Deep Learning based Automated Image Deblurring

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Abstract. Image deblurring is a challenging task that aims to restore a sharp and clear image from a blurred one. This problem is usually caused by camera motion or defocus blur. The objective of this paper is to develop a model that can effectively remove Gaussian blur from an image and improve its quality using deep learning techniques. Automated image deblurring is achieved using deep learning, this approach involves implementing a combination of convolutional neural networks (CNN) and simple auto encoders to train the model on a dataset of blurred and corresponding sharp images. The model is then used to deblur the test images and improve their quality. The paper uses a dataset of blurred and corresponding sharp images to train the model, and the performance of the model is evaluated based on metrics such as PSNR and SSIM. The results and discussions focus on the effectiveness of the model in removing Gaussian blur and improving the quality of the images. In conclusion, the paper demonstrates the effectiveness of using deep learning techniques for image deblurring and provides scope for future enhancements such as incorporating more complex models and exploring other types of blur removal techniques.

1 Introduction

Deep learning is a subset of machine learning that focuses on training artificial neural networks with multiple layers to learn and extract complex patterns from data. It is inspired by the structure and function of the human brain, with each layer of the network processing and transforming input data to generate meaningful output. Deep learning has demonstrated remarkable success in various domains, including computer vision, natural language processing, and speech recognition. It power lies in its ability to automatically extract features and discover intricate patterns, making it highly effective in solving complex and large-scale problems.

The roots of deep learning can be traced back to the 1940s and 1950s when researchers began developing mathematical models inspired by the structure and function of the human brain. However, it wasn’t until the 1980s and 1990s that significant advancements were made in neural network research, particularly with the development of back propagation, a

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key algorithm for training deep neural networks. Deep learning experienced resurgence in the late 2000s with the introduction of deep neural networks and availability of large-scale datasets. Since then, deep learning has continued to evolve rapidly, with advancements in network architectures, optimization techniques, and the availability of high-performance computing, leading to its widespread adoption and numerous breakthroughs in various fields.

The working principle involves training a deep neural network to learn the mapping between blurry images and their corresponding sharp images. The network architecture typically consists of convolutional layers that extract hierarchical features from the input image, followed by deconvolutional layers that reconstruct the sharp image. During training, the network learns to minimize the difference between the predicted sharp image and the ground truth sharp image using loss functions such as mean squared error. The network parameters are updated iteratively through backpropagation and gradient descent. Once trained, the network can be used to deblur new test images by passing them through the network, which then outputs a deblurred version of an image.

Developing a deep learning implementation comes with its fair share of challenges and pitfalls. Firstly, acquiring and preparing a high-quality dataset can be time-consuming and expensive, especially for niche domains. Secondly, choosing the right architecture and hyperparameters requires extensive experimentation and can be computationally demanding. Thirdly, overfitting is a common pitfall, where the model performs well on training data but fails to generalize to unseen examples. Fourthly, training deep learning models often requires significant computational resources. Lastly, deploying and scaling deep learning models in production can be complex and may require additional infrastructure and maintenance efforts.

2 Existing Methods

Image deblurring is a field within computer vision that focuses on the restoration of blurred images to recover sharp and clear versions. It aims to reverse the effects of blurring caused by various factors, such as motion blur, out-of-focus blur, or camera shake. Deblurring algorithms typically involve the estimation of the blur kernel or Point Spread Function (PSF) and applying a deconvolution process to recover the latent sharp image. Recent advancements in deep learning have led to the development of deep neural networks specifically designed for automated image deblurring, which have shown promising results in handling various types of blurring scenarios.

The approach [14] utilized advanced deep learning with global threshold to improve E-commerce product classification, achieving high accuracy and challenging existing technology. Authors [15] introduced an efficient method for early-stage disease detection in tomato plants using image processing techniques. Moreover, present work employed clustering, feature extraction, and neural networks, demonstrating superior performance compared to existing methods. Author [16] presented text classification algorithms for various applications and explores the use of machine learning in detecting phishing attacks. Authors [17] highlighted the significance of ML in prediction, pattern recognition and error reduction across diverse fields, emphasizing the impact of AI in broad domain. Author [18] presented text classification algorithms for various applications and explores the use of machine learning in detecting phishing attacks. Authors [19] discussed the use of machine learning and neural networks, especially CNN, for recognizing handwriting patterns, with a focus on Telugu film industry names, achieving high accuracy (98.3%).
Table 1. Summary of existing approaches.

