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Enhancement in Skin Cancer Detection using Image Super Resolution and Convolutional Neural Network

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Abstract

Skin cancer has been one of the major worldwide public health issue with more than 1 million cases every year. Skin cancer is classified into three categories: Basal Cell Carcinoma, Melanoma and Squamous Cell Carcinoma [1]. Melanoma is the most critical category of skin cancer with very thin chances of recovery and survival of the patient. Early diagnosis of skin cancer can drastically improve survival rate to as high as 95 percent. This served as a motivation to contribute to this noble cause using technology based solutions. In the process of diagnosis for the disease, the process is divided into four basic components: image processing including hair removal, noise removal, sharpening, and increasing the resolution of the image given to the skin dimension. Recent developments in identification of skin cancer technology uses machine learning and in-depth based reading segmentation algorithms. Most used algorithms are: InceptionV3, ResNet, VGGNet. This paper suggests an artificial skin cancer screening process using techniques like image processing and machine learning. Image super-resolution (ISR) techniques recreate an image with high resolution or sequence from visual LR images. An approach using deep learning on the Image super resolution was used to boost the accuracy of the convolutional neural network model. This model was developed using the Keras backend and tested the model by modifying the layers of neural network which are used for training. The model is built on publicly sourced dataset from the ISIC data archives.

Keywords: Melanoma Skin Cancer ; Image Super Resolution ; Generative Adversarial Network ; Convolutional Neural Network ; Deep Learning ; Image Recognition.

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1. Introduction

Skin cancer has been on the rise in recent decades, owing to longer exposure to damaging UV rays, climate change, and ozone layer loss, all of which are contributing to the rise. It is the world's most frequent cancer. Skin cancer is divided into two further categories: Non-Melanoma and Melanoma skin cancer. In the year 2018, the Melanoma skin cancer accounted for 132,000 instances of skin cancer, whereas Non-Melanoma accounted for more than a million cases. Skin cancer is identified in one out of every three cancer cases, and the World Health Organization estimates that one out in five Americans will get skin cancer during their lifetime.

A 10 percent reduction in ozone layers of Earth in the atmosphere will result in an increase of 4,500 melanoma skin cancer cases globally and 300,000 non-melanoma skin cancer cases. Melanoma skin cancer, on the other hand, is responsible for 75 percent of all skin cancer deaths. Doctors today rely on manually inspecting each suspected skin lesions. An early stage detection of the disease can significantly reduce treatment costs and complexity. Using a deep convolutional neural network, an Artificial Intelligence tool can analyze and detect the appropriate classification of the type of skin cancer more effectively [2]. This tool can ensure rapid and accurate testing and evaluation of skin lesions.

The proposed model uses Deep learning networks like ResNet, VGG16 and InceptionV3 and the Image Super Resolution (ISR) package to improve and upscale the low resolution images in a computer-aided technique for skin cancer detection. The neural networks have been trained to process and analyse numerous features of Skin Cancer such as border, color, symmetry, and diameter in relation to texture, size, and shape for feature selection and classification between normal skin and Skin Cancer using images.

CNN was chosen because it provides more accuracy in image and signal processing applications [3]. A multilayer convolutional network is used by CNN. The dermatologist's image-based input and the collected information make up the first input layer. The input is processed and forwarded to the next layer that is the pooling layer, which conducts min pool and max pool before sending the data to the smoothing layer, which converts the input information into a one-dimensional vector. A clear skin lesion location is acquired using the dermoscopy procedures by removing any chances of reflection. Similar visuals of melanoma and non-melanoma, physical features of the skin make it difficult for the automatic detection of skin lesions. Pre-processing can be used to reduce this task. Segmentation techniques are applied to identify the specific location of skin lesion.

Skin cancer has always been one of the worst diseases, and before time detection is crucial. Manual diagnosis takes time and is unreliable. The detection will get more exact and dependable as scientific research progresses. Artificial intelligence-based learning models are one of the unique features that have been employed thus far. Deep learning research could improve the model's efficiency. The distinguishing of malignant cells can be made easier with image super-resolution. As a result, image super resolution is employed for data pre-processing, CNN based models, will be used to more often to correctly detect malignant cells.

