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Abstract

The resurrection of the quick-response (QR) code has been made possible by the expansion of mobile network coverage combined with a rise in smartphone online content over the years. They have become much more accessible by integrating a code reader in smart devices, thus removing several unpleasant procedures and providing faster access to crucial information. However, noise in the printed images is unavoidable owing to printer processes and restricted printing technology, thus may decrease the quality of a QR code image during digital image collection and transmission which may eventually cause failure while scanning and extracting actual information. As a result, this study proposes an intelligent image classification strategy to correctly identify noisy and original QR code types. For this, a new dataset is built, containing 20,000 images pertaining to the original QR code and noisy QR codes. Later, the study exploited three well-known machine learning algorithms (logistic regression (LG), support vector machine (SVM), and convolutional neural network (CNN)) to segregate noisy images among original QR code images. The experimental results show that SVM outperformed others by attaining an overall performance accuracy of 97.5%, precision of 97.50%, recall of 97.5%, and F1-score of 97.5%, while LG almost competes by achieving 97.25% accuracy, 97.31% precision, 97.22% recall, and 97.25% F1-score.

Keywords
(separated by '-')

Noisy images - Quick-response code - Noise identification - CNN - SVM - Logistic regression

Noisy QR Code Smart Identification System



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Abstract The resurrection of the quick-response (QR) code has been made possible by the expansion of mobile network coverage combined with a rise in smartphone online content over the years. They have become much more accessible by integrating a code reader in smart devices, thus removing several unpleasant procedures and providing faster access to crucial information. However, noise in the printed images is unavoidable owing to printer processes and restricted printing technology, thus may decrease the quality of a QR code image during digital image collection and transmission which may eventually cause failure while scanning and extracting actual information. As a result, this study proposes an intelligent image classification strategy to correctly identify noisy and original QR code types. For this, a new dataset is built, containing 20,000 images pertaining to the original QR code and noisy QR codes. Later, the study exploited three well-known machine learning algorithms (logistic regression (LG), support vector machine (SVM), and convolutional neural network (CNN)) to segregate noisy images among original QR code images. The experimental results show that SVM outperformed others by attaining an overall performance accuracy of 97.5%, precision of 97.50%, recall of 97.5%, and F1-score of 97.5%, while LG almost competes by achieving 97.25% accuracy, 97.31% precision, 97.22% recall, and 97.25% F1-score.

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19 **Keywords** Noisy images · Quick-response code · Noise identification · CNN ·
20 SVM · Logistic regression

21 **1 Introduction**

22 A quick-response (QR) code is a machine-readable optical label that carries information
23 about the associated item or product [1]. Information in barcodes is coded in just
24 one direction or dimension. In contrast, information in a two-dimensional code, such
25 as the QR code, is coded in two directions, horizontally and vertically. It is simple to
26 read and can store a large amount of information. Denso Wave Incorporated in Japan
27 invented the QR code in 1994 [2]. From then on, it was widely used as an identifying
28 mark for a wide range of commercial items, marketing, and public notices. However,
29 noise in the printed images is unavoidable owing to printer processes and restricted
30 printing technology.

31 Various noises, such as Gaussian, salt and pepper, Poisson, speckle, and many
32 more, may decrease the quality of a QR code image during digital image collection
33 and transmission [3]. These noises are caused by poor environmental circumstances
34 such as compression, a short focal length, incorrect memory allocation, and other
35 issues. Noisy images and QR codes are detrimental elements in the training of models,
36 lowering the networks' classification performance that's why some effective methods
37 for distinguishing between original and noisy QR codes are required.

38 Machine learning, a popular topic in the technology business nowadays [4], and
39 deep learning, a subfield of machine learning [5] and one of the biggest accomplish-
40 ments and research hotspots lately, approaches and algorithms are very accurate
41 for computer vision applications. As a deep neural network, convolutional neural
42 network (CNN) learns feature detection by alternating between tens or hundreds of
43 hidden layers, allowing us to stack deep layers and handle a wide range of image
44 input properties [6]. With each layer, the complexity of the acquired properties rises,
45 and it is a potent image categorization strategy [7, 8].

46 Support vector machine (SVM) is well-known pattern recognition and image
47 classification technique [9, 10]. Based on a kernel function, SVM generates the best
48 separating hyperplanes. Each data item in the SVM technique is plotted as a point
49 in n-dimensional space, where n is the number of features, and the value of each
50 feature is the value of a certain coordinate. In terms of binary classification and
51 prediction, logistic regression has been extensively employed as a comprehensive
52 data processing approach [11]. Logistic regression is mostly used to classify data
53 [12]. Its data points are not organized in rows. It might be a lot, which is a pile,
54 with each pile representing a category and each kind of data point having the same
55 category name.

