A project report on

IMAGE RESTORATION

Submitted in partial fulfillment of the requirements for the Degree of

B. Tech in Computer Science & Engineering

by

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November 2020

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CERTIFICATE

This is to certify that the project report entitled **"Image Restoration"** submitted by

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in partial fulfillment of the requirements for the award of the **Degree of Bachelor of Technology** in **Discipline of Engineering** is a bonafide record of the work carried out under my(our) guidance and supervision at School of Computer Science, Kalinga Institute of Industrial Technology, Deemed to be University.

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Kalinga Institute of Industrial Technology

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The Project was evaluated by us on 25/11/2020

Manjusha Pandey

ACKNOWLEDGEMENTS

It is with a sense of satisfaction that our group is able to complete and compile this project. However, it would not have been possible without the aid from our project guide. We would like to express our gratitude to Prof. Manjusha Pandey, whose advice and guidance has proven invaluable in bringing about the end product. I would also go on to acknowledge the support and aid that was given to us by the Dean of our School of Computer Engineering, Prof. Bhabani Shankar Prasad Mishra and our Director Prof. Samaresh Mishra. It is with the help from all of these individuals that we have been able to see our project through to completion.

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ABSTRACT

It is not uncommon for image data to be corrupted due to unforeseen factors. There are a number of reasons which render the photos corrupt such as accumulation of bad sectors on the storage media, some bits missing, scratch on CDs/DVDs, and so on. Not to mention the issues of the camera itself that may occur causing noise in the image due to another variety of reasons. While there are preventative solutions to this, the restoration of these images is not so often seen. Even if they are seen, usually it is a time consuming and arduous process. This predicament of image restoration is what we are attempting to solve through our project. We achieve this through deep learning models. But not only are we attempting to restore the original image once it has been corrupted, we are also training the model to be the most efficient model possible that can achieve this. Our final models obtained are two multi-layer deep learning models, optimized further by the appropriate loss functions to produce very accurate and clear images as output from noised input images.

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CHAPTER 1

INTRODUCTION

Tells the reader what the report is about, aims and objectives of the project work and how the report is organized into different chapters.

1.1 Problem Statement

It is not uncommon for image data to be corrupted due to unforeseen factors. There are a number of reasons which render the photos corrupt such as accumulation of bad sectors on the storage media, some bits missing, scratch on CDs/DVDs, and so on.[1] Not to mention the issues of the camera itself that may occur causing noise in the image due to another variety of reasons. While there are preventative solutions to this, the restoration of these images is not very commonly utilized or seen.

1.2 Project Description

We are working with a small dataset of images where we apply a number of different noises on the image, then we attempt to introduce these corrupted images to the model and train it to adapt to the various different possible noises that it may encounter in its life cycle. This is how we are producing a self supervising model that can deal with any kind of image corruption and achieve versatility and efficiency.

This project is being made as a major project by KIIT students. This is a Machine Learning Project. We have collected the Dataset of images, apply a number of different types of noise on the images and then use our model to restore the image. By growing our model we have attempted to find the best possible model we could.

1.3 Project Report

The project report will initially give an insight into the problem statement and why it is important for the issue to be resolved and it will give clarity on our approach to this issue and how we differentiate from other approaches. Finally, we will provide the results obtained from our hard work.

CHAPTER 2

BACKGROUND

2.1 Reading Material

The following medical research and machine learning repositories were studied to form a basis of the solution for our problem statement.

1.) “Introduction to image denoising” by Nabil Madali

2.) Image Restoration, Computer Vision

3.) Multi-Scale Structural Similarity Index for Image Quality

4.) Stanford Engineering, CS, Image Processing and All You Need to Know, Prof. Wang Lee, Prof. Elliot Junes

2.2 Related Theory/Terms

Deep learning is an artificial intelligence (AI) function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabeled. Also known as deep neural learning or deep neural network.[2]

Deep Learning models, with their multi-level structures are very helpful in extracting complicated information from input images. Convolutional neural networks are also able to drastically reduce computation time by taking advantage of GPU for computation which many networks fail to utilize.

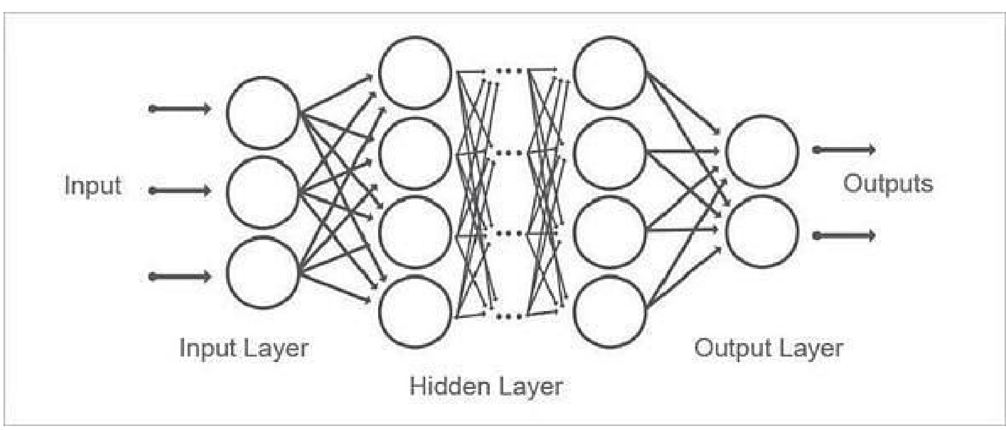


Fig 2.1 - Convolutional Neural Network

There are many sources of noise in images, and these noises come from various aspects such as image acquisition, transmission, and compression. The types of noise are also different, such as salt and pepper noise, Gaussian noise, etc. There are different processing algorithms for different noises.