General Adversarial networks are a category of generative models based on deep learning techniques. These can be trained for generating new content from existing images, sounds, music or text format. But for our application, the solution intends to use GANs for the image generative model. The networks follow deep learning-based model architecture used mainly for training a generative model.

A GAN structure is made up of two parts: 1.Generators; 2.Discriminators.

The generator's ability to produce plausible data grows. The discriminator uses the created occurrences as negative training examples. The discriminator learns to discriminate between the generator's bogus and true data [4]. The discriminator penalises the generator if it produces implausible outcomes. Both the discriminator and the generator use neural networks. The discriminator input is directly connected to the generator output. The discriminator's categorization creates a signal that the generator uses to back propagate its weights.

Generator: The generator element of a Generative Adversarial Networks creates spurious data by mixing input provided by the discriminator. It honed its skills in persuading the discriminator that the commodity it's offering is genuine. More training is required for the generator than for the discriminator, and more training is required for the integration of the two. The randomised input of the generator network is reversible. If the generator fails to trick the discriminator, the generated data is passed to a network of data instance discriminators, which classifies and penalises it.

Discriminator: In a GAN, the discriminator is just a classifier. It tries to differentiate between the data generated by the generator and the genuine data. Any network architecture relevant to the type of data it's classifying could be used. The training data for the discriminator originates from two places. Realworld data examples, as in our case the photos of different categories of cancer cells. During training, the discriminator considers these examples as positive examples. The generator generates fake data instances. During training, the discriminator uses these situations as negative examples.

Since the paper focuses on image classification for different types of cancer cells. The focus will be more on training of discriminator as it is used for classification of image to for identification of real and non-real images. Here labels will be modified with two different names instead of real and fake. During training, the two networks (generator and discriminator) have opposing goals. The discriminator always wants to classify the data as accurately as it can. The generator produces fake data that looks like the true data to fool the discriminator. Two loss functions are connected to the discriminator. The discriminator only uses the discriminator loss during training and ignores the generator loss. During generator training, we use the generator loss, as stated in the next section. During the training of discriminators. The discriminator separates actual data from bogus data generated by the generator. The discriminator is penalized if a real instance is misclassified as fake or a fake instance is misclassified as real. Backpropagation from the discriminator loss through the discriminator network changes the discriminator's weights. Thus, the model weights are updated after every successful iteration of the training process. The model weights of the discriminator network are updated for the decrease in classification error and the model weights of the classification model are updated to increase the classification error.

Image Super Resolution (ISR) is a Keras-based implementation technique for upscaling and improving the quality of low-resolution photos. It raises the size of small images while maintaining the image quality. It's also a technique for restoring high-resolution images using low resolution details extracted from low-resolution images. Image processing, image/video enhancing software, medical image processing, and satellite image analysis are all applications for this technology. Noise reduction, image upscaling, and colour modifications are among image improvement approaches. In this research methodology, we have applied deep learning with (General adversarial Networks) to produce high resolution images.

There are primarily three techniques for enhancing the resolution of images:

- Prediction based methods.
- Nearest Neighbor methods.
- GANs based approach.

Prediction based approach: This was the initial methodology for image super resolution where filter based approach was used to remove sharp edges and reduce contrast by interpolating pixel values in the image. Nearest neighbor methods: The technique is commonly used in applications of computer vision. In this approach, the areas of low resolution patches are identified and up scaled which results in the image being reconstructed. This takes place based on pixel values of the nearest pixel. GANs: In unsupervised machine learning, GANs are a type of AI algorithm. The proposed network consists of two components: discriminator and generator. The discriminator functions as a judge in the generative mode, which generates data from a probability distribution. The technique that follows conducts a direct edge mapping between primary and secondary images. The mapping is represented by a CNN, which takes the moderate image as input and delivers a clear image.

