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LUNG CANCER CLASSIFICATION AND DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

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DENIZ NISHAM ANWER SAFAR

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Asst. Prof. Dr. Serkan ÖZBAY

by

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November 2020

I here by declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Deniz Nisham Anwer SAFAR

ABSTRACT

LUNG CANCER CLASSIFICATION AND DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

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M.Sc. in Electrical and Electronics Engineering
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The immense growth of technology has led to a booming development in the medical science research field. One of the major focuses of researchers is cancer detection in different organs like brain, breast, lung, etc. Lung cancer has a higher cause of death amongst the other cancer types all over the world. Undoubtedly, the most critical point in lung cancer is its early detection where it can lead many patients to survive against the illness. Therefore, one of the most important parts in fighting against lung cancer is detecting it in earlier stages and that's why many systems are being developed with the technology development for achieving this goal. In this work, a recognition system for identifying some lung cancer types including small cell lung cancer, adenocarcinoma, squamous cell cancer, large cell carcinoma, undifferentiated non-small cell lung cancer and also for identifying normal lung is proposed. The proposed algorithm is based on deep learning and convolutional neural network. The system is implemented by transfer learning of MATLAB GUI and it is trained and tested by the data which is collected in K1 hospital located in Kirkuk city, Iraq. The system's convolutional neural network architecture has been developed in deep learning network and it is designed with seven layers and trained in transfer learning with almost 100 samples for each lung cancer type and 50 samples for normal lung. It is found that the proposed system has been successfully worked for the defined purposes.

Key Words: Lung Cancer, Tumor Detection, Deep Learning, CNN

ÖZET

KONVOLÜSYONEL SINIR AĞLARI KULLANILARAK AKCIĞER KANSERI SINIFLAMASI VE TESPITI

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Teknolojinin muazzam büyümesi, tıp bilimi araştırma alanında hızlı bir gelişmeye yol açtı. Araştırmacıların ana odak noktalarından biri, beyin, meme, akciğer vb. gibi farklı organlarda kanser tespitidir. Akciğer kanseri, tüm dünyada diğer kanser türleri arasında daha yüksek bir ölüm nedenine sahiptir. Kuşkusuz akciğer kanserinde en kritik nokta, birçok hastanın hastalığa karşı hayatta kalmasını sağlayabileceği erken teşhisdir. Bu nedenle akciğer kanseriyle mücadelede en önemli kısımlardan biri daha erken aşamalarda tespitedilmesidir ve bu nedenle bu amaca ulaşmak için teknolojik gelişmelerle birlikte bir çok sistem geliştirilmektedir. Bu çalışmada, küçük hücreli akciğer kanseri, adenokarsinom, skuamöz hücreli kanser, büyük hücreli karsinom, farklılaşmamış küçük hücreli olmayan akciğer kanseri dahil olmak üzere bazı akciğer kanseri türlerinin tanımlanması ve ayrıca normal akciğerin tanımlanması için bir tanıma sistemi önerilmektedir. Önerilen algoritma, derin öğrenmeye ve evrişimli sinir ağına dayanmaktadır. Sistem, Matlab GUI'nin transfer öğrenmesi ile uygulanmakta ve Irak'ın Kerkük şehrinde bulunan K1 hastanesinde toplanan veriler ile eğitilmekte ve test edilmektedir. Sistemin evrişimli sinir ağı mimarisi, derin öğrenme ağında geliştirilmiştir ve yedi katmanlı olarak tasarlanmıştır ve her akciğer kanseri türü için yaklaşık 100 örnek ve normal akciğer için 50 örnekle transfer öğrenmede eğitilmiştir. Önerilen sistemin tanımlan anamaçlar için başarıyla çalıştığı bulunmuştur.

Anahtar Kelimeler: Akciğer Kanseri, Tümör Tespiti, Derin uğrenme, CNN

''Dedicated to my family''

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Thanks for k1 hospital for supplying required dataset.

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LIST OF SYMBOLS

θ	Theta the weight of function.
η	The metric tensor in Quantum Field.
∇	Nabla the change / difference of gradient.
γ	Gamma the inverse of the standard deviation.

LIST OFABBREVIATIONS

AIS	Artificial Intelligence Science
AL	Artificial Intelligence
ANN	Artificial Neural Network
BP	Back-Propagation
CADS	Computer Aided Systems
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CRFS	Conditional Random Fields
CT	Computed Tomography
DBNs	Deep belief network
DICOM	Digital Imaging And Communications In Medicine
DNNS	Deep Neuronal Networks
GMMS	Gaussian Mixture Models
GPGPUS	General-Purpose Computing On Graphics Processing Units
GPU	Graphics Processing Units
GUI	Graphical User Interface
HCI	Human-Computer Interaction
KNN	K-Nearest Neighbor
MAXENT	Maximum Entropy
MCWSA	Marker-Controlled Watershed Segmentation Algorithm
MLO	Medio-Lateral Oblique
MLP	Multilayer Perceptron
MRI	Magnetic Resonance Imaging
NN	Neural Network
PET	Positron Emission Tomography

ROI	Region Of Interest
ROC	Receiving Operating Curve
RFs	Random Forests
SVMS	Support Vector Machine
SDAE	Stacked Denoising Auto-Encoder
TDNN	Time Delay Neural Network
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

Cancer is one of the most common diseases for humans. According to the World Health Organization (WHO), cancer has led to 9.6 million deaths in 2018, and lung cancer is on top of the cancer types, with 1.76 million deaths [1]. Figure 1.1 shows the typical lung cancer diagnosed patients by region [1]. Furthermore, lung cancer is also considered one of the most dreadful illnesses in developing countries with a death rate of 19.4% [1]. There are many reasons lung cancer is caused by mutations in the gene by growing a cancerous mass of cells developed into a tumor.

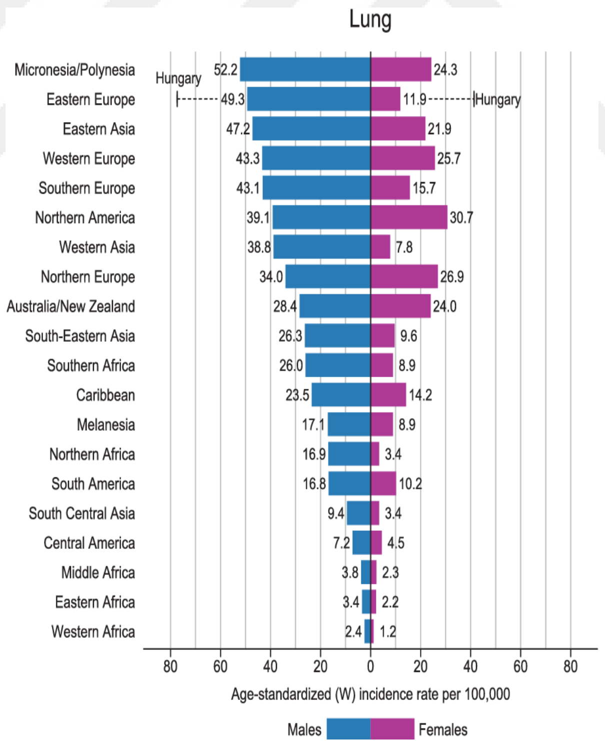


Figure 1.1 Lung cancer's world deaths [1]

Currently, designing and implementing systems that can interact between humans and computers have become prevailing, and these systems are used in a broad range of applications because of their remarkable properties. Computers are becoming more potent for developing state-of-the-art devices for Human-Computer Interaction (HCI) in conjunction with the latest improvements and accomplishments in the field of computer science and electronics. One of the application areas of HCI devices can be seen in sign language recognition as proposed by [2] and [3] for three different languages and gesture recognition as proposed by [4]. Those applications include recognizing patterns, computer vision, and linguistics [5].

Moreover, the significant improvement of technology has helped many researchers to find ways for early detection of cancer. Many techniques were done for early detection of lung cancer like Computed Tomography (CT) scans, Sputum Cytology, Chest X-ray, and Magnetic Resonance Imaging (MRI). Detecting a tumor means to classify the tumor into two categories: (i) Benign tumor (Non-cancerous) and (ii) Malignant (Cancerous) [6].

According to the national lung screening trail, lung cancer death rate can be reduced by 15-20% [7], [8] by applying a low-dose of computed tomography (CT) screening. The CTs show the tumors on images of the body called slices. A three-dimensional (3D) structure can be reconstructed by arranging these slices together where these slices allow the doctors to have a more detailed analysis of the tumors. Nevertheless, the computed tomography (CT) in terms of time and effort is expensive, and many suffer from observes of variation [9]. Thus, the need for automated interpretations of computed tomography (CT) scans seems very crucial. Computer-aided systems (CADs) are heads of technologies in order to make some achievements to help in cancer diagnosis, especially in biomedical engineering. For this purpose, modern image processing and machine learning techniques have been used by many researchers.

Chances to survive such a disease in its advanced stages are much less than when to get treatment in the illness's earlier stages. The techniques of image processing can significantly enhance such analysis and diagnostics methods. Many researchers have used these techniques for the early detection of lung cancer. However, the early detection of cancer is still not prominently better. Therefore, with the significant progress of machine learning techniques, the early detection and diagnosis of cancer are sought by many scientists and researchers. Because neural networks have played an essential role in the cancer cells' recognition amongst the normal ones, it basically offers an effectual means to create a useful Artificial Intelligence (AI) based cancer detection approach. The curing of cancer can be more effective once the tumor cells are correctly parted from the normal ones, so the classification of the tumor cells can be done with training the neural network, which forms the foundation of the machine learning-based cancer diagnosis [10]. Additionally, one of the techniques for this purpose is deep learning, which is the improved artificial neural network version. In particular, for the computer vision field, generally, the Convolutional Neural Network (CNN) is used [11].

A deep learning algorithm, a machine learning method, has also been involved in research for diagnosing cancer. Moreover, for classification and image segmentation, CNN is one of the most common methods used in deep learning technology. Additionally, CNN is also used for feature extraction purposes, training, and testing processes where the input dataset, which goes through some layers with weights and biases. CNN basically consists of a convolution layer, pooling layer, fully connected network layer, activation layer, and output layer. [11]

1.1 Problem Statement and Motivation

Many challenges are facing the cancer recognition systems like maximum performance of the device, a good adjusting of the parameters of used methods like machine learning and deep learning. Because of these recognition systems are not always reliable to flexibility of the images of the cancer among of the screening model parameters and CT scans, so a developed system with less problems and a modern system having satisfactory results are always required. [12]

One problem of the recognition system for cancer is detecting the nodules in the input images where the designed approach must try to use the classifier network to extract features from the nodules segmentation, then the system uses it to determine whatever the CT scan has cancer or not. [13] The CT scan size and the number of them are large; therefore, a computer with high GPU and CPU was required for training and testing processes.

This work's primary motivation is the increase of the survival chances of human lives, because early detection of any type of cancer, specifically lung cancer, is vital to save lives [14].

1.2 Objectives and Aim

This work aims to design and implement a deep learning convolutional neural network to detect the different types of lung cancer and prepare a system for early detection using MATLAB GUI.

1.3 Thesis Organization

Chapter One: Delivers an introductory view of the cancer detection systems, problem statement, objectives, and thesis organization.
Chapter Two: Demonstrates information on the anatomy of the lung, lung cancer, and related work.
Chapter Three: Provides information about the methodology, analysis, and tools used for implementing the system.
Chapter Four: Explains the design and the implementation behind this work, showing how the proposed system has been implemented.
Chapter Five: Provides the results and a brief discussion behind the obtained results.
Chapter Six: Provides the overall conclusion drawn up from the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Background

In this chapter, a brief background of lung cancer was explained. Basically, lung cancer's anatomies, information on lung cancer, the types of lung cancer, and its stages, as well as the screening methods, were given. Besides, a section in this chapter was dedicated to the previous related works done in this area.

2.1.1 Anatomy of the Lung

Lungs are placed in the thorax lateral to the heart and on the top part of the diaphragm, and it is a pair of vast and spongy organs [15]. As shown in Figure 2.1, because the heart is on the left side near the lung, both right and left lungs are not equal exactly, i.e., there are some small differences between them in size and shape. The lungs are covered by a membrane that allows the lungs to expand by giving it space. The differences in size make the left lung slighter than the right one and that because of those differences, the right lung has three lobes, while the left one has only two lobes. The lungs' inner part is composed of approximately thirty million bags, which are named the alveoli. Alveoli are covered with thin, simple squamous epithelium that permits air entering the alveoli to give-and-take its gases with the blood passing through the vessels. The standard air which contains oxygen and other gases enters into the human body through the lungs. In the lungs, during inhalation, the oxygen is exchanged into the blood-stream and moved through the body. Red blood cells gather the carbon dioxide and carry it back to the lungs, leaving the body during exhalation.

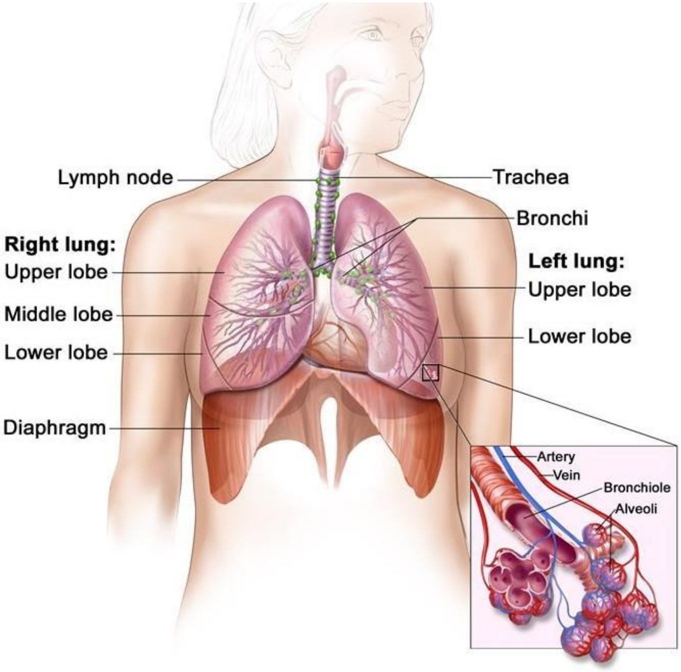


Figure 2.1 Anatomy of the lung [15]

2.1.2 Lung Cancer

Like all other cancers, lung cancer is the uncontrolled growth of a cell in tissues of the lung [16]. Throughout cells' growth, they are spread in the lung from tissue to other tissues or another part of the body, and the abnormal cell is called a tumor. Lung cancer is classified into three main types which are:

1- Non-small cell lung cancer (NSCLC).
2- Small cell lung cancer.
3- Carcinoid lung cancer.

According to [17], the most common type of lung cancers is non-small cell lung cancer. Lung cancer is the most common reason for cancer-related deaths in the world. It is estimated that nearly 1.6 million people (19.4% of all cancer deaths) have died because of lung cancer in 2012 [17], 1.88 million people in 2017, and 1.7 million people in 2018 [17]. In general, the risk that a man will grow lung cancer in his lifespan is about 1 in 14; for a woman, it is about 1 in 17 [18]. There are many reasons causing DNA changes, affecting the cell's normal functions and increasing the risk of cancer [18]. Smoking, mainly of cigarettes, is one of the main contributors to lung cancer

[18]. Cigarette smoke causes at least 73 known cancers [17]. A person who lives with a smoker is called passive smoker and that according to studies from the USA and Europe [19], it is shown that the risk of getting lung cancer in the case of a passive smoker is by 20-30%. Another risk factor for lung cancer is a colorless and odorless gas called radon gas, which is created by the failure of radioactive radium. Radon can be considered as the second-most common cause of lung cancer in the USA [20], with approximately 21,000 deaths each year [20]. Air pollution and asbestos are also risk factors for lung cancer, where outdoor air pollution has a minor influence on increasing the risk of lung cancer [18]. Besides the aforementioned risk factors, lung cancer can be caused because of genetic or miscellaneous with 8% [20], where the chromosomes 5,6 and 15 are ones who effect and elevate lung cancer risks [20].

The most common indicators of lung cancer are: [20]

1- Cough (with blood)
2- Difficulty in swallowing
3- Shortness of breath
4- Wheezing
5- Chest pain
6- Feeling tired or weak

The most common lung cancer causes are either direct smoking or second-hand smoke, and also a small percentage of lung cancer happens due to other reasons.

According to the World Health Organization, the large-sized lung cancer is also divided into the parts which are listed below: [1], [21]

- Adenocarcinoma
    - Lepidic
    - Acinar
    - Papillary
    - Micropapillary
    - Solid
    - Invasive mucinous
    - Colloid

    - Fetal
    - Enteric
    - Minimally invasive
- Squamous cell carcinoma
- Neuroendocrine tumors
    - Carcinoid tumors
    - Typical carcinoid
    - Atypical carcinoid
    - Small cell carcinoma
    - Large cell neuroendocrine carcinoma
- Large cell carcinoma
- Adenosquamous carcinoma
- Pleomorphic carcinoma
- Spindle cell carcinoma
- Giant cell carcinoma
- Carcinosarcoma
- Pulmonary blastoma

Other and unclassified carcinomas

The following tables classify lung cancer with its stages according to American Joint Committee on Cancer where the (T) refers to tumor and how much large the tumor is, (N) refers to nodes where it shows if cancer spreads near to the lymph nodes and (M) refers to metastasis, whether cancer has been spread to other organs or not [22]. The following figures also show the stages in more details [23] and the Table 2.1 shows the levels of the lung cancer.

Table 2.1 Lung cancer size's levels

Tx	Primary tumor cannot be assessed
T0	No sign of primary tumor
Tis	Carcinoma in situ
T1	Tumor is 3 cm or less
T1mi	Minimally invasive adenocarcinoma
T1a	The tumor size is between 0-1 cm

T1b	The tumor size is between 1-2 cm
T1c	The tumor size is between 2-3 cm
T2	The tumor size is more than 3 cm
T2a	The tumor size is between 3.1-4 cm
T2b	The tumor size is between 4-5 cm
T3	The tumor size is between 5.1-7 cm
T4	The tumor size is more than 7 cm

Table 2.2 Lung cancer's stage.

