# Image DeblurringUsingDeepLearning

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***Abstract*** — *The proposed method is highly efficient forremoving mild blur from blurred images. Blind imagedeblurringwhichisbasedondeeplearningplaysanimpor tant role in solving image blur problem. We focusonremovingmildblurwhichwillgenerallyruinthequality of the images. These types of blurs will occur dueto out of focus lens, and slight camera motion. In theproposed method we are preparing our own blur images dataset.We have the datas et which cons is to high-resolution images, then we add gaussian blur to thesesharp images to degrade the quality of sharp images inorder to obtain a new dataset. We will call this dataset asdeblur dataset. A deep learning architecture is applied togetbackhigh-resolution image from low resolution deblurred images.CNNarchitecture isused for image deblurring.*

***IndexTerms*—**imagedeblurring,deeplearning,convolutionalneural networks.

## 1. INTRODUCTIOIN

Image Deblurring is an old problem in the realm of image processing, one that continues to garner attention from academics and businesses alike. It has applications in many different real-world problems and serves as an easy way to visualize examples of a larger range of inverse problems in many fields. Image deblurring seeks to take a blurry image and restore it to its original form algorithmically. When deblurring images, a mathematical description of how it was blurred is very important to maximizing the effectiveness of the deblurring process. With real-world photos, we do not have the luxury of knowing the mathematical function by which the image was blurred. However, there exist methods to approximate how blur occurred. There are many different sources of blur in a photograph, such as motion blur, camera shake and long exposure times. Even a relatively small amount of any of these effects can be enough to ruin an otherwise good photograph. Image deblurring tools and research seek to solve this problem by taking the blurred images and attempting to restore or alter them to a sharper, clearer state. In the following section, some background information on image deblurring and associated techniques will be presented. Following that, we will discuss the results that were obtained, as well as discussing some of the

weaknesses and limitations in the investigation. Image sharpness is undoubtedly one of the most relevant attributes defining the visual quality of a photograph. Blur is caused by numerous factors such as the camera's focus not being correctly adjusted, objects appearing at different depths, or when relative motion between the camera and the scene occurs during exposure. Deep learning is a subfield of machine learning that has had significant impact in the field of image processing. In image processing, deep learning algorithms such as Convolutional Neural Networks (CNNs) are used for tasks such as image classification, object detection, semantic segmentation, and image deblurring. In image deblurring, a deep learning model is trained to remove blur from a blurred image and restore the original, sharp image. This is done by learning a mapping from the blurred image to the sharp image, which is then used to deblur new images. Overall, deep learning has become a powerful tool for image processing tasks and is likely to continue to play an important role in this field in the future. CNN (convolutional neural network) have become a popular choice for image processing tasks due to their ability to automatically learn useful features from the image data and their high accuracy in a wide range of tasks. CNNs are important in image deblurring because they can effectively learn the mapping between the blurred image and the sharp image. Image deblurring is a challenging problem because it requires the removal of significant amounts of noise and blur, which can cause loss of detail and resolution in the final deblurred image. By using a deep learning approach, a CNN can learn the complex mapping between the blurred image and the sharp image, allowing it to effectively remove the blur and recover the details of the image. The convolutional layers in the network can be trained to learn features that are robust to the presence of blur and noise, allowing the network to produce high-quality deblurred images. Additionally, CNNs can be trained end-to-end, allowing the network to learn the entire mapping from the input blurred image to the output deblurred image in a single pass. This makes the deblurring process more efficient and eliminates the need for complex pre-processing or post-processing steps. In conclusion, the ability of CNNs to learn complex mappings and their high accuracy make them an important tool for image deblurring tasks.

## 2. RELATEDWORK

### A. ConvolutionalNeuralNetworks

Convolutional neural networks (CNNs) have gained popularity in image processing tasks, particularly in image deblurring. Their effectiveness in learning useful features from image data and achieving high accuracy in a wide range of tasks make them a preferred option. Image deblurring is a difficult problem that requires removing substantial amounts of noise and blur while maintaining the resolution and details of the final image. A deep learning approach that utilizes a CNN can learn the intricate mapping between a blurred image and a sharp image, enabling it to effectively remove the blur and recover the image's details. The network's convolutional layers can learn to recognize features that are resistant to noise and blur, which produces high-quality deblurred images.Moreover, CNNs can be trained end-to-end, which means the network can learn the complete mapping from the blurred image input to the deblurred image output in one go. This simplifies the deblurring process, streamlining it without requiring any complicated pre-processing or post-processing stages. Consequently, the ability of CNNs to learn complicated mappings and their remarkable accuracy render them an essential tool for image deblurring tasks.