Traditional SR approaches can also be seen as a deep convolutional network, as shown. The current methods which optimize each component independently, the method improves all layers simultaneously. Deep CNN features a lightweight framework that delivers quick performance for practical on-line use while demonstrating state-of-the-art restoration quality. To accomplish compromises between performance and speed, we investigate various network architectures and parameter settings.

Real world benefits to hospitals: Hospitals usually handle terabytes of patient's data like medical reports, MRI Scan images, X-Ray images etc. Storing all these images in their original high resolution format can be take up expensive storage space. Hence, this is not an economically viable option. With the help of ISR (Image super resolution), the images can be stored in the database with low resolution formats and can be converted into a high resolution image whenever it is being accessed by the physician. This makes the storage more efficient and reduces operational costs.

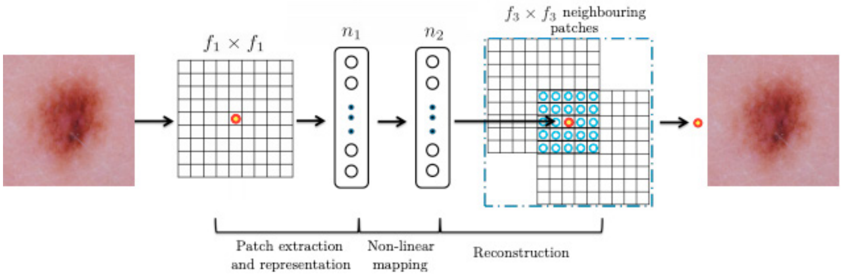

Fig. 1. Proposed use of Image Super-Resolution in Skin Cancer Detection.

CNNs are quite analogous to organic neurons in our brain (CNN). It can recognise a specific object in multiple forms because it understands translation invariance [5]. A typical feed forward network will only recognise an object if it has a single pattern, but will not recognise an image if the object is located offcenter or somewhere else in the image. This is why we use CNN for training and testing real-world datasets that generally include raw and unprocessed pictures.

VGG16 is a convolutional neural network (CNN) which was first proposed in the research work [6]. The model input is an RGB image of size 224*224. The input is then processed further by going through further multi convolutional layers [7].

It is then passed through a 3*3 filter. In a few configurations, the VGG16 also uses a 1*1 convolution filter, it is responsible for the linear transformation of the input image. After compression, the high resolution is preserved. A dimensional pixel window and stride have been used for max pooling.

The Fully-Connected (FC) layers follow a depth of convolutional layers with varying depths. The final stage is called the softmax layer. The fully connected layers have similar configuration in all networks. ReLU is equipped on all hidden layers. Local response normalization is not included in most of the networks as it does not lead to performance improvement but leads to increase in memory consumption and adds to the computational requirements.

The breakthrough in the computer vision and deep learning community was during the successful implementation of AlexNet. The newer version ResNet enabled researchers to train up to thousands of layers and achieve the desired performance. Formatting the title, authors and affiliations Please follow these instructions as carefully as possible so all articles within a conference have the same style to the title page. This paragraph follows a section title so it should not be indented.

A traditional single layer feedforward network can be used to represent any function. It is prone to overfitting the data and building a massive layer between input and output. The problem with any deep neural network is that of reducing gradient. The error rate for training and testing will also increase as we increase the number of layers.

Residual block : The architecture of residual block is used to solve the problem of disappearing gradient. A ‘skip connection’ technique is used where in the previous layer output is passed to the subsequent layer from the residual block. The training skips some layers in between and directly connect to the output in ‘skip connections’.

Inception v3 focuses on using less computing power by upgrading previous Inception architectures. Inception Networks GoogLeNet have been found to be more computationally efficient with respect to the parameters and time spent doing so (memory and other resources). If an Inception Network is modified, more caution must be exercised to ensure that the computational gains are not lost. As a result of the unknown efficiency of the new network, customising an Inception network for multiple use cases becomes a challenge.

The architecture of an Inception v3 network is built one step at a time, as shown below:

1. Factorized Convolutions: This results in reduction of the parameters in a network, making it more efficient to compute. It also keeps track of the network’s performance.

