

# Effect of Image Noise on the Classification of Skin Lesions Using Deep Convolutional Neural Networks

Xiaoyu Fan, Muzhi Dai, Chenxi Liu, Fan Wu, Xiangda Yan, Ye Feng, Yongqiang Feng, and Baiquan Su\*

**Abstract:** Skin lesions are in a category of disease that is both common in humans and a major cause of death. The classification accuracy of skin lesions is a crucial determinant of the success rate of curing lethal diseases. Deep Convolutional Neural Networks (CNNs) are now the most prevalent computer algorithms for the purpose of disease classification. As with all algorithms, CNNs are sensitive to noise from imaging devices, which often contaminates the quality of the images that are fed into them. In this paper, a deep CNN (Inception-v3) is used to study the effect of image noise on the classification of skin lesions. Gaussian noise, impulse noise, and noise made up of a compound of the two are added to an image dataset, namely the Dermofit Image Library from the University of Edinburgh. Evaluations, based on t-distributed Stochastic Neighbor Embedding (t-SNE) visualization, Receiver Operating Characteristic (ROC) analysis, and saliency maps, demonstrate the reliability of the Inception-v3 deep CNN in classifying noisy skin lesion images.

**Key words:** skin lesion; deep convolutional neural network; image noise

## 1 Introduction

Skin, the largest organ in the human body and interface for interacting with environment<sup>[1,2]</sup>, protects the body from various extracorporeal intrusions but can also develop lesions and malignant tumors that present a threat to human life<sup>[3]</sup>. According to the American Cancer Society<sup>[4]</sup>, skin cancer was among the ten leading cancer types in 2018 with an estimated 99 550 new cases. Diagnosis is the first step for recovering

healthy skin, and early diagnosis is a major determinant of the prognosis for patients suffering from malignant lesions. Among the various types of lesions, melanoma is one of the most dangerous cancers<sup>[5]</sup>. Nonetheless, a timely diagnosis of melanoma can give a survival rate of almost 90%<sup>[6]</sup>. The five- and ten-year survival rates based on the Tumor Node Metastasis (TNM) Staging Categories for Cutaneous Melanoma are 97% and 93%, respectively, for patients with early stage T1aNOM0 melanomas, and 53% and 39%, respectively, for patients with final stage T4bNOM0 melanomas<sup>[7]</sup>. Thus, early diagnosis of skin lesions and cancers is critical to the health outcomes of patients and their chances of survival.

Smartphone-based skin lesion diagnosis is a convenient means of early diagnosis for skin disease, especially for tiny lesions that people tend to neglect. Recent breakthroughs in machine learning have led to a proliferation of smartphone-based skin lesion Computer Aided Diagnosis (CAD) apps<sup>[8]</sup>. In 2017, there were 43 apps available for smartphones for the monitoring and tracking of skin lesions<sup>[9]</sup>. For example, MoleScope

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connects with the DermEngine web platform to track and monitor moles, providing information and preventing neglect due to deterioration<sup>[10]</sup>. However, melanoma detection with these smartphone applications has a low diagnostic accuracy<sup>[11]</sup>. A test of four such applications gives disappointing results: the lowest sensitivity is 6.8%, the lowest specificity is 30.4%, the lowest positive predictive value is 33.3%, and the highest negative predictive value is 97.0%. Applications that use automated algorithms to analyze images have the lowest sensitivity<sup>[11]</sup>. Thus, even the newest smartphone-based skin lesion diagnosis methods are heavily prone to misdiagnosis.

Misdiagnosis can mean that the best moment for diagnosis is lost, and can thereby endanger the life of patients. There are several reasons for medical misdiagnoses, among which is low quality images being obtained from medical imaging devices. According to recent results<sup>[3]</sup>, the quality of images, which are affected by light, angle, and noise, has a strong impact on the classification accuracy of machine learning. Photos taken by smartphones are often of low quality, which contributes to diagnostic inaccuracy. Smartphone-captured images are subject to various types of distortion, such as illumination variations, motion blur, and defocus aberrations<sup>[5]</sup>. Due to the physical limitations of mobile devices, photos are inevitably contaminated by noise, mainly a compound of Gaussian and impulse noise. Thus, to achieve better diagnosis results it is necessary to address the effects of image noise on the deep Convolutional Neural Network (CNN) classification of skin lesions.