STAGE	T	N	M
Occult	TX	N0	M0
0	Tis	N0	M0
IA1	T1a(mi)/T1a	N0	M0
IA2	T1b	N0	M0
IA3	T1c	N0	M0
IB	T2a	N0	M0
IIA	T2b	N0	M0
IIB	T1a-T2b	N1	M0
	T3	N0	M0
IIIA	T1a-T2b	N2	M0
	T3	N1	M0
	T4	N0/N1	M0
IIIB	T1a-T2b	N3	M0
	T3/T4	N2	M0
IIIC	T3/T4	N3	M0
IVA	Any T	Any N	M1a/M1b
IVB	Any T	Any N	M1c

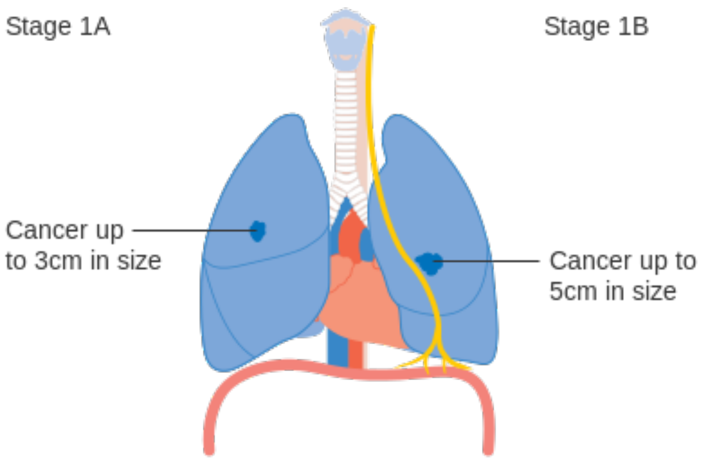


Figure 2.2 Stage IA and IB lung cancer

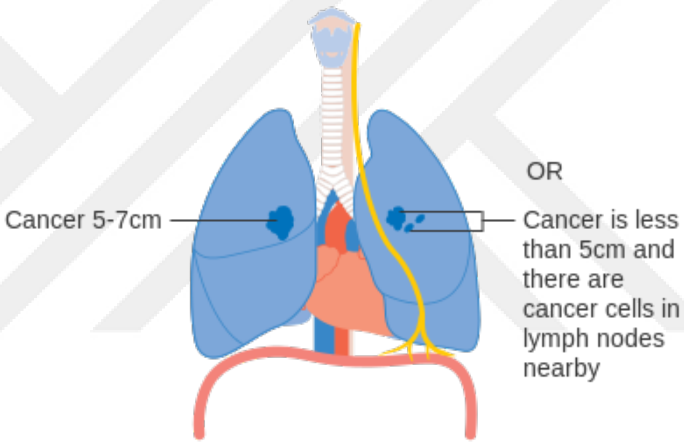


Figure 2.3 Stage IIA lung cancer

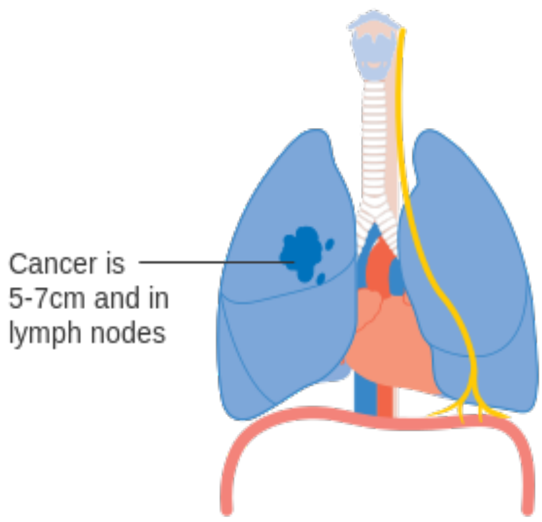


Figure 2.4 Stage IIB lung cancer

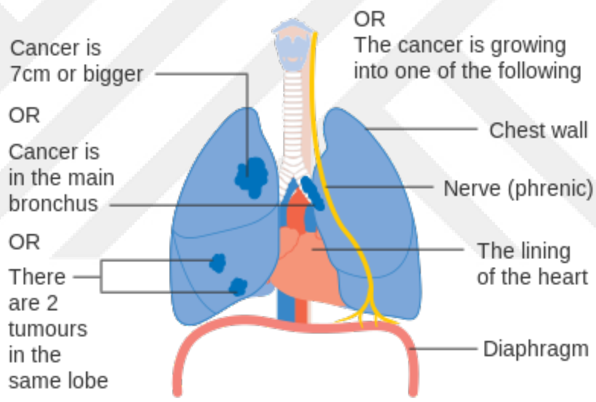


Figure 2.5 Stage IIB lung cancer with T2b

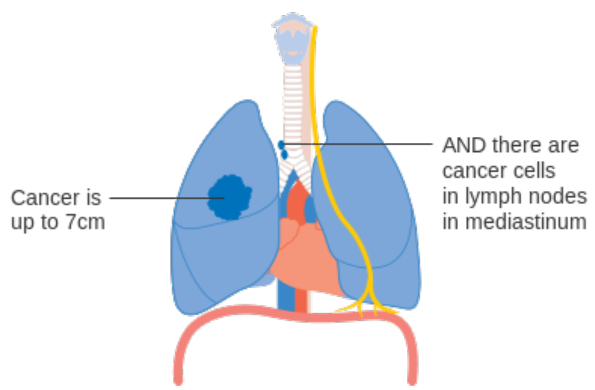


Figure 2.6 Stage IIIA lung cancer

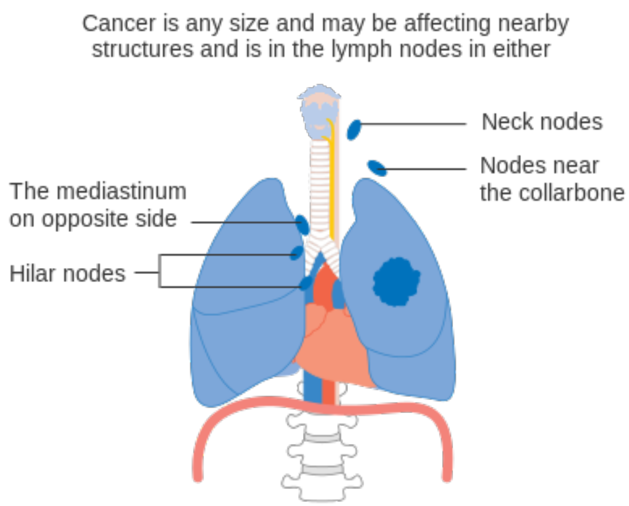


Figure 2.7 Stage IIIB lung cancer

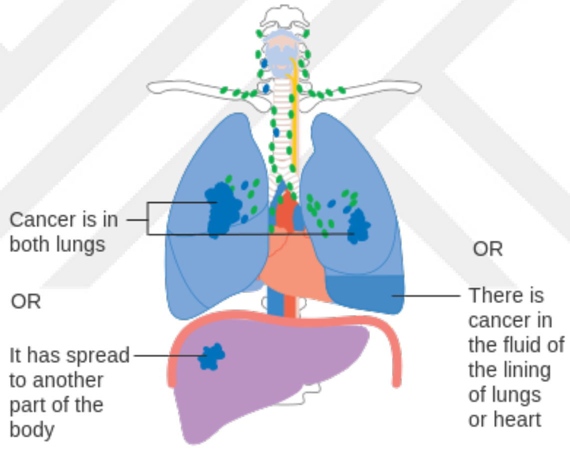


Figure 2.8 Stage IV lung cancer

2.2 History of Deep Learning

Many of the machine learning techniques and image processing techniques were until recently based on architectures with minimal surface structures, as these architectures contained two levels of transfers of non-linear properties at most. Examples of these surface architectures are: [24]

1- Linear and non-linear dynamic systems
2- Support Vector Machine (SVMs)
3- Gaussian mixture models (GMMs)
4- Kernel Regression

5- Maximum Entropy (MaxEnt)
6- Conditional Random Fields (CRFs)
7- Logistic Regression
8- And others [25].

These surface architectures were successful in fixing well-built or straightforward problems. Nevertheless, their incomplete form and figurative ability led to difficulties in facing more complex real applications such as applications that contain natural signs like human speech, visual scenes, natural language, and natural images [25].

However, the human-processing and data-processing mechanisms need architecture to draw out complex arrangements and make internal demonstrations by using the given input, such as speech production systems and receiving systems, set with hierarchical class arrangements to transfer data from the waveform layer to the linguistic layer. Also, the human visual system is naturally hierarchical, not only in the reception part but also in part generating information [26].

Deep learning emerged from the research field of neuronal artificial intelligence networks, and pre-fed neuronal networks equipped with hidden layers (called deep neuronal networks (DNNs)) are an excellent example of deep structural models. Backpropagation (BP), which became popular in the 1980s, was a famous procedure for learning its coefficients. However, the posterior proliferation alone did not work well with the learning networks that have a large number of hidden layers, and the struggle was the more significant the depth of these networks [27].

After many research and experiments, the use of hidden layers within many neurons within the deep neural network improves the strength of modeling these networks and begins to form many idealized formations. Even if a transformed path is disrupted, the resulting deep neuron network will continue to perform well [28].

Nevertheless, the use of deep and wide networks requires a large mathematical rule during the training activity, and this is the reason why researchers refrain from working with these networks until recently. Also, better education algorithms contributed to the success of deep neuronal networks, and SGD - stochastic gradient descent algorithms were the most effective with large training groups, and this is the case of most applications, as has recently proven its effectiveness in branch work through several machines in an asynchronous mode, or via several GPUs through Back-propagation [29].

2.3 History of Convolutional Neural Network (CNN)

"Neocognitron" was presented by [30] in 1980. It was motivated by another work [31] where it was presented the two essential kinds of layers in CNN networks which are convolutional layer and reductive layer. Furthermore, it described a filter as a set of adaptive parameters of such an element of the layers and presented the hierarchical and multilevel neural network where the layers that include elements whose receptor arenas cover rest layer's corrections [32].

In a different of a new component named chrysocetron, Fukushima's spatial mean is in its place. The max-pooling is a technique where the reduction unit calculates the extreme activation units in its correction [33].

Some supervised and non-supervised learning procedures have been projected over the decades to train the new component's weights. Nowadays, nonetheless, CNN construction is typically trained by using backpropagation.

Multiple network locations were initially required on CNN by neocognitron to have standard weights in the same network. Furthermore, to analyze, time-changing signals neocognitrons were adjusted for the first time in 1988 [34].

In 1987, a Time Delay Neural Network (TDNN) neural network for the temporal delay was presented by [35]. It was the first CNN, where it accomplished an effort for stability. Furthermore, weight updating was used with Backpropagation training. Therefore, using a hierarchical arrangement in neocognitron science resulted in a universal improvement of weights, rather than the limited level [35].

TDNN networks are CN that distributes weights in the period of processing. It allows signals to be permanently managed. In 1990, [36] presented a different shape that twisted 2D. Meanwhile, these TDNNs operate on the spectrum; the developing of voice recognition system has been consistent in both cases, as time and time change. This is a constant translation inspiration for image processing with CNN networks. The tiling of neuronal outputs can cover the time stages [36].

It was done by combining TDNN and best networks to achieve a separate, isolated speech recognition system. The TDNN network results were combined on the input signal using maximum aggregation, and then the aggregation layer outputs were transferred to the networks that perform the actual word classification [37].

In 1989, backpropagation was used to comprehend the kernel constants straightforwardly from handwritten images. It was fully automatic learning and implemented well comparing to non-automatic lab designs and was suitable for a wider array of image identification applications, and it has become the basis for modern computer vision [38].

In 1998, many banks applied the numbers categorized to recognize handwritten numbers on British checks: digital checks at 32 x 32 pixels. The capability to procedure high-resolution images needs more layers of CNN, and therefore this technique is reserved by the obtainability of computer resources [39].

Likewise, [39] for medical image processing was established as a stable NN. The NN is used to identify a character of input with image type in 1988 while in 1991the design and training system of an NN was modified and applied like cancer recognition in the breast.

The decomposition of one-dimensional photoelectric signals in 1988, using torsion was recommended to apply. Moreover, from here, it started to be the base for twisting-based designs [39].

Lateral connections and feedback have expanded an automatic feeding structure of the convolutional neural networks in the pyramid of neural abstraction. The CN permits the flexible integration of relative information to solve the limited problem. Unlike previous models, image-like outputs were created with the highest accuracy [40].

In the 1980s, a CNN was designed, its innovation in the two millennia of the last century required fast applications to GPUs. In 2004, [41] showed that standard NN could be enormously enhanced on GPUs where it is 20 times faster than CPU application.

The oldest CNN GPU app was explained in 2006 by [41]. It was four times quicker than the corresponding CPU execution. The following work used GPUs and, primarily, for other types of NN that were different from CNNs [41].

While in another work [42] in 2015, The DalleMolle Institute for Artificial Intelligence Research presented a deep standard NN combined with several layers that can be speedily trained on the GPU through backpropagation. The proposed network has beaten old machine learning approaches over the handwritten MNIST number index. While at 2011, they expanded their proposed approach to CNNs, accomplishing 60 quickening coefficients, with remarkable results, by using CNN networks on the GPU to win a photo identification tournament when they performed a special implementation for humanity. Among May 15, 2011, and September 30, 2012, the CNN networks have won at least four photo competitions. Later an expressively upgraded implementation in the literature of databases. [42]

Next, a related Graphics Processing Unit built CNN by [43]. The project won the ImageNet Large Scale Challenge 2012, and Microsoft won the ImageNet 2015 competition [43]. Compared to training CNNs using GPUs, slight notice has been paid to the Intel Xeon Phi processor. The observed growth is a parallel technique of training CNN on Intel Xeon Phi, called Hogwild Measured, with an arbitrary command for CHAOS synchronization. CHAOS takes advantage of both thread-level parallelism and SIMD available on Intel Xeon Phi [44].

Nevertheless, due to the complete interconnection among the nodes, it did a good measure with high-resolution images within a dimensional curse. An RGB color with a 1000 x 1000pixel image is too big to be effectively processed on a large scale with full connectivity. For example, in CIFAR-10, only images are 32 x 32 x 3 32, 32 channels, three-color colors, so one neuron completely linked to the normal nervousness's hidden layer would be the mesh 32 * 32 * 3 = 3, 072 weights. However, the 200 x 200 image would result in neurons having 200 * 200 * 3 = 120,000 weights [45].

Likewise, the intensity of calculating the spatial structure of the data has not been recorded in network architecture and treating the input pixels that are different from each other in a matching way as pixels adjacent to each other. This reference location is ignored in image data, mathematically, and semantic. Consequently, neurons' complete conduction is wasted for reasons like an image recognition controlled by local spatial input patterns [46].

CNN is biologically inspired modifications of multi-layer sensory perception proposed to simulate a psychologist's behavior. These representations mitigate the experiments modeled by the multi-layer perceptron structure by exploiting the reliable limited spatial connection found in natural images. Unlike multi-layer perceptron, CNN networks are based on [47].

- Distinguishing features:

The feature lets CNN succeed in simplification of computer vision problems. Weight updating greatly decreases the number of learned parameters, therefore reducing memory requests for CNN operation and permitting for the training of big and more powerful CNN networks [48].

- Building blocks:

The network structure is created with a set of different layers that converts entered size to the output volume, for example, asset row grades with a different function. A limited kind of layer is frequently used. The building block is the primary bypass layer of the CNN network. The parameters contain a set of learnable kernels with a small approximate field. However, the extent of full-depth is in the input size. Later, each kernel is bound within the volume's width and height, which calculates the point produce among the kernels and the input and produces. Consequently, the network discovers that filters are activated when a particular form of operation is found in any spatial location in the stream. Stacking maps with all filters along the dimension will deepen the entire warp layer output layer size. Increasing items of production size can be construed as the product of a neuron that scans a small area in the input and shares neuron variables within the same activation map. [49]

It is not feasible to link neurons to any previous volume neurons while working with high dimensional inputs like images; as such network engineering does not understand the data's spatial structure. CN uses the local spatial connection by implementing a random pattern of local contact between neurons with neighboring layers: each neuron is linked to a small input volume area [50].

The distance of the conductivity is a hyperlink known as the neuron receptor field. Connections are local along width and height in space, but they always spread throughout the whole input range. This structure ensures that the learned filters respond to the local spatial input pattern most strongly [50].

2.4 Related Work

As mentioned before, many researchers' goal in the medical field is the attempt to develop systems that can have an advantage against cancer disease and that these systems can detect cancer in its earlier stages, so the chances of recovery are higher. This section will review some of the literature of similar and previous approaches. The proposed works are based on different machine learning algorithms and different types of cancer.

A work done by [51] used deep learning and CNN for lung cancer detection. The work is based on computed tomography (CT) scans; the CT scans are trained by using a double convolutional Deep Neural Network. The developed system is used to detect the Tx cancer stage, which can help to determine the possibility of lung cancer. The system was divided into two main parts: the first was to make the convolutional Deep Neural Network which is more intensive by per classifying the inputs of CT scan images from a dataset by using K-means algorithm, and the next step was built on a double convolutional deep neural network and that the results of the tests have shown an improvement in the accuracy from regular convolutional Deep Neural Network where the double convolutional Deep Neural Network was 0.9962, and the normal was 0.876.

In [52], detection and classification of breast cancer were done using analysis and gene-back proportional neural network algorithm. The researchers used two algorithms, which are K-nearest neighbor (KNN) and Naïve Bayes, to determine breast cancer. The dataset that was used was collected from the University of California, Irvine. Their main aim of the work was to predict the features of the dataset by using machine learning. The proposed system started with the preprocessing stage to find the dataset's missed attributes after that the system found the feature vectors. The test for detection has been done by using the Gene-back propagation neural network approach and kernel principal component analysis. The results showed improvements in the error rate, which was less and higher accuracy.

A similar work [53] tried to prove that the convolutional neural network can deal in conjunction with encoding schemes. Their proposed work was based on a convolutional neural network for cell detection, and the system encoded the output pixel space. The researcher uses random projections to encode the images to a vector of set dimension, and then, regressing the vector is done by CNN from the input pixels. In this work, the researchers used seven typical datasets with different target cells and other evaluation and comparison approach.

