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A Survey of Deep Learning Methods for Noise Classification and Detection in Historical Image Analysis

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Abstract*: Historical images often suffer from various types of noise due to aging, degradation, and other environmental factors, which can significantly impact their quality and usability. The advent of deep learning has revolutionized the field of image processing, offering robust methods for noise classification and detection. This survey provides a comprehensive overview of the current state-of-the-art deep learning techniques employed in historical image analysis for identifying and mitigating different types of noise. We review various deep learning architectures, including convolutional neural networks (CNNs), generative adversarial networks (GANs), and auto encoders, that have been applied to this problem. The paper discusses the strengths and limitations of each approach, highlights key challenges such as data scarcity and variability in noise types, and explores future directions in this field. The survey aims to serve as a resource for researchers and practitioners by summarizing the most effective methods, evaluating their performance on different datasets, and outlining potential avenues for further research.*

Keywords: Deep Learning, - Noise Classification, - Noise Detection, - Historical Image Analysis, - Image Restoration, - CNNs, - GANs, - Auto encoders

I. INTRODUCTION

Historical images are invaluable resources for understanding the past, but they often suffer from various types of noise and degradation due to aging, environmental factors, and handling over time. These distortions can significantly impair the quality and usability of these images, making it challenging to extract meaningful information from them. The preservation and restoration of historical images are crucial for maintaining cultural heritage and facilitating historical research.

In recent years, deep learning has emerged as a powerful tool in image processing, offering innovative solutions for noise classification and detection. Deep learning models, such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and autoencoders, have demonstrated remarkable capabilities in identifying and mitigating different types of noise in images. These models can learn complex patterns from data and adapt to various noise types, making them highly effective in restoring historical images.

This survey aims to provide a comprehensive overview of the current state-of-the-art deep learning methods used for noise classification and detection in historical image analysis. We will review the key architectures, discuss their strengths and limitations, and highlight the challenges associated with applying these techniques to historical images. Additionally, we will evaluate the performance of these methods on different datasets and explore future directions in this field. By summarizing the most effective approaches and outlining potential avenues for further research, this survey seeks to serve as a valuable resource for researchers and practitioners working in the domain of historical image restoration. This introduction sets the stage by highlighting the importance of preserving historical images, the challenges posed by noise and degradation, and the potential of deep learning techniques in addressing these issues. It also outlines the scope and objectives of the survey paper.

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II. SURVEY

Recent Trends in Deep Learning Architectures

In recent years, several surveys have highlighted the advancements in deep learning architectures specifically tailored for historical image analysis. For instance, a survey by Authors focused on the application of convolutional neural networks (CNNs) and generative adversarial networks (GANs) for noise removal and image restoration. The authors emphasized the effectiveness of CNNs in feature extraction and classification of noise types, while GANs were found to be particularly useful in generating synthetic data to augment limited datasets.

Hybrid Approaches and Multi-Task Learning

Another significant trend identified in recent surveys is the use of hybrid approaches that combine different deep learning models or integrate traditional image processing techniques with deep learning. A survey by [Authors discussed the benefits of multi-task learning where a single model is trained to perform multiple tasks such as noise detection, denoising, and image enhancement simultaneously. This approach has shown promising results in improving overall image quality and reducing computational overhead.

Advances in Autoencoders and Variational Autoencoders

Autoencoders and variational autoencoders have also gained attention for their ability to learn compact representations of images, which is crucial for denoising historical images.

A survey by Authors explored the application of autoencoders in historical image restoration, highlighting their ability to capture complex patterns and anomalies in images. The use of variational autoencoders was particularly noted for their capability to handle high-dimensional data and generate new samples that can be used for data augmentation.

Noise estimation is performed in the spatial and transformation domain. Spatial domain noise is estimated using PCA [1], a fuzzy model in MRI images [2]. In transformation, domain noise is estimated using DWT coefficients [3]. Both spatial and transformation domain are used to find the noise amount [4].

The presence of noise was identified by applying the DCT to obtain the kurtosis. The kurtosis values decrease with an increase in the noise density. The threshold value is computed by observing the kurtosis value for every image in the dataset. The absolute deviation for the noisy and noise-free images is calculated to decide image is noisy or not. They have considered the SIPI MISC dataset of natural images. The noise type detected is impulse, achieving an accuracy of 97% [5].

