Image Noise Prediction:Noise Reduction Techniques

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***Abstract*—In digital imaging, image noise is a prevalent problem that can deteriorate the clarity and interpretability of visual data. We propose a method for the classification of different kinds of noise which can be part in photos by CNN in this research. Noise Types Five major types of noise are considered in this work: (1) Gaussian, (2) Poisson, (3) Speckle, (4) Shot and (5) Quantization. This labeled dataset served as a comprehensive training and testing corpus, whose noise varieties were added to a set of pristine images.**

Our solution is to design a new CNN model from scratch and train it in order to get discriminative features for accurate noise classification. Evaluation metrics which are PSNR, MSE, MAE and other metrics such as Precision, and Recall were used to measure the classification performances of the suggested model on diverse noise types.

The findings indicate the model's robustness in identifying noise patterns, producing high classification accuracy with strong precision and recall. This study provides valuable information for image denoising and quality evaluation applications.

***Index Terms*—Image Noise Prediction, Convolutional Neural Network (CNN), Gaussian Noise, Poisson Noise, Speckle Noise, Shot Noise, Quantization Noise, PSNR, MSE, MAE.**

I. Introduction

In digital imaging systems, image noise is a common problem induced by procedures related to capture, transmission or storage. The detection and classification of this noise are important since they may severely degrade the image quality, and subsequently affect the efficiency of later image analysis operation. Each of these noise types — Gaussian, Poisson, Speckle, Shot, and Quantization noise — affect images differently and call for different strategies to mitigation.

These researches tackles this problem by providing a Convolutional Neural Network(CNN)architecture based precisely classifying them all five types of noise. CNNs are good candidates for image classification tasks since they can learn complex spatial features. We use a diverse set of photos defaced with different types of noise to train the proposed model.

We evaluate how well our model is doing on Quantification metrics like Precision, Recall, F1-Score and also obtained the MSE, MAE, PSNR to get an idea if the model really understands to categorize correctly. The purpose of this research is to improve the area by providing a repeatable automated way to detect and sort various types of noise, thus relative to the more expensive methods for image enhancement and audio redution.

A. Types of Noise

1.Gaussian Noise: Additive Gaussian noise is invariably present in images. But it is called the Gaussian(or normal) distribution,which is given by its mean and variance. This noise is generally due to thermal noise in sensors or due to low light conditions.

2.Poisson Noise: Poisson noise is a type of noise that arises due to the statistical nature and discrete properties of light—the photons striking the image sensor. Similar to the other areas, the noise follows the visual cue.

3.Speckle Noise: Speckle noise appears as granular noise, which often arises in radar and medical imaging (e.g., ultrasound). It is multiplicative in nature, meaning that it scales the pixel values of the image.It's the result of constructive and destructive interference between coherent light waves that are scattered by the object being imaged.

4.Shot Noise: Shot noise, distinct from speckle or Gaussian noise, results from the discrete nature of electrical charge and the random fluctuations in photon arrival rates at the sensor. It can be expressed as a random impulse or "shot" that affects some pixels more than others.

5.Quantization Noise: Quantization noise occurs when an analog signal is converted into a digital form. During quantization, the continuous range of pixel values is divided into discrete levels. The error introduced by mapping continuous values to discrete levels is called quantization noise.

B. Types of Filter

1.Mean Filter: It replaces each pixel value with the average values of a neighborhood (e.g., 5x5) to smooth away small fluctuations in intensity. One nice thing however is that more or less, each pixel in the output image will be replaced with the average of the pixels in this kernel area.

2.Gaussian Filter: This is a Gaussian function that averages out over the pixel being targeted The weights have less effect the farther a pixel is from the central pixel to compare with mean filter. Best for reducing Gaussian noise, as it directly counteracts the spread of pixel intensity variations typical of Gaussian-distributed noise.

3.Median Filter: It replaces the value of each pixel by edge a median with adjacent pixels. It can especially remove salt-and-pepper noise, which appears as random bright white pixels or dark black pixels. Ideal for impulse noise problems like salt-and-pepper noise where the outliers are significant.

4. Bilateral Filter: The bilateral filter considers both the spatial proximity and pixel intensity similarity. It smoothens the image while preserving edges by only averaging pixels with similar intensities.It is used when retaining edge details is crucial, such as in facial images, textures, or medical imaging.

