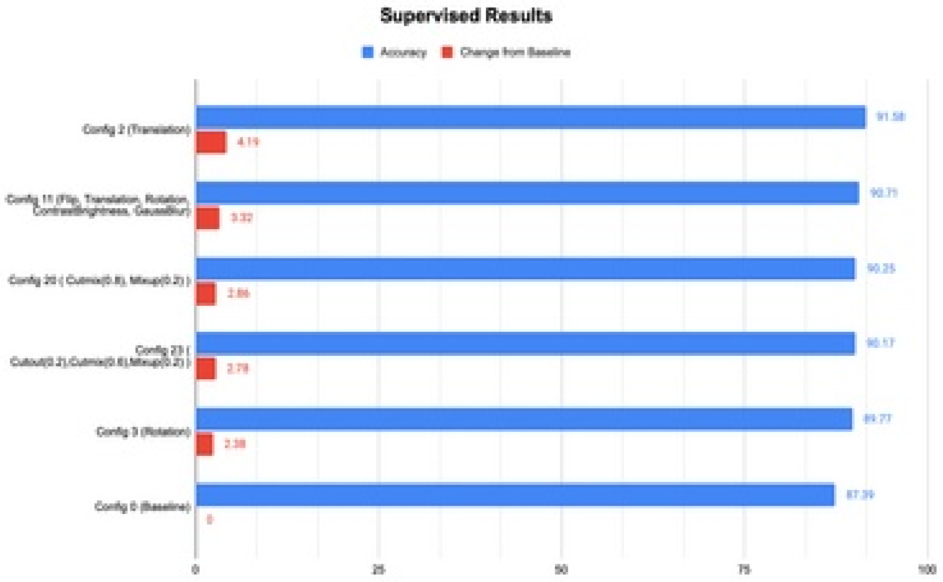



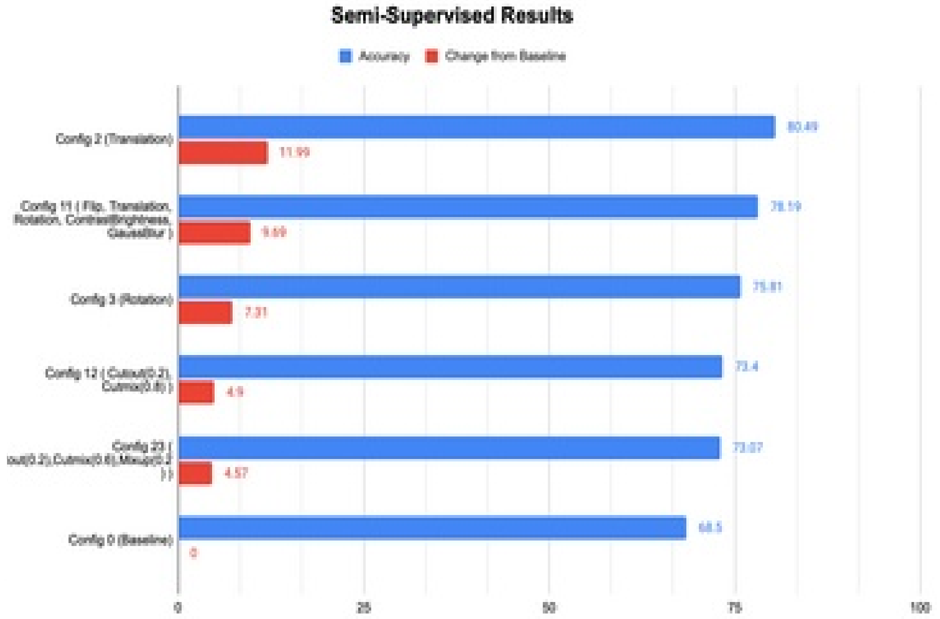

Q. Which data augmentation technique individually performs best in Supervised and Semi-supervised settings ?

Supervised Learning - Translation (Config 2)
Semi-Supervised Learning - Translation (Config 2)