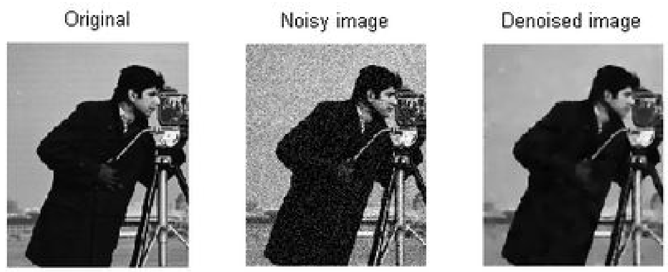


Fig 2.2 - Image, Noisy and Denoised

We see the importance of perceptually-motivated losses when the resulting image is to be evaluated by a human observer. We compare the performance of several losses, and utilize a variety of differentiable error functions for our model. We show that the quality of the results improves significantly with better loss functions, even when the network architecture is left unchanged.[1]

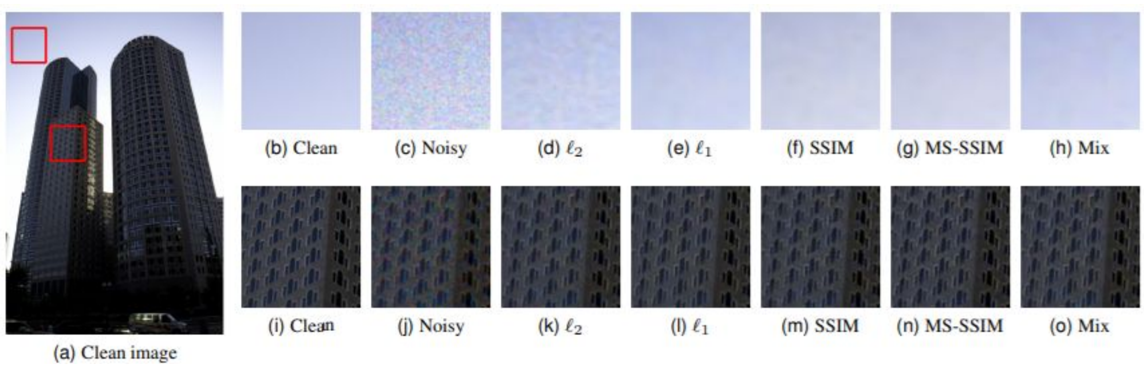


Fig 2.3 - Loss Function Variations

And finally, we deal with Data Augmentation. It is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collecting new data. Data augmentation techniques such as cropping, padding, horizontal flipping are used to train large neural networks.[7]

Fig 2.4 - Data Augmentation Chart

CHAPTER 3

PROJECT ANALYSIS/ PROJECT IMPLEMENTATION

3.1 Technology Used and Basic Framework

The basic working principle of the project is dependent upon Deep Learning algorithms through which we analyze the noisy and corrupted image and run it through an optimized model that we have trained to give the most accurate results in as little time as possible.

The implementation of the Deep Learning algorithm is done through Python mainly and by making use of third-party libraries that are commonly used for Machine Learning projects to make working much more easier. They are:

- **NumPy:** It is a library for the Python programming language, adding support for large, multidimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.
- **Google Colab Patches:** Collaboration specific python libraries with a variety of different functions that provide ease of use.
- **TensorFlow:** It is a software library for data flow and differentiable programming across a range of tasks.
- **Multiprocessing:** It is a package that supports spawning processes using an API similar to the threading module.

3.2 Details of the Deep Learning Model

3.2.1 Workflow

A simple flowchart of the standard methodology is given below. The provided flow chart forms the basis of most Machine Learning operations though depending on the conditions, a step may be minimized or expanded. For example, for a dataset that has already been cleaned and provided to the researcher, the data cleaning and transformation part of data extraction is thoroughly minimized. In our current project, we follow each and every step in order to produce the output required by the problem statement.[3]

Dataset - We have used the Dogs vs Cats dataset. It contains pictures of cats and dogs. The reason to pick this dataset was that it was very not very convenient to upload 600 MB of dataset repeatedly in google collab. Since we had its fast API, we were able to train many models with the collab instances. Also, we wanted the Neural Network model to understand the picture. The model should understand the images and use its knowledge to fill the noise. (e.g. If an eye of the cat is 'noised' than the model should know how an 'eye' looks like to fill in the noise) Since to do the last part in the real world would require lots more data and computational power, the above dataset was adequate to train a prototype.While doing our training, we used 2000 images for training and another 1000 images for validation. While feeding the images to the pipeline, it gets resized to (512,512). This size was chosen because it would provide denoising on a reasonably decent size of an image and was computationally less expensive.

