Deblurring of Images using Novel Deconvolutional Neural Network (DNN) Algorithm to Enhance the Accuracy and Comparing with Richardson-Lucy Deconvolution Algorithm (RLD)

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Abstract

*Aim- Machine learning techniques are rapidly used in the area of digital image processing research due to its impressive results in deconvolution and deblurring of images. The objective of this study is to evaluate the performance of Novel DNN algorithm in deblurring of images by comparing it with the RLD algorithm. **Materials and Methods -** Novel Deconvolutional Neural Network (DNN) and Richardson-Lucy Deconvolution (RLD) algorithms were implemented to deblur the input images upto 256 pixels range. These algorithms were implemented to enhance the accuracy rate of deblurred images using MATLAB Software and analyzed by collecting the dataset of 40 samples with 80% of pretest power. **Results -** From the MATLAB simulation result, DNN achieves image deblurring rate with 98% accuracy and RLD method achieves image deblurring rate with 92% accuracy. The significance value obtained as (P < 0.002). **Conclusion -** Novel DNN classifier appears to have better accuracy compared to RLD Classifier.*

Key-words: Digital Image Processing, Blur Classification, Point Spread Function, Deblurring, Novel DNN Algorithm, RLD Algorithm.

1. Introduction

A natural image might be blurred for various reasons which includes defocusing and atmospheric turbulence (Gong and Zhang 2019). Most of those photos are captured on smartphones. So due to the popularity of smartphones, image deblurring has attracted researchers (D. Zhang, Liang,

and Shao 2020). Motion deblurring plays a vital role in degradation of images due to camera shakes during photography and image degradation appears with a blur and statistical noise(Ljubenović et al. 2020). The process of inverting convolution operation is called deconvolution (Tirer and Giryes 2019). This image restoration is used for applications such as electron microscopy, remote sensing, medical imaging and planetary imaging(Hosseini and Plataniotis 2020).

Gupta et al. proposed a CNN algorithm for image deblurring using neural networks from the degraded blur images along with detecting accuracy rate and SNR ratio (Gupta et al. 2018). Li et al. proposed a deep unrolling approach for deblurring images using blind deconvolution and back propagation of design for optimising parameters into a neural network (Li et al. 2020). Ziyi Shen et al. proposed an efficient face deblurring algorithm using the DCNN algorithm by exploiting semantic cues for restoring sharp face images with more accurate face details (Shen et al. 2020). Nan Y et al. proposed a deep learning algorithm for handling erroneous kernel uncertainty using simulation with NN based priors on both blurred images and correction terms (Nan and Ji 2020). Ren et al. proposed an algorithm to solve an unconstrained neural deconvolution to gain effective blur estimation and for obtaining a clean image with clear text visual on images (Ren et al. 2020). Zhang et al. proposed a FCNN algorithm to remove noise and ringing artifacts in an iterative-wise model to preserve image details with high quality and increase performance of image restoration using non-blind deconvolution (J. Zhang et al. 2017). Jin et al. proposed a novel method to detect the level of noise in blurred images with direct application of MAP to enhance noise-adoptive deblurring and boosting of significant performance (Jin, Roth, and Favaro 2017) .

Previously our team has a rich experience in working on various research projects across multiple disciplines (Sathish and Karthick 2020; Varghese, Ramesh, and Veeraiyan 2019; S. R. Samuel, Acharya, and Rao 2020; Venu, Raju, and Subramani 2019; M. S. Samuel et al. 2019; Venu, Subramani, and Raju 2019; Mehta et al. 2019; Sharma et al. 2019; Malli Sureshbabu et al. 2019; Krishnaswamy et al. 2020; Muthukrishnan et al. 2020; Gheena and Ezhilarasan 2019; Vignesh et al. 2019; Ke et al. 2019; Vijayakumar Jain et al. 2019; Jose, Ajitha, and Subbaiyan 2020). Now the growing trend in this area motivated us to pursue this project.