2. Smaller convolutions: Using smaller convolutions instead of larger convolutions speeds up training dramatically. A 5x5 filter, for example, has 25 parameters; instead of a 5x5 convolution, two 3x3 filters have just 18 (3*3 + 3*3) parameters.

The organization of the paper is as follows: The first section provides the introduction for the research in the skin cancer field. The next section includes discussion of the previous work done in the area of skin cancer using CNN and different ML/AI methods. It is followed by the brief explanation of the proposed methodology. The next section includes the detailed discussion about the results. After results sections we have comparison section for the results of different CNN models. Finally we scope for extension of work is presented and concluding remarks are recorded.

2. Literature Review

Brinker and Hekler [8] provide a cutting-edge classifier based on CNN that may be used to classify skin cancer pictures in a way that is comparable to dermatologists' classifications. This could allow for lifesaving and diagnosis outside of hospitals utilizing portable devices. CNNs also do well in skin lesions classifiers.

Yang et al.[9] proposed a deep learning method for superresolution of a single image. The method clearly learns a low-to-high-resolution image mapping from start to finish. A CNN is used to simulate the mapping, which accepts the image in a low-resolution format as input and produces the highresolution image. Traditional sparse-coding-based SR approaches, as shown, can also be seen as a deep CNN. Despite the fact that it is constructed of light materials, the deep CNN has a high repair quality.

Tamura et al. [10] demonstrates how convolutional neural networks classify image information using visual texture and structure as discriminative criteria. Image enhancement techniques can be used as preprocessing processes to improve overall image quality and thus the overall efficacy of a CNN.

Existing image enhancement approaches, on the other hand, are designed to improve a human observer's percepti66on of an image. Ly et al. [11] paper we can understand the CNNs that can simulate image enhancement and restoration, but with the purpose of increasing image categorization rather than human perception.

Vidya et al. [12] obtained unique features for prior detection of skin lesions using the ABCD rule, HOG feature extraction and GLCM. To improve the image's quality and clarity, pre-processing processes are used. GAC was used, which was successful for feature extraction as well as segmenting the lesion area independently. Symmetry, border, color, and diameter properties were extracted using the ABCD scoring system. HOG and GLCM were used to extract textural features.

According to Esteva et al. [13], considering dermoscopic study, a biopsy, and histological evaluation, the classification problem in deep learning is challenging considering various factors in the variability of the input skin lesion images. Yang, Jianchao, et al [14], explains function that represents a minority signal and can be used to solve a single image. According to image statistics, the ideal way to express visual tracts is to combine a tiny line of sections from a well-chosen over-word vocabulary.

Vijayalakshmi M M [15] presents, the three steps of the model which are data gathering and augmentation, model construction, and prediction. Convolutional Neural Networks and Support Vector Machines, among other AI techniques, were integrated with image processing technologies to build a superior structure with an accuracy of 85 percent.

According to Refianti et al.[16], manufacturing this program involves steps such as analysis, design and the actual implementation along with testing. This method uses deep learning to identify images using a CNN algorithm and also the algorithm called LeNet5. In an experiment using 176 image data, the result was 93% in training and 100% in testing. Along with fine-tuning and data expansion, authors

Hosny et al. [17] used transfer learning to replace the last layer with Softmax. Utilized and classified unique lesions. The ph2 data is used to train and evaluate the proposed model.

Ahmet DEMR [18] developed a viable method for early detection of skin cancer. Our dataset contains 2437 training photos. Various deep learning architectures are used to complete classification challenges. Analyzing the data, the ResNet 101 architecture achieved an answer rate of 84.09 percent and the Inception v3 architecture achieved an answer rate of 87.42 percent.

A variety of treatments have been suggested to improve the accuracy of skin cancer diagnosis. An epiluminescence microscope, also known as a dermoscope, is a non-invasive diagnostic tool that uses incident magnification. In the late 80s, it was released for the first time. A variety of methodologies and processes have been tried to investigate automatic skin cancer diagnosis throughout the last few decades.