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<td>[1]</td>
<td>Deep Convolutional neural networks (SRCNN) for single image super-resolution</td>
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### 3 Problem Statement and Objectives

#### 3.1 Problem Statement

Image blurring is a common issue that can occur for various reasons, such as camera shake when taking a photo, motion blur caused by movement of the object being captured or the camera itself, and defocus blur when the lens of the camera fails to focus properly on the object. When an image is blurred, it can cause important details to become less clear or even completely lost, resulting in a reduction in image quality. Blurred images can also make it difficult to perform tasks such as object recognition or identification, as the details required for such tasks may be lost. Traditional image deblurring methods are based on mathematical models and make assumptions about the blur kernel and the image. These methods usually assume that the blur kernel is known and that it is either spatially invariant or spatially varying but known. However, in real-world scenarios, the blur kernel can be complex and unknown, making it difficult to estimate the kernel accurately.

#### 3.2 Objective

- To train a deep learning model using large-scale datasets of blurry and sharp image pairs for image deblurring and optimize the deep learning model to achieve fast and efficient image deblurring results.
- To improve the quality of blurry images by removing the blur and restoring the original details and features and develop a user-friendly interface that allows users to upload blurry images and obtain deblurred images. To generate an automated image deblurring using deep learning.
4 Proposed Method

The paper aims to develop an image deblurring system using a combination of convolutional neural networks (CNNs) and auto encoders. The system involves training a deep learning model by leveraging the power of CNNs for feature extraction and auto encoders for image reconstruction. The trained model is then saved and integrated into a GUI interface. Users can input a blurred image through the GUI, and the system will utilize the saved model to perform image deblurring. The GUI interface will display the automated deblurred output, providing users with an intuitive and user-friendly tool to enhance the visual quality of blurred images.

4.1 Architecture of the proposed work

4.1.1 Model Development

1. Blurred image dataset: RealBlur dataset serves as the starting point for the architecture. This dataset is specifically curated to contain a collection of images that exhibit varying degrees of blurriness. These images are typically sourced from various real-world scenarios or collected under specific conditions that induce blurriness, such as motion blur or defocus blur.

2. Data preprocessing is an essential step in preparing the blurred images from the RealBlur dataset for training and evaluation. In this step, several operations are performed to transform the raw image data into a suitable format for feeding into a neural network. The main operations typically include conversion to tensors and resizing.

3. Splitting the preprocessed data into three subsets (training, validation, and testing) is a common practice in machine learning to assess and evaluate the performance of models effectively. The training subset is used to train the model, allowing it to learn from the data and adjust its internal parameters or weights. The validation subset is used to fine-tune the hyper parameters of the model and evaluate its performance during training. The testing subset serves as an unbiased evaluation set to assess the final model’s performance.

4. Model development is a crucial step in building a hybrid architecture that combines auto encoders and convolutional neural networks (CNNs) for working with the RealBlur Dataset. In the model development step, auto encoders are utilized to learn a compressed representation of the blurred images, capturing essential features that contribute to the blurriness. In the model development step, CNNs are incorporated to leverage their spatial feature extraction capabilities.

5. Model testing is a crucial step in evaluating the performance and generalization ability of the trained model. In this step, the model is tested using the preprocessed validation data, which consists of unseen images from the RealBlur dataset.

   a. Data The preprocessed validation data consists of a separate set of images from the RealBlur Dataset that were not used during model training.

   b. Model prediction on validation data: during the model testing step, the preprocessed validation images are fed into the trained model.

   c. The model’s performance on validation data is evaluated based on the comparison between the reconstructed images and the ground truth images.

6. Model evaluation: in this step, the model is evaluated using the preprocessed testing data, which consist of unseen images from the images from the RealBlur dataset that were not used during model training or validation. By evaluating the model on the testing data, a comprehensive assessment of its performance can be obtained.
7. Saving the final model saving the model involves storing its learned parameters, architecture, and other relevant information necessary to reproduce the model’s behavior. This includes the weights and biases of the model’s layers, as well as any additional configuration settings or hyperparameters that define the model architecture and training process. By saving the model as a ‘.pth’ file, it becomes a self-contained entity that can be loaded and utilized in other applications or environments without having to retrain the model from scratch.

![Image deblurring architecture diagram.](image.png)

4.1.2 User interface

1. User input of blurred image the architecture involves user interaction to initiate the deblurring process. The user provides a blurred image as the input for the system. The user can obtain the blurred image from various sources. Based on the user’s input and selection, the system acquires the chosen blurred image.

2. Image preprocessing one of the key preprocessing steps is resizing the input image to a standard tensor size, typically 224x224 pixels. This resizing is necessary to ensure that
the image is compatible with the deep learning model’s requirements. Resizing the image to a fixed size ensures that the model can process it consistently.

3. Displaying blurred image in GUI window once the preprocessing of the blurred image is complete, the GUI window displays the original blurred image to the user. This display allows the user to observe the initial stage of the image before any deblurring or enhancement takes place.