### B. DeepLearning

Deep learning is a subset of machine learning that has greatly impacted the field of image processing. It has enabled the use of advanced algorithms like Convolutional Neural Networks (CNNs) for various tasks such as object detection, semantic segmentation, image classification, and image deblurring. In image deblurring, deep learning models are trained to eliminate blurs from a blurred image and restore the original, clear image. The model does this by learning the correlation between the blurred and sharp image and uses this information to deblur new images.All in all, deep learning has proven to be a powerful tool for image processing tasks and is poised to continue playing a significant role in this field.

### C. ImageSuperResolution

Image super-resolution (SR) refers to the process of enhancing the resolution of an image while retaining its visual content. It has a wide range of applications, such as computer vision, graphics, and image processing. Various techniques exist for achieving image SR, including traditional ones like bicubic interpolation, and modern ones like single image super-resolution (SISR) methods, which utilize machine learning, particularly deep learning, to reconstruct high-resolution images from low-resolution inputs. SISR techniques, such as SRCNN (Super-Resolution Convolutional Neural Network) and DBSRCNN (Deep Back-Projection Networks for Super-Resolution Convolutional Neural Network), are founded on convolutional neural networks (CNNs) and can achieve exceptional results on diverse image super-resolution benchmarks. They are trained on vast datasets containing pairs of high and low-resolution images, and deep learning algorithms are employed to learn the mapping from low to high-resolution images. Although SISR methods demonstrate promising results, there are still challenges that need to be addressed, such as high computational requirements, the difficulty in obtaining large and diverse training datasets, and the existing limitations of SR algorithms in preserving fine details in the high-resolution output.

## 3. LITERATURE SURVEY

[1] Yu-An Chen has developed a novel approach for deblurring images directly from raw data. The method utilizes a dataset that contains both raw and sRGB images, and the proposed model is designed to effectively exploit the unique features of raw images during the deblurring process. The author's findings indicate that the performance of current deblurring models can be enhanced by utilizing raw images for training the model. In essence, this method offers a significant improvement in the deblurring process by taking advantage of the distinctive properties of raw images.

[2] Damien Kelly has introduced a new method for blind image restoration that is specifically aimed at removing mild blur from natural images, with a particular focus on mobile phone images. The proposed method involves estimating the blur of an image and subsequently removing it. According to the author, this approach is more efficient than both traditional and modern blind image restoration techniques. The study highlights the effectiveness of the proposed method in improving the quality of images captured on mobile phones by removing mild blurring.

[3] S. Hosseini has presented a novel approach to image deblurring, which involves using a one-shot convolution filtering method to directly restore naturally blurred images. The proposed method utilizes Finite Impulse Response (FIR) and Point Spread Function (PSF) to achieve the desired results. In addition, Gaussian low pass filters are employed to address image edge deblurring and to reduce noise in the images. This approach represents a promising new direction in the field of image deblurring, with the potential to produce high-quality results in a more efficient and effective manner.

[4] Jiangxin has introduced a new approach for estimating inliers and outliers during the image deblurring process. The method employs a deep convolutional neural network that generates a confidence map, allowing for the identification of both inliers and outliers. The proposed approach has the potential to improve both blind and non-blind image deblurring processes. This innovative technique represents a significant advancement in the field of image processing, with the potential to enhance the accuracy and effectiveness of deblurring methods.

[5] Ying He has proposed a novel approach for image deblurring that does not require estimation of the blur kernel. Instead, a pair of images consisting of a blurred image and a noisy image are used as input. The blurred image is then divided into smaller patches, and each patch is analyzed and compared to the corresponding patch in the noisy image to determine the optical flow between the two images. The Gaussian mixture model (GMM) is utilized to identify the intensity distribution of each patch, which is then used to estimate the latent sharp image. This approach eliminates the need for blur kernel estimation, which can be a challenging task, especially in cases where the blur is complex and not well-defined. By utilizing the information from both the blurred and noisy images, the proposed method can effectively remove the blur and restore the sharpness of the image.