In this paper, to investigate the aforementioned problem, the Dermofit Image Library dataset from Edinburgh Innovations Ltd. at the University of Edinburgh<sup>[12]</sup> is used to train a deep CNN (Inception-v3) to study the effect of image noise on the deep CNN classification of skin lesions.

## 2 Method

### 2.1 Dataset

The Dermofit Image Library<sup>[12]</sup> from Edinburgh Innovations Ltd. at the University of Edinburgh is the original dataset used for training. This library includes 1300 high quality dermofit images and contains the ten most common dermofit categories: Malignant Melanoma, Seborrheic Keratosis, Basal Cell Carcinoma, Actinic Keratosis, Dermatofibroma,

Haemangioma, Intraepithelial Carcinoma, Pyogenic Granuloma, Melanocytic Nevus, and Seborrheic Keratosis. Each image has been photographed under a uniform standard and detected through professional skin pathology.

According to the clinical characteristics of skin diseases, a group of dermofit images is selected from the Dermofit Image Library dataset based on whether the skin lesion has a high incidence or high death rate. The group includes three malignancies: Squamous Cell Carcinoma, Malignant Melanoma, and Basal Cell Carcinoma. Of these, Squamous Cell Carcinoma often occurs with Tumor Infiltrating Lymphocytes (TILs)<sup>[13]</sup> and Basal Cell Carcinoma is a very common cutaneous carcinoma, making up 75%–80% of all of the non-melanoma forms of cutaneous carcinoma. This group of images is used to analyze the effect of noise on skin lesion classification.

### 2.2 Deep CNN network model

A deep CNN model, Inception-v3, developed and pre-trained by the Google TensorFlow team, is employed for the classification of skin lesions with noisy images. Inception-v3 is a new version of Inception-v1 and Inception-v2 that has been pre-trained on the ImageNet database (containing 1 280 000 universal images). In this paper, the transfer learning approach is employed with Inception-v3<sup>[14]</sup>. Transfer learning is a new method of machine learning which can transfer a well-trained network to a new situation to solve new problems, allowing it to acquire a relatively high accuracy with a limited dataset and limited training time. Inception-v3 is a deep convolutional network that is difficult to train with a small-scale dataset and a low performance computer. The transfer learning method relies on training the final layer of Inception-v3 with the new dataset<sup>[14]</sup>.

The network architecture of Inception-v3 is shown in Fig. 1, with the following training procedure. Due to the limited size of the image set, we freeze the model structure except for the last fully connected layer. The fully connected layer is removed and a new connected layer is built with the output equal to the total target classification, then the Inception-v3 network is retrained. The original images and contaminated images, produced by adding various kinds and levels of noise, are used to train the network. The training results are then used to analyze the effect of different noise-contaminated images on the performance of the

