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A Deep Learning and Machine Learning Approach for Image Denoising

[1] Ashly Roy, [2] Anju P, [3] Linnet Tomy, [4] Dr.M.Rajeswari

[1][2] PG Scholar, CSE Dept, SCET, Thrissur, Kerala, India
[3] Assistant Professor, CSE Dept, SCET, Thrissur, Kerala, India
[4] Head of Dept, CSE Dept, SCET, Thrissur, Kerala, India

***Abstract*----Image denoising is the way toward elimi- nating any distortions in an image and numerous pro- cedures exists for this reason. The traditional image denoising methods comprises of spatial domain filter- ing and transform domain filtering. These techniques eliminated commotion to a more prominent stretch out from an image yet neglected to preserve image textures and information's. To counter this issue deep learning came right into it. It's strong learning capacity made convolutional neural network the best and exact answer for image denoising. This paper discusses on one such CNN approach that utilize LeNet architecture for image denoising.We additionally presented the machine learning approach in image denoising to get an obvious thought on which learning is more effective in eliminating the distortions. K-Nearest Neighbor, Na¨ıve Bayes, Support Vector Machine, Random Forest and Decision Tree are the main five algorithms utilized in the machine learning approach. At long last, a correlation is made between machine learning algorithms and deep learning approach based on accuracy and an effective algorithm for image denoising is found.**

***Keywords*--- Deep Learning, Machine Learning, Image Denoising**

I. INTRODUCTION

Image denoising is the way toward acquiring a perfect image from a boisterous image. It is one of the fundamental assignments in the exploration fields like image processing and computer vision. The commotion is presented in an image by various methods. It tends to be of the blemishes in some image catching gadgets, the commotion sources encompassing the image catching gadgets, lossy compressions, memory area abandons, dispersing, because of some barometrical conditions or others. It's not simply a sort of commotion in an image however an assortment of others clamors can likewise be available in it including gaussian, salt and pepper, periodic, gamma, white, uniform, Rayleigh and Poisson. The principle objective is to recuperate a spotless picture x from an uproarious picture y that follows a picture corruption model of $y = x + v$, where v is the added substance additive white Gaussian noise (AWGN) with the standard deviation sigma σ [2,3,4].

The noise in an image can be displayed de- pendent on the likelihood dispersion. It very well may be classified as white and shading commotion dependent on relationship, added substance clamor dependent on nature and photon commotion de- pendent on source [7].The greater part of the CNN models explores different avenues regarding gaussian clamor and its variations. Different techniques were presented dependent on the picture debasement model to stifle the clamor from the uproarious images in the previous years. To lessen the computational cost and improve the presentation inadequate techniques were utilized [8].

Deep learning strategies have now become the prevailing procedures to tackle all the above downsides in denoising because of its solid learning capacity. Among deep learning strategies, deep CNN's with adaptable models are a lot of reasonable for image applications, particularly for image denoising [19,22]. The absolute initially proposed model is denoising convolutional neural network (DnCNN) [19] alongside residual learning (RL) [21] and batch normalization (BN) [20]. DnCNN was the awesome arrangement with multi denoising assignments, including gaussian uproarious, JPEG and low-goal pictures. Deeply recursive convolution network used the leftover learning procedure by utilizing the data of each layer into definite layer and subsequently improving the denoising execution [24].A portion of the residual dense network [25] has high memory utilization and computational expense and some deep networks doesn't utilize the impacts from the shallow layers. Other than these two issues, the other is that they disregard the way that unpredictable foundation shrouds a portion of the key highlights.

In this paper, we examine on the machine learning and deep learning approach in detail on how it eliminates the commotion from the information image and holds every one of the highlights of the image to give an exact clamor free image. The image denoising execution is estimated by raw pixel intensity. We think about the exhibition of both the ways to deal with know which method is the awesome precision and can give preferable outcomes over the other. In machine learning approach, we utilize K-nearest neighbor (KNN), support vector machine(SVM),random forest, decision tree and naive bayes algorithms. In DL approach, we make use of CNN algorithm with LeNet architecture.

The rest of the paper are coordinated as follows. Section II gives the elated techniques that are as of now existing in image denoising. The proposed approaches, both in machine learning and deep learning are talked about in Section III. In Section IV, the test consequences of the models, the dataset utilized and the presentation correlation is introduced. At long last, in Section V, the paper is closed with in general conclusions of the proposed work.