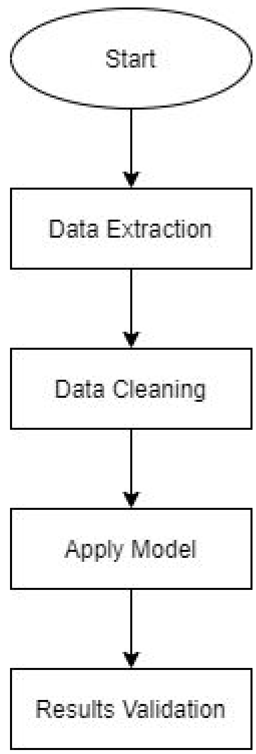


Fig 3.1 - Planning Model

The process by which we have obtained these models is done through exposure to different types of noises, data augmentation of the image database and finally, giving it a self supervising nature. The details of which are as follows.

3.2.2 Noise

In this project, we have considered three noises. The Neural Network will be trained to take care of all these three noises. The noises taken into consideration are: pepper, salt, localvar. [5]

Salt-and-pepper noise is a form of noise sometimes seen on images. It is also known as impulse noise. This noise can be caused by sharp and sudden disturbances in the image signal.

While **localvar** is zero-mean Gaussian white noise with an intensity-dependent variance.

Before the image is fed to model for training. It would be assigned layers of any of the above three noises randomly with equal probability.

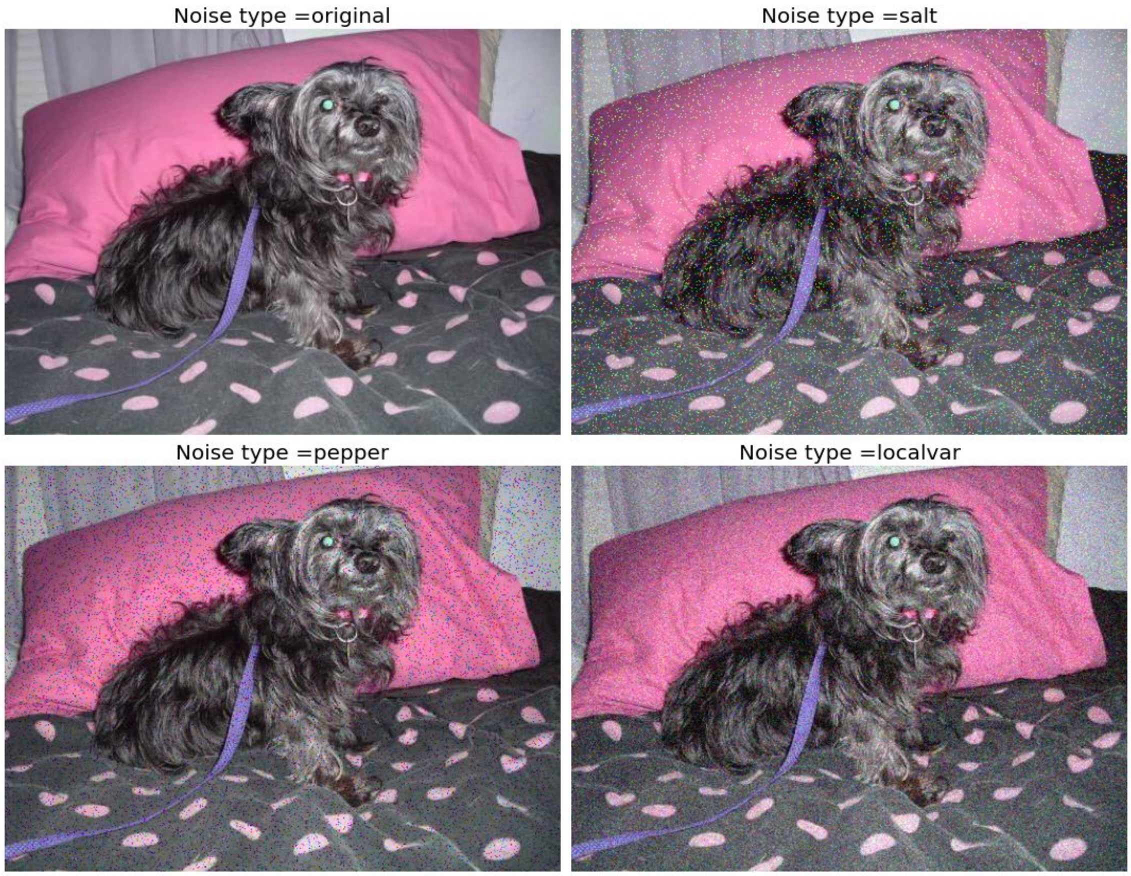


Fig 3.2 - Noise Chart

3.2.3 Data Augmentation

Data augmentation is used when we don’t have enough training data. Also, it has the effect of regularization. In dealing with deep learning models, too much learning is also bad for the model to predict with unseen data. If we get good results in training data and poor results in unseen data (test data, validation data) then it is framed as an overfitting problem. [2]

The usual way of doing the data augmentation is by flipping, cropping, flipping, zooming, shearing etc. But here we have taken a different approach. Every time the noise produced by the noise function differ, even if the noise-type and the image are the same. This helps us to feed the model with unique images every time. Apart from this, as discussed above each image fed to the model would be randomly assigned a noise type in every epoch. Thus creating even more augmentation.

3.2.4 Self-Supervising Nature

Given a task and enough labels, supervised learning can solve it well. Good performance usually requires a decent amount of labels, but collecting manual labels is expensive and hard to be scaled up. So to get examples of images which are first corrupted and another image which is clean manually is expensive.

