Geometrical Transformation Techniques				
S. No	**Techniques**	**Description**	**Advantages**	**Remarks**
1.	**Rotation**	Rotating the image at arbitrary angles with respect to random centre or fixed centre.	Improves the model's generalizability, makes the model robust to variations in terms of orientation of the data.	It makes the model robust to variations to some extend but it is very inefficient approach as we need to generate new data and train it.
2.	**Shifting**	We will shift the image at random number of pixels both horizontally as well as vertically.	It handles the issues of positional bias of the model. And ensures that the model stands robust to shift variations in the input.	Since, CNNs are translation equivariant to some extent, the impact of this technique is not that much.
3.	**Scaling**	We will zoom in or zoom out the image at random ratio.	It helps the model to stand robust to variations in the scale /size of the subject in the frame.	It makes the model robust to scale variations to some extend but it is inefficient as need to generate new data for already existing data. And also, it does not guarantee that the model is invariant to scale.
4.	**Sheering**	We will sheer or rotate the image with respect to imaginary axis which rotate the image in terms of depth.	It helps the model to understand the structure of the object better so that the model can perform well in real-time.	It is one of high impacting technique in the model's generalizability. But we can still incorporate the information in the architecture (which is better approach).
5.	**Flipping**	We will flip or invert the spatial information with respective to x-axis or y-axis.	It helps the model to understand the relative information of the pixels. It helps the model in developing the symmetrical kernels.	It is one of the high impacting techniques. As we are making the kernels symmetric, we can improve the activations of the kernels for various features.

6.	**Resizing**	We will change the resolution of the image. Increasing the pixels or decreasing the pixels.	This technique helps the model to detect the features much better as we are conveying the model that for the single image, it can be represented with a smaller number of pixels or many pixels. So, we will be forcing model to detect the structures.	Resizing has its disadvantage as we need to change the input layer for different resolution.
7.	**Cropping**	We will select only a specific part of the image and discard the rest of the image. The way we can select part of the image can be random.	It improves the model's generalizability as we are showing only some part of the subject. That's, we are hiding some parts of the object and training. It improves the inference mechanism of the model, as it need to infer the object based on less information.	It is very good technique to improve the models. It gives us the impact of two techniques one is scaling and another one is occlusion. But the issues with this technique is that if the cropped part is not having the subject or the subject is not properly visible, then that can harm the performance of the model.
8.	**Distortion**	We will wrap the image into different deformations.	It improves the model's ability to withstand small variations in the structure of the object.	It is a good technique to improve the model's performance but it is limited is where is can be used and improper usage can harm the performance.

Color Space Transformation Techniques				
S. No	**Techniques**	**Description**	**Advantages**	**Remarks**
1.	**Brightness**	We will increase or decrease the brightness of the image. This is done by increasing every pixel value at some ratio.	It improves the model's robustness to lightning conditions.	It is one of the best techniques to ensure that the model develop certain thresholds that are activated irrespective of lighting conditions. In other words, the model considers structure rather than pixel values.
2.	**Contrast**	We will increase or decrease the contrast of the image. It is done by increasing the brightness of bright areas and increasing the darkness of dark areas.	It improves the edge detection of the model as edges are nothing but sudden change in the intensity of bright region and dark region.	It is very good technique to improve the edge detection of the model but we can get the most out of it, if we combine this technique with some other augmentation technique.
3.	**Gamma**	It is used to correct the brightness of the image as the brightness values represented by the camera is different to the brightness values represented by the monition. So, correct the different as similar to human view of brightness we are using gamma.	Improves in making the model invariant to brightness.	Rather than gamma, directly handling brightness improves the model's robustness to lightning conditions.
4.	**Saturation**	It is used to adjust the color intensity of an image for a particular color. It does this but increasing or decreasing the related pixel values.	It improves the color dependency of the model.	It is a good technique if we need to maintain the information color specific class.
5.	**Hue**	It is used to produce different shades of a same color.	It is improving the model's performance on different shades of a same color.	It is a good technique if we need to make the model perform same on different shades of same color.

