Medical Image denosy base on Machine Learning

[1]Dipali Bhausaheb Jadhav, [2]Rani Laxman Nankar, [3]Arati Ravindra Deshmukh, [4]Bhagyashri Vijay Deshmukh, [5]Prof. Dalvi. A. S

Computer Department
S.N.D. College of Engineering and research Centre, Yeola

***Abstract*- Image Enhancement is an important step in Medical research. The basic intent of image enhancing is to convert a blur image into a crystal-clear image for the Medical research. Paper discusses the technique for improving Medical image enhancement, these Medical images usually suffers from motion blur effect due to turbulence in the flow of water and non – uniform illumination and limited contrast. Due to the presence of distortion, captured Medical image needs to be processed in different ways. Medical images captured in deep low light environment, are of worst quality and these images are low contrast, cause blurring effect, low contrast, scattering, absorption, noise color variation, clarity of image is reduced, quality get degrades and these Medical images cannot be directly used for various scientific research, marine biology research, Medical vehicles, submarine operations. While capturing Medical images some major obstacles are there such as minerals, salt, sand, planktons. These particles produce haziness in deep Medical captured image. To beat this, transfer learning base of Features model is taken in this paper. [1]**

***Keywords*: Medical Image, Image Enhancement, Transfer Learning, Light Scattering.**

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INTRODUCTION

The Medical image enhancement techniques is used, because the earth is planet having 70 of its surface is covered by water, and Medical imaging has vast application as the river, sea, lakes, and oceans contain many valuable resources inside them, So, scientists and researchers have shown great interest in capturing Medical life. It is observed that the effect of scattering and absorption of light in water are the major causes of it. When light enters from air to water it suffers dispersion, scattering effect, when it strikes particles of sand and minerals dissolved in water. Scattering deflects light in different directions reducing the amount of light falling on the object captured Medical images have also been an important source of interest in various branches of technology and scientific research. These techniques are widely used in numerous applications, such as the inspection of submarine infrastructure and cables. Image enhancement is to bring more visibility to the image and make it more appropriate to the required application. In today's scenario, the process of Medical image enhancement becomes an important area of study. The quality of Medical images deteriorates due to the physical properties of the aquatic medium, light scattering, reflection, and becomes more and less visible as water depth increases. The haziness is caused by suspended particles such as sand, minerals, and plankton that exist in lakes, oceans, rivers, sea. As the light reflected from the objects advances towards the camera, a part of the light meets these suspended particles, which absorb and disperse the light. Capturing clear images Medical is a challenge, mainly due to the turbidity caused by the dispersion of the color, in addition to the color emitted by the attenuation of the variable light at different wavelengths. Color dispersion and color emission produce blurred subjects and low-intensity contrast in Medical images. [2]

LITURATURE SURVEY

This chapter contains the existing and established theory and research in this report range. This will give a context for work which is to be done. This will explain the depth of the system. Review of literature gives a clearness and better understanding of the exploration/venture. A literature survey represents a study of previously existing material on the topic of the report. This literature survey will logically explain this system. [3]

Enhance the Medical images that are degraded because of the scattering, absorption of the medium. single image method for Medical images which calculate the white balance and then two variants of the image made one for which the correction is being calculated and other for which the sharpening is calculated from the resultant image which is white balanced then the weight-maps are being applied and finally multi-fusion technique is applied for getting the final result their approach is able to improve many varieties of images captured under the water with accuracy. [4]

Multi-scale Fusion technique calculated for Laplacian pyramid guided by the weight maps Number of pyramids increase with the image size, they introduce multi-scale fusion based on Laplacian decomposition. The Medical environments suffer from dispersion and absorption phenomena that disturb the visualization of the image and propagation of light, degrading the quality of Medical images. A physical model of light propagation method and the use of previous statistical data can restore the image quality achieved in the typical Medical scene.[5]

Medical exploration has increased in recent years exponentially. Equipment currently available for data collection (side scan sonar, multi-beam sonar, subbottom profiler, remotely operated vehicle) Medical research and observations not only provide data on objects and species. It also provides data on sea level. For this purpose, the selection of suitable characteristics is hard work. Classification is difficult due to limited Medical datasets Objects/features from Medical images. To overcome this, machine learning. A bag-of-features model is used in this document. Because there is little light in optical Medical images, the strength that makes feature classification a difficult task. SURF (Speeded Up Robust Features) and SVM (Support Vector Machines) algorithms are implemented. Achieve maximum accuracy with the Bag of Features model. Performance evaluation Combining training and testing datasets improves performance. [6]