# IFT6759

## **Result -** Combinations vs best individual techniques

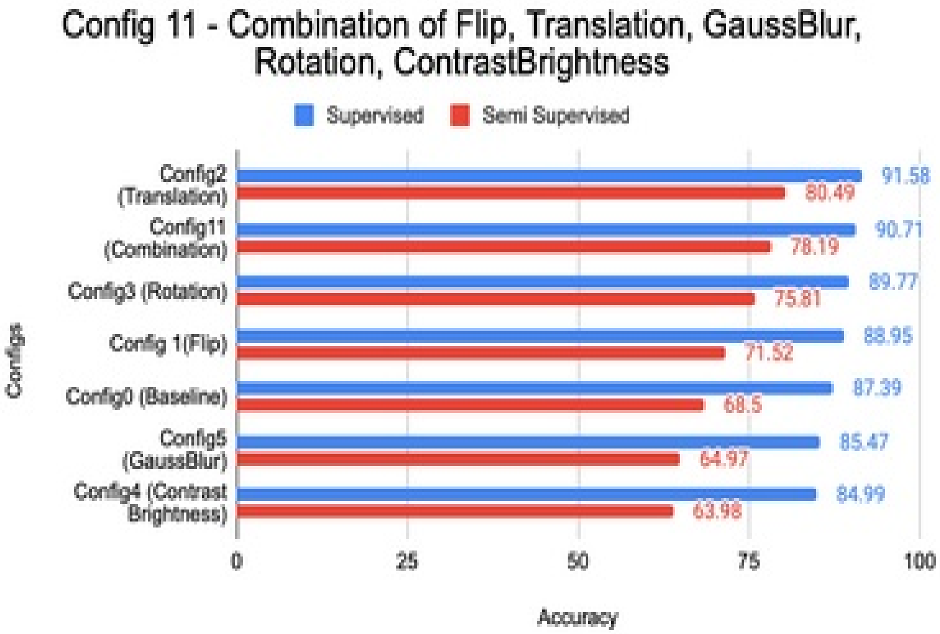


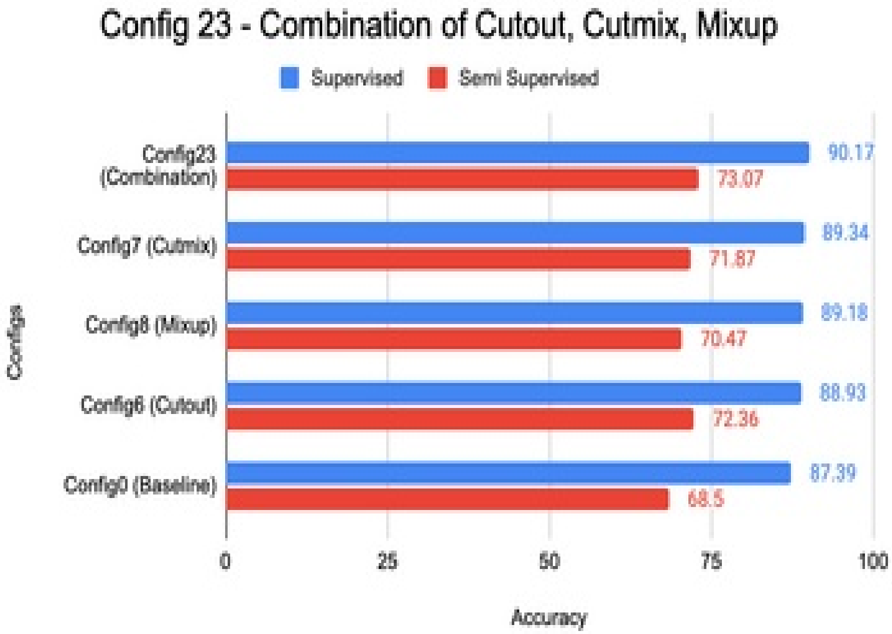




Q. Do combinations of these techniques outperform the best individual techniques ?

Few combinations like Config 11, outperform individual techniques except the Translation method.

Result - Best Combinations vs Its Individual Components




Q. How does the combination perform when compared with their individual techniques, do they complement each other ?

It does seem like each individual component contributes differently to the final result of the combination wrt to the baseline.

# Conclusion

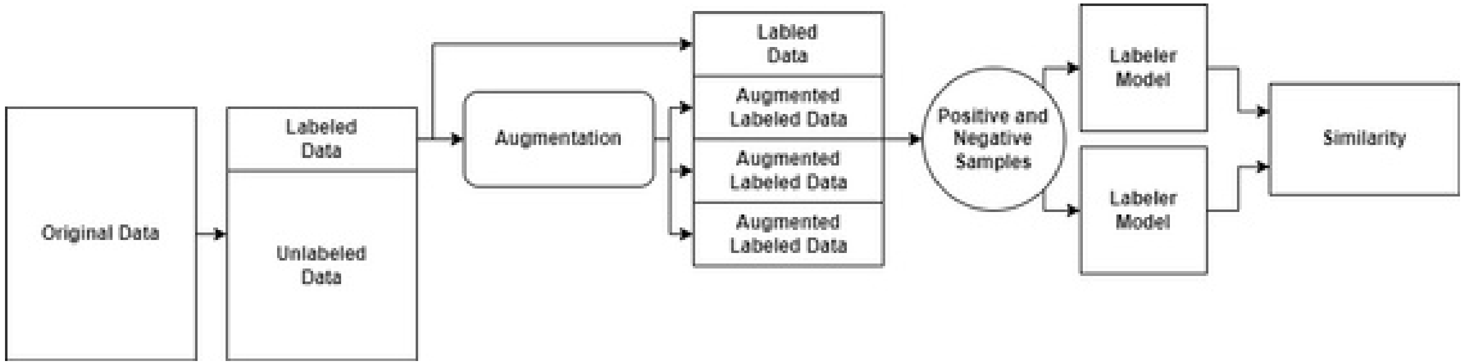
- Surprised : That the advanced img augmentation techniques by themselves did not outperform the basic techniques.
    - There could be following reasons for this :
        - Adv. techniques could possibly work better with more and high resolution data.
        - The performance gain that papers (of adv. techniques show) are always built in top of these basic techniques so it is possible that combining basic + advanced techniques would result in better performance.

