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Artificial Neural Network-Based Image Noise Identification

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Abstract- *A two-dimensional view of a three-dimensional scene is called an image. Image noise is any unnecessary information that is present in an image. During a number of processes, such as picture capture, processing, transmission, etc., noise can be added to the image. The introduction of noise into an image is unrelated to the content that is there. Understanding the noise is crucial to removing it; after the pattern of the noise is recognized, an appropriate filtering approach can be used to remove the undesirable information while keeping the important details of the image. Many writers have done research in the area of noise identification, however our work outlines a few limitations that remain. Impulse noise and electronic noise are the two types of noise that we have examined in our work.*
Keywords: *Image noise, Electronic noise, Impulse noise, ANN.*

I. INTRODUCTION

An image's noise level may cause variations in the image's brightness or color scheme. This technique may transpire at any stage of the image acquisition, image processing, or image transmission process. The acquisition procedure may create noise addition because to camera defects (heat from the sensor, excessive light absorption by the camera), or environmental problems (inadequate brightness, dust, humidity). Noise distortion distorts the original image's content and may deceive viewers or scholars. Therefore, it is crucial to remove this unwanted information that has been added to the image. Rather than just applying a filter, it is preferable to identify the noise in the image and then apply the appropriate filter based on its presence. An image can have different types of noise added to it, such as electronic noise, periodic noise, Rayleigh noise, impulse noise, speckle noise, photon noise, and so on. Generally speaking, a lot of algorithms focus on eliminating or at least decreasing a specific kind of noise, such as data drop noise [3], multiplicative noise [2], and additive noise [1]. When manual picture restoration is required, the approach of identifying individual noise in an image is very helpful; however, when automated image restoration is taken into consideration, these techniques do not function well. The first step in applying any image processing approach—whether to restore, segment, or identify items in an image—is to eliminate noise from the image. This will allow the technique to be applied more effectively and yield better results. To silence the commotion, we need to understand what type of noise is present in it so that a suitable filtering technique can be applied to remove a particular noise. These days, region segmentation and image fusion are used to handle the feature evidence of digital images. Connected domain recognition and neighborhood procedure of an entire image are used to identify noise in images, and a few researchers have demonstrated convincing research results using these techniques. However, there are still a lot of issues with the algorithms designed for noise detection, like incorrect computation, noise rate misjudgment, and truth rate misjudgment.

Our survey on literature gave us information that work has been carried out in identifying the noise by considering the statistical parameters in the given image [4], work has also been carried out by considering the soft computing method [5],graphical based methods are also used in identifying the noise [6] and noise identification techniques based on gradient function methods [7] are also used.

In our work, we identified the different types of noise present in an image using the concept of a neural network. At the moment, we are focusing on analyzing two different kinds of noise and categorizing them according to whether they are salt and pepper or gaussian noise. The experimental findings demonstrate that the suggested algorithm's False Alarming Ratio (FAR) is lower, indicating that we can precisely determine the kind of noise that is there as well as its location.

NOISEMODEL

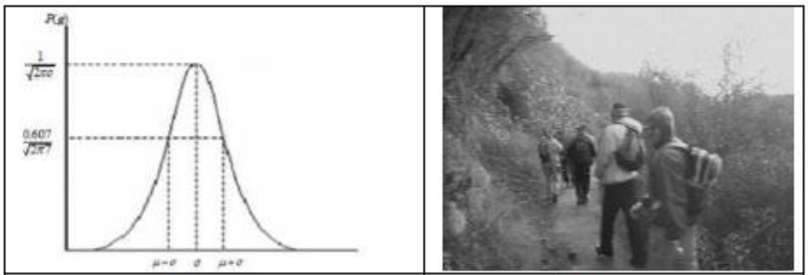
Noise is an unwanted by-product of image capture that complements non-essential data into the image [8]. Two forms of noise like Electronic noise and Impulsive noise have been considered for our study. If original image is represented by O(x,y), noise is represented by N(x,y) and degraded image is represented by D(x,y) then mathematically it can be shown as

$D(x,y)=O(x,y) + N(x,y) \quad 0 \le x \le m, 0 \le j \le n$ where m represents the number of rows in an image and n represents the number of columns in an image hence m*nis the size of the image.