In [54], the implementation of ANN Classifier using MATLAB for detecting skin cancer was proposed. In this study, a computer-aided classification and dermoscopy image of skin cancer have been used, and many preprocessing steps and segmentation to separate the cancer skin part from normal skin were applied. Some features have been extracted by using the ANN classifier and classified the data into cancerous and non-cancerous.

A similar work where [55] artificial neural network has been efficiently tested on two cases; in both pre-clinical and post-clinical diagnosis. Their work's primary purpose is to support clinicians in medical diagnostics to improve functioning and easy-to-use systems, procedures, and techniques. The work was based on analyzing demographic records from lung cancer patients to develop diagnostic systems that may increase the emergency unit's triage practices.

In [56], a brain tumor detection and classification with feed-forward backpropagation neural network has been developed. In this work, a process on the images is taken from MRI to present a statistical analysis morphological and thresholding techniques where feed-forward backpropagation neural network is used to classify the tumors, this technique results in high accuracy and fewer iterations recognition. The validation performance extended the maximum, where the specificity was 97.2%, accuracy is 99.2%, and sensitivity is 97.2%. The proposed system's comparison results with other existing systems show that the proposed system gave additional accurate results.

In [57], breast cancer recognition pictures are the typical clinical practice for the diagnosis and prognosis of breast cancer. In work, the authors have presented a full algorithm for the recognition of abnormal masses by anatomical segmentation of the Breast Region of Interest (ROI) by using the mediolateral oblique (MLO) view of mammograms. The suggested system is based on the marker-controlled watershed segmentation algorithm (MCWSA) by using MATLAB. The suggested system results displayed that the algorithm has a higher computational efficiency besides the worthy functioning for image segmentation problems if it is matched to the conventional methods where the systems are faster and more efficient with specifying an automatic value for the threshold.

The aim behind reviewing the mentioned related works is to show the importance of machine learning in medical research recently and specifically in the early detection of any type of cancer. Different types of cancer detection systems have been reviewed with different methodologies of machine learning. In this proposed work, a deep convolutional neural network to recognize lung cancer types and normal lung has been developed in order to understand how deep learning and convolutional neural network work, how to build the network layers and train and test the CT scans, and to understand the parts of the lung under the CT scan, as it is shown in Figure 2.9.

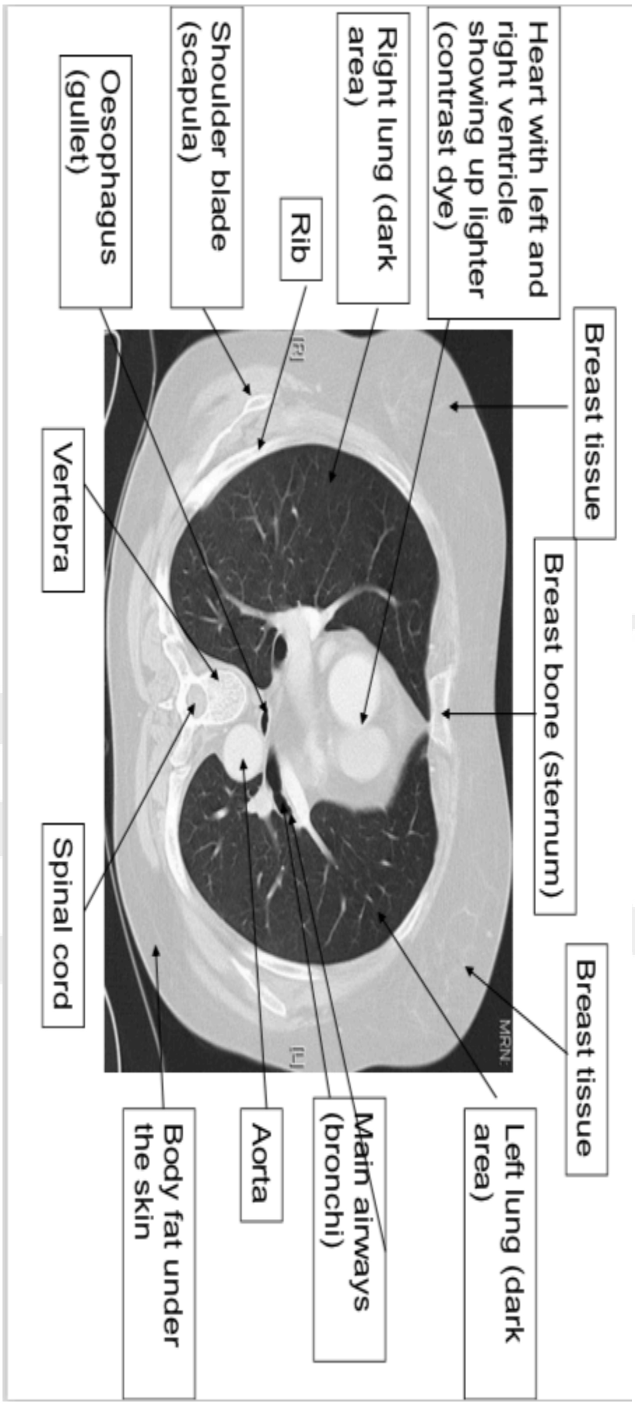


Figure 2.9 Normal CT scan of the chest

CHAPTER 3

METHODOLOGY, DATA COLLECTION, AND TOOLS

In this chapter, the methodology is mainly studied in the design of the identification system for the approaches used in this work, and the essential functions of the planned methodologies are discussed.

3.1 Machine Learning

Artificial intelligence has recently captured the entire world's attention and it is one of the most critical research fields where the world seeks to achieve technological development and unprecedented progress. Indeed, that interest was not in vain; many models have emerged confirming that artificial intelligence has approached competition of human intelligence, and this has been noticed by creating self-driving cars, robots, and many more smart devices [58]. With this being achieved, success after another, the area of interest has increased more and more with what is known as machine learning and the development to move towards more significant successes in employing artificial intelligence. However, what is machine learning, its importance and principle of its work will be described in the next sections.

3.1.1 What is Machine Learning

Computer training alluded to by the ML acronym will simplify the idea of machine learning as a branch of the Artificial Intelligence Science (AIS). Based on the different modes of computer programming, the ML will function and execute instructions assigned to the learning system on the basis of the available data. It is notable that in 1959, the word machine learning was instigated in IBM laboratories by the founder of artificial intelligence [59]. The computer should also be responsible for making decisions as appropriate and deciding what tasks will be carried out, where, how, and why without any human help. This should ultimately lead as efficiently as possible to completing tasks as humans are spending time completing tasks [59].

3.1.2 The Principle of Machine Learning

At first, it can be challenging to understand the machine and how it can be achieved, which seems unlikely, but many practical applications of artificial intelligence based on the theory of machine learning have emerged, including the Sofia robot [60]. Concerning the principle of its function, algorithms form the basis on which machine training is implemented since such algorithms are composed of a set of orders, instructions, and instructions required to direct the machine or computer to perform tasks. As the strategist performs the role of algorithms in a computer due to data heterogeneity, it is obtained, analyzed, and eventually dependent on the data analyzed to determine how the task is to be done [61].

Machine learning algorithms are based on a range of graphical models and decision-making techniques such as the decision tree, natural language processing, and artificial neuronal networks to carry out the task of automating and analyzed data and processing. In this way, the computer is driven to make choices and efficiently execute its assigned tasks. It is important to remember that the artificial neural networks used in machine learning play an essential part, similar to the nerves' functionality and their network in the human body and brain. Starting with the complex role of algorithms and devices, there is an immediate need for what is called deep learning [61].

3.1.3 The Goals of Machine Learning

The importance of machine learning can be explained in the following points:

- The large size and diversity of data
- The increase in computing power
- Data processing and the increase in the storage capacity of data
- Analyze data more volumes and more complex and reach faster and more accurate results
- Produces or generates high-value forecasts.

Computer schooling can more effectively predict actions and understand habits than human beings. Machine learning, thousands of models can produce [62].

3.1.4 Types of Problems and Tasks for Machine Learning

Machine learning problems and functions are classified into three groups according to the existence of the learning signal or input available for the learning system as follows [63]:

3.1.4.1 Supervised learning

It is also named as predictive learning. In this kind of learning, via pre-defined inputs the machine is trained, such as a group of pre-classified, task or non-task, and how the input is required to link inputs with outputs to make a prediction of the input of any type of input in the future for any type of prediction. A machine learning system is most classified into these types [63]:

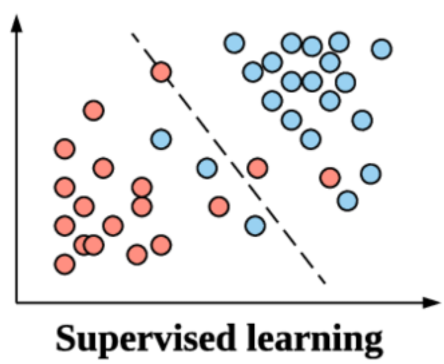


Figure 3.1 Supervised Learning

- Classification

It is the type that is most commonly used in learning the machine. In this type, the income is filtered into two types or more [63].

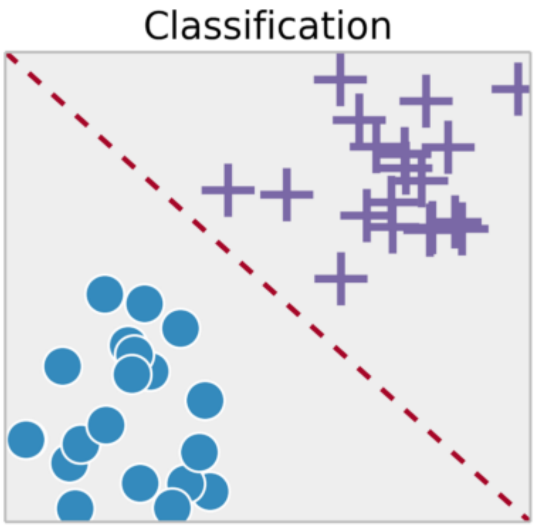


Figure 3.2 Classification

- Regression

This type is similar to classification, but it predicts continuous values rather than separating classes. There are many applications for this type as well, such as forecasting stock prices and forecasting temperature inside the building, depending on weather information, time, and sensors available [64].

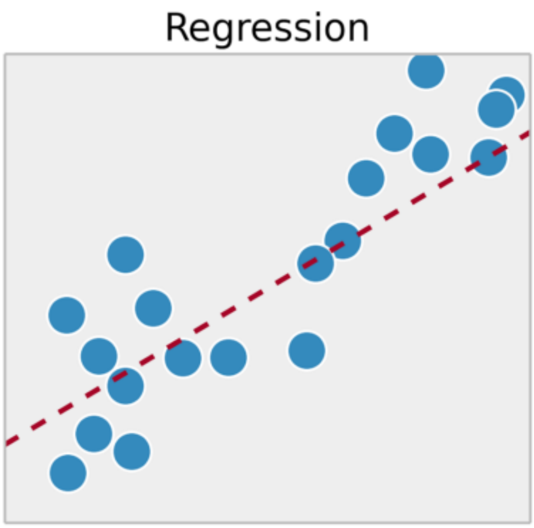


Figure 3.3 Regression

3.1.4.2 Unsupervised learning

It's named descriptive learning, this kind of learning is machine trained in the input data without any previously known outputs, and the goal here is to infer new copies and hidden relationships between the data [64].

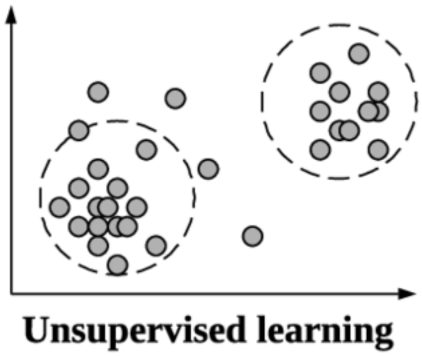


Figure 3.4 Unsupervised learning

- Clustering

In this type, the difference is sorted by entering into previously unknown groups. Its applications learn the person's movements standing in front of the camera, recording to their movements. So that the system can subsequently get familiarized with these movements, linking them to the appropriate response, and from other applications in the field of their purchase in the process of collecting and using each user's process in the process of collecting them and using them in their collection [65].

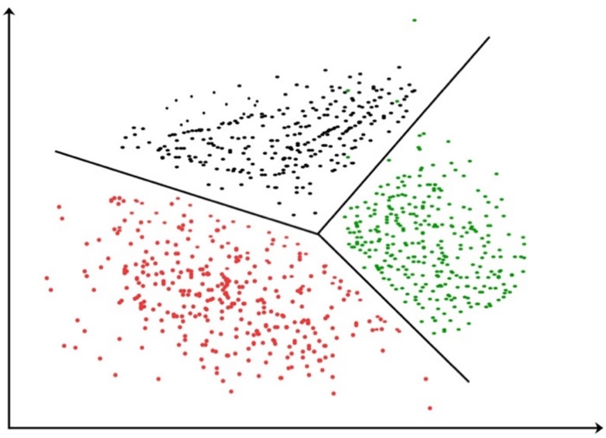


Figure 3.5 Clustering

3.1.4.3 Reinforcement Learning

In this type, learning how to behave at a specified event is set by giving signs of reward or punishment based on the current behavior [66].

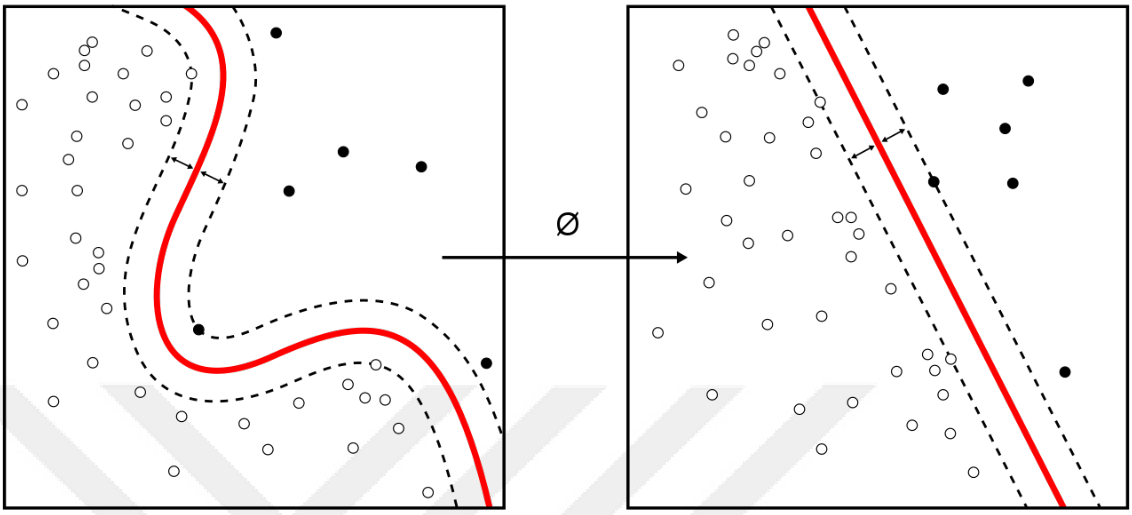


Figure 3.6 Reinforcement learning

3.1.5 Machine Learning Algorithms

In machine learning algorithms, usually, the program will learn what it must do on the data automatically, without specific commands from the programmer. For example, facial recognition, the program automatically extracts distinct features that help it differentiate between different faces, and then uses it when entering a new face image to recognize it automatically. The process of extracting the distinctive features is in the stage of learning or training, and then the program can be used and ascertained in the testing phase when entering a new image.

There are many of machine learning algorithms, some of which are aimed at finding the best mathematical equation to represent data, some of which are based on statistical concepts such as probability, and others that use different theories such as Graph Theory, as well as a group based on Heuristic rules. The common factor among all of these algorithms is their attempt to find the best model, which reduces the data given in a way that includes generalization when using new data [67].

3.1.6 Neuron

To understand CNN and ANN algorithms, the structure of the biological neuron must be explained. Neuron, which is the primary nerve unit or nerve cell, has nerve fibers that are, in turn, the nerves in association with other neurons. Each neuron consists of the primary cell body that contains all the animal cellular organelles but is characterized by having many ramifications that connect it to other neurons, as it has a single branch long supported by a hard sheath called the axon [68] as it shown in Figure 3.7.

The human nerve cell consists of:

- Dendrite: Thin fibers around the cell body. The branch receives information from neighboring cells through the axon, which acts as transmission lines.
- Axon: is a cylindrical connection that carries pulses from the cell. Each branch of the axis is connected to branches (dendrites) to neighboring cells.
- Synapse: Axon and synapse are called dendrite [69].

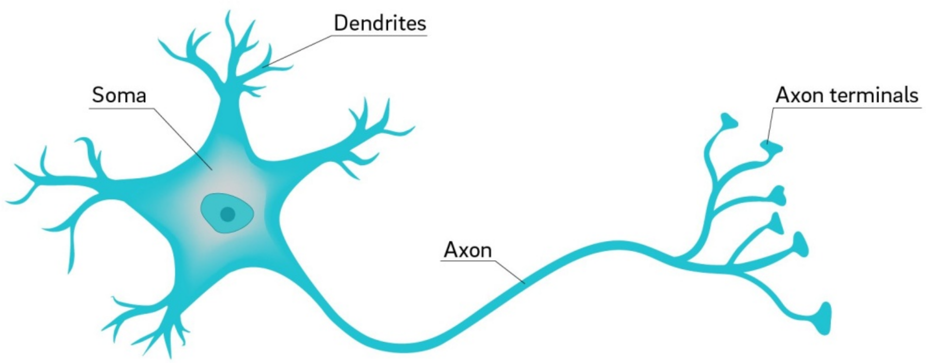


Figure 3.7 Neuron [70]

3.2 Deep Learning

Deep learning and analysis techniques in recent years have evolved and have influenced a wide spectrum of study, both conventional and new, on signal and information processing in the specific fields of machine learning and the fundamental principles of artificial intelligence. There are many descriptions of deep learning, mainly [71]. Deep learning is a class of machine-learning techniques that can utilize many layers of non-linear processing of information to retrieve and distribute, besides examining and classifying patterns, properties with or without supervision.