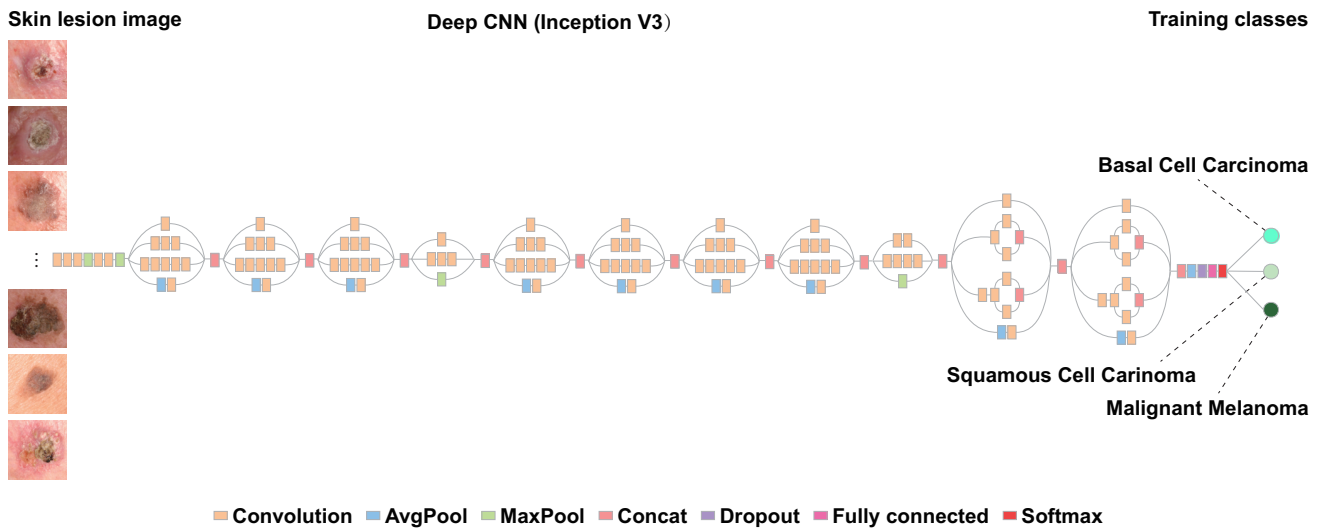


Fig. 1 Network architecture of Inception-v3.

machine learning algorithm.

### 2.3 Image processing

Two types of noises are introduced into the images in the original dataset. Photos taken with digital devices are most often contaminated by compounds of Gaussian and impulse noise<sup>[15]</sup>. Therefore, to simulate photos with a realistic image quality, different levels of Gaussian and impulse noise and a compound of the two are added to the images, with the clean and noisy datasets used separately to train the network. To produce Gaussian noise, we add a random offset obeying the Gaussian distribution to each pixel in each

of the Red Green Blue (RGB) channels. To produce impulse noise we change some pixel values to the maximum or minimum with a fixed proportion; this simulates sudden interference in the signal transmission process, such as from the failure or saturation of the inductors.

In all, five types of noise are added to the original dataset of skin lesion images, to create five corresponding sub-datasets. The first two sub-datasets have Gaussian noise added, with standard deviations of 25 and 35. The next two have impulse noise added, with 0.02 and 0.04 proportions. Example images from these four contaminated datasets are shown in Fig. 2.

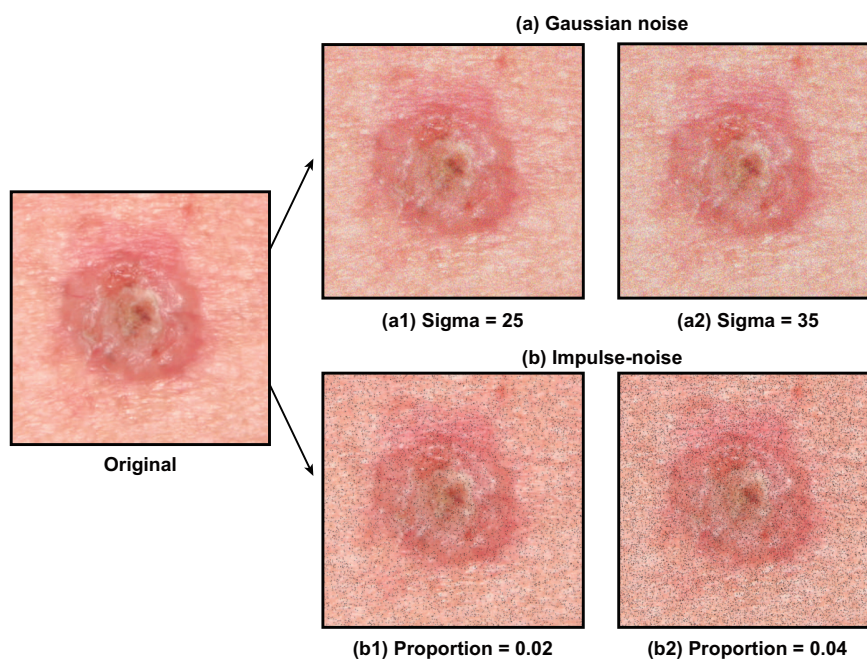


Fig. 2 Contaminated images with four single noises.

Due to the fact that, in practice, images taken by smartphones are contaminated with a hybrid of different types of noise, a further sub-dataset of compound noise is created by adding both Gaussian noise, with a standard deviation of 25, and impulse noise, with a 0.02 proportion. Example images with this compound noise added are shown in Fig. 3. Finally, the Inception-v3 network is trained with the above five datasets, with the results discussed in the next section.

