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Lung Nodule Classificatin And Segmentation

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on 19/06/ 2023 in front of the committee members:

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DEDICATION I

First and foremost, Praises and Thanks to the God, The almighty, for all the opportunities and strength that have been given me to finish the thesis. My humblest gratitude to the holy Prophet Muhammad (Peace be upon him) whose way of life has been a continuous guidance for me.
I would like to sincerely thank my supervisor Dr.KHALDI Belal for his guidance, understanding and patience. It has been a great pleasure and honor to have him as my supervisor.
My deepest gratitude goes to all of my family members who encouraged me and supported me and prayed for me throughout the time of my studies. This thesis is heartily dedicated to my parents whose love and guidance are with me in whatever I pursue. They are the ultimate role models. May the Almighty God richly bless all of you. .

Fatima Nour BOUBLAL

Thank you.

DEDICATION II

After praising and thanking God for the number of grains of sand and pebbles, and prayers and peace be upon his Messenger. I dedicate this research to every person who supported me with advice or mocked me so they motivated me and push me to give my best.

Ahlam DIDA

Thank you.

Abstract

One of the top causes of death worldwide, both in developing and underdeveloped nations, is lung cancer, and in particular, lung nodule. The early detection of lung nodules allows patients to have proper treatment before further complications, which improve the survival rate. in computed tomography (CT) images are essential for the diagnosis of lung cancer. However, robust nodule detection has proven to be a difficult issue because of the heterogeneity of the lung nodules and the complexity of the surrounding area. In this thesis, we examine the impact of using some machine learning approaches for the classification and segmentation of lung nodules from CT images. In the first contribution, we propose a convolution neural network architecture for lung nodule classification. The CNN architecture consist in two convolution, two max-pooling and one soft max layers. This not too deep architecture grants rapidity in response. For purposes of comparison, we experiment other pretrained CNN models like VGG and RESNET for the same task of classification. For the task of segmentation, the pretrained UNET model has been used for the purpose of image semantic segmentation. The proposed classification and segmentation methods have been experimentally verified on the (IQ-OTH/NCCD) lung cancer dataset and the Decathlon dataset, respectively. Experimental results show that employing such techniques could immensely help medicine experts in taking decision. This study examines the use of computer-aided diagnosis in the medical field. We recognize that while machine learning (ML) is already being utilized, it is still in its early stages with ongoing developments of more beneficial upgrades.

Keywords: Lung Nodule, Classification, Segmentation , Machine Learning, Deep Learning

Résumé

Le cancer du poumon est l'une des principales causes de décès dans le monde, tant dans les pays en développement que dans les pays sous-développés. Le cancer du poumon est un type de nodule pulmonaire, c'est-à-dire une excroissance anormale de forme ronde plus dense que le tissu pulmonaire normal. La détection précoce des nodules pulmonaires peut permettre aux patients de bénéficier d'un traitement approprié s'ils sont cancéreux et constituer un moyen efficace d'améliorer leur taux de survie. La détection précise des nodules pulmonaires dans les images de tomodensitométrie (CT) est essentielle pour le diagnostic du cancer du poumon. Cependant, la détection robuste des nodules s'est avérée être un problème difficile en raison de l'hétérogénéité des nodules pulmonaires et de la complexité du milieu environnant. Dans cette thèse, nous proposons quelques approches utilisant l'intelligence artificielle qui aident à la classification et à la segmentation des nodules pulmonaires.

Dans la première contribution, nous proposons une architecture de réseau neuronal convolutif pour la classification des nodules pulmonaires. L'architecture CNN contient deux couches de convolution suivies de couches de mise en commun maximale pour identifier et séparer les différentes caractéristiques de l'image à des fins d'analyse dans le cadre d'un processus appelé "extraction de caractéristiques". En utilisant la sortie de la partie convolutionnelle, nous avons deux couches entièrement connectées pour prédire la classe de l'image en utilisant les caractéristiques extraites à l'étape précédente. Ensuite, nous avons tenté des expériences de classification en utilisant d'autres modèles pré-entraînés comme VGG et RESNET pour comparer nos résultats. Nous avons également évalué notre modèle en termes de performances : évaluation des paramètres, stabilité du modèle face au bruit ou à tout changement dans les données, impact de la taille de l'entraînement et temps de traitement.