Subashini and Bharathi [6] extracted the statistical features such as kurtosis and skewness to determine the Gaussian, speckle, and salt,-and-pepper noises using the minimum distance pattern classifier. The experiment is conducted on satellite, X-ray, MRI, and digital images. The Gaussian and impulse noise identification and removal by using the intensity equalization technique where the author calculates the distance between the histograms, the maximum distance becomes the threshold depending on the value of the type of noises identified the noises and the adaptive filters are employed to remove the noises .

Kumar and Nagaraju [7] designed a methodology to denoise the grayscale image by collecting the features such as entropy, information gain, and skewness and carried out a comparative analysis on the six classifiers and achieved the PSNR, SSIM, and SDME values of 47.27, 0.97 and 61.63 dB, respectively. The regression methods such as the kernel greedy algorithm are employed to detect the Gaussian noise using the orthogonal matching pursuit algorithm and achieve a mean square error of 0.033. The speckle noise is determined using the CNN, which has the two cascaded CNN models designed.

The first stage will estimate the noise and give the input to the second module along with the noise image to remove the noise. Four layers in both the sets of CNN are designed with input dimension $40 \times 40 \times 3$. The dataset: 1,000 CT images of size 256×256 (National Biomedical Imaging Archive) is employed and achieved the PSNR of 23.05. To estimate the presence of noise, a fuzzy model and DWT coefficients are used. Very few authors have contributed in identifying noise type. Most of the authors concentrate on denoising the specific type of noised images .

The CNN model is employed to identify the noises such as impulse, Gaussian, and Poisson noises. They have used the SIPI MISC natural image dataset, noised with one and multiple combinations of noises of the dataset size 12,650

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image, for training 11,000 and testing 1,650. To reduce the computation time, PCA filters are used at every layer; 21 layers are present in the model and achieved an overall accuracy of 96.3%.

The nature of the noise is preassumed based on the imaging modality used. These assumptions have saturated the performance of the filters. Many of the authors have proposed different techniques to identify impulse noise in a window of varying sizes. Very few authors have contributed to identify the noise type of the image. Dataset used is of natural images, and size is less. Hence, there is a need for detecting noise type of an image. After identifying noise type, a better denoising technique can be applied. Knowing the nature and distribution of noise plays a vital role. Hence, it is essential to characterize the noise type and noise level present in the images.

Ref.	Methodology	Dataset	Performance measure and accuracy	Gaps identified
7	Noise identification and denoising from the grayscale image; Noise: impulse noise	Dataset: Baboon, Cameraman, Lena, peppers, and Pemaquid images (512×512 image resolution)	Accuracy: PSNR = 47.278, SSIM = 0.978, SDME = 61.637	The image size is only five; Identify only noisy pixels
8	Noises: impulse and electronic; Statistical features: kurtosis and skewness fed to the ANN	Dataset: Kaggle dataset of natural images; Two hundred images of both noises. Training 60%, testing 40%	Accuracy 94.37%	Lesser number of images are considered for training and testing
9	Noises: Gaussian; Estimate noise level using DWT coefficients	Dataset: MRI images of T1 and T2 weighted	Estimate noise	No classification
10	Noise: Gaussian, speckle, line pattern stripes, and circle pattern ring; Two-cascaded CNN model is designed.	BSD dataset and 1,000 CT dataset from NBIA, 300 SEM dataset from Dartmouth	Performance measure: PSNR and SSIM; PSNR-37.46, SSIM-0.9001	They are estimating the noise and denoising using CNN
11	Noises: impulse, Gaussian, speckle, and Poisson; To reduce the computation time, the PCA filters are used	Dataset: natural images from SIPI dataset– misc	We have carried out three experiments. Four types of noise combinations of noises; Overall accuracy 86.3%	They are considered four types of noise impulse, Gaussian, speckle, and Poisson, with eight classifiers
12	Noise: impulse; DCT to obtain the kurtosis in terms of a sum of absolute deviation to identify impulse noise	Dataset: natural images USC-SIPI Image database; Size 170 images of different noise levels	Accuracy: 97%	The data set is small and natural images. Considers only impulse noise
13	Noise: Gaussian, Speckle, and salt and pepper; Statistical features such as kurtosis and skewness	Dataset: few images from natural and medical	Features: kurtosis, skewness; Accuracy: not given	Few images
14	Noises: Gaussian, speckle, salt-and-pepper; Features: kurtosis and skewness. Method: PNN	Dataset: natural images; Size: not mentioned	Accuracy: 82%	NA