Deep learning can be considered as a sub-field in machine learning where such algorithms are used for the modeling of complex relationships within datasets. Therefore, characteristics and high-level models are classified based on what they are, for example (cars are known for their parts and wheels are known for their parts, etc.), and such a structure is known a hierarchy [72].

Machine learning is part of a larger class of methods in computer representation learning where the research contains ways to find and identify, and how these representations are to be taught which that's known as deep learning. So, a deep learning like any learning system relies on many layers of representations, which correspond to a frame of characteristics, factors or concepts, and high-level features. Like an image can be displayed in many forms (such as a beam of pixels), or any representations in order for the learning to done easily [43]. A deep learning is also known as set of algorithms based on machine learning to be taught at many stages that suit the same complexity and using artificial neural networks [43].

While many researchers try to bring new innovations within the world of machine learning, however, the actual aim is to get machine learning back to one of its core goals which is artificial intelligence. As well as, to concentrate on learning the various layers of representation and inference that help better understand data like pictures, videos, and texts [73]. The two fundamental general principles of machine learning are found in the below definitions:

- The development of structures consisting of several non-linear stages of information processing.
- Learning approaches representing more abstract qualities at higher levels, with or without supervision.

There are many areas in which deep learning is positioned within, and they are neural network science, artificial intelligence, graphical simulation, optimization, pattern recognition, and signal processing [74].

The increased capacities of chip computing, such as graphics (GPGPUs), are the reason to make machine learning prevalent and common, also, they help to have bigger amount of data during training.

The effectiveness of deep learning can be seen in a variety of different fields, such as computer vision, verbal recognition, voice testing, identification of expressions, photography and rhetorical coding, comprehending of natural languages, semantic speech classifying, handwritten recognition, processing of voice, data extraction, robotics, and molecular analysis which have shown to be successful. [11]

3.2.1 Deep Learning Network Classes

As mentioned earlier, deep learning handles several layers of non-linear, hierarchical, naturally occurring information processing. Depending on how the structures and techniques are used (formation, identification, or classification), it is possible to classify work in this field into three categories:

1- Deep networks for learning without or without supervision

It is used when no information is available on the number of target rows or their designations as these networks capture high-level correlation of income data trying to analyze it and reveal patterns in these data [43].

2- Deep Networks for Observed Learning

It is excellent for classifying patterns by accurately describing the target rows according to the visual data. The defined target data is always available, either directly or indirectly. Networks, in this case, are called deep discriminative networks [43].

3- Hybrid Deep Networks

Deep learning algorithms have almost the same algorithms as Neural Networks, which already acronym with NN. This is, to some degree, true. However, the only distinction between the two forms of NN and DL is the extent of its depth or the amount of hidden layer existing in the algorithm, as seen in the Figures 3.8 and 3.9 below. Deep learning algorithms, therefore, constitute a natural extension of neural network algorithms. However, the number of hidden layers relative to neural networks in deep learning, as mentioned earlier, has further complicated learning in deep learning. This was very difficult in the past, both for the complexity of the algorithm and the need for or for the low technical capabilities compared to the need [43].

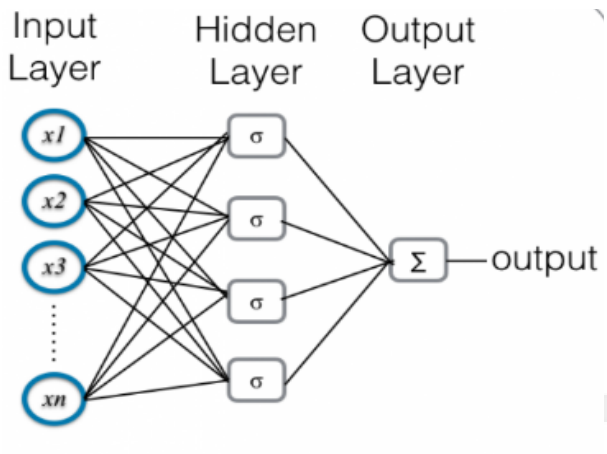


Figure 3.8 Hybrid Deep Networks

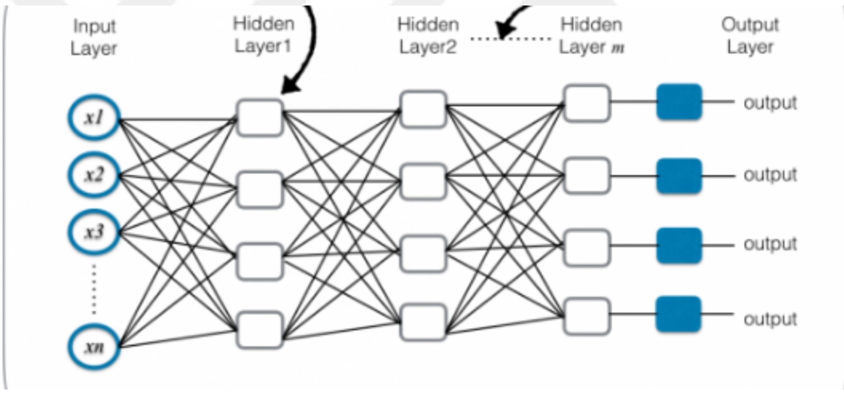


Figure 3.9 Hybrid deep networks with more information

3.3 Convolutional Networks

It is a subset of deep neural networks, typically used for visual image processing. A CNN or ConvNet in deep learning is known as shift invariant or space invariant artificial neural networks which is based on specific weight architecture and the properties in translation invariance. They include image and video recognition tools, guidance programs, image processing, medical image interpretation, and natural language [75].They include image and video recognition tools, guidance programs, image processing, medical image interpretation, and natural language [75].

3.3.1 Contents

CNN networks consist of frequent multi-layer knowledge updates. Multi-layer perception typically involves networks that are entirely connected, implying that each neuron in one layer is related to all neurons in the next. Such networks' "complete connection" renders them susceptible to data synthesis. Typical regulatory approaches require the application of a sort of weight to the loss function. Throughout the operational method, the CNN networks utilize structured data structures and extract more complex trends utilizing fewer, more accessible trends. CNNs are thus situated at the lower end of the interconnection and complexity scale [75].

Biological processes have been inspired by convolution networks as the pattern of communication between neurons is close to the animal's visual cortex. Specific cortical neurons only respond to stimuli in a small visual field region known as the receptor field. The receptor fields of different neurons partly overlap and occupy the whole visible region [76].

In comparison to other image recognition algorithms, CNNs use very few preset. The network thus discovers filters that are manually programmed in conventional algorithms. This freedom from previous experience and human activity is a significant asset in product design [76].

The concept of "Convolutionary neuralgia" relates to a statistical mechanism called convolution being used by the network. Torsion is a type of linear process that is specialized. Convolutionary networks are essentially neural networks that multiply over at least one layer by a convolution rather than the general matrix [76].

3.3.2 Design

The convolutional neural network is composed of a matrix of input and output, as well as numerous hidden layers. The hidden layers of CNN typically consist of a sequence of bypass layers. The activation feature is typically the RELU layer, preceded later by other grids such as the add-on layer, the fully linked layers, and the normalization sheet, often referred to as hidden layers as the activation mechanism, and the final wrapping covers their inputs and outputs. In addition, the final torsion requires the back dumping to raise the exact weight of the finished component [77].

While layers are regarded as chopping colloquially, it is only carried out through consensus mathematically, scientifically it is either a sliding point component or while programming CNN, the input is a tensor can be calculated by:

$$N * W * H * D \tag{3.1}$$

Where N is number of image shapes, and W is width of the picture, H is height of the picture and D is the depth of the picture.

Then the image is abstract in the function diagram where it is equal to:

$$N * W * H * F \tag{3.2}$$

Where the N is number of picture types, W is diagram width, while H is function map height and F is feature map channels [77].

Data is inserted into the convolutional layers entrance, and the output is passed to the next stage. This is equivalent to the reaction of neurons to a specific stimulation in the visual cortex. Every neuron process data can include local or global grouping layers for simplifying the basic calculation only for Convolutional networks. Aggregation layers minimize data size by integrating neuronal community outputs into a neuron in one layer in the next layer. The classification of geographic aggregations blends multiple classes, typically 2 x 2. The global aggregation operates in the convolutional layer on all neurons. The accumulation may also be measured as a maximum or average. The maximum pool uses the maximum value of each neuron category in the preceding row. The median aggregation uses in the preceding layer of the median value of every neuron group [78].

Each neuron in one layer is fully linked to each neuron in another. It is precisely the same as the conventional MLP multi-layer neural network. The matrix is flattened to bind to the picture classification in the entire layer [78].

Every neuron generates feedback from a variety of positions in the last layer of neural networks. Each neuron receives feedback from each of the previous layers in a fully connected layer network. Neurons obtain only contributions from a small sub-region in the convolutional layer of the previous sheet. The semi-region is typically square, e.g., dimension 5 by 5. The region of neuronal penetration is called the field of the receptor. Therefore, the reception area of a fully connected layer is the entire previous layer. The receiving area in the convolutional layer is smaller than the whole previous layer [78].

In the NN, each neuron determines the outputs' importance by adding a specific function to the inputs from the receptor field in the preceding layer. The function that is utilized for the input values is calculated by the vector of weight and bias, typically real numbers. Learning enhances the neural network by iterative modification of these biases and weights [79].

The filters are called weight and bias vectors, which reflect other input features such as a particular form. CNN networks are characterized by the fact that multiple neurons may use the same filter. It decreases the memory size the vector weights are utilized in every receiving field that has shared that specific filter, contrary to each receptive field that possesses its vector weight and bias [79].

CNN design follows the work of adjacent vision processing cells containing similar, overlapping, rough fields. The area of the future changes size and location regularly across the crust to form a comprehensive map of the visible area. The shell of each hemisphere refers to two different cell types of the brain defined from their 1968 paper: Hubel and Wiesel have proposed that these two cell types may be included in the pattern recognition exercises as cascading patterns [79].

3.3.3 Basic Operations in ConNet

There are four basic operations in ConNet in Figure as follows:[33]

1- Convolution

2- Non-Linearity (or as it’s known it by using ReLU)

3- Pooling or Subsampling

4- Classification

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Figure 3.10 The input image

Also, assuming another 3x3 smaller matrix, that would be the kernel.

1	0	1
0	1	0
1	0	1

Figure 3.11 3x3 smaller matrix

1-Convolution

What will happen now, as shown in Figures 3.12 – 3.19 is that the properties resulting from the wrapping process (known as the feature map or Convolved Feature) will be extracted by swiping the Kernel box (the yellow matrix) over the green matrix (the original image). In each step (Stride), the two matrices will be multiplied together, and the product of the multiplication will be added to extract one value in the properties map (the pink matrix), which will be 3x3 size. It should be noted that the yellow Kernel square only sees a portion of the image entered in each pass [33].

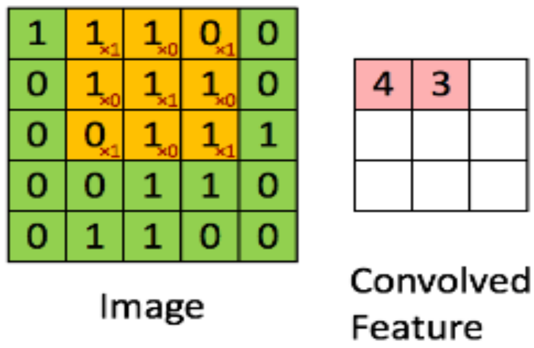


Figure 3.12 Wrapping process step 1

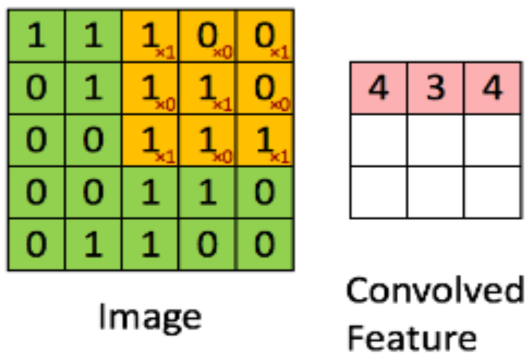


Figure 3.13 Wrapping process step 2

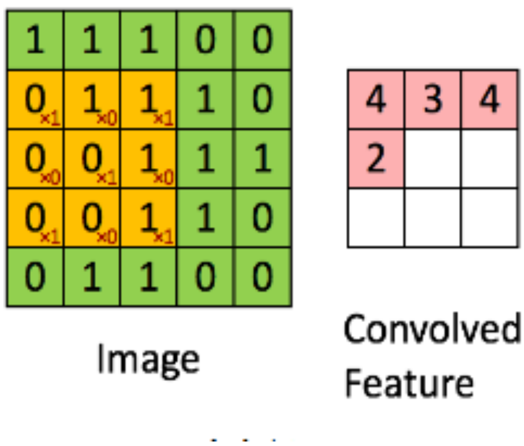


Figure 3.14 Wrapping process step 3

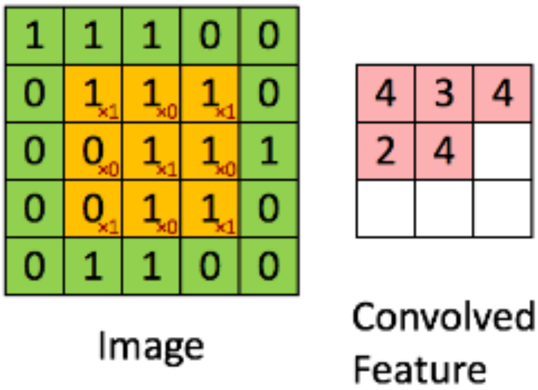


Figure 3.15 Wrapping process step 4

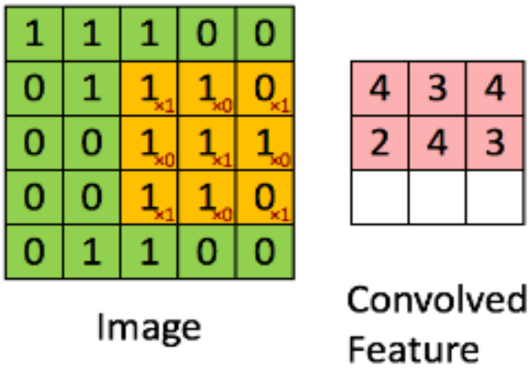


Figure 3.16 Wrapping process step 5

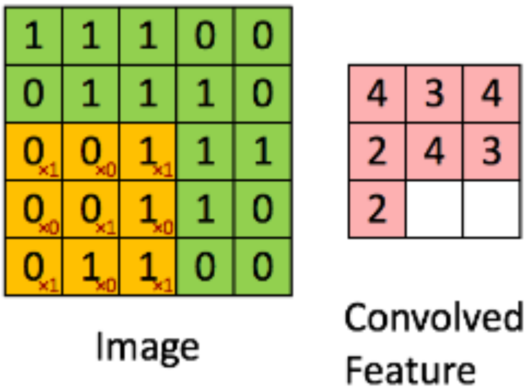


Figure 3.17 Wrapping process step 6

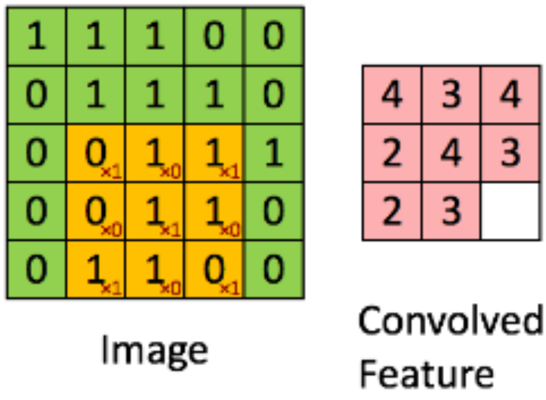


Figure 3.18 Wrapping process step 7

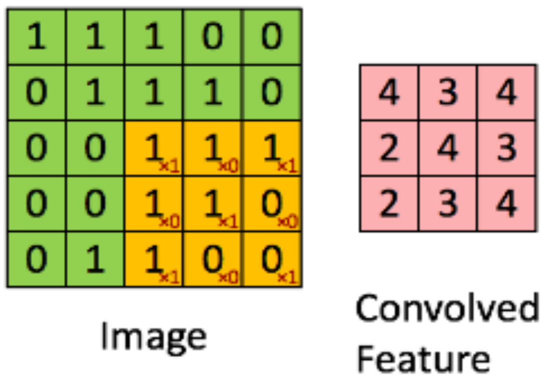


Figure 3.19 Wrapping process step 8

The properties' size map (wrapped properties) is determined via three fundamental parameters that must be known before performing the first step (The Convolution step):

- Depth

The depth denotes the number of filters used for the wrapping process, as shown in the Figure 3.20 where it has implemented the wrapping process on the original image using three different filters, thus, three feature maps of the input image will be generated as if they were three matrices stacked on top of each other. Thus the "depth" of the properties map becomes three [33].

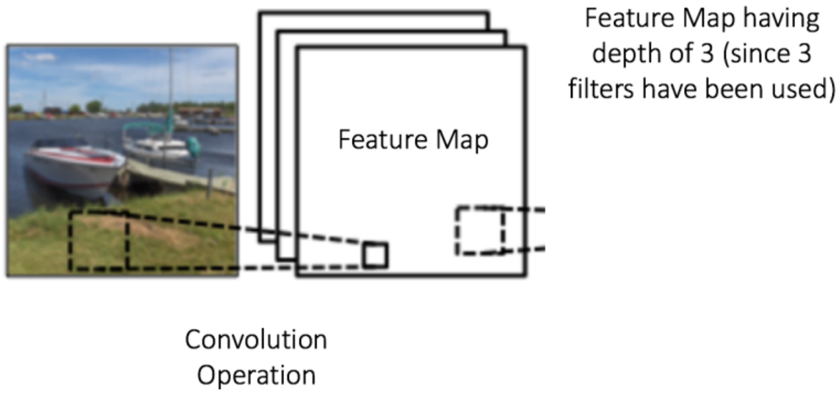


Figure 3.20 Wrapping process depth's

- Stride pass-through

Pass step is the number of pixels used when passing the filter matrix onto the input image matrix. When the pass step value is one, it moves the filter only one pixel in succession, and when the value becomes two, then the filter jumps two pixels at a time. It should be noted that when it has a large size of the passed step, this means that we will get maps of small size properties [33].