## 4. DEBLUR DATASET

For training purpose, we will prepare our own dataset and we call this dataset as Deblur dataset. First step is to prepare dataset sharp images and then we will add Gaussian blur to these sharp images to obtain new blurred dataset.

To add Gaussian blur, first we import OpenCV, NumPy, os, and tqdm libraries and modules. We need all these libraries and modules. Then we will read all the images from sharp dataset, and we will add Gaussian blur to these images using GaussianBlur () function. Finally, we will store blurred images back into the dataset. Now we have both blurred Images and their original sharp images in our dataset.

Gaussianfunctionis:

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}\right).$$

Where, $\sigma$is standarddeviation.


## 5. PROPOSEDMETHOD

In this section, we will discuss the proposed method in detailparticularly the network architecture that has been developedforimagedeblurringprocess.

**A. NetworkArchitecture**

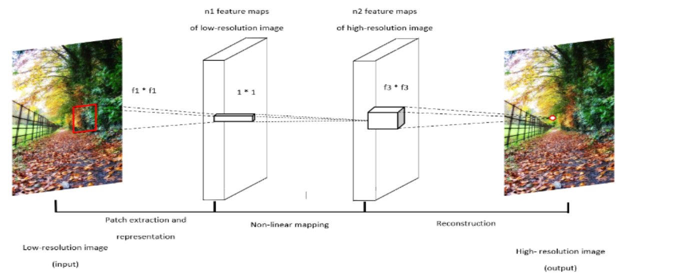


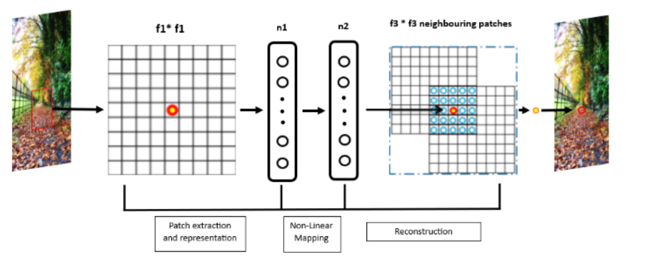

**Fig. 1**overview of the Convolutional neural networkarchitecture

**Fig. 2**Convolutional neural network architecture

The network architecture that has been used is shown infigure 1 and figure 2. The architecture used is DBCNN (DeepBack-Projection Convolutional Neural Network). DBCNN isathreelayeredconvolutionalneuralnetworkarchitecture,and the layersare discussed below:

Input Layer: low resolution blurred images are fed into thearchitecture for feature extraction. The input images containGaussian blur.

Patchextractionandrepresentation**:**Inthishiddenlayerextractionofo




verlappingpatchesfromtheinputimageisdoneandeachpatchisrepresentedasahigh-dimensionalvector. A Rectified Linear Unit (ReLU) activation function $F_1$is used in this layer of architecture. This function operatingwith $n_1$feature maps.

Non-linear mapping: In this hidden layer output of previoushidden layer (high-dimensional vector) is taken as input andeachhigh-dimensionalvectorisagainmappedtoanotherhigh-dimensionalvector,representingthehigh-resolutionpatch. ReLU activation function is operating with $n_2$featuremaps. Thisprocessisdoneforfeature enhancement.

Reconstruction:Thisistheoutputlayerandperformsreconstruction operation. It combines all the high-resolutionpatches which we get as output from previous layer. The high-resolution images are reconstructed by aggregating the patch-wiserepresentation.

Now we will discuss each layer of the network architecture indetail.

**Fig. 3** Our proposed network architecture DBCNN

firstconvolutionallayerofthearchitecture(DBCNN),thefollo wing stepshappen:

In the first layer extraction of overlapping patches from the inputimageisdoneandeachpatchisrepresentedasahigh-dimensionalvector.In the second hidden layer each high-dimensional vector is againmappedtoanotherhigh-dimensionalvectorforfeatureenhancement.Inthe thirdlayerthesepatchesarecombinedtoreconstructthefinaldeblur redhigh-resolutionimageF(M).