Statistical noise is what is sometimes referred to as electronics noise, amplifier noise, or Gaussian noise. Gaussian noise's probability density function (Pdf) is identical to the normal distribution function's. It can be mathematically represented as below:

$$P(g)= \frac{1}{\sqrt{(2\pi)}\sigma} e^{\wedge \frac{-(g-\mu)2}{2\sigma 2}}$$

Where g indicates gray level value, σ indicates standard deviation and μ indicates mean.

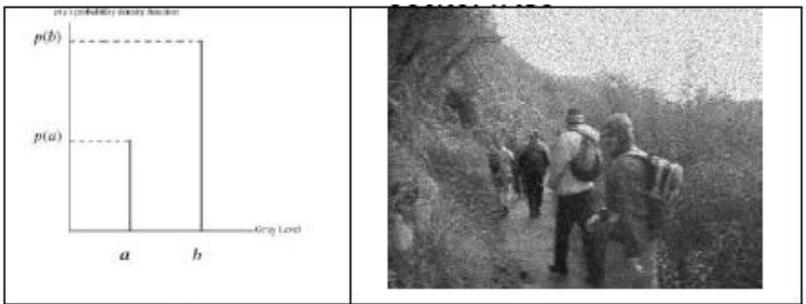


(a) PDF of Electronic noise	(b) Image with Electronic noise

Fig1: Electronic Noise model

Salt & pepper noise is also termed as spike noise or impulse noise. The Probability density function (Pdf) of this noise has only two values either as alt value(255-pixelvalue)ora pepper value (0-pixel value) indicating, "an image containing this type of noise will have dark pixels in brighter regions and bright pixels in darker regions"[19].Probability density function (Pdf) for the noise can be mathematically represented as below:

$$P(g)=\begin{cases} Pa\forall\ g=a \\ Pb\forall g=b \\ 0 otherwise \end{cases}$$



(a) PDF of Salt & Pepper noise	(b) Image with Salt & Pepper noise

Fig2: Salt& pepper Noisemodel

II. NEURALNETWORKTRAINING AND CLASSIFICATION

For our application we have considered the network architecture as multilayer feed forward network. Based on this architecture the number of hidden layers and the number of neurons in each layer are decided. Until the desired output is achieved the process is continued by trial-and-error method based on the performance function. "Statistical moments kurtos is and skewness are the input variables to the input layer, having one hidden layer with nodes one greater than the nodes in input layer. The weights between the layers are initialized randomly and the weights are adjusted by means of back propagation on training the neural network" [19].

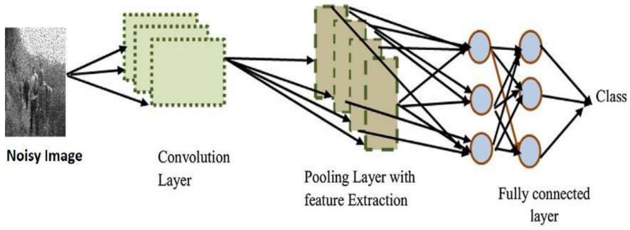


Fig3:Convolutionneural network model

The input size of the network must match with our images in order to train a network and make proper predictions on any new data. In case if the images don’t match with the network then we can perform some processing technique like rescale or crop or resize the data so as to achieve the required size. The volume of training data can be improved by applying randomized *augmentation* to our data.

Augmentation helps us to get images with different invariant features of an image which can be used to train the network. This also helps to build a larger volume of dataset from a smaller number of images being considered like by using the rotating, translating or flipping of an image. For example, we can translate the input images so that a network is invariant to the presence of the object in an image. An augmented Image Data store provides a beneficial means to apply a limited set of augmentations to two dimensional images for classification of images.