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The factors that affect deblur process are image quality and sensitivity (Pan et al. 2017). A partially saturated blur image with compression errors cannot be degraded in many existing approaches (Lai et al. 2016). Many methods are proposed on above mentioned issues but still shortcomings are there in the image deblurring. Since deconvolution may involve many neighboring pixel elements and its result in very complex non-linear degradation (Agarwal, Singh, and Nagaria 2017). A new method of work implemented to overcome the factors affecting the deblur of images and enhance the accuracy of deblurred images using DNN classifier ("License Plate Recognition with Feature Salience and Neural Network" 2019).

2. Materials and Methods

This study was conducted at an image processing lab in Saveetha School of Engineering. This study was based on accuracy enhancement of deblurring image using DNN with handling of noise before deblurring using poisson distribution. Dataset of degraded images was considered for two groups, each dataset contains 20 samples, totally 40 samples with a pretest power of 80% to test the samples (Kane, Phar, and BCPS n.d.). In group 1, sample preparation was taken as a RLD method and In group 2, sample preparation was taken as a DNN algorithm for testing purposes. For group 1, 20 samples trained using RLD and for group 2, 20 samples trained using DNN. WUXIA monitor with resolution of 1920*1080 pixels with configuration of 8th Gen, i5, 8GB RAM, 1TB HDD and MATLAB software with add-ons required for testing purpose.

2.1. RLD Algorithm

The Richardson Lucy Deconvolution was an iterative method for restoration of underlying images that can be blurred by a point spread function. An underlying image can operate by a transition matrix process. A two dimensional detected image was a convolution of an underlying image with 2-Dimensional point spread function that can be added by noise. After that using deconvolution, image blur can be removed in the presence of additive noise by using wiener filters.

The steps to implement the process of RLD method was

Step 1: Read Image.

Step 2: Simulate a Blur and Noise.

Step 3: Restore the Blurred and Noisy Image.

Step 4: Iterate to Explore the Restoration.

Step 5: Control the Noise Amplification by damping.

Step 6: Create a sample Image.

Step 7: Simulate a blur.

Step 8: Provide the weight array.

Step 9: Provide a finer-sampled Point Spread Function (PSF).

Step 10: Deblurred using non-blind deconvolution.

2.2. Novel DNN Algorithm

A DNN machine learning algorithm was proposed to deblur an image that was degraded from the input image. Multiple blur images can be loaded as input. Restoration of those blur images can be done with the use of this proposed Novel DNN algorithm. It has been used to perform the images as dense classification and degradation by point spread function (PSF) and noise removal using Gaussian filters and poisson distribution.

The steps for this Novel DNN algorithm process was:

Step 1: Browse Input Image.

Step 2: Simulate a Blur and Noise.

Step 3: Restore the Blurred and Noisy Image.

Step 4: Degrade the Image using Initial Point Spread Function.

Step 5: Estimation of blur using true and oversized Point Spread Function.

Step 6: Applying the Gaussian filter to control Noise amplification

Step 7: It provides a weight array.

Step 8: Restoring the original image using DNN coding.

Step 9: Provide Simulated Deblurring image.

2.3. Statistical Analysis

SPSS version 21 (Statistical Package for the Social Sciences) was used for statistical analysis for various varieties of research. Independent variables in this work were Intensity, pixel size, sensitivity, mean. Intensity is the quality of being intense and corresponds to the brightness of grayscale images. Image sensitivity was the RMS thermal noise expected in a single polarized image.

Dependent variables in this work were accuracy, efficiency, mean square error. Analysis done in this work on the parameters of Accuracy, Sensitivity, Specificit,M-ID.
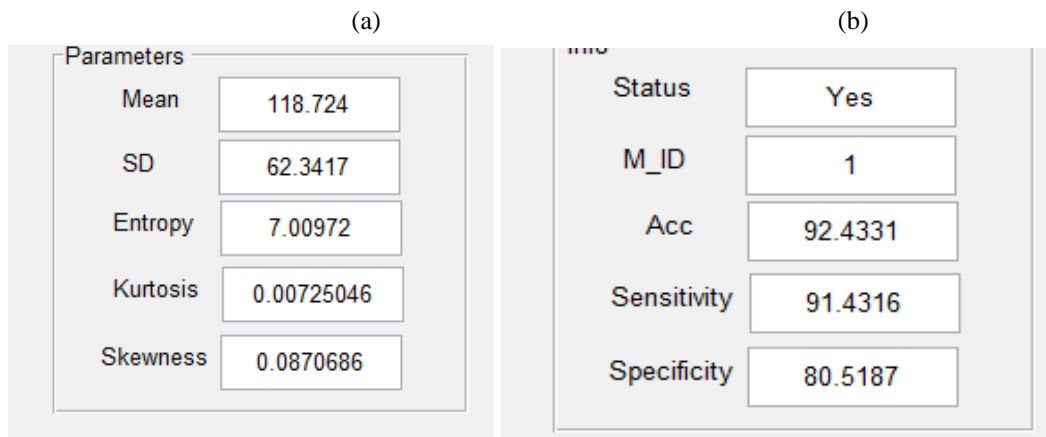
3. Results