II. Research Tools

For a research project focused on image noise classification using deep learning, the following tools and technologies are essential for different stages of the research process, including data preprocessing, model development, evaluation, and result visualization.

A. Convolutional Neural Network

Convolutional Neural Networks (CNNs): made for image classification but used for noise identification. Their architecture consists of input layers, convolutional layers that extract features using local filters, pooling layers that down-sample the data, fully connected layers for classification, and an output layer that produces probabilities for different noise types. CNNs leverage local connectivity and parameter sharing, enabling efficient learning of hierarchical features from images. The training process involves preparing the data, applying Adam optimization techniques and employing loss functions such as category cross-entropy. CNNs Learn Specific Visual Patterns in Your ProjectOn many types of image noise — Gaussian, Salt-And-Pepper, Poisson noise, etc., CNNs develop specific visual patterns to segment it and you achieve a better level of feet to your image processing and analysis pipeline.

B. Deep Learning Frameworks

- ***Keras:*** High-level neural network API, written in Python. It is a user-friendly front end for TensorFlow, which helps in experimentation and building deep learning models more easily. Keras simplifies model building, training, and evaluation processes.
- ***PyTorch:*** PyTorch is also based on a dynamic computation graph, developed by Facebook AI Research for easy of use in research and experimentation. It is intuitive, has high-performing GPU acceleration and a customizable touch.

C. Machine Learning Libraries

- ***scikit-learn****:* Python machine learning library Scikit-learn Popular and very flexible, easy to use for putting a model up and running. We implement supervised and unsupervised learning algorithms, including clustering, regression, classification and dimensionality reduction.
- ***matplotlib/seaborn:*** Matplotlib is a good choice for the data visualization library of python that makes static, animated and interactive samples. Plotly is able to handle a large variety of charts, such as scatter plots, bar charts, histograms or line graphs. Seaborn builds on top of Matplotlib and creates a very high-level, stylish graphics that are not otherwise easily obtainable.
- ***OpenCV:*** OpenCV is a comprehensive library of programming Functions aimed at real-time image processing and computer vision. It comes with various useful tools that can be employed to do things such as object identification, feature extraction, image manipulation etc.

D. Evaluation Metrics

- ***Confusion Matrix:*** This tool is used to classify models based on the performances. It even tells how many of each TP, TN, FP or FN exist which allows me to do a detailed review of the performance of my model.
- ***Mean Absolute Error****:* The MAE is a good evaluation metric which calculates the average magnitude of errors in a set of forecasts without considering their direction. It is computed as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |I_1 - I_2| \tag{1}$$

- ***Mean Squared Error:*** MSE is the average of the sum for all values, which makes larger errors more significant. The equation is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (I_1 - I_2)^2 \tag{2}$$

- ***Peak Signal-to-Noise Ratio:*** PSNR tells us how good a picture looks if we compare the original version of a noisy or reconstructed picture with that. The reference to the version is:

$$PSNR = 10\log_{10}\left(R^2/MSE\right) \tag{3}$$

III. Methodology

The methodology is intended to methodically evaluate how well models based on convolutional neural networks (CNNs) categorize different kinds of picture noise.The steps which constitutes the methodology are:

A. Data Collection and Dataset Preparation

They started by gathering a bunch of clean images that act as different lids for real-world conditions. Five types of noise—

- Gaussian
- Poisson
- Speckle
- Shot
- Quantization

Adding noises to these images produced noisy versions. This is followed by stratified sampling to split the dataset into training (80%), validation (10%) and test (10%) samples such that no noise category is under-represented. Finally, a CSV file that included all the image metadata i.e. image name, type of noise and etc was created for considering a more organized outline for analysis.

