International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

Diagnosis of Pneumonia Using Deep Learning

Alaa M. A. Barhoom and Prof. Dr. Samy S. Abu Naser

Deprtment of Information Technology,
Faculty of Engineering and Information Technology,
Al-Azhar University, Gaza, Palestine

***Abstract**: Artificial intelligence (AI) is an area of computer science that emphasizes the creation of intelligent machines or software that work and react like humans. Some of the activities computers with artificial intelligence are designed for include, Speech, recognition, Learning, Planning and Problem solving. Deep learning is a collection of algorithms used in machine learning, It is part of a broad family of methods used for machine learning that are based on learning representations of data. Deep learning is a technique used to produce Pneumonia detection and classification models using x-ray imaging for rapid and easy detection and identification of pneumonia. In this thesis, we review ways and mechanisms to use deep learning techniques to produce a model for Pneumonia detection. The goal is find a good and effective way to detect pneumonia based on X-rays to help the chest doctor in decision-making easily and accuracy and speed. The model will be designed and implemented, including both Dataset of image and Pneumonia detection through the use of Deep learning algorithms based on neural networks. The test and evaluation will be applied to a range of chest x-ray images and the results will be presented in detail and discussed. This thesis uses deep learning to detect pneumonia and its classification.*

Keywords: Artificial intelligence; deep learning; machine learning; pneumonia detection; chest X-rays; neural networks; dataset; classification.

1.1 Introduction

Machine learning is a subfield of artificial intelligence (AI). The goal of machine learning generally is to understand the structure of data and fit that data into models that can be understood and utilized by people [1].

Although machine learning is a field within computer science, it differs from traditional computational approaches. In traditional computing, algorithms are sets of explicitly programmed instructions used by computers to calculate or problem solve. Machine learning algorithms instead allow for computers to train on data inputs and use statistical analysis in order to output values that fall within a specific range. Because of this, machine learning facilitates computers in building models from sample data in order to automate decision-making processes based on data inputs [1].
In machine learning, tasks are generally classified into broad categories. These categories are based on how learning is received or how feedback on the learning is given to the system developed [2].
Two of the most widely adopted machine learning methods are supervised learning which trains algorithms based on example input and output data that is labeled by humans, and unsupervised learning which provides the algorithm with no labeled data in order to allow it to find structure within its input data [2].

1.2 Deep Learning

Deep learning is a subset of machine learning where artificial neural networks, algorithms inspired by the human brain, learn from large amounts of data. Similarly to how we learn from experience, the deep learning algorithm would perform a task repeatedly, each time tweaking it a little to improve the outcome, So that teaches computers to do what comes naturally to humans: learn by example[3].
Deep learning is a key technology behind driverless cars, enabling them to recognize a stop sign, or to distinguish a pedestrian from a lamppost. It is the key to voice control in consumer devices like phones, tablets, TVs, and hands-free speakers [3]. Deep learning is getting lots of attention lately and for good reason. It’s achieving results that were not possible before [4].

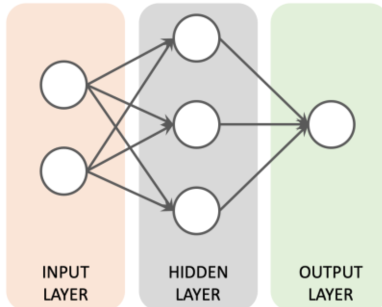

Figure 1: Layers in an Feed Forward Artificial Neural Network

In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labeled data and neural network architectures that contain many layers[4].

Most deep learning methods use neural network architectures, which is why deep learning models are often referred to as deep neural networks,

The term “deep” usually refers to the number of hidden layers in the neural network. Traditional neural networks only contain 2-3 hidden layers, while deep networks can have as many as 150[5].

Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction[5].

1.3 Pneumonia

Pneumonia is an infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus (purulent material), causing cough with phlegm or pus, fever, chills, and difficulty breathing. A variety of organisms, including bacteria, viruses and fungi, can cause pneumonia.

Pneumonia can range in seriousness from mild to life-threatening. It is most serious for infants and young children, people older than age 65, and people with health problems or weakened immune systems, in the United States (U.S.), around 1 million people are treated in the hospital for pneumonia each year, and around 50,000 die from the disease[6].

The major types of pneumonia are classified by the cause of the infection, where the infection was transmitted, and how the infection was acquired[6]:

- Bacterial pneumonia: The most common cause of bacterial pneumonia is Streptococcus pneumonia. Chlamydophila pneumonia and Legionella pneumophila can also cause bacterial pneumonia.
- Viral pneumonia: Respiratory viruses are often the cause of pneumonia, especially in young children and older people. Viral pneumonia is usually not serious and lasts for a shorter time than bacterial pneumonia.

Pneumonia can be diagnosed with the physical exam and the chest X-ray, but depending on the severity of your symptoms and your risk of complications, an x-ray exam will allow your doctor to see your lungs, heart and blood vessels to help determine if you have pneumonia. When interpreting the x-ray, the radiologist will look for white spots in the lungs (called infiltrates) that identify an infection. This exam will also help determine if you have any complications related to pneumonia such as abscesses or pleural effusions (fluid surrounding the lungs)[7].

1.4 Problem Statement

Physicians often use chest X-rays to quickly and cheaply diagnose disease associated with the area. However, it is much more difficult to make clinical diagnoses with chest X-rays than with other imaging modalities such as CT or MRI[8]. With computer-aided diagnosis, physicians can make chest X-ray diagnoses more quickly and accurately.

Remind, pneumonia is an infection in one or both lungs. It can be caused by bacteria, viruses, or fungi. Bacterial pneumonia is the most common type in adults, pneumonia causes inflammation in the air sacs in your lungs, which are called alveoli. The alveoli fill with fluid or pus, making it difficult to breathe[6].

Pneumonia is often diagnosed with chest X-Rays and kills around 50,000 people each year (Center for Disease Control and Prevention, 2016). With computer aided diagnosis of pneumonia specifically, physicians can more accurately and efficiently diagnose the disease[8].

In this application, we hope to train a model using the dataset to help physicians in making diagnoses of pneumonia in chest X-Rays.
Computerized applications can be using deep learning techniques to increase accuracy and efficiency in diagnosis.
These include chest X-ray images, image processing techniques and data analysis.

1.5 Objectives of the Thesis

The objectives of this thesis are:

1. **Main objective:** Implementation a software model used to detect and classify pneumonia if found in chest x-ray images by the following types:
    - Bacterial pneumonia.
    - Viral pneumonia.
    - Normal

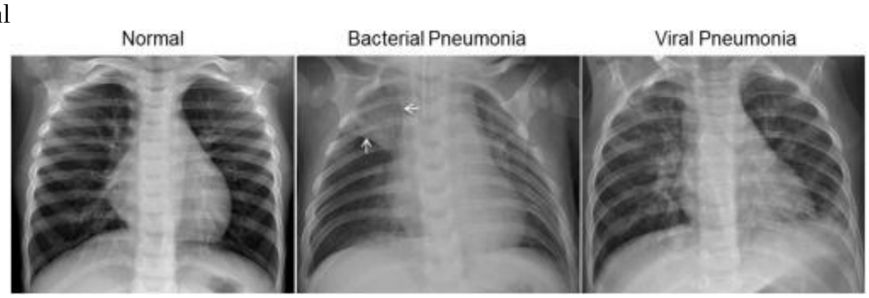

Figure 2: Chest X-Ray Images (Pneumonia types)

2. **Specific objectives:**
    - Rapid diagnosis and detection of pneumonia.
    - Reduce the cost of diagnosis and repetitive images.
    - Increase proficiency using deep learning techniques to detect

2.1 Pneumonia

Pneumonia is the single leading cause of mortality in children under five and is a major cause of child mortality in every region of the world, with most deaths occurring in Africa and South Asia. Pneumonia kills more children under five than AIDS, malaria, and measles combined, yet increased attention in recent years have been on the latter diseases[9].

Pneumonia is a form of acute respiratory tract infection (ARTI) that affects the lungs. When an individual has pneumonia, the alveoli in the lungs are filled with pus and fluid, which makes breathing painful and limits oxygen intake. Pneumonia has many possible causes, but the most common are bacteria and viruses[9].

In a healthy lung, inhaled air flows through the airways and alveolar ducts to the alveoli. The alveoli are air sacs surrounded by very thin walls containing blood. At this site, gases (oxygen and carbon dioxide) exchange between air and blood[10].

The response to infection – the pus accumulating in the lungs – is crucial to outcome. This pus contains blood elements, white blood cells (particularly a group of cells called neutrophils) and plasma proteins (particularly a group of proteins called opsonins). These cells and proteins are essential to killing the microbes and overcoming infection. Therefore, when we have pneumonia, we have to get these cells and proteins to where the microbes are, in the lungs, or we may succumb to the infection. However, this same pus is dangerous. Neutrophils make toxic and derivative products that are useful in killing microbes, but they can also damage the lungs. An example is hypochlorite, the active chemical in bleach, which is synthesized by neutrophils in pneumonic lungs – good for killing bacteria, but not so great for lung cells. In addition, the accumulation of plasma proteins results in a fluid build-up in the lungs, called pulmonary edema. Pulmonary edema makes it harder to breathe and harder for oxygen and carbon dioxide to pass between blood in the lungs and inhaled air, as these gases need to do for the body to function. Therefore, regulation of this accumulation of pus is critical; we need enough to fight the microbes, but not so much that our lungs have trouble working properly[11].

