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Theme

Effect of Image Enhancement Techniques on COVID-19 Detection Using Deep Learning

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Before we choose the title of the memory, our focus was on who would frame us. And always was your desire to choose you as our best teacher. And indeed we had the honor of having you accompany us along the path of our accomplishment. No matter how much we thank you, we will not fulfill your right and your efforts to guide and help us We never fully felt the pressure to complete the memory thanks to God and you.

So Thank you a lot and God bless you and we wish you all the best in your path and your life Dr.Chrif Fella and Dr.benchabanne Abderzzak.

Dedication

we dedicate our dissertation work to our families and many friends. A special feeling of gratitude to our loving parents. And all who supported us and gives us his words of encouragement and push for tenacity ring in our ears.

we also dedicate this dissertation to our many friends who have supported us throughout the process. we will always appreciate all they have done.

we dedicate this work and give special thanks to all our teachers in our entire educational path in university.Thank you a lot for being helpful.

with all our respect.

Thank you..

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General Introduction

The World has experienced outbreaks of coronavirus infections during the last two years. Reliable and early detection of COVID-19 has the utmost importance to stop the spread of the virus. Currently, reverse transcription of polymerase chain reaction (RT-PCR) arrays and chest imaging techniques, such as computed tomography (CT) scans and chest X-ray (CXR) imaging are the diagnostic tools to detect COVID-19. CT scans and CXRs are recommended as an alternative or secondary diagnostic strategy [1,2]. Sine CT scans are not available especially in countries with low resources so the X RAY was widely used because it's cheaper, faster, and easily accessible method with a reduced risk of radiation exposure compared to CT.Artificial intelligence and automated patient data analysis was a very good solution for fasterdiagnosis and low detection error. So, in this research, we have used some deep learning techniques to analyze and classify patient using X-rays images [1].

It has shown also that image enhancement techniques can improve significantly the classification performance [3,4]. The main objective of this study is to find the best contrast enhancement technique for an accurate and faster detection of COVID-19 using deep learning-based radiology image analysis method. Three enhancement methods; Histogram Equalization, Contrast limited adaptive histogram equalization and Gamma correction have been considered[4].

The study is organized as follows: chapter one contains details about the image enhancement techniques. In the second chapter we will present the deep learning. Results and Discussion section presents the experimental results including classification accuracy, sensitivity and F1-score obtained from the proposed work. Finally, the study is achieved by a conclusion.

Chapter 1

Medical images enhancements

1.1. Introduction

Image processing is a set of methods that perform certain functions on digital images in order to get an enhanced image or extract other useful information from it. Nowadays, medical images and computerized analysis become very important tools for medical diagnosis and disease detection.

The beginning of medical imaging dates back to 1895, when Röntgen discovered the X-rays which are the basis of radiography, the only imaging method in beginning of the last century. A radiograph is obtained by exposing a film to X-rays that have passed through the human body.The result is an analog image two-dimensional which is the projection on an X-ray film of organs in three dimensions to give high-quality images, which are often sufficient to obtain a reliable diagnosis and for low-cost screening. Figure (1.1) shows an X-rays processed image. We can see that the processed image is far better and can be used for better diagnostics.Scanner, Ultrasound and Magnetic Resonance Imaging (MRI) have in turn appeared during the 20th century. Those imaging modalities are used today to obtain information anatomical, physiological, metabolic and functional of the human body [5].

Figure1.2: Showing the effect of image enhancement

1.2. Medical Imaging for COVID-19 disease detection

Corona disease is currently considered one of the most widespread, dangerous and fastest diseases, so it is necessary to find ways and methods to detect infected cases and diagnose them in the fastest and clearest way. In Real-time RT-PCR is a nuclear-derived technique that detects the presence of geneticmaterial specific to a pathogen, including a virus. A formal diagnosis of COVID-19 requires a laboratory test (RT-PCR) of nose and throat samples. RT-PCR requires specialist equipment and takes at least 24 hours to produce a result.figure (1.2) shows different phase of the RT-PCR test. It is not completely accurate, and may require a second RT-PCR or a different test to confirm diagnosis. And People with suspected COVID-19 need to know quickly whether they are infected, so they can receive appropriate treatment, self-isolate, and inform close contacts[1,2].

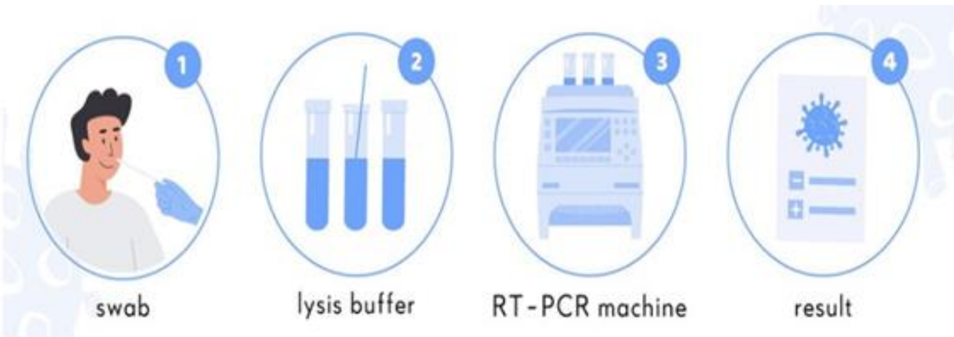

Figure1.2:RT-PCR test procedure

The radiology images show typical COVID pneumonia in the lungs and the numerous complicationsthe virus causes in the body. The radiology imaging modalities include computed tomography (CT), radiograph X-rays, ultrasound, echocardiograms and magnetic resonance imaging (MRI).These imaging modalities optimize and greatly facilitate the process of discovering affected areas in the body.

1.2.1. X-Rays

X-rays images have been used in the clinic for more than 120 years. They still used for looking at bones and finding problems in certain types of tissues, like pneumonia in the lungs,(see figure 1.3). X-ray imaging works by passing an energy beam through a part of body, bones or other body parts will block some of the X-ray beams from passing through. That makes their shapes appear on the detectors used to capture the beams. The detector turns the X-rays into a digital image for a radiologist to look at. X-ray beams use radiation which is energy that's released as invisible particles or waves. People are naturally exposed to radiation from many sources, such as the sky, rocks, and soil.

Figure 1.3: Chest X-ray process

In case of COVID-19, X-rays of a person's chest are taken to look at lung tissue. This test is used for patients with respiratory symptoms resulting from COVID-19. X-rays are also used to monitor the progression of the disease and make decisions about treatment and follow-up. Figure (1.4) shows some X-rays images of a lung infected by the virus [4].

Figure 1.4: Chest X-ray images for covid-19

1.2.2. Computedtompography (CT)

A computerized tomography (CT) is a rotating (360) X-ray scanner that creates a cross-sectional image of the body that introduce the ability to display three-dimensional images of organs such as the head, heart or lungs. Also shows the soft tissues, blood vessels, and bones in various parts of the body. CT images are more detailed than conventional x-ray images so it reveal the abnormal structures more clearly to help the doctor to plan and monitor treatments.

Figure 1.5:CT scan process

In case of COVID-19, Chest CT has a high sensitivity for diagnosing COVID-19 and can be considered as an alternative primary screening tool for COVID-19 in endemic areas. In addition, CT scans can be used to make screening decisions. Doctors emphasized that although CT scans are more sensitive, chest X-rays may be the preferred method, but a positive CT scan result can indicate infection with COVID-19 due to the accuracy and speed of diagnosis. Figure 1.6 shows CT images of lungs of persons with coronavirus disease pneumonia [1].

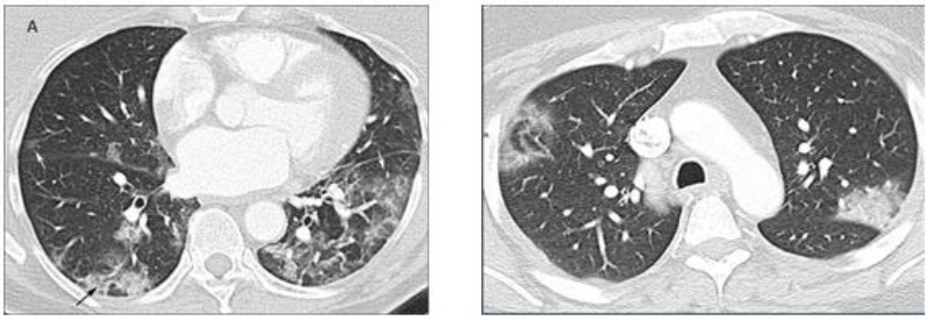

Figure 1.6:CT images of lungs of persons with coronavirus disease pneumonia

1.2.3. Magnetic resonance imaging (MRI)

An MRI scan uses large magnets, radio waves, and a computer to create a detailed cross-sectional picture of internal organs and structures. The scanner itself usually has the same method of movement as the CT scanner, it is like a large tube with a table in the middle, allowing the patient to slide.An MRI scan differs from a CT scan and X-ray, because it does not use harmful ionizing radiation.

Figure 1.7: MRIscan process

MRI can be used to diagnose COVID-19infection.MRI provides a radiation-free alternative to other modalities such as computed tomography (CT) and single photon emission computed tomography (SPECT), which are commonly used for cardiac evaluation, and it provides accurate anatomic information along with advanced soft tissue contrast [4].

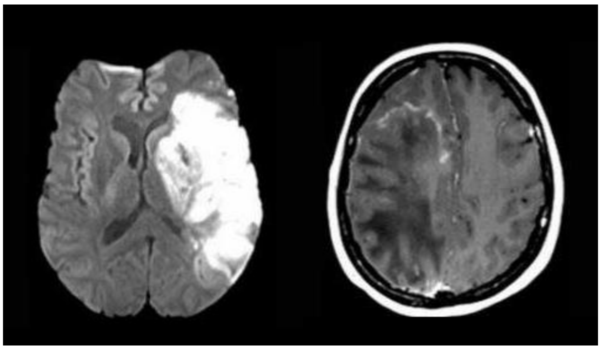

Figure 1.8:MRI of brains of persons with coronavirus disease

1.3. Image enhancement Techniques

Image Enhancement is very essential and important technique used in image processing. Its aim is to improve the visual details of the image, or to provide a “better” transform representation for appropriate usage in image processing in different fields like medical, satellite images, aerial images and even real life pictures suffer from poor contrast and high noise (loss of information). The enhancement methods can broadly be divided in to the following two categories; spatial domain methods which are based on direct manipulation of pixels in an image and frequency domain methods based on modifying the Fourier transform of the image.

1.3.1. Image enhancement based histogram

The histogram of a digital image with intensity levels in the range [0, L-1] is a discrete function with the following representation [4]:

$$h(r_k) = n_k \tag{1.1}$$

Where r_k is the kth intensity value, n_k is the number of pixels in the image with intensity andr_kHistograms are frequently normalized by the total number of pixels in the image. In the case of an M x N image, a normalized histogram is related to the probability of occurrence of r_k in the image, as shown in equation 1.2.

$$p(rk) = \frac{nk}{M \times N} \tag{1.2}$$

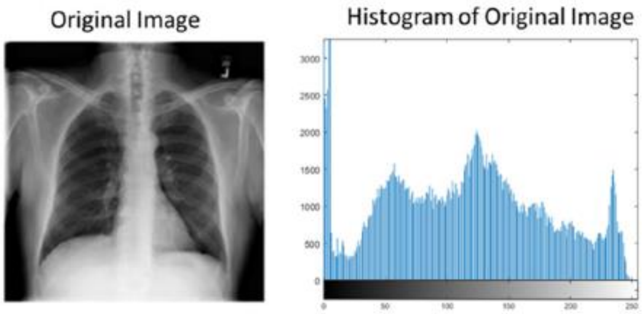

Figure 1.9: Representing an image with its histogram

Histogram Equalization (HE)

Histogram Equalization (HE) is a technique for adjusting the contrast of an image using the image's histogram. This technique is a transformation that stretches the contrast by redistributing the gray-level values uniformly and remapping the scene's histogram to a histogram with a near-uniform probability density function [1,3].

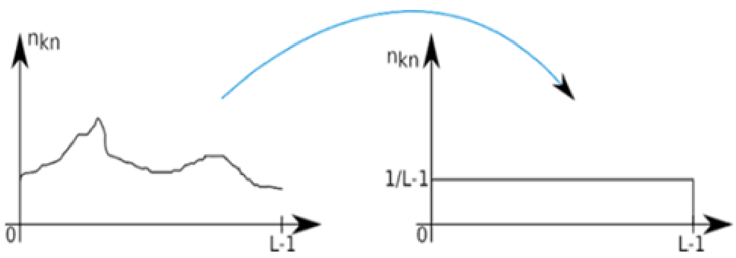

Figure 1.10:Basic histogram equalization

If an image's histogram contains many peaks and valleys, it will still contain peaks and valleys after equalization, but the peaks and valleys will be shifted. The goal of Histogram Equalization is to obtain a uniform histogram, which improves contrast.

Figure 1.10 shows original input image before applying histogram equalization and output image after applying histogram equalization [3].

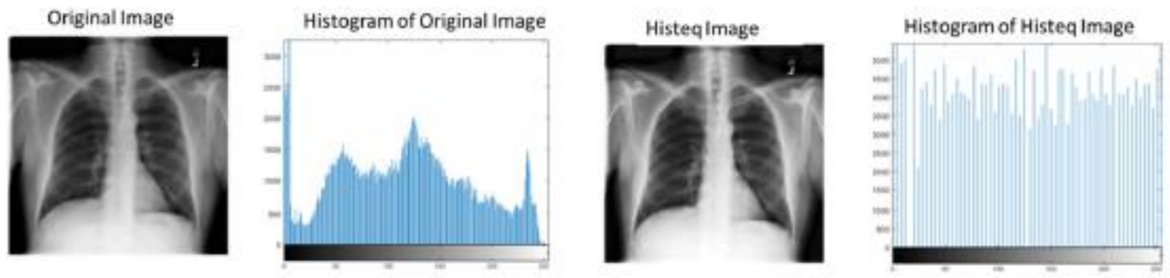

Figure 1.11: Example of histogram equalization

Adaptive histogram equalization (AHE)

Adaptive histogram equalizationis a computer image processing technique used to improve the contrast in images, adaptive histogram equalization works by dividing an image into an M x N grid and then applying histogram equalization locally to each grid. The result is an output image that overall has higher contrast with (ideally) the noise still suppressed [1].