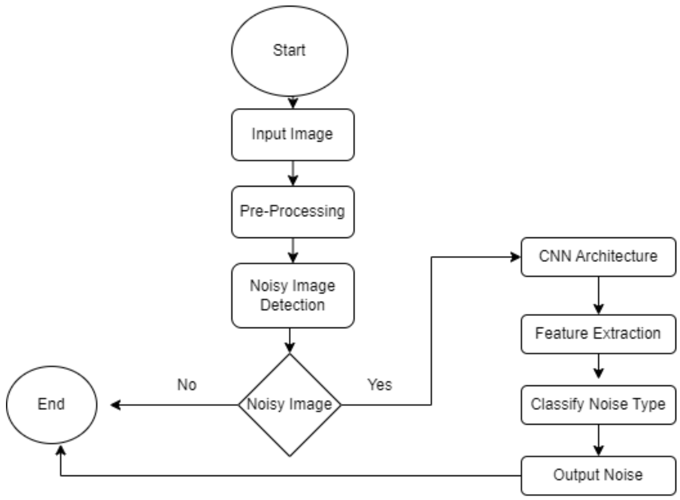

Fig. 1. Flow Chart of Proposed Method

B. Proposed CNN Model

The proposed CNN model architecture is a simple but effective design intended for noise pattern detection, and it is used to classify different types of image noise. This structure increases several layers to complete classification, dimensionality reduction and feature extraction. The below are the high level components of the model architecture:-

1. Input Layer: Accepts images with three color channels An RGB and fixed size (e.g., 128x128pixels). The photos trained are anyway pre-processed to make the pixel values equal for the efficient training.

2. Convolutional Layers:To generate these faces, a sequence of convolutional layers extract the information present in input photos. Each convolutional layer applies a collection of learnable filters, or kernels,to identify various features- such as edges, textures, and noise patterns. This layers is linear layer shown will help it to learn local patterns in the image by applying a small receptive field over it.

3. Activation Functions (ReLU): After each convolutional layer, we followed by the activation function of Rectified Linear Unit (ReLU). Because it introduces non-linearity into the network, allowing the model to learn complex patterns.

4. Pooling Layers: All the feature maps are down sampled with some max pooling. Various pooling layers exist to conserve and maximize the most important parts while lessening the spatial dimensions of the feature maps. Further, it helps in Reducing the reduces the number of parameters avoids overfitting.

5. Flatten Layer: The next layer is a flatten which takes the 2D feature maps from convolution/pooling layers and converts them into a 1D vector. This vector then flows into the fully connected layers.

6. Fully linked (Dense) Layers: To learn the high-level representations of the features, one or more fully linked layers are added. These layers combine the features that have been extracted to determine the kind of noise that is present in the photos.

7. Dropout Layers:Dropout is probably the most widespread and well-known technique for preventing overfitting: it consists in "dropping out", randomly setting to zero a fraction of input units (also known as feature maps).

8. Output Layer: A softmax activation function with the same number of neurons as the noise categories (e.g., Gaussian, Poisson, Speckle, Shot, and Quantization) is used in the last output layer. The probabilities of each form of noise are output by this layer, enabling categorization.

TABLE I
PROPOSED CNN ARCHITECTURE

Layers	***Shape***	***Params***
conv2d_8 (Conv2D)	(None, 126, 126, 64)	1,792
batch_normalization_8	(None, 126, 126, 64)	256
max_pooling2d_8 (MaxPooling2D)	(None, 63, 63, 64)	0
conv2d_9 (Conv2D)	(None, 61, 61, 128)	73,856
batch_normalization_9	(None, 61, 61, 128)	512
max_pooling2d_9 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_10 (Conv2D)	(None, 28, 28, 256)	295,168
batch_normalization_10	(None, 28, 28, 256)	1,024
max_pooling2d_10 (MaxPooling2D)	(None, 14, 14, 256)	0
conv_11 (Conv2D)	(None, 12, 12, 512)	1,180,160
batch_normalization_11	(None, 12, 12, 512)	2,048
max_pooling2d_11 (MaxPooling2D)	None, 6, 6, 512)	0
global_average_pooling2d	(None, 512)	0
dense (Dense)	(None, 512)	262,656
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 5)	2,565
Total parameters: 1,820,037		
Trainable parameters: 1,818,117		

C. Noise Classification

The process of recognizing and classifying the many forms of noise that are present in images which can seriously deteriorate their quality and impact further analysis is known as noise classification. The suggested CNN model is trained to categorize different kinds of noise, including Speckle, Shot, Poisson, Gaussian, and Salt-and-Pepper noise. This equability depending on a specific it a set of images which had been repeatedly used for the moduling a hold of the exact types together with boat noise patterns. This classification not only serves to understand the impact noise has on image quality, but also makes it easier to develop targeted denoising techniques that restore visual clarity.