From Fig.1, it was observed that the simulation process of deblurring an input blurred image. From the original image, blur was degraded using the point spread function and then spread out the blur with the initial point using a pad array. By initialising the PSF, a weight array can be formed. At last, using Gaussian and poisson filters, blur can be removed using a deconvolution algorithm.

Fig. 1 - Simulation results of image deblurring and it corresponds to a relatively small network. It is composed of four layers that the original image can appear in Fig.1a, Deblurring with INITPSF can appear in Fig.1b and weight array can appear in Fig.1c and at last the deblurred image can appear in Fig.1d.


From Fig.2, it was observed that the peak accuracy rate of deblurred images in the RLD method is 92%. Due to the presence of low accuracy rate, the performance of deblurring the blurred images in RLD decreases. It takes the input image with a mean value of 118.72 and entropy of 7.009. The image has been deblurred with sensitivity of 91% and specificity of 81%.

Fig. 2 - Simulated input and output parameters at matlab software using the RLD algorithm. The input image contains a mean of 118.72 and entropy of 7.009. The image has been deblurred with accuracy of 92.43%.

(a)   (b)

Parameters		Info	
Mean	118.724	Status	Yes
SD	62.3417	M_ID	1
Entropy	7.00972	Acc	92.4331
Kurtosis	0.00725046	Sensitivity	91.4316
Skewness	0.0870686	Specificity	80.5187

From Fig.3, it was observed that the peak accuracy rate of deblurred images in the Novel DNN method is 98%. It takes the input image with a mean value of 118.72 and entropy of 7.009. The image has been deblurred with sensitivity of 100% and specitivity of 90%.

Fig. 3 - Simulated input and output parameters at matlab software using the DNN algorithm. The input image contains a mean of 118.72 and entropy of 7.009. The image has been deblurred with accuracy of 98.28%.

(a)   (b)
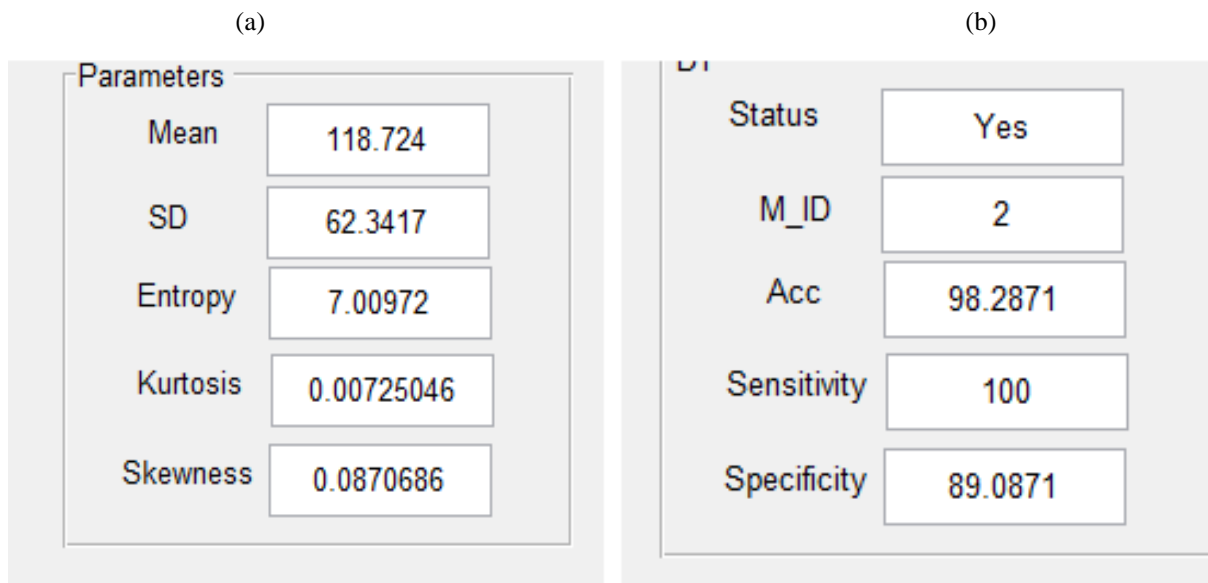
In performing statistical analysis of 20 samples, RLD obtained 2.85 standard deviation with 0.52 standard error while DNN obtained 1.18 standard deviation with 0.26 standard error (Table 1). The significance value smaller than 0.002 showed that our hypothesis holds good. With respect to changes in the input values (independent variables) the corresponding output values (dependent variables) also changes. Independent t-test was used to compare the accuracy of two algorithms and a statistically significant difference was noticed $P < 0.002$ (Table 2).

