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SOFT COMPUTING APPROACHES FOR IMAGE RESTORATION USING HYBRID FILTERS

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Abstract: ***Image is a key of digital data which is used in many studies and research work as dataset. These datasets are compromised due to distortion which is caused by the presence of noise. Occurrence of noise is found while capturing image, transmission of pictorial data over different networks, etc. Noise plays a vital role in image corruption and this noise can also exist individually with varying intensities of different noise factor or also as hybrid noise [i.e Combination of different noises]. In general, the results of denoising have a strong influence on the quality of the image processing techniques. The nature of the noise removal problem depends on the type of the noise corrupting the image. The most commonly affected noises in image are Salt and Pepper, Speckle, Gaussian and Poisson noise.***

To restore these degraded images, many de-noising algorithm has been developed and one among them are filtering techniques. In this research work, three filters are considered for denoising i.e. Weiner filter, Gaussian filter and Median filter. The current work is implemented on gray scale and colored [RGB] images and the evaluation of these algorithms is done by the measure of the PSNR and MSE values. In addition, we propose to use hybrid filter along with deep learning algorithm for denoising coloured images. The main purpose of using AlexNet is to train and classify the dataset. Successful training and classification of the dataset is based on the accuracy of training session of AlexNet and the accuracy of confusion matrix.

Index Terms – Image Restoration, Hybrid Noise, Hybrid Filter, Deep Learning, AlexNet

1. INTRODUCTION:

The field of digital image processing entails the use of a computer to process digital images. An image's composition is made up of a limited number of pieces, each with its own placement and value. Picture elements, image elements, pels and pixels are all terms used to describe these elements. The term "pixel" is most commonly used to describe the components of a digital image. An image is a two-dimensional function that represents a measure of some attribute of an observed scene, such as brightness or colour. A projection of a three-dimensional scene into a two-dimensional projection plane is called an image. Gray level is a phrase that is frequently used to describe the intensity of monochrome images. Color images are created by combining discrete 2-D images.

Image restoration is a process for enhancing the appearance of an image. When exhibited, all natural photos have been corrupted in some way, whether in display mode, capture mode, or processing mode. The primary goal of restoration is to improve the quality of a digital image that has been deteriorated due to various types of noise or obscurity superimposed onto it. In image processing, noise removal is a crucial step. Various types of noise can make a picture illegible and clear, which can be a problem in many image processing applications. These include Gaussian noise, Salt & Pepper noise, Speckle and Poisson noise or a hybrid of the above mentioned noises.

Degradation is a process that works on a degradation function which in turn works on an input image along with an additional noise term. The corrupted image is given in the spatial domain by $g(x,y)=f(x,y)*h(x,y)+\eta(x,y)$ if the degradation model is a linear position invariant process . Here the $h(x,y)$ is spatial representation of degradation function and also the symbol * represents convolution. In frequency domain this equation can be written as $G(u,v)=F(u,v)H(u,v)+N(u,v)$ .The Fourier Transform of the corresponding terms in the spatial domain are the terms in capital letters.

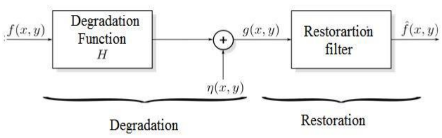


Fig 1.1 Restoration/ Degradation Model

The noise has influenced the images up to some extent, that's unexplained selection in information: disturbances in image intensity that don't seem to be the ROI. If the noise could be removed then the image analysis is commonly simplified. In a comparable to seem to way, in science to liberate the fluids from the suspended pollutions ,the filters concept is applied by going through the suspended pollutions a layer of sand or charcoal. Engineers operating in signal processing have expanded the importance of the term filter to include operations which highlights the features of interest in images. Thus filters can attenuate the noises and improve the other features of the image. The images are rectified utilizing different filters like linear filters, non-linear filters , hybrid filters, decision- based filters, etc so as to recover the original properties or characteristics of the original image. In this work Median filter, Gaussian filter, Weiner filter and a hybrid of the mentioned filters are used.

AI (Artificial intelligence) is a branch of computer science in which machines are programmed and given a cognitive ability to think and mimic actions like humans and animals. The benchmark for AI is human intelligence regarding reasoning, speech, learning, vision, and problem solving, which is far off in the future.

ML (Machine Learning) is a type of AI in which a computer is trained to automate tasks that are exhaustive or impossible for human beings. It is the best tool to analyze, understand, and identify patterns in data based on the study of computer algorithms. Machine learning can make decisions with minimal human intervention.

Deep learning is a computer software that mimics the network of neurons in a brain. It is a subset of machine learning and is called deep learning because it makes use of deep neural networks. The machine uses different layers to learn from the data. The depth of the model is represented by the number of layers in the model. Deep learning is the new state of the art in term of AI. In deep learning, the learning phase is done through a neural network. A neural network is an architecture where the layers are stacked on top of each other.