56 Various studies have attempted to categorize noise in images to the best of
57 our knowledge. For instance, paper [13] used two different convolutional neural
58 networks, VGG-16 and Inception-v3, to automatically identify noise distributions,
59 whereas the paper [14] demonstrated how to recognize image noise of various types

60 and intensities using a CNN method, as well as a backpropagation algorithm and
61 stochastic gradient descent optimization approaches. Tripathi [15] created, imple-
62 mented, and evaluated a CNN-based classifier to detect noisy pictures with high
63 validation and training accuracy, as well as a UNET-based model to denoise images
64 with ideal peak-signal-to-noise ratio and structural similarity index measure values.

65 Geng et al. evaluate image quality evaluation methodologies, fitting curves, mean
66 opinion score, and creating two neural networks to provide an image noise level clas-
67 sification strategy for diverse application settings [16]. Momeny et al. [17] presents a
68 noise-robust CNN for classifying noisy images without any pre-processing for noise
69 reduction and to improve CNN classification performance for noisy images. Further-
70 more, the proposed CNN does not need any pre-processing for noise reduction, which
71 speeds up the classification of noisy images.

72 When the user scans the printed visual QR code, it is accompanied by a noise
73 phenomenon that interferes with recognition and causes failure. As a result, we
74 are looking into constructing an intelligent image classification strategy for noisy
75 and original QR code types. Although the capacity to minimize noise is crucial,
76 it is equally important to determine if the QR code image contains noise or is an
77 original one. We suggested CNN, logistic regression (LG), and SVM-based models,
78 to successfully identify the original and noisy QR code images to overcome this
79 problem. Following are the contributions of this study:

- 80 • Provides detailed literature work to show that no noisy QR dataset exists.
- 81 • Generated new dataset noisy QR code image dataset comprised of 20,000 images.
- 82 • Exploited four different noises while generating image.
- 83 • Analyzed three machine learning classifiers to distinguish noisy image and actual
84 image.

85 The paper is further divided into sections as follows: The suggested technique
86 is discussed in Sect. 2. Section 3 discusses the experimental findings as well as the
87 comparison/discussion. Section 4 describes the conclusion.

88 2 Proposed Methods

89 The purpose of this research is to create a classification model that takes QR code
90 images as input and classifies them as original or noisy QR codes. This paper develops
91 its own dataset of QR code images and added several noises (Gaussian, Poisson,
92 speckle, and salt and paper) to the generated images. The study's goal is to analyze
93 generated QR code images, resize images, map noise to the original QR code images,
94 encode the labels, train the proposed CNN, LG, and SVM models, detect the type
95 of QR code image, and output the classified class/label whether it is the original QR
96 code image or has noise.

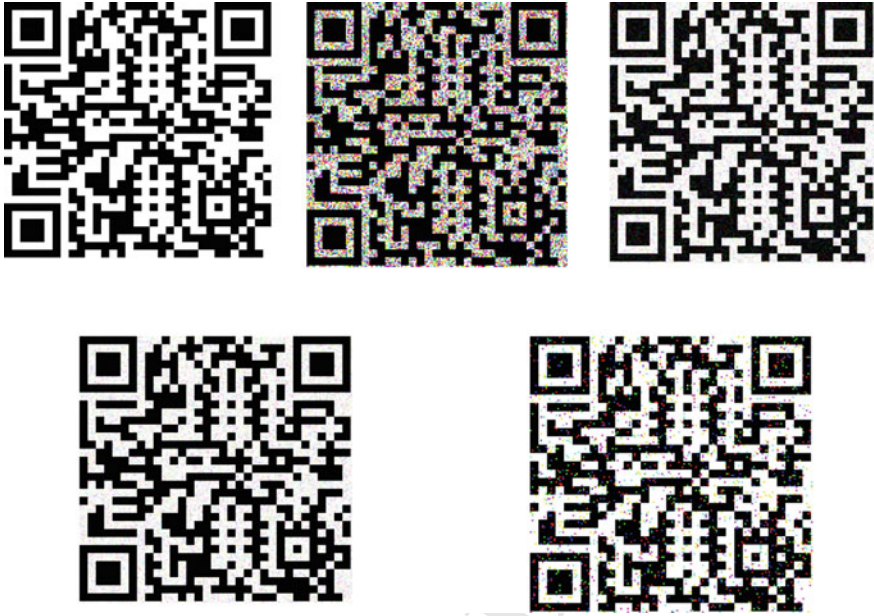


Fig. 1 Sample of dataset images; the original image with four types of mapped noise as noisy images