D'autre part, le modèle UNET pré-entraîné a été utilisé pour la segmentation d'images, une technique de segmentation sémantique proposée à l'origine pour la segmentation d'images médicales.

Les méthodes proposées ont été vérifiées expérimentalement sur l'ensemble de données du cancer du poumon (IQ-OTH/NCCD) pour la classification et sur l'ensemble de données Decathlon pour la segmentation. Les résultats expérimentaux montrent que les architectures CNN et UNET proposées peuvent atteindre des performances compétitives.

Cette étude examine l'utilisation du diagnostic assisté par ordinateur dans le domaine médical, et nous pensons sincèrement que l'utilisation de la ML dans ce domaine en est encore à ses débuts, que de plus en plus d'améliorations bénéfiques sont en cours de développement, et nous pensons que le problème des ressources n'aura pas d'impact à l'avenir parce que toutes les nouvelles machines sont très performantes. En effet, il nous a été difficile de trouver des matériaux de qualité, en particulier pour le matériel.

Mots-clés: Nodule Pulmonaire, classification, segmentation, apprentissage automatique, apprentissage profond

ملخص

يعد سرطان الرئة أحد أهم أسباب الوفاة في جميع أنحاء العالم ، سواء في الدول النامية أو المتخلفة. سرطان الرئة هو نوع من عقيدات الرئة ، وهو نمو غير طبيعي في شكل دائري أكثر كثافة من أنسجة الرئة الطبيعية. قد يسمح الاكتشاف المبكر للعقيدات الرئوية للمرضى بالحصول على العلاج المناسب إذا كانوا سرطانيين ويكون وسيلة فعالة لتحسين معدل بقائهم على قيد الحياة. يعد الكشف الدقيق عن عقيدات الرئة في التصوير المقطعي المحوسب ضروريًا لتشخيص سرطان الرئة. ومع ذلك ، فقد ثبت أن الاكتشاف القوي للعقيدات يمثل مشكلة صعبة بسبب عدم تجانس العقيدات الرئوية وتعقيد البيئة المحيطة. في هذه الرسالة ، نقترح بعض الأساليب باستخدام الذكاء الاصطناعي التي تساعد في تصنيف وتجزئة العقيدات الرئوية.

في المساهمة الأولى ، نقترح بنية شبكة عصبية تلافيفية لتصنيف العقيدات الرئوية. تحتوي بنية CNN على طبقتين التفاف متبوعين بطبقات تجمع أقصى لتحديد وفصل الميزات المختلفة للصورة للتحليل في عملية تسمى استخراج الميزة. باستخدام الإخراج من الجزء التلافيفي ، لدينا طبقتان متصلتان تمامًا للتنبؤ بفئة الصورة باستخدام الميزات المستخرجة في المرحلة السابقة. بعد ذلك ، جربنا تجارب التصنيف باستخدام نماذج أخرى مدربة مسبقًا مثل VGG و RESNET لمقارنة نتائجنا. وتقييم نموذجنا من حيث الأداء: تقييم المعلمات ، واستقرار النموذج في مواجهة الضوضاء أو أي تغييرات في البيانات ، وتأثير حجم التدريب ، ووقت المعالجة.

من ناحية أخرى ، تم استخدام نموذج UNET المُدرب مسبقًا لغرض تجزئة الصور وهي تقنية تجزئة دلالية مقترحة في الأصل لتجزئة التصوير الطبي.

تم التحقق من الطرق المقترحة بشكل تجريبي على مجموعة بيانات سرطان الرئة (IQ-OTH / NCCD) للتصنيف ومجموعة بيانات Decathlon للتجزئة. تظهر النتائج التجريبية أن بنى CNN و UNET المقترحة يمكن أن تحقق أداءً تنافسيًا.