In order to identify the noise in an image we used the concept of Transfer learning which basically is a learning method to train a machine and develop a model for a task. This model is reprocessed as the introductory idea for a model on a second task.

III. METHODOLOGY

Our methodology invokes to classify noise utilizing a pre trained neural network using transfer learning. Here we have considered two types of noise; Electronic noise and Impulse noise. For transfer learning google net is been used. Firstly, the images in the data t set are renamed and a data set for each of the noise model is being created. The data which are stored in multiple files like disk, or a database as a single entity or say in are mote location can be read and processed with the help of this data store. If the data is too big to fit in a memory then the data store function generates a data store, which acts as a store house for gathering of all the data. Later, all the images in the data store are considered into two sets one for training and the other for testing the images. Based on the training provided to the network model, it can classify the test images accordingly as either Gaussian noise or say the impulse noise.

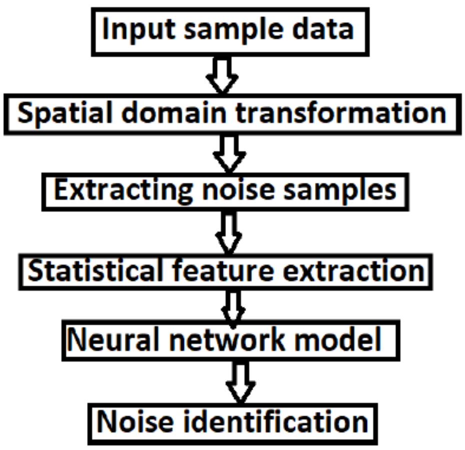


Fig4:Flowchartoftheproposed model

IV. RESULTS & DISCUSSION

In our paper, we have considered 400 different images among which 200 images are for each noise namely Electronic noise and Impulse noise present in an image. Amongthese,200imagesareofaGaussiannoise,whichare spiltupinto60%fortrainingand40%fortestingthatis120 images which are used for training the neural network and 80imagesareusedfortestingpurpose.Similarly,forsalt& pepper noise among 200 images being considered, 120 imagesareusedfortrainingand80areusedfortesting. The image used for our purpose are considered from Kaggle database to train and test the neural network.

There are four possible test results which are as follows:

1. The Electronic noise present is identified correctly
2. The Electronic noise present is falsely detected as salt& pepper noise.
3. The salt & pepper noise is identified correctly.
4. The salt & pepper noise is falsely detected as Electronic noise.

Below table-1 and the fig-5 shows the evaluation measure values obtained for Electronic noise and Impulse noise present in an image.

Table-1:Evaluativemeasuresvalues

Noise / prediction	Correct detection	Wrong detection	Accuracy
Electronic Noise	75	5	93.75%
Impulse Noise	76	4	95%

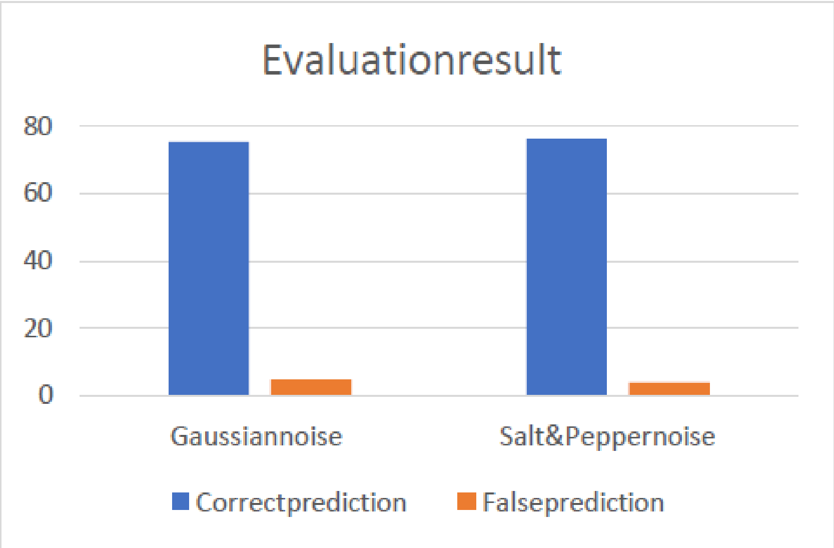


Fig5:Graph of evaluation results

The below table-2 shows the performance parameters obtained for the proposed method:

Table-2:Performanceparametersvaluesofproposed method

Parameters	**Value**
Classcategory	2
Maximumepoch	6
Minimumbatchsize	10
Elapsedtime	6min4sec
AverageAccuracyobtained	94.37%
Total Iteration	144
Iterationperepoch	24

Fig6showstheresultofidentificationofsalt&peppernoise and fig-7 shows the correct identification of the Electronic noise. Final fig-8 show the performance of training progress.

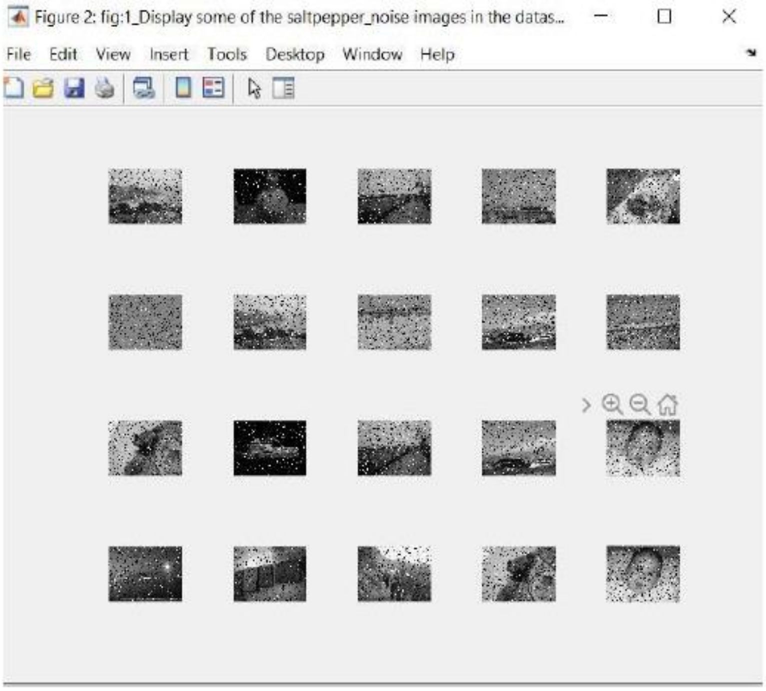


Fig6:Sampleimagesofsalt&peppernoiseidentified

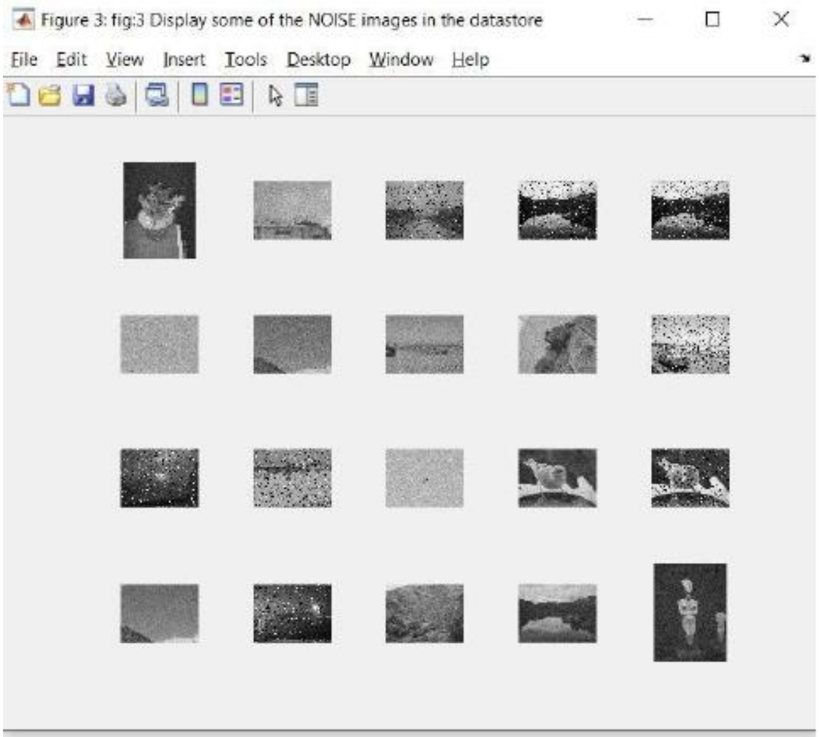


Fig7:SampleimagesofElectronicnoise identified

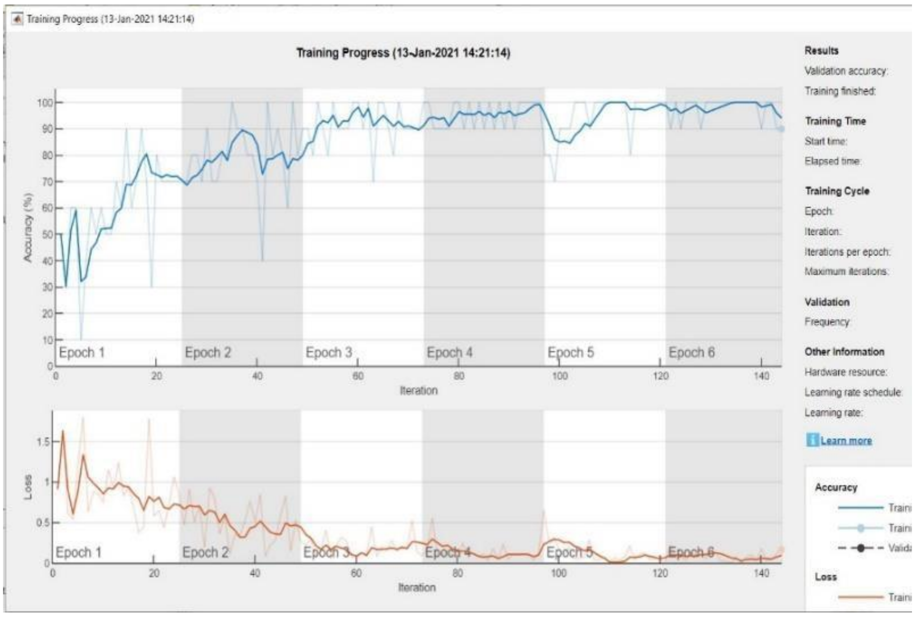


Fig8:Graphshowingperformanceoftrainingprogress

V. CONCLUSION

We suggested a technique that uses a neural network to separate the noise from the image. In general, impulse noise and electronic noise were the two categories of noise that we looked at. The measuring factors used in our work are accurateness rate(AR)and erroneous identification(EI)as shown in equation below

AR = (number of images accurately recognized/ total number of images verified) * 100

$AR=(I_c/I_t)*100$ $EI = 100 - AR$

Where I_C indicates total number of images accurately recognized, $I_t$indicates total number of images verified. 95% accurateness of salt & pepper noise confirms the robustness of our proposed work. Accurateness of 93.75% for the Gaussian noise is being achieved. Two ways this study could be expanded are, first, by using additional photos to train and test the network, and second, by experimenting with different kinds of noises in an image.

REFERENCES

[1]. Poungponsri, S., & Yu, X. H. (2013). An adaptive filteringapproach for electrocardiogram (ECG) signal noise reduction usingneural networks. Neurocomputing, 117, 206-213.

[2]. Maity, A., Pattanaik, A., Sagnika, S., & Pani, S. (2015, January).A comparative study on approaches to speckle noise reduction inimages. In2015 International Conference on ComputationalIntelligence and Networks (pp. 148-155). IEEE.