2.1 Data Analysis

The dataset we are using for this work includes 20,000 images of the original QR code and noisy ones. The dataset is highly varied; as our models take a fixed-size input that's why we pre-processed the images to resize them into a fixed size of (160×160) ratio for the CNN model and (50×50) for LG and SVM models. Figure 1 shows the original image and different noise types to the original image. Our dataset is divided into two distinct classes, the original one and the noisy one which we generated by adding four different types of noises such as Gaussian, salt and pepper, Poisson, and speckle to the original type.

2.2 CNN Model Architecture

We created a CNN model to classify the original and noisy QR code images. The developed CNN network architecture is depicted in Table 1. It is made up of four convolutional layers, four pooling layers, one dropout layer, one flatten layer, and a fully connected layer.

Table 1 Proposed CNN model network topology

Layers	Output shape	Parameters
Conv2D	(None, 158, 158, 16)	448
MaxPooling2D	(None, 79, 79, 16)	0
Conv2D	(None, 77, 77, 32)	4640
MaxPooling2D	(None, 38, 38, 32)	0
Conv2D	(None, 36, 36, 64)	18,496
MaxPooling2D	(None, 18, 18, 64)	0
Conv2D	(None, 16, 16, 128)	73,856
MaxPooling2D	(None, 8, 8, 128)	0
Flatten	(None, 8192)	0
Dropout	(None, 8192)	0
Dense	(None, 2)	16,386

Total parameters: 113,826
 Optimizer: Adam
 Epochs: 300
 Batch size: 90
 Loss: categorical_crossentropy
 Metrics: accuracy

Table 2 Hyperparameteric values of the proposed logistic regression model

CV	Number of jobs	Random state
10	-1	1234

Max. iteration: 1000
 Solver: liblinear
 Class weight: balanced

111 **2.3 LG Model Architecture**

112 In the LG before feeding data to the model, we first resized and reshaped our data,
 113 then used the standard scaler to resize the distribution of values so that the mean
 114 of the observed values is 0 and the standard deviation is 1. That means it removes
 115 the mean and scales each feature/variable to unit variance. The developed logistic
 116 regression network architecture and hyperparameters tuning fitting tenfold cross-
 117 validation for each candidate, equating ten fits with parallel (-1) number of jobs
 118 using backend LokyBackend with eight concurrent workers are depicted in Table 2.

119 **2.4 SVM Model Architecture**

120 In the SVM model, we apply some pre-processing of data like resizing it to (50 × 50)
 121 ratio and shuffling the data to reorganize the order of the items. The developed SVM

Table 3 Proposed SVM model parametric values

C	Gamma	Kernel
1	Auto	poly

network architecture is depicted in Table 3. In the experimental setup for SVM, C (the penalty parameter of the error term) is set to 1 in order to control the error while gamma is auto-tuned to provide the decision boundary curvature weight. Moreover, the poly kernel is used to express the similarity of training samples in a feature set over polynomials of the original variables, enabling nonlinear models to be learned.

3 Result and Discussion

To evaluate the model accuracy, we used the dataset which contains 20,000 images of QR codes with four types of noises. The dataset was divided into the train and test sets with ratios of 70/30 correspondently. More details about the dataset split can be found in Table 4.

After successful training, the accuracy was computed using all images from the test dataset in each iteration. Figures 2 and 3 show the training accuracy and loss of the proposed CNN model. Our models' usefulness and performance were evaluated using four metrics: accuracy, precision, recall, and F1-score. Accuracy, precision, recall, and F1-score for two-class classification problem are measured by (1)–(4).

$$\text{precision} = \frac{tp}{fp + tp} \quad (1)$$

$$\text{recall} = \frac{tp}{fn + tp} \quad (2)$$

$$\text{F1-score} = \frac{2 * \text{recall} * \text{precision}}{\text{recall} + \text{precision}} \quad (3)$$

Table 4 QR code images dataset information

Label/class	Training set	Testing set	Total
<i>Original type</i>			
Normal/original QR	7000	3000	10,000
<i>Noisy type</i>			
Salt and pepper	1750	750	2500
Speckle	1750	750	2500
Poisson	1750	750	2500
Gaussian	1750	750	2500
Total	14,000	6000	20,000

148

$$\text{accuracy} = \frac{tp + tn}{fp + fn + tp + tn} \tag{4}$$

145

Table 5 lists the performance of proposed models on test data in terms of various

146

metrics. The confusion matrix in test data for all QR code images CNN, LG, and

147

SVM models is depicted correspondingly in Figs. 4, 5 and 6.