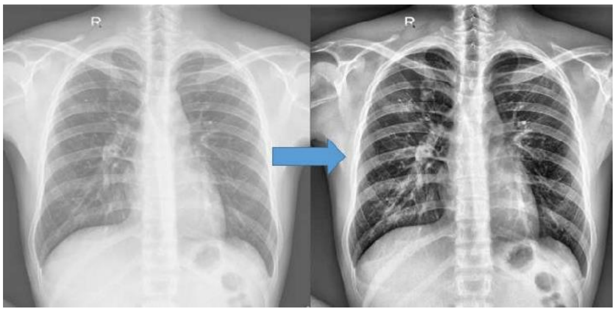

Figure 1.12:X-Ray adaptive histogram equalization

Cumulative histogram

Also called the Cumulative Distribution Function (CDF), it is a mapping that counts the cumulative number of pixel intensity values in all of the bins up to the current bin. The cumulative histogram Mi of a histogram mj is given by [4]:

$$Mi = \sum_{j=1}^{i} m_j \tag{1.3}$$

The cumulative histogram is useful for some image operations that use histograms: such as Image histogram equalization.

Quadratic dynamic histogram equalization

This technique produces better brightness preservation with natural looking compared to other existing techniques. Figure 1.13 shows the four processes of the QDHE algorithm that are histogram partitioning, clipping, gray levels redistribution and histogram equalization[3,4].

Figure 1.13: Procedure of the quadratic dynamic histogram equalization algorithm.

Histogram partitioning: it segments the number of pixels equally in each sub histogram

Clipping: It modifies the shape of the input histogram by reducing or increasing the value in the histogram's bins based on a threshold/clipping limit/threshold, Tc that is equal to the average of the image-intensity values.

*Gray level range allocation:*To balance the enhancement space for each sub-histogram, equation shows the new gray level dynamic range allocation based on the ratio of gray level spans and the total number of pixels in each sub-histogram.

$$spani = m_{i+1} - m_i \tag{1.4}$$

$$range_i = (L-1) \times \frac{spani}{\sum_{k=1}^{4} spank} \tag{1.5}$$

where :*spani* is the dynamic grey level of the ith sub-histogram and range$i$ is the dynamic level range for ith sub-histogram in the output image.

Histogram equalization: the last step of QDHE is applying HE algorithm for each sub-histogram independently.

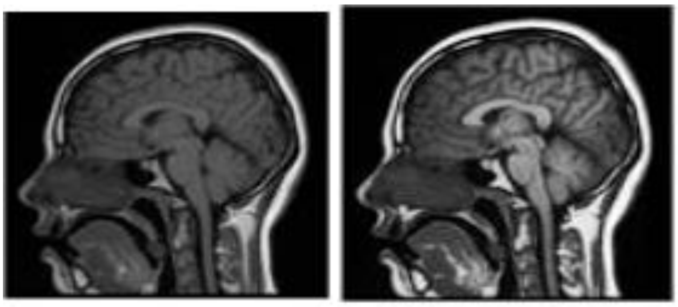

Figure 1.14: Example of quadratic dynamic histogram equalization

Contrast limited adaptive histogram equalization (CLAHE)

CLAHE is a generalization of the Adaptive Histogram Equalization (AHE). For a given input image, CLAHE was originally developed for enhancement of low-contrast medical images. The algorithm of CLAHE creates non-overlapping contextual regions (also called sub-images, tiles or blocks) and then applies the histogram equalization to each contextual region, clips the original histogram to a specific value and then redistributes the clipped pixels to each gray level. The clipping level determines how much noise in the histogram should be smoothed and hence how much the contrast should be enhanced [1,3].

However, images enhanced with Contrast limited Adaptive Histogram Equalization (CLAHE) are more natural in appearance than those produced by HE [3].

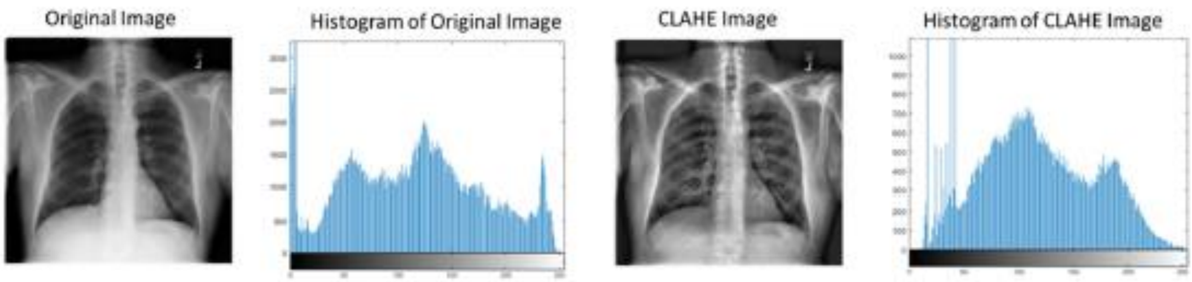

Figure 1.15: Example of Contrast limited Adaptive Histogram Equalizationwith its histogram

1.3.2. Image enhancement based on linear space processing

The image inversion or complement is a technique where the zeros become ones and the ones become zeros so black and white are reversed in a binary image. In an 8-bit gray scale image, the original pixel is subtracted from the maximum intensity value, 255, and the difference will be used to construct a new image's pixel values.For x-ray images, the dark spots turn into lighter and light spots becomedarker.

The mathematical expression is simply [3]:

$$y = 255 - x \tag{1.6}$$

where x And y are the intensity values of the original and the transformed (new) images. This technique shows the lungs area (i.e., the region of interest) lighter and the bones are dark er. As this is a standard procedure, which was used widely by radiologists, it may equally help deep networks for a better classification. It can be noted that the histogram for the complemented image is a flipped copy of the original image [1].

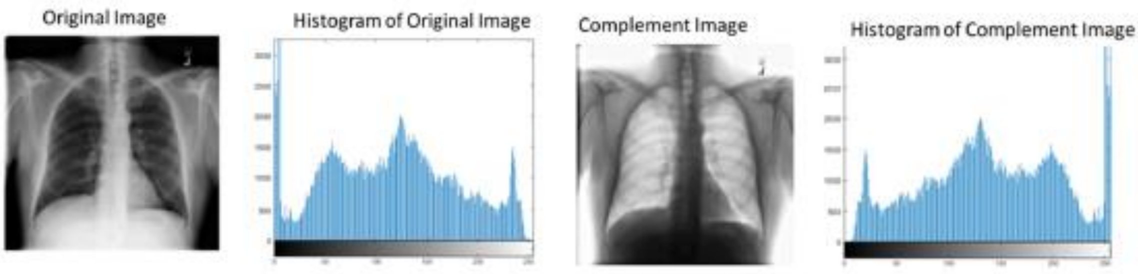

Figure 1.16: Example of image inversion with its histogram

1.3.3. Image enhancement based on nonlinear space processing

Gamma correction

Gamma correction is a nonlinear adaptation applied to each and every pixel value. Generally linear methods like addition, subtraction, and multiplication are applied on all the pixels. Gamma correction is responsible for performing nonlinear methods on the pixels of the input image and thereby remodeling the saturation of the image. It is necessary to maintain the stable gamma value; it should neither be too minimum or maximum. Gamma corrections alternate the pixel value to improve the Image using the projection relationship between the value of the pixel and the value of gamma according to the internal map [3].

The relationship in this case between the input and the output is that the output is proportional to the input raised to the gamma power. The formula for calculating the resulting output is as follows, our image pixel intensities must be scaled from the range [0, 255]to [0, 1.0]:

$$I' = 255 \times (\frac{I}{255})^{\gamma} \qquad (1.7)$$

Note that using gamma 1, the input is equal to the output to produce a straight line.To calculate the gamma correction, the input value is raised to the power of the inverse gamma. The formula for this is as follows [1]:

$$I' = 255 \times (\frac{I}{255})^{\frac{1}{\gamma}} \qquad (1.8)$$

The following graph shows a comparison between the gamma curve and the gamma correction curve:

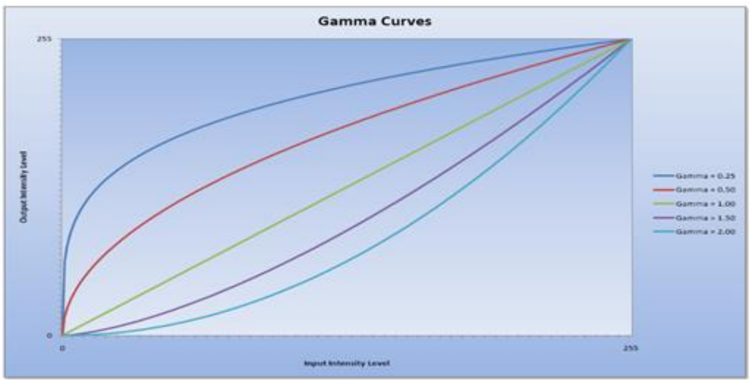

Figure 1.17: Various Gamma curves

Gamma values < 1 will shift the image towards the darker end of the spectrum while gamma values > 1 will make the image appear lighter. A gamma value of $\gamma = 1$will have no effect on the input image.

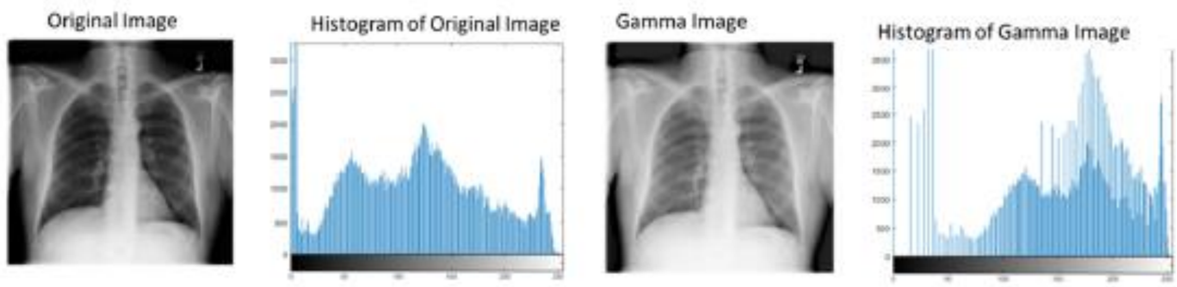

Figure 1.18: Example of Gamma correction with its histogram

Figure 1.19: Examples of Gamma correction ($\gamma = 06\ , 1\ and\ 3$)

Balance ContrastEnhancement Technique (BCET)

This technique provides solution to biased color (RGB) composition. The contrast of the image can be stretched or compressed without changing the histogram pattern of the input image(x). The solution is based on the parabolic function obtained from the input image.The general form of the parabolic function is defined as [1,4]:

$$y = a(x - b)^2 + c \tag{1.9}$$

The three coefficients '**a**','**b**' and **'c'**are derived from the following inputs,

- Minimum value of the output image(**y**)
- Maximum value of the output image
- Mean value of the output image

$$b = \frac{h^2(E-L)-S(H-L)+L^2(H-E)}{2[h(E-L)-e(H-L)+l(H-E)} \tag{1.10}$$

$$a = \frac{H-L}{(h-l)(h-l+2b)} \tag{1.11}$$

$$c = L - a(l - b)^2 \tag{1.12}$$

Where

- **'l'** represents the minimum value of the input image
- **'h'** denotes the maximum value of the input image
- **'e'** denotes the mean value of the input image
- **'L'** represents the minimum value of the output image
- **'H'** denotes the maximum value of the output image
- **'E'** denotes the mean value of the output image
- **'s'** denotes the mean square sum of the input image.

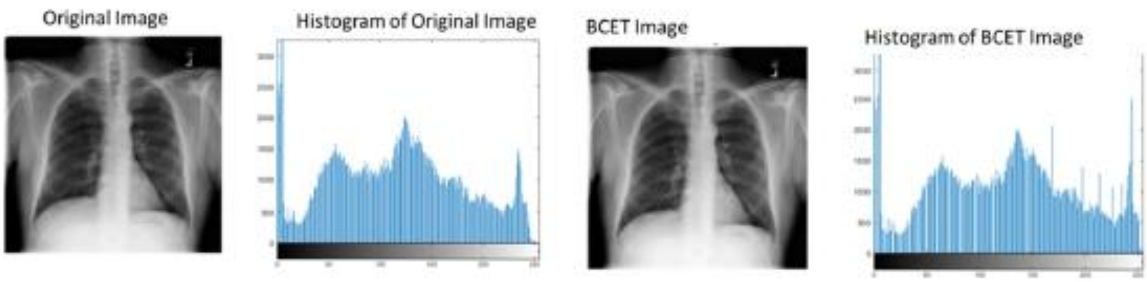

Figure 1.20: Example of Balance Contrast Enhancement Technique with its histogram

1.4. Conclusion

Since the outbreak of the Corona epidemic, many studies have been conducted about the detection of Covid-19 infection, whether using chest x-rays or computed tomography.The medical images quality that obtained each time is not sufficient always to obtain an accurate diagnosis. Therefore, a study should be carried out to improve the quality of the image obtained automatically, and its effects on the covid-19 detection. Enhancement techniques that previously mentioned provide a more accurate diagnosis and faster results.

Chapter 2

Deep Learning

1.5. Introduction

Artificial intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems. One of the tasks which can be achieved by AI iscomputer vision, which is the ability for computers to process and analyze images, aiming to mimic human vision. One of the main tasks of computer vision is image classification, which is the process of labeling images into “classes”. One common way to execute image classification is through convolutional neural networks, a technique implementing deep learning, which is a subset of machine learning, which is in turn a subset of AI [5].