[3]. Kaliraj, G., & Baskar, S. (2010). An efficient approach for theremoval of impulse noise from the corrupted image using neuralnetworkbasedimpulsedetector. ImageandVisionComputing, 28(3), 458-466.

[4]. Collins, J. D., Hart, G. C., Hasselman, T. K., & Kennedy, B.(1974).Statisticalidentificationofstructures.AIAAjournal,12(2),185-190.

[5]. Wahab, A., Quek, C., Tan, C. K., & Takeda, K. (2009). Drivingprofile modeling and recognition based on soft computingapproach. IEEE transactions on neural networks, 20(4), 563-582.

[6]. Pok, G., Liu, J. C., & Nair, A. S. (2003). Selective removal ofimpulse noise based on homogeneity level information. IEEETransactions on Image Processing, 12(1), 85-92.

[7]. Karibasappa, K. G., Hiremath, S., & Karibasappa, K. (2011).Neural network-based noise identification in digital images. TheAssociation of Computer Electronics and Electrical EngineersInternational Journal on Network Security, 2(3), 28-31.

[8]. Hiremath, S., & Rani, A. S. (2020). A Concise Report on ImageTypes, Image File Format and Noise Model for ImagePreprocessing.

[9]. Elhoseny, M., & Shankar, K. (2019). Optimal bilateral filter andconvolutional neural network based denoising method of medicalimage measurements. Measurement, 143, 125-135.

[10]. Aishwarya, R., Ashwatha, C., Deepthi, A., & Beschi Raja, J.(2019).ANovelAdaptableApproachforSentimentAnalysis.InternationalJournalofScientificResearchinComputerScience, Engineering and Information Technology, 5(2).

[11]. Chen, Y., &Das, M. (2007, August). An automated technique forimage noise identification using a simple pattern classificationapproach. In 2007 50th Midwest Symposium on Circuits andSystems (pp. 819-822). IEEE.

[12]. Liu,X.,&Chen,Z.(2008,December).Researchonnoisedetectionbased on improved gradient function. In 2008 InternationalSymposiumonComputerScienceandComputationalTechnology (Vol. 2, pp. 476-479). IEEE.

[13]. Motwani, M. C., Gadiya, M. C., Motwani, R. C., & Harris, F. C.(2004,September).Surveyofimagedenoisingtechniques.In Proceedings of GSPX (Vol. 27, pp. 27-30).

[14]. Tian,C.,Fei,L.,Zheng,W.,Xu,Y.,Zuo,W.,&Lin,C.W.(2020).

[15]. Deeplearningonimagedenoising:Anoverview.NeuralNetworks.

[16]. Goyal, B., Dogra, A., Agrawal, S., Sohi, B. S., & Sharma, A.(2020). Imagedenoising review: From classicalto state-of-the-artapproaches. Information fusion, 55, 220-244.

[17]. Nicolae, M., Vlăsceanu, G. V., & Boiangiu, C. A. (2020).ADAPTIVEIMAGEDENOISINGSOLUTION. Journalof

[18]. InformationSystems&OperationsManagement,14(2),138-146.

[19]. Karimi,D.,Dou,H.,Warfield,S.K.,&Gholipour,A.(2020).Deeplearning with noisy labels: Exploring techniques and remedies

inmedical image analysis. Medical Image Analysis, 65, 101759.
[20]. Hiremath, S. (2021). Computer Processing of an Image: AnIntroduction. InHandbook of Research on Deep Learning-BasedImage Analysis Under Constrained and UnconstrainedEnvironments (pp. 1-22). IGI Global.
[21]. Vasuki, P., Bhavana, C., Roomi, S. M. M., & Deebikaa, E. L.(2012,December).Automaticnoiseidentificationinimagesusingmomentsandneuralnetwork.In2012internationalconferenceonmachine vision and image processing (MVIP) (pp. 61-64). IEEE.