Fig. 2 Accuracy increment of training and validation data

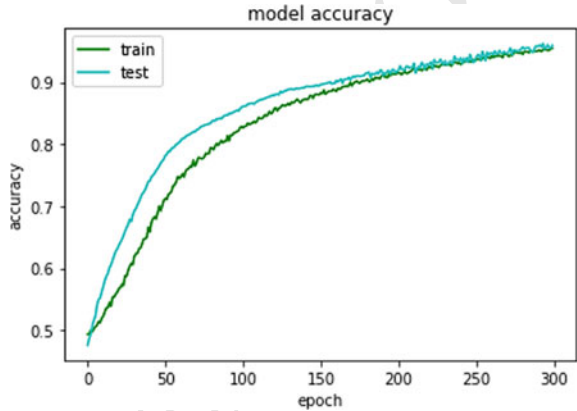


Fig. 3 Loss decrement of training and validation data

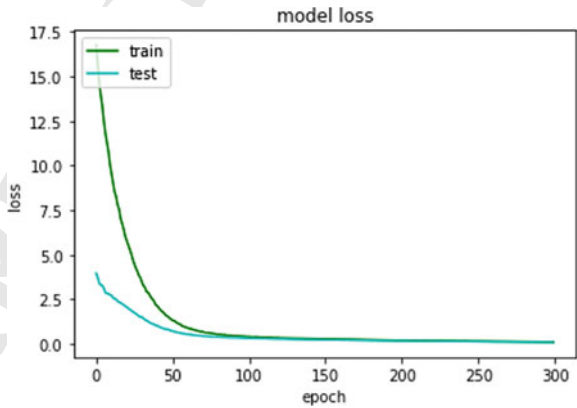


Table 5 Performance metrics of proposed CNN, SVM, and logistic regression models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	95.95	96.1	96	96
SVM	97.50	97.50	97.50	97.50
Logistic regression	97.25	97.31	97.22	97.25