The most common pathogens are Streptococcus pneumonia, Homophiles influenza type b (Hib), and respiratory syncytial virus (RSV). S. pneumonia is the most common cause of bacterial pneumonia in children under five years in the developing world, the second most common cause of bacterial pneumonia in children is Hib, followed by RSV - the most common cause of viral pneumonia in children under two years, the populations most at risk for pneumonia are children under five years, people aged 65 or over, and people with pre-existing health problems.
In addition, people with certain medical conditions, such as chronic heart, lung, or liver diseases, or sickle cell anemia are also at increased risk for pneumococcal diseases. People living with HIV/AIDS or people who have had organ transplants and are taking medications that decrease their immunity to infection are also at high risk of getting this disease[6].

Physicians have good tools to fight lung infections. Vaccines prevent some microbes from causing lung infections, and antibiotics cure patients of many types of pneumonia. Despite these useful tools, lung infections remain a critical public health concern. No vaccines are available for many microbes that infect the lungs. People with compromised immune functions are difficult or impossible to effectively vaccinate even if vaccines are available. Microbes develop resistance to previously effective antibiotics. Some microbes are not susceptible to any known drugs. Even when successful, the eradication of microbes is sometimes insufficient to save patients succumbing to inflammatory injury such as the acute respiratory distress syndrome[8].

2.2 Convolutional Neural Network

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision[12].

The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm — a Convolutional Neural Network[12].

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics[5].

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area[14].

A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better[15].

Convolutional networks rely on 3D architecture - height, width, and depth - to scale for image recognition. Data is fed into the input layer and then processed through a series of hidden layers before revealing the solution. The solution is the final or output layer. It expands machine learning by working through each previous layer to create the classification. There is a sequence of layers that process the data. Instead of each layer being fully connected to all the others, the three layers scale down the complexity to allow for image recognition. The convolutional layer, pooling layer, and the fully connected layer work together to reduce the image to a set of class scores. The input image goes through each layer until classified at the outset. The number of parameters can vary, and from the first layer to the output layer, the process is unsupervised[16].

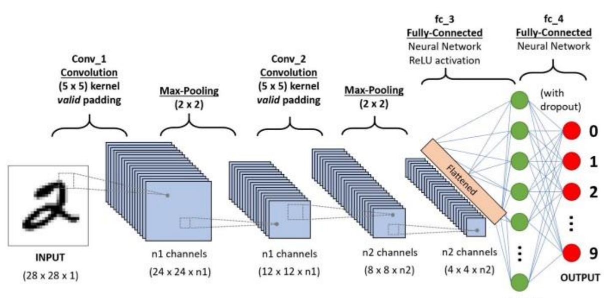

Figure 3: A CNN sequence to classify handwritten digits[11]

The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction,
this is important when we are to design an architecture which is not only good at learning features but also is scalable to massive datasets[17].

2.2.1 Convolutional Layer

Technically, deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernals), Pooling, fully connected layers (FC) and apply Softmax function to classify an object with probabilistic values between 0 and 1[17].

Convolution is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel[17].

A convolutional layer contains a set of filters whose parameters need to be learned. The height and weight of the filters are smaller than those of the input volume. Each filter is convolved with the input volume to compute an activation map made of neurons. In other words, the filter is slid across the width and height of the input and the dot products between the input and filter are computed at every spatial position. The output volume of the convolutional layer is obtained by stacking the activation maps of all filters along the depth dimension. Since the width and height of each filter is designed to be smaller than the input, each neuron in the activation map is only connected to a small local region of the input volume. In other words, the receptive field size of each neuron is small, and is equal to the filter size. The local connectivity is motivated by the architecture of the animal visual cortex where the receptive fields of the cells are small[18]. The local connectivity of the convolutional layer allows the network to learn filters which maximally respond to a local region of the input, thus exploiting the spatial local correlation of the input (for an input image, a pixel is more correlated to the nearby pixels than to the distant pixels). In addition, as the activation map is obtained by performing convolution between the filter and the input, the filter parameters are shared for all local positions. The weight sharing reduces the number of parameters for efficiency of expression, efficiency of learning, and good generalization[19].

2.2.2 Pooling Layer

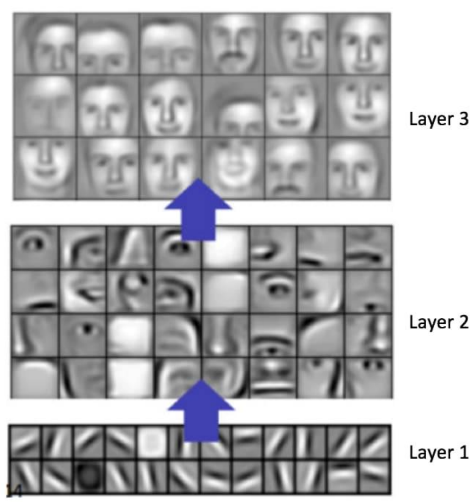

Figure 4: Learned features from a Convolutional Layers[12]

It is common to periodically insert a Pooling layer in-between successive Conv layers in a ConvNet architecture. Its function is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network, and hence to also control overfitting. The Pooling Layer operates independently on every depth slice of the input and resizes it spatially, using the MAX operation. The most common form is a pooling layer with filters of size 2x2 applied with a stride of 2 down samples every depth slice in the input by 2 along both width and height, discarding 75% of the activations. Every MAX operation would in this case be taking a max over 4 numbers (little 2x2 region in some depth slice)[20].

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

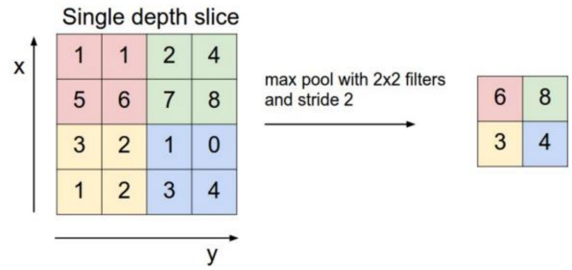

Figure 5: Example of action Pooling Layer

There are several pooling functions such as the average of the rectangular neighborhood, L2 norm of the rectangular neighborhood, and a weighted average based on the distance from the central pixel. However, the most popular process is max pooling, which reports the maximum output from the neighborhood[20].

2.2.3 Rectified Linear Unit Layer

The Rectified Linear Unit is the most commonly used activation function in deep learning models. The function returns 0 if it receives any negative input, but for any positive value xx it returns that value back. So it can be written f(x)=max(0,x)[20].

A nonlinear function is always used in CNNs. This replicates the nonlinearity in biological image processing, as well as helps reduce data growth. Typically, this is the rectified linear unit, abbreviated as ReLU. The ReLU function will zero the value if it is negative (less than zero), otherwise will pass unchanged. This is similar to the rectification performed by a diode, hence the name. Other nonlinear functions are hyperbolic tangent and sigmoid function. However, ReLU is generally preferred because of the simplicity of computation. ReLU also has an advantage in training, where derivatives are computed to obtain gradients. For greater than zero, the gradient of ReLU equals 1, and for less than zero the gradient is of course zero[22].

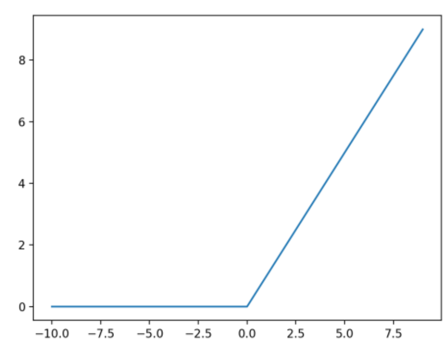

Figure 6: Line Plot of Rectified Linear Activation for Negative and Positive Inputs

2.2.4 Dropout Layer

The term “dropout” refers to dropping out units (both hidden and visible) in a neural network, simply put, dropout refers to ignoring units (i.e. neurons) during the training phase of certain set of neurons which is chosen at random. By “ignoring”, I mean these units are not considered during a particular forward or backward pass[23].

More technically, At each training stage, individual nodes are either dropped out of the net with probability 1-p or kept with probability p, so that a reduced network is left; incoming and outgoing edges to a dropped-out node are also removed.