D. Model Training

The CNN architecture model training process consisted of a number of important phases that were able to successfully classify different types of picture noise. After all, the dataset was originally noisy photos labeled with five different types of noise. The original pictures were first preprocessed and then passed into the Convolutional Neural Network which learnt the relevant information by running it through some convolutional layers followed by an activation function and a pooling layer. The model in assembled using an Adam optimizer with a learning rate of 1e-5 and categorical cross entropy as cost function. Training of 20 epochs with batch size of 32. To avoid overfitting, the performance was tracked using validation accuracy. The model that performed the best was kept for additional optimization.

E. Filtering Methods

After predicting the type and level of noise in an image, different filters are applied to reduce the identified noise while preserving key image features. Every filter is good at removing some types of noise characteristic in the following manner:

1. ***Mean Filter*** The goal of smoothen random noise by averaging pixel values which can handle mild Gaussian noise but tend to cause blurring.
2. ***Gaussian Filter*** We apply a Gaussian Filter which targets Gaussian noise by performing weighted averages to induce controlled 'smoothing' that does retain some details.
3. ***Median Filter***Median Filter is Opportune to removing salt and-paper noise using are placement type based on the half-value of pixels in a local neighborhood, so still retain information about or have edges..
4. ***Bilateral Filter*** Bilateral Filter preserves edge information by reducing noise,includes spatial and intensity variations,hence suited for images where edges play a vital role. We compare the metrics such as MSE, PSNR,and MAE to find the most effective noise reduction strategy for the given prediction by using these filters.

IV. Literature Review

1. Noise in Image Processing: Noise is a prevalent problem that can seriously affect the interpretation and quality of images. It usually results from things like ambient conditions, transmission faults, and sensor limits. Gaussian, Poisson, Speckle, Shot, and quantization noise are among the different types of noise; each has unique properties and impacts on images. Accurate image interpretation and subsequent analysis activities are dependent on proper noise classification.

2.Machine Learning Approaches: With evolution in Deep Learning and Convolutional Neural Networks (CNNs), the domain of noise reduction and classification has been revolutionized. CNN's area suitable for them because they can recognize patterns with in the form of images and hierarchical structures. They excely in handling complex visual structures and can classify noise of different types keeping this ability mind. The model stake many key features into account and perhaps deal with the more complex variation reasoning than their traditional counter parts, allowing for better score performance in given benchmarks as well as category noisy images far better.

3. Research on CNN-Based Noise Classification: Deep Convolution Neural Networks have been shown to be very effective in practice at Noise classification tasks as highlighted. Using a Customized CNN architecture as an example, this method was able to obtain high accuracy in the Gaussian and Poisson noise detection tasks. Another study explored transfer learning and provided more successful results with lower training time by using pre-trained models such as VGG16. These developments imply that CNNs can capture minor noise features that are hard to pick up on with traditional approaches.

4. Difficulties and Future Directions: Although CNNs have been successful in classifying noise, there are still a number of difficulties. These include the heterogeneity of noise characteristics across different datasets and the requirement for large, labeled datasets for efficient training. Researchers are investigating unsupervised and semi-supervised learning strategies to use unlabeled data for model training in order to get around these restrictions. Additionally, data augmentation is essential for managing various noise kinds and intensities and enhancing model generalization.

5. Contribution of the Project: By employing a unique CNN architecture to categorize different kinds of noise, this study seeks to expand on the results of earlier studies. This research covers a variety of noise forms, offering a thorough framework for noise classification, in contrast to studies that concentrate on particular categories. A noteworthy contribution to the field of picture noise classification is made by the suggested CNN model, which is trained on noisy images produced from pristine photos and whose performance is assessed using conventional measures.

V. Result And Discussion

A. Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR)

The fed-in filters for noise removal is assessed based on MSE and PSNR evaluation metrics. Lower MSE values are indicative of a closer match between the filtered image and original, implying that noise has been very effectively removed.