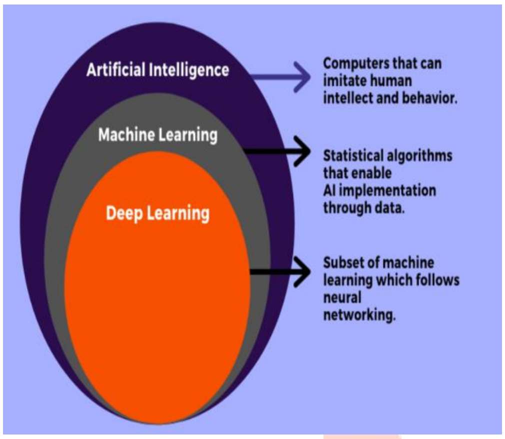


Fig 1.2 Overview of AI, ML and Deep Learning

Deep Convolutional Neural Networks (DCNNs) are consists of compound layers of networks that are essentially learnt through each layer. Nonetheless, the feature extraction develops with the level of layers. Transfer Learning gives the capacity to use the pre-trained networks by fine-tuning it with domain-specific information. The essential part of transfer learning is to reuse information accomplished in a previous training process, to boost the learning strategy in new or more perplexing mission. As such, transfer learning gives an appropriate key to accelerating the learning strategy in image classification , image recognition , eye tracking and gaming. This idea is particularly useful for the challenging task of learning classifiers that need to perform well when just hardly any training models are given . Learning a new task begins from scratch and requires a huge amount of training data. Transfer learning proposes a solution to reuse the previously learned knowledge to other issues where little information is available to further improve the learning task.

2. LITERATURE SURVEY:

[1]Bhausaheb Shinde Dnyandeo Mhaske, Machindra Patare A.R. Dani (2012) The outcomes given by Weiner Filter and Median Filter are better contrasted with different filters to eliminate Speckle noise, Gaussian noise and Poisson noise and other noises present in the image. Weiner filter's benefit is it eliminates the additive noise and inverts the blurring simultaneously . Median filter's benefit is to eliminate outlines of an image while the quality of the image is not reduced..

[2] Rakesh M.R , Ajeya B , Mohan A.R (2013) Linear filters and non-linear filters are utilized to remove noise. The primary drawback of linear filters are they cannot totally remove the salt &pepper noise as they have a tendency to obscure the edges of an image while the non linear filters are mostly used to remove impulse noise .In this work ,the different filters used to denoise the colored images are examined .This method guarantees noise free and better quality of the images. The principle benefits of this median filter are the de-noising capability of the destroyed color component differences. But the fundamental downside is this method builds the computational intricacy.

[3]Medhavi Aggarwal, Ranjit Kaur and Beant Kaur (2014) The median filter is ideal contrasted with mean filter and adaptive filter to eliminate salt and pepper noise. The adaptive filter performs better than the mean filter but the drawback is it has additional time intricacy.

[4]Gurpinder Kaur Sivia, Amanpreet Kaur (2014) This paper presents Hybrid Filling-in technique for image restoration in which two filling-in procedures are utilized to reestablish the damaged image. In the first place, in the hybrid technique the distortion in the pixels is found out by executing Probabilistic Recovery Filling-in strategy . In this procedure, utilizing data from the surrounding pixels, the corrupted and missing pixels are established by low density of pixels and restored. Next the proposed filling-in technique is carried out to restore the noisy and distorted image where the GLCM is used to filter the properties of image. In the proposed work a thresholding strategy is created for restoration where the image can resist to the noise and any other distortion, and retain the property of the image in the original stage . After applying Probabilistic Recovery Filling-in technique, there are some distortions left which are eliminated to a large extent generally by carrying out proposed filling-in method. It tends to be presumed that the combination of these two strategies gives better outcomes.

[5]Abdalla Mohamed Hambal , Dr. Zhijun Pei, Faustini Libent Ishabailu(2015) There is a improved filter called hybrid median filter which preserves the corners and eliminates the impulse noise better than median filter. The benefits of hybrid median filter are it is easy to comprehend, it preserves the brightness difference and edges better than the median filter. The downside of hybrid median filter is only impulse noise can be denoised, the computational expense is high and it is a non-linear filter. Over rehashed application, the hybrid median filter does not inordinately smoothen the image details.

[6]Monika Kohli, Harmeet Kaur (2015) A comparative study of the proposed filter, Median filter and Adaptive median filter is done. The proposed Median filter is utilized to filter Impulse noise. The procured results indicate that the proposed strategy is much better than the standard median filter and the adaptive median filter. The Peak Signal to Noise Ratio (PSNR) is improved utilizing this strategy and the original features of the images are preserved.

[7]Ankita, Er. Lavina (2016) The proposed filter is a decision based filtering technique which combines the K-means and PCA procedure that is utilized for diminishing the undesirable noise henceforth gives better quality of images. The limitation of the hybrid filter is overcome by this suggested decision based filtering technique and the experimental results recommends better outcomes for decision based filtering technique contrasted with the hybrid filter.