6.	**RGB to HSV**	Here, instead of using RGB color format, we will use HSV format.	In HSV, we have a clear advantage of isolated information. So, Hue, Saturation and Value are represented in 3 separate channels.	We need to convert the inputted RGB image into HSV before passing it into the model. But it may lose the information of the associations of RGB. And also, it is not the way human visual system works.
7.	**RGB to YIQ**	Here, instead of using RGB color format, we will use YIQ format. Y - Luminance, I - In-Phase, Q = Quadrature.	Here, Y = Stores the information of the brightness, I = Stores color from Orange to Blue, Q = From Purple to Green	same as above
8.	**RGB to YUV**	Here, we will be using YUV format. Y = Luma, U = Blue - Luma, V = Red - Luma.	Y = Brightness, U = Blue projection, V = Red Production	Same as above

Spatial Augmentation Techniques

S. No	Technique	Description	Advantages	Remarks
1.	**Random Erasing**	Here, randomly we will generate coordinates of a block which can be filed with noise or neutral colors like grey and placed on the image.	This creates effect of occlusion and forces the model to look for the other features.	It is great technique to force the model to look for other parts of subject but due to its random nature, it may harm the performance of the model, if there are too many new images where the complete subject is blocked.
2.	**CutMix**	It is the next version of random erasing. Here, after selecting the random box, we will fill that with another image in the training dataset	The main goal if this technique is to improve the efficiency of the computation. Here, the operations performed on the blocked area in the random erasing is not wasted as we fill that with another image.	It is good technique to improve the generalizability of the model. But, CNNs are known to be sensitive to edges, those edges can influence the inference mechanism. And also, the CutMix approach

				does not make any sense to a human.
3.	**MixUp**	Here, we will select two random images which are belonging to same class and we will stack them or mix them in such a way that the features from both images are preserved.	This technique produces additional constraint on the data (which is beneficial for model's learning)	It does not make much sense to humans and also, improve usage can harm the model's performance.

Kernel Based Techniques

S. No	**Techniques**	**Description**	**Advantages**	**Remarks**
1.	**Blurring**	We will perform a convolution on the image with a specific kernel that spreads the edge details of the image or it blurs the image.	By blurring the image, we are guiding the model to look for shapes and structures rather than texture or pixel level information.	It is good technique but the amount of blur and the image will decide its impact.
2.	**Sharpening**	It is opposite to Blurring	BY sharpening, we will force the model to look for the texture information.	If we have noisy pixel, then the model will learn and this can harm the performance of the model.
3.	**Laplacian**	It is a specific kernel using which we can detect edges.	It guides the model in the detect of edges.	Since, it only displays edges, the model may not make sense of the information it learned or it may just not able to apply that in the real-time data.
4.	**Noise Injection**	We will augment at pixel level with random values or in order words, we will damage some of the pixel level information using noise.	As we are damaging some of the pixel level information. The model is forced to become less sensitive to the noise. This in turn improves the generalizability of the model.	It is good technique but the amount of impact varies based on the data. And also, there are ways in which we can ensure that the model is less sensitive to noise by adding blur pool layers which is much better approaches as we are addressing at architecture level.

There are many kernel/filters which can output image in different forms. Each of them has its own advantage.

Deep Learning Techniques

S. No	Techniques	Description	Advantages	Remarks
1.	**Neural Style Transfer**	Here, using neural network we will convert a normal image into something of an art form.	Even after converting the entire image into some art, we are still preserving the information of main structures in the image. This helps the model in better structure detection.	Whenever, we are using NN, the biggest disadvantage we have it the computation. So, we cannot implement this in the runtime augmentation.
2.	**GAN based**	Here, we have concept of Generator and Discriminator. The goal of the generator is to generate a new image that cannot be detected by the discriminator that it is an computer generated image.	The main advantage of GANs, it is that they can generate realistic images. Due to that, we can consider the new generated image as original image. This overall improves the quality of the data.	Computation and amount of other resources required are the biggest disadvantage of this approach.
3.	**Hybrid**	Here, we will apply multiple augmentations in a single pipeline.	It is much more efficient approach as multiple augmentations impact can be gathered in a single iteration	It is hard to know the impact of single technique.

