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RETINAL IMAGE ENHANCEMENT USING DEEP NEURAL NETWORK

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Abstract
In the development of smart healthcare systems based on IoT, autonomous diagnoses have become very popular, on which various medical professionals have spent their precious time. For autonomous diagnosis, the image quality is one of the crucial steps, regardless of whether the diagnosis is made manually or automatically, because it has a direct impact on the outcome of the diagnosis in both scenarios. Due to advances in technology using computer vision and machine learning techniques, it has become possible to offer several ways to increase the effectiveness of such diagnosis through improving the image quality. Motivated by the same, the present work has been devoted to approaches to the process of turning low-resolution (LR) retinal images into high-resolution (HR) retinal images for their autonomous diagnosis, which can further be integrated into the Internet of Things (IoT) healthcare system. For this study, the author has developed a deep convolutional neural network and simulated it on the RIMONE retinal images dataset. The evolution of the proposed technique has been done based on mean square error (MSE) and peak signal-to-noise ratio (PSNR).
Keyword: Retinal Image**,** Image Enhancement, Deep Neural Network and Internet of Things (IoT) healthcare system.

1. Introduction

IoTs have found a broad range of applications, which has resulted in the persistence of and continued research in this field. Healthcare, in contrast to other application areas of IoT, has become the interest of many medical professionals as well as scientists due to the quick and precise response requirements in this field. Healthcare practitioners can expand their reach outside of the conventional clinical setting using the Internet of Things. Now a day IoT-healthcare is one of the key applications of the technology. The Internet of Things (IoT) has sparked a revolution that is reshaping health care with bright technological, economic, and social futures [1] [2].
In smart healthcare, IoT concepts allow for efficient coordination among doctors and patients. IoT healthcare can successfully monitor the physiological characteristics of patients from a distance [3]. In addition to this, patients' geolocations assist practitioners in keeping track of them. With little to no human involvement, wearable computing technologies elevate remote health monitoring to its highest level.

Autonomous diagnoses have found to be a demanding research area in smart health care systems. It can result in reducing the burden on health professionals and letting them spend their time caring for their patients while employing these technologies to make an immediate and accurate diagnosis. For effective diagnosis, whether autonomous or manual, high-resolution images are a prime requirement. Poor-quality images can lead to an ineffective diagnosis and further to poor treatment of the patient.
Due to advances in technology using computer vision and machine learning techniques, it has become possible to offer several ways to increase the effectiveness of such diagnosis through improving the image quality.
The present research work is the result of motivation from the same. In the present research work, author has been done on the RIMONE retinal images. The dataset for the same has been available on https://rimone.isaatc.ull.es/. For the retinal image enhancement, deep neural network has been proposed in this work.

2. Literature review

The advances in smart health monitoring systems are closely linked to the subject of computer vision. In the current era, the effective performance of healthcare systems has been directly impacted by the efficient implementation of computer vision systems. Smart health monitoring systems need to be periodically checked for their effectiveness when one has been developed for tracking the patient's wellness in response to their treatment. In all of this, digital images have been typically used by computer vision systems to make choices, and the efficiency of such systems is greatly influenced by a digital image's resolution. High-resolution images can help predict the findings more accurately using the software through image analysis, and this is because the High-resolution digital images have a higher pixel density as well as more usable information than low-resolution images. As results of this, high-resolution digital images are preferred in each and every application of computer vision. Previously various authors has conducted research on medical images quality enhancement for example,tn their paper [4], the authors present a single-shot, deep image-based prior method for enhancing the retinal images. The method is also known as the DIP method. The solution given by the author doesn't need data for its training. In contrast to this, the author has employed conventional deep learning-based techniques that can learn the underlying image. The author has demonstrated that degraded forms of the retinal picture can be utilized to create an augmented image because the convolutional neural network's architecture imposes a strong image prior strong enough to capture the statistics. In [5], the author proposed his work to address the concern of upgrading the imprecise retinal images in conventional PSO systems. The work proposed by the author offers a novel particle swarm optimization (PSO) along with a fuzzy framework. This whole network has been developed for retinal image enhancement. The author of [6] shows the recent triumphs of deep learning techniques in medical imaging, which served as inspiration for the unique speckle reduction technique. The same has been presented in this paper. In order to represent the demands and preferences of different end users, the author has given two versions of the network. Very specifically, the author has used training with either (1) mean-squared error or (2) a generative adversarial network (GAN) based on Wasserstein distance and perceptual similarity to denoise cross-sections from OCT volumes of healthy eyes. The results of this article have shown that the former technique facilitated the layer segmentation approach during the offering of state-of-the-art improvements in quantitative measurements like PSNR and SSIM.