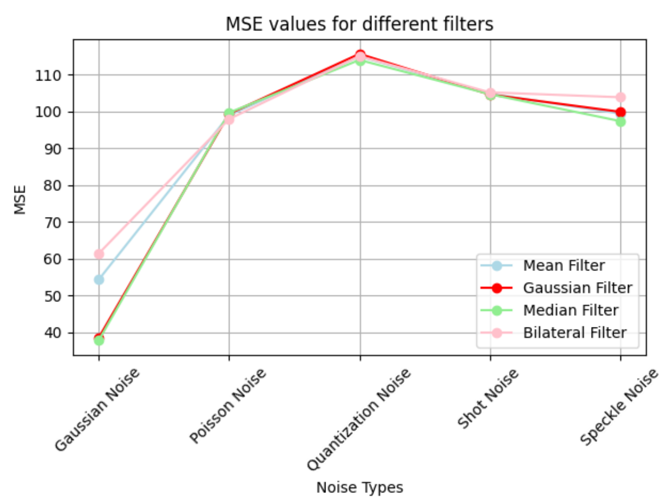

Fig. 2. Mean Squared Error

TABLE II
MEAN SQUARED ERROR (MSE)

Noise & Filters	*Mean*	*Gaussian*	*Median*	*Bilateral*
Gaussian Noise	54.329	38.576	37.862	61.400
Poisson Noise	98.901	99.299	99.602	97.866
Quantization Noise	114.895	115.570	113.908	114.957
Shot Noise	104.760	104.533	104.611	105.120
Speckle Noise	99.353	99.844	97.327	103.793

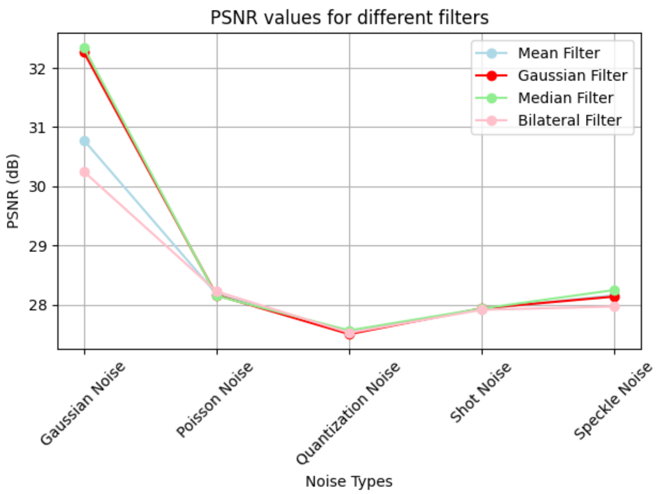

Fig. 3. Peak Signal To Noise Ratio (PSNR)

TABLE III
PEAK SIGNAL TO NOISE RATIO

Noise & Filters	*Mean*	*Gaussian*	*Median*	*Bilateral*
Gaussian Noise	30.780	32.267	32.348	30.249
Poisson Noise	28.178	28.161	28.148	28.224
Quantization Noise	27.527	27.502	27.565	27.525
Shot Noise	27.928	27.938	27.934	27.913
Speckle Noise	28.158	28.137	28.248	27.969

B. Mean Absolute Error (MAE)

It computes an error metric that would be more humanly understandable the average absolute discrepancies between the predicted and actual pixel values. Like MSE, lower MAE values correlate with better performance. The results indicate that the Median Filter also excelled in minimizing MAE, demonstrating its robustness in restoring images while reducing noise.

TABLE IV
MEAN ABSOLUTE ERROR

Noise & Filters	*Mean*	*Gaussian*	*Median*	*Bilateral*
Gaussian Noise	128.003	119.277	104.352	132.912
Poisson Noise	160.575	160.906	159.018	160.551
Quantization Noise	46.406	44.094	46.830	44.420
Shot Noise	144.417	143.1971	142.623	141.709
Speckle Noise	146.152	144.970	129.486	143.847