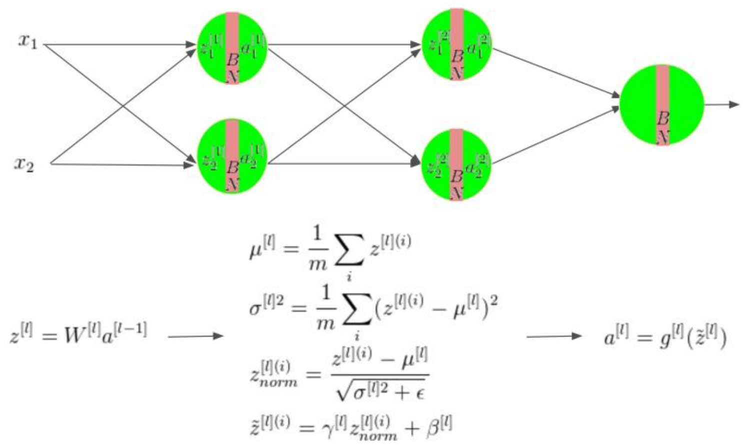

Figure 7: Dropout is a simple way to prevent neural networks from overfitting

Dropout is an approach to regularization in neural networks which helps reducing interdependent learning amongst the neurons. Dropout is a technique used to improve over-fit on neural networks[23].

Basically during training half of neurons on a particular layer will be deactivated. This improve generalization because force your layer to learn with different neurons the same "concept", during the prediction phase the dropout is deactivated[24].

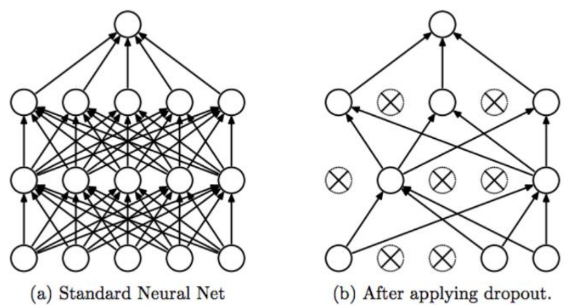

Figure 8: Batch Normalization on a simple network.

Dropout forces a neural network to learn more robust features that are useful in conjunction with many different random subsets of the other neurons.
Dropout roughly doubles the number of iterations required to converge. However, training time for each epoch is less.
With H hidden units, each of which can be dropped, we have 2^H possible models.
In testing phase, the entire network is considered and each activation is reduced by a factor p[24].

2.2.5 Batch Normalization Layer

Batch normalization is a technique designed to automatically standardize the inputs to a layer in a deep learning neural network.
Once implemented, batch normalization has the effect of dramatically accelerating the training process of a neural network, and in some cases improves the performance of the model via a modest regularization effect[25].
Technically, the layer will transform inputs so that they are standardized, meaning that they will have a mean of zero and a standard deviation of one, during training, the layer will keep track of statistics for each input variable and use them to standardize the data, Further, the standardized output can be scaled using the learned parameters of Beta and Gamma that define the new mean

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

and standard deviation for the output of the transform. The layer can be configured to control whether these additional parameters will be used or not via the “center” and “scale” attributes respectively. By default, they are enabled.

The statistics used to perform the standardization, e.g. the mean and standard deviation of each variable, are updated for each mini batch and a running average is maintained[25].

Batch normalization can be used at most points in a model and with most types of deep learning neural networks.
It has been shown that adding batch normalization layers creates a network that need 14 times fewer training step but still provides the same accuracy.

2.2.6 Fully Connected Layer

Fully connected layers are an essential component of Convolutional Neural Networks (CNNs), which have been proven very successful in recognizing and classifying images for computer vision. The CNN process begins with convolution and pooling, breaking down the image into features, and analyzing them independently. The result of this process feeds into a fully connected neural network structure that drives the final classification decision[24].

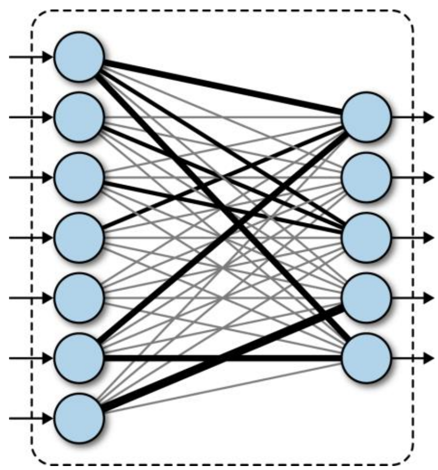

Figure 9:Example of A fully connected layer in a deep network.

Fully Connected Layer is simply, feed forward neural networks. Fully Connected Layers form the last few layers in the network, the input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.

Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks. Their activations can hence be computed with a matrix multiplication followed by a bias offset[5].

2.2.7 Softmax

A Softmax function is a type of squashing function. Squashing functions limit the output of the function into the range 0 to 1. This allows the output to be interpreted directly as a probability. Similarly, softmax functions are multi-class sigmoids, meaning they are used in determining probability of multiple classes at once. Since the outputs of a softmax function can be interpreted as a probability (i.e. They must sum to 1), a softmax layer is typically the final layer used in neural network functions. It is important to note that a softmax layer must have the same number of nodes as the output later[24].

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

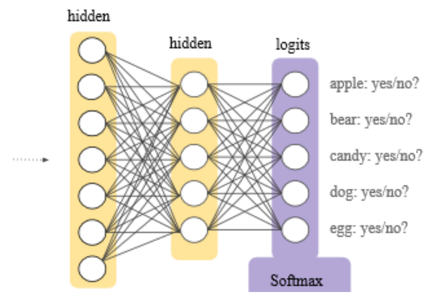

Figure 10: A Softmax layer within a neural network.

A neural network may be attempting to determine if there is a dog in an image. It may be able to produce a probability that a dog is, or is not, in the image, but it would do so individually, for each input. A softmax layer, allows the neural network to run a multi-class function. In short, the neural network will now be able to determine the probability that the dog is in the image, as well as the probability that additional objects are included as well[2].

Softmax layers are great at determining multi-class probabilities, however there are limits. Softmax can become costly as the number of classes grows. In those situations, candidate sampling can be an effective workaround. With candidate sampling, a softmax layer will limit the scope of its calculations to a specific set of classes. For example, when determining if an image of a bowl of fruit has apples, the probability does not need to be calculated for every type of fruit, just the apples. Additionally, a softmax layer assumes that there is only one member per class, and in situations where an object belongs to multiple classes, a softmax layer will not work. In that case, the alternative is to use multiple logistic regressions instead[26].

2.2.8 Backpropagation

Backpropagation, short for "backward propagation of errors," is an algorithm for supervised learning of artificial neural networks using gradient descent. Given an artificial neural network and an error function, the method calculates the gradient of the error function with respect to the neural network's weights. It is a generalization of the delta rule for perceptron's to multilayer feedforward neural networks[2].

The "backwards" part of the name stems from the fact that calculation of the gradient proceeds backwards through the network, with the gradient of the final layer of weights being calculated first and the gradient of the first layer of weights being calculated last. Partial computations of the gradient from one layer are reused in the computation of the gradient for the previous layer. This backwards flow of the error information allows for efficient computation of the gradient at each layer versus the naive approach of calculating the gradient of each layer separately[15].

Backpropagation's popularity has experienced a recent resurgence given the widespread adoption of deep neural networks for image recognition and speech recognition. It is considered an efficient algorithm, and modern implementations take advantage of specialized GPUs to further improve performance[27].

Backpropagation was one of the first methods able to demonstrate that artificial neural networks could learn good internal representations, i.e. their hidden layers learned nontrivial features. Experts examining multilayer feedforward networks trained using backpropagation actually found that many nodes learned features similar to those designed by human experts and those found by neuroscientists investigating biological neural networks in mammalian brains (e.g. certain nodes learned to detect edges, while others computed Gabor filters). Even more importantly, because of the efficiency of the algorithm and the fact that domain experts were no longer required to discover appropriate features, backpropagation allowed artificial neural networks to be applied to a much wider field of problems that were previously off-limits due to time and cost constraints[22].

2.2.9 Adam optimization

The Adam optimization algorithm is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications in computer vision and natural language processing, that's been designed specifically for training deep neural networks[28].

The algorithms leverages the power of adaptive learning rates methods to find individual learning rates for each parameter. It also has advantages of Adagrad, which works really well in settings with sparse gradients, but struggles in non-convex optimization of neural networks, and RMSprop, which tackles to resolve some of the problems of Adagrad and works really well in on-line settings.

Adam can be looked at as a combination of RMSprop and Stochastic Gradient Descent with momentum. It uses the squared gradients to scale the learning rate like RMSprop and it takes advantage of momentum by using moving average of the gradient instead of gradient itself like SGD with momentum[29].

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

Adam is an adaptive learning rate method, which means, it computes individual learning rates for different parameters. Its name is derived from adaptive moment estimation, and the reason it's called that is because Adam uses estimations of first and second moments of gradient to adapt the learning rate for each weight of the neural network, that can used instead of the classical stochastic gradient descent procedure to update network weights iterative based in training data[30].