A computer vision method for identifying skin cancer has been created by a group of experts. Computer vision analyses picture defects by offering a human-like level of similarity to computers. A Convolution Neural Network (CNN) with multi classification is used on the 2018 ISIC dataset of HAM10000 images [19].

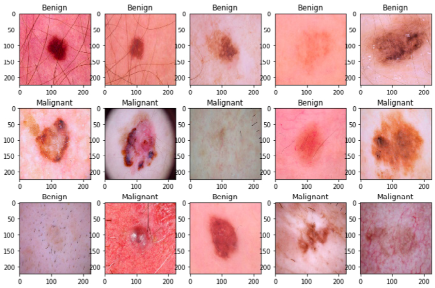

Fig. 2. Classification Images for Malignant and Benign Skin Cancer Cells.

By identifying the photos in the dataset as benign or malignant, Ahmet [18] wants to develop a viable method for early detection of skin cancer. Our dataset contains 2437 training photos, 660 test photos and 200 validation photos. ResNet 101 and Inception v3 deep learning architectures are used to complete classification challenges. Analyzing the data, the ResNet 101 architecture achieved an answer rate of 84.09 percent and the Inception v3 architecture achieved an answer rate of 87.42 percent.

Esteva et al [13], using 129,450 clinical skin cancer photographs, created the first skin cancer classification using a pre-trained model. The reported classification accuracy is 72.1. Yu et al. In 2016, we constructed nearly 50 layers of CNN to classify malignant melanoma. The highest classification accuracy for this task was 85.5%. Hänssleetal. In 2018, it showed 86.6% sensitivity and specificity. Dorje et al. Created a multiclass classifier for classifying multiclass data using ECOCSVM and deep learning CNNs. The percentage of accuracy in this survey is given as 95.1%. RefHan et al.

3. Proposed Methodology

The section elaborates the proposed methodology in detail and describes about the experimental setup used for implementing the suggested method. It also evaluates the impact of a number of variables affecting different neural networks function. We list the major topics covered in the paper in the sections below. The following section contains key features of the proposed methodology.

The suggested method is divided in three phases: 1. Acquiring dataset for the skin cancer images; 2. Applying proposed image super resolution algorithm on the dataset. The purpose is to modify the resolution of the input dataset images to feed into the neural network. 3. Classifying the modified images using suggested algorithm following the below methodology. The application of the proposed methodology can be extended to other medical domains to obtain better output.

3.1. Experimental setup

The following method was implemented on a personal computer with the specifications: Windows 10 Operating system equipped with a Core i5 CPU 9th Gen, 16 GB of random access memory (RAM), 1 Terabyte solid state drive, and Nvidia GeForce GTX 1650 Graphic processor. The IDE by Anaconda was used in order to run the proposed model.

3.2. Data Acquisition

The first phase in the project is to acquire skin lesion image databases from the ISIC. This study's database includes both benign and malignant melanoma skin lesions. In all, there are 1800 images of malignant lesions and 1497 images of malignant melanoma lesions. ISIC databases were used to collect skin lesions. Images are in standard JPEG format. For training and testing purposes, the skin lesion photos were separated into 80:20 ratios.

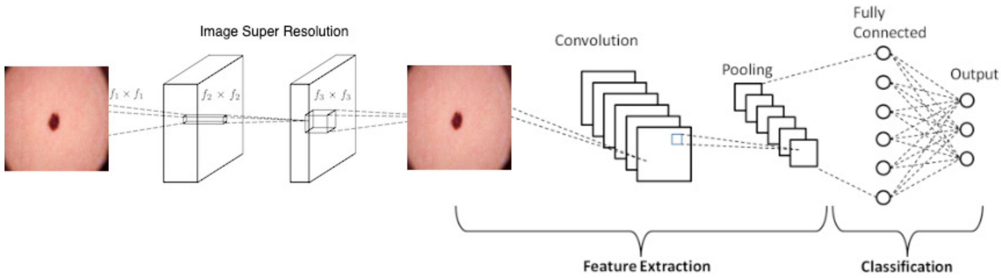

Fig. 3. Classification Images for Malignant and Benign Skin Cancer Cells.