Fig. 4 Confusion matrix of proposed CNN models with the test data

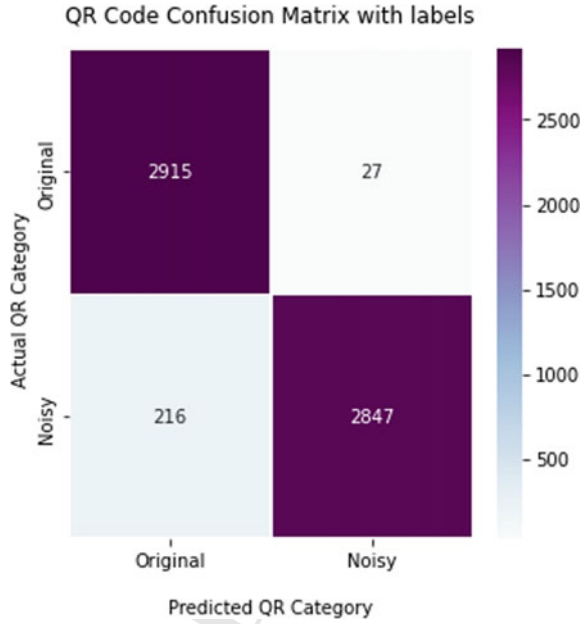


Fig. 5 Confusion matrix of proposed LG model with the test data

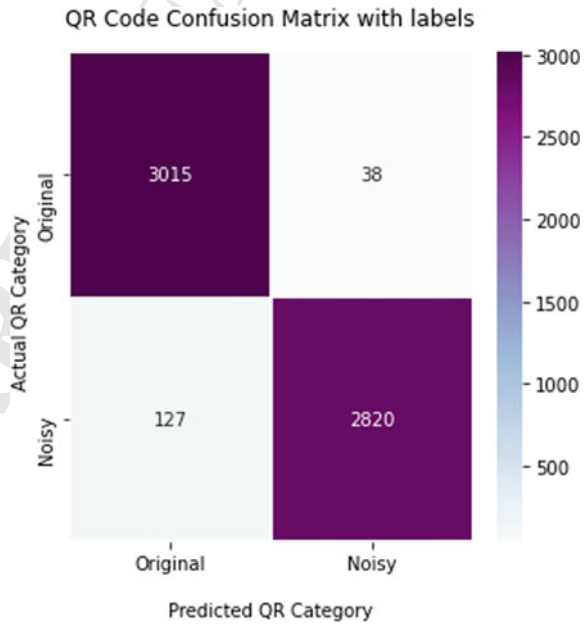
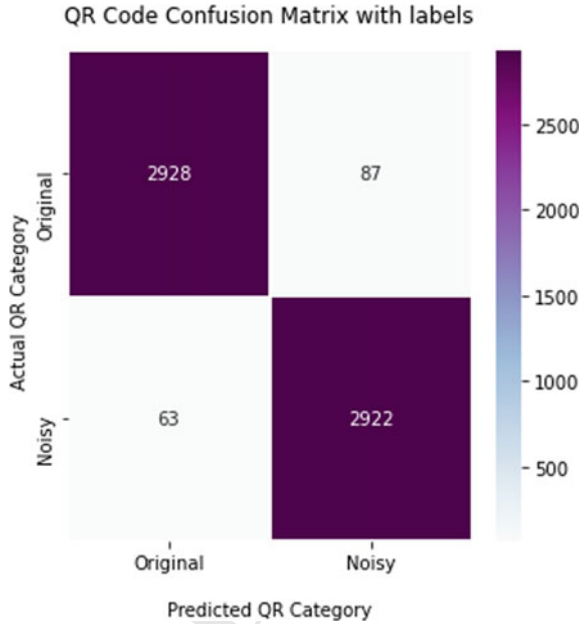


Fig. 6 Confusion matrix of SVM model with the test data



4 Conclusion

When a user scans a printed visual QR code, generally it is accompanied by a noise phenomenon that interferes with recognition and causes failure. Therefore, the study aims to develop an intelligent image classification strategy to segregate the noisy and original QR code types. Although the capacity to minimize noise is crucial, it is equally important to determine if the QR code image contains noise or is an original one. This study suggested CNN, LG, and SVM-based models, to successfully identify the original and noisy QR code images to overcome this problem. To achieve this, the study developed a new dataset of QR code images that also contains various noises. Results show that SVM and LG achieved promising results by securing 97.5% and 97.25% accuracies, respectively. For proposed models, specially for CNN, all images must be of fixed (same) size. This limitation can be overcome in next study. In the future, we aim to exploit other machine learning classifiers along with other computer vision techniques to propose a classification system that can also identify the type of noise.

References

1. Chang, J. H. (2014). An introduction to using QR codes in scholarly journals. *Sci Ed, 1*, 113–117. <https://doi.org/10.6087/kcse.2014.1.113>