In [7], untrained and pre-trained neural networks have been employed to enhancement retinal images. Author has proposed a single-shot deep image prior based method for improving retinal images. In this work the enhancement of retinal image has been considered as a layer decomposition problem and look at the usage of two well-known analytical priors, namely the dark channel prior (DCP) and bright channel prior (BCP), for estimating ambient light.Author demonstrated the ability of both untrained and pertained neural networks for the image enhancement using a single degraded image. Work presented in [8], focused on effectively improving the source's (training) high resolution for improved algorithm performance. In this work, through utilizing generators, classification techniques, and the antagonistic nature of GANs, author had created a super-resolution-based images dataset. The PSNR, SSIM, and loss functions were used to verify the RET's effectiveness. GAN's author built a convolutional neural network (CNN) with the original dataset photos and super-resolution data to test the Ret-GAN-generated images. On Ret-GAN-generated picture data, article has obtained an efficiency of 0.9825, while on original data; article has obtained an efficiency of 0.9525. Author in [9], expected to increase the standard of colour fundus images has conducted his research. In the research. The author has proposed an algorithm for image quality enhancement. The author did this by reducing noise and increasing contrast in the image. However, image enhancement research has been going on for so long that it has required special attention in medical diagnosis. Because ambiguous image information can lead to misdiagnosis, hence, the present research work has been conducted for retinal image quality enhancement. The major contribution of the present research work in term of novelty has been presented below.

1. For the given dataset of retinal images, the author proposed to develop a deep learning model.
2. The major functions that are supposed to be performed by the proposed CNN on the retinal images dataset are patch categorization, non-linear mapping, and image reconstruction.
3. The performance assessment of the proposed CNN model has been evaluated based on mean square error (MSE) and peak signal-to-noise ratio (PSNR) for image reconstruction with high resolution.

3. Material and methodology

For the proposed research work the material and methodology used has been described in the following sections.

3.1 Material

The proposed approach aims to create a model for medical image enhancement. The publicly available retinal image data was gathered to verify the suggested methodology. Deep learning (DL) methods have been used to simulate this dataset in order to increase their resolution with

"Image Super Resolution." The dataset for the present research work has been taken from https://rimone.isaatc.ull.es/.

The sample image of low resolution from the dataset has been presented below in Figure 1.