II. RELATED WORKS

The way toward eliminating characteristic clamor from an image is named as denoising of an image and for these various sorts of methods are accessible. The denoising strategies are basically arranged into three fundamental classifications:

- Spatial Domain Methods
- Transform Domain Methods
- CNN-based Methods

These three classifications are additionally separated more dependent on certain boundaries. In this segment we will examine in insight regarding these current methods to get an obvious thought on how these clamors are taken out from an image previously.

Spatial Domain Methods

Spatial domain methods intend to eliminate commotion by ascertaining the dark worth of every pixel dependent on the relationship between pixels patches in the first image. Spatial domain techniques can be partitioned into two classifications: spatial domain filtering and variational denoising techniques.

1) Spatial Domain Filtering

One of the conventional approaches to eliminate commotion from an image is to utilize spatial filters. Commotion decrease, interjection, and re-testing are a portion of the fundamental capacities in sifting. The channels are chosen by the sort of assignments they perform. Spatial domain filters are grouped into two: Linear filters and Non-linear filters.

Linear Filters: Linear filters are mostly used to eliminate commotion in pictures that has added substance clamor present in it. In any case, the issue is that linear filters doesn't preserve the picture textures. It incorporates Mean filters and Weiner filters. The primary impediments of linear filters are obscure sharp edges, annihilate lines and other fine picture subtleties, and perform inadequately within the sight of sign ward commotion.

Non-Linear Filters: Non-linear filters are utilized to eliminate commotion in pictures with multiplicative and function-based clamor happen. It smothers the clamor without making any endeavours for distinguishing proof unequivocally. It incorporates median filters and weighted median filters which are powerful filters that are utilized for giving perfection in image processing and time arrangement handling. The serious issues with the median filters are that it is moderately costly and is difficult to process.

2) Variational Denoising Techniques

For the variational denoising strategies, the key is to track down a reasonable image prior (R(x)).Fruitful earlier models incorporate angle priors, non-local self-similarity (NSS) priors, sparse priors, and low position priors. Most basic variational denoising techniques are as per the following: Total Variation Regularization was proposed to settle the issue of smoothness. This is the most powerful research in the field of picture denoising. Non-Local Regularization utilized the weighted separating of the NSS prior before accomplish picture denoising. The disadvantage is that the structural information isn't very much preserver by these techniques, which corrupts the visual picture quality. Sparse Representation only necessitates that each picture fix can be addressed as a direct blend of a few patches from an over-complete word reference. Low-rank Minimization arrangements comparative patches as a lattice. Every section of this lattice is an extended fix vector. By abusing the low-rank prior of the grid, this model can successfully lessen the commotion in a picture. Albeit, the computational expense of the iterative boosting step is moderately high.

Transform Domain Methods

Transform domain methods were created from the Fourier transform. Transform domain methods utilize the accompanying perception: the qualities of picture data also, commotion are diverse in the transform domain. An assortment of transform domain strategies slowly arose, for example, cosine transform, wavelet area techniques, and block-matching and 3D filtering(BM3D).

1) Transform Domain Filtering

Transform domain filtering methods initially change the given uproarious picture to another space, and afterward they apply a denoising methodology on the changed picture as indicated by the various attributes of the picture

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and its clamor. The transform domain filtering methods can be partitioned by the picked premise transform capacities, which might be data adaptive or non-data adaptive. Independent component analysis (ICA) and PCA capacities are received as the change instruments on the given boisterous pictures. Non-data Adaptive Transform strategies can be additionally partitioned into two areas, specifically spatial-frequency domain and wavelet domain. Spatial-frequency domain filtering strategies utilize low pass sifting by planning a recurrence space channel that passes all frequencies lower than and lessens all frequencies higher than a remove recurrence. Wavelet transform breaks down the data information into a scale-space portrayal. It has been demonstrated that wavelets can effectively eliminate commotion while protecting the picture attributes, paying little heed to its recurrence content.

2) BM3D

Block-matching and 3D filtering is a 3-D square coordinating with calculation utilized essentially for commotion decrease in pictures. A piece is assembled if its uniqueness with a reference section falls under a predefined limit. This gathering procedure is called block-coordinating, it is ordinarily used to bunch comparative gatherings across various casings of a computerized video, BM3D then again may bunch macroblocks inside a solitary edge. All picture sections in a gathering are then stacked together to frame 3D chamber like shapes. In any case, when the commotion increments continuously, the denoising execution of BM3D diminishes enormously and relics are presented, particularly in level zones.