- Zero-padding

Sometimes, it is convincing that it can line the input image matrix with zeros around the edges of the image and thus pass a filter over these edges. The properties extracted from the zero paddings allow it to control the feature maps' size. The addition of zero linings is commonly identified as wide convolution, and narrow convolution is known for not adding [33].

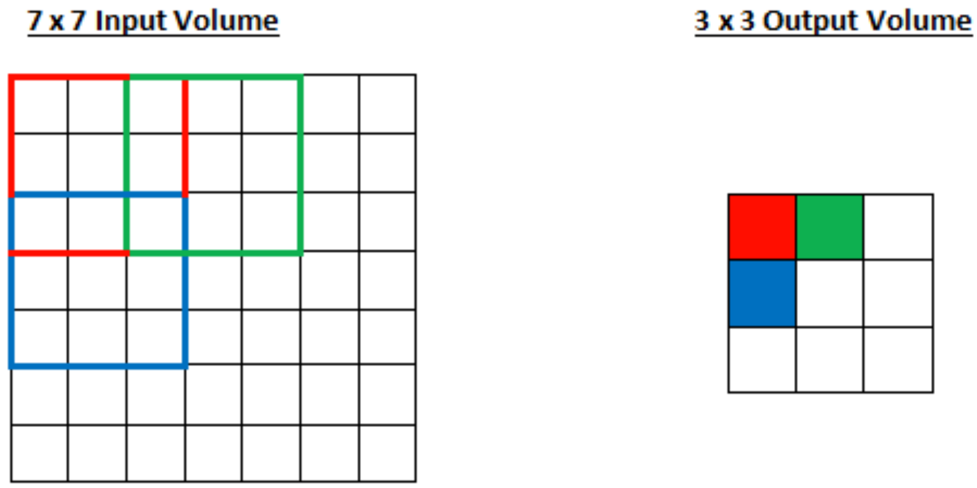


Figure 3.21 Wrapping process zero padding

2- Non-Linearity

Another process, named ReLU, is utilized following each convolution process. ReLU is an acronym for Rectified Linear Unit, which is basically a non-linear process whose output is as follows.

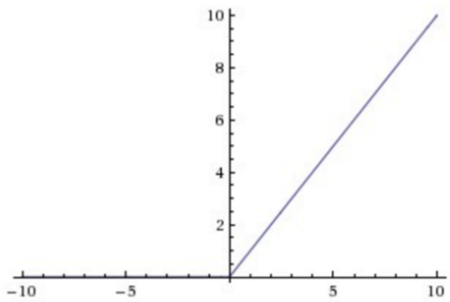


Figure 3.22 ReLU

where

$$\text{Output} = \text{MAX}\ (\text{zero}, \text{Input}) \tag{3.1}$$

ReLU is a process that is applied per each pixel; in other words, an element-level process that substitutes all negative pixel values in the property map with zero. The goal is to bring out non-linearity in ConvNet as most actual projects are non-linear. Basically, convolution is a linear element-level linear process in terms of multiplication and addition operations. So, it uses non-linearity by RelLet in ConvNet [33].

The ReLU process can be clearly assimilated, as it shows the application of ReLU to one of the characteristic maps extracted from. Resulting from the application of the ReLU to the feature map is known as the Rectified feature map [33].

The ReLU function is not the only non-linear function. There are other functions such as tanh or sigmoid, but the ReLU was characterized by better performance in most cases.

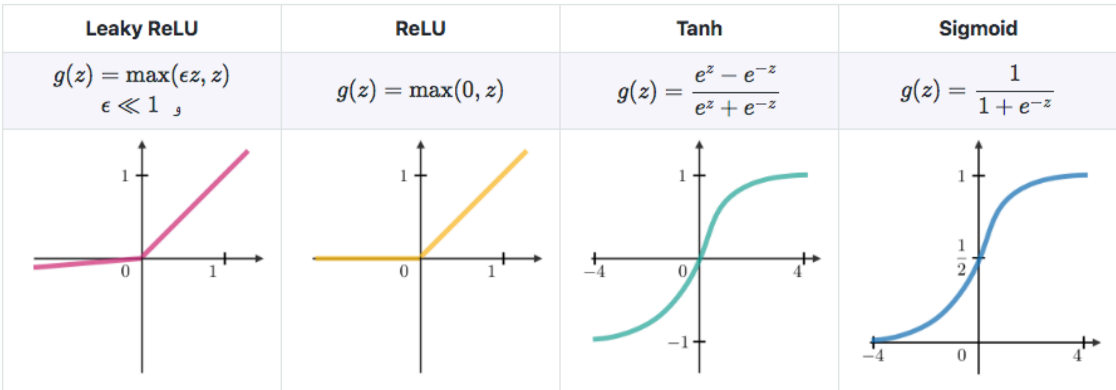


Figure 3.23 Functions

3- Pooling or Subsampling

Spatial aggregation, or also known as subsampling or downsampling, decreases the dimensions of every feature map with regard to maintaining important information. The spatial aggregation has several types, such as Max (Average value), Average (Sum calculation). In the case of grouping using the highest Max Pooling value, it defines the contiguous spatial region (a 2x2 window for example) and extracts the element (pixel) with the highest value in the specified window from the map of the corrected properties. In the same way, if it uses average, it will calculate the average numbers in that window only or their sum in the case of the sum. In general, aggregation using the highest max-pooling value showed a better performance [80].

Figure3.24 shows an example of using aggregation using the highest Max Pooling value on the map of the corrected properties extracted after the convolution process in addition to the ReLU process using a 2x2 window.

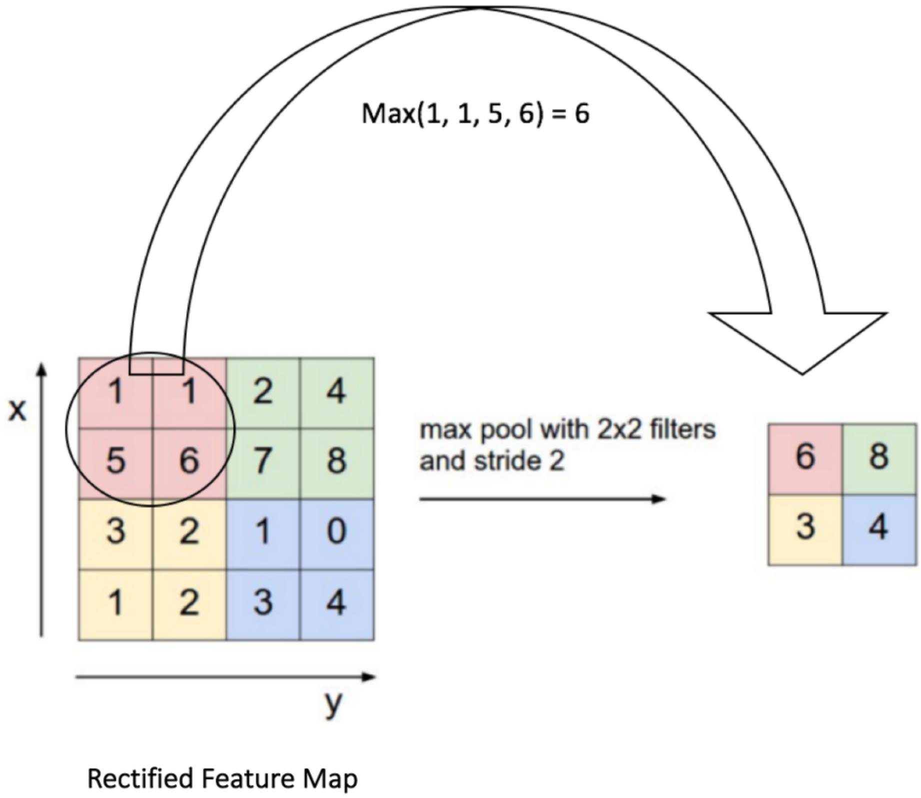


Figure 3.24 Pooling or subsampling

It passed a 2x2 window where the stride pass value was two, and then it took the highest value in every spatial region. As noted in the figure, this process decreases the properties map's dimensions from 4x4 to 2x2 [80].

In the grid demonstrated in the Figure 3.25, the pooling process was applied independently to each feature map, and accordingly, it obtained three resulting maps from three entered maps [80].

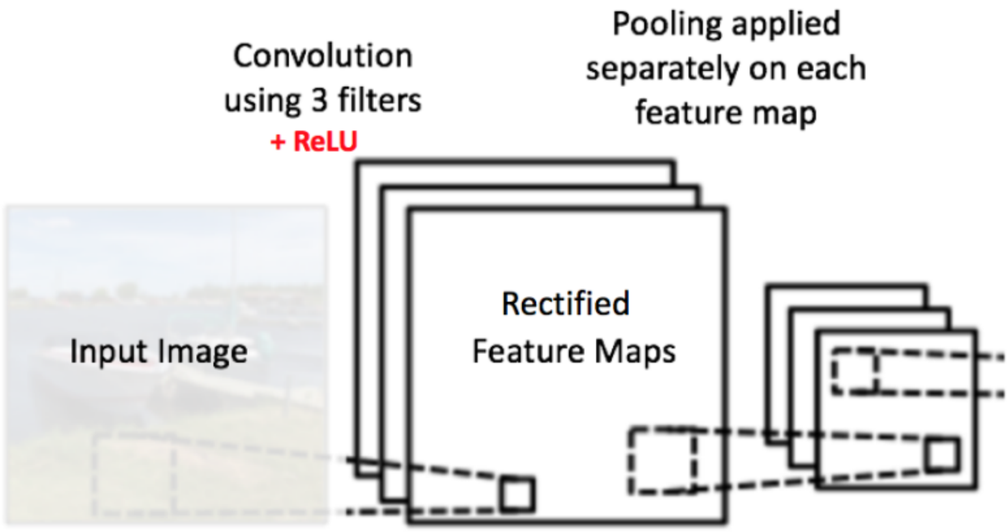


Figure 3.25 The pooling process

The pooling process continuously reduces the size of the spatial inputs, and in detail, it does the following:

- It makes the representation of the inputs in the properties' matrix smaller in terms of the size of the array dimensions, and therefore their management is more straightforward.
- It reduces transaction volume and network account size, and thus the overfitting problem can be controlled.
- It makes the grid steady and resistant to minor changes, distortions, and shifts in the input image (meaning that slight distortion in the inputs will not alter the pooling process's output since the maximum/average value in the adjacent local area is taken.
- It assists in achieving a stable and stable illustration of the image (the precise expression is equivariant), and this is a compelling feature because it enables the identification of the objects in the image regardless of their whereabouts [80].

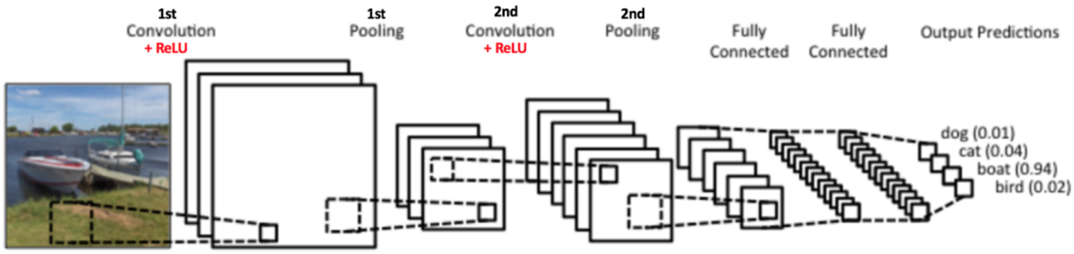


Figure 3.26 The full process of pooling

4- Classification

The fully connected layer is the conventional multi-layer layer that utilizes the softmax activation function in the output layer (it is possible to use other classifiers in the output layer such as the SVM support vector. [81], but in this thesis, the explanation will stick to the softmax function). The term "fully contacted" indicates that each neuron in the previous layer is connected to every neuron in the next layer.

The outputs from the Convolution and pooling layers denote the high-level properties of the input image. Therefore, the full contact layer's goal is to employ these properties to classify the input image into several categories based on training data. For example, the tasks of classifying the input image that we previously made have four possibilities (dog, cat, compound, bird), as shown in the Figure 3.27 where it does not show the connections between neurons in the entire contact layer [81].

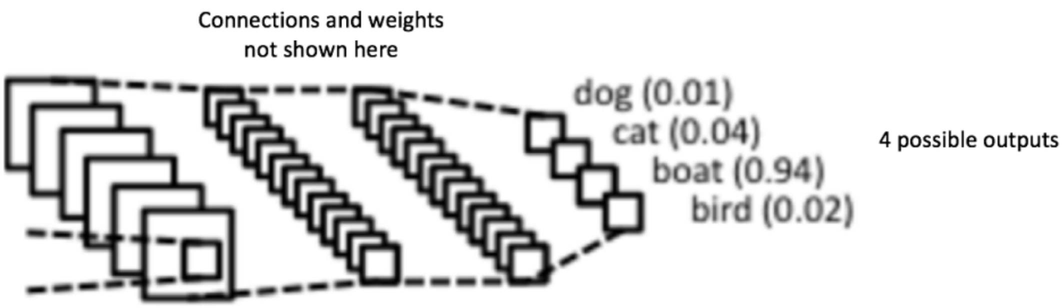


Figure 3.27 Fully Connected Layer

Beyond the classification process, adding the fully connected layer is usually an inexpensive way to teach non-linear compounds of these properties. Most of the properties extracted from the Convolution and pooling layers could be useful for classification purposes, but compounds consisting of these properties may be better.

The sum of the probabilities output from the fully connected layer is equal to the value one, and this is what the softmax activation function verifies in the output layer in the full contact layer. The softmax activation function takes a random vector of real values and then crushes it into vector with values that are between zero and one so that the sum of their sum equals one [81].

3.4 Backpropagation

Backpropagation is considered as one of the teaching approaches for neural networks that secure the transfer of information in the reverse direction of the original direction of information arrival.

This approach is based on the controlled learning theory. During the training process, specific data are required to provide the network with the necessary input data with the correct output data, supplemented by inputs to the income data in order to reach the network's output value. Then the estimated output corresponds to the expected performance. When the outcome does not fit, for any outcome layer neuron representing an error value, the network calculates the difference value between them. Instead, the backpropagation step happens where the network recalculates the error value for each neuron hidden network. The weight change stage eventually falls through. The network recalculates and replaces all weights with new values [82].

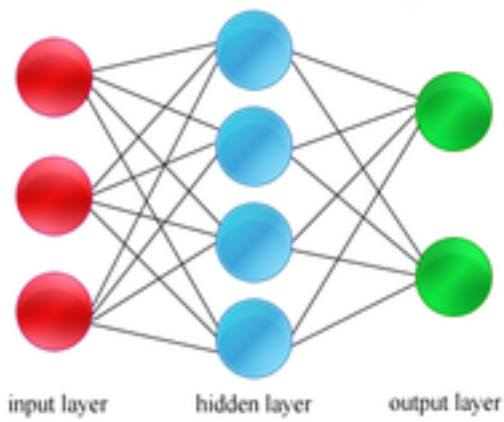


Figure 3.28 The NN

For posterior diffusion, the activation functions that neurons use are derivative. This is because, at the stage of updating weights, the activation function's derivative function is utilized for the calculation of the new values [82].

The learning stages that the network depends on are divided into two stages:

- The first stage: Proliferation for each sample of income data where it should be done: Front feed to the network with an input data sample to calculate the output data, and then the results obtained are compared with the desired results and the difference that represents the error value is calculated Background feed where the error value is calculated in each stick belonging to the hidden layers [83].
- The second stage: updating the values of weights, the value of the weights of each of the neurons belonging to the hidden layers is updated.

3.4.1 Backpropagation Algorithm Details

To understand how it works, it can consider one neuron. This neuron receives income (numbers) data. The output value of this neuron is the weighted sum of the numbers entered. It means each number will be multiplied by the weight attributed to each buckle.

Then this sum is divided by the summation of weights to give the output value to the neuron.

First and before training the neuron, weights are given to the synapse randomly. Then the neuron is extended with the input and output data.

The neuron will calculate the output given the income and weights data. Of course, these weights are at first random. Thus, the calculated output Y will not correspond to the correct output T. The task of the neuron then is to change the weights until it has an output that matches or approaches the correct output. The method for calculating the difference between the two values is based on the mean squared mean error [83].

3.5 Data Collection of the CT scans

The congestion of machine learning is data collection where the main reason why the data collection is a critical issue because a large amount of data which are labeled is required where recently many machine learning is developed with not enough dataset which is labeled. Data collection is divided into three main parts data acquisition, labeled and using existing data.

- Firstly, data acquisition is the way to find the dataset that can be trained in machine learning models. Also, it is divided into three main parts:
  Data generation where no dataset has been created before for access, and it generates it automatically or manually.
  The second way is data augmentation, where the datasets are available and have been created, but a new dataset can be added on the pre-trained dataset.
  Moreover, lastly is data discovery where the datasets are shared for training proposes.
- Labeled data; the next step is having a label on the data if some of the data are labeled, semi-supervised learning can be applied for predicting the rest, and if the data are not labeled, then it can be done manually.
- The last part of data collection is using existing datasets for improving the results or relabeling the dataset.

3.6 Tools

3.6.1 MATLAB

MATLAB is considered one of the high-level programming languages, and it is also an interactive environment that relies on developing algorithms. MATLAB does data analysis, and it is also an integral part of creating applications and models. It provides the user with a set of mathematical tools and functions that help find high-speed solutions by adopting on spreadsheets or even traditional programming languages. Among the most prominent are Java (JAVA, C ++, C), and its use increases among the community of programmers of control systems, computational biology, and other fields [84].

MATLAB is also a matrix or algorithm created explicitly for the purpose of creating a digital computing environment with multiple models, and high-level language provides the opportunity to develop and change matrices and methods of planning and applying data as algorithms, and leaves an exact imprint in the creation User Interfaces and linking with programs written in other languages such as Python and Fortran Java [84].

MATLAB's language overwhelms a set of characteristics that make it distinct from other programming languages, and among the most prominent of these characteristics:

Ease of use, as it allows its users to access solutions in standard mathematical methods.