Therefore we are using self-supervised learning, where using a subset of the information we are trying to predict the whole information. In our project, the subset being the corrupted image in which some information has been destroyed by corruption and the Deep Learning model are tasked to find the original image which has full information.

In the context of an optimization algorithm, the function used to evaluate a candidate solution (i.e. a set of weights) is referred to as the objective function. We may seek to maximize or minimize the objective function, meaning that we are searching for a candidate solution that has the highest or lowest score respectively. Typically, with neural networks, we seek to minimize the error. As such, the objective function is often referred to as a cost function or a loss function and the value calculated by the loss function is referred to as simply “loss.” The cost or loss function has an important job in that it must faithfully distill all aspects of the model down into a single number in such a way that improvements in that number are a sign of a better model. In this project, we have used five loss functions to evaluate our models: **binary cross-entropy, mean absolute error, mean squared error, mean squared logarithmic error, root mean square error**.[6]

3.2.5 Evaluation Methodology

As stated earlier, we would be utilizing novel differentiable loss functions to further optimize our models. Since our models would be training with different loss functions, how would we decide which of this loss function is most suitable for that model? Since each training will be optimized for its respective loss function, it is hard to judge based on the loss function we are training. For that, we introduce two metric called PSNR and SSIM. [4]

PSNR - Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). When comparing compression codecs, PSNR is an approximation to the human perception of reconstruction quality.

SSIM - structural similarity index measure is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. The difference with other techniques such as PSNR is that these approaches estimate absolute errors. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene.

Visual Inspection - We might have a good SSIM or PSNR it still does not convey the complete information. For example, while doing the task, we came across moments where one loss function would have a better result compared to another loss function but it did not have the same visual appearance as it would be in greyscale. But the other one was at least colourful. Therefore we would give more preference to the latter one.

Note - In this project, the SSIM and PSNR are tweaked a little because they were initially meant to be a loss function. Generally speaking the more the score for the above two parameters the better, but to be used as a loss function, we have subtracted the score from a constant. For SSIM it gets subtracted from the constant 1, for PSNR it's 100.

Utilizing all the above concepts, our end result provides us with two different multi-layer model plans, the details of which are given as follows.

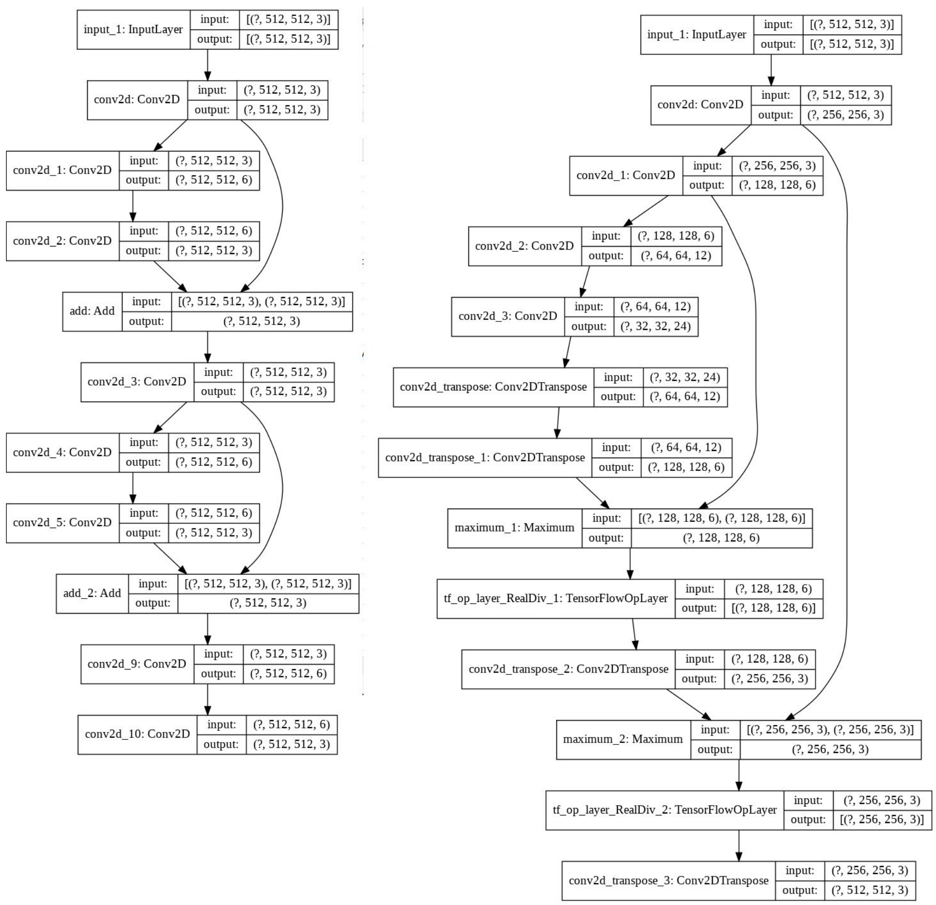


Fig 3.3 - Model 1(left) and 2(right)

CHAPTER 4

RESULTS & DISCUSSIONS

We have obtained multi-layer keras models that can produce our desired outputs and have some slight variations over different loss functions. In total we trained 6 models 5 times each to get the perfect model.