[8] Roy, S. S., Ahmed, M., &Akhand, M. A. H. (2018) In this paper the fundamental goal was to look at the DNN-based better noisy image classification model . First the autoencoder (AE)- based denoising strategies are applied to recreate the corrupted picture to recover the original image . Later the convolutional neural organization (CNN) is applied to classify the reconstructed image . An assortment of existing AEs, to be specific denoising autoencoder (DAE), convolutional denoising autoencoder (CDAE) and denoising variational autoencoder (DVAE) just as hybrid AEs (DAE-CDAE and DVAECDAE) are utilized in the denoising step. This exploration work proposed five supervised deep architectures named DAE-CNN, CDAE-CNN, DVAE-CNN, DAE-CDAE-CNN and DVAE-CDAE-CNN among which the initial three designs give better outcomes when a modest quantity of noise is added to the images though, the last two designs are utilized when the images are exposed to enormous noise.

[9] Ali Abd Almisreb, Nursuriati Jamil, N. Md Din (2018) This paper intends to explore the usage of the Transfer Learning in the space of human acknowledgment dependent on the ear image . Propelled by the way that the moved CNNs need less amount of information contrasted with the CNNs trained from scratch , AlexNet is used in this paper. The calibrated AlexNet CNN is embraced to suit the difficulty in the domain . The last fully connected layer is supplanted with another completely fully connected layer to perceive 10 classes rather than 1000 classes. Another Rectified Linear Unit (ReLU) layer is additionally added to improve the non-linear problem-solving ability of the network. Then, at that point the AlexNet is fine-tuned dependent on the datasets. The proposed fine-tuned network accomplished 100% accuracy for static pictures.

[10] Cheng Dong, Zhiwang Zhang, Jun Yue, Li Zhou (2018) To improve the classification accuracy of strawberry diseases and pests, this paper proposed an improved operator-based convolutional neural network (CNN) approach for classification of images of strawberry diseases and pests. First and foremost, by utilizing the deep learning technique of Pytorch, the AlexNet model is calibrated with the goal that it was utilized to train the image dataset of strawberry diseases and pests. Next, combining inner product with 2 -norm, a new operator is proposed to supplant the inner product operator between input values and weights in the fully connected layers of the AlexNet model. Then the proposed operator was applied to classification of strawberry diseases and pests. Then, at that point the proposed administrator was applied to order of strawberry diseases and pests. The exploratory outcomes verified that the proposed strategy can promote the accuracy of classification for strawberry diseases and pests effectively under same parameters.

[11] Mayur Thakur, Sofia K. Pillai (2019) In this paper, the primary goal is to inspect the DNN-based improved noisy image classification model. A hybrid of denoising auto-encoder, convolutional denoising auto-encoder then utilizing a classifier which is a fusion of two distinct models one is Convolutional Neural Network (CNN) and the other is outrageous Gradient Boosting (XGBOOST) are utilized. By applying CNN as a trainable component for extracting features from the input dataset and at the last stage XGBoost as an identifier can be utilized for improving and precise outcomes. The noise elimination as well as classification outcome has been tested on the MNIST dataset .

[12]Reeturaj Mishra , Neetu Mittal , Sunil Kumar Khatri (2019) In this paper, a comparsion of Median filter, Weiner filter and Lucy Richardson filter is made. The evaluation parameters used are Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE) and Structural Similarity Index(SSIM) .From the trial results obtained, it very well may be inferred that Lucy Richardson algorithm is the best image restoration procedure which is assessed utilizing the parameters, such as PSNR, SSIM, and MSE . In an image with Gaussian blur noise model, every one of the three strategies have great outcomes however Lucy-Richardson algorithm ends up being the best. The Lucy-Richardson algorithm likewise ends up being a preferable strategy over the Weiner filter to eliminate the Gaussian noise .Additionally the PSNR values acquired indicate that each algorithm has an insufficient margin with each other and also with the other evaluating parameters.

[13] Fumio Hashimoto, Hiroyuki, Kibo Ote, Astushi Teramoto, Hideo Tsukada (2019) The proposed work have the dynamic PET image denoising utilizing a DIP approach. Positron emission tomography (PET) is a non-invasive imaging methodology for progressively estimating the pharmacokinetics of target-explicit PET tracers in a living body. It is applied not exclusively to malignant growth conclusion yet in addition to the early discovery of neurodegenerative infections like Alzheimer's and Parkinson's illness. In the proposed work the DIP technique is utilized for computer simulations and furthermore to the real data procured from a living monkey cerebrum with F-flfluoro-2-deoxy-D-glucose(F-FDG). As a simulation result, the DIP strategy delivered have not so much noise but rather more more accurate dynamic images than the other algorithms.Computer simulation dependent on F-FDG kinetics demonstrated that the DIP strategy diminished the statistical noise, while preserving the cortex structures, and accomplished an improved quantitative TAC precision, contrasted with different algorithms. In addition, real F-FDG data, acquired from a living monkey brain, indicated that the DIP method outperformed the other algorithms in terms of CNR.

[14] Ding Liu, Bihan Wen, Jianbo Jiao, Xianming Liu, Zhangyang Wang, Thomas S.Huang (2020)This paper explores the connection between low-level image processing and high level semantic errands has extraordinary viable worth in different utilizations of computer vision. This paper handles these two segments in a straightforward yet proficient manner by permitting the high level semantic data to stream back to the low-level image processing part, which accomplishes prevalent execution in both image denoising and various high-level vision tasks. The denoiser trained for one high-level vision task thusly has the robustness to other high-level vision tasks.