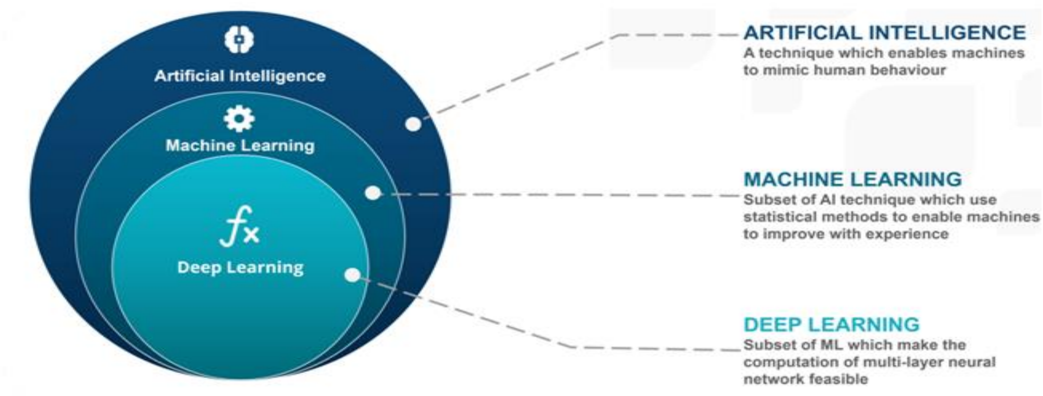

Figure 2.1: Relation Between machine learning and deep learning

1.6. Artificial Neural Networks

Inspired by the functioning of the human brain, artificial neural networks play a prominent role in several fields of engineering sciences. The formal neuron often named perceptron developed by McCulloch and Pitts is the basic building block of a neural network. It is an elementary processor which receives a number of inputs, each of which is associated with a weight representing the strength of the connection and delivers an output. A neuron operates in two stages; it calculates its internal excitation state based on the weighted inputs and then it outputs a result through a function called the activation function [6].

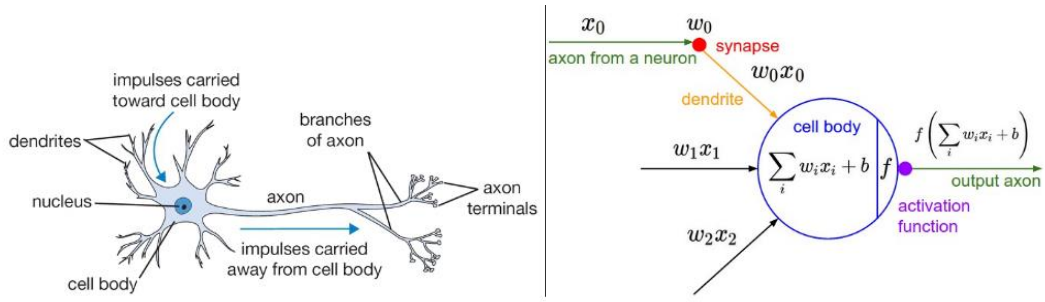

Figure 2.2: biological neuron (a),artificial neuron (b).

In multilayer perceptron, the neurons are organized in successive layers and whose information propagates forward from layer to layer. The outputs of neurons in one layer serve as inputs to neurons in the next layer. Within the same layer, the neurons are not connected to each other. The first layer is called the input layer, the last the output layer and the layers in between are called the hidden layers. A multilayer network has the following characteristics [7]:

- It has a single input layer or receiving layer, receives information from the outside.
- It has a single output layer which gives the system response.
- It has one or more hidden layers. The input of each neuron of a layer is connected to all the outputs of the neurons of the previous layer. The output of each neuron in one layer is connected to the input of each subsequent neuron. [6,7]

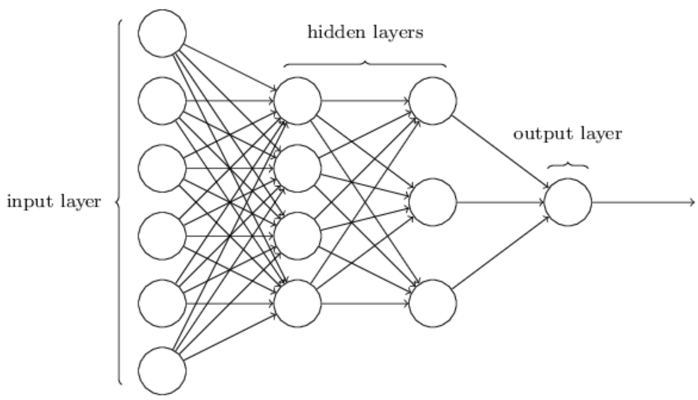

Figure 2.3: Architecture of multilayer neural network

1.7. Machine Learningversus Deep Learning

2.3.3. Machine Learning

Machine Learning is a subcategory of artificial intelligence and a set of statistical or geometric tools and computer algorithms that make it possible to discover "patterns", specifically recurring patterns in data sets, This data can be numbers, words, images, statistics... Anything that can be stored digitally can be used as data for machine learning, also make it possible to automate the construction of a function of prediction "f" from a set of observations called the set of learning. The model of machine learning can build prediction function "f" from a training dataset. Once trained, the algorithm will be able to find patterns in new data. There are three types of machine learning, supervised learning, unsupervised learning, reinforcement learning. Machine learning is characterized by:

- Simple Activation function.
- Simple neural networks.
- Learning rate or activation functions cannot be learned by the learning algorithm; they constitute model hyper-parameters and must be set manually or determined by an optimization routine.
- Produce superior result in cases of limited training data availability[7].

2.3.4. Deep learning

Deep learning is a subfield of machine learning; it's a group of algorithms that analyzes a set of data in order to drive rules that will allow conclusions to be drawn aboutthe new data, in the sense that learns to represent data using successive layers. The result of every layer considered as input of the next layer. The advances in deep learning have been possible due to the increase in the power of computers and the development of large data bases (big Data). Deep learning is characterized by[7,8]:

- The hidden layer organized in deeply nested network architecture
- Advanced neural networks.
- Automatically discover a representation that is needed for the corresponding learning tasks.
- More useful in domains with large and high dimensional Data.

3.3.1. Difference between deep learning and Machine learning

Such as Deep learning is a subfield of Machine learning, it represents the evolution of artificial neural networks (ANNs) towards increasingly deep neural network architectures with improved learning capabilities.In figure(2.2) we will try to explain more about the differences between DL and ML[7]

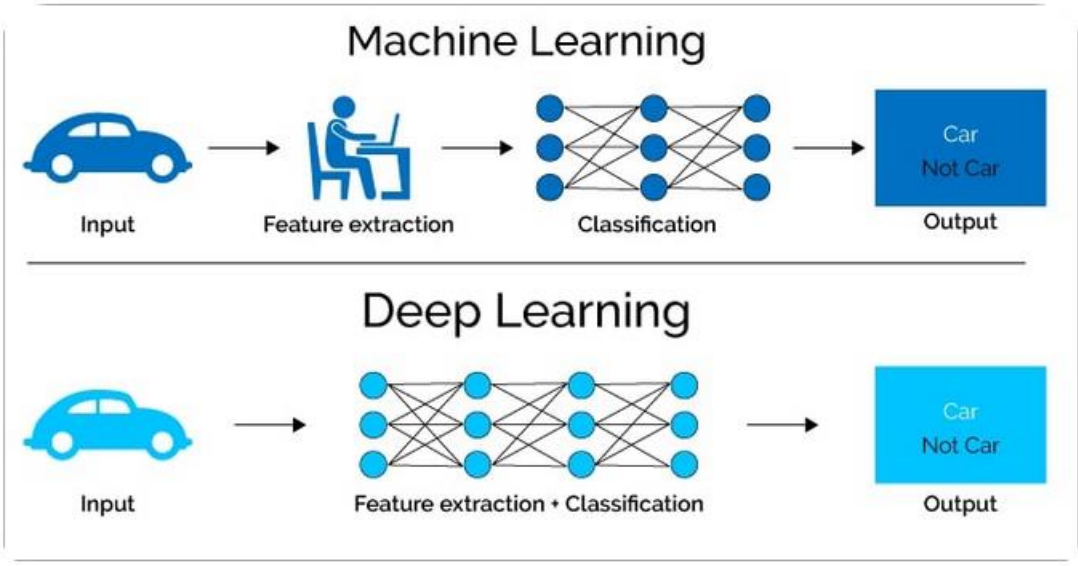

Figure 2.4: Deference between machine learning and deep learning

1.8. Convolutional neural networks

Convolutional Neural Network (CNN), also called ConvNet, is a type of Artificial Neural Network(ANN).The convolutional neural network (CNN) employs convolution instead of generalmatrix multiplication in at least one of its layers.CNN provide automatic features extraction and includes a list of layers that transform input volume to output volume. It performs a series of convolution and pooling operations followed by a number of fully connected layers, and those was the main layers that used in features extraction. [9]

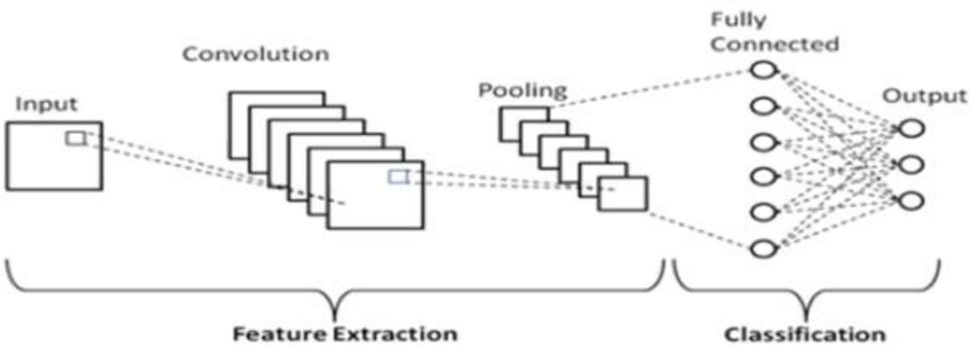

Figure 2.5: Architecture of Convolutional Neural Network

2.4.1. Convolution layer

The main building block of CNN is the convolution layer. Convolution is a mathematical operation to merge two sets of information. Convolution layer performsfeature extraction by sliding the filter over the input image. The output or the convolved feature is the element wise product of filters in the image and their sum for every sliding action.The figure 2.6 shows the convolution operation[9,10].

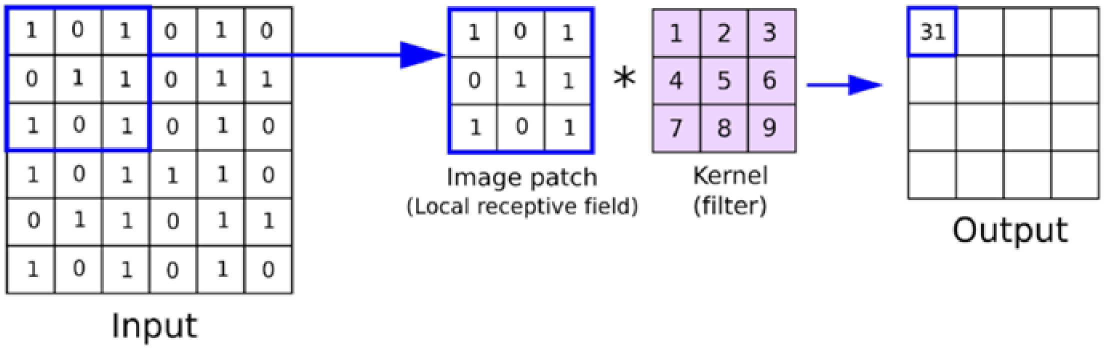

Figure 2.6. : A visual representation of a convolutional layer

2.4.2. Pooling layer

After a convolution operation we usually perform pooling to reduce the dimensionality. This gives us the ability to reduce the number of parameters, which both shortens the training time and combats over fitting. Pooling layers is done independently on each depth dimension, reducing the height and width, keeping the depth intact.

There are two types of pooling layers: max pooling and average pooling. The figure(2.7) shows an example of max pooling which just takes the max value in the pooling window[1,4,5,6].