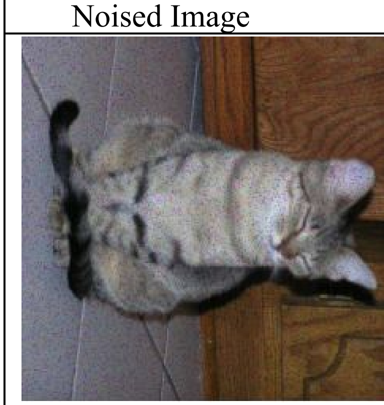
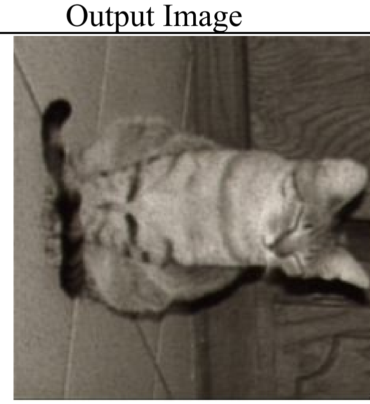
Initially we implemented the models on a smaller scale to not overuse on functional power of the device, however the results yielded were not quite optimal.This was basic CNN without any fancy reduction or enhancement.

4.1 Small Model 1

	psnr	ssim	val_psnr	val_ssim
mean_absolute_error	77.5180512	0.164697319	77.39402008	0.160369664
mean_squared_error	77.468277	0.182225436	77.43453979	0.180910692
mean_squared_logarithmic_error	77.5390015	0.176632673	77.3629303	0.172862947
binary_crossentropy	92.4231644	0.618482411	92.51177216	0.617099345
root_mean_square_error	77.6619263	0.159340799	77.5745163	0.157089517

Table 4.1 - Loss Function Table, Small Model 1

Mean Absolute Error:

Noised Image	Original Image	Output Image
		

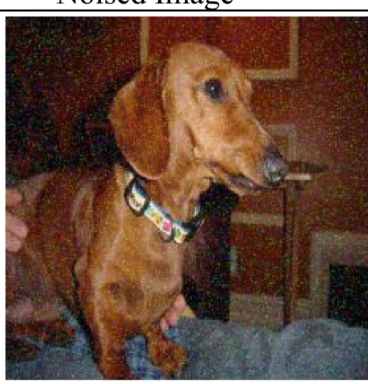
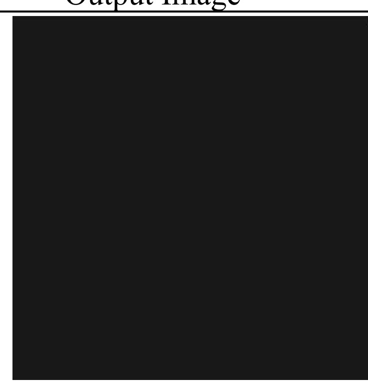
Mean Squared Error:

Noised Image	Original Image	Output Image
		

Mean Squared Logarithmic Error:

Noised Image	Original Image	Output Image
		

Binary Cross-entropy:

Noised Image	Original Image	Output Image
		

Root Mean Squared Error:

Noised Image	Original Image	Output Image

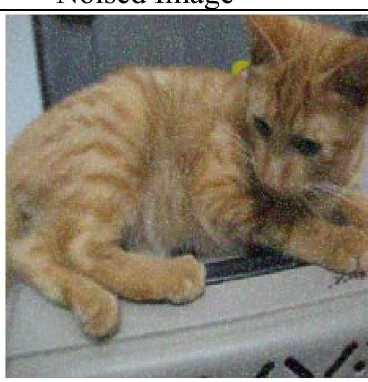
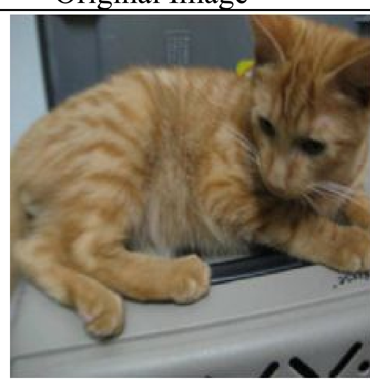
Table 4.2 Small Model 1 Results

4.2 Small Model 2

	psnr	ssim	val_psnr	val_ssim
mean_absolute_error	77.2016907	0.161936164	77.02906036	0.157870173
mean_squared_error	77.1237412	0.167407557	76.99915314	0.164021268
mean_squared_logarithmic_error	77.1833572	0.169199675	77.06600189	0.164938614
binary_crossentropy	78.6688232	0.188216522	78.57487488	0.185146853
root_mean_square_error	77.5634155	0.159660667	77.26954651	0.154742107

Table 4.3 - Loss Function Table, Small Model 2

Mean Absolute Error:

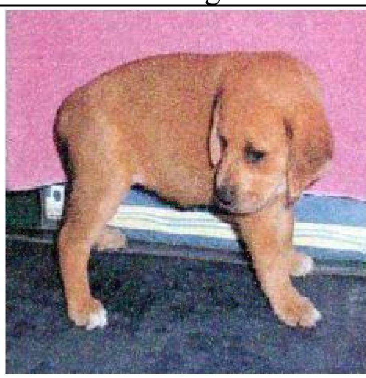
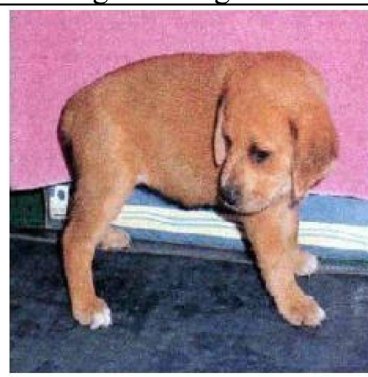
Noised Image	Original Image	Output Image
		

Mean Squared Error:

Noised Image	Original Image	Output Image

Mean Squared Logarithmic Error:

Noised Image	Original Image	Output Image
		

Binary Cross-entropy:

Noised Image	Original Image	Output Image
		

Root Mean Squared Error:

Noised Image	Original Image	Output Image

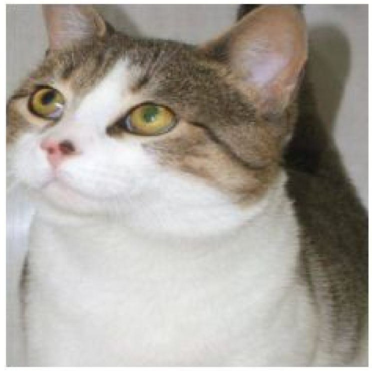
		

Table 4.4 Small Model 2 Results

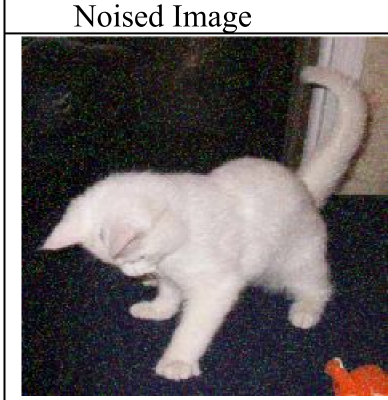
Looking at the results of the small scale models, we can see the output images are not up to mark. At the expense of denoising, there is a great color desaturation. In case of Model 1 with Binary Cross Entropy, the output image cannot even be produced successfully. Therefore we can conclude that working on a small scale model to reduce expense of processing power will not produce satisfactory results, therefore we will run the models now on the intended scale and note the outputs.

4.3 Normal Model 1

	psnr	ssim	val_psnr	val_ssim
mean_absolute_error	74.6228714	0.150534526	74.59646606	0.146914408
mean_squared_error	75.0358505	0.167864487	74.84015656	0.16260846
mean_squared_logarithmic_error	74.9759979	0.168272495	74.84119415	0.16342856
binary_crossentropy	76.6885681	0.220203519	76.5831604	0.216193229
root_mean_square_error	74.6463547	0.146015182	74.45915222	0.140886039

Table 4.5 - Loss Function Table, Regular Model 1

Mean Absolute Error:

Noised Image	Original Image	Output Image
		

Mean Squared Error:

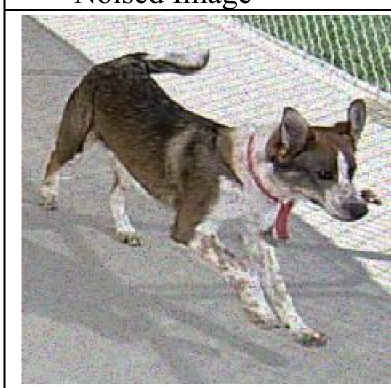
Noised Image	Original Image	Output Image

Mean Squared Logarithmic Error:

Noised Image	Original Image	Output Image
		

Binary Cross-entropy:

Noised Image	Original Image	Output Image
		

Root Mean Squared Error:

Noised Image	Original Image	Output Image

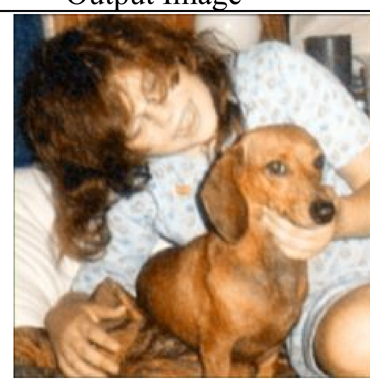
Table 4.6 Model 1 Results

4.4 Normal Model 2

	psnr	ssim	val_psnr	val_ssim
mean_absolute_error	75.2403183	0.181876406	75.13365173	0.175980255
mean_squared_error	75.6628876	0.209590882	75.50311279	0.202494204
mean_squared_logarithmic_error	75.9857788	0.219460398	75.90711212	0.212991104
binary_crossentropy	78.6676712	0.252135158	78.50704193	0.245239481
root_mean_square_error	75.1729813	0.164756015	75.26517487	0.162057608

Table 4.7 - Loss Function Table, Regular Model 2

Mean Absolute Error:

Noised Image	Original Image	Output Image
		

Mean Squared Error:

Noised Image	Original Image	Output Image

Mean Squared Logarithmic Error:

Noised Image	Original Image	Output Image
		

Binary Cross-entropy:

Noised Image	Original Image	Output Image
		

Root Mean Squared Error:

Noised Image	Original Image	Output Image

Table 4.8 Model 2 Results

The above models were a bit advanced compared to the small models. The Model 1 had skip connection for faster gradient descent. While model 2 was symmetric skip autoencoder. After looking at the working of models on the intended scale, we can conclude that our objective is being accomplished to some degree. Our model can definitely recognize the subject of the image and reduce noise to a great degree, however the issue of desaturation is not fully dealt with. We can make this statement because the subject of the picture has little to no desaturation, however the colors of the background are warped to some degree. And despite successful denoising, there is a loss in clarity somewhat. Also we see the effect of auto encoder blurring to some effect. Therefore, we have attempted to optimize the model to see if even better results are yielded.