2.3 Network Architectures

Convolutional Neural Networks have a different architecture than regular Neural Networks. Regular Neural Networks transform an input by putting it through a series of hidden layers. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. Finally, there is a last fully-connected layer - the output layer - that represent the predictions[17].

Convolutional Neural Networks are a bit different. First of all, the layers are organized in 3 dimensions: width, height and depth. Further, the neurons in one layer do not connect to all the neurons in the next layer but only to a small region of it. Lastly, the final output will be reduced to a single vector of probability scores, organized along the depth dimension[18].

2.3.1 VGG

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Figure 11: VGG ConvNet configurations[13]

It usually refers to a deep convolutional network for object recognition developed and trained by Oxford's renowned Visual Geometry Group (VGG), which achieved very good performance on the ImageNet dataset, they proposed total 5 configurations, named as A-E. But VGG16 and VGG19 are famous, the main concept is stacking of convolutional layers to create deep neural networks, the important point they wanted to make at that time, using these networks is, accuracy increases as we increase the depth of the convolutional neural networks[19].

2.3.2 ResNet

During each iteration of training a neural network, all weights receive an update proportional to the partial derivative of the error function with respect to the current weight. If the gradient is very small then the weights will not be change effectively and it may completely stop the neural network from further training. The phenomenon is called vanishing gradients. More specifically we can say that the data is disappearing through the layers of the deep neural network due to very slow gradient descent[21].

ResNet, short for Residual Networks is a classic neural network used as a backbone for many computer vision tasks. This model was the winner of ImageNet challenge in 2015. The fundamental breakthrough with ResNet was it allowed us to train

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

extremely deep neural networks with 150+layers successfully. Prior to ResNet training very deep neural networks was difficult due to the problem of vanishing gradients[31].

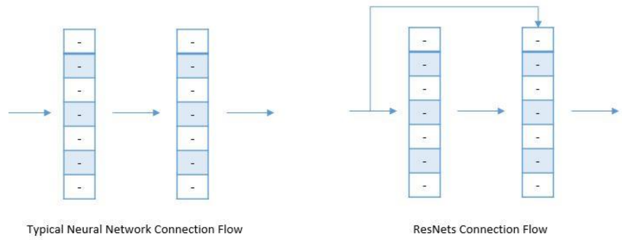

Figure 12: ResNets Vs Plain Neural Network

Microsoft research found that splitting a deep network into three layer chunks and passing the input into each chunk straight through to the next chunk, along with the residual output of the chunk minus the input to the chunk that is reintroduced, helped eliminate much of this disappearing signal problem. No extra parameters or changes to the learning algorithm were needed. In other words, ResNets breaks down a very deep plain neural network into small chunks of network connected through skip or shortcut connections to form a bigger network[32].

Two main types of blocks are used in a ResNet, depending mainly on whether the input/output dimensions are same or different.

A- Identity Block: The identity block is the standard block used in ResNets and corresponds to the case where the input activation (say a[l]) has the same dimension as the output activation (say a[l+2]). Below is an example of identity block where the upper path is the "shortcut path" and the lower path is the "main path".

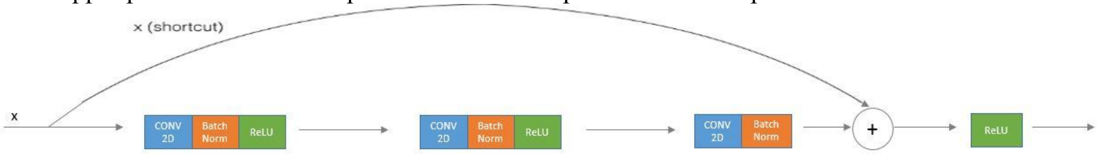

Figure 13: ResNets Identity block

B- Convolutional Block: When the input and output dimensions don't match up, we add a convolutional layer in the shortcut path. The arrangement is called convolutional block.

Building a Full ResNet model (50 layers), the necessary blocks to build a very deep ResNet. The following figure

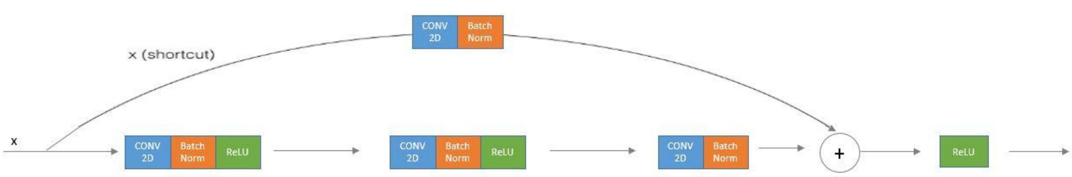

Figure 14: ResNets convolutional block

describes in detail the architecture of this neural network. "ID BLOCK" in the diagram stands for "Identity block," and "ID BLOCK x3" means should stack 3 identity blocks together[29].

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

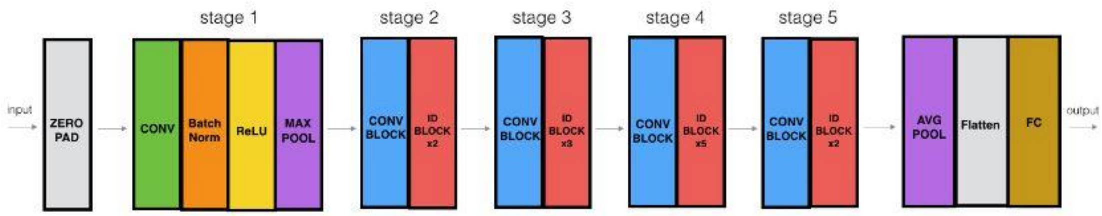

Figure 15: 50 layers ResNets Architecture

Very deep neural networks (plain network) are not practical to implement as they are hard to train due to vanishing gradients, The skip-connections help to address the Vanishing Gradient problem. They also make it easy for a ResNet block to learn an identity function, There are two main types of ResNets blocks: The identity block and the convolutional block, Very deep Residual Networks are built by stacking these blocks together.

2.4 Data Processing

2.4.1 Laplacian as focus measure

Shape from focus (SFF) uses focus measure operator for depth measurement from a sequence of images, from the analysis of defocused image, it is observed that the focus measure operator should respond to high frequency variations of image intensity and produce maximum values when the image is perfectly focused. Therefore, an effective focus measure operator must be a high-pass filter[33].

Laplacian is mostly used as focus measure operator in the previous SFF methods, generalized Laplacian is used as focus measure operator for better shape recovery of objects.

The Laplacian can be expressed using the mask :

The focus of the image is measured by the variance of the Laplacian[33].

$$L = \begin{pmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{pmatrix}$$

2.4.2 Normalization

Images are comprised of matrices of pixel values, black and white images are single matrix of pixels, whereas color images have a separate array of pixel values for each color channel, such as red, green, and blue[17].

Pixel values are often unsigned integers in the range between 0 and 255. Although these pixel values can be presented directly to neural network models in their raw format, this can result in challenges during modeling, such as in the slower than expected training of the model[17].

Instead, there can be great benefit in preparing the image pixel values prior to modeling, such as simply scaling pixel values to the range 0-1 to centering and even standardizing the values[19].

In which each pixel in the image is subtracted with the mean value for all pixels then the whole image is divided by the standard deviation of the original image[33].

2.4.3 Augmentation

Collecting more data is a tedious and expensive process. If can't do it, should try to make data appear as if it was more diverse. To do that, we use data augmentation techniques so that each time a sample is processed by the model, it's slightly different from the previous time to prevent overfitting in Training Process without the need for change original images in dataset[4].

Figure 16: By Augmentation each iteration sees as different variation of the original sample.

2.5 Model Evaluation

The ultimate goal of a deep Learning is to develop a Model in order to get good predictions on data, a good model is not the one that gives accurate predictions on the known data or training data but the one which gives good predictions on the new data and avoids overfitting and underfitting, so we use one of model evaluation techniques[34].

2.5.1 Performance Estimation

A performance model enables us to reason about the behavior of an implementation in future execution contexts. Additionally, it can predict the performance of different CNN architectures with various number of images and epochs, this is applied by dividing all predictions into four categories they are correctly classified samples "true positive ", correctly classified samples that do not belong to the class "true negative", samples that were incorrectly assigned to the class "false positive " and samples that belongs to the class but were not correctly classified "false negative ", then the final output will be a measure of both average accuracy and score[34].

3.1 Previous Studies

Many research papers have been published to use artificial intelligence, expert systems and neural networks to improve the detection of pneumonia or other diseases, Recently, medical centers and hospitals have begun to introduce artificial intelligence systems and applications in some disciplines to increase the accuracy of disease detection, many methods and models have been introduced that have contributed to increased diagnostic efficiency.

The most important of which has been developed an algorithm that can detect Some types of inflammation from chest X-rays at a level ex-ceding practicing radiologists, CheXNet algorithm, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. find that CheXNet exceeds average radiologist performance on inflammation detection on both sensitivity and specificity[35].