تبحث هذه الدراسة في استخدام التشخيص بمساعدة الكمبيوتر في المجال الطبي ، ونعتقد أن استخدام ML في هذا المجال لا يزال في مراحله الأولى ، وهناك المزيد والمزيد من الترقيات المفيدة قيد التطوير ، ونعتقد أن مشكلة الموارد لن يكون لها تأثير في المستقبل لأن جميع الآلات الجديدة تتمتع بقدرات عالية. لأنه كان من الصعب علينا إيجاد مواد جيدة ، خاصة للأجهزة.

الكلمات المفتاحية: العقدة الرئوية، التعلم الالي، التعلم العميق، التصنيف، التحديد

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Chapter 1

General Introduction

Diseases continue to be a significant health challenge in today's world, such as cancer, diabetes, and heart disease. Lung cancer is a particularly concerning condition that affects millions of people worldwide, with more than 2.21 million cases a year and 1.8 million deaths, according to the World Cancer Research Fund International. Lung cancer is one of the two types of lung nodules: malignant (cancerous) and benign, which is a small, round, or oval-shaped growth in the lungs. Respiratory illnesses and infections can cause nodules to form in the lungs. Most people find out they have a lung nodule after getting an imaging test in preparation for a procedure or for another purpose. Lung nodules show up on imaging scans like X-rays or CT scans. A healthcare provider may refer to the growth as a spot on the lung, coin lesion, or shadow. AI techniques are highly efficient in identifying the diagnosis of different types of diseases when it comes to the use of technology in the detection of diseases. In many tumor types, the likelihood of undergoing successful therapy or treatment increases with an early cancer diagnosis. One important strategy is to assess patients who are at risk but have no symptoms, like our case with lung nodules. Early cancer diagnosis could be revolutionized by machine learning.

1.1 Lung nodules

A pulmonary nodule is an abnormal growth with a typically spherical shape. It can form in either one or both However, nearby anatomical features like arteries and the pleural surface may confound it. Nodules can occur in different places in the lung tissues and can have different sizes and forms, as seen on a CT scan. Nodules on the lungs are often benign (not malignant). The pathologist may refer to the growth as a coin lesion, a patch on the lung, or a shadow. Pulmonary nodules are rarely an indication of lung cancer. About 95% of lung nodules are benign. Many things can cause benign lung nodules, including infections and scarring. If you have a pulmonary nodule, your healthcare provider may want to perform additional tests to determine the cause and rule out lung cancer. Despite the fact that pulmonary nodules are rarely cancerous but the number of lung cancer is still high in fact lung cancer is the second most common cancer worldwide It is the most common cancer in men and the second most common cancer in women. There were more than 2.2 million new cases of lung cancer in 2020, according to the World Cancer Research Fund International. This means that it is widely spread, and this disease must be studied and solutions sought.

In Table 1.1, we present the global cancer incidence and rates in 2020, as well as the ten countries with the highest rates of lung cancer and the highest number of deaths from lung cancer in the same year. On major indicator used in this table is age-standardized rate (ASR) which is summary the rate of disease that a population would have if it had a standard age structure. Standardization is necessary when comparing populations that differ with respect to age because age has a powerful influence on the risk of dying from cancer.

rank	country	number	ASR/100,000
/	world	2,206,771	22.4
1	Hungary	10,274	50.1
2	Serbia	8,048	47.3
3	France	166	42.9
4	French Polynesia	144	40.4
5	Turkey	41,264	40.0
6	Montenegro	443	39.7
7	Belgium	9,646	38.3
8	Bosnia	2,513	37.8
9	North Korea	13,672	37.0
10	Denmark	5,047	36.8

Table 1.1: Lung cancer statistics based on countries in 2020. ASR is the age-standardized rate

From Table 1.1, we notice that Hungary had the highest overall mortality rate from lung cancer in 2020, followed by Serbia. And it is due to smoking and tobacco consumption.[11]

Lung nodules are often detected incidentally during imaging tests such as X-rays or CT scans. The process of diagnosing a lung nodule involves several steps, which may include[16]:

- Review of medical history and physical examination: A doctor will review a patient's medical history and perform a physical examination to determine if any symptoms are present.