MATLAB provides tools where these tools deliver solutions to problems facing applications and their development. MATLAB is considered as a practical and a standard educational means in many fields, including principles of engineering, mathematics, science, and others.

Some of MATLAB advantages:

- An accurate model for achieving software development and advancement.
- The best option for writing programs that need a moderate range of commands and editing in problem-solving.
- The overall language performance shortcut for controlling and changing numbers MATLAB Language. [85]
- A high-level array that is inherently compatible with data flow control and data structuring, and overshadowed by object-oriented programming features.

The MATLAB working environment where it can be referred to as the scope in which the tools for the MATLAB language are employed. As well as on which the programmer relies on writing the program to effect change or create the task entrusted to the programmer, this environment embraces the processes of importing and exporting data and controlling language-based data and files. [85]

Additionally, it is a specialized graphical system based on a set of special commands for the purpose of creating a visualization of data of two and three dimensions. Also, it includes a process of accurate processing of images, animations, and presentation graphics. It is not impossible to have low-level commands in it at all, as it completes orders written in the high-level language to reach the desired result [85].

3.6.2 OsiriX

Many applications are used for image processing of DICOM files in this work OsiriX application is used to read CT scan files. The application gives many options in viewing the CT scans or MRI and PET as well as allowing the user to visualize the images into 2D, 3D, 4D, and 5D [86].

CHAPTER 4

DESIGN AND IMPLEMENTATION

4.1 Design

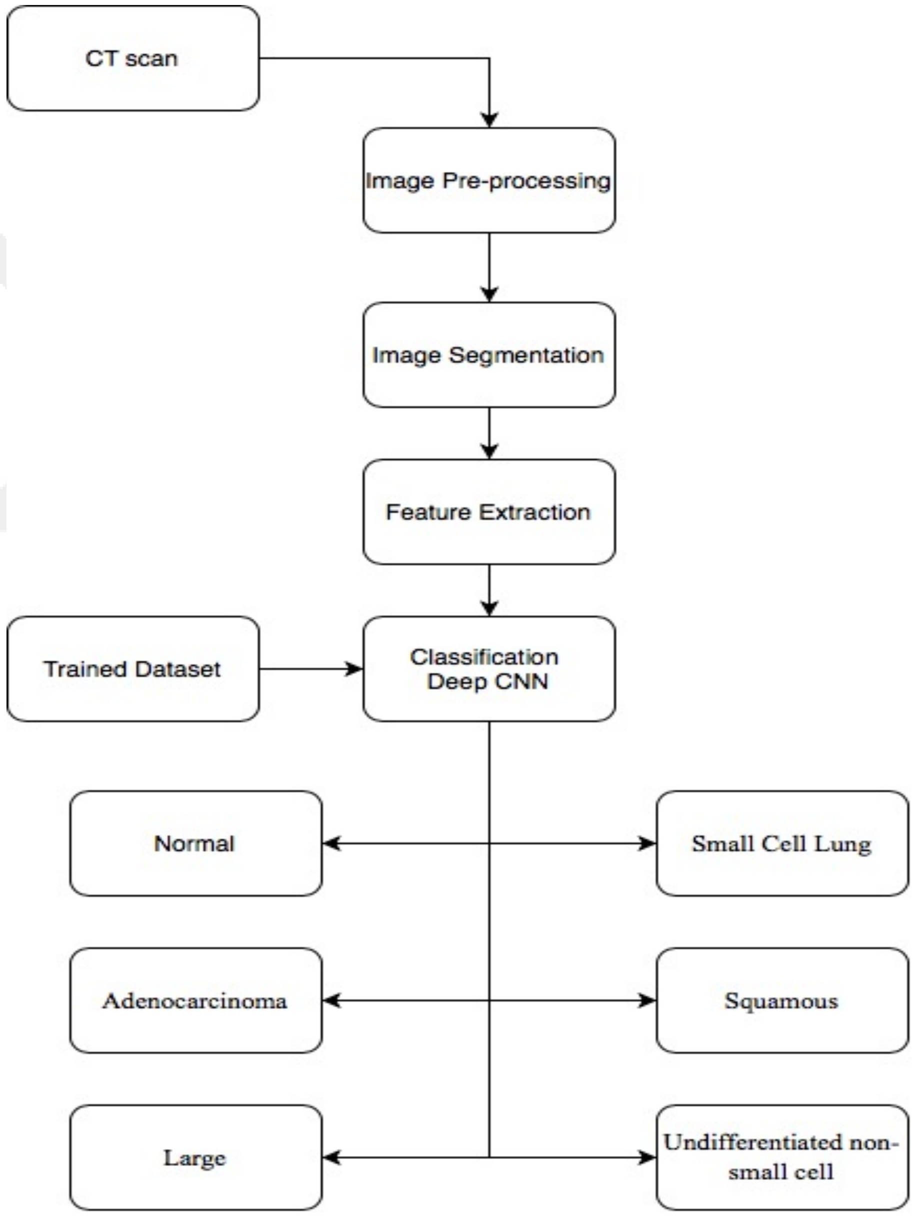


Figure 4.1 The system overall diagram

In this section, an overall view of the proposed system is shown in Figure 4.1where the CT scan is collected and then preprocessing from segmentation, and feature extraction applied on the dataset then as it shows the classification part will start based on the data from training sets and it predicts whenever the lung is clean, or it has cancer. The implementation of the system is discussed in the next sections.

4.2 Implementation

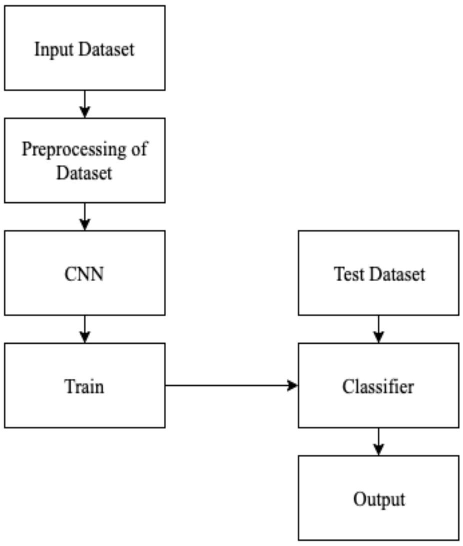
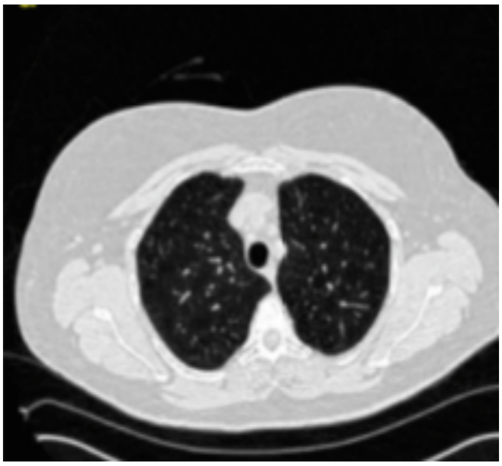


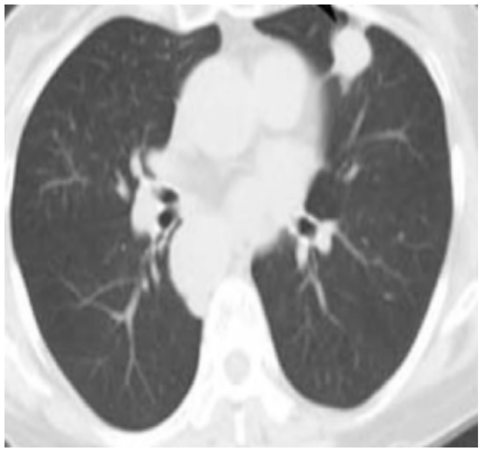
Figure 4.2 System's architecture

The Figure 4.2 shows the system's architecture where the network has been designed in deep learning, and it will be used in transfer learning to train and predict with the ratios of 85% for training and 15 % for testing.

The proposed system is to develop a system that can detect the lung cancer in the earlier stages based on deep learning convolutional neural network using MATLAB GUI by transfer learning for most common lung cancer types which are: small cell lung cancer, adenocarcinoma, squamous cell cancer, large cell carcinoma and undifferentiated non-small cell lung cancer which can be seen in the Figure 4.3.

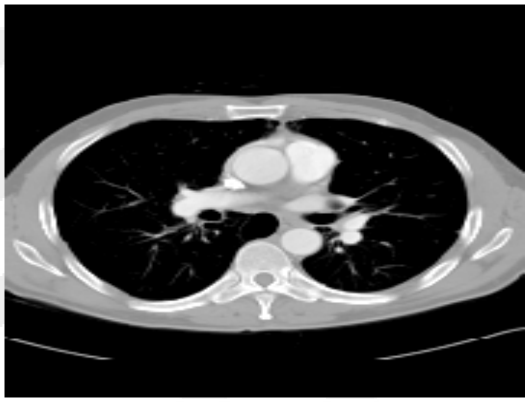


A. Normal lung



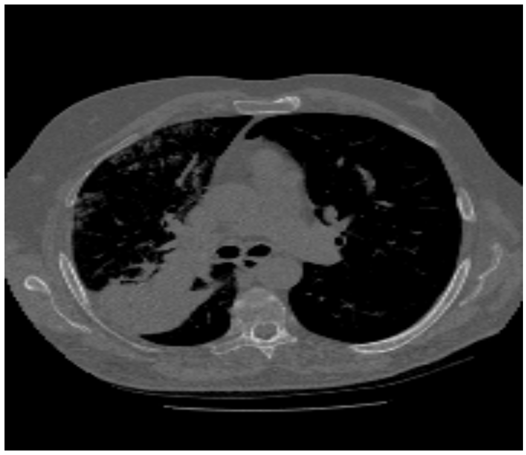
B. Small Cell Lung

C. Adenocarcinoma



D .Squamous

E. Large



F. Undifferentiated non-small cell

Figure 4.3 Types of lung cancers

As mentioned before, machine learning is part of artificial intelligence, and deep learning is a subsection of machine learning, and machine learning algorithms like neural network usually use the central processing unit (CPU) for training the dataset while the deep learning uses graphics processing unit (GPU) for better performance of the implemented network model.

The proposed system's network is developed and designed by using a deep network designer.

The overall architecture is as follows:

The input layer: The dataset is taken from K1 hospital in Kirkuk, Iraq [87]. Moreover, some are taken from Frederick Nat. Lab for Cancer Research at the University of Marburg [88], and Siemens Healthcare.

Preprocessing: The data needed to be cleaned up before applying the training system. For improving the dataset, preprocessing is required for training because the original input images are not in a form that is difficult for the deep learning to represent it. Therefore, all the images should be standardized in the same shape so that all their pixels are in the same representation range as 227 x 227. About 100 images have been used for each type of cancer, and 50 have been used for the average healthy lungs' images while 60 random images of the cases used to test the system's performance as it will be explained in next chapter. And then, image segmentation where each image will be divided into parts for changing the format and make it simple for training to analyze it.

Convolution layer: This layer is for analyzing the visual imagery. CNNs are standardized types of multi-layer perceptrons. In other words, a fully connected network where each neuron in one layer is connected to all the neurons in the subsequent layer. In the Figure 4.5 a 2-layer neural network needs to be designed in a deep network designer using MATLAB in the app, as it is shown in the Figure 4.4.

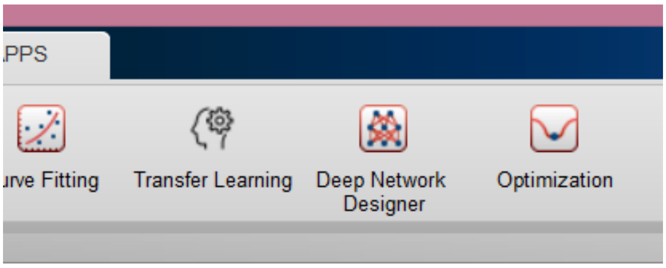


Figure 4.4 Creating CNN

And then, in the layout, see the Figure 4.5 of the application the network layers are designed.

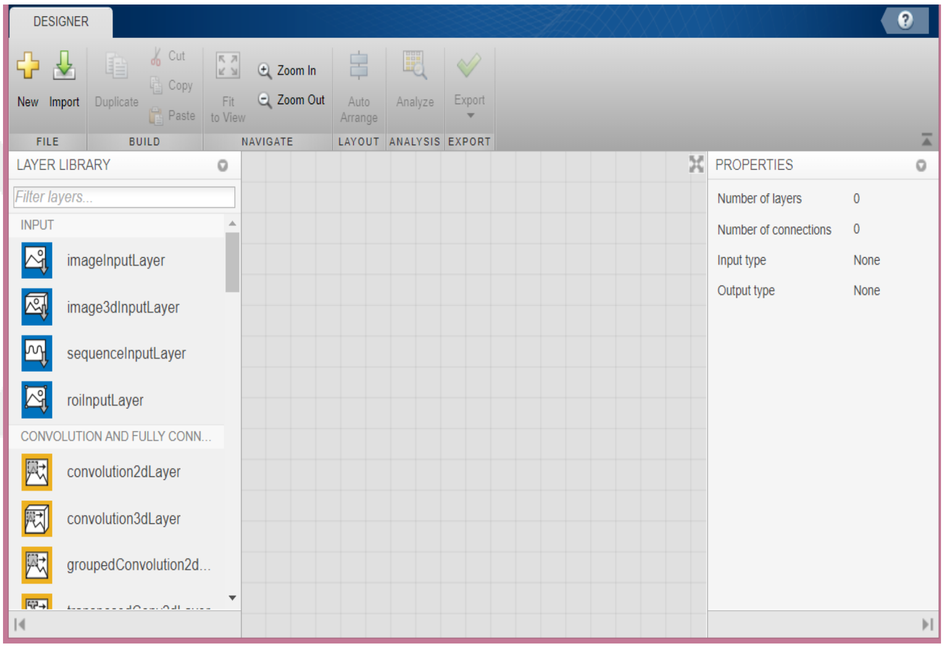


Figure 4.5 Application layout

The network layers with six neurons and input layer is shown in Figure 4.6.

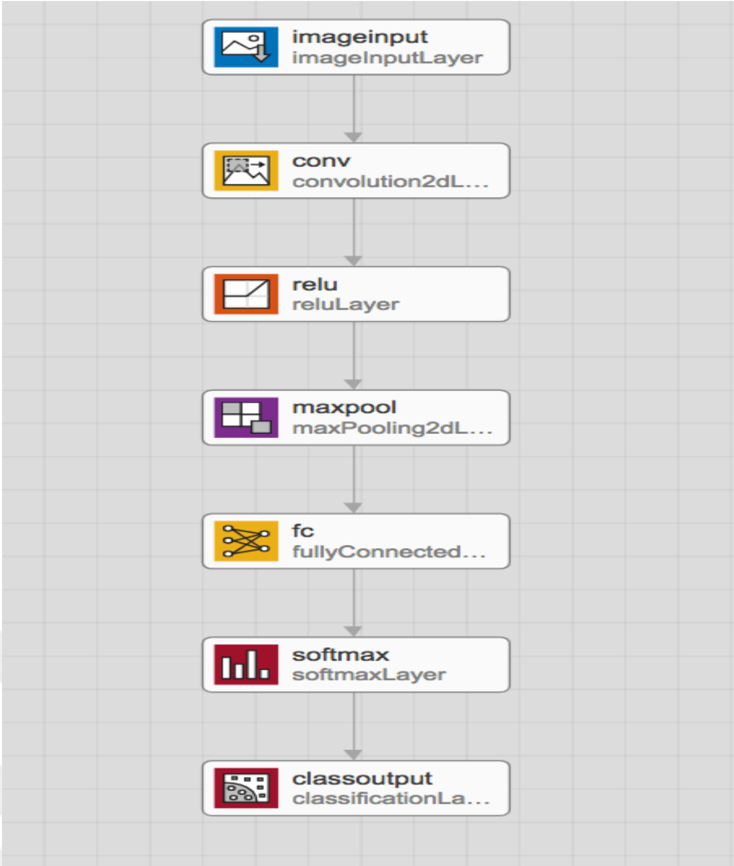


Figure 4.6 CNN layers

The basic CNN layers:

The primary CNN layers:

ReLu layer: An activation function is applied.

Pooling layer: This layer provides down-sampling.

Fully connected layer: It provides the prediction.

Softmax layer: It is the part of the previous layer.

Output layer: It provides the output.

This network is exported as an output MAT file that will be loaded into transfer learning, see Figure 4.7, where transfer learning allows the training of an extensive dataset and reduces training time.

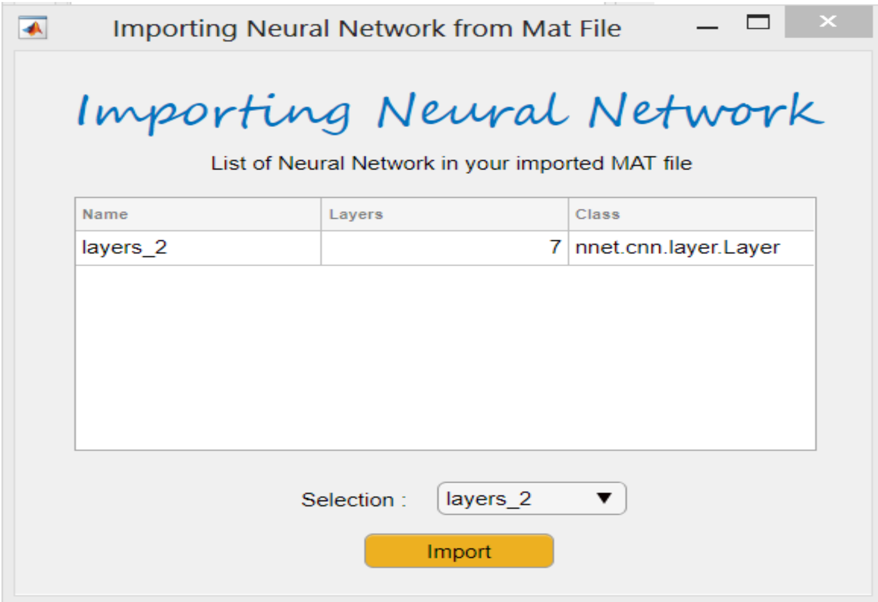


Figure 4.7 Importing the network

After importing the network, dataset is imported as shown in Figure 4.8.