The recent development of artificial intelligence combined with the accumulation of large volumes of medical images opens up new opportunities for building CAD systems in the medical applications. Artificial intelligence methods (including shallow learning and deep learning, etc.), especially deep learning, mainly replace the process of feature extraction and disease classification in the traditional CAD systems. Artificial intelligence methods have also been widely used in image segmentation and bone suppression of chest X-ray[36].

Used 1.2 million chest x-rays and their corresponding radiology reports to train convolutional neural networks (CNNs) to identify chest x-ray abnormality. Has been developed natural language processing (NLP) algorithms to parse unstructured radiology reports and extract information about the presence and nature of chest x-ray abnormality. These extracted findings were used as labels when training CNNs. Individual networks were trained to identify normal x-rays, and the following chest x-ray findings: ‘blunted CP angle’, ‘calcification’, ‘cardiomegaly’, ‘cavity’, ‘consolidation’, ‘fibrosis’, ‘hilar enlargement’, ‘opacity’ and ‘pleural effusion’. Deep Learning (DL) algorithms have been proposed as a solution to expedite, automate, and improve the interpretation of several imaging examinations including CXR[37].

Prior studies have reported encouraging results of various DL algorithms for assessment of specific conditions such as pulmonary tuberculosis, cystic fibrosis, lines and tubes (position of peripherally inserted central catheters and endotracheal tubes), pneumoconiosis and lung nodules on CXR. Another DL algorithm, now a commercially available application, subtracts ribs from single energy CXR to aid and expedite their interpretation by the radiologists[18].

Combining multi-modality brain data for disease diagnosis commonly leads to improved performance, a challenge in using multi-modality data is that the data are commonly incomplete; namely, some modality might be missing for some subjects, a group of researchers from Old Dominion University in USA proposed a deep learning based framework for estimating multi-modality imaging data, this method takes the form of convolutional neural networks, where the input and output are two volumetric modalities, the network contains a large number of trainable parameters that capture the relationship between input and output modalities. When trained on subjects with all modalities, the network can estimate the output modality given the input modality. After evaluated this method on the Alzheimer's Disease Neuroimaging Initiative (ADNI) database, where the input and output modalities are MRI and PET images, respectively. Results showed that method significantly outperformed prior methods[38].

The volume and complexity of diagnostic imaging is increasing at a pace faster than the availability of human expertise to interpret it. Artificial intelligence has shown great promise in classifying two-dimensional photographs of some common diseases and typically relies on databases of millions of annotated images. Until now, the challenge of reaching the performance of expert clinicians in a real-world clinical pathway with three-dimensional diagnostic scans has remained unsolved. Here, Olaf Ronneberger and Joseph R. Ledsam from the UK presented research and application apply a novel deep learning architecture to a clinically heterogeneous set of three-dimensional optical coherence tomography scans from patients referred to a major eye hospital. They came demonstrate performance in making a referral recommendation that reaches or exceeds that of experts on a range of sight-threatening retinal diseases after training on only 14,884 scans. Moreover, They also clarified demonstrate that the tissue segmentations produced by him architecture act as a device-independent representation; referral accuracy is maintained when using tissue segmentations from a different type of device. Where their work removes previous barriers to wider clinical use without prohibitive training data requirements across multiple pathologies in a real-world setting[16].

Joseph R. Ledsam and Julia H. Miao of New York University School of Medicine developed advanced deep neural network approach is developed and utilized to predict coronary heart disease in patients and increase diagnostic accuracy using classification and prediction models based on deep learning.

Their study included developed classification and diagnosis models contain two parts: a deep neural network learning-based training model and a prediction model for the presence of heart disease. The training model, So that was created using deep learning algorithms based on a deeper multilayer perceptron with regularization and dropout in system and architecture. Based on the training model, the diagnosis model is then utilized to predict whether or not patients have coronary heart disease. The subsequent performance of the deep learning model for heart disease diagnosis is evaluated in terms of the performance measure parameters, including diagnostic accuracy, probability of misclassification error, sensitivity, specificity, precision, area under the ROC curve (AUC), Kolmogorov-Smirnov (K-S) measure, receiver operating characteristic (ROC), and F-score[28].

Many neurodegenerative diseases affect human gait. These pathologies may have similarities that make difficult their correct classification, so it is essential to distinguish them with a high degree of accuracy to prescribe appropriate treatment. This study was presented by researchers at the Instituto Tecnol´ogico Superior de Misantla, Mexico, they worked with gait biomarkers of a public dataset and then we implemented an ANN in order to obtain competitive results comparing to those from the literature. Our result shows that with only one machine learning algorithm, it is not possible to increase the percentages until an optimal classification in multiclass classification performed. Based on this, they made a propose the study of the multiclass classification of gait in the neurodegenerative diseases with four perspectives[39].

Parkinson's Disease (PD) automatic identification in early stages is one of the most challenging medicine-related tasks to date, since a patient may have a similar behavior to that of a healthy individual at the very early stage of the disease. At the 29th SIBGRAPI 2016 Conference on Graphics, Patterns and Images in SIBGRAPI, researchers presented a study and application explains mechanism they of cope with PD automatic identification by means of a Convolutional Neural Network (CNN), which aims at learning features from a signal extracted during the individual's exam by means of a smart pen composed of a series of sensors that can extract information from handwritten dynamics. They showed have CNNs are able to learn relevant information, thus outperforming results obtained from raw data. Also, Their work aimed at building a public dataset to be used by researchers worldwide in order to foster PD-related research[40].

Importance Retinopathy of prematurity (ROP) is a leading cause of childhood blindness worldwide, the decision to treat is primarily based on the presence of plus disease, defined as dilation and tortuosity of retinal vessels. However, clinical diagnosis of plus disease is highly subjective and variable, to implement and validate an algorithm based on deep learning to automatically diagnose plus disease from retinal photographs, James M. BrownIn 2018, trained a deep convolutional neural network was trained using a data set of 5511 retinal photographs, each image was previously assigned a reference standard diagnosis (RSD) based on consensus of image grading by 3 experts and clinical diagnosis by 1 expert (ie, normal, pre–plus disease, or plus disease), the algorithm was evaluated by 5-fold cross-validation and tested on an independent set of 100 images. Images were collected from 8 academic institutions participating in the Imaging and Informatics in ROP (i-ROP) cohort study. The deep learning algorithm was tested against 8 ROP experts, each of whom had more than 10 years of clinical experience and more than 5 peer-reviewed publications about ROP, after the results this fully automated algorithm diagnosed plus disease in ROP with comparable or better accuracy than human experts. This has potential applications in disease detection, monitoring, and prognosis in infants at risk of ROP[41].

.2 Comment about previous Studies

In the shadow of the observed deep neural network revolution, its use in various industrial and service fields. Deep neural networks worked through a complex composition of layers to offer us many endless functions.

Also deep learning has not only given us solutions but can predict the future with information from his production, so we can describe it as the wealth of the present and the future.

After studying and observing many recent studies that preceded us in this field, it turned out that deep learning technologies can learning from complex data that huge and huge volumes of data, unlike any other technology for image recognition and categorization, ensures high processing speed and accurate results.

The most famous areas of applications of deep learning is medical diagnosis that directly serve humanity, through use it in health informatics, biomedicine, and magnetic resonance image MRI analysis, Also diagnosis, classification, prediction, and detection of bone diseases.

So we can say that deep learning has surpassed the usual and old diagnostic method through automatic learning and training from data set and update data by himself.

4.1 Dataset

I will use the Chest X-Ray Images (Pneumonia) Dataset obtained from the National Institutes of Health (NIH) database; The NIH Clinical Center recently released a set of chest x-ray images and their corresponding data to the scientific community. The release allows us as researchers to freely access the datasets to train convolutional neural networks to how detect and diagnose disease.

Dataset organized into two folders (training: new-chest-x-rays, test: chest-x-rays-test) and contains subfolders (Pneumonia-viral, Pneumonia-Bactria, Normal). There are 9,057 X-Ray images (JPEG) divided to three categories as follows:

Categories	Number of training images	Number of testing images	Image size
Pneumonia viral	3035	300	128 x 128 pixels
Pneumonia Bactria	3002	300	128 x 128 pixels
Normal	3011	300	128 x 128 pixels

Table 1: Distribution of Images in dataset

Figure 18: Sample of Normal chest-x-ray

Figure 19:Sample of Viral pneumonia chest-x-ray

Figure 17: Sample of Bactria pneumonia chest-x-ray

4.2 Language and tool used

I used Python programming language in Google Colab environment. Google Colab is a research tool for machine learning education and research. It’s a Jupyter notebook environment that requires no setup to use. Colab offers a free GPU cloud service hosted by Google to encourage collaboration in the field of Deep Learning, without worrying about the hardware requirements; importantly it supports to develop deep learning applications using popular libraries such as Keras, TensorFlow.

Since Colab is working on Google Drive, I uploaded the dataset to the Google Drive account, to be shared with Google Colab environment, to be called by Python programming language and implement algorithms and convolutional neural network training down to the test.