CNN-based Methods

CNN-based denoising techniques endeavor to become familiar with a planning capacity by streamlining a misfortune work on a preparation set that contains debased clean picture sets. As of late, CNN-based techniques have been grown quickly and have performed well in some low-level computer vision errands. The utilization of a CNN for picture denoising can be followed back, where a five-layer network was created. Numerous CNN-based denoising techniques have been proposed. Besides, CNN-based denoising techniques can be isolated into two classes: multi-layer perception (MLP)models and deep learning strategies.

1) MLP Models

MLP-based picture denoising models incorporate auto encoders. A feed-forward profound organization called the trainable non-linear reaction diffusion (TNRD) model, which accomplished a superior denoising impact was proposed. This class of strategies has a few benefits. To start with, these strategies work effectively attributable to less ratiocination steps. Besides, on the grounds that enhancement calculations can infer the discriminative engineering, these strategies have better interpretability. In any case, interpretability can expand the expense of execution; for instance, the MLP model limits the learned priors and deduction method.

2) Deep Learning Methods

The best in class profound picking up denoising techniques are ordinarily founded on CNNs. Residual learning and clump normalization were brought into picture denoising interestingly; they likewise proposed feed-forward denoising CNNs (DnCNNs).There are two principle qualities of DnCNNs: the model applies a leftover learning detailing to get familiar with a planning capacity, and it joins it with clump standardization to speed up the preparation system while improving the denoising results. Another significant commitment is that FFDNet follows up on down-tested sub-pictures, which speeds up the preparing and testing and furthermore extends the responsive field. In this way, FFDNet is very adaptable to various clamors. Albeit this strategy is compelling and has a short running time, the time intricacy of the learning interaction is high. The advancement of CNN-based denoising strategies has upgraded the learning of undeniable level highlights by utilizing a various leveled network..

III. PROPOSED APPROACHES

Since the strong learning capacity of deep learning made convolutional neural network the best and precise answer for image denoising our first methodology is a deep learning-based CNN approach that utilization LeNet architecture for image denoising. After that the machine learning approach in image denoising is examined to get an obvious thought on which learning is more productive in eliminating the noise. K-Nearest Neighbor, Naïve Bayes, Support Vector Machine, Random Forest and Decision Tree are the primary five algorithms utilized in the machine learning approach.

A. Deep Learning Approach

In this segment, we present the proposed denoising CNN model. For network architecture design, we use LeNet architecture to make it appropriate for image denoising. The LeNet architecture is a great first design for Convolutional Neural Networks. It comprises of seven layers. Notwithstanding input, each and every other layer can prepare boundaries.

LeNet-5 includes 7 layers, not including the info, all of which contain trainable parameters (weights). The information is a 32x32 pixel picture. This is fundamentally bigger than the biggest character in the data set. Layer C1 is a convolutional layer with 6 component maps and is associated with a 5x5 neighborhood in the information. Layer S2 is a sub examining layer with include component maps of size 14x14 and is associated with a 2x2 neighborhood in the comparing highlight map in C1. Layer C3 is a convolutional layer with 16 component maps and is associated with a few 5x5 neighborhoods at indistinguishable areas in a subset of S2's element maps. Layer S4 is a sub testing layer with include component map of size 5x5 and is associated with a 2x2 neighborhood in the relating highlight map in C3, along these lines as C1 and S2.Layer C5 is a convolutional layer with 120 component maps and is associated with a 5x5 neighborhood on the entirety of S4's component maps. Layer F6 contains 84 units and is completely associated with C5.At long last, the yield layer is made out of Euclidean Radial Basis Function units (RBF), one for each class with inputs each. The first LeNet design utilized tanh actuation works as opposed to ReLU. The explanation we use ReLU here is on the grounds that it will in general give much better arrangement precision because of various decent, attractive properties.

B. Machine Learning Approach

Machine Learning is an umbrella term utilized for computational strategies that attempt to mimic human learning exercises through PCs to consequently find and procure information.

1) K-Nearest Neighbor

K-nearest neighbor clustering is one of the unaided ML algorithms, which targets sorting out characterized bunches in the dataset given k as the worth of bunch gatherings. Groups are shaped dependent on the closeness attributes among all information focuses in the dataset. First and foremost, k number of centroids is assessed among m information focuses. Then, in view of Euclidean distance estimates m information focuses x1, x2,.., xm are doled out to its closest centroids. Repeat all through the calculation until any information point can't adjust any bunch centroids.