[15] Asavaron Limshuebchuey, Rakkrit Duangsoithong, Mongkol Saejia August (2020) In this work, a correlation of the image denoising algorithm utilizing peak signal to noise ratio (PSNR) among traditional and deep learning techniques on Gaussian noise and Salt and pepper noise condition is performed. Additionally, this experiment likewise contrasted the PSNR value of deep learning between noisy images to noisy image (N2N) learning scheme and noisy image to filtered image (N2C) learning scheme. As indicated by the outcomes, profound learning technique has PSNR outcome higher than traditional strategy and N2C learning scheme has PSNR outcome higher than N2N learning scheme.
As indicated by the outcomes, N2C strategy reestablishes and retains the image subtleties better than N2N calculation. ResNet architecture has higher PSNR than U-Net architecture. In any case, deep learning strategy has high intricacy to calculate.

[16] Kurian Thomas, Pranav E, Supriya M.H. (2020) In this paper, an assessment of the performance of the convolutional neural organization (CNN) is contrasted and other existing image denoising algorithms. To classify and perceive any sort of noisyimages, a generalized Deep Convolutional Neural Network model is suggested. In this work two kinds of models are looked at. The first model utilizes the Adam optimizer and the second model utilizes the Stochastic Gradient Descent (SGD) optimizer. In this test Poisson Noise, Gaussian Noise and Salt and Pepper Noise are added to the input images and experimented for the two models. Subsequent to training and testing the images it tends to be presumed that SGD optimizer model gives more exact outcomes when contrasted with the Adam optimizer model.

3. Proposed Work

The proposed work is divided into two parts. Part-A discusses about Image processing model that has been used in the work to denoise the image. Part-B discusses about deep learning model that has been used in the work to detect the noise present in the image.

PART – A

The proposed part of the work discusses denoising technique's which involves using individual and hybrid filter to denoise the images which are corrupted by individual or hybrid noise. The estimation of filtering techniques on the corrupted images is evaluated by Performance Parameters such as PSNR and MSE. Depending on the values obtained after filtering, best filter to denoise the input image will be chosen, for a better filtering analysis hybrid of the above filters is used.

- Images taken for consideration: Gray Scale image.
- Software used: MATLAB 2014 version.
- Base Noise: Gaussian Noise, Salt and Pepper Noise, Speckle Noise, Poisson Noise.
- Base Filters: Gaussian Filter, Median Filter, Wiener Filter.
- Performance Parameters taken into consideration are: PSNR and MSE

1) **Peak signal-to-noise ratio** The Peak Signal to Noise Ratio (PSNR) is the ratio of the quality of the original image to the reconstructed image. If the PSNR is high it indicates that the quality of the filtered image is better.
2**) Mean Square Error**: The MSE represents the cumulative squared error between the reconstructed image and the original image. It is a measure of the peak error. If the MSE is low it indicates that the error is low between the filtered image and the original images.

Block Diagram of Image Processing:

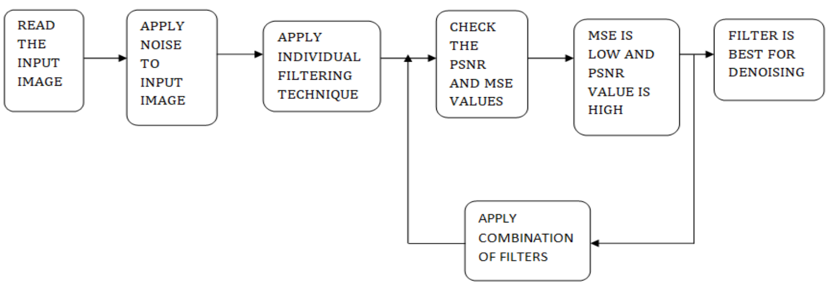


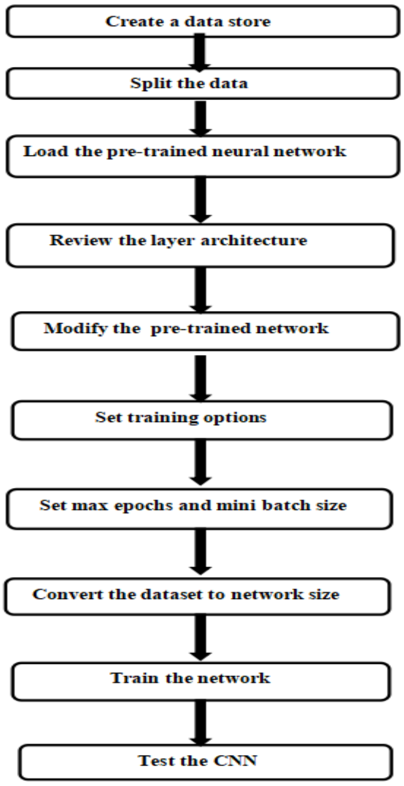
Fig 3: Methodology

The major steps of denoising algorithm on degraded images are as follows:
Step 1: Grayscale images are taken as input data set.
Step 2: By applying individual noise and hybrid noise for a better study.
Step 3: Analyze the type of noise and then apply denoising algorithm such as filtering techniques to eliminate noise and restore the image.
Step 4: Apply individual filters for denoising and also hybrid filters for better analyses.
Step 5: For choosing better filter among the applied filters, Performance Parameters such as MSE and PSNR are into consideration.
Step 6: If the value of MSE is low and PSNR is high then the filter applied is best for denoising.