Keras deep learning framework was used for building the convolutional neural network. Necessary libraries were imported from Keras to train the model.

4.3 Image format

Dataset was collected from a set of X-Ray images, (JPEG) format, In order to fit well with the model used to give the desired results.

4.4 Preprocessing

One of the important things in the data preprocessing was to resize the Chest-X-Ray images as the images were of various sizes, the images were resized to 128 by 128 Pixels, this image size struck a balance between providing a high enough resolution for Pneumonia Diagnosis by the model and efficient training. All images were normalized to ImageNet standards.

Then the images collection has been categorized into three types, uploaded to a Google Drive account and verified to be properly and accurately uploaded using Python code in the Google Colab environment.

4.5 Data augmentation

More data often means that the model will be more robust and prevent overfiting.

Having a large dataset is crucial for the performance of the deep learning model. However, I improved the performance of the model by augmenting the data I already have without collecting new data. Deep learning frameworks usually have built-in data augmentation utilities; I utilized five augmentation strategies to generate new training sets, (Rotation, width shift, height shift, horizontal flip, vertical flip).

Rotation augmentations are done by rotating the image right or left on an axis between 1° and 359°. The safety of rotation augmentations is heavily determined by the rotation degree parameter. Shifting and flipping images are a very useful transformation to encapsulating more details about objects of interest.

Figure 20: Original Chest-X-ray image

Figure 21: Chest-x-ray image is rotated by 30 degrees

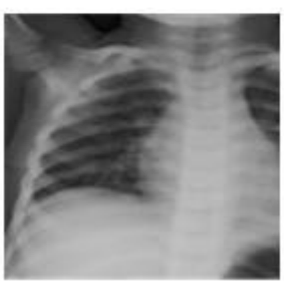

Figure 22: Chest-x-ray image after width shift

Figure 23: Chest-x-ray image after height shift

Figure 24: Chest-x-ray image flipped horizontally

Figure 25: Chest-x-ray image flipped vertically

4.6 Network Architecture

Developed the networks based on VGG network model, The size of networks is indicated by " k ", Whereas "K" controls the number of outputs in the first layers, after the implementation a pooling operation model, the results showed that the value of "k" had increased and doubled, also the value of k controls the number of features in the fully connected layers.

I'll used a pre-trained model called VGG16 network with 16 convolutional layers followed by a fully connected hidden layer, also used dropout layers in between, dropout regularizes the networks to prevents the network from overfitting, all layers have ReLU activations except the output layer.

Output layer uses softmax activation as it has to output the probability for each of the classes, to optimize the network Adam optimization used the best value of k for networks were then evaluated using K-Fold cross validation.

4.7 Training the Model

Model is ready to train, during the training, the model will iterate over batches of the training set, each of size batch_size. For each batch, gradients will be computed and updates will be made to the weights of the network automatically. One iteration over all of the training set is referred to as an epoch. Training is usually run until the loss converges to a constant.

I added one of features to training, Model checkpoint: to save the model with best validation accuracy. This is useful because the network might start overfitting after a certain number of epochs, but I want the best model. These feature is implemented via the callback feature of Keras. callback are a set of functions that will applied at given stages of training procedure like end of an epoch of training. Keras provides inbuilt functions for both learning rate scheduling and model checkpointing.

It is important to mention that. This training module was implemented with enhanced images as inputs by data augmentation, in other words, the training was not based on the number of original dataset images. For output classes coding it was considered as the following: {'pneumonia-viral':0, 'pneumonia-Bactria':1, 'normal':2 }

Note that the networks are first pre-trained as they are deep networks, pre-training means that the networks are first trained layer by layer, Once the networks finish pre-training, it is then fine-tuned using the conventional backpropagation algorithm. Here, the input images are labeled therefore, output neurons are three which means that network is being trained to classify the images into three classes: pneumonia viral, pneumonia Bactria, normal.

Note following figure 26 the value accuracy "val_acc" starts increasing. That means model built is learning and working fine. It has an accuracy rate of approximately 100 %, but there is a decrease and an increase of loss and validation loss.

```
Epoch 1/10
70/70 [==============================] - 7s 95ms/step - loss: 0.9501 - acc: 0.5634 - fscore: 0.5221 - val_loss: 0.5046 - val_acc: 0.7500 - val_fscore: 0.7500
Epoch 2/10
70/70 [==============================] - 7s 99ms/step - loss: 0.8332 - acc: 0.5938 - fscore: 0.5198 - val_loss: 0.1817 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 3/10
70/70 [==============================] - 7s 102ms/step - loss: 0.7823 - acc: 0.6174 - fscore: 0.5454 - val_loss: 0.1444 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 4/10
70/70 [==============================] - 7s 100ms/step - loss: 0.8155 - acc: 0.5911 - fscore: 0.5377 - val_loss: 0.2114 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 5/10
70/70 [==============================] - 7s 104ms/step - loss: 0.7930 - acc: 0.6290 - fscore: 0.5599 - val_loss: 0.0646 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 6/10
70/70 [==============================] - 7s 104ms/step - loss: 0.7887 - acc: 0.6063 - fscore: 0.5427 - val_loss: 0.1263 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 7/10
70/70 [==============================] - 7s 103ms/step - loss: 0.8027 - acc: 0.6004 - fscore: 0.5331 - val_loss: 0.1416 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 8/10
70/70 [==============================] - 7s 104ms/step - loss: 0.8036 - acc: 0.6040 - fscore: 0.5377 - val_loss: 0.1524 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 9/10
70/70 [==============================] - 7s 100ms/step - loss: 0.7790 - acc: 0.6110 - fscore: 0.5434 - val_loss: 0.0970 - val_acc: 1.0000 - val_fscore: 1.0000
Epoch 10/10
70/70 [==============================] - 7s 93ms/step - loss: 0.7916 - acc: 0.6179 - fscore: 0.5435 - val_loss: 0.1210 - val_acc: 1.0000 - val_fscore: 1.0000
```

Figure 26: The model starts training and logs the losses and accuracies.

To track and monitor the training model status, I used Matplotlib to draw plot the training and validation loss side by side, as well as the training and validation accuracy.

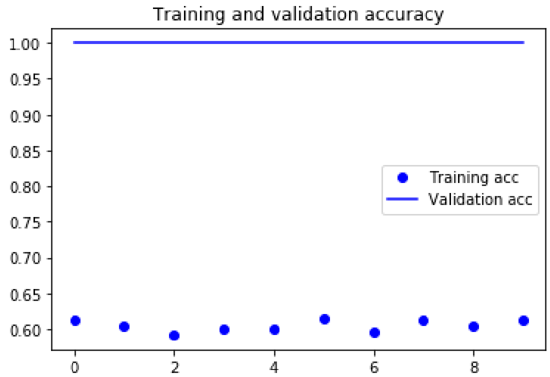

Figure 27: Plot of initial training, 10 epochs, loss

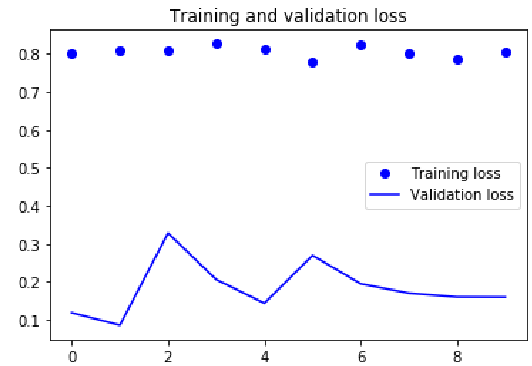

Figure 28: Plot of initial training, 10 epochs, accuracy

4.8 Validation of the Model

It is important to note, I used validation set to check the performance of the model on unseen images. It is done through the train_test_split() function of the sklearn.model_selection module to randomly divide images into training and validation set.

To check and validate work of the model, taking into account, the correct results of the previous training round, which were saved in Model Checkpoint. I trained the model one more time on 9048 images that are fed into it without any processing or enhancement technique. This deep model is composed of one input layer, also the input images size is 128*128 pixels, also, it has an output layer of three neurons as the output classes are only three.

To observe the difference between this training and the previous training, to validate the model works, also I used "Matplotlib" to draw plots the training and validation.

Figure 30 shows the learning curve of the network during training. It is seen that the validation loss and training loss were decreasing with the number of iterations, that's great, it proved that the model works well. Also figure 29 shows the learning curve of the network during training. It is seen that the validation accuracy and training accuracy were increasing, reached to 100% training accuracy.