4. Deep learning model: In this step, the deep learning model, which is specifically designed for image deblurring, is retrieved from a saved file with the extension `.pth`. The `.pth` file contains the trained weights, architecture, and other relevant information necessary to reproduce the model’s behavior. Once the saved model is retrieved from the `.pth` file, the deep learning framework or library loads the model’s architecture and initialize the model’s parameters with the saved weights.

5. Displaying both blurred and automated deblurred image in GUI window once the deblurring process is complete, both the original blurred image and the corresponding automated deblurred images are displayed side by side in the GUI window.

5 Results and discussions

The RealBlur dataset is a large-scale dataset of real-world blurry and sharp image pairs that was developed for image deblurring research. The dataset contains over 8,000 pairs of images that cover a wide range of scenarios such as camera shake, motion blur, and defocus blur. The RealBlur Dataset was created to address the limitations of existing datasets that often rely on synthetic images, which may not accurately represent real-world scenarios. The dataset includes a variety of scenes such as indoor and outdoor environments, different lighting conditions, and different levels of blur intensity.

The blurry images were captured using a variety of cameras with different settings, including smartphones, digital cameras, and surveillance cameras, to ensure the diversity of the blur patterns. The sharp images were captured simultaneously with the blurry images using the same camera settings to ensure that the only difference between the two images is the blur. The dataset contains images of different resolution ranging from 480p to 1080p, and the images are in various formats such as JPEG and PNG.

A deep learning based automated image deblurring application is significant, which utilizes convolutional neural networks (CNNs) and auto encoders. This can be useful for a variety of purposes, such as,

1. Medical imaging the proposed method using CNN and auto encoders can enhance the quality of medical images, making it easier for medical professionals to accurately identify and diagnose various medical conditions. The ability to extract clear and detailed features from medical images can help doctors in identifying diseases or disorders at an early stage, leading to timely and effective treatment.

2. Forensics forensic investigations often rely on the analysis of images from security cameras, crime scenes, and other sources. However, these images may be blurred or low-quality, making it difficult to identify important details. The proposed method using CNN and auto encoders can enhance the clarity and quality of these images, making it easier for investigators to identify suspects or evidence.

3. Surveillance image deblurring using deep learning models such as CNN and auto encoders can improve the quality of surveillance footage in various ways. It can make images clearer and easier to analyze, allowing for better identification of individuals and events. This can be particularly important for surveillance applications in public safety, where clear and accurate images can be used to prevent and solve crimes. Furthermore, the real-time processing capability of the proposed method can enhance
the efficiency of surveillance systems, making them more effective in detecting and preventing potential threats. The potential for customization also allows for the adaption of the proposed method to specific surveillance applications, further increasing its significance in the fields.

4. Photography blurry images can be a common problem in photography due to various factors such as motion blur, camera shake, or low lighting conditions. By using the proposed method, photographers can significantly improve the quality of their blurry images, making them clearer and more visually appealing. Moreover, the proposed method can also be used to create artistic effects by intentionally deblurring images.

![Diagram of Image deblurring application user interface architecture.](image.png)

**Fig. 2.** Image deblurring application user interface architecture.
Fig. 3. Generation of User Interface.

Fig. 4. Opening of file dialog box.

Fig. 5. Uploading photo to the user interface.
5. Industrial inspection In addition to quality control inspections and defect detection, image deblurring can also be used in industrial applications to enhance images for visual analysis and inspection. This can be especially useful in industries such as manufacturing, where the identification and correction of defects is critical to product quality and safety. The proposed method can help improve the accuracy and efficiency of these inspections, potentially reducing the need for manual inspections and improving overall product quality.

6. Conclusion and future enhancements

Image deblurring using deep learning is a technique that utilizes deep learning models, specifically CNNs and auto encoders, to remove blur from images. The techniques involves training the model on a dataset of blurred and clear images to learn how to extract features and remove blur from the images. Once trained, the model can be used to automatically deblur new images. The proposed method in this paper involves using a Tkinter GUI to allow the user to upload an image and view the deblurred output in a window. This makes the technique accessible and user-friendly.

The training of the model on a large dataset of blurred and corresponding clear images is crucial for achieving high performance. The availability of large datasets and advances in
computing hardware have made it possible to train deep learning models with high accuracy and efficiency. Overall, the adopted method for image deblurring using deep learning with Tkinter GUI provides a user-friendly and efficient solution for improving the visual quality of blurred images. With further improvements in hardware and optimization techniques, the future of image deblurring using deep learning holds great potential for a wide range of applications. There are several potential future enhancements of Image deblurring using deep learning that can improve the performance and usability of the models.

References