Step7: Finally, we can get a better denoised image which removes noise better than the other filters.

PART- B

Block Diagram of Deep Learning:



A. Collecting the dataset

- The collected dataset contains the images of aircraft and the source of dataset is Kaggle. In total we have collected 1800 images of aircraft. The dataset has been grouped into training and testing data. The software used is MATLAB 2020 version.
- Pre-processing has been done by adding noise to the image. Both the groups will have noised images as the final dataset. The noised images are again classified into 15 different noises. These noises are obtained from the previous experimental data.
- The noised images are classified by labels and in this case the label name is noise name. Hence both the groups consist of 15 classes which comprise the noised images under each label.
- The noised image is considered as the input to the layers. The input image is cropped to the standard dimension of the input layer of AlexNet i.e. [227x227]

Fig 3.1: Aircraft image from the dataset before adding noise

Fig 3.2: Aircraft image from the grouped dataset after adding noise.

B. AlexNet Architecture

- There are many network models present in deep learning, we have opted AlexNet as our network because of the hardware compatibility and reduced complexity of training the network.
- AlexNet is most suitable network for our work as it has greater accuracy and speed. It can be used for classifying maximum of 1000 classes, as our work requires classification of 15 layers; hence it is the best network that could be used for training.
- The opted AlexNet is 8 layers deep and the pre-trained network model consists of 25 network layers.
- Each layer is assigned to perform a specific task. Few layers get repeated in pattern for performing the
- advanced tasks. The main layers of the network are discussed below:

Layer	Layer Name	Layer Type	Layer Details
1	'input'	Image Input	227x227x3 images with 'zerocenter'normalization
2	'conv1'	Convolution	96 11x11x3 convolutions with stride[4 4] and padding[0 0 0 0]
3	'relu1'	ReLU	ReLU
4	'norm1'	Cross Channel Normalization	Cross channel normalization with 5 channels per element
5	'pool1'	Max Pooling	3x 3 max pooling stride [2 2] and padding [0 0 0 0]
6	'conv2'	Convolution	256 5x5x48 convolutions with stride[1 1] and padding[2 2 2 2]
7	'relu2'	ReLU	ReLU
8	'norm2'	Cross Channel Normalization	Cross channel normalization with 5 channels per element
9	'pool2'	Max Pooling	3x 3 max pooling stride [2 2] and padding [0 0 0 0]
10	'conv3'	Convolution	384 3x3x256 convolutions with stride[1 1] and padding[1 1 1 1]
11	'relu3'	ReLU	ReLU
12	'conv4'	Convolution	384 3x3x192 convolutions with stride[1 1] and padding[1 1 1 1]
13	'relu4'	ReLU	ReLU
14	'conv5'	Convolution	256 3x3x192 convolutions with stride[1 1] and padding[1 1 1 1]
15	'relu5'	ReLU	ReLU
16	'pool5'	Max Pooling	3x 3 max pooling stride [2 2] and padding [0 0 0 0]
17	'fc6'	Fully Connected	4096 fully connected layer
18	'relu6'	ReLU	ReLU
19	'drop6'	Dropout	50% dropout
20	'fc7'	Fully Connected	4096 fully connected layer
21	'relu7'	ReLU	ReLU
22	'drop7'	Dropout	50% dropout
23	'fc8'	Fully Connected	1000 fully connected layer
24	'prob'	Softmax	Softmax

25	'classification layer'	Classification output	Crossentropyex

Table 3.1: Layers of Pre-trained Alexnet model

C. Modified Architecture

The pre-trained network model is modified according to the requirement

- Layer 23 [fc (fully connected layer)] is converted from 1000 layers to 15 layers.
- Layer 25 is modified to classify images under 15 noise labels. Only one noise label has to be triggered in the noise output out of 15 noise label.

22	'drop7'	Dropout	50% dropout
23	**'fc'**	**Fully Connected**	**15 fully connected layer**
24	'prob'	Softmax	Softmax
25	**'classoutput'**	**Classification output**	**Crossentropyex with 'Gaussian' and 14 other classes**

Table 3.2: Modified Layers of Pre-trained Alexnet

D. Performance Parameters

- We have used confusion matrix as a parameter to evaluate the process of classification. Confusion matrix used to check the accuracy of the training process if the images are classified correctly under the right label or not.
- Classification becomes more precise when accuracy of confusion matrix is high among both training and testing dataset.

4. RESULTS AND DISCUSSIONS:

Fig 4.1: The input image (cameraman.tif) is noised with combination of all the 4 noises i.e (salt & pepper + Gaussian + Speckle + Poisson) noise. Here the noisy image acts as an input image to the filters. Noise is added externally to note the changes. The noised image is denoised using Gaussian, wiener, medianfilter

Table 4.1: VALUES OF PSNR AND MSE OF INDIVIDUAL NOISE, INDIVIDUAL FILTER AND COMBINATION OF FILTER.