### 3 Results

#### 3.1 Training results

A comparison of the classification accuracy of the trained Inception-v3 deep CNN between the original images and the corresponding images contaminated by the different noise is shown in Table 1, which shows a variance in impact for different types and degrees of noise using the trained Inception-v3 neural network with a fixed network structure, amount of training, and number of images. For the original image

**Table 1 Training result.**

Type of images	Test accuracy (%)
Original	96.50
Gaussian noise (Sigma=25)	94.30
Gaussian noise (Sigma=35)	93.70
Impulse noise (Proportion = 0.02)	90.10
Impulse noise (Proportion = 0.04)	85.40
Compound noise	88.80

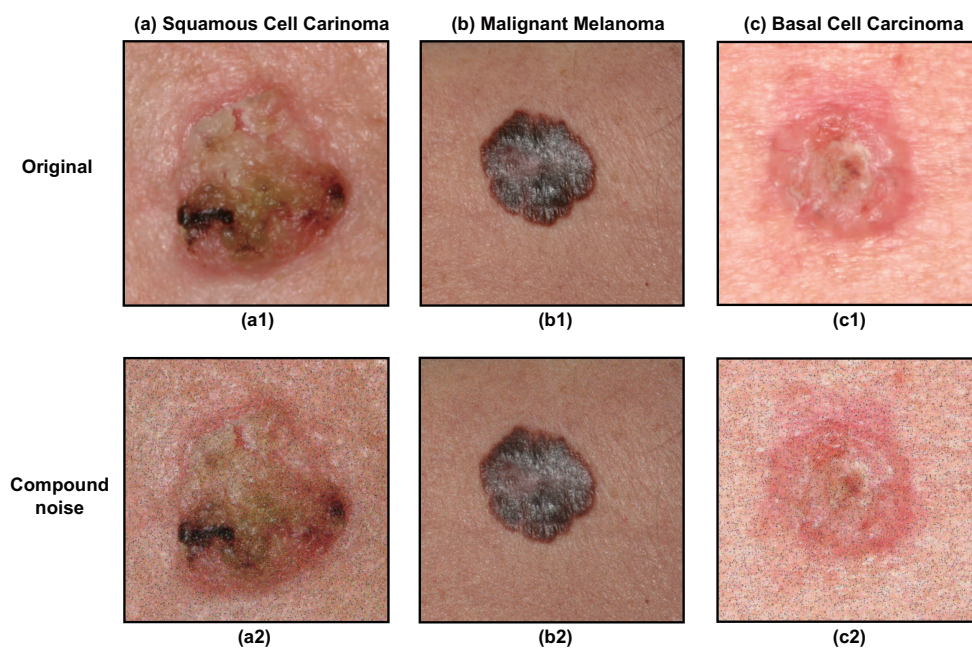
dataset, the skin lesion classification accuracy varies between 95% and 98%. The effect of Gaussian noise contaminated images on lesion classification is minor, with a barely distinguishable reduction in accuracy. However, when impulse noise is added to the original images, the deterioration in classification accuracy is evident. Therefore, with the existence of noise in images taken by smartphone, training CNNs using images contaminated by noise with practical parameters will increase the accuracy of smartphone skin lesion diagnostic apps. The analysis results for accuracy and loss of the CNN are plotted in Fig. 4. With respect to step increment, classification accuracy increases to a high value and then oscillates around it, and training loss converges to zero near the 2000th step. The accuracy of skin lesion classification decreases under the effect of noise being added to the original image dataset, and decreases further as the sigma of Gaussian noise or the proportion value of impulse noise increases.