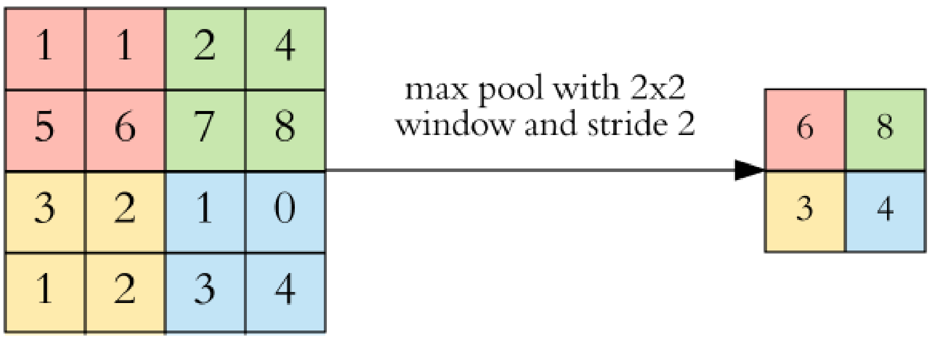

Figure 2.7. : Example of max pooling

2.4.3. Fully connected layer

After the convolution and pooling layers, we add a couple of fully connected layers to wrap up the CNN architecture. The output from the pooling layer is flattened into a one-dimensional vector and then given as input to the fully connected layer.Fully connected layers are where classification actually happens.[9,10]

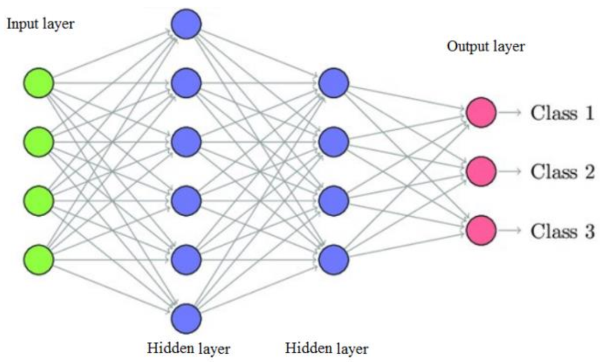

Figure 2.8: Fullyconnectednetwork

2.4.4. Activation functions

There are several activation functions such as:Linear, Sigmoid, Tanh, ReLU,Swish ,SoftMax. The commonly used activation functions are [11]:

Rectification Linear Unit (ReLU :ReLU stands for rectified linear unit and is a non-linear activation function that is widely used in neural networks and almost the most popular activation function used in deep neural networks.The definition of ReLU is as follows:

$$g(x) = \max(0, x) = \begin{cases} x & if \;\; x \geq 0 \\ 0 & if \;\; x < 0 \end{cases} \tag{2.1}$$

The derivatives of ReLU can be defined as:

$$g'(x) = \begin{cases} 1 & if \;\; x \geq 0 \\ 0 & if \;\; x < 0 \end{cases} \tag{2.2}$$

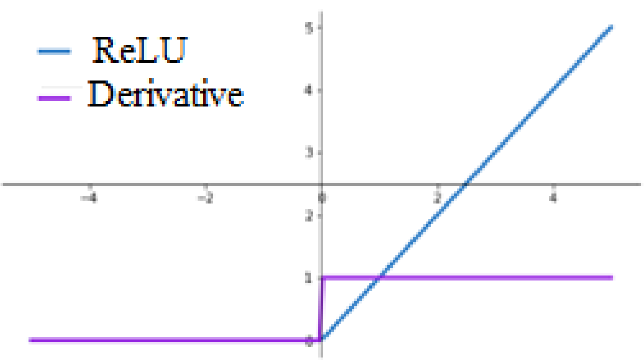

Figure 2.9: ReLUcurve and its derivative

Sigmoid function: Sigmoid function is one of the most common forms of activation functions, and it's a nonlinear function. Sigmoid function transforms the values in the range 0 to 1. It can be defined as:

$$f(x) = \frac{1}{1+ e^{-x}} \tag{2.3}$$

Sigmoid function is a continuous function, which means that it is differentiable everywhere. The derivatives of sigmoid function can be defined as:

$$f'(x) = \frac{e^{-x}}{(1+ e^{-x})^2} \tag{2.4}$$

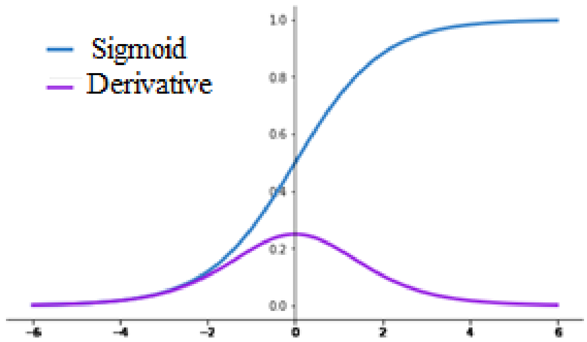

Figure 2.10: Sigmoid functioncurve and its derivative

The ability of differentiability that the sigmoid has helps a lot in modeling and training process of a multilayer neural network, because it can be divided into two parts: forward propagation and back propagation and the derivatives of activation function should be calculated in each layer and in both ways.

Softmaxfunction:Softmax function is a combination of multiple sigmoid functions, which can be used for multiclass classification problems, it can be expressed as:

$$(2.5) f(x_j) = \frac{e^{x_j}}{\sum_{k=1}^{k} e^{x_k}} \; for \; j = 1, \ldots \ldots, k.$$

The output layer of model for multiple class classification will have the same number of neurons as the number of classes in the target.[1,2,8]

1.9. Transfer Learning

Transfer learning is the improvement of learning in a new task through the transfer of knowledge from a related task that has already been learned.Transfer learning solves significantly the detection task using a single CNN model with different image fields. Transfer learning in CNN is done using Knowledge gained by training models in a certain domain and using it in another field. It reduces the amount of computation in training and generalizes CNN models in different domains. Furthermore, transfer learning is beneficial when there is not enough data to learn from scratch,see figure 2.11[10].

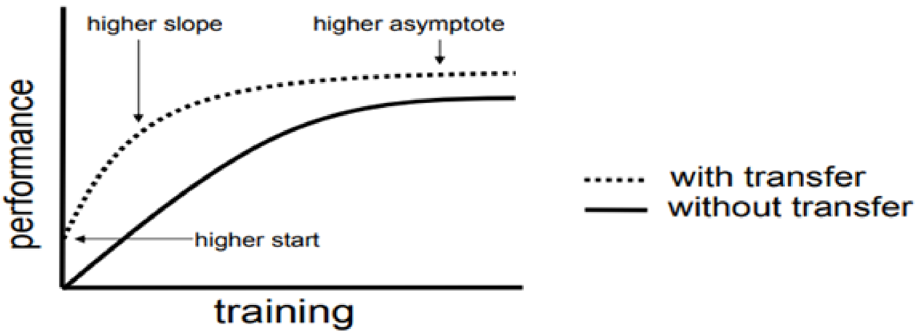

Figure 2.11: Three ways in which transfer might improve learning

1.10. Pre-trained neural networks

Convolution neural networks have several types for its architecture includes:**LeNet, AlexNet, ZFNet and overfeat, GOOGLENet, VGGNet, ResNet, DenseNet..**.

2.6.1. AlexNet neural networks

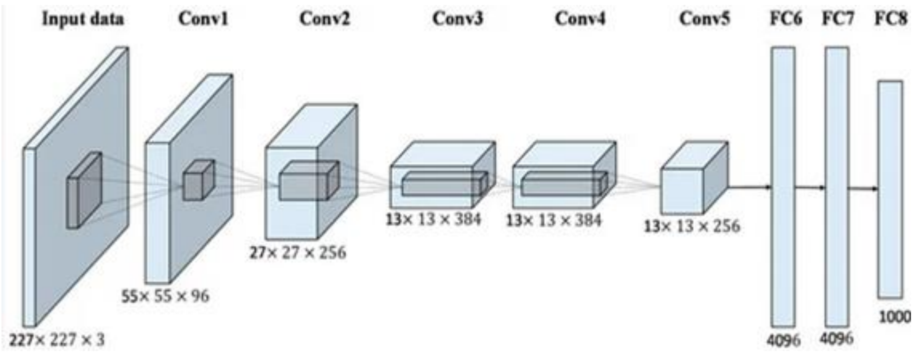

Figure2.12 : AlexNet Architecture

2.6.2. ResNet50

ResNet was developed by Kaiming He from Microsoft and introduced the idea of‘identity skip connection’ to solve vanishing gradient problem by proposing the Resnet model. It was the winner of ILSVRC 2015 challenge with a big leap in performance; it reduces the top-5 error rate to 3.6% that even skip human level performance on same dataset. All of that sets new standers in performance for classification, detection, localization tasks. Although the ResNet (with 152 Layer) is 8 times deeper than VGGNets (22 layers), it has complexity lower than VGGNets (16/19).ResNet has several versions with different depth, the most popular one is ResNet50 that has total of 50 layers 49 CNN and one fully connected layer [10].

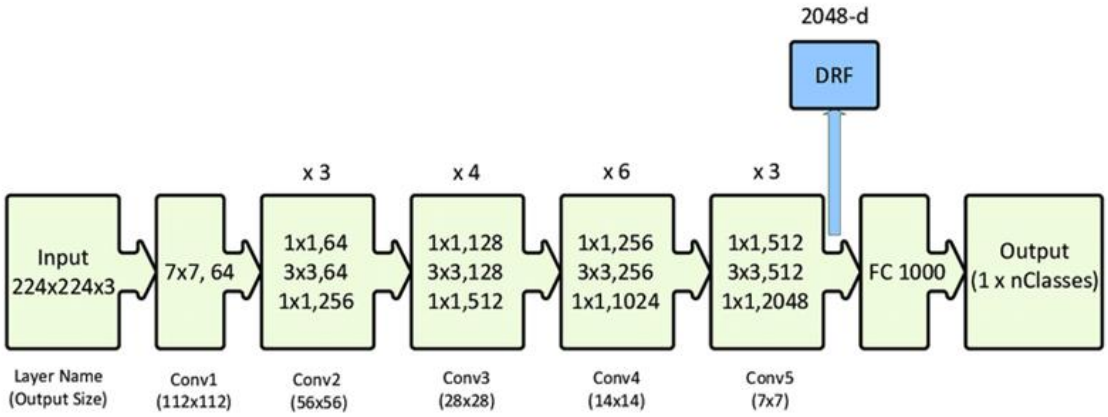

Figure 2.13: ResNet 50 Architecture

2.6.3. DenseNet201

DenseNet was introduced by Huang et al in 2016 and it becomes the winner of ILSVRC-2016. It came with the idea of residual mapping by propagating the output of each block to all subsequent blocks inside each dense block in the network and By propagating the information in both forward and backward directions during the training of the model it strengthens feature propagation ability and solve the vanishing gradient problem [10].

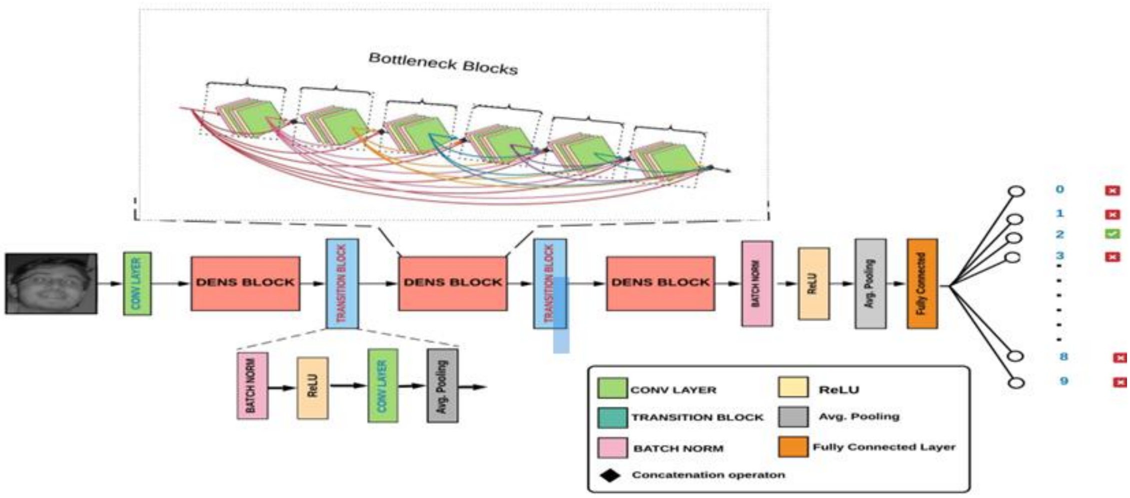

Figure 2.14: DenseNet Architecture

1.11. Conclusion

In this chapter we get into the most common and used branches in the field of artificial intelligence, the "machine learning" and the "deep learning". We explained the difference between the two as a beginning than we get deeper into the "deep learning" which is the main element in this chapter, we explained how does it work and its mechanisms and the most popular deep neural networks (its layers, functions including activation functions...) used in machine training and we showed the fields and applications that every neural network can we use it in. we have also investigate AlexNet, ResNet50 and DenseNet201 used in chapter three.

Chapter 3

Classification and image enhancement:

Test and results

3.1. Introduction

In this chapter, we will test the proposed classification method on COVID-19 chest x-ray images.We will show throw many computer simulations the, All simulations are made by MATLAB 2020 using a computer whose technical characteristics are as follows: Processor: intel(R) Core i5-3320M CPU 2,60 GHz RAM 4GB

3.2. COVID-19 Database

The Dataset of chest X-ray images used in this chapter for classifying negative and positive COVID-19 cases is available at(https://github.com/muhammedtalo/COVID-19). It contains 125 chest x-ray images of COVID-19 case and 500 chest x-ray images of Non-COVID-19 [12]. The data distribution between classes is 50% of images were used for training and 50% for testing and the follow figures show some samples that have been used in our simulation.

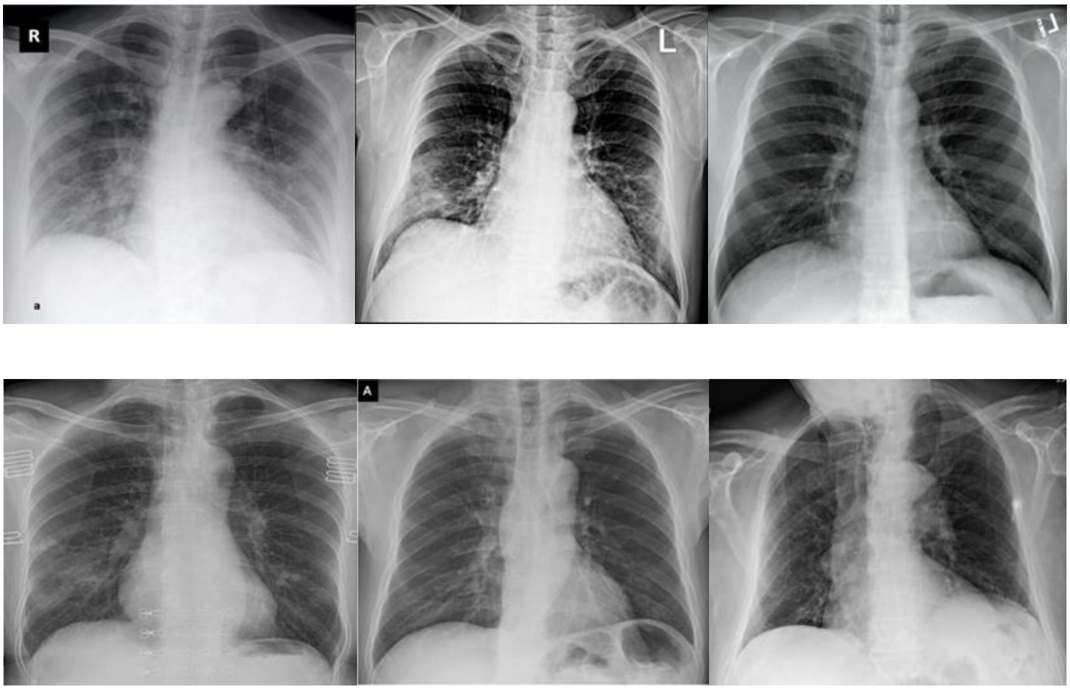

Figure 3.1:*Samples of chest X-ray images that used in the dataset as COVID-19 case*