- Imaging tests: Imaging tests such as chest X-rays, CT scans, or PET scans may be ordered to visualize the lung nodule and determine its characteristics, such as size, shape, and location.

- Biopsy: If the imaging tests suggest that the nodule may be cancerous, a biopsy may be performed to obtain a sample of tissue for examination under a microscope. This can be done through several methods, including a needle biopsy, bronchoscopy, or surgery.

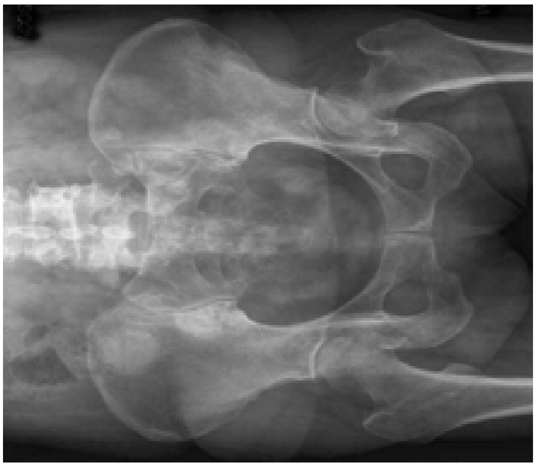
- Follow-up imaging: If the nodule is not cancerous or the biopsy is inconclusive, the doctor may recommend follow-up imaging tests at regular intervals to monitor the nodule's growth and appearance.

The specific diagnostic approach for lung nodules can vary depending on factors such as the patient's age, medical history, and the nodule's characteristics.

1.2 medical image

Medical imaging is the process of visual representation of the structure and function of different tissues and organs of the human body for clinical purposes, and medical science is the detailed study of normal and abnormal anatomy and physiology of the body. Medical imaging techniques are used to show internal structures under the skin and bones, as well as to diagnose abnormalities and treat diseases. Medical imaging is a central part of the improved outcomes of modern medicine. Different types of medical imaging procedures include:

- X-rays: are high-energy electromagnetic radiation that can penetrate solids. and ionize gases. X-ray passes through the body, they are absorbed or attenuated at differing levels, according to the density and atomic number of the different tissues, creating a profile. The X-ray profile is registered on a detector, creating an image.[12] Figure 1.1 shows two examples of X-ray images.



(a) (b)

Figure 1.1: X_Ray images of the pelvis and the shoulder

- XRay Computed Tomography: Computed Tomography (CT) is a diagnostic technology that combines X-ray equipment with a computer and a cathode ray tube display to produce images of cross-sections of the human body. The radiographic film is replaced by a detector that measures the X-ray profile. Inside the CT scanner, there is a rotating frame that has an X-ray tube mounted on one side. and the detector mounted on the opposite side. A beam of X-rays is generated by a rotating frame that spins the X-ray tube and detector around the patient. Each time the X-ray tube and detector make one complete rotation, an image or slice is acquired. As the X-ray tube and detector make this rotation, the detector takes numerous profiles of the attenuated X-ray beam. Each profile is reconstructed by the computer into a 2D image of the slice that was scanned.[12] Some examples of CT scans are shown in Figure 1.2.