6 New Techniques of Augmentation

S. No	Techniques	Description	Advantages	Remarks
		In this approach, we will train the model on the existing data and after that, we will extract the feature vectors of the last layer and find the top n (n can be 1 - 6), and fill these spots with a neutral color like gray and blur the edges of the spot. And	It is an efficient technique as it directly depends on the model's performance, so we are addressing according to the model. As we are block the high activated	To perform this augmentation, we need to train a model first and generate data. This can be time consuming. And also, sometimes, if the subject is very small

1.	**Activation Suppression**	also, we will apply a stylizing effect like oil paint, cartoonization, etc.	regions, the model is forced to learn the other features. And with oil paint augmentation, the model is guided to learn the structures rather than pixel level information.	in the frame, then those suppressions can completely cover the subject and this can have negative effect. But this can be handled if we reduce the number of suppressions or the size of each suppression.
2.	**1 Pixel Shift**	In this approach, we will flip the image and shift the image one pixel both horizontally as well as vertically.	The main motive regarding this technique is to handle the issue of max pooling. In Max pooling, we will totally neglect the information of even spaced pixels, so, but flipping and shifting, we are preserving that information. This technique can improve the performance of the model where we need to learn texture information.	It is simple technique which ensures that the model has all the information. But, the effect of this technique is negligible if texture information is not the required one.
3.	**Adaptive Color Scheme**	In this approach, for each image we will extract the histogram information and find the top least shades in the image and overlay those particular shades.	In technique is inspired from contrast learning. So, as we are providing the shades on the image which are not at all in the image, we will be forcing the model to look for features rather than getting biased with color.	It is good technique but it is naïve in its approach as we cannot be sure that training with those particular shades guarantees that the model is invariant to colors.
4.	**Tiles Shuffle**	In this approach, we will divide an image into 9 equal tiles and shuffle them.	This technique is developed to ensure that the model learns the spatial information of related features. This is one of the fundamental flaws of CNNs. So, using this technique we can address this issue to some extent. And	The main issue with this technique can be the generation time. And also, for some images where the whole subject is fitted into a single tile, the effect of this technique is negligible

			another advantage is that, using this technique, we can generate as much data as we want.	
5.	**Low-Level Residual**	In this approach, we will try to hide the details of the edges which the model already know so that we will end up with the residual or the edges which the model is not able to detect before.	The main objective of this technique is to improve the edge detection of the model. So, rather than training the model on the edges which it already learned, in this technique we will train the model with the residual or the edges which it is not able to detect before. Next, except the first layer, we will freeze all the other layers from training. Due to that, there is no vanishing gradient problem and changes in the edge detection will have direct impact on the model's output. And as we are introducing artifacts into the image, it creates a similar impact of noise injection augmentation also.	If all edges have been learned by the model, applying this augmentation may not improve the model's performance.
6.	**Texture Information Encoder**	The goal of this technique is to improve the texture detection of the model. We do this my encoding the information of evenly spaced pixels onto the oddly spaced pixels.	Using this technique, we can address the issue of pooling layers. We know that, the pooling, we have a window which slides in non-overlapping regions. Due to this, information between the evenly spaced pixels is not considered. And this results in loss of information. Using this technique, we will incorporate the information from even	If the texture information is not the main priority, this augmentation may not give much impact on the model's performance.

			spaced pixels onto the odd spaced pixels, due to this, there is no information loss and the texture information is preserved.	

Methods of Training During Execution				
S. No	**Techniques**	**Description**	**Advantages**	**Remarks**
1.	**Sequential Learning**	Here, we will place the augmentations of the same image at same place and pass into the model sequentially.	This approach has benefit of learning the required information for the augmentation batch of same image as everything is provided sequentially. Otherwise, the model weights keep fluctuating from one image to another. So, we can say that this approach will improve the training time.	In order to do this, we need all augmentations generated before training and placed sequentially. This can be a tedious task.
2.	**Contrastive Learning**	Here, we will provide the contrastive features for the model. Due to this, it is can improve is range of feature detection.	For example, we will provide image with high brightness and low brightness and pass it into the model. As we are providing two extremities, the model will expand its range for feature detection.	In order to do this, we need to find ways of contrastive features for every aspect.

3.	**Isolated Learning**	Here, rather than combining all generated images into a single folder, we will keep the separated.	Here, the idea is to isolate the model training to fixed augmentation, due to that, the model is forced to look for specific augmentation. The training is faster as we need to handle only less data at a time.	This sometimes can have negative effect as the model may be guided more towards the augmentation rather than generalization. In other words, overfitting.
4.	**Transfer Learning**	Here, the idea is that, whenever it is possible to transfer the information, we will simply transfer it, rather than learning the additional information separately.	In this approach, we will train the model to learn the required features, after that, in order to make it rotational invariant, we will simply transfer the learned information to the rotated kernels. This approach is an efficient way of using the resources as well as information. The training time and size of model can be reduced drastically if implemented correctly.	This main disadvantage of this approach is that, the efficiency that we are talking about is only achieve if the knowledge is transferable.