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15	Gaussian, speckle, salt-and-pepper; Features: kurtosis and skewness. ANN for classification	Dataset: natural images; Size: 180 images	Accuracy: average 84%	NA
16	Noises: Gaussian, speckle, salt-and-pepper; Features: kurtosis and skewness. Method: KNN, NN	Dataset: natural images; Size: 70	Accuracy: ANN: 87%, NN: 90%	Seventy natural images such as cameraman are used

III. EXISTING METHODOLOGY

Step	Description	Techniques/Models	Expected Outcome
1. Literature Review	Study existing deep learning approaches for noise classification and detection in image analysis.	Review CNNs, RNNs, Autoencoders, GANs, and hybrid models in academic papers and case studies.	Comprehensive understanding of the state-of-the-art techniques.
2. Dataset Collection	Collect and preprocess historical image datasets with diverse noise characteristics.	Utilize datasets like Historic ImageNet, DFD (Degraded Film Dataset), or create a custom dataset.	Dataset with diverse historical noise types (e.g., scratches, fading, artifacts).
3. Noise Categorization	Identify and categorize noise types (e.g., Gaussian noise, motion blur, scratches, compressionartifacts).	Use domain knowledge and initial classification tools to label data manually or semi-automatically.	Noise taxonomy specific to historical image degradation.
4. Model Selection	Choose and adapt deep learning models based on survey findings.	CNNs for spatial features, RNNs for sequential patterns, GANs for restoration, and self-supervised models.	Selection of models best suited for historical image noise detection and classification.
5. Model Training	Train models on labeled and/or augmented datasets with specific loss functions for noise detection.	Use supervised, unsupervised, or hybrid learning frameworks with transfer learning for improved results.	Well-trained models capable of detecting and classifying noise accurately.
6. Testing and Validation	Evaluate model performance on unseen historical images.	Metrics: PSNR, SSIM, F1-score, precision, recall.	Quantitative assessment of model effectiveness in noise classification and detection.
7. Comparative Analysis	Compare proposed models with existing methods from the survey.	Baseline comparisons using standard benchmarks or datasets.	Establishment of relative strengths and weaknesses of proposed methods.
8. Applications	Demonstrate real-world applications for the developed models.	Examples: Artifact removal, restoration of archival footage, and enhanced analysis of historical records.	Validation of the practical utility of the proposed methodology.

IV. POSSIBLE OUTCOME OF THE RESEARCH WORK

The research on A Survey of Deep Learning Methods for Noise Classification and Detection in Historical Image Analysis is expected to yield several impactful outcomes. It will provide a comprehensive understanding of the existing state-of-the-art techniques, highlighting their strengths, limitations, and applicability to historical image analysis. This work can lead to the development of a detailed taxonomy of noise types commonly found in historical images, such as scratches, fading, and artifacts, which will aid in better dataset preparation and model development. Additionally, the research may contribute to the creation or enhancement of specialized datasets for benchmarking, enabling more robust

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evaluation of models. By exploring innovative deep learning architectures, such as hybrid models combining CNNs and Transformers, the study has the potential to introduce optimized techniques for noise classification and removal, enhancing the quality and usability of restored images. Furthermore, an evaluation framework with robust metrics like PSNR, SSIM, and F1-score will ensure consistent assessment of model performance. Practical applications of the findings could include improved restoration of archival footage, enhanced analysis of historical documents, and broader use cases in other domains such as medical imaging and cultural heritage preservation. Overall, this research will identify gaps in current methodologies, inspire future advancements, and contribute to preserving historical records for academic and cultural purposes.

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