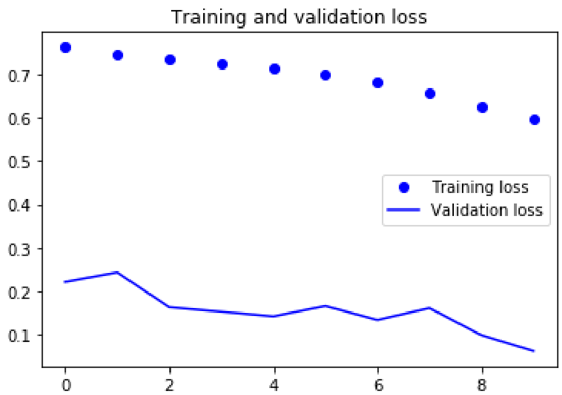

Figure 30: Plot of Retraining, 10 epochs, loss

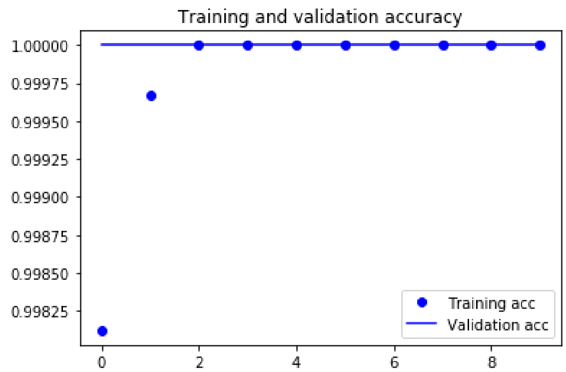

Figure 29: Plot of Retraining, 10 epochs, accuracy

All of the above which indicates a good learning results of the networks during all stages.

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 6 Issue 2, February - 2022, Pages:48-68

5.1 Data Set for testing the model

Testing dataset organized into one folder (chest-x-rays-test) and contains 900 of chest X-Ray images, (JPEG) format, different from the images that used in original dataset for training; they are images of three classifications of pneumonia, distributed as in the following table:

Categories	Number of testing images	Image size
Pneumonia viral	300	128 x 128 pixels
Pneumonia Bactria	300	128 x 128 pixels
Normal	300	128 x 128 pixels

Table 2: Distribution of Images in test dataset

Figure 31 shows samples of the chest x-rays images used for testing the networks.

5.2

Figure 31: Samples of the chest x-rays images in test dataset

Testing the model

After training and evaluated the model on the validation, the network are tested using 900 chest X-rays images, among them, 300 Pneumonia viral, 300 Pneumonia Bactria and 300 Normal.

Testing the model is done through load the test images and predict their classes using the model.predict_classes() function, probabilities of each image belonging to a specific class were calculated, by the following classification: (0:'pneumonia-viral', 1:'pneumonia-bactria', 2:'normal').

The model prints the first 9 results immediately after the prediction is completed as shown in figure 32:

```
      file Type of chest x-ray diagnosis
0  B3.jpeg            PNEUMONIA-Bactria
1  N3.jpeg                       NORMAL
2  V2.jpeg              PNEUMONIA-viral
3  N1.jpeg                       NORMAL
4  N2.jpeg                       NORMAL
5  V1.jpeg              PNEUMONIA-viral
6  B2.jpeg            PNEUMONIA-Bactria
7  B1.jpeg            PNEUMONIA-Bactria
8  V3.jpeg              PNEUMONIA-viral
```

Figure 32: The first 9 results of pneumonia diagnosis testing model

Note the classification rates of network during testing, it was a surprise, the probability of results in the classification appeared 100% correct, for all test images.

5.3Result and Discussion

We trained our custom model on the training dataset using 9048 images for a total of 10 epochs (20 cycles), the results were as follows:

	First training model	Last training model	Testing model
Training Loss	0.791	0.0011	
Validation accuracy	100 %	100 %	
Validation loss	12.1 %	90.4%	
Testing model classification rate			100 %

Based on the previous results, I concluded that the retraining process gives better results and validation loss, based on Data augmentation to achieve a better diagnosis of pneumonia in chest X-rays images.

This thesis presents a deep learning approach for diagnosis through the classification of chest X-ray images into pneumonia bacteria, pneumonia viral or normal.

I accomplished just this using a custom model based of the VGG architecture, our model was able to correctly diagnose pneumonia in chest x-ray images with a balanced accuracy approximately 100% on the validation and the test set after only training for 10 epochs, 20 cycles, thanks to techniques such as Adam optimization, data augmentation , dropout and others, it was possible to enhance the accuracy of model without sacrificing training efficiency, because one of the problems with machine learning, including deep learning, is overfitting. Overfitting occurs when the trained model does not generalize well to unseen cases, but fits the training data well. This becomes more apparent when the training sample size is small.

Assessment of the plot training can be used to assess the possibility of overfitting. From the curve, it is apparent that the data loss is similar for both validation and training datasets. If there were overfitting, the loss on the training data would be much greater than that of the validation data. In addition, for this reason, the cases were split three ways (training, validation, and test).

It is conceivable that the use of larger training datasets, additional image augmentation methods, and additional machine learning approaches with more ensembles could improve this result.

Connecting the our technically results with the medical field, this may be helpful in Some remote and poor areas where access to radiologists is lacking or cost prohibitive to diagnose pneumonia, in which an automated method could solely interpret a large portion of the cases, and only the equivocal cases are sent to a radiologist. One could also imagine a system with multiple classifiers to diagnose all chest diseases that appear in the X-ray image, which may further improve accuracy to detect, because a highly accurate automated system would be more desirable in this regard.

6.1 Conclusion

In this thesis, convolutional neural network (CNN) is designed for Pneumonia diagnosis in chest x-ray. Showed outperformance is mainly due to the deep structure of CNN that uses the power of extracting different level features, which resulted in a better generalization capability. CNN models such as VGG16 networks have upper generalization capabilities and accuracies compared to other networks, obtained results have demonstrated the high recognition rates of the proposed CNN, It gave very accurate results in Pneumonia diagnosis in chest x-ray then classification Pneumonia to three type, Pneumonia bacterial, Pneumonia viral, normal.

All the above Confirms to us, Deep learning methods have a wide application in the medical field, medical diagnosis is conducted through use-cases of deep learning networks. As mentioned before, these include detection, segmentation, classification, prediction and other. The results of the study indicate that deep learning methods can be far superior in comparison to other high-performing algorithms. Therefore, it is safe to assume that deep learning is will continue to diversify its uses in various fields to form the revolution of the present and the future.

6.2 Future Work

Future work could involve improving the model as follows:

Use others of convolutional networks such as ZF Net to expanding the size of the middle convolutional layers and making the stride and filter size on the first layer smaller. Use GoogLeNet to reduce the number of parameters in the network.

Addition of more Data augmentation techniques to increase the efficiency of training and use larger datasets to increase accuracy.

Design an online application to diagnose pneumonia in chest x-ray images, to serve the largest possible number of slums who lack health care and do not have the price of diagnosis.