Considered as object-based image analysis (OBIA). It is an effective technique for high spatial resolution (HSR) imaging. Classification by a clear and intuitive technical process. However, OBIA relies on manual adjustment of the image. Classification function. This is tricky work. Deep learning (DL) The technology automatically learns image features from a large number of images, Achieving higher image classification accuracy than before Technique. The study uses a new method called object scale adaptive convolutional neural networks (OSA-CNN), Combine OBIA and CNN, recommended for HSR images classification. First, OSA-CNN collects image blobs principal axis of the object primitive taken from the image segmentation; the size of the former is determined automatically by the axial width of the latter. This step generates the input Units required for CNN(Convolutional Neural Network) classification. Second The squeeze and excitation blocks are extracted from the SE network. [7]

The network structure of Google Net that realizes this Improved weighted merging for multiscale convolution functions Suppress useful functions and suppress useless functions. when classifying stadium, multiscale image segmentation, CNN classification. It is fused using the object scale adaptation mechanism. contradiction at the end. Primitives are classified by majority vote over the image dirt. Changes in network structure, multiscale classification fusion and other improvements gradually integrate these steps into the original Google Net. Trials show these improvements are effective improved image classification accuracy. This research an effective way to leverage a combination of OBIA(Object-Based Image Analysis) and DL(Deep Learning) techniques advantages of both approaches and promotion of HSR(High Spatial Resolution) image classification. [8]

An accurate and robust classification method for sea ice and sea ice open water is important for many applications. Synthesis Aperture Radar (SAR) imaging capabilities a meteorological condition, often used to classify sea ice. U-Net, a deep learning framework, is doing great work Success in the field of biomedical image classification. The study builds a U-Net-based ’end-to-end’ model. Classify sea ice and open water pixels in SAR images. Five SAR images taken in the Gulf of Alaska near Bering, A strait is used in this case study. Manually label the SAR an image of ice and water. Images labeled from scratch four SAR images. [9]

LIMITATION OF LITERATURE SURVEY

- Costing
- Technology Complexity
- Time Consuming Feature
- Not Easy to Understand

PROJECT SCOPE

During the past few years, Medical image enhancement has drawn considerable attention in both image processing and Medical vision. Due to the complicated Medical environment and lighting conditions, enhancing Medical image is a challenging problem. Usually, an Medical image is degraded by wave length dependent absorption and scattering including forward scattering and backward scattering. In addition, the marine snow introduces noise and increases the effects of scattering. These adverse effects reduce visibility, decrease contrast, and even introduce color casts, which limit the practical applications of Medical images and videos in marine biology and archaeology, marine ecological, to name a few. To solve this problem, earlier methods rely on multiple Medical images or polarization filters, while recent algorithms deal with this problem by using only information from a single image.

SYSTEM ARCHITECTURE

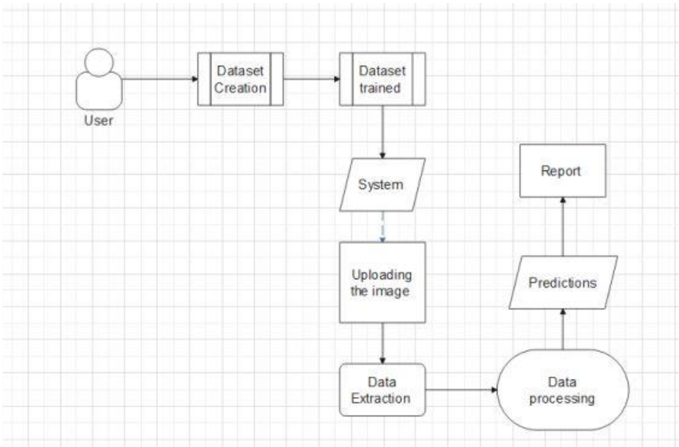

Fig -1: System Architecture Diagram

In fig-1, we have mentioned the work of our system where firstly will upload the image to system, in that process the system will take input and start the process of filtering, where extra noise and header is removed and formed a regression, system save it. The system then extraction process is carried out same as previous like noise and frame header removal. After that, the result is stored separately. Then the two results are combined and the system matches the difference and provides output.

ALGORITHM

Pretrained Model Choice:

Pick a pretrained model that has been prepared for a huge scope dataset, like ImageNet, to catch general picture highlights. On the other hand, you can choose a model pretrained on clinical imaging datasets if accessible.

Eliminate Assignment Explicit Layers:

Eliminate the assignment explicit layers of the pretrained model, normally the characterization layers. Hold the lower-level layers answerable for include extraction.