#### 3.2 Evaluations of the network

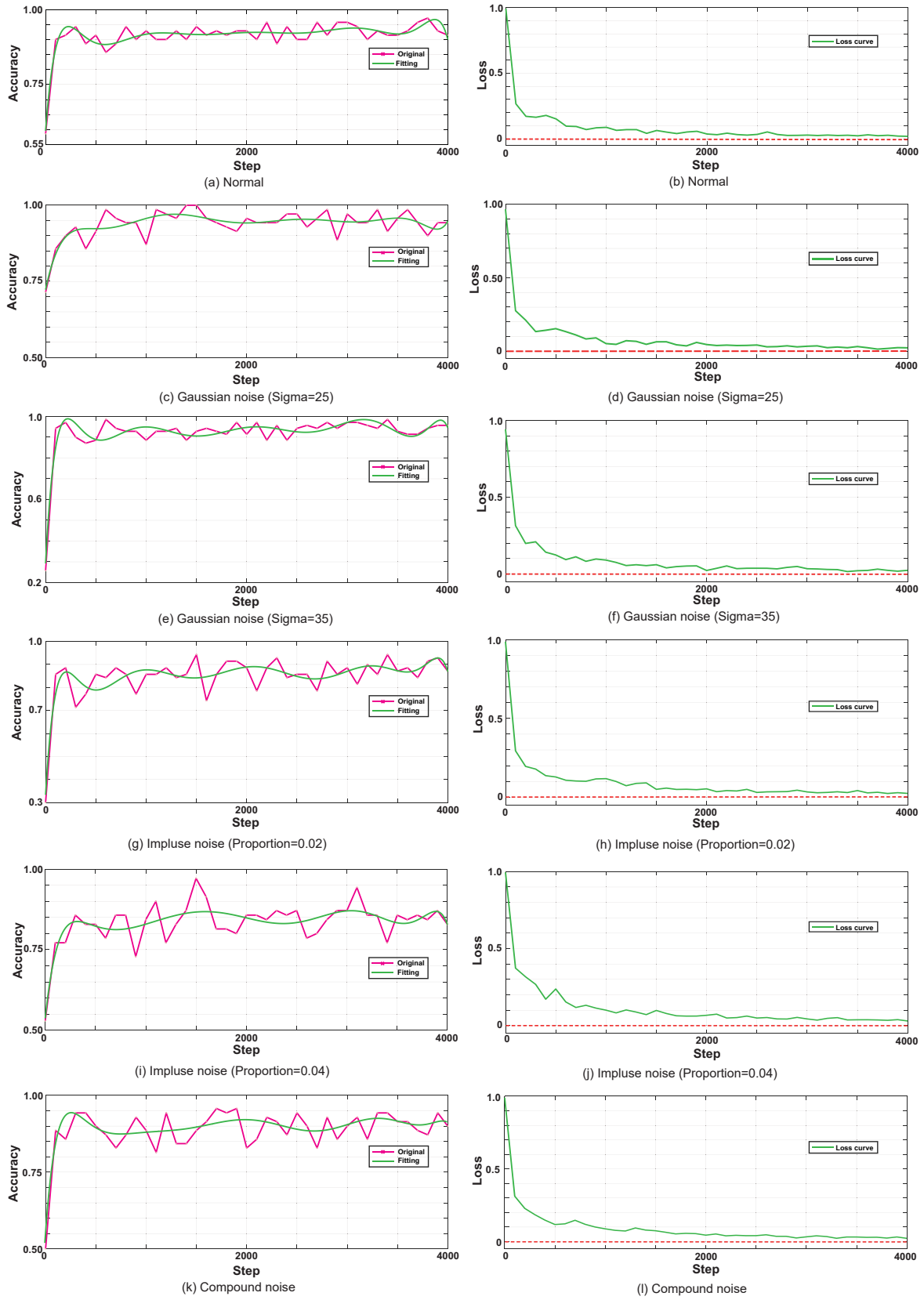
To further evaluate the suitability of Inception-v3 for the skin lesion images, three evaluation methods are employed: t-distributed Stochastic Neighbor Embedding (t-SNE) visualization, Receiver Operating Characteristic (ROC) analysis, and saliency maps.

##### 3.2.1 Index I: t-SNE visualization

To visualize the datasets we use the t-SNE method, which converts high-dimensional datasets into pairwise



**Fig. 3 Contaminated images with compound noise.**



**Fig. 4** Accuracy and loss of the original dataset and the datasets contaminated by five type noises.

similarity matrices. This method is a variant of the random neighbor embedding approach<sup>[16]</sup>, but it is easier to optimize and can produce better visualizations by reducing the tendency to gather points together at the center of the output map. t-SNE is good at capturing most local structures in a group of high-dimensional data, and can also reveal global structures, such as clustering on several scales. Drawing on these benefits, t-SNE is used in this study to show the classification results, giving the output shown in Fig. 5.