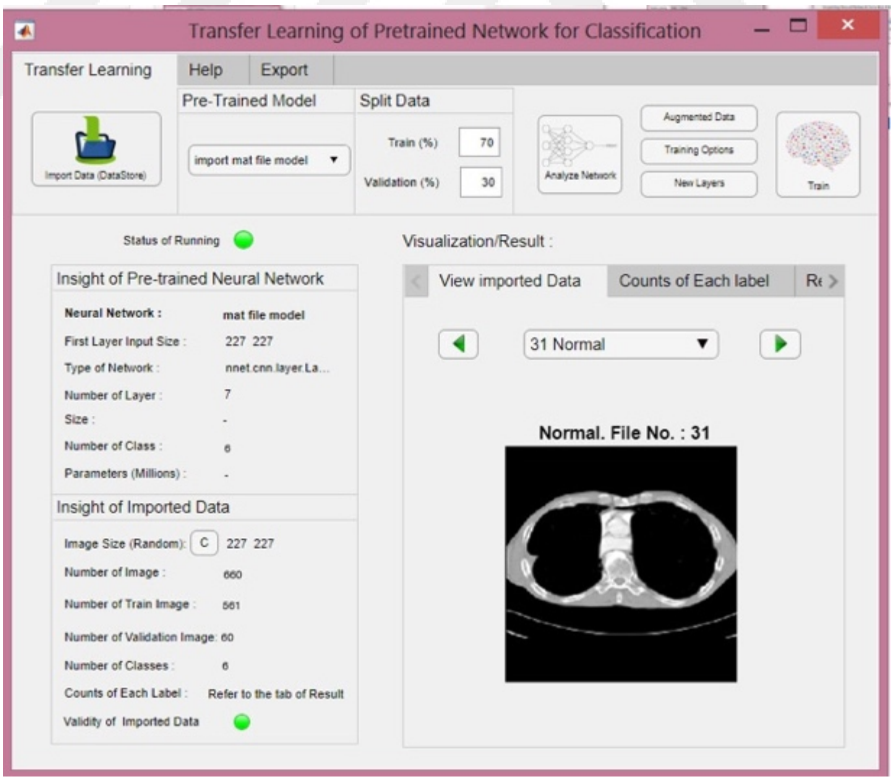


Figure 4.8 Importing the dataset

Furthermore, the system is ready for the training setup, which will be discussed in the next chapter.

CHAPTER 5

RESULTS AND DISCUSSION

The Convolution Network training process can be summarized in the following steps:

Step 1: Configure all filters, parameters, and weights with random initial values. Figure 5.1 shows the configuration of the training process that has been used, stochastic gradient descent with momentum as solver, it will calculate the gradient and update cost function and reduces it for each epoch, which has been determined as 5.1. By using the following formula:

$$\theta = \theta - \eta \cdot \nabla\theta J(\theta; x(i); \gamma(i)). \tag{5.1}$$

Furthermore, by adding a fraction of last updated, it will speed up the calculation of the cost function as the following formula 5.2:

$$vt = \gamma vt - 1 + \eta\nabla\theta J(\theta) \tag{5.2}$$

$$\theta=\theta-vt$$

where θ means Theta while η is the metric tensor in Quantum Field, ∇ is refer to Nabla and γ is the gamma.

A backpropagation has been used where it was described in the previous chapter. The system is set to use L2 – Norm, so the network will not get diverging.

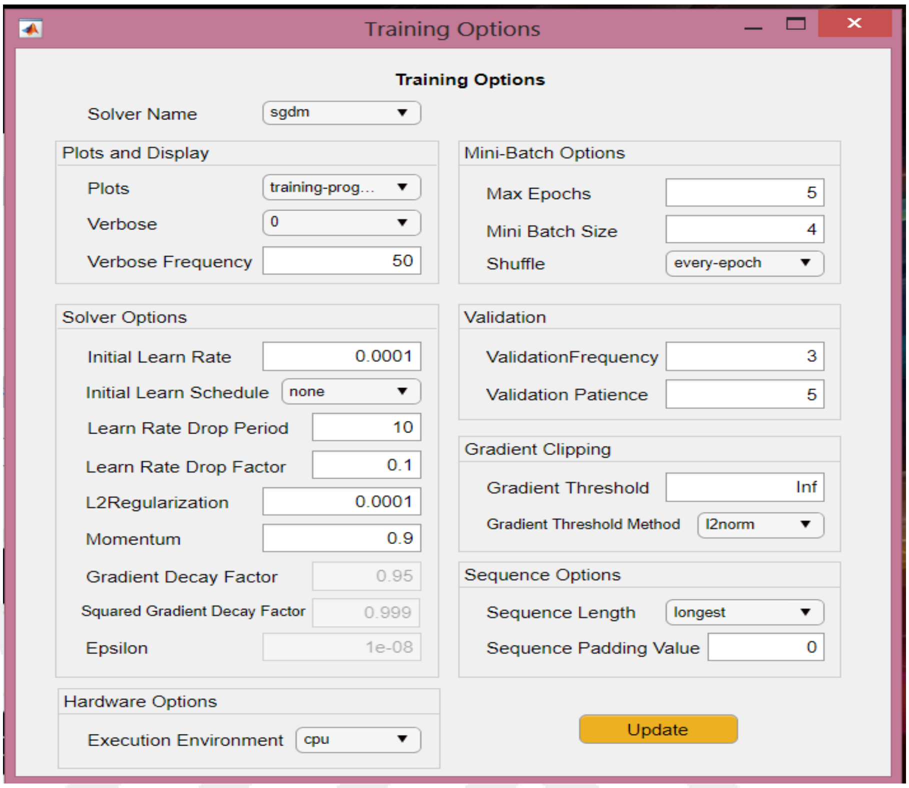


Figure 5.1 Training set options

Step 2: Take the input training image and go through the forward propagation process.

Step 3: Calculate the sum of the errors in the output layer (which is the sum of all four categories using the equation below)

$$TotalError = \sum t\left(t\arg etprobability - outputprobability\right)^2 \tag{5.3}$$

Step 4: Use the gradient descent to update all the weights and coefficients to reduce the output error rate.

Step 5: Repetition of steps 2 through 4 with the entire pictures entered into the training package.

The figure below shows the training with 195 iterations with 93.33% accuracy.

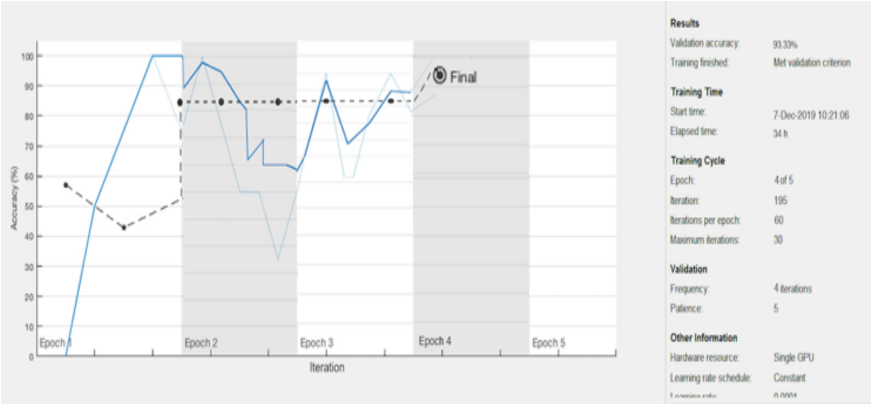
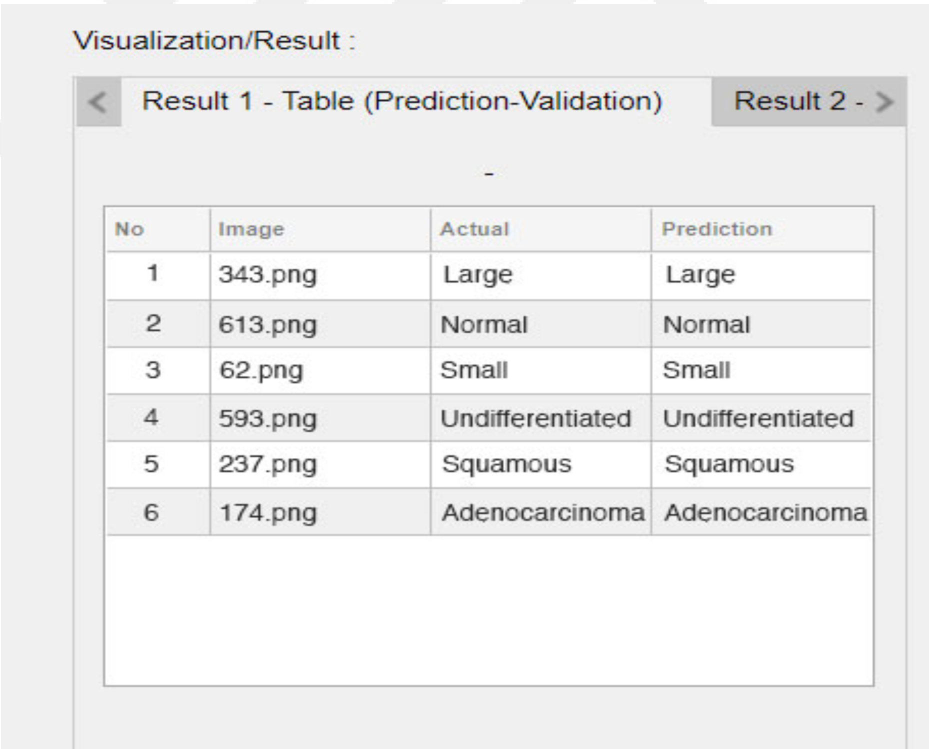


Figure 5.2 Training

In the end, the result is visualized to show the randomly chosen images when they go throughout the testing part, and the table shows the original image where the system indicates whether it is cancer or standard by the prediction as shown in next Figure 5.3:



No	Image	Actual	Prediction
1	343.png	Large	Large
2	613.png	Normal	Normal
3	62.png	Small	Small
4	593.png	Undifferentiated	Undifferentiated
5	237.png	Squamous	Squamous
6	174.png	Adenocarcinoma	Adenocarcinoma

Figure 5.3 The results

Table 5.1 shows some performance metrics for analysis of the system.

Table 5.1 Confusion Matrix

		Actual	
		Positive	**Negative**
Estimated	Positive	TP	FP
	Negative	FN	TN

TP is representing true positives: Meaning the image that is really of cancer and was assessed by the system as cancer.

TN is representing true negatives: the image that is in real regular and was predicted by the system as usual.

FP is representing false positives: the image that is supposed to be expected but predicted by the system as cancer.

FN is representing false negatives: the image which is really supposed to be cancer but estimated by the system as usual where 60 images were tested in transfer learning.

Equation (5.4) is used to find the accuracy to measure the classification performance, and it showed to be 93.33%, as seen below in (5.5). For the purpose of recognizing patterns, retrieving and classifying information, precision and recall are also used [24]. Precision is defined as the fraction of actual occurrences among the retrieved occurrences, while recall is defined as the fraction of the total amount of actual occurrences that were retrieved actually [24].

Therefore, using (5.6) the precision was found to be 92.59%, as shown in (5.7), while with (5.8), the recall was found to be one as indicated in (5.9).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5.4}$$

$$\frac{50+6}{50+4+6+0} = 93.33\% \tag{5.5}$$

$$Precision = \frac{TP}{TP+FP} \tag{5.6}$$

$$\frac{50}{50+4} = 92.59\% \tag{5.7}$$

(5.8)

$$\mathrm{Re}call = \frac{TP}{TP+FN}$$

(5.9)

$$\frac{50}{50+0} = 1$$

A specialist doctor was consulted to select the CT scans with cancerous tumors in the lungs or normal lungs. The specialist also helped while understanding all the scans and to know where to exactly screenshot the right place and which type it is.

As mentioned in implementation chapter about 100 images have been used for each type of cancer, and 50 have been used for the average healthy lungs. Without high performance computer the training and testing weren't easy because the time needed to train the data and test it was about 34 hours. Furthermore, the system performed satisfactorily considering the large amount of data used as input.

Table 5.2 A comparison between different activation functions used.

Activation functions	Accuracy	Precision	Recall
Relu	93.33%	92.59%	100%
Tanh	80%	84.44%	88.37%
Sigmod	78.33%	86.95%	85.10%

Table 5.3 A comparison between different solver used.

Solver	Accuracy	Precision	Recall
SGDM	93.33%	92.59%	100%
RMSProp	51.66%	48%	46.15%
Adam	NA	NA	NA

Table 5.2 shows the differences in the results with the change in activation functions. Relu's results showed to be the best and suitable for the proposed system. While table 5.3 shows how the other solver that was used doesn't working efficiently. That's why; the proposed system used SGDM as solver. In comparison to other pervious works, the current system shows a better overall performance in regards to the calculated factors of precision, accuracy, and recall. Table 5.4 compares the current approach of this proposed system with a couple of similar works.

Table 5.4 A comparison between current work and similar works.

		Accuracy	**Precision**	**Recall**
Current work	Deep CNN	93.33%	92.59%	100%
[9]	CNN	87.69%	-	97.46%
	Double CNN	99%	-	99%
[23]	NIN	90%	99%	68%
	CNN	90%	85%	85%
[89]	RCO & RFs	86.54%	84.6%	84.37%
[90]	CNN	79.40%	-	-
	DBNs	81.19%	-	-
	SDAE	79.29%	-	-
[91]	KNN	96.58 %	-	-
[92]	PET-based	76.9%	80.4%	74.6%
	NN	77.2%	80.7%	75.0%
[93]	Optimal DNN & LDA	94.56%	94.2%	96.2%

CHAPTER 6

CONCLUSION AND FUTURE WORK

The advances of technology have inevitably affected all the other disciplines, particularly the medical field. It is well known that cancer is one of the most challenging diseases to be cured. Many scientists and researchers are trying to come up with ways to detect cancerous cells earlier to increase survival chances. One of the approaches scientists for early cancer detection is done by machine learning, which is considered one of the most efficient techniques. That is why an early lung cancer detection system is proposed in this work with five different types of lung cancer with 100 CT scan images with 227x227 for each type. A deep learning convolutional neural network with seven layers has been used and designed in a deep network designer. The training and testing were done by using transfer learning, and the accuracy was done by using a confusion matrix, which gave 93.33% accuracy, a precision of 92.59%, and a 100% recall. These results were compared with other similar works and were tabulated, which showed that this current work's overall result is better.

In future work, it would be interesting to continue with the work line of this project and have a complete application for detecting more cancer type, at same time the program to have the ability predict of growing of the tumors and how much they can grow and the level that they can reach.

REFERENCES

[1] World Health Organization (2019). Cancer Program Available at: Https://Www.Who.Int/News-Room/Fact-Sheets/Detail/Cancer.

[2] Özbay, S., Safar, M. (2017). Real-Time Sign Languages Recognition Based on Hausdorff Distance, Hu Invariants and Neural Network. *International Conference on Engineering and Technology*. Available at: 10.1109/Icengtechnol.2017.8308204

[3] Sefer, M., Agha, R., Özbay, S. (2018). Comparison of Neural Network and Hausdorff Distance Methods in American, British and Turkish Sign Languages Recognition. *Proceedings of The First International Conference on Data Science, E-Learning and Information Systems*. Available at: 10.1145/3279996.3280007

[4] Zou, H., Zhou, Y., Yang, J., Jiang, H., Xie, L. And C. Spanos. (2018). Wifi-Enabled Device-Free Gesture Recognition for Smart Home Automation. *Ieee 14th International Conference on Control and Automation (Icca)*. Available: 10.1109/Icca.2018.8444331

[5] Aran, O. (2002). Vision Based Sign Language Recognition: Modeling and Recognizing Isolated Signs with Manual and Non-Manual Components. *Cmpe., Bo ˘Gazi ¸Ci University*.

[6] Beek, E. (2015). Lung Cancer Screening: Computed Tomography or Chest Radiographs. *World Journal of Radiology*. 7, 8-189. Available at :10.4329/Wjr.V7.I8.189

[7] Ko, J. (2013). Thoracic Imaging, *An Issue of Radiologic Clinics Of North America*. Elsevier.

[8] National Cancer Institute: Comprehensive Cancer Information. (2020). *National Lung Screening Trial*, Questions and Answers.

[9] Vance, Eric , Xie, Xiaojin, Henry, Andrew, Wernz, Christian & Slonim, Anthony. (2013). Computed Tomography Scan Use Variation: Patient, Hospital, And Geographic Factors. *The American Journal of Managed Care*. 19. E93-E9

[10] Kourou, K., Exarchos, T., Exarchos, K., Karamouzis, M., Fotiadis, D. (2015). Machine Learning Applications in Cancer Prognosis And Prediction. *Computational and Structural Biotechnology Journal*, **13,** 8-17. Doi: 10.1016/J.Csbj.2014.11.005

[11] Gu, J, Wang, Z, Kuen, J, Ma, L, Shahroudy, A.,Shuai, B. Et Al. (2018). Recent Advances in Convolutional Neural Networks. *Pattern Recognition*, **77**, 354-377. Doi: 10.1016/J.Patcog.2017.10.013

[12] Guo, H., Zhuang, X., Rabczuk, T. (2019). A Deep Collocation Method for The Bending Analysis of Kirchhoff Plate. *Comput Mater Continua*, **59(2)**, 433-456

[13] Coccia, M. (2020). Deep Learning Technology for Improving Cancer Care In Society: New Directions In Cancer Imaging Driven by Artificial Intelligence. *Technology in Society*, **60**, 101198.

[14] Didkowska, J., Wojciechowska, U., Mańczuk, M., Łobaszewski, J. (2016). Lung Cancer Epidemiology: Contemporary and Future Challenges Worldwide. *Annals of Translational Medicine*, 4(8).

[15] Chaudhry, R, Bordoni, B. (2017). Anatomy, *Thorax*, Lungs.

[16] Cooper, G. M. (2000). The Cell: *A Molecular* Approach 2nd Edition.

[17] American Cancer Society. (2020). Facts & Figures, *American Cancer Society*. Atlanta, Ga.

[18] American Cancer Society. (2019). Cancer Facts & Figures for African Americans 2019-2021. *American Cancer Society*. Atlanta, Ga.