3.3. Pre-processing

The approach was to take the photos from the testing dataset and use the Image Super Resolution approach on them. It now had two sets of training data, one consisting of the dataset's original images and the other consisting of images upgraded with Image Super Resolution techniques. Now it was verified if the CNN, ResNet, VGGNet models can more accurately evaluate and predict skin cancer images using these improved photos.

3.4. Segmentation

The pre-processed photos are segmented in the third phase. The segmentation procedure is used to determine the precise location of a skin lesion. Image super resolution was used to segment the data in this study. Image super resolution (ISR) upscales and improves the quality of low resolution images for the skin lesion's images [20].

3.5. Feature Extraction

To upscale the images, the Keras framework is used for different networks for one Image SuperResolution, as well as dataset to teach these networks with content and loss components. The model takes as input a generator that produces SR images. Conditionally, also a discriminator network and a feature extractor to build the components of the perceptual loss. Compiles the model(s) and trains in a GANS fashion if a discriminator is provided, otherwise carries a regular ISR training. Then it compresses the image into the jpeg format to introduce compression artifacts and lose some information.

4. Results

4.1. Performance Metrics

In a classification assignment, only one statistic, such as Accuracy, can correctly find the total model efficiency. As a result, for both variety of skin lesion conditions, we evaluate Accuracy, Precision, Sensitivity, and F1 Score.

1. Accuracy: It is a metric for evaluating how many predictions our model got correct out of all data points.
2. Precision: It is one measure of a machine learning model's performance – the accuracy of a model's positive prediction.
3. Sensitivity/Recall: The capacity of a model to predict true positives in each accessible category is measured by sensitivity. The capacity of a model to predict true negatives in each accessible category is measured by its specificity.
4. F1 Score: The precision and sensitivity values are combined to create the score, which is a weighted average. Its maximum value is 1 and its minimum value is 0. Both sensitivity and precision play a role in calculating the score.

4.2. Hyper-parameters

Table 1. Hyperparameter for training CNN model.

Parameters	Specifications
Optimizer	Adam
Learning rate	0.0001
Epochs	100
Loss function	Binary cross-entropy
Batch size	32
Dropout	0.5

5. Comparison and Discussion

5.1. Performance Metrics

As shown above, three different Neural Network models were used and trained on the same dataset by dividing the dataset into training and test datasets, the training, and test datasets were divided in the ratio of 80:20. Here the work is to compare the results or rather the accuracy which each model has obtained while training on the same dataset. The dataset which was used here is taken from ISIC archives as mentioned above. Here each model will have a different batch size but the same number of epochs. The total samples will be divided by the batch size giving a total number of batches that will hold the same batch size by which it is divided. If a dataset has 100 epochs, then the total number of batches for the entire training process will be epochs * batches. The modified aspect includes enhancing the input image using ISR and comparing the results for all the three models.

Table 2. Performance metrics comparison for all CNN networks with and without ISR.

Parameters	Without ISR			With ISR		
	VGG16	ResNet	Inception V3	VGG16	ResNet	Inception V3
Accuracy	54.55%	72.72%	83.48%	70.17%	86.57%	91.26%
Precision	0.53	0.70	0.81	0.68	0.87	0.89
Sensitivity	0.56	0.73	0.88	0.69	0.87	0.92
F1 Score	0.54	0.73	0.83	0.73	0.87	0.92
Micro Average	0.56	0.71	0.83	0.70	0.85	0.91
Weighted Average	0.55	0.73	0.84	0.70	0.86	0.92

5.1.1. VGG16

This neural network is 16 layers deep built for the purpose of image classification. This model accepts the image of size 224 x 224 x 3. Each layer has a number of filters starting with 64 filters at the start of the network and all the way up to 512 filters till the last layer in the network. Here again epoch is set to 100 and batch size is set to 32. The final accuracy we achieve with this network is around 54.55 percent. The input images are now modified using Image Super Resolution and finally, when the training of the model was completed the test accuracy was 70.14 percent.