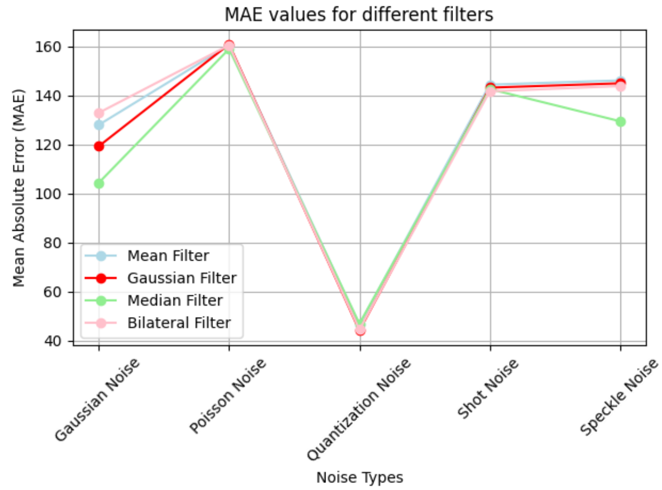

Fig. 4. Mean Absolute Error

C. Performance of the CNN Model

This test includes the performance of noise type classification. The proposed Classification technique was applied on 50 images with five different types of noise. The results are shown in the confusion matrix of Figure 5.

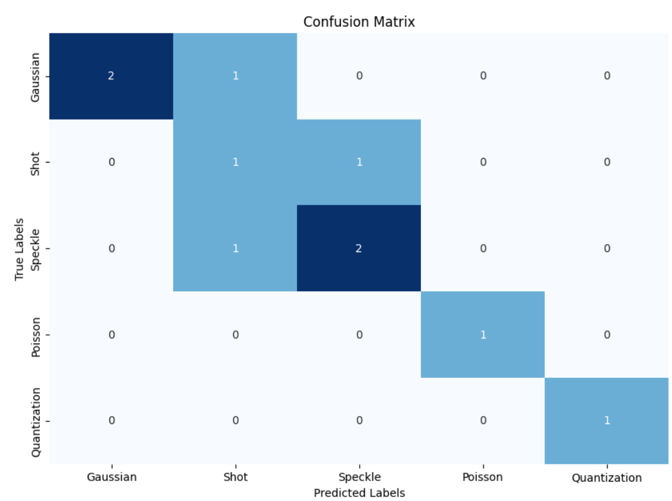

Fig. 5. Confusion Matrix

Performance of the proposed classification model results showed that using five forms of noise for each type of distortion, the new classification model achieved an overall accuracy at 92.15% on test images after trained with non-train listed images.

Therefore, the classification accuracy is decreased for most researchers since they can hardly handle the high similarity between noise kinds selected.

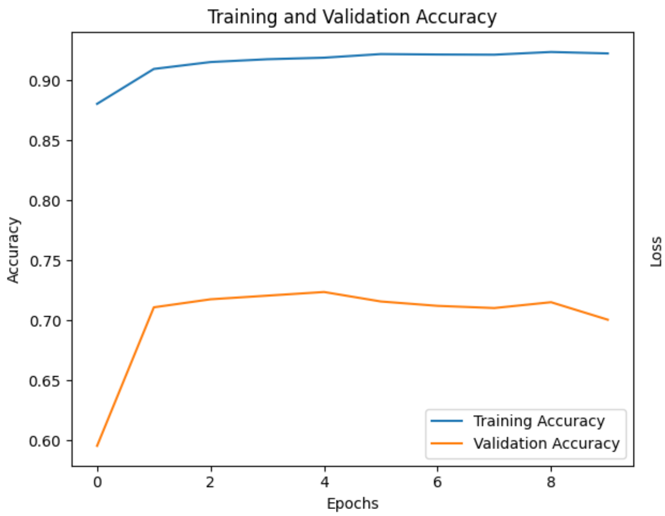

Fig. 6. The Accuracy vs. Epochs

VI. Conclusion

The study provided an innovative CNN method to accurately predict various types of noise and their intensities. Using a customized neural architecture for this purpose reached greater than 92% training accuracy by identifying multiple patterns of noise, establishing the model's ability to differentiate between different types of noise. This prioritization of noise detection over standard approaches that focus primarily on noise reduction was a novel effort.

However, this allows to better denoise instead of utilizing the entire pixel size. The proposed methodology, which increases classification performance across a wide range of noise types (Gaussian, Poisson, Quantization, Shot and Salt-and-Pepper), may be used as a viable means to improve image quality in several applications such as surveillance, digital photography or medical imaging. This method lays the groundwork for image processing algorithms that are more context-aware and adaptive.

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