[19] Desantis CE, Miller KD, Sauer AG, Jemal A, Siegel RL. (2019). Cancer Statistics for African Americans. *CA. A Cancer Journal for Clinicians*. **69**, 211-233.

[20] Howlader N, Noone AM, Krapcho M, Miller D, Brest A, Yu M, Ruhl J, Tatalovich Z, Mariotto A, Lewis DR, Chen HS, Feuer EJ, Cronin KA (Eds). (2019). *SEER Cancer Statistics Review, National Cancer Institute*. Bethesda, MD, Available At: Https://Seer.Cancer.Gov/Csr/1975_2016/

[21] Zheng, M. (2016). Classification and Pathology of Lung Cancer. *Surgical Oncology Clinics*, **25**(3), 447-468.

[22] ASOCO. (2020). Stages of Cancer. American Society of Clinical Oncology. Available at Https://www.cancer.net/Navigating-Cancer-Care/Diagnosing-Cancer/Stages-Cancer

[23] Husband, J., Reznek, R. H., Husband, J. E. Eds. (2016*). Imaging in Oncology. CRC Press.*

[24] Mei, Q., Gül, M. (2020). Multi-Level Feature Fusion in Densely Connected Deep-Learning Architecture and Depth-First Search for Crack Segmentation on Images Collected with Smartphones. Structural Health Monitoring. Https://Doi.Org/10.1177/1475921719896813

[25] Akkus, Z., Galimzianova, A., Hoogi, A., Rubin, D., Erickson, B. (2017). Deep Learning for Brain MRI Segmentation: State of The Art and Future Directions. *Journal of Digital Imaging*, **30(4)**, 449-459. Doi: 10.1007/S10278-017-9983-4

[26]. Laplante, P. A. (2004). Real-Time Systems Design and Analysis. *The Institute of Electrical and Electronics Engineers*.

[27] Sze, V., Chen, Y., Yang, T., Emer, J. (2017). Efficient Processing of Deep Neural Networks: A Tutorial and Survey. *Proceedings of The Ieee*, 105(12), 2295-2329. Doi: 10.1109/Jproc.2017.2761740

[28] Whittington, J. C., Bogacz, R. (2019). Theories of Error Back-Propagation In The Brain. *Trends in Cognitive Sciences*, **23(3)**, 235-250.

[29] N. Khalifa, M. Taha, A. Hassanien And H. Mohamed. (2019) Deep Iris: Deep Learning For Gender Classification Through Iris Patterns. *Acta Informatica Medica*, **27**,2-96. Available At: 10.5455/Aim.2019.27.96-102.

[30] Yamashita, R., Nishio, M., Do, R. K. G., Togashi, K. (2018). Convolutional Neural Networks: An Overview and Application in Radiology. *Insights into Imaging*, 9(4), 611-629.

[31]. Fukushima, K. (2013). Artificial Vision by Multi-Layered Neural Networks: Neocognitron And Its Advances. *Neural Networks*, 37, 103-119.

[32] Kurenkov, A. (2015). A Brief History of Neural Nets and Deep Learning. *Andreykurenkov*

[33] Fei-Fei Li. (2020). CS231n Convolutional Neural Networks for Visual Recognition. *Stanford University*. Available at Https://Cs231n.Github.Io/Convolutional-Networks/

[34] Homma, Toshiteru, Les Atlas, Robert Marks II. (1988). An Artificial Neural Network for Spatio-Temporal Bipolar Patters: Application to Phoneme Classification. *Advances in Neural Information Processing Systems*. **1**, 31–40.

[35] Kim, H. J., Shin, K. S., Park, K. (2005). Time Delay Neural Networks and Genetic Algorithms for Detecting Temporal Patterns in Stock Markets. *International Conference on Natural Computation*, Springer, Berlin, Heidelberg.1247-1255

[36] Gaier, A., Ha, D. (2019). Weight Agnostic Neural Networks. *Advances in Neural Information Processing Systems*. 5364-5378.

[37] Toledano, D. T., Fernández-Gallego, M. P., Lozano-Diez, A. (2018). Multi-Resolution Speech Analysis for Automatic Speech Recognition Using Deep Neural Networks: *Experiments on Timit*. *Plos One*, **13**(10), E0205355.

[38] Schmidt, J., Marques, M. R., Botti, S., Marques, M. A. (2019). Recent Advances and Applications of Machine Learning in Solid-State Materials Science. *Npj Computational Materials*, **5(1)**, 1-36.

[39] Lecun, Y., Bottou, L., Bengio, Y., Haffner, P. (1998). Gradient-Based Learning Applied to Document Recognition. *Proceedings of The Ieee*, **86**(11), 2278-2324.

[40] Hesamian, M. H., Jia, W., He, X., Kennedy, P. (2019). Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges. *Journal of Digital Imaging*, **32**(4), 582-596.

[41] Wang, H., Peng, H., Chang, Y., Liang, D. (2018). A Survey Of GPU-Based Acceleration Techniques in MRI Reconstructions. *Quantitative Imaging in Medicine and Surgery,* **8**(2), 196.

[42] Schmidhuber, J. (2015). Deep Learning in Neural Networks: An Overview. *Neural Networks*, **61**, 85-117.

[43] Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., ... Asari, V. K. (2018). The History Began from Alexnet: A Comprehensive Survey on Deep Learning Approaches. *Arxiv Preprint Arxiv*.1803.01164.

[44] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., R. M. (2016). Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. *Ieee Transactions on Medical Imaging*, 35(5), 1285-1298.

[45] D’souza, R. N., Huang, P. Y., Yeh, F. C. (2018). Small Data Challenge: Structural Analysis and Optimization of Convolutional Neural Networks with A Small Sample Size. *Biorxiv*, 402610.

[46] Khan, A., Sohail, A., Zahoora, U., Qureshi, A. S. (2020). A Survey of The Recent Architectures of Deep Convolutional Neural Networks. *Artificial Intelligence Review*, 1-62.

[47] Castro, W., Oblitas, J., Santa-Cruz, R., Avila-George, H. (2017). Multilayer Perceptron Architecture Optimization Using Parallel Computing Techniques. *Plos One*, **12**(12), E0189369.

[48] He, K., & Sun, J. (2015). Convolutional Neural Networks at Constrained Time Cost. *Proceedings of The Ieee Conference on Computer Vision and Pattern Recognition*, 5353-5360.

[49] Dshahid. (2020). Convolutional Neural Network. *Towards Data Science*. Available At: Https://Towardsdatascience.Com/Covolutional-Neural-Network-Cb0883dd6529

[50] Burguillo, J. C. (2014). Using Self-Organizing Maps with Complex Network Topologies and Coalitions for Time Series Prediction. *Soft Computing*, **18**(4), 695-705.

[51] G. Jakimovski And D. Davcev. (2019). Using Double Convolution Neural Network for Lung Cancer Stage Detection. *Applied Sciences*, **9**,3-427. Available At: 10.3390/App9030427

[52] A. Kaur And P. Kaur. (2019). Breast Cancer Detection and Classification Using Analysis and Gene-Back Proportional Neural Network Algorithm. *International Journal of Innovative Technology and Exploring Engineering*.

[53] X. Yao And N. Ray. (2019). Cell Detection in Microscopy Images with Deep Convolutional Neural Network and Compressed Sensing. *Arxiv*.

[54] A. R.B, J. Abdul Jaleel And S. Salim. (2013). Implementation of ANN Classifier Using MATLAB For Skin Cancer Detection. *International Journal of Computer Science and Mobile Computing*.

[55] National Academies of Sciences Engineering and Medicine. (2015). The Diagnostic Process. *Improving Diagnosis in Health Care*.

[56] Rani, N., Vashisth, S. (2017). Brain Tumor Detection and Classification with Feed Forward Back-Prop Neural Network. *Arxiv Preprint Arxiv*, 1706.06411.

[57] Kadhim, D. A. (2012). Development Algorithm-Computer Program of Digital Mammograms Segmentation for Detection of Masses Breast Using Marker-Controlled Watershed in MATLAB Environment. *Journal of Kerbala University,* **1**,114-123

[58] Kile, F. (2013). Artificial Intelligence and Society: A Furtive Transformation. *AI Society*, **28**(1), 107-115.

[59] Boutaba, R., Salahuddin, M. A., Limam, N., Ayoubi, S., Shahriar, N., Estrada-Solano, F., Caicedo, O. M. (2018). A Comprehensive Survey on Machine Learning For Networking: Evolution, Applications And Research Opportunities. *Journal of Internet Services and Applications*, **9**(1), 16.

[60] Braunschweig, B. (2016). Artificial Intelligence. Current Challenges and Inria's Engagement-Inria. *White Paper*.

[61] Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., Arshad, H. (2018). State-Of-The-Art in Artificial Neural Network Applications: A Survey. *Heliyon*, **4**(11), E00938.

[62] Qiu, J., Wu, Q., Ding, G., Xu, Y., Feng, S. (2016). A Survey of Machine Learning for Big Data Processing. *Eurasip Journal on Advances in Signal Processing*, (1), 67.

[63] Fumo, D. (2017). Types of Machine Learning Algorithms You Should Know. *Towards Data Science*.

[64] Zhu, X., Goldberg, A. B. (2009). Introduction to Semi-Supervised Learning. *Synthesis Lectures on Artificial Intelligence and Machine Learning*, **3**(1), 1-130.

[65] Lu, Z., Leen, T. K. (2005). Semi-Supervised Learning with Penalized Probabilistic Clustering. *Advances in Neural Information Processing Systems* ,849-856.

[66] Barto, A. G., Dietterich, T. G. (2004). Reinforcement Learning and Its Relationship to Supervised Learning. *Handbook of Learning and Approximate Dynamic Programming,* 10, 9780470544785.

[67] Ferguson, A. L. (2017). Machine Learning and Data Science in Soft Materials Engineering. *Journal of Physics: Condensed Matter*, 30(4), 043002.

[68] Conte, E., Pierri, G., Federici, A., Mendolicchio, L., Zbilut, J. P. (2006). A Model of Biological Neuron with Terminal Chaos and Quantum-Like Features. Chaos, *Solitons & Fractals*, 30(4), 774-780.

[69] Manor, Y., & Nadim, F. (2001). Frequency Regulation Demonstrated by Coupling A Model and A Biological Neuron. *Neurocomputing*, **38**, 269-278.

[70] Baillot, D. (2020). Why Are Neuron Axons Long and Spindly? Study Shows They're Optimizing Signaling Efficiency. *University of California - San Diego* Available at Https://Medicalxpress.Com/News/2018-07-Neuron-Axons-Spindly-Theyre-Optimizing.Html

[71] Lee, J. G., Jun, S., Cho, Y. W., Lee, H., Kim, G. B., Seo, J. B., Kim, N. (2017). Deep Learning In Medical Imaging: General Overview. *Korean Journal of Radiology*, **18**(4), 570-584.

[72] Razzak, M. I., Naz, S., Zaib, A. (2018). Deep Learning for Medical Image Processing: Overview, Challenges and The Future. *Classification in Bioapps Springer, Cham*, 323-350.

[73] Warburton, K. (2003). Deep Learning and Education for Sustainability. *International Journal of Sustainability in Higher Education*, **4**(1), 44-56.

[74] I. Goodfellow, Y. Bengio, A. Courville. (2011). *Deep Learning*.

[75] Schmidhuber, J. (2015). Deep Learning in Neural Networks: An Overview. *Neural Networks*, 61, 85-117.

[76] Medathati, N. K., Neumann, H., Masson, G. S., Kornprobst, P. (2016). Bio-Inspired Computer Vision: Towards A Synergistic Approach of Artificial and Biological Vision. *Computer Vision and Image Understanding*, 150, 1-30.

[77] Yosinski, J., Clune, J., Nguyen, A., Fuchs, T., Lipson, H. (2015). Understanding Neural Networks Through Deep Visualization. *Arxiv Preprint Arxiv*, 1506.06579.

[78] Torres, J. (2018). Convolutional Neural Networks for Beginners. *Practical Guide with Python and Keras*.

[79] Inampudi, S., Mosallaei, H. (2018). Neural Network-Based Design of Metagratings. *Applied Physics Letters*, **112**(24), 241102.

[80]. Scherer, D., Müller, A., & Behnke, S. (2010). Evaluation of Pooling Operations in Convolutional Architectures for Object Recognition. *International Conference on Artificial Neural Networks Springer*, Berlin, Heidelberg. 92-101.

[81] Nakahara, H., Fujii, T., & Sato, S. (2017). A Fully Connected Layer Elimination for A Binarizec Convolutional Neural Network on an FPGA. 27th *International Conference on Field Programmable Logic and Applications*.

[82] Hecht-Nielsen, R. (1992). Theory of The Backpropagation Neural Network. *Neural Networks for Perception*. Academic Press.65-93 .

[83] Chauvin, Y., Rumelhart, D. E. Eds. (1995). Backpropagation: Theory, Architectures, And Applications. *Psychology Press*.

[84] Trefethen, L. N. (2000). Spectral Methods In MATLAB. *Society for Industrial and Applied Mathematics*.

[85] Moore, H., Sanadhya, S. (2007). MATLAB For Engineers. Upper Saddle River, NJ: *Pearson Prentice Hall*.

[86] Rosset, A., Spadola, L., Ratib, O. (2004). Osirix: An Open-Source Software for Navigating In Multidimensional DICOM Images. *Journal of Digital Imaging*, **17**(3), 205-216.

[87] K1. (2019). *K1 Hospital Kirkuk*, Iraq.

[88] Frederick Nat. (2019*). Lab for Cancer Research* at The University Of Marburg.

[89] Cai, Z., Xu, D., Zhang, Q., Zhang, J., Ngai, S. M., Shao, J. (2015). Classification of Lung Cancer Using Ensemble-Based Feature Selection And Machine Learning Methods. *Molecular Biosystems*, **11**(3), 791-800.

[90] Sun, W., Zheng, B., & Qian, W. (2016). Computer Aided Lung Cancer Diagnosis with Deep Learning Algorithms. In Medical Imaging: Computer-Aided Diagnosis, *International Society for Optics and Photonics*.

[91] Al-Absi, H. R., Samir, B. B., Shaban, K. B., & Sulaiman, S. (2012). Computer Aided Diagnosis System Based on Machine Learning Techniques for Lung Cancer. *International Conference on Computer & Information Science*.

[92] Hyun, S. H., Ahn, M. S., Koh, Y. W., & Lee, S. J. (2019). A Machine-Learning Approach Using PET-Based Radiomics To Predict the Histological Subtypes of Lung Cancer. *Clinical Nuclear Medicine*, **44**(12), 956-960.

[93] Lakshmanaprabu, S. K., Mohanty, S. N., Shankar, K., Arunkumar, N., & Ramirez, G. (2019). Optimal Deep Learning Model for Classification Of Lung Cancer On CT Images. *Future Generation Computer Systems*, **92**, 374-382.

Curriculum Vitae

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PROFILE

Take a challenging and high-performance oriented role in the field of Computer, and implement the expertise and experience gained in this field to develop complex project with efficiency and quality.

EDUCATION

Northern Technical University– Kirkuk, Iraq *2005 – 2009*

- **BSc**, Software Engineering, Technical College Kirkuk.

JOB EXPERIENCE

Center for Computing and The Internet-Technical College Kirkuk. *2013 –*

- Head of the center
- Instructor of Following Courses:
  - Surveillance Cameras (IP Camera, Analog) Training Course.
  - Microsoft Office 2014 (Word, Excel, Access, PowerPoint) Training Course.
  - AutoCAD 2014 Training Course.
  - Adobe Photoshop 2014 Training Course.
  - Internet Training Course.
  - MYSQL Training Course.

- MATLAB Training Course.
- Html Training Course.
- php Training Course.
- oracle Training Course.
- Introduction to Network Training Course.
- Virtual Basic 6 Training Course.

Technical College Kirkuk – Kirkuk, Iraq *2009*

–

- Department of Pathological Analysis.
- Department of Environmental pollution Engineering techniques
- Department of Software Engineering.
- Department of Electronics Engineering techniques and control
- Department ofRefrigeration and air conditioning engineering techniques

- Lecturer of Following Courses:
  - Computer Application
  - Virtual Basic 6
  - Oracle
  - SPSS
  - MSDOS
  - AutoCAD
  - Engineering
  - Drawing
  - C++
  - Introduction to Windows
  - Logic Design
  - Computer Networks
  - Microsoft Office Word, Excel, Access, PowerPoint

PUBLICATIONS

1- "Lung Cancer Classification and Detection Using Convolutional Neural Networks"

ISBN: 978-1-4503-7736-2/20/06**DOI**>https://doi.org/10.1145/3410352.3410822

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COURSES

- Cisco Career Certifications as (Cisco Certified Network Associate).
- English Course.

AWARDS, CERTIFICATES and RECOGNITIONS

- Certificate of participation the" Digital Technologies in Education, Science and Industry" 2020, International IT University, Almaty Kazakhstan

ADDITIONAL INFORMATION

Technical Skills:

Proficient in: Excel, Access, Word, PowerPoint, Office Project, and Outlook.

*Design & Programming:*Xcode (App for IOS), Microsoft Visual Studio, 3Dmax, Photoshop, Android Studio, Xamarin, Matlab, Cisco Packet Tracer, Riverbed, SQL Management Studio, Unity AR, Meshlab.

*Network:*Design, Implementation, & Configuration.

Languages: C++, JavaScript, Java, PHP, HTML, Objective-C, Natural Language, Fourth-Generation language (SQL), C Language (hardware Development).

Operating System: OS X (Macintosh), Microsoft Windows OS, Linux (Ubuntu) OS.

Languages:

- Turkumani – Native
- Arabic – Fluent
- Turkish – Fluent
- English – Very Good

Personal Skills:

- Excellent Communication skill to present points precisely and clearly.
- Good problem-solving ability and analytic skill to solve the problem efficiently.
- Good team player and have excellent interaction skill to lead and work within a team.
- Excellent Technical Skills.
- Ability to work under pressure and deliver on time.

External Projects

- Power scope for measuring current, voltage and THD FOR AC
- Controlling a car by android (Samsung note 3)
- ECG Device
- Sun Tracking System for Solar PV
- Website for real estate
- Students Grade System

REFERENCES AVAILABLE UPON REQUEST