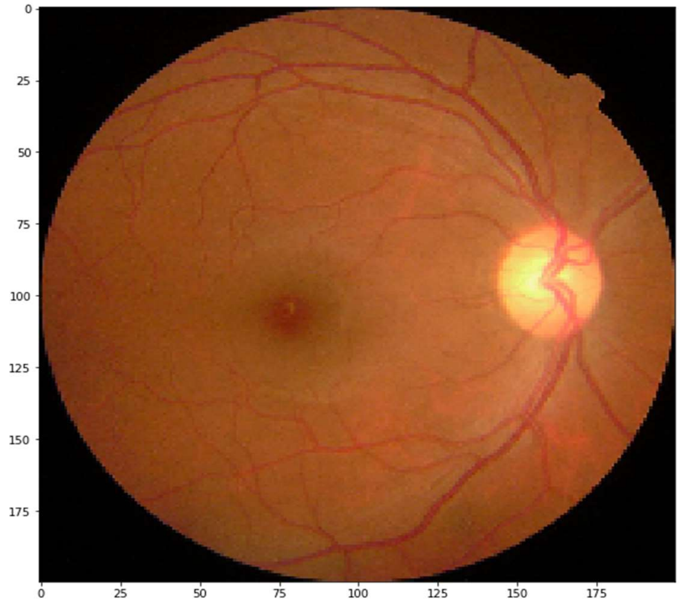

Figure 1: Sample image 1

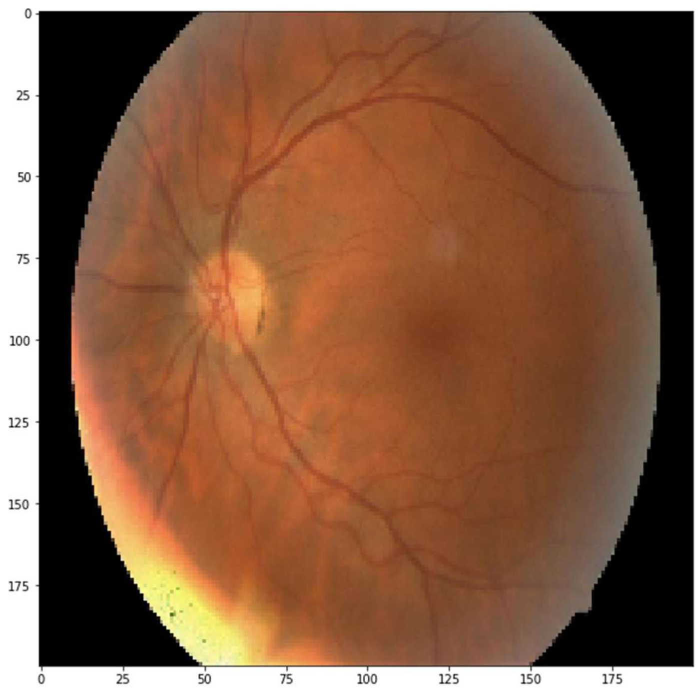

Figure 2: Sample image 2

3.2 Dataset splitting

As is commonly known, the neural network uses a learning-based methodology with a pre-existing dataset. Therefore, the given dataset has to be divided into two sets for effective learning of the same. A training set is the first set, and a testing set is the second set. A two-part dataset is one that is used for training the algorithm and the other is used for testing or statistical analysis of the data. In data science, data splitting is essential, especially when creating models from data. The dataset has been divided into training and testing sets using a 4:1 ratio for the sake of the current research project.

3.4 Deep learning model

The deep learning model for the proposed research work has been presented in figure 2

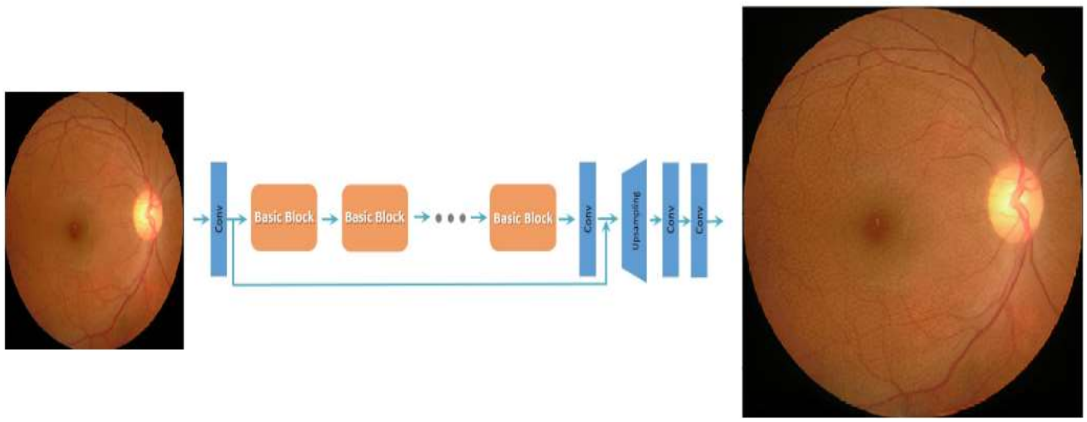

Figure 2: Proposed CNN model

The majority of the time, an Deep neural network can be thought of as a parallel processing processor that has been set up to store and test results for potential future uses.
For this, the entire network architecture learns from data in a data-learning phase and saves the knowledge utilizing information about the synaptic weight between neurons throughout the network's many layers.
The input layer, hidden layers, and output layer are the three general divisions of an network. Each and every neuron in the layer is connected to every other neuron in the layer above it via weights (for instance, WiI, WiJ, and Win are the various weights across various network levels). Each and every node receives weighted output from other nodes during the learning phase. Initially, the weights are accumulated in the node, and the node's summed weighted output has been given an activation function.
The overall or activated results from the preceding node have also been transferred to the input of the subsequent node. It has been continuously carried out at every single node of a full network.
The various parameters of the model has been given in table 1