- 166 2. Chen, J., Huang, B., Mao, J., & Li, B. (2019). A novel correction algorithm for distorted QR-
 167 code image. In *2019 3rd International conference on electronic information technology and*
 168 *computer engineering (EITCE)* (pp 380–384). IEEE. [https://doi.org/10.1109/EITCE47263.](https://doi.org/10.1109/EITCE47263.2019.9095073)
 169 [2019.9095073](https://doi.org/10.1109/EITCE47263.2019.9095073)
- 170 3. Hosseini, H., Hesar, F., & Marvasti, F. (2015). Real-time impulse noise suppression from
 171 images using an efficient weighted-average filtering. *IEEE Signal Processing Letters*, 22, 1050–
 172 1054. <https://doi.org/10.1109/LSP.2014.2381649>
- 173 4. Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría,
 174 J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: Concepts,
 175 CNN architectures, challenges, applications, future directions. *Journal of Big Data*, 8, 53.
- 176 5. Al-Saffar, A. A. M., Tao, H., & Talab, M. A. (2017). Review of deep convolution neural network
 177 in image classification. In *2017 International conference on radar, antenna, microwave, elec-*
 178 *tronics, and telecommunications (ICRAMET)* (pp. 26–31). IEEE. <https://doi.org/10.1109/ICRAMET.2017.8253139>
- 179 6. Yim, J., & Sohn, K. -A. (2017). Enhancing the performance of convolutional neural networks
 180 on quality degraded datasets. In *2017 International conference on digital image computing:*
 181 *techniques and applications (DICTA)* (pp. 1–8). IEEE. [https://doi.org/10.1109/DICTA.2017.](https://doi.org/10.1109/DICTA.2017.8227427)
 182 [8227427](https://doi.org/10.1109/DICTA.2017.8227427)
- 183 7. Rasheed, J., Hameed, A. A., Djeddi, C., Jamil, A., & Al-Turjman, F. (2021). A machine
 184 learning-based framework for diagnosis of COVID-19 from chest X-ray images. *Interdisci-*
 185 *plinary Sciences: Computational Life Sciences*, 13, 103–117. [https://doi.org/10.1007/s12539-](https://doi.org/10.1007/s12539-020-00403-6)
 186 [020-00403-6](https://doi.org/10.1007/s12539-020-00403-6)
- 187 8. Rasheed, J. (2021). A sustainable deep learning based computationally intelligent seafood
 188 monitoring system for fish species screening. In *2021 International conference on artificial*
 189 *intelligence of things (ICAIoT)* (pp. 1–6). IEEE. [https://doi.org/10.1109/ICAIoT53762.2021.](https://doi.org/10.1109/ICAIoT53762.2021.00008)
 190 [00008](https://doi.org/10.1109/ICAIoT53762.2021.00008)
- 191 9. Yahyaoui, A., Jamil, A., Rasheed, J., & Yesiltepe, M. (2019). A decision support system
 192 for diabetes prediction using machine learning and deep learning techniques. In *2019 1st*
 193 *International informatics and software engineering conference (UBMYK)*. (pp. 1–4). IEEE.
 194 <https://doi.org/10.1109/UBMYK48245.2019.8965556>
- 195 10. Thai, L. H., Hai, T. S., & Thuy, N. T. (2012). Image classification using support vector machine
 196 and artificial neural network. *International Journal of Information Technology and Computer*
 197 *Science*, 4, 32–38. <https://doi.org/10.5815/ijitcs.2012.05.05>
- 198 11. Zou, X., Hu, Y., Tian, Z., & Shen, K. (2019). Logistic regression model optimization and
 199 case analysis. In *2019 IEEE 7th international conference on computer science and network*
 200 *technology (ICCSNT)* (pp. 135–139). IEEE. [https://doi.org/10.1109/ICCSNT47585.2019.896](https://doi.org/10.1109/ICCSNT47585.2019.8962457)
 201 [2457](https://doi.org/10.1109/ICCSNT47585.2019.8962457)
- 202 12. Rasheed, J., Dogru, H. B., & Jamil, A. (2020). Turkish text detection system from videos using
 203 machine learning and deep learning techniques. In *2020 IEEE Third international conference*
 204 *on data stream mining & processing (DSMP)* (pp. 116–120). IEEE. [https://doi.org/10.1109/](https://doi.org/10.1109/DSMP47368.2020.9204036)
 205 [DSMP47368.2020.9204036](https://doi.org/10.1109/DSMP47368.2020.9204036)
- 206 13. Sil, D., Dutta, A., & Chandra, A. (2019). Convolutional neural networks for noise classification
 207 and denoising of images. In *TENCON 2019—2019 IEEE region 10 conference (TENCON)*
 208 (pp. 447–451). IEEE. <https://doi.org/10.1109/TENCON.2019.8929277>
- 209 14. Khaw, H. Y., Soon, F. C., Chuah, J. H., & Chow, C. (2017). Image noise types recognition using
 210 convolutional neural network with principal components analysis. *IET Image Processing*, 11,
 211 1238–1245. <https://doi.org/10.1049/iet-ipr.2017.0374>
- 212 15. Tripathi, M. (2021). Facial image noise classification and denoising using neural network.
 213 *Sustainable Engineering and Innovation*, 3, 102–111. <https://doi.org/10.37868/sei.v3i2.id142>
- 214 16. Geng, L., Zicheng, Z., Qian, L., Chun, L., & Jie, B. (2020). Image noise level classification
 215 technique based on image quality assessment. In *2020 IEEE international conference on power,*
 216 *intelligent computing and systems (ICPICS)* (pp. 651–656). IEEE. [https://doi.org/10.1109/ICP](https://doi.org/10.1109/ICPICS50287.2020.9202118)
 217 [ICS50287.2020.9202118](https://doi.org/10.1109/ICPICS50287.2020.9202118)
- 218

- 219 17. Momeny, M., Latif, A. M., Agha Sarram, M., Sheikhpour, R., & Zhang, Y. D. (2021). A
220 noise robust convolutional neural network for image classification. *Results in Engineering*, 10,
221 100225. <https://doi.org/10.1016/j.rineng.2021.100225>

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