- Values of MSE are indicated in bold.
- Values which are not bold are PSNR values and they are in terms of db.

		Gaussian Filter	Wiener filter	Median filter	Median ,wiener Filter	Gaussian, Wiener Filter	Gaussian, Median Filter	Gaussian, Median, wiener Filter
Salt & pepper noise	MSE	**26.29**	**40.60**	**17.10**	**39.73**	**43.29**	**22.89**	**31.37**
	PSNR	33.9662115	32.0798093	35.8358405	32.1732138	31.8013038	34.5675859	33.1994626
Gaussian Noise	MSE	**84.44**	**63.04**	**85.12**	**58.14**	**60.76**	**78.22**	**58.74**
	PSNR	28.8992965	30.1684464	28.8644764	30.5203671	30.3289460	29.2316033	30.4758126
Speckle Noise	MSE	**69.73**	**42.18**	**67.37**	**41.99**	**42.90**	**63.63**	**51.27**
	PSNR	29.7307949	31.9135316	29.8799482	31.9329691	31.8400246	30.1281016	31.0663920
Poisson Noise	MSE	**30.83**	**26.94**	**28.05**	**29.33**	**31.02**	**29.83**	**33.79**
	PSNR	33.2746468	33.8604836	33.6850048	33.4909916	33.2490644	33.4181088	32.8771379

Table 4.2: Values of PSNR and MSE of combination of two noises, individual filter and combination of filter

Salt & pepper, Gaussian Noise	MSE	**84.40**	**66.49**	**84.74**	**63.56**	**66.78**	**80.49**	**61.45**
	PSNR	28.9013477	29.9370532	28.8838229	30.1330221	29.9183561	29.1071402	30.2795753
Salt & pepper, Speckle Noise	MSE	**73.26**	**54.87**	**69.17**	**52.00**	**55.31**	**66.42**	**54.17**
	PSNR	29.5160328	30.7716735	29.7657673	31.0043887	30.7368492	29.9418167	30.8274240
Salt & pepper, Poisson Noise	MSE	**40.63**	**42.85**	**30.76**	**41.44**	**45.44**	**31.91**	**35.16**
	PSNR	32.0766242	31.8448219	33.2855357	31.9906432	31.5904946	33.1253189	32.7043008
Gaussian, Speckle Noise	MSE	**95.11**	**78.97**	**105.94**	**76.67**	**77.62**	**100.16**	**88.14**
	PSNR	28.3823898	29.1899932	27.9140244	29.3185940	29.2649095	28.1578937	28.7130110
Gaussian, Poisson Noise	MSE	**85.87**	**65.47**	**87.07**	**60.19**	**62.80**	**79.80**	**60.80**
	PSNR	28.8262769	30.0042331	28.7659506	30.3695392	30.1850518	29.1446523	30.3259137
Speckle, Poisson Noise	MSE	**71.41**	**44.80**	**69.40**	**43.91**	**45.10**	**65.89**	**53.77**
	PSNR	29.6273758	31.6518857	29.7514112	31.7392974	31.6232802	29.9769100	30.8597264

Table 4.3: Values of PSNR and MSE of combination of three noises, individual filter and combination of filter

Salt& pepper, Gaussian, Speckle Noise	MSE	**94.86**	**83.52**	**105.00**	**84.35**	**85.46**	**102.50**	**92.12**
	PSNR	28.3938409	28.9466927	27.9527264	28.9037572	28.8470173	28.0575413	28.5213171
Salt & pepper, Gaussian, Poisson Noise	MSE	**85.92**	**69.34**	**86.95**	**66.41**	**69.47**	**82.78**	**64.05**
	PSNR	28.8241058	29.7552106	28.7722050	29.9422467	29.7466078	28.9853690	30.0996450
Salt & pepper, Speckle, Poisson Noise	MSE	**96.13**	**82.13**	**107.16**	**80.35**	**81.16**	**101.47**	**89.68**
	PSNR	28.3361814	29.0196961	27.8646094	29.1148725	29.0713550	28.1012529	28.6380158
Gaussian Speckle, Poisson Noise	MSE	**50.94**	**45.54**	**40.75**	**42.81**	**46.68**	**38.59**	**37.87**
	PSNR	31.0943424	31.5807576	32.0639005	31.8498303	31.4737840	32.2998957	32.3814566
Salt & pepper, Gaussian, Speckle, Poisson Noise	MSE	**96.12**	**86.61**	**106.43**	**88.21**	**89.06**	**103.99**	**93.96**
	PSNR	28.3368467	28.7889253	27.8940120	28.7098364	28.6679175	27.9949763	28.4355156

Tables4.1, 4.2, 4.3 contains the values of different MSE and PSNR values. First table has values of individual noise vs individual filter and combination of filters. Second table has values of combination of two noises vs individual filter and combination of filters. Third table has values of combination of three noises and all noises vs individual filter and combination of filter. This data is necessary to choose the best filter over the other filters. The outcomes of all filters employed for the noise are compared using MSE and PSNR calculations for all filtering methods. The obtained results are more informative and prove to be valuable for general analysis, as the noised image can be de-noised using the best filtering algorithm.