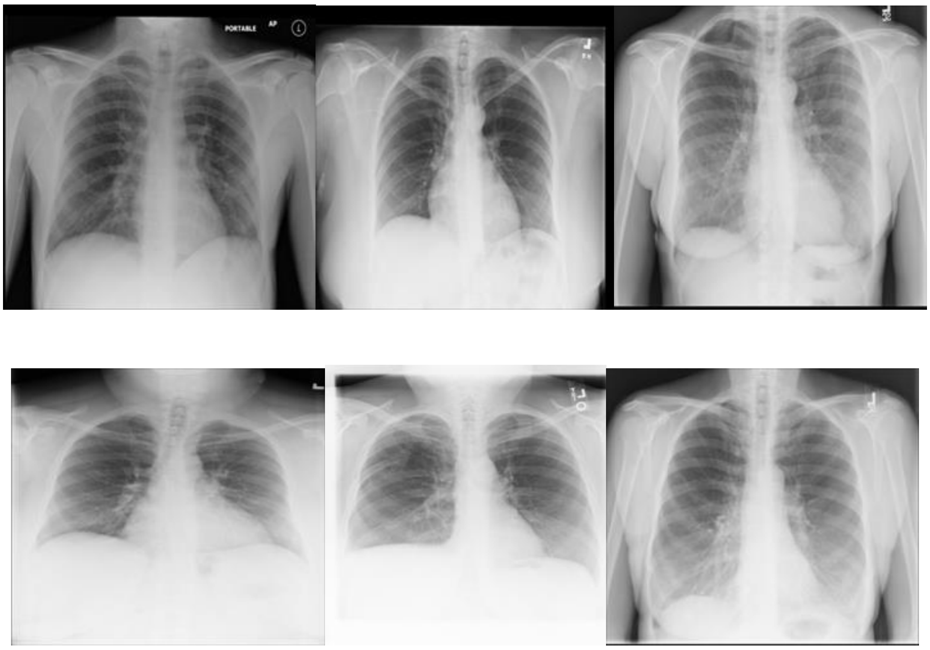

Figure 3.2:*Samples of chest x-ray images that used in dataset as Non Covid-19*

3.3. Methodology

The first aim part of this study is the training and testing of the AlexNet model with original data CXR images, then training and testing the same CNN model with the three common enhancement methods (Histogram Equalization, Contrast limited adaptive histogram equalization and Gamma correction).After, the major experiments that are carried out in the study is the combination of the enhancement methods each time which are will improve or decrease the four performance metrics rates (especially the accuracy).

In figure 3.3, we see the obtained image after enhancement. We clearly notice the improvement of the accuracy on the picture on each method with varying proportion, When see the original image, we notice the presence of a light cloud that is almost invisible, and as we know that the quality of the image indirectly determines the way of enhancement it needed. As for CLAH enhancement, we clearly see the presence of a cloudy layer on part of the right lung like we see that also with HE+CLAHE and CLAHE+Gamma and HE+CLAHE+Gamma. The detailed methodology adopted in the study shown in the following figure 3.4.

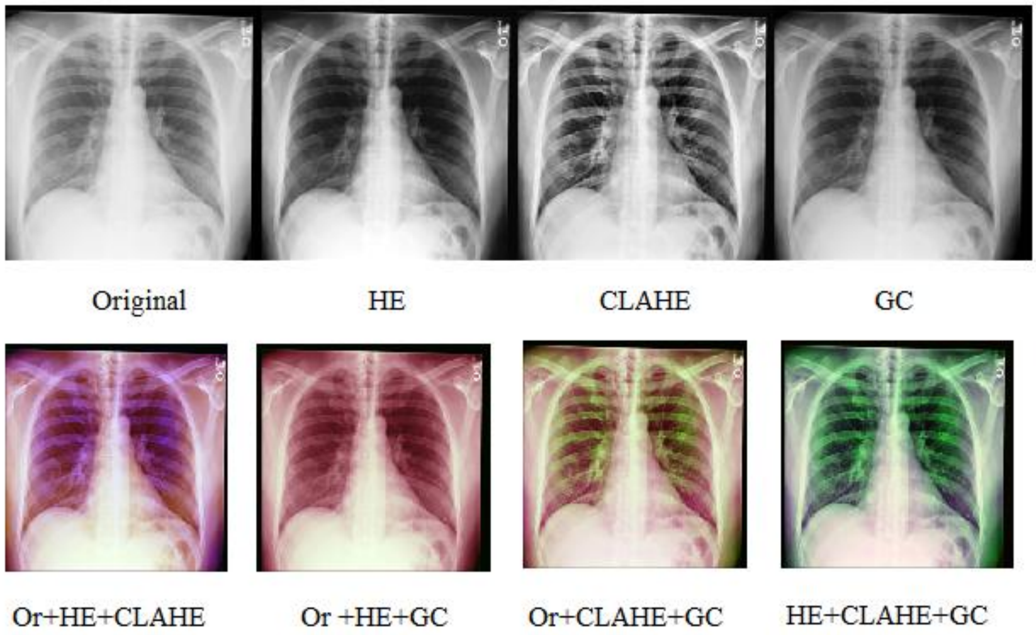

Figure 3.3: *Enhancement techniques differences on the CXR image*

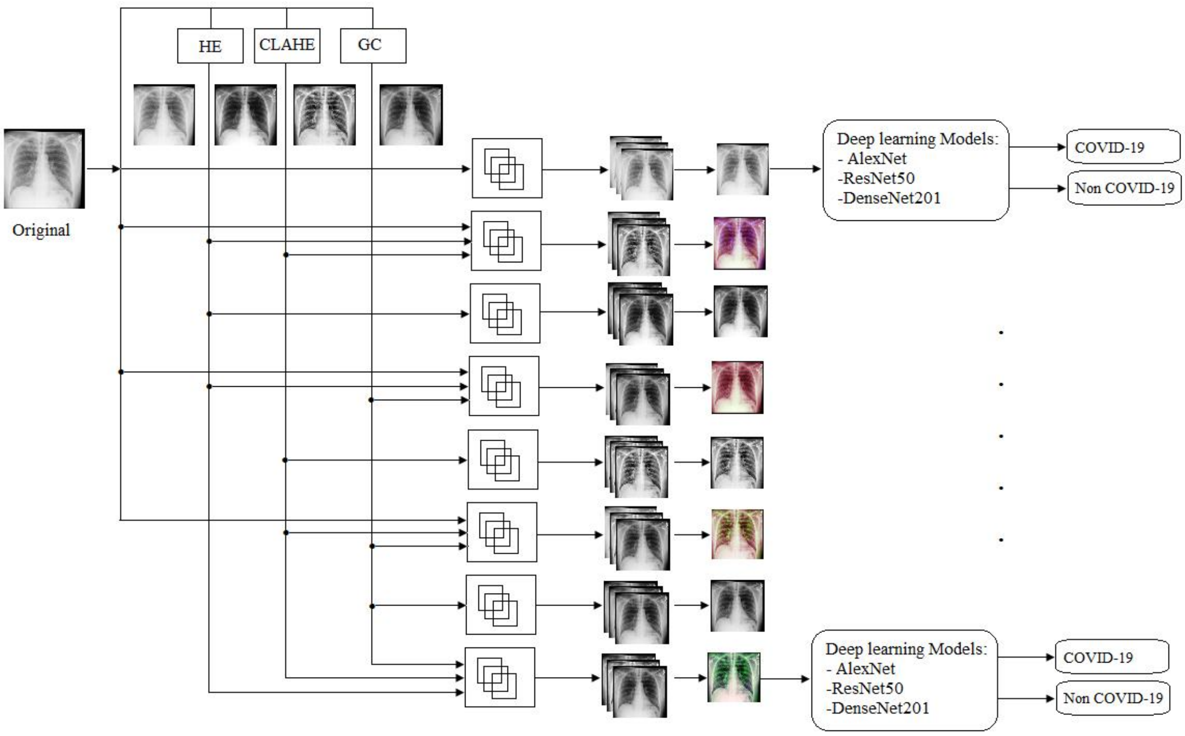

Figure 3.4:*Block diagram of the system methodology*

3.4. Chest X-ray Pre-trained Convolutional Neural Network (CNN)

The first part of this studying will contains the classification of people who considered as positive COVID-19 case (infected) using AlexNetwhich have the following proprieties shown in table 3.1.

Model	Depth	Size	Parameters(Millions)	Image Input Size
AlexNet	8	227 MB	61	227×227

Table 3.1:*Pre-trained AlexNet Proprieties*

3.4.1. Performance metrics

The reason of choosing onlythe pre-trained CNN AlexNetinstead of other CNN architectures is due to the unsatisfactoryAlexNet's performance metrics (accuracy, sensitivity, specificity, f1 score) results to our dataset we had before start application, which is may need more enhancement.These performance metrics are expressed as [1,2]:

$$Accuracy = \frac{(TP+TN)}{(TP+FN)+(FP+TN)} \times 100 \qquad (3.1)$$

$$Sensivity = \frac{(TP)}{(TP+FN)} \times 100 \qquad (3.2)$$

$$Specifity = \frac{(TN)}{(FP+TN)} \times 100 \qquad (3.3)$$

$$f1\ score = \frac{(2\times TP)}{(2\times TP+FN+FP)} \times 100 \qquad (3.4)$$

TP, TN, FN, TN are the consequences of crossing the predicted rows and the actual columns in the confusion matrix

3.4.2. Confusion matrix

It is one of the fundamental concepts in deep learning [10]. Combined with cross validation, it's how we decide which method would be best for our dataset

	Actual positive	Actual Negative
Predicted positive	True Positives	False Positives
Predicted Negative	False Negative	True Negatives

Table 3.2:*Confusion Matrix*

The rows in the confusion matrix correspond to what the algorithm predicted,and the columns correspond to the known truth , since that we have only two categories to choose; COVID-19 or Non COVID-19 , then the left top corner contains the true positives. These are the people that are infected by COVID-19 and were correctly identified by the algorithm. The True Negatives are in the bottom right corner, these are people that didn't infected by COVID-19 and were correctly identified by the algorithm, the bottom left corner contains False Negatives which concern people infected by COVID-19 but the algorithm say they didn't. Lastly the top right corner contains false positives which are people they didn't infected by Covid-19 but the algorithm says they do.

3.5. Performance evaluation without enhancement (original)

In this part we will see and discuss the results of training and testing the AlexNetusing images without any enhancement methods.

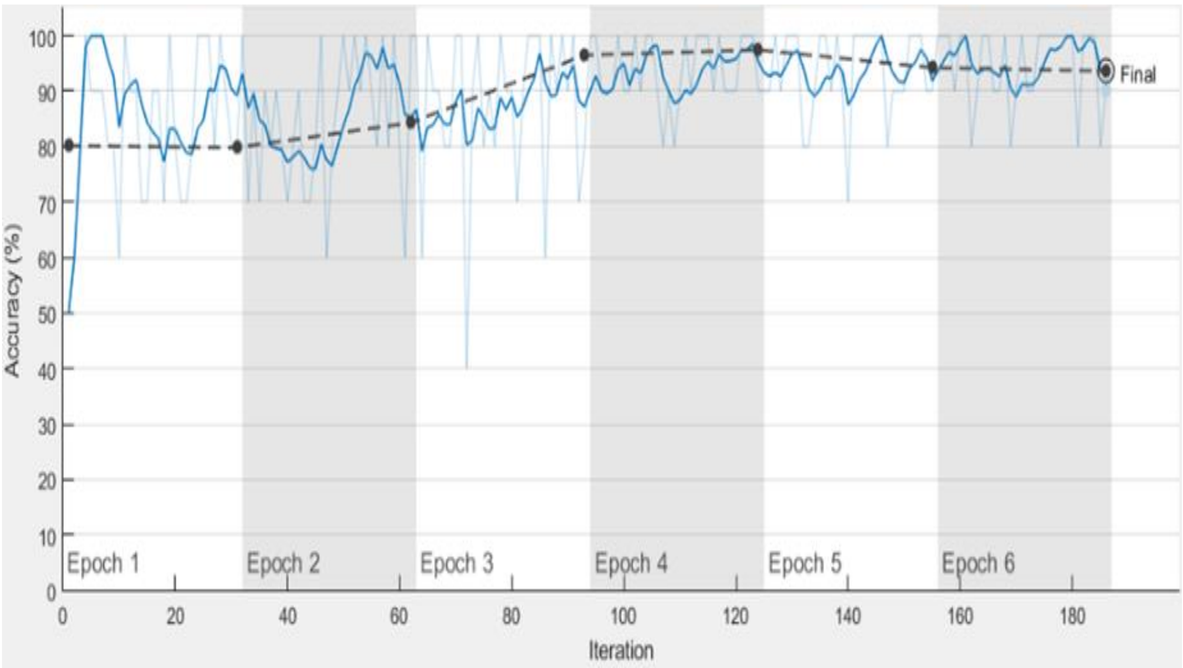

Figure3.5:*Training process of AlexNet*

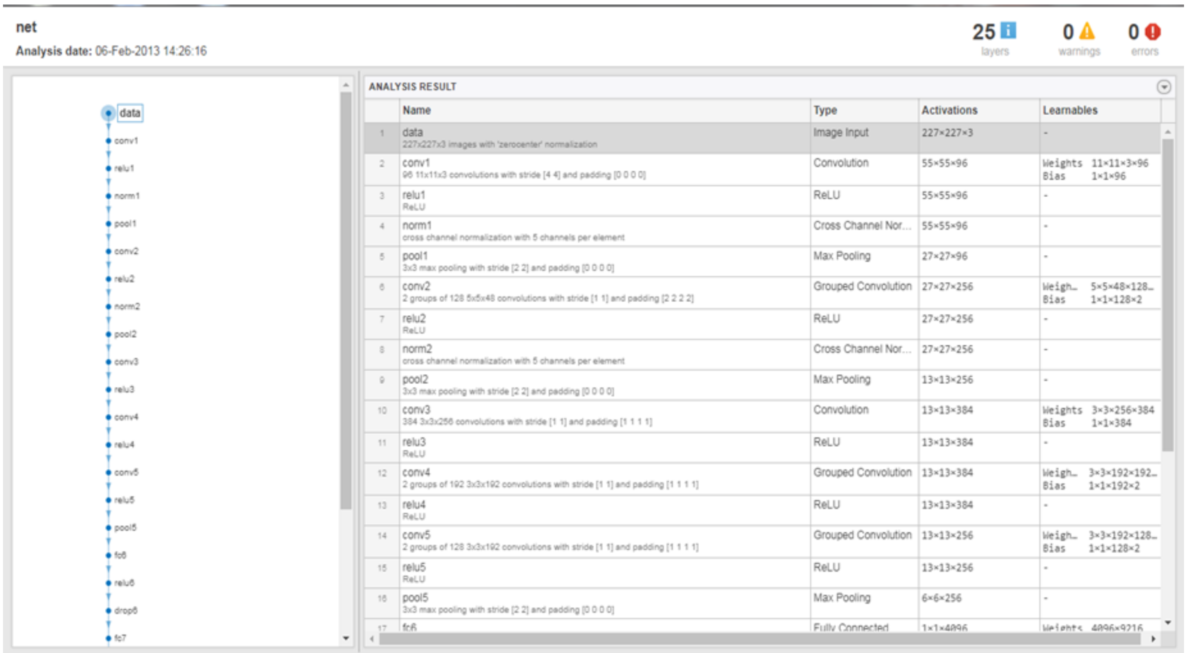

Figure 3.6: AlexNet Layers

In this process we noticed that the validation accuracy was reached 93.59% taking 10min and 31sec, and it contains 25layers.To evaluate these results; we should analysis the confusion matrix:

Table 3.3: *Learning Confusion matrix*

	Covid-19	Non covid-19
Covid-19	63 (100%)	0 (0%)
Non covid-19	6 (2.4%)	244 (97.6%)

We notice in the learning confusion matrix obtained that the true positive covid-19 section classified with rate 100%, was higher than the True Negative Non covid-19 section classified with rate 97.6%. All this classification made with accuracy rate 98.08%

Table 3.4:*Testing confusing matrix*

	Covid-19	Non covid-19
Covid-19	57 (90.47%)	5 (7.93%)
Non covid-19	15 (6%)	235 (94%)

We notice in the testing confusion matrix obtained that the true positive covid-19 section classified with rate 90.4% was less than the True Negative Non covid-19 section classified with rate 94%. All this classification made with accuracy rate 93.59%.

3.6. Performance evaluation with image enhancement methods

In this part we will train and test our data with Alexnet and different image enhancement methods and discuss the results.

3.6.1.Performance evaluation with Histogram equalization

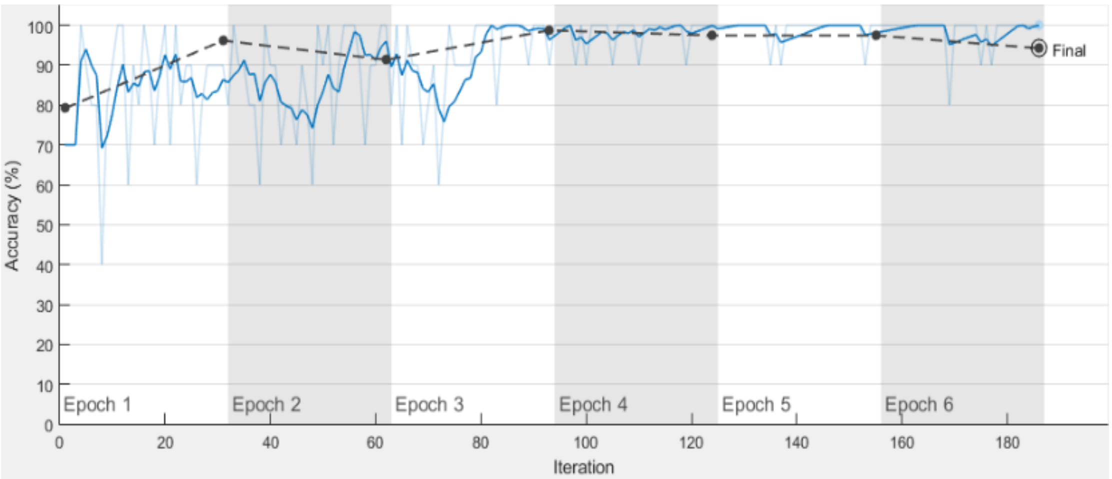

Figure 3.7:*Training of AlexNet with HE*

In this process we noticed that the validation accuracy was reached 94.23% with taking time estimated by 10min and 44sec.

Table 3.5:*lLarning confusion matrix with HE*

	Covid-19	Non covid-19
Covid-19	63 (100%)	0 (0%)
Non covid-19	9 (3.6%)	241 (96.4%)

We notice in the learning confusion matrix with HE obtained that the true positive covid-19 section classified with rate 100%, was higher than the True Negative Non covid-19 section classified with rate 96.4%. All this classification made with accuracy rate 97.12%

Table 3.6:*Testing confusing matrix with HE*

	Covid-19	Non covid-19
Covid-19	60 (95.23%)	2 (3.17%)
Non covid-19	16 (6.4%)	234 (93.6%)

We notice in the testing confusion matrix with HE obtained that the true positive covid-19 section classified with rate 95.23% was higher than the True Negative Non covid-19 section classified with rate 93.6%. All this classification made with accuracy rate 94.23%

Note1: we can notice clearly the slight improvement about the accuracy performance in the enhancement with the HE method.

3.6.2.Performance evaluation with Contrast limited adaptive histogram equalization (CLAHE)

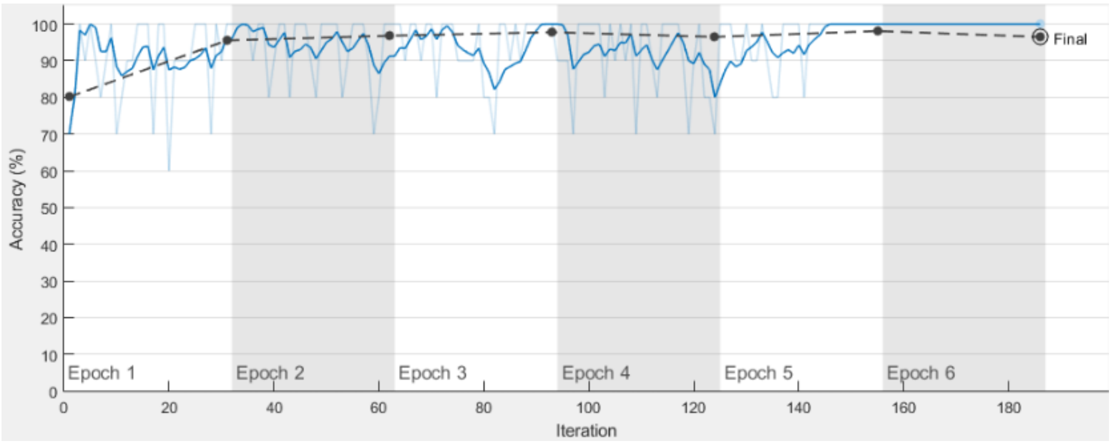

Figure 3.8:*Training of AlexNet with CLAHE*

In this process we noticed that the validation accuracy was reached 96.47% with taking time estimated by 13min and 5sec.

Table 3.7: *Learning confusion matrix with CLAHE*

	Covid-19	Non covid-19
Covid-19	62 (98.41%)	1 (1.58%)
Non covid-19	0 (0%)	250 (100%)

We notice in the learning confusion matrix with CLAHE obtained that the true positive covid-19 section classified with rate 98.41%, was less than the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 99.68%

Table 3.8:*Testing confusing matrix with CLAHE*

	Covid-19	Non covid-19
Covid-19	5180.95%)	11 (17.46%)
Non covid-19	0 (0%)	250 (100%)

We notice in the testing confusion matrix with CLAHE obtained that the true positive covid-19 section classified with rate 80.95% was less than the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 96.47%

Note2: we can clearly notice the improvement of accuracy performance with the enhancement CLAHE method than the HE method improvement

3.6.3.Performance evaluation with gamma correction

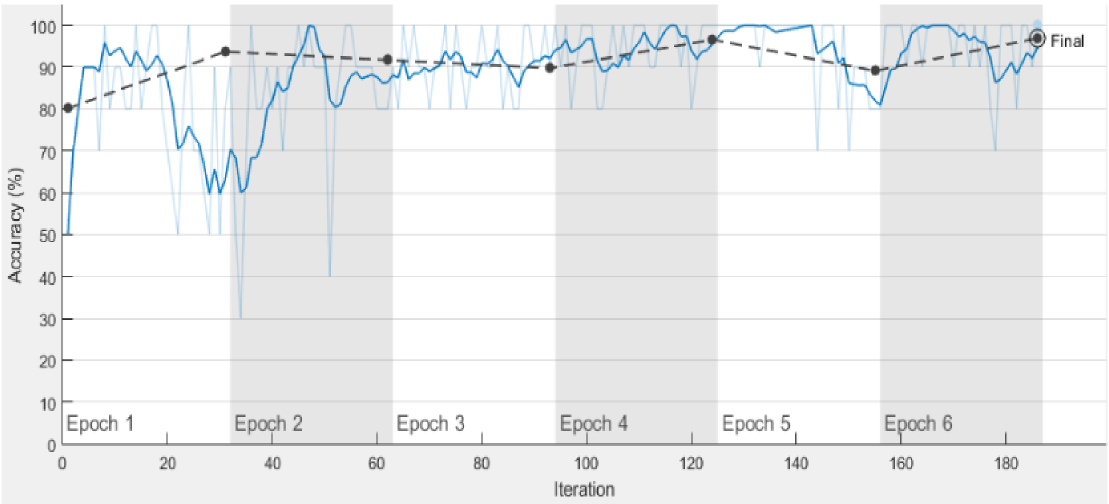

Figure 3.9:*Training of AlexNet with gamma correction*

In this process we noticed that the validation accuracy was reached 96.79% with taking time estimated by 10min and 39sec.

Table 3.9:*Learning confusion matrix with gamma*

	Covid-19	Non covid-19
Covid-19	63 (100%)	0 (0%)
Non covid-19	9 (3.6%)	241 (96.4%)

We notice in the learning confusion matrix with gamma correction obtained that the true positive covid-19 section classified with rate 100%, was higher than the True Negative Non covid-19 section classified with rate 96.4%. All this classification made with accuracy rate 97.12%.

Table 3.10:*Testing confusing matrix with gamma*

	Covid-19	Non covid-19
Covid-19	58 (92.06%)	4 (6.3%)
Non covid-19	6 (2.4%)	244 (97.6%)

We notice in the testing confusion matrix with gamma correction obtained that the true positive covid-19 section classified with rate 92.06% was less than the True Negative Non_covid-19 section classified with rate 97.6%. All this classification made with accuracy rate 96.79%.

Note3: we can notice the accuracy performance improvement with the enhancement gamma correction method than the CLAHE and HE methods improvement, Also it took less time to simulate.

3.7. Performance evaluation with image enhancement methods combination

In this part we will also train and test with AlexNet but with combination of two or three image enhancement methods and compare the results.

3.7.1. HE and CLAHE Combination

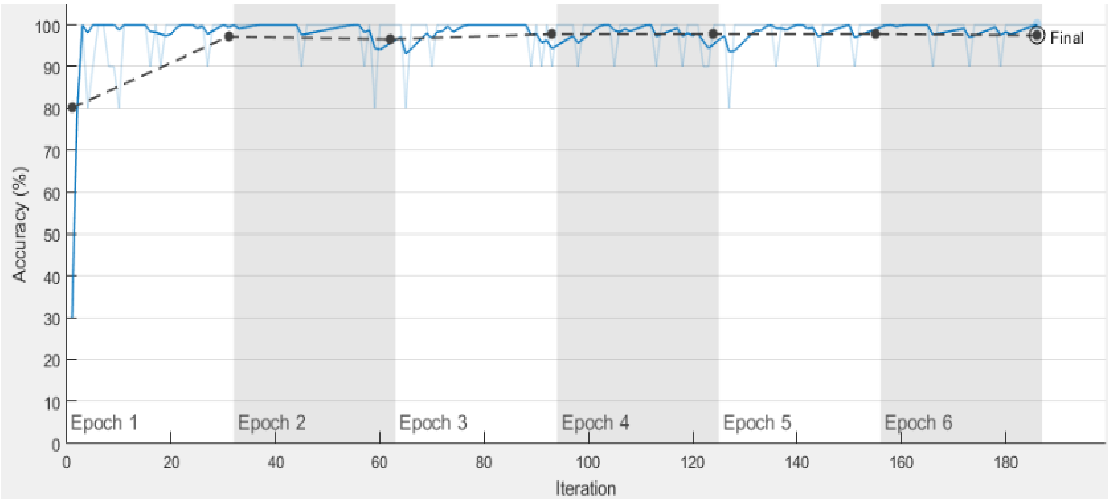

Figure 3.10:*Training process with Alexnet and HE, CLAHE*

In this process we noticed that the validation accuracy was reached 97.44% with taking time estimated by 12min and 58sec.

Table 3.11:*Learning confusing matrix with HE+CLAHE*

	Covid-19	Non covid-19
Covid-19	62 (98.41%)	1 (1.58%)
Non covid-19	0 (0%)	250 (100%)

We notice in the learning confusion matrix withHE and CLAHEcombination obtained that the true positive covid-19 section classified with rate 98.41%, was less than the True

Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 99.68%

Table 3.12: *Testing confusing matrix with HE+CLAHE*

	Covid-19	Non covid-19
Covid-19	54 (85.71%)	8 (12.69%)
Non covid-19	0 (0%)	250 (100%)

We notice in the testing confusion matrix with HE and CLAHE combination obtained that the true positive covid-19 section classified with rate 885.71% was less than the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 97.43%.