In Fig. 5, the red, orange, and blue points indicate Basal Cell Carcinoma, Malignant Melanoma, and Squamous Cell Carcinoma images, respectively. In addition, each point represents the position of a picture mapped from 2048-dimensional space to 2-dimensional space. Clustering is quite clear in the 2-dimensional plane, especially the distinction between the red points and the other two. The clarity of this distinction indicates that the computer-recognized features of Basal Cell Carcinoma are obviously different from Malignant Melanoma and Squamous Cell Carcinoma, whereas Squamous Cell Carcinoma and Malignant Melanoma are hard to distinguish in this model.

### 3.2.2 Index II: ROC analysis

The results of the ROC analysis are as follows: Precision = 98.182%, Sensitivity = 98.182%, Specificity = 94.118%, False Positive Rate (FPR) = 5.882%, and False Negative Rate (FNR) = 1.818%. With a precision of identifying Malignant Melanoma and Benign Melanocytes of over 98% and

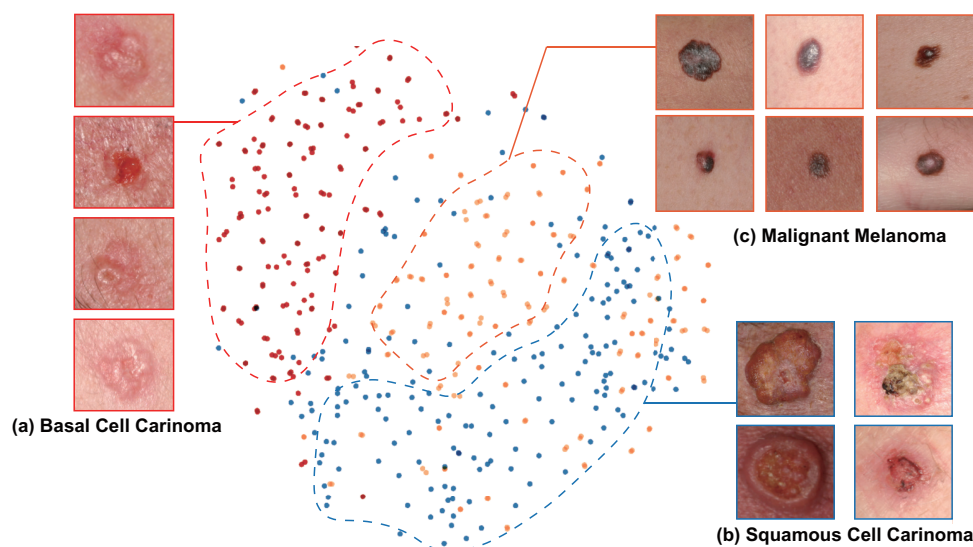
sensitivity and specificity both over 90%, the trained neural network is highly creditable for skin lesion classification based on the Dermofit Image Library<sup>[12]</sup> dataset and the datasets of noise contaminated images based upon it.

### 3.2.3 Index III: Saliency map

A saliency map is a simple method for computer visual saliency detection. By analyzing the log spectrum of the input image, the spectral residuals of the image are extracted in the spectral domain to construct a corresponding spatial domain saliency map. The type and characteristics of images and the knowledge domain they belong to are not relevant to this analysis, which is only related to the analytical features. We analyze the original skin lesion images in the Inception-v3 network to check the parts of the images that have the greatest influence on computer recognition, and inspect and compare the changes in their saliency maps after the various types of noise are introduced. Comparisons between a selection of the generated image saliency maps and the original images are presented in Fig. 6.

From Fig. 6 it can be seen that when the computer analyzes the images, along with the effectively identified disease texture, some of the messy information having negative effects on texture extraction can also be erroneously extracted. These negative effects are listed as follows.

(1) Skin texture. When a skin lesion classification CNN processes images, the skin texture affects the classification result. Some obvious textures produce a



**Fig. 5** t-SNE visualization of the results. Red, orange, and blue points indicate Basal Cell Carcinoma, Malignant Melanoma, and Squamous Cell Carcinoma images, respectively. In addition, each point represents the position of a picture mapped from 2048-dimensional space to 2-dimensional space.

clear gray in the resultant saliency map, such as the area enclosed by a red rectangle in Fig. 6a.

(2) Light. Under some illumination conditions, some areas of an image will be brighter than others. These bright regions, such as the area enclosed by a red rectangle in Fig. 6b, do not indicate skin disease, but will affect the classification of skin lesions. Comparing the three image classes in Fig. 6, the effect of light on machine visualization is the most significant.