LIST OF DIFFERENT NOISE'S AND BEST FILTERING TECHNIQUE USED FOR DENOISING

TYPES OF NOISES	BEST FILTER
SALT & PEPPER	MEDIAN
GAUSSIAN	MEDIAN + WIENER
SPECKLE	MEDIAN + WIENER
POISSON	WEINER
SALT&PEPPER,GAUSSIAN	GAUSSIAN + MEDIAN + WIENER
SALT&PEPPER,SPECKLE	MEDIAN + WIENER
SALT&PEPPER,POISSON	MEDIAN
GAUSSIAN,SPECKLE	MEDIAN + WIENER
GAUSSIAN,POISSON	MEDIAN + WIENER
SPECKLE,POISSON	MEDIAN + WIENER
SALT&PEPPER,GAUSSIAN, SPECKL	WIENER
SALT&PEPPER,GAUSSIAN, POISSON	GAUSSIAN + MEDIAN+ WIENER
SALT&PEPPER,SPECKLE, POISSON	MEDIAN + WIENER
GAUSSIAN,SPECKLE, POISSON	GAUSSIAN + MEDIAN + WIENER
SALT & PEPPER,GAUSSIAN, SPECKLE,POISSON	WIENER

Table 4.4 consists of the best filtering algorithm for the type of noise present in an image.

- The data in the above table is considered as the input for the deep learning algorithm.
- The output of the work is dependent on the accuracy of the training AlexNet and the accuracy of the confusion matrix. The final output shows the noised image and the best filter to denoise it.
- The accuracy is dependent on the epoch and no of iterations the data is being trained.
- Hence to get maximum accuracy we have tried with different values of epoch and different no of iteration.
- For better analysis of the work we have considered certain set of data to be trained and some of the data set to be used specifically for testing.
- The results of the work are supported by below attached screenshots.

- The final output of the work consists of a window which has 2 sections that display noised and denoised image, it is also supported with beneficial data such as type of noise corrupting the image and also best filters recommended to denoise the noised image.
- There three push buttons provided in this window.
  a. Browse button
  b. Classify button
- The function of each button is as follows:
- ➢ Browse button: it is used for browsing the noised image from the dataset folder which consists of noised images in 15 different noise types.
- ➢ Classify button: it is used for classifying the noised image to get the type of noise corrupting the image and also best filter recommendation. filters recommended to denoise the noised images.

LIST OF VARIOUS PARAMETERS TAKEN INTO CONSIDERATION FOR A BETTER ANALYSIS:

	Case 1	Case 2	Case 3
Training images	15	400	100
Testing images	5	100	20
Total images for 15 different noise	20x15 =300	500x4 =2000	120x15 =1800
Epoch	800/800	153 of 900	360/900
Iteration	800/800	2291/13500	3950/9900
Accuracy of AlexNet	99%	100%	100%
Accuracy of confusion matrix	76%	93.8%	97.4%

Table 4.5 consists of various parameters taken into consideration for the deeplearning algorithm .

Among the three cases from the above table, we have considered case 3 as our final case and we have done a brief study on it, for a better analysis and visualization screenshots of the work is attached below.

- The following dataset consists of 120 images of aircraft for each noise type, the dataset is split as 100 images for training the dataset and rest 20 for testing purpose and it's done for all the 15 noise type.
- Epoch: 355/900,360/900
- No of iterations: 3900/9900, 3950/9900
- Iteration per epoch: 11
- Learning rate: default value for 'rmsprop' and 'adam' solvers is [0.0001]
- Accuracy of alexnet obtained is: 100%
- Accuracy of Confusion Matrix for training data obtained is: 95.1%
- Accuracy of Confusion Matrix for testing data obtained is: 97.4%

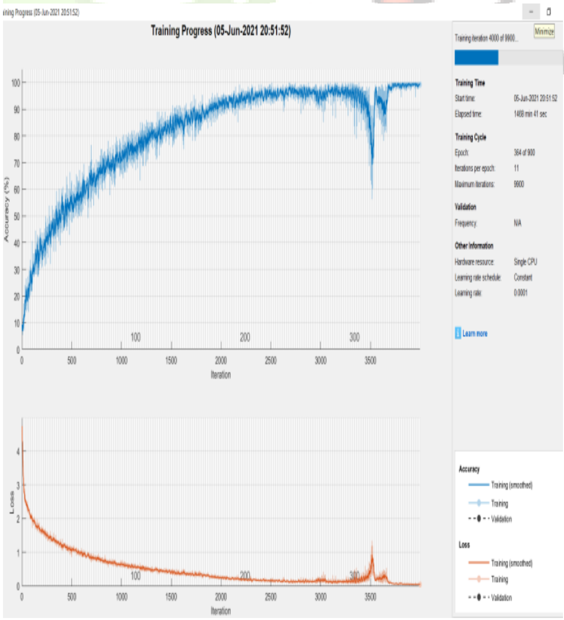


Fig 4.2: This figure shows the graphical representation of the accuracy and loss of the training process.