Note4: we can notice the improvement of the accuracy performance with the enhancement methods HE and CLAHE combination than all the previous alone methods.

3.7.2.CLAHE and GAMMA correction combination

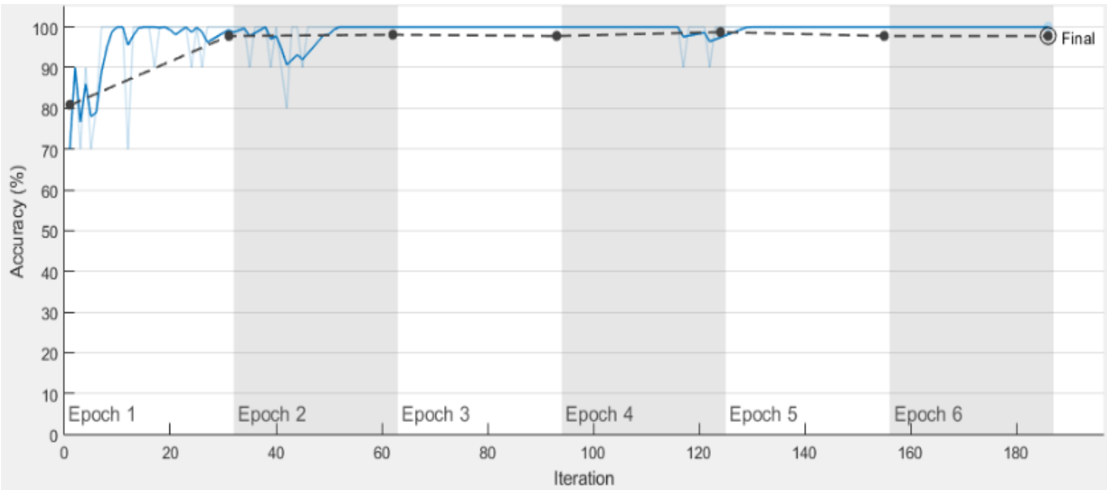

Figure 3.11: *Training process with Alexnet and CLAHE,Gamma correction*

In this process we noticed that the validation accuracy was reached 97.76% with taking time estimated by 10min and 51sec.

Table 3.13: *Learning confusing matrix with CLAHE+Gamma*

	Covid-19	Non covid-19
Covid-19	63 (100%)	0 (0%)
Non covid-19	0 (0%)	250 (100%)

We notice in the learning confusion matrix with CLAHE and Gammacombination obtained that the true positive covid-19 section classified with rate 100%, was equal to the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 100%.

Table 3.14:*Testing confusing matrix with CLAHE+Gamma*

	Covid-19	Non covid-19
Covid-19	55 (87.30%)	7 (11.11%)
Non covid-19	0 (0%)	250 (100%)

We notice in the testing confusion matrix with CLAHE and Gammacombination obtained that the true positive covid-19 section classified with rate 87.30%, was less than the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 97.75%.

Note5: we can notice the improvement of the accuracy performance with the enhancement methods CLAHE and Gamma than the last HE and CLAHE combination and all the previous methods.Also it took less time to simulate.

3.7.3.HE and GAMMA correction Combination

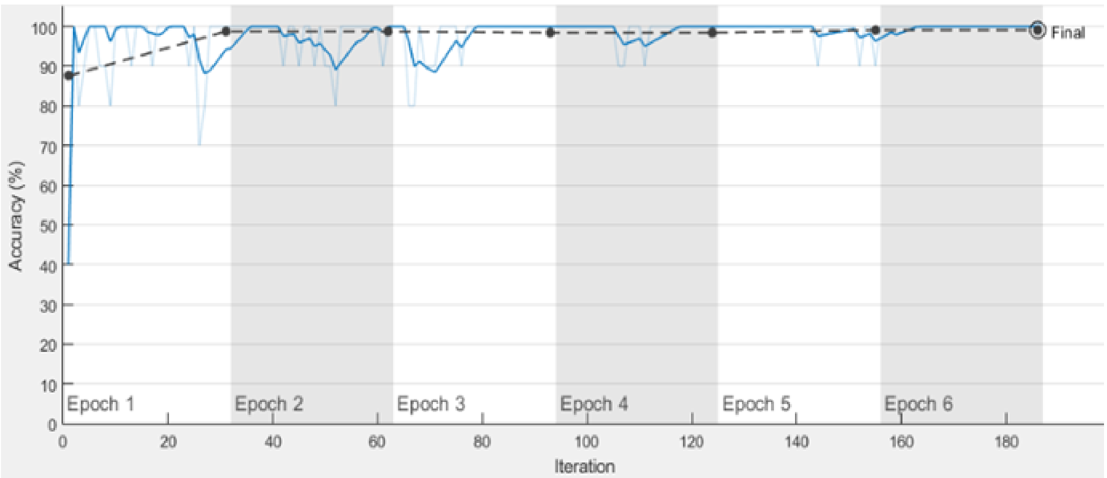

Figure 3.12:*Training process with Alexnet and HE,Gamma correction*

In this process we noticed that the validation accuracy was reached 99.04% with taking time estimated by 12min and 42sec.

Table 3.15:*Learning confusing matrix with HE+Gamma*

	Covid-19	Non covid-19
Covid-19	63 (100%)	0 (0%)
Non covid-19	0 (0%)	250 (100%)

We notice in the learning confusion matrix with HE and Gammacombination obtained that the true positive covid-19 section classified with rate 100%, was equal to the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 100%.

Table 3.16:*Testing confusing matrix with HE+Gamma*

	Covid-19	Non covid-19
Covid-19	59 (93.65%)	3 (4.76%)
Non covid-19	0 (0%)	250 (100%)

We notice in the testing confusion matrix with HE and Gammacombination obtained that the true positive covid-19 section classified with rate 93.65%, was less than the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 99.038%.

Note 6:we can notice the accuracy performance improvement with the enhancement combined methods HE and Gamma than the last all last combinations, but it took more time to simulate.

3.7.4.HE and CLAHE and GAMMA correction combination

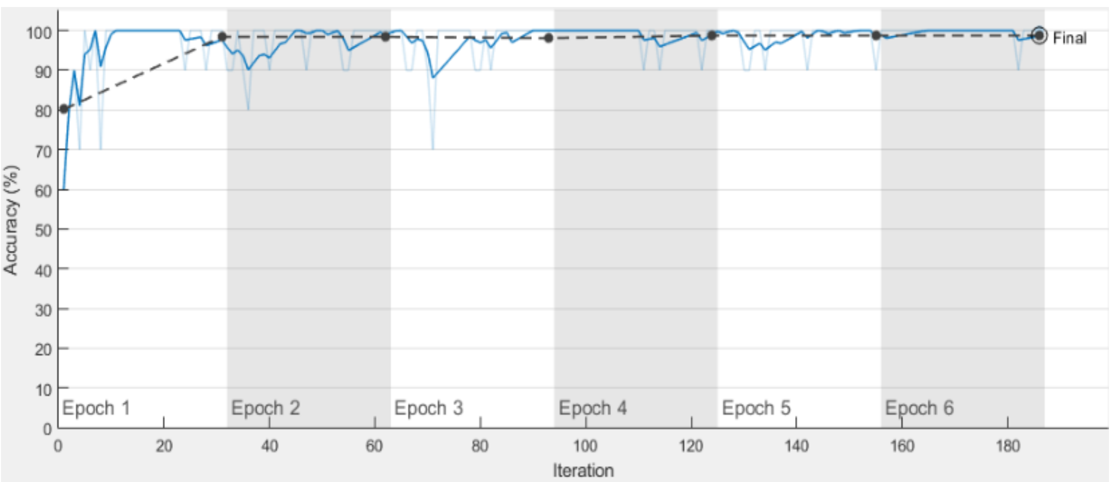

Figure 3.13:*Training process with Alexnet and HE,CLAHE,Gamma correction*

In this process we noticed that the validation accuracy was reached 98.72% with taking time estimated by 13min and 07sec.

Table 3.17:*Learning confusing matrix with HE+CLAHE+Gamma*

	Covid-19	Non covid-19
Covid-19	63 (100%)	0 (0%)
Non covid-19	0 (0%)	250 (100%)

We notice in the learning confusion matrix with HE and CLAHE, Gammacombination obtained that the true positive covid-19 section classified with rate 100%, was equal to the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 100%.

Table 3.18:*Testing confusing matrix with HE+CLAHE+Gamma*

	Covid-19	Non covid-19
Covid-19	58 (92.06%)	4 (6.34%)
Non covid-19	0 (0%)	250 (100%)

We notice in the testing confusion matrix with HE and CLAHE,Gammacombination obtained that the true positive covid-19 section classified with rate 92.06%, was less than the True Negative Non covid-19 section classified with rate 100%. All this classification made with accuracy rate 98.71%.

Note 7: we notice that there is no performance accuracy improvement, we see accuracy rate decreasethan the last combination and took more time to simulate.

Table 3.19: C*lassification comparison of enhancement methods with AlexNet training*

Methode	Evaluation Metrics (%)			
	Acc	Sen	Spe	F1
AlexNet	93.58	94.00	91.93	95.92
HE	94.23	93.60	96.77	96.30
CLAHE	96.47	100	82.25	97.85
Gamma	96.79	97.60	93.54	97.99
HE+CLAHE	97.43	100	87.09	98.43
CLAHE+Gamma	97.75	100	88.70	98.62
HE+Gamma	99.03	100	95.16	99.40
HE+CLAHE+Gamma	98.71	100	93.54	99.21

In summary, the best enhancement method was the Histogram Equalization and Gamma correction combination with the higher accuracy, but that is not enough, let's compare all the rest performance metrics (accuracy, sensitivity, specificity, f1score) of all methods.

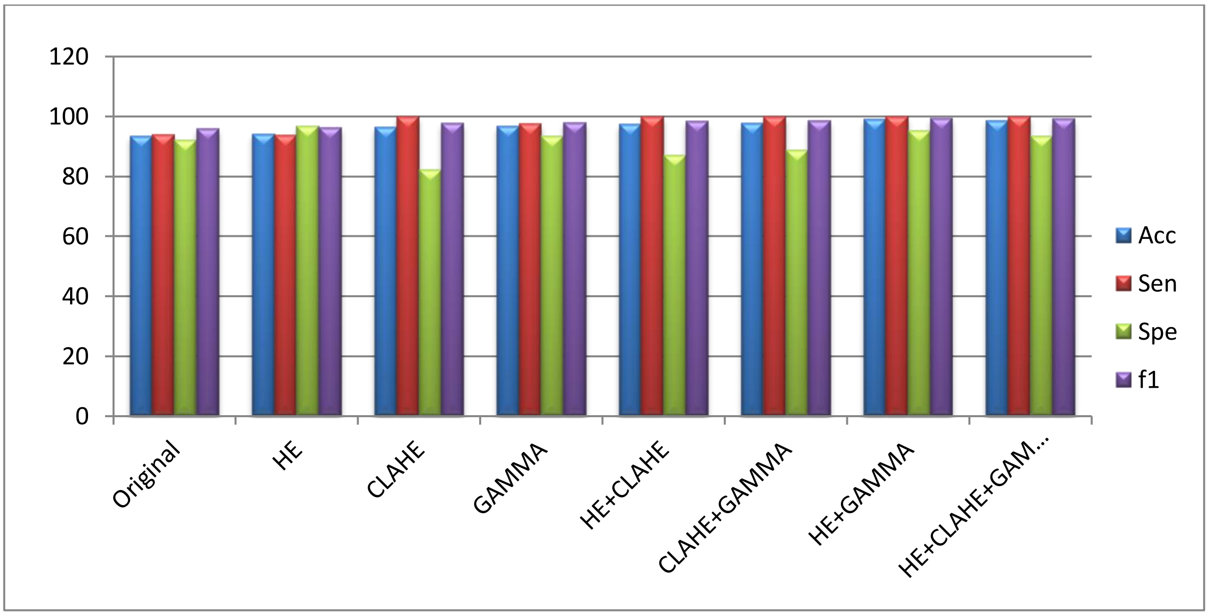

Figure 3.14:*Chart obtain percentage of each enhancement method performance metrics*

According to the methods comparison table and chart, we conclude that the best method is Histogram Equalization and Gamma correction by giving the best performance metrics.But before we conclude, we need to compare the time took by each method

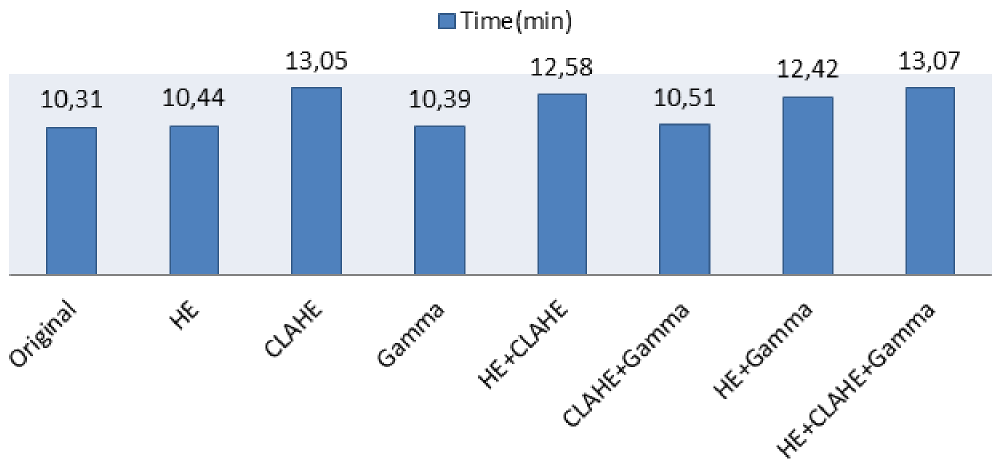

Figure 3.15: *Chart shows the time taken by each method*

We see that longest enhancement method during is the last one HE+CLAHE+Gamma method and the shortest method during isGamma correction method.