(3) Hair blockage. When a skin lesion is photographed, the image often includes some hair, as shown by the area enclosed with a red rectangle in Fig. 6c. These hairs will cause disturbances with the CNN training.

Next, a significance analysis is presented for the noise contaminated pictures. Here, relatively high-resolution pictures and relatively low-resolution pictures are selected for analysis, as shown in Fig. 7. With the naked human eye the original image dataset and the four

sub-datasets with noise added are almost the same, but the differences among the original dataset and the noise contaminated datasets are recognized by the CNN.

### 4 Discussion

The choice of dataset has a great impact on the training of a deep CNN. The Dermofit Image Library chosen for this study is a collection of 1300 focal high-quality skin lesion images collected under standardized conditions with internal color standards. The lesions span across ten different classes, including melanomas, Seborrheic Keratosis, and Basal Cell Carcinomas. Each image is a snapshot of the lesion surrounded by some normal skin, with a binary segmentation mask that denotes the lesion area. One advantage of the Dermofit Image Library is that each image comes with a gold standard diagnosis based on expert opinion (including dermatologists and dermatopathologists). Another advantage is the high image quality. The disadvantages of the Dermofit Image

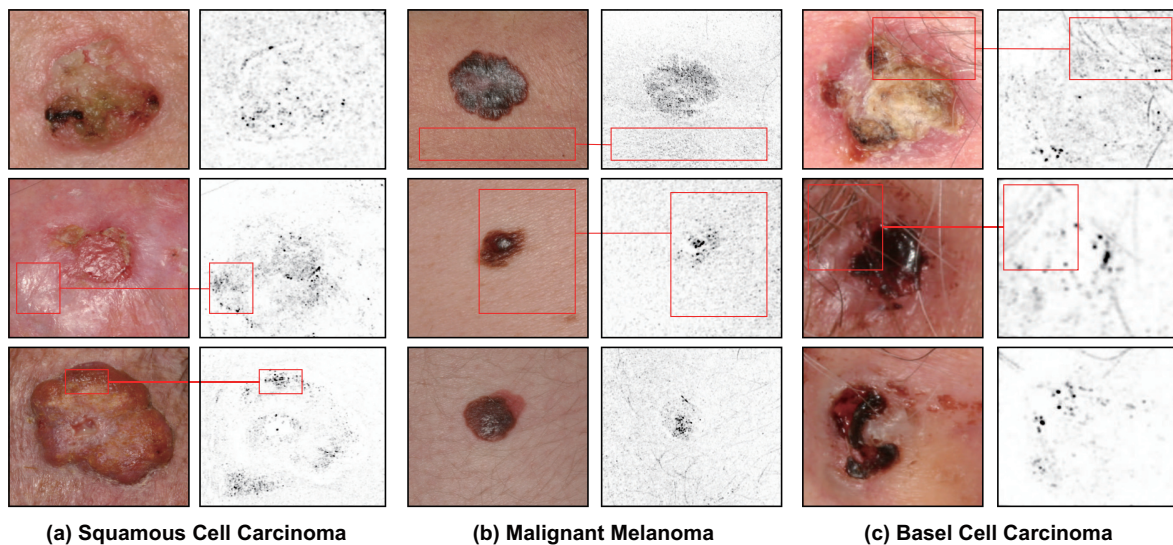


Fig. 6 Different kinds of noises with significant influence illustrated by corresponding salience map.