(a) CT scan image of the lung in 2D

(b) CT scan image of the skull in 3D

Figure 1.2: Two images captured using XRay Computed Tomography imaging technology

- Magnetic resonance imaging: MRI is a diagnostic technology that uses magnetic and radio frequency fields to image the body tissues and monitor body chemistry. The MRI used for visualizing morphological alterations rests on its ability to detect changes in proton density and magnetic spin relaxation times. The MR scanner consists of three main components. The main magnet is a permanent magnet that generates a magnetic field. The magnetic field gradient system normally consists of three orthogonal gradient coils, which are essential for signal localization. The RF (Radio-frequency) system consists of a transmitter coil that is capable of generating a rotating magnetic field for exciting a spin system, and a receiver coil that converts a processing magnetization into an electrical signal. The signals are measured by the MR scanner, and a digital computer reconstructs these signals into images.[12] figure 1.3 an example of MRI image.

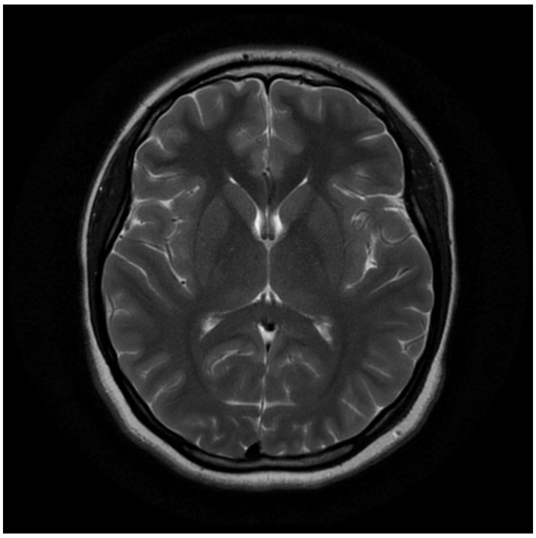


Figure 1.3: MRI image of the brain

- Ultrasounds: Ultrasound imaging technology was used earlier as a diagnostic tool for brain images. Today, ultrasound is a widespread imaging technology used in diagnostic laboratories and clinics. It is free from radiation exposure risk, comparatively less expensive, and highly portable as compared to other imaging techniques like MRI and CT. Ultrasound uses sound waves of high frequency to diagnose the organs and structure of the body. The ultrasound system operates at a high frequency. Special technicians or doctors use it to observe the kidneys, heart, liver, blood vessels, and other body organs. The most critical component of ultrasound is a transducer. An ultrasonic image, or sonogram, is formed by transmitting pulses of sound waves into tissues using a special probe. Different tissues reflect these sounds to different degrees.These reflected sound waves (echoes) are detected and presented as an image with the operator's help.[12] we can see an example of a normal heart ultrasound scan in figure 1.4

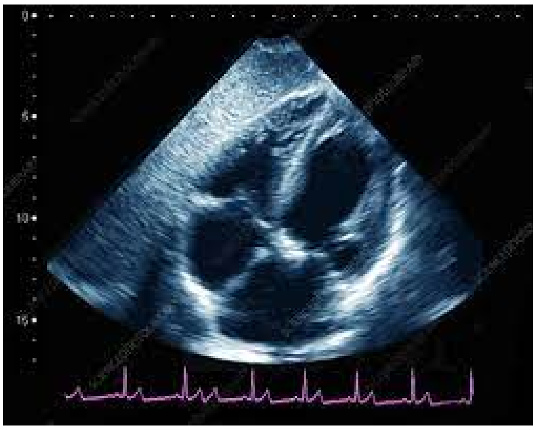


Figure 1.4: A heart ultrasound scan

1.3 CAD of lung nodules

As previously stated, early detection of lung nodules, a type of cancer, is crucial as it can prevent many potential situations that may otherwise lead to fatal outcomes. The most typical method of lung cancer diagnosis is by a pathologist. Although this is the most effective method, it has several drawbacks:

- Primary-level hospitals and clinics struggle to find qualified pathologists because of how difficult it is to inherit or innovate upon the professional background and extensive experience of pathologists;
- The time- and the money-consuming task is tedious;
- Pathologists who are overworked may make incorrect diagnoses.