Highlight Extraction:

Freeze the loads of the leftover layers in the pretrained model to safeguard the learned component portrayals.Pass uproarious clinical pictures through the changed pretrained model to extricate highlights.

Add Denoising Layers:

Affix new layers well defined for denoising on top of the adjusted pretrained model.These denoising layers can be planned as convolutional layers or other denoising-explicit models. Assess the presentation of the exchange learning model on a different approval or test set of uproarious clinical pictures. Figure denoising-explicit measurements like PSNR, SSIM, or other area explicit measurements to evaluate the nature of denoising.

Arrangement and Surmising:

Send the prepared model for denoising new, inconspicuous uproarious clinical pictures. Apply the model to the boisterous pictures to acquire denoised variants for additional examination or analysis.

PSEUDO CODE

```
# Import required libraries
import tensorflow as tf
from tensorflow.keras.applications import VGG16
from tensorflow.keras.layers import Conv2D, UpSampling2D
from tensorflow.keras.models import Model

# Load pre-trained VGG16 model
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(image_height, image_width, 3))

# Freeze layers in the base model
for layer in base_model.layers:
    layer.trainable = False

# Create a denoising model using transfer learning
input_image = tf.keras.Input(shape=(image_height, image_width, 3))

# Encoder layers
x = Conv2D(64, kernel_size=(3, 3), activation='relu', padding='same')(input_image)
x = Conv2D(64, kernel_size=(3, 3), activation='relu', padding='same')(x)
encoded = base_model(x)

# Decoder layers
x = Conv2D(64, kernel_size=(3, 3), activation='relu', padding='same')(encoded)
x = Conv2D(64, kernel_size=(3, 3), activation='relu', padding='same')(x)
decoded = UpSampling2D(size=(2, 2))(x)

# Create the denoising model
denoising_model = Model(inputs=input_image, outputs=decoded)

# Compile the denoising model
denoising_model.compile(optimizer='adam', loss='mse')

# Train the denoising model
denoising_model.fit(train_images, train_labels, epochs=num_epochs, batch_size=batch_size)

# Perform denoising on test images
denoised_images = denoising_model.predict(test_images)
```

1. Import the necessary libraries and frameworks, such as TensorFlow or PyTorch.
2. Define the generator network, which takes a low-resolution input image and outputs a high-resolution image. The generator typically consists of multiple convolutional layers, activation functions (e.g., ReLU), and upsampling layers to increase the resolution.
3. Define the discriminator network, which distinguishes between real high-resolution images and generated (upscaled) high-resolution images. The discriminator can be a convolutional neural network or a patch-based discriminator that operates on image patches.
4. Create the ESRGAN model by combining the generator and discriminator networks. The generator aims to generate high-resolution images that the discriminator cannot distinguish from real high-resolution images.
5. Define the loss functions. ESRGAN typically utilizes two loss functions: a content loss (e.g., mean squared error) to ensure the generated image retains the content of the input image and a GAN loss to encourage the generator to produce realistic high-resolution images.
6. Train the ESRGAN model using a dataset of paired low-resolution and high-resolution images. During training, the generator is updated to minimize the content loss and fool the discriminator, while the discriminator is updated to distinguish between real and generated images.
7. Once the ESRGAN model is trained, it can be used to enhance the resolution of new low-resolution images. The generator takes a low-resolution input image and produces an upscaled high-resolution image.

RESULT ANALYSIS

- Quantitative Measurements
- Visual Investigation
- Near Examination
- Mistake Examination
- Speculation and Power
- Conversation of Discoveries

CONCLUSION

For finding crystal clear Medical images is a great challenge, and the presence of scattering and absorption in Medical pictures create difficulties, one examines a technique for enhancement which have been specifically developed for the Medical pictures, and one can find results from the output image. These methods work on all the Medical images, which eliminate obstacles and develops a simpler and more effective image. Similarly, one can sort these images in the output in this project, one has constructed an Medical image enhancement benchmark dataset that provides a large number of real Medical images and related reference images. This benchmark dataset enables us to comprehensively study the existing Medical image enhancement methods, and easily train CNNs for Medical image enhancement. As analyzed in qualitative and quantitative evaluations, there is no method which always wins in terms of full- and no-reference metrics. In addition, effective non-reference Medical image quality evaluation metrics are highly desirable. To promote the development of deep learning-based Medical image enhancement methods, one can propose an Medical image enhanced CNN trained by the generated dataset. Experimental results demonstrate the proposed CNN model performs favorably against the state-of-the-art methods, and also verify the generalization of the constructed dataset for training CNNs. [11]

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