2) Support Vector Machine

The SVM, quite possibly the most famous algorithm, is a managed learning algorithm that means to discover an isolating hyperplane in the element space among its classes. The hyperplane is picked so that the distance between the hyperplane and its nearest information point is augmented. The objective of the SVM is to accurately order preparing information when y=+1 utilizing wx_i+b>=1 and when y=-1 utilizing wx_i+<=1.

3) Decision-Tree

A DT is a standard based tree-organized arrangement model where every vertex (hub) of the tree addresses a quality and each branch decides the esteem that quality can have. The highest vertex in a tree is known as the root, which contains most data acquire (contrasts in entropy) among all highlights and is used to ideally part all preparation information. The base hubs are called leaves. Each leaf addresses each class.

4) Random Forest

Random forest is a managed learning algorithm which is utilized for both grouping and regression. Yet, nonetheless, it is primarily utilized for classification problems. As we realize that a backwoods is comprised of trees and more trees implies more robust forest. Additionally, random forest algorithm makes choice trees on information tests and afterward gets the expectation from every one of them lastly chooses the best arrangement through casting a ballot.

5) Naive Bayes

The Naive Bayes' classifier is a probabilistic-based regulated learning calculation, which gives the likelihood of a class given all highlights as input. The Naive Bayes' classifier depends on Bayes' rule. It is additionally called the generative model. The fundamental benefit of the Naive Bayes' classifier is that it is hearty with uproarious preparing information. As this classifier depends on the probabilistic worth, everything being equal, low preparing tests with this classifier don't corrupt execution.

I. EXPERIMENTAL RESULTS

In this section, we primarily present the test results from the accompanying perspectives: datasets and accuracy analysis of machine learning and deep learning algorithms to discover more proficient one among them.

A. Datasets

To train the model, we utilize 3,859 pictures from Waterloo Exploration Database and were trimmed into 20 x 58,319 patches. The size of the patch was set to 50 x 50. To test the model we use CBSD68, Kodak24 and McMaster datasets. Colour Berkeley Segmentation Dataset 68 incorporates 68 pictures of size 481 x 321 or 321 x 481.Kodak24 and McMaster has 24 and 18 colour pictures separately of size 500 x 500.

B. Accuracy Analysis

The accuracy of the proposed picture denoising models are determined utilizing the exactness of confusion matrix. A confusion matrix is a synopsis of forecast results on a grouping issue. Accuracy is determined as the quantity of all right expectations partitioned by the absolute number of the dataset. It is determined by the formula:

$$Accuracy = (TP+TN) / (TP+FP+TN+FN)$$

Where, TP is True Positives: The cases in which we anticipated yes and the genuine yield was additionally yes.TN is True Negatives: The cases in which we anticipated no and the real yield was no. FP is False Positives: The cases in which we anticipated yes and the real yield was no. Furthermore, FN is False Negatives: The cases in which we anticipated no and the genuine yield was yes.

Table.1: ACCURACY OF PROPOSED MODELS.

Accuracy	Algorithm
89.69%	CNN with LeNet
66.66%	K-Nearest Neighbor
73.21%	Decision Tree
75.51%	Support Vector Machine
83.78%	Random Forest
92.59%	Naive Bayes

The above table gives the accuracy of the proposed models of both machine learning algorithms and CNN algorithm with LeNet architecture. It's very clear from the table the Naive Bayes algorithm shows the promising result when compared to other machine learning algorithms and CNN algorithm in terms of accuracy and therefore it can be taken as the best denoising model for the image denoising, without losing any of the features of the original image.

IV. CONCLUSION

In this paper, we were discussing on different image denoising models based on CNN algorithm with LeNet architecture and Machine learning algorithms to find the best in providing the accurate denoised image as output in performance and accuracy without losing any of its features. First, we focused on some existing techniques which includes the non-CNN methods and traditional methods for image denoising. Then, a detailed architecture of proposed CNN model with figure is described in the third section. The third section also include another proposed method for image denoising using machine learning algorithms. Then we examined about the experimental results and Naïve Bayes is having promising performance than all other models, with an accuracy of 92.59\%.In future, these models can be used to make it possible for denoising blurred or low light images.

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