3.8. Extra results

In this additional part we want to explore more information and results by training our dataset with two more CNNs resnet50 and densenet201 with the precedent image enhancement methods, but first we should mention that these two CNNs contain more layers then AlexNet, which has important role in training process cause taking a lot of processing time but also more accuracy validation rate. The results were as follow:

Table 3.20:*Classification comparison of enhancement methods with resnet50 training*

Method	Evaluation Metrics (%)			
	Acc	Sen	Spe	F1
Resnet50	97.43	99.60	88.70	98.42
HE	99.35	99.60	98.38	99.60
CLAHE	99.67	99.60	100	99.80
Gamma	96.79	100	83.87	98.04
HE+CLAHE	99.03	100	95.16	99.40
CLAHE+Gamma	98.07	100	90.32	98.81
HE+Gamma	98.71	100	93.54	99.21
HE+CLAHE+Gamma	97.75	100	88.70	98.62

Table 3.21:*Classification comparison of enhancement methods with Densenet201 training*

Method	Evaluation Metrics (%)			
	Acc	Sen	Spe	F1
Densenet201	98.39	99.20	95.16	99.00
HE	98.39	100	91.93	99.01
CLAHE	98.71	100	93.54	99.21
Gamma	99.35	99.60	98.38	99.60
HE+CLAHE	98.39	100	91.93	99.01
CLAHE+Gamma	100	100	100	100
HE+Gamma	100	100	100	100
HE+CLAHE+Gamma	99.03	100	95.16	99.40

We choosedCLAHE+Gamma correction as the best enhancement method instead of HE+Gamma correction due to the shortest processing time.

Note: we notice that each CNN's model has a specific enhancement method can respond with it by giving the best performance metrics rate.

As a summary we will compare and find the best enhancement method for each network for the Covid-19 classification using original and CLAHE and (HE+Gamma) and (CLAHE+Gamma), And compare the different CNNs models we used in this study, The results showing in the following tables3.22-23 and figure 3.16.

Table 3.22:*Comparison the best enhancement method for each network*

Enhancement method	**Model**	**PM**			
		Acc	Sen	Spe	F1
CLAHE	Resnet50	99.67	99.60	100	99.80
HE+Gamma	AlexNet	99.03	100	95.16	99.40
CLAHE+Gamma	**Densenet201**	**100**	**100**	**100**	**100**

Table 3.23:*Comparison of different enhancement method for each network*

Enhancement method	**Model**	**PM**			
		Acc	Sen	Spe	F1
Original	AlexNet	93.58	94.00	91.93	95.92
	Resnet50	97.43	99.60	88.70	98.42
	Densenet201	98.39	99.20	95.16	99.00
HE	AlexNet	94.23	93.60	96.77	96.30
	Resnet50	99.35	99.60	98.38	99.60
	Densenet201	98.39	100	91.93	99.01
CLAHE	AlexNet	96.47	100	82.25	97.85
	Resnet50	99.67	99.60	100	99.80
	Densenet201	98.71	100	93.54	99.21
Gamma	AlexNet	96.79	97.60	93.54	97.99
	Resnet50	96.79	100	83.87	98.04
	Densenet201	99.35	99.60	98.38	99.60
HE+CLAHE	AlexNet	97.43	100	87.09	98.43
	Resnet50	99.03	100	95.16	99.40
	Densenet201	98.39	100	91.93	99.01
CLAHE+Gamma	AlexNet	97.75	100	88.70	98.62
	Resnet50	98.07	100	90.32	98.81
	Densenet201	100	100	100	100
HE+Gamma	AlexNet	99.03	100	95.16	99.40
	Resnet50	98.71	100	93.54	99.21
	Densenet201	100	100	100	100
HE+CLAHE+ Gamma	AlexNet	98.71	100	93.54	99.21
	Resnet50	97.75	100	88.70	98.62
	Densenet201	99.03	100	95.16	99.40

In order to compare the processing time of precedent models we need to calculate the mean time of all enhancement methods, as we see in the following figure 3.17.

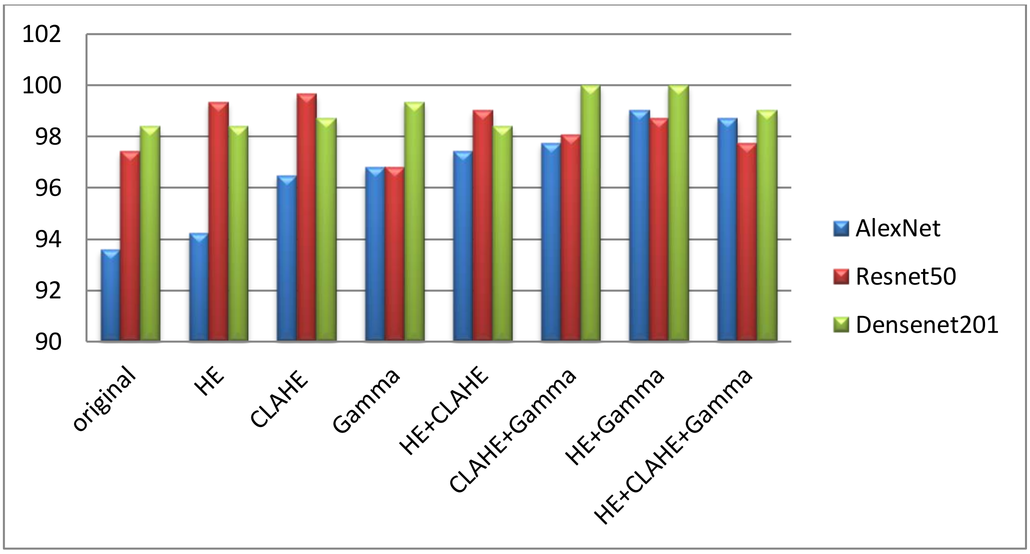

Figure 3.16:*Comparison of CNNs models accuracy with different enhancement methods*

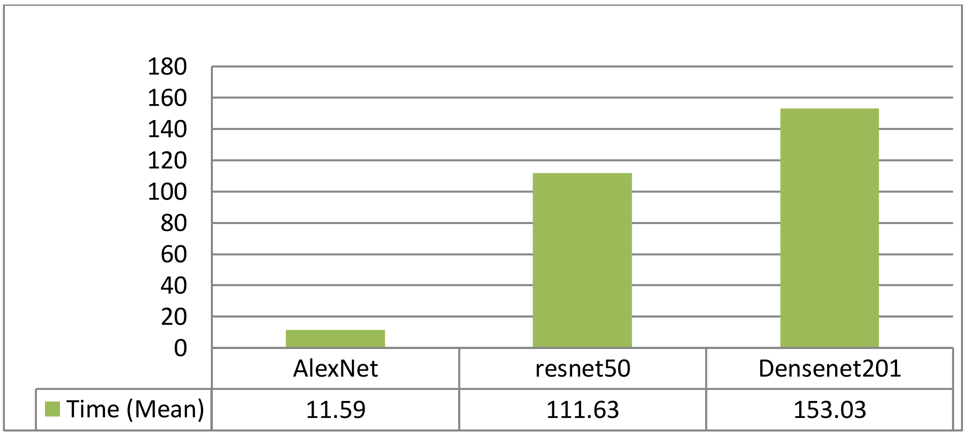

Figure 3.17:*Comparison of the Mean time of each CNN model*

3.9. Conclusion

This study explores the effects of different image enhancement techniques in the automatic detection of covid-19 from CXR images using deep convolution neural networks.The performance of three different CNNs models for eight different enhancement techniques was evaluated for classification covid-19 and Non Covid-19. From simulation results, AlexNet model with HE and gamma correction technique provides the best accuracy with a rate of 99.03% which is equivalent to an improvement of 5.45%when using original image. Resnet50 and Densenet201 reached the best accuracy rate with CLAHE and CLAHE+Gamma correction techniques respectively. For Resnet50the accuracy rated 99.67% with an equals to 2.24%. For Densenet201, the accuracy rated100% with an improvement difference from the original equals to 1.61.

Conclusion

During the last three years corona virus was the most infecting and deadly epidemics. So facing disease, many detecting methods have been proposed and where the aim is to obtain results in a faster and more accurate way.

Recent studies have resorted to use the intelligence artificial especially on image processing for detecting Covid-19 due to the more precision and the shortest time to get results. However, not often, dataset used is clear and accurate enough to give the right decision and it may need an enhancement.

In this thesis, we have proposed to combined some image enhancement methods on X-rays images and explore the enhancing effect on the accuracy of the classification..

When we trained our dataset with the CNN modelsAlexNet, ResNet50 and DenseNet201, we have found that the accuracy obtained with enhanced images is higher than that obtained without enhancement. The best enhancement technique with AlexNet training was HE+Gamma which gave the best accuracy with a rate of 99.03% .For DenseNet, we found that the CLAHE+Gammagave the best performance metrics rates.

In summary we conclude:

- There is no perfect enhancement technique for all CNNs models, each model deal with certain enhancement technique.
- Densenet201 considered as the best model with the best enhancement technique CLAHE+Gamma by giving all performance metrics equals to 100%
- Not any big combination gives best results; it may just force the training more and giving low results.
- The number of layers plays important role in results which is the most model with bigger number of layers gives the best results (Densenet201>Resnet50>AlexNet).
- The model with smallest number of layers takes less processing time like we had AlexNet<Resnet50<Densenet201.
- CLAHE considered as the longest processing time technique comparing to other alone techniques (HE and Gamma).

References

[1]. T. Qiblawey Y, Khandakar A, Rahman T, Khurshid U, Musharavati F, Islam MT, Kiranyaz S, Al-Maadeed S, Chowdhury MEH. ‘Deep Learning for Reliable Classification of COVID-19, MERS, and SARS from Chest X-ray Images’. CognitComput. 2022 .

[2]. R.Sarki,K. Ahmed , H. Wang,Y. Zhang ,K. Wang ,’ Automated detection of COVID-19 through convolutional neural network using chest x-ray images’. PLoS ONE 17(1), 2022.

[3]. T.Rahman, A. Khandakar, Y. Qiblawey, A. Tahir, S. Kiranyaz, S. Bin AbulKashem, M. Tariqul Islam, S. Al Maadeed, S. M. Zughaier, M. Salman Khan, M. E.H. Chowdhury,’Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images’,Computers in Biology and Medicine,Volume 132,2021.

[4]. N. Salem, H. Malik, A. Shams,’Medical image enhancement based on histogram algorithms’,Procedia Computer Science,Volume 163,, 300-311 ,2019

[5]. H. Dao, ‘ Image classification using convolutional neural networks ‘,Bachelor’s Thesis, Information Technology, Oulu University of Applied Sciences.2020.

[6]. S.Siddharth, S.Simone , ‘ Activation Functions In Neural Networks ‘ International Journal of Engineering Applied Sciences and Technology, Vol. 4, Issue 12, ISSN No. 2455-2143, 310-316 , 2020.

[7]. .Janiesch, C., Zschech, P. & Heinrich, K. Machine learning and deep learning. Electron Markets 31, 685–695 ,2021.

[8]. M.Boughaba,B.Boukhris, L`apprentissage profond (Deep Learning) pour la classification et la recherche d’images par le contenu, Mémoire Master Professionnel. University of KasdiMerbahOuargla.2017 .

[9]. A.Ghosh ,A.Sufian, F. Sultana , A.Chakrabarti , D. De, ‘Fundamental Concepts of Convolutional Neural Network’, In book: Recent Trends and Advances in Artificial Intelligence and Internet of Things,2020.

[10]. S.Patel , A. Patel, ‘Deep Leaning Architectures and its Applications: A Survey’ ,International journal of computer sciences and engineering 6(6):1177-1183 ,2018.

[11]. B. Ding, H.Qian, J.Zhou, ‘Activation Functions and their characteristics in DNN’, Chinese Control And Decision Conference (CCDC), 2018.

[12]. https://github.com/muhammedtalo/COVID-19

Effect of Image Enhancement Techniques on COVID-19 Detection using deep learning

Summary _ Corona virus is considered one of the most dangerous and fastest growing diseases today due to the rapid spread of the infection and the large number of victims. Referring to direct diagnostic methods which have become ineffective due to the severity of the virus, it is necessary to develop methods that lead to rapid and accurate diagnosis. In this work, we propose to improve X-ray images by different enhancement techniques to increase the performance of automatic diagnosis using deep learning.

Keywords: *Corona, detection, Artificial Intelligence, enhancement, Effect, accuracy*

آثار طرق تحسين الصور في تشخيص كوفيد باستخدام التعلم العميق

ملخص _ يعتبر فيروس كورونا من أخطر الأمراض وأسرعها نموا اليوم بسبب سرعة انتشار العدوى وكثرة الضحايا . نظرا إلى طرق التشخيص المباشر التي أصبحت غير فعالة بسبب شدة الفيروس، أصبح من الضروري تطوير طرق تؤدي إلى التشخيص السريع و الدقيق. في هذا العمل، نقترح تحسين صور الأشعة السينية بتقنيات تحسين مختلفة لزيادة أداء التشخيص التلقائي باستخدام التعلم العميق..

الكلمات الدالة: *كورونا, التشخيص, الذكاء الاصطناعي, تحسين, تأثير, واضحة*

Effet des techniques d’amélioration de l’image sur la détection de la COVID-19 au moyen de l’apprentissage en profondeur

Résumé _ Le virus Corona est considéré comme l'une des maladies les plus dangereuses et les plus rapides à l'heure actuelle en raison de la propagation rapide de l'infection et le nombre important des victimes. Se référant aux méthodes de diagnostic directes qui sont devenues inefficaces devant la gravité du virus, Il est nécessaire de développer des méthodes qui mènent à un diagnostic rapide et précis. Dans ce travail, on proposer d'améliorer les images en rayons X par différentes techniques d'amélioration pour augmenter la performance du diagnostic automatique utilisant l'apprentissage profond.

Mots-clés : *Corona, détection, Intelligence artificielle, amélioration, Effet, précision*