Patchextractionandrepresentation:Inthishiddenlayerextractiono foverlappingpatchesfrom the input image is done and each patch is represented asa high-dimensional vector. A Rectified Linear Unit (ReLU)activation function $F_1$is used in this layer of architecture.Thisfunctionoperateswithn$_1$feature maps.Conventionally,thefirstlayerisexpressedas:

$F_1(M) = \max(0, W_1 * M + B_1)$

Where,$W_1$representthefilters,heresizeof$W_1$is$C*f_1*f_1*n_1$,

C = number of channels in the input image, $f_1$= spatialsize of a filter, $n_1$= number of filters,$B_1$representsthebiases, $B_1$=$n_1$dimensionalvectorandeachelementof$B_1$isassociated witha filter.

Non-linearmapping:Inthis hiddenlayeroutput of previous hiddenlayer(high-dimensional vector) is taken as input and each high-dimensionalvectorisagainmappedtoanotherhigh-dimensional vector, representing the high-resolution patch.ReLU activation function is operating with $n_2$feature maps.This process is done for feature enhancement.Inthe firstlayerforeachpatchn$_1$dimensionalfeatureareextracted.Then,e achextractedn$_1$dimensionalvectorismapped into an $n_2$ dimensional vector. The second layer isexpressed as:

$$F_2(M)=\max(0, W_2 * F_1(M)+B_2)$$

Where,sizeof$W_2$is$n_1*1*1*n_2$.

$B_2$= $n_2$dimensionalvector, eachn$_2$dimensionalvectorrepresentsahigh-resolutionpatch that willbe usedforreconstruction.

Reconstruction:Thisistheoutputlayerandperformsreconstructio noperation. It combines all the high-resolution patches whichwe get as output from the previous layer. The high-resolutionimagesarereconstructedbyaggregatingthepatch-wiserepresentation.

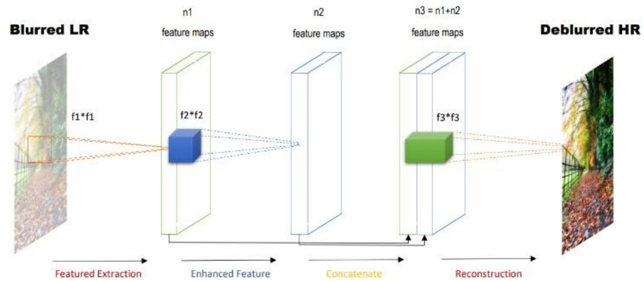
Final convolutional layer is expressed as:

$$F(M)= W_3 * F_2(M) + B_3$$

Where, size of$W_3$is$n_2*f_3*f_3*C$.

**B. DBCNN(DeepBack-ProjectionConvolutionalNeuralNetwork)**

DBCNNcanalsobeusedforimagedeblurring,inaddition to its use for image super-resolution. In the contextof image deblurring, DBCNN can be trained to restore theoriginalsharpimage fromablurredinput.




ThearchitectureofDBCNNforimagedeblurringissimilarto its architecture for image super-resolution. It consists ofmultipleconvolutionallayers,ReLUactivationfunctions,andback-projectionlayers. Theconvolutional layersareusedto extract features from the blurred input image, while theback-projectionlayersrefinethesharpimagepredictiongeneratedbythefea tureextractionlayers.Thefinallayercombines the blurred input and the sharp image prediction toproducethe deblurredoutput.DBCNNhasbeenshowntoachievepromisingresul tsonvariousimagedeblurringbenchmarks,anditsuseofback-projectionlayershelpstopreservethefinedetailsinthedeblurred output. However, the performance of DBCNN forimage deblurring may depend on several factors, including thequalityofthetrainingdata,thecomplexityoftheblur,andthecomp utationalresourcesavailable.