Table 1: Parameters of Model

Parameters	Value
Input Shape	1024 *768
Dataset Division	Random
Model	Sequential
Training	Levenberg-Marquardt
Convolutional Layers	4

Activation Function for Hidden Layers	Sigmoid
Activation Function for Convolutional Layers Layer	Relu
Loss Function	Sparse categorical cross entropy
Optimizer	Adam
Metrics	, MSE,RMSE
Validation Check	6
Epochs	16

3.5 Performance measurement

As knowing how frequently the model under consideration is erroneous is insufficient in many situations. Understanding how frequently it is unable to correctly anticipate a particular outcome will be more important. The performance evaluation parameters provide insightful information about the model's capacity to handle a certain outcome

The proposed methodology has been worked based on following three different criteria's.

1Start from a low resolution images

2. Increase their resolution with "Image Super Resolution"

3. Compare the results with the original ones

In order to compare the results with the original ones various performance evaluation parameters has been chosen. The details of the same have been given below.

MSE

MSE is an abbreviation for Mean Squared Error. It basically lets you know how closely a regression line resembles a set of data points for the given dataset. In actuality, being a risk function, it corresponds to the squared error loss's expected value. The average, more particularly the mean, of errors squared from data related to a function is used to determine the mean square error. The MSE has been representing by the equation 2.

$$\mathrm{MSE} = 1/n \sum_{i=1}^{n} (\mathrm{y_i} - y\hat{}_i)^2 \quad (1)$$

RMSE

The model's error in predicting quantitative data has been measured using the Root Mean Square Error (RMSE). The RMSE is representing in equation 3.

$$RMSE = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{(\mathrm{y_i} - y\hat{}_i)^2}{\mathrm{n}}} \quad (2)$$

4. Results and analysis

In this section the detailed results analysis of proposed DNN model for images quality enhancement for retinal dataset has been presented. The results in term of training parameters results and regression with various errors MSE, RMSE has been presented below.

4.1 Results of an input images

Here in this section, a results of an input image fed to the network has been presented. The picture of an input image is shown in figure 3

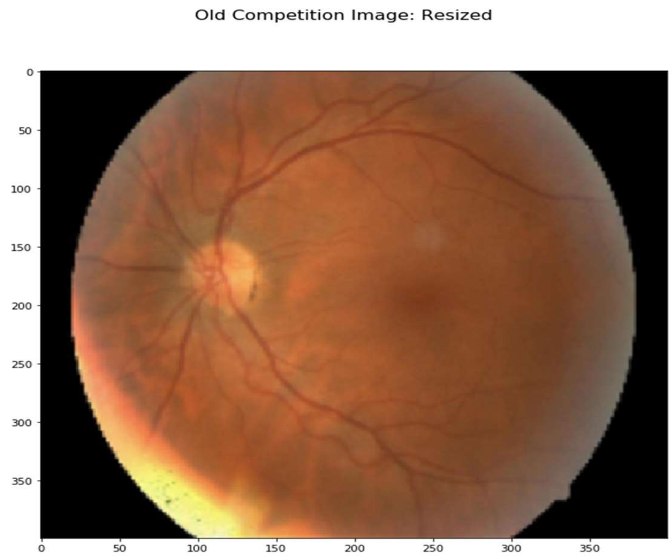

Figure 3: Input image to the network

The input image was processed by the network at several stages, yielding the results in the form of a high resolution image.