4.5 Enhanced Model 1

	psnr	ssim	val_psnr	val_ssim
mean_absolute_error	72.8025818	0.12716563	72.67139435	0.123514801
mean_squared_error	72.3105621	0.131467521	72.30859375	0.128433138
mean_squared_logarithmic_error	72.3086853	0.128427878	72.43410492	0.127882451
binary_crossentropy	73.7378922	0.139767364	73.70685577	0.13732329
root_mean_square_error	73.2003021	0.128107086	73.05870819	0.125998452

Table 4.9 - Loss Function Table, Enhanced Model 1

Mean Absolute Error:

Noised Image	Original Image	Output Image

Mean Squared Error:

Noised Image	Original Image	Output Image
		

Mean Squared Logarithmic Error:

Noised Image	Original Image	Output Image
		

Binary Cross-entropy:

Noised Image	Original Image	Output Image

Root Mean Squared Error:

Noised Image	Original Image	Output Image
		

Table 4.10 Enhanced Model 1 Results

4.6 Enhanced Model 2

	psnr	ssim	val_psnr	val_ssim
mean_absolute_error	71.5238724	0.120229304	71.41674042	0.117946759
mean_squared_error	71.0620346	0.121074967	70.92246246	0.119652778
mean_squared_logarithmic_error	71.1240158	0.11828728	71.01902771	0.116523519
binary_crossentropy	71.7444916	0.122045636	71.63186646	0.120339848
root_mean_square_error	71.5531998	0.117445268	71.49491119	0.116963819

Table 4.11 - Loss Function Table, Enhanced Model 2

Mean Absolute Error:

Noised Image	Original Image	Output Image

Mean Squared Error:

Noised Image	Original Image	Output Image
		

Mean Squared Logarithmic Error:

Noised Image	Original Image	Output Image
		

Binary Cross-entropy:

Noised Image	Original Image	Output Image

Root Mean Squared Error:

Noised Image	Original Image	Output Image
		

Table 4.12 Enhanced Model 2 Results

The model 2 was an autoencoder model which took an image, compressed it using an encoder and then again expanded on it by a decoder. So we thought about using an inverted form of autoencoder.(i.e. We first expand the image with the help of encoder and then compress it to its right size). Looking at the results from the enhanced models we can see that the issues of desaturation and loss of clarity have been almost completely eradicated, leaving us with an almost fully accurate image restoration. Thus our desired result was finally achieved. One interesting observation we saw during this was that noise on subjects was removed much better than the background noise. It shows that the neural network learned how a cat of dogs looks and uses its knowledge to fill the noise on them much better.

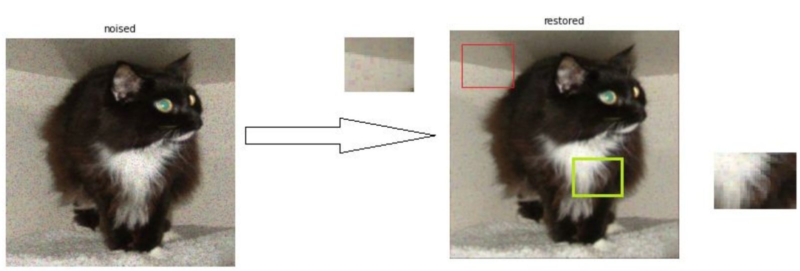


Fig 4.1 - Showing the observation where the model denoised the portion of cat nicely(Green box) but was not able to fill the noise of background(red box).

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

As we can see, utilizing multi-layer deep learning models and applying differentiable loss functions as hyperparameters, we can effectively restore noised images through some decent processing power. Initially we attempted to achieve the same through small scale models, however it resulted in total desaturation of output image. Hence we used the intended scale which gave us better results with subject recognition and minimization of desaturation, however loss of clarity remained an issue. Thus finally, we used fully optimized and enhanced models which produced nearly fully accurate restorations.

5.2 Future Work

Now that we have effectively produced self-supervising models with variations that can adapt to multiple types of noise, our future scope would be to make our work more easily approachable by providing its services through a mobile application or online website. This would allow a layman with no knowledge of using python systems to utilize the image de-noising service.