## 5. CONCLUSION

Inconclusion,thisprojectaimedtoevaluatetheeffectivenes s of using CNNs for image deblurring. We haveshown that deep learning-based approaches can achieve state-of-the-artperformanceinremovingnon-uniformblurfromimages. We learned how to deblur Gaussian blurred imagesusingdeeplearningandconvolutional neural networks.OurexperimentsdemonstratethepotentialofCNNsforima gedeblurring and highlight the importance of carefully designingthenetworkarchitectureandtraining procedure.

We have also shown that combining different techniques, suchas residual networks and skip connections, can further improvethe performance of CNNs for image deblurring. In future work,we plan to evaluate the performance of the network architecturethat we have proposed on a larger and more diverse dataset ofblurredimages.

Overall,thisprojecthasprovidedvaluableinsightsinto the use of CNNs for image deblurring and highlights thepotential for deep learning techniques to tackle complex imageprocessingproblems.

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## REFERENCES

[1] Chih-HungLiang,Yu-AnChen,Yueh-ChengLiu,andWinstonH.Hsu,"RawImageDeblurring",IEEETRANSACTIONSONMULTIMEDIA, 2020

[2] B. Lu, J.-C. Chen, and R. Chellappa, "Unsupervised domain-specificdeblurring via disentangled representations," in *Proceedings of the IEEEConferenceonComputerVision andPatternRecognition*,2019,pp.10225–10234.

[3] MauricioDelbracio,IgnacioGarcia-Dorado,SungjoonChoi,Damien Kelly,andPeymanMilanfar,"Polyblur:RemovingMildBlurbyPolynomial Reblurring"IEEEtransactionsonComputionalImaging, Vol7,2021

[4] S.-D. Yang, H.-T. Su, W. H. Hsu, and W.-C. Chen, "Deccnet: Depthenhanced crowd counting," in *The IEEE International Conference onComputerVision(ICCV)Workshops*,Oct2019.

[5] X. Tao, H. Gao, X. Shen, J. Wang, and J. Jia, "Scale-recurrent networkfor deep image deblurring," in *Proceedings of the IEEE Conference onComputerVisionandPatternRecognition*,2018,pp.8174–8182.

[6] H. Zhang, Y. Dai, H. Li, and P. Koniusz, "Deep stacked hierarchicalmulti-patch network for image deblurring," in *Proceedings of the IEEEConference on Computer Vision and Pattern Recognition*, 2019, pp.5978–5986.

[7] S. Nah, T. Hyun Kim, and K. Mu Lee, "Deep multi-scale convolutionalneural network for dynamic scene deblurring," in *Proceedings of theIEEE Conference on Computer Vision and Pattern Recognition*, 2017,pp.3883–3891.

[8] S. Su, M. Delbracio, J. Wang, G. Sapiro, W. Heidrich, and O. Wang,"Deep video deblurring for hand-held cameras," in *Proceedings of theIEEE Conference on Computer Vision and Pattern Recognition*, 2017,pp.1279–1288.

[9] C.Chen,Q.Chen,J.Xu,andV.Koltun,"Learningtoseeinthedark,"in *Proceedings of the IEEE Conference on Computer Vision and PatternRecognition*,2018,pp.3291–3300.

[10] X. Xu, Y. Ma, and W. Sun, "Towards real scene super-resolution withrawimages,"in*ProceedingsoftheIEEEConferenceonComputerVision andPatternRecognition*,2019,pp.1723–1731.

[11] X. Zhang, Q. Chen, R. Ng, and V. Koltun, "Zoom to learn, learn tozoom," in *Proceedings of the IEEE Conference on Computer Vision andPatternRecognition*,2019.

[12] D. Gong, J. Yang, L. Liu, Y. Zhang, I. Reid, C. Shen, A. Van Den Hen-gel, and Q. Shi, "From motion blur to motion flow: a deep learningsolutionforremovingheterogeneousmotionblur,"in*Proceedingsof theIEEE Conference on Computer Vision and Pattern Recognition*, 2017,pp.2319–2328.

[13] C.Ledig,L.Theis,F.Huszár,J.Caballero,A.Cunningham,A.Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang *et al.*, "Photo-realistic singleimagesuper-resolutionusingagenerativeadversarialnetwork,"in*Proceedings of the IEEE conference on computer vision and patternrecognition*,2017,pp.4681–4690.