Table 1 - Group statistics of image deblurring can be done by analysis of accuracy comparison between RLD and DNN algorithms. RLD has mean accuracy of 92.8 and standard deviation of 2.85. DNN has mean accuracy of 97.1 and standard deviation of 1.18

Parameter	Group	N	Mean	Std. deviation	Std. Error Mean
Accuracy	**RLD**	20	92.8050	2.85307	.52728
	DNN	20	97.1000	1.18322	.26458

Table 2 - The independent sample T-test is analysed for equal variances assumed and equal variances not assumed. In this statistical analysis, F-score for levene's test value is 11.523. Significance for statistical accuracy analysis is obtained as 0.002.

		Levene's test for Equality of Variances		T-test for Equality of Means						95% confidence interval of the difference	
		F	Sig	t	df	Sig. (2-tailed)	Mean difference	Std. Error difference		Lower	Upper
Accuracy	Equal Variances assumed	11.523	.002	-7.28	38	.000	-4.2	.589		-5.4	-3.1
	Equal Variances not assumed			-7.28	27.9	.000	-4.2	.589		-5.5	-3.0

From Fig. 4, it was observed that the DNN model obtained 98% accuracy in statistical analysis. Lucy-Richardson, wiener filtering, Regularization approach techniques obtained an accuracy of 92%, 84% and 76% respectively. The performance of the proposed DNN algorithm appears to be better accuracy than the RLD algorithm.

Fig. 4- Comparison of DNN algorithm and RLD method in terms of mean accuracy. The mean accuracy of DNN is better than RLD and the standard deviation of DNN is slightly better than RLD. X-Axis: DNN vs RLD Algorithm and Y-Axis: Mean accuracy of detection ± 1 SD.
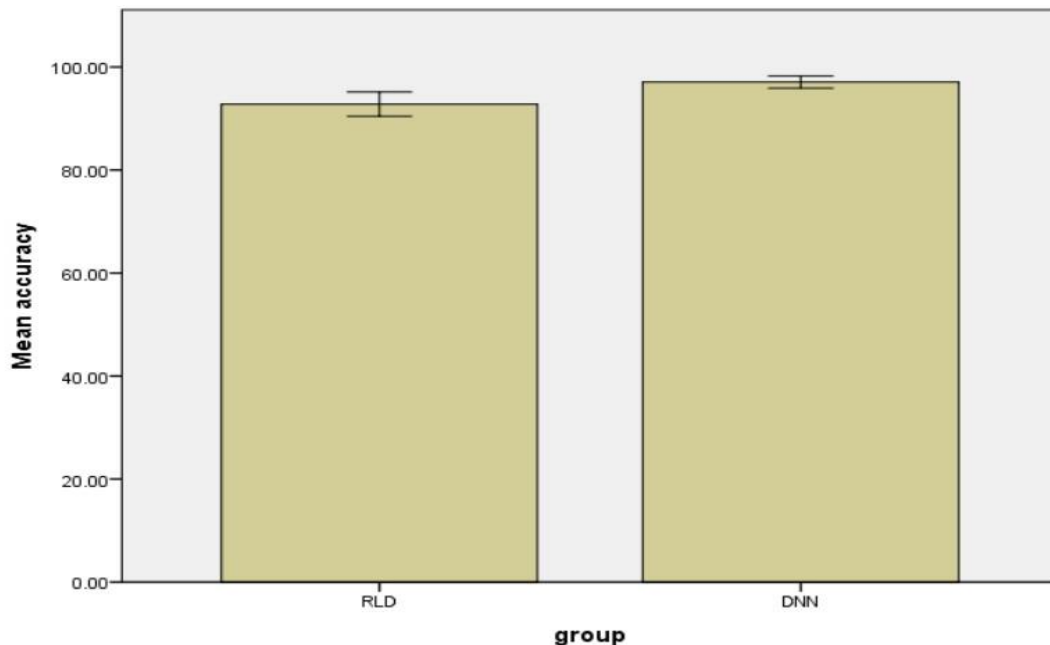
4. Discussion