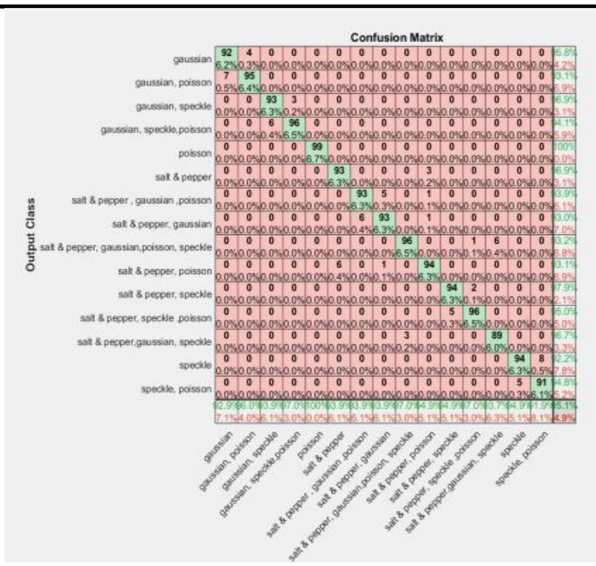


Fig 4.3: This figure indicates a representation of confusion matrix about the accuracy and loss of the training dataset.

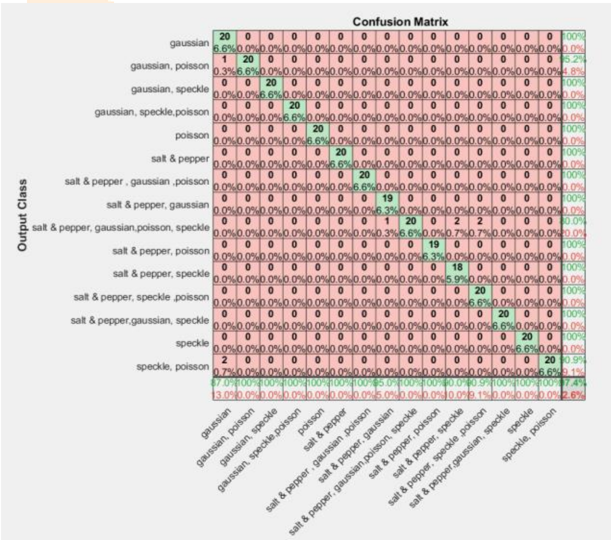


Fig 4.4: This figure indicates a representation of confusion matrix about the accuracy and loss of the testing dataset.

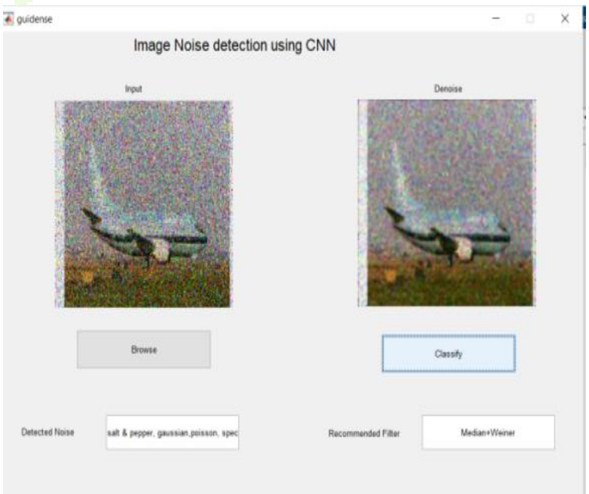


Fig 4.5: This figure indicates the representation of the final output where the classify button is pushed and the image. information about detected noise [Salt & Pepper + Gaussian + Speckle +Poisson] Recommended filter [Median + Wiener] is displayed also with the denoised image.

5. CONCLUSION

In this work, at first a set of Gray scale images are considered for noise removal. The dataset need not be corrupted by an individual noise; it can likewise be degraded by hybrid noise. Hence the study involves degrading the images by both individual and hybrid noise. Salt &Pepper, Gaussian, Speckle and Poisson noise and a hybrid of the mentioned noises are applied on the input images. The above input images are then denoised by applying various filtering methods like Median Filtering, Gaussian Filtering, Weiner Filtering and a hybrid of the mentioned filters to get precise outcomes. The filters mentioned in the above table prove to be the best to denoise the corrupted image. For performance analysis and assessment, parameters like PSNR (peak signal to Noise ratio) and MSE (Mean square Error) are considered. The above table is taken as pre-requisite for training the colored image dataset and the entire training and classification is done by deep learning algorithm. The network used is AlexNet and we have used 25 layers. Training and classification of the dataset is based on the accuracy of training session of AlexNet and the accuracy of confusion matrix. This work delivers denoised image along with other information such as the noise used to corrupt the image and the recommended filter to denoise.

6. FUTURESCOPE

This work can be extended on remote sensing data [Ex: LANDSAT 9], Agricultural dataset, biomedical images, etc. It can be performed on hyperspectral and multispectral images as well. Further we can deploy the same work on GPU with larger dataset for better analysis.

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