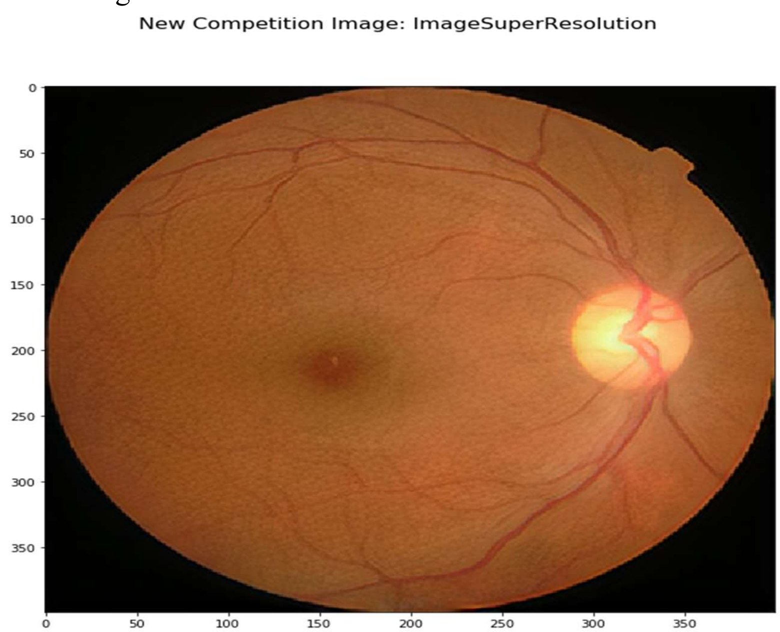

Figure 4 : Results of Super resolution

It has been observed that the picture quality has improved when the image has been passed through our model.

Figure 5 displays the curve representation for training, test. The little circle displays how the model represents the data. The diagnosis of the model is crucial to confirming the goodness of fit after the regression plot has been built.

This demonstrates that the established model and the network's training, testing, and validation procedures are largely acceptable.

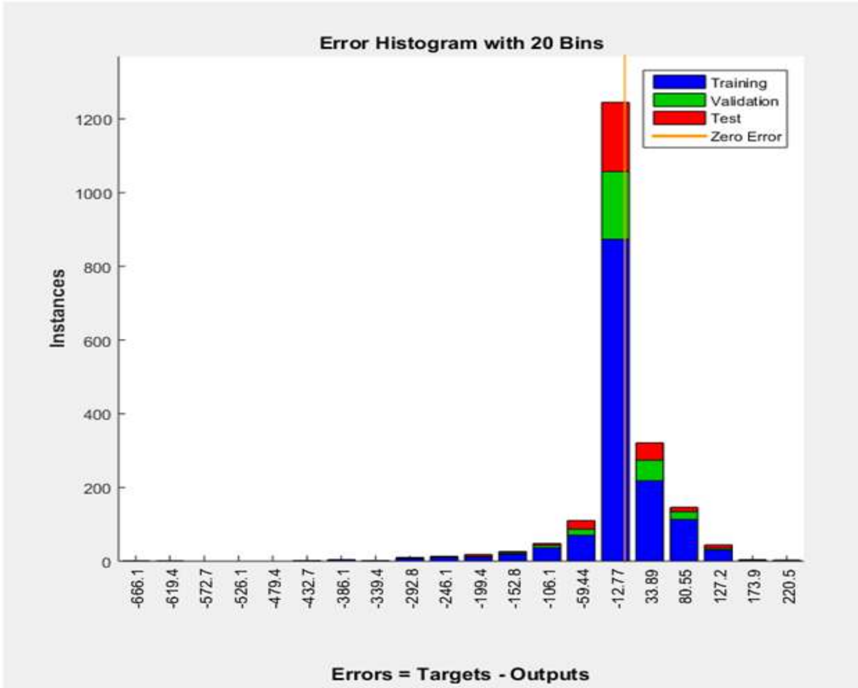

Figure 5 : Error histogram for proposed DNN model

Other than this, obtained values of Rsquared and RMSE are 0.9976 and 24.8364, respectively.

5. Conclusion

As a result of the existence of common poor imaging conditions or visual artefacts such as turbid refractive medium, motion blur, etc. the retinal images captured using fundus cameras can result in poor manual or autonomous diagnoses. Furthermore, eye conditions may aslo result in cataracts that cause the retinal image to become blurry. Due to all of these visual distortions, the usefulness of a computer-aided detection and diagnostic system or an expert ophthalmologist's diagnosis procedure is diminished.

In order tackle this issue, an image enhancement technique has been proposed in this work after image capturing. The image enhancement technique will produced high-resolution retinal images from low-resolution retinal images. For this CNN model will be used. The proposed model for image reconstruction at high resolution will be tested on the RIMONE retinal image dataset.

The proposed work will be evaluated using mean square error (MSE) and peak signal-to-noise ratio (PSNR) for image reconstruction.

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