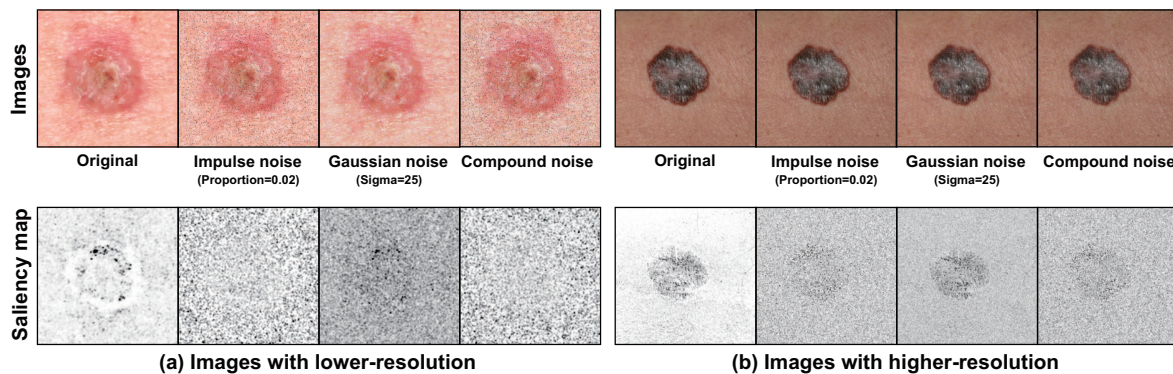


Fig. 7 Comparison of salience maps with different kinds and different level noises contaminated.

Library include a relatively low number of lesion types and a low number of images for each type. There is also a relatively low range of ethnicities and skin colors represented. Lesions can be particular to a given human skin type and the classification is not always applicable to others. Although all existing studies on skin lesion classification have their own advantages and disadvantages regarding the training and testing datasets, classification could be further optimized for this study by collecting additional images.

Cutaneous components, such as hair and skin texture, and factors affecting image quality, such as light, both generate characteristics that algorithms detect as similar to that of lesions, and thus contribute to classification inaccuracies. These characteristics often result in a low accuracy of skin lesion classification and can lead to misdiagnosis. If hair, light, and cutaneous texture could be removed physically or by the use of algorithms similar to that found in Ref. [17], the classification accuracy will greatly increase. Therefore, the effects of the removal of hair, light, and skin texture on classification results is worthy of further study.

No comparison of skin lesion classification between the results in this paper and that by doctors is performed; this is different to other lesion classification studies that depend only on an image dataset and the adjustment of parameters. The reason for this lies in the specific objective of this study, to look at the influence of noise on lesion images. Referring to the top row of Fig. 7, the classification results by doctors for each of the images are the same, despite the noise contamination. While a computer algorithm can distinguish between the contaminated images and the originals, they are barely distinguishable to the naked eye; the noise has a great effect on computer-aided lesion classification but almost no effect on human classification. A detailed comparison of skin lesion classification between the algorithm used in this paper and doctors may nonetheless be usefully pursued at a later date.

Gaussian and impulse noises are selected to simulate the images obtained from digital cameras embedded in smartphones owned by average consumers. These two types of noise are the most widely studied targets in the computer vision field for their universality across various photos. Despite the generality of Gaussian and impulse noises, there do exist various other types of image noise in images taken on smartphones: banding

noise, fixed pattern noise, Rayleigh noise, etc. The effects of different compounds of these additional types of noise on skin lesion classification need further study. Furthermore, a comparison between computer simulated noise and the noise actually produced by typical digital cameras is needed to judge the confidence level of the simulated noise.

The deep CNN adopted for this study is the Inception-v3 model. The advantages of this model include its fast training speed and highly efficient transfer learning, having being well trained via a large training dataset with several million images. The model has been verified by its use for several other types of lesions, such as lung cancer<sup>[18]</sup>, diabetic retinopathy screening<sup>[19]</sup>, and breast cancer histology<sup>[20]</sup>. Alternative CNN architectures that have proven to be effective, such as AlexNet, ResNet, and VGG16, could be used to investigate skin lesion classification. Dataset screening on the training and testing datasets can weaken the applicability of the trained Inception-v3 deep CNN. In Ref. [3], the extent of the training and test dataset of Inception-v3 outperforms that of other studies for lesion classification. However, both the training and test datasets exclude vague images and low-quality images taken from a long distance. Thus, the skin lesion classification is obtained based on dataset screening, and difficulties are likely to emerge from this when translating to medical practice.

## 5 Conclusion

The Inception-v3 deep convolutional neural network architecture is used to demonstrate the effect of image noises on the classification of skin lesions, based on the Dermofit Image Library dataset from the University of Edinburgh. Gaussian noise, impulse noise, and a compound of the two are added to the original images. Three methods of evaluation, namely t-SNE visualization, ROC analysis, and saliency maps, demonstrate the reliability of the approach. The accuracy of skin lesion classification decreases under the effect of noise when compared with the original image dataset. In the future, besides Gaussian and impulse noises, other types of noise existing in medical images will be added into images to study the effect of a greater range of noise on the classification of skin lesions.



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