- In our experiments we combined Basic + Basic techniques, or Adv. + Adv. techniques and none of them were able to outperform Translation (Basic) at least on this small low resolution dataset.

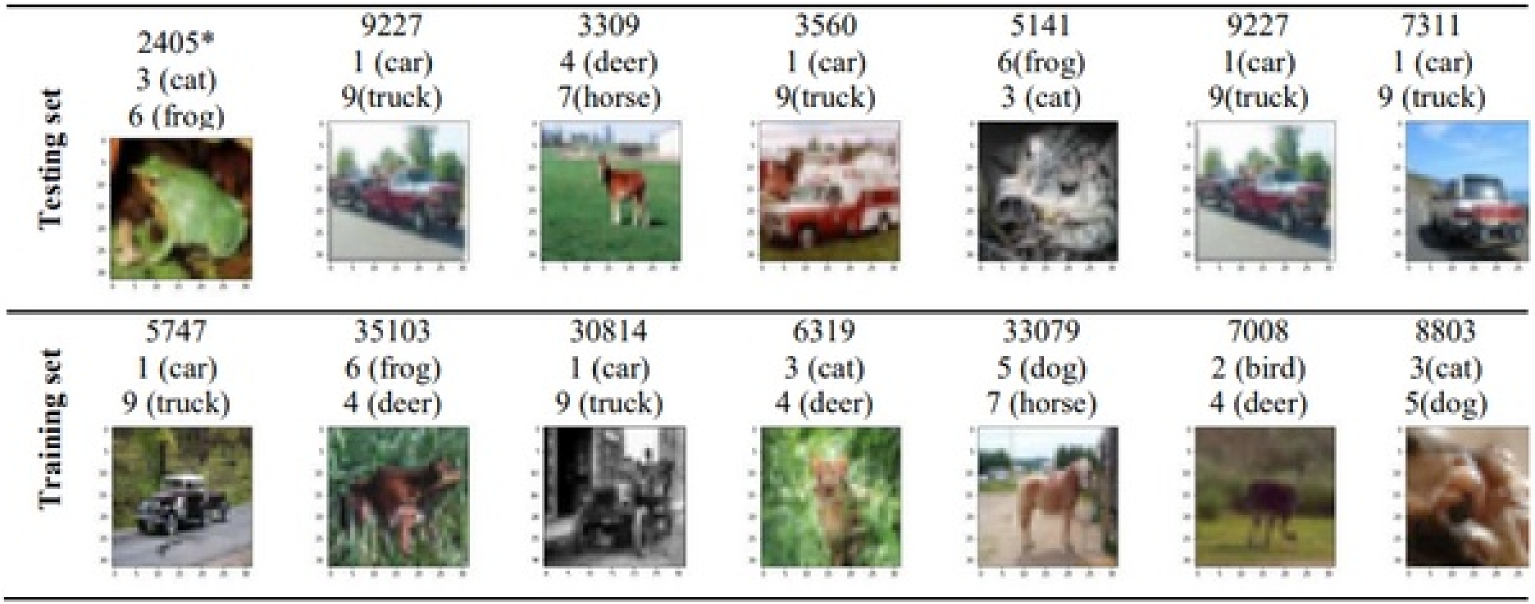
- We did observe that most combinations did perform better than their individual components.
    - This suggests that the information gained by these different methods is different and complements each other.

# Future Work

- Different model architecture
- Different dataset
- Different amount of augmented data
- Few-shot learning
- Visual explanation method (e.g. Score-CAM)



# Questions and Discussions




* Index (The Index of the image in CIFAR10); Original label; Predicted label; and Image of Predicted label.

Ref: Al-Rawi, Mohammed, and Dimosthenis Karatzas. "On the Labeling Correctness in Computer Vision Datasets." IAL@ PKDD/ECML. 2018.