In this study, we observed that Novel DNN appears to be better than RLD classifier with an accuracy of 98.28% (p<0.05). In this analysis, accuracy rate of RLD and Novel DNN algorithms are

analyzed by varying the dataset values of input image and weight array. Accuracy has been simulated for different pixel size images ranging from (1-256) pixels. Accuracy rate in RLD method deblurring is 92.8050% and Accuracy rate in Novel DNN algorithm is 98.1000%. After analyzing the results obtained from MATLAB, samples are collected from the resulting images. By performing the group statistical and independent sample T-test analysis, it is observed that the accuracy rate of the Novel DNN algorithm appears to be better when compared to the RLD method of deblurring an image.

Pixels are the formation of an image that determines the size of the image and resolution with graphic display. It is used to know the thermal noise in an image. Noise is a random variety of image density and it is visible as grain film. The blur is an effect to average out rapid changes in intensity. A distortion affects the change in display resolution because that is not set correctly at pointed places in pixels. Visualisation of images blurring and deblurring can be processed by using Neural networks with AlexNet and VGGNet with train images as data to analyze the accuracy rate as 84.52% (Wang, Liu, and Cheng 2018). It is having low accuracy because using NNs with inverse transformations cannot get low significance. A unified design model for camera shake blur to restore motion blur from a single blurred image with perceptual level loss of 10 dB (Zeng and Diao 2020). The proposed DNN algorithm has a higher accuracy rate due to its low significance and noise ratio. Deblurring of images with fast and full resolution using neural networks in the light field obtained an accuracy rate of 92%. Since it has less accuracy due to issues limited motion blur and reduced spatial size (Lumentut et al. 2019).

Our institution is passionate about high quality evidence based research and has excelled in various fields ((Vijayashree Priyadharsini 2019; Ezhilarasan, Apoorva, and Ashok Vardhan 2019; Ramesh et al. 2018; Mathew et al. 2020; Sridharan et al. 2019; Pc, Marimuthu, and Devadoss 2018; Ramadurai et al. 2019). We hope this study adds to this rich legacy.

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Deblurring of images is difficult for higher range pixel size images that are optimized with blur effect. For higher significance images, deblurring is quite difficult and motion blur having different directions of images can cause data loss problems while deblurring. For future extension, this work can further improve by using various algorithms in machine learning and AI programs to enhance the accuracy rate and quality of an image for higher range pixel size images and video clips.

5. Conclusion

The proposed work is implemented for image restoration from the degraded image to enhance the accuracy. Novel DNN algorithm enhances the accuracy rate of deblurring images that appears to be 98%. The accuracy rate of the RLD method is 92%. Image deblurring can be done using the deconvolution method of DNN algorithm in machine learning approach. It concludes that DNN algorithm accuracy appears to be significantly better when compared with RLD.

Declarations

Conflict of Interests: No conflict of interest in this manuscript.

Author Contributions

Author SD was involved in data collection, data analysis and manuscript writing. Author GU was involved in the conceptualization, data validation and critical review of the manuscript.

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