[14] W.-S. Lai, J.-B. Huang, N. Ahuja, and M.-H. Yang, "Deep laplacianpyramidnetworksforfastandaccuratesuper-resolution,"in*Proceedingsof the IEEE conference on computer vision and pattern recognition*,2017,pp.624–632.

[15] B. Lim, S. Son, H. Kim, S. Nah, and K. Mu Lee, "Enhanced deepresidualnetworksforsingleimagesuper-resolution,"in*Proceedingsof the IEEE conference on computer visionand pattern recognitionworkshops*,2017,pp.136–144.

[16] Y.Tai,J.Yang,andX.Liu,"Imagesuper-resolutionviadeeprecursive residual network," in *Proceedings of the IEEE conference oncomputervisionandpatternrecognition*,2017,pp.3147–3155.

[17] J.Caballero,C.Ledig,A.Aitken,A.Acosta,J.Totz,Z.Wang,and W.Shi,"Real-timevideosuper-resolutionwithspatio-temporalnetworks andmotioncompensation,"in*ProceedingsoftheIEEEConference on Computer Vision and Pattern Recognition*, 2017, pp.4778–4787.

[18] X.Yang,H.Mei,J.Zhang,K.Xu,B.Yin,Q.Zhang,andX.Wei, "Drfn:Deeprecurrentfusion networkfor single-image super-resolution withlargefactors,"*IEEETransactionsonMultimedia*,vol.21,no.2,pp.328–337,2018.

[19] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a gaussiandenoiser: Residual learning of deep cnn for image denoising," *IEEETransactions onImageProcessing*, vol.26, no. 7, pp. 3142–3155,2017.

[20] X.LiaoandX.Zhang,"Multi-scalemutualfeatureconvolutionalneural network for depth image denoise and enhancement," in *2017IEEEVisual Communications and Image Processing (VCIP)*.IEEE,2017,pp.1–4.

[21] X. Cai and B. Song, "Semantic object removal withconvolutionalneuralnetworkfeature-basedinpaintingapproach,"*MultimediaSystems*,vol.24,no.5,pp.597–609,2018.

[22] J. Chen, C.-H. Tan, J. Hou, L.-P. Chau, and H. Li, "Robust videocontent alignmentandcompensationforrainremovalinacnnframework," in*Proceedings of the IEEE Conference onComputerVisionandPatternRecognition*,2018,pp.6286–6295.

[23] F.Luan,S.Paris,E.Shechtman,andK.Bala,"Deepphotostyletransfer," in *Proceedings of the IEEE Conference on Computer VisionandPatternRecognition*,2017,pp.4990–4998.

[24] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translationwithconditionaladversarialnetworks,"in*ProceedingsoftheIEEE conference on computer vision and pattern recognition*, 2017, pp. 1125–1134.

[25] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-imagetranslation using cycle-consistent adversarial networks," in *Proceedingsof the IEEE international conference on computer vision*, 2017, pp.2223–2232.

[26] O.Kupyn,V.Budzan,M.Mykhailych,D.Mishkin,andJ.Matas,"Deblurgan: Blind motion deblurring using conditional adversarial net-works,"in*ProceedingsoftheIEEEConferenceonComputerVisionandPatte rnRecognition*,2018,pp.8183–8192.

[27] J.Zhang,J.Pan,J. Ren,Y.Song,L. Bao,R.W.Lau,andM.-H.Yang,"Dynamicscenedeblurringusingspatiallyvariantrecurrentneuraln etworks," in *Proceedings of the IEEE Conference on Computer VisionandPatternRecognition*,2018,pp.2521–2529.

[28] L. Xu, J. S. Ren, C. Liu, and J. Jia, "Deep convolutional neural networkfor image deconvolution," in *Advances in neural information processingsystems*,2014,pp.1790–1798.

[29] T. Plotz and S. Roth, "Benchmarking denoising algorithms with realphotographs," in*Proceedings of the IEEE Conference on ComputerVisionandPatternRecognition*,2017,pp.1586–1595.

[30] E.Schwartz,R.Giryes,andA.M.Bronstein,"Deepisp:Towardlearningan end-to-end image processing pipeline," IEEE Transactions in ImageProcessing,vol28,no.2,pp.912-923,208