References

1. Al Barsh, Y. I., et al. (2020). "MPG Prediction Using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 4(11): 7-16.
2. Alajrami, E., et al. (2019). "Blood Donation Prediction using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(10): 1-7.
3. Alajrami, E., et al. (2020). "Handwritten Signature Verification using Deep Learning." International Journal of Academic Multidisciplinary Research (IJAMR) 3(12): 39-44.
4. Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31.
5. Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 74-81.
6. Pneumonia: The forgotten killer of children. Geneva, UNICEF/WHO, (2006).
7. Alghoul, A., et al. (2018). "Email Classification Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 8-14.
8. Center for Disease Control and Prevention. Pneumonia. [online] Available at: https://www.cdc.gov/nchs/fastats/pneumonia.htm [Accessed 10 Aug. 2019].
9. Abu Nada, A. M., et al. (2020). "Age and Gender Prediction and Validation Through Single User Images Using CNN." International Journal of Academic Engineering Research (IJAER) 4(8): 21-24.
10. UNICEF, One is too many: Ending child deaths from pneumonia and diarrhea, UNICEF, New York, (2016).
11. Abu Nada, A. M., et al. (2020). "Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach." International Journal of Academic Information Systems Research (IJAISR) 4(8): 6-9.
12. Abu-Saqer, M. M., et al. (2020). "Type of Grapefruit Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 4(1): 1-5.
13. Afana, M., et al. (2018). "Artificial Neural Network for Forecasting Car Mileage per Gallon in the City." International Journal of Advanced Science and Technology 124: 51-59.
14. Al-Araj, R. S. A., et al. (2020). "Classification of Animal Species Using Neural Network." International Journal of Academic Engineering Research (IJAER) 4(10): 23-31.
15. Al-Atrash, Y. E., et al. (2020). "Modeling Cognitive Development of the Balance Scale Task Using ANN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 74-81.
16. Alghoul, A., et al. (2018). "Email Classification Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 8-14.
17. Al-Kahlout, M. M., et al. (2020). "Neural Network Approach to Predict Forest Fires using Meteorological Data." International Journal of Academic Engineering Research (IJAER) 4(9): 68-72.
18. Alkronz, E. S., et al. (2019). "Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network." International Journal of Academic and Applied Research (IJAAR) 3(2): 1-8.
19. Al-Madhoun, O. S. E.-D., et al. (2020). "Low Birth Weight Prediction Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 8-14.
20. Al-Massri, R., et al. (2018). "Classification Prediction of SBRCTs Cancers Using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 2(11): 1-7.
21. Al-Mobayed, A. A., et al. (2020). "Artificial Neural Network for Predicting Car Performance Using JNN." International Journal of Engineering and Information Systems (IJEAIS) 4(9): 139-145.
22. Al-Mubayyed, O. M., et al. (2019). "Predicting Overall Car Performance Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAR) 3(1): 1-5.
23. Alshawwa, I. A., et al. (2020). "Analyzing Types of Cherry Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 4(1): 1-5.
24. Al-Shawwa, M., et al. (2018). "Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(9): 1-6.
25. Ashqar, B. A., et al. (2019). "Plant Seedlings Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 3(1): 7-14.
26. Bakr, M. A. H. A., et al. (2020). "Breast Cancer Prediction using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(10): 1-8.
27. Barhoom, A. M., et al. (2019). "Predicting Titanic Survivors using Artificial Neural Network." International Journal of Academic Engineering Research (IJAER) 3(9): 8-12.
28. Belbeisi, H. Z., et al. (2020). "Effect of Oxygen Consumption of Thylakoid Membranes (Chloroplasts) From Spinach after Inhibition Using JNN." International Journal of Academic Health and Medical Research (IJAHMR) 4(11): 1-7.
29. Dalffa, M. A., et al. (2019). "Tic-Tac-Toe Learning Using Artificial Neural Networks." International Journal of Engineering and Information Systems (IJEAIS) 3(2): 9-19.
30. Dawood, K. J., et al. (2020). "Artificial Neural Network for Mushroom Prediction." International Journal of Academic Information Systems Research (IJAISR) 4(10): 9-17.
31. Dheir, I. M., et al. (2020). "Classifying Nuts Types Using Convolutional Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(12): 12-18.
32. El-Khatib, M. J., et al. (2019). "Glass Classification Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(2): 25-31.
33. El-Mahelawi, J. K., et al. (2020). "Tumor Classification Using Artificial Neural Networks." International Journal of Academic Engineering Research (IJAER) 4(11): 8-15.
34. El-Mashharawi, H. Q., et al. (2020). "Grape Type Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 41-45.
35. Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, et al. Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225, (2017).
36. Elzamly, A., et al. (2015). "Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process." International Journal of Advanced Science and Technology 81: 35-48.
37. Elzamly, A., et al. (2015). "Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods." Int. J. Adv. Inf. Sci. Technol 38(38): 108-115.
38. Elzamly, A., et al. (2017). "Predicting Critical Cloud Computing Security Issues using Artificial Neural Network (ANNs) Algorithms in Banking Organizations." International Journal of Information Technology and Electrical Engineering 6(2): 40-45.
39. Habib, N. S., et al. (2020). "Presence of Amphibian Species Prediction Using Features Obtained from GIS and Satellite Images." International Journal of Academic and Applied Research (IJAAR) 4(11): 13-22.
40. Harz, H. H., et al. (2020). "Artificial Neural Network for Predicting Diabetes Using JNN." International Journal of Academic Engineering Research (IJAER) 4(10): 14-22.
41. Hassanein, R. A. A., et al. (2020). "Artificial Neural Network for Predicting Workplace Absenteeism." International Journal of Academic Engineering Research (IJAER) 4(9): 62-67.
42. Heriz, H. H., et al. (2018). "English Alphabet Prediction Using Artificial Neural Networks." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 8-14.
43. Jaber, A. S., et al. (2020). "Evolving Efficient Classification Patterns in Lymphography Using EasyNN." International Journal of Academic Information Systems Research (IJAISR) 4(9): 66-73.
44. Kashf, D. W. A., et al. (2018). "Predicting DNA Lung Cancer using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(10): 6-13.
45. Khalil, A. J., et al. (2019). "Energy Efficiency Predicting using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 3(9): 1-8.
46. Kweik, O. M. A., et al. (2020). "Artificial Neural Network for Lung Cancer Detection." International Journal of Academic Engineering Research (IJAER) 4(11): 1-7.
47. Maghari, A. M., et al. (2020). "Books' Rating Prediction Using Just Neural Network." International Journal of Engineering and Information Systems (IJEAIS) 4(10): 17-22.
48. Mettleq, A. S. A., et al. (2020). "Mango Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 3(12): 22-29.
49. Metwally, N. F., et al. (2018). "Diagnosis of Hepatitis Virus Using Artificial Neural Network." International Journal of Academic Pedagogical Research (IJAPR) 2(11): 1-7.
50. Mohammed, G. R., et al. (2020). "Predicting the Age of Abalone from Physical Measurements Using Artificial Neural Network." International Journal of Academic and Applied Research (IJAAR) 4(11): 7-12.
51. Musleh, M. M., et al. (2019). "Predicting Liver Patients using Artificial Neural Network." International Journal of Academic Information Systems Research (IJAISR) 3(10): 1-11.
52. Oriban, A. J. A., et al. (2020). "Antibiotic Susceptibility Prediction Using JNN." International Journal of Academic Information Systems Research (IJAISR) 4(11): 1-6.
53. Qwaider, S. R., et al. (2020). "Artificial Neural Network Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza." International Journal of Academic Information Systems Research (IJAISR) 4(8): 16-22.
54. Sadek, R. M., et al. (2019). "Parkinson's Disease Prediction Using Artificial Neural Network." International Journal of Academic Health and Medical Research (IJAHMR) 3(1): 1-8.
55. Salah, M., et al. (2018). "Predicting Medical Expenses Using Artificial Neural Network." International Journal of Engineering and Information Systems (IJEAIS) 2(20): 11-17.
56. Salman, F. M., et al. (2020). "COVID-19 Detection using Artificial Intelligence." International Journal of Academic Engineering Research (IJAER) 4(3): 18-25.
57. Samra, M. N. A., et al. (2020). "ANN Model for Predicting Protein Localization Sites in Cells." International Journal of Academic and Applied Research (IJAAR) 4(9): 43-50.
58. Shawarib, M. Z. A., et al. (2020). "Breast Cancer Diagnosis and Survival Prediction Using JNN." International Journal of Engineering and Information Systems (IJEAIS) 4(10): 23-30.
59. Zaqout, I., et al. (2015). "Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology." International Journal of Hybrid Information Technology 8(2): 221-228.
60. Saleh, A. et al. (2020). "Brain Tumor Classification Using Deep Learning." 2020 International Conference on Assistive and Rehabilitation Technologies (iCareTech). IEEE, 2020.
61. Almadhoun, H. et al. (2021). "Classification of Alzheimer's Disease Using Traditional Classifiers with Pre-Trained CNN." International Journal of Academic Health and Medical Research (IJAHMR) 5(4):17-21.
62. El-Habil, B. et al. (2022). "Cantaloupe Classification Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 5(12): 7-17.
63. Alkahlout, M. A. et al. (2022). "Classification of Fruits Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 5(12): 56-63.
64. Alfarra, A. H. et al. (2022). "Classification of Pineapple Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 5(12): 37-41.
65. Al-Masawabe, M. M. et al. (2022). "Papaya maturity Classification Using Deep Convolutional Neural Networks." International Journal of Engineering and Information Systems (IJEAIS) 5(12): 60-67.
66. Abu-Jamie, T. N., et al. (2022). "Six Fruits Classification Using Deep Learning." International Journal of Academic Information Systems Research (IJAISR) 6(1): 1-8.
67. Aish, M. A., et al. (2022). "Classification of pepper Using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(1): 24-31.
68. Alsaqqa, A. H., et al. (2022). "Using Deep Learning to Classify Different types of Vitamin." International Journal of Academic Engineering Research (IJAER) 6(1): 1-6.
69. MAlnajjar, M. K. and S. S. Abu-Naser (2022). "Heart Sounds Analysis and Classification for Cardiovascular Diseases Diagnosis using Deep Learning." International Journal of Academic Engineering Research (IJAER) 6(1): 7-23.
70. Aldammagh, Z., Abdeljawad, R., & Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Financial Internet Quarterly, 17(3), 35-46.
71. Obaid, T. (2021). Predicting Mobile Banking Adoption: An Integration of TAM and TPB with Trust and Perceived Risk. Available at SSRN 3761669.
72. Jouda, H., Abu Jarad, A., Obaid, T., Abu Mdallalah, S., & Awaja, A. (2020). Mobile Banking Adoption: Decomposed Theory of Planned Behavior with Perceived Trust. Available at SSRN 3660403.
73. Obaid, T., Abdaljawad, R., & Mdallalahc, S. A. (2020). Factors Driving E-Learning Adoption In Palestine: An Integration of Technology Acceptance Model And IS Success Model. Available at SSRN 3686490.
74. Obaid, T. F., & Eneizan, B. M. (2016). Transfer of training and post-training on job performance in Middle Eastern countries. Review of Public Administration and Management, 400(3786), 1-11.
75. Obaid, T. F., Zainon, M. S., Eneizan, P. D. B. M., & Wahab, K. A. TRANSFER OF TRAINING AND POST-TRAINING ON JOB PERFORMANCE IN MIDDLE EASTERN COUNTRIES.