5. 3 Planning And Project Management

Activity	**Starting week**	**Number of weeks**
Background Study and Research	1st week of July	4
Finalizing Plan/Approach	1st week of August	1
Data Augmentation of Image Database	2nd week of August	2
Noising of Images	1st week of September	1
Designing the Model	2nd week of September	3
Applying Loss Functions	2nd week of October	2

Optimizing Model	1st week of November	2

Table 5.1 Schedule

The Gantt chart is shown below:

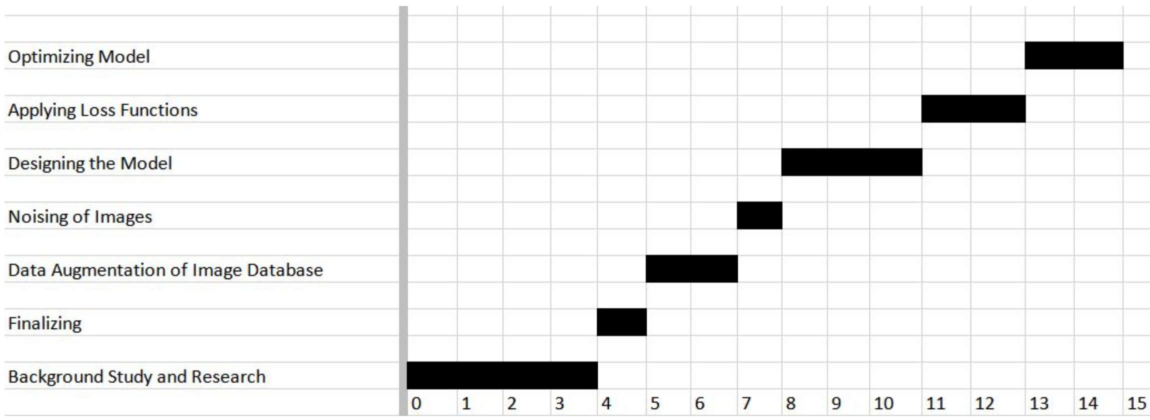


Fig 5.1 Gantt Chart

REFERENCES

[1] *https://www.cambridgeincolour.com/tutorials/image-noise-2.htm*

[2] *https://cs.stanford.edu/people/rak248/VG_100K_2/*

[3] *https://deepai.org/machine-learning-glossary-and-terms/*

[4] *https://matplotlib.org/*

[5] "Introduction to image de-noising" by Nabil Madali

[6] Image Restoration, Computer Vision

[7] Multi-Scale Structural Similarity Index for Image Quality

[8] Standford Engineering, CS, Image Processing and All You Need to Know, Prof. Wang Lee, Prof. Elliot Junes

INDIVIDUAL CONTRIBUTION REPORT:

IMAGE RESTORATION

BISWAJEET SAHOO

1705689

Abstract: The commonly occurring issue of image restoration is what we are attempting to solve through our project. We achieve this through deep learning models. But not only are we attempting to restore the original image once it has been corrupted, we are also training the model to be the most efficient model possible that can also adapt to new types of noise and produce an accurate output image.

Individual contribution and findings: I worked on model creation along with my fellow teammate Kush. In addition to that, I was mainly involved in training and testing the models as well as evaluating them in an attempt to find out the best possible model for our project. I was also involved in some visualization work.

Individual contribution to project report preparation: My contribution to project report preparation was regarding model training, their results and its evaluation.

Individual contribution for project presentation and demonstration: During the presentation I was responsible for the work in producing the slides related to my individual contribution to the bulk of the project, as well as being responsible for any explanation or demonstration related to them.

Full Signature of Supervisor:

……………………………

Full signature of student:

Biswajeet Sahoo

INDIVIDUAL CONTRIBUTION REPORT:

IMAGE RESTORATION

DAIBIK DASGUPTA

1705692

Abstract: The commonly occurring issue of image restoration is what we are attempting to solve through our project. We achieve this through deep learning models. But not only are we attempting to restore the original image once it has been corrupted, we are also training the model to be the most efficient model possible that can also adapt to new types of noise and produce an accurate output image.

Individual contribution and findings: I have worked on the initial research of prior attempts at image restoration model along with fellow teammate Kush. Through our findings, we were able to develop the plan to produce a growing and adaptive model, as well as the specifics about how to go about it, and how to make a model as efficient and accurate as possible in this domain.

Individual contribution to project report preparation: I was involved in initial research of producing a model that can achieve our end goal. I also worked on finding suitable image databases that we can work with. Finally, I have aided in the writing of basic concepts regarding the same.

Individual contribution for project presentation and demonstration: During the presentation I was responsible for the work in producing the slides related with my individual contribution to the bulk of the project, as well as being responsible for any explanation or demonstration related to them.

Full Signature of Supervisor:

…………………………….

Full signature of student:

DDasGupta.

Daibik DasGupta

INDIVIDUAL CONTRIBUTION REPORT:

IMAGE RESTORATION

KUSH JAYANK PANDYA

1705701

Abstract: The commonly occurring issue of image restoration is what we are attempting to solve through our project. We achieve this through deep learning models. But not only are we attempting to restore the original image once it has been corrupted, we are also training the model to be the most efficient model possible that can also adapt to new types of noise and produce an accurate output image.

Individual contribution and findings: I have worked on the initial research of prior attempts at image restoration model along with fellow teammate Daibik. With respect to finding I was mainly involved in evaluation parameters and augmentation. I was also involved in creating end to end pipelining for our model evaluation. Because of which we were able to train multiple models. Also I was involved with my fellow team members Biswajeet for model creation.

Individual contribution to project report preparation: My contribution to project report preparation was with respect pipelining and evaluation and data augmentation.

Individual contribution for project presentation and demonstration: During the presentation I was responsible for the work in producing the slides related with my individual contribution to the bulk of the project, as well as being responsible for any explanation or demonstration related to them.

Full Signature of Supervisor: Full signature of student:

Kush

……………………………. Kush Jayank Pandya

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