5.1.2. ResNet

This neural network is 50 layers deep built for the purpose of image classification. This model accepts the image of size 224 x 224 x 3. The batch size for this model is 16 which means the dataset is divided into 625 batches with each batch having 16 samples. The model weights will update after each batch size of 16 samples. The final accuracy we achieved was around 72.72 percent. Which is significantly high compared to our previous CNN model. The input images are now modified using Image Super Resolution and finally, when the training of the model was completed the test accuracy was 86.57 percent.

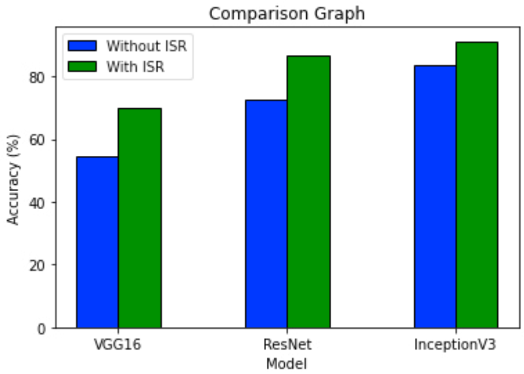

Fig. 4. Model Comparison Graph.

5.1.3. InceptionV3

This model is the first model we have trained using the dataset. The CNN model uses a 224 x 224 x 64 size image as an input. The CNN model uses a batch size of 32 which means the dataset is divided into approx. 312.5 batches with each batch holding 32 samples, which means the model weights will be updated after each batch of 32 samples. The input images are now modified using Image Super Resolution and finally, when the training of the model was completed the test accuracy was 91.26 percent.

5.2. Comparing Existing Systems

As shown above, three different Neural Network models were used and trained on the same dataset by dividing the dataset into training and test datasets, the training, and test datasets were divided in the ratio of 80:2. Here we have used Image Super resolution for increasing the accuracy while detecting the type of skin cancer from the images provided to the Convolution Neural Network which basically enhances the image quality provided to the CNN network for further evaluation, hence giving more accuracy and precision. When we compared our technique to other methods which were using the same CNN networks for detection of skin cancer through images we found that the these networks were just fine tuned at individual layers which did not help in increasing the accuracy by a large margin. According to [21] the max accuracy achieved by just fine tuning the layer was 86.92 percent for Inception V3 where as we were able to achieve an accuracy of 91.26 percent using Image Super Resolution same goes for ResNet we were able to achieve 86.57 percent and just using fine tuning by [21] they were able to get only 80.82 percent accuracy.

6. Conclusion and Future Work

In this paper, we proposed the classification approach for the skin cancer images using different algorithms like VGG16, ResNet, InceptionV3 with the core methodology to modify the input images using the GAN concept of image super resolution and then passing the images in the neural network. Medical tutor imaging is a crucial foundation for diagnosing disorders by surgeons. The imaging environment, physical imaging system limits, and quality constraints all contribute to reduce medical tumor image resolution. In this study, we provided a Residual Dense Network approach for improving the input image resolution, where the basic build component is the residual dense block (RDB). Dense connections between layers in each RDB enable maximum utilisation of local layers. A dense residual network completes the simple build module for the ISR. Then the RDN permits the local layers for dense connection among different layers. The global feature fusion methodology is proposed for extracting the hierarchical features. Moreover, the proposed methodology enhances the initial accuracy by 15.59% for VGG16, 13.85% for ResNet and 7.78% for InceptionV3. Thorough benchmark assessments demonstrate that our proposed approach provides dominance over state-of-the-art procedures.

Our methodology is now only applicable towards the skin cancer detection problem. To ensure that the model can deliver outstanding results into more medical imaging applications, we intend to adapt the approach to the other medical image recognition challenges in future study. Also, for enabling a broader and even more successful application, more clinical data for skin cancer can be utilized as well. In additional studies, the model performance can be improved by combining the ISR reconstruction technique with the semantic segmentation method.

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