Exploiting computational techniques, such as Computer-Aided Diagnosis (CAD) systems, assists radiologists in image processing and aids pathologists in decision making. CAD systems serve as a second opinion by automatically locating lung nodules, potentially improving detection rates and assisting in cases where radiologists may have missed nodules. These systems provide additional information, including distinguishing between benign, malignant, and non-nodular formations, while also reducing reading times and allowing radiologists to focus on image interpretation. Traditional methods for lung nodule detection on Chest X-Ray (CXR) images relied on hand-crafted features, which had limitations in terms of effectiveness and required manual design and tuning. In contrast, deep learning-based CAD systems offer advantages by automatically learning features that optimize nodule categorization and detection, leveraging large labeled training datasets. However, challenges exist, such as the need for substantial labeled training data and addressing three subproblems: lung area segmentation, candidate nodule detection, and reducing false positives through candidate classification. The utilization of CAD systems, particularly those based on deep learning, enhances the performance and reliability of lung nodule detection, thereby improving overall diagnostic capabilities in the field of radiology.

1.4 Problematic and Objective

Relying solely on humans for diagnosis can be slow, as it involves waiting for the pathologist's results, and there is a risk of incorrect diagnoses due to human or machine errors, especially since Computer-Aided Diagnosis (CAD) and artificial intelligence are still in their early stages. The current approaches used for lung nodule analysis lack accuracy and speed, despite lung cancer being the second-most common cancer globally and the most common cancer in men, and the second most common in women. Therefore, it is crucial to develop more accurate systems for lung nodule diagnosis.

In our study, we use a not too deep CNN architecture along with other pretrained deep Convolutional Neural Networks (CNNs) for lung nodule classification on CT scan images. Additionally, we employ the U-Net model for nodule segmentation. Our primary objective is to enhance the accuracy of deep learning-based recognition and localization of lung nodules. To assess the efficacy of our proposed method, we conducted various experiments as part of our research. Consequently, we shifted our focus towards the utilization of deep learning, and machine learning in general, for the diagnosis of lung nodules.

In the second chapter (10), we provide an overview of the literature works that are closely related to our research. These works share a common objective, focusing on lung nodule classification and detection. We situate our work within the context of these existing studies, highlighting their contributions and identifying the gap that our research aims to address.

Moving on to chapter 3 (17), we present our method, which involves utilizing Convolutional Neural Networks (CNN) for classification and the U-Net model for segmentation. We describe the methods in detail.

In chapter 4 (27), we discuss the outcomes of the various experiments conducted using the selected methods. We analyze and interpret the results to assess the effectiveness and robustness of each model. This evaluation allows us to draw conclusions regarding the performance and capabilities of the tested methods in lung nodule classification and detection.

Chapter 2

Related work

CT imaging technology has been widely used in the early clinical identification of lung nodules. In this chapter, we describe some of the existing approaches of lung nodules classification and segmentation using CT scan images. To make this chapter clearer, a table that summarized all these work along with their proposed methods, used datasets, and results achieved has been provided at the end of this chapter.

In order to classify the benignity and malignancy of lung nodules, a unique deep convolutional network approach was suggested in [1]. First, lung nodule pictures were retrieved, segmented, and whitened using zero-phase component analysis. Then, a deep convolution network was built by adding a multi-layer perceptron to the framework. Finally, the deep convolution network is adjusted to avoid gradient dispersion using the mini-batch stochastic gradient descent approach with a momentum coefficient. The achieved accuracy was 96.0% which demonstrates that the suggested approach can offer a precise and effective solution to the issue of identifying benign and malignant lung nodules in medical images.

In [2], and for the purpose of detecting lung nodules, a two-stage convolution neural network architecture (TSCNN) has been developed. The upgraded UNet segmentation network serves as the foundation for the CNN architecture's initial detection of lung nodules. In addition, offline hard mining is employed for training and prediction in accordance with the proposed cascaded prediction algorithm in order to achieve a high recall rate. The proposed dual pooling structure, which is integrated into three 3D CNN classification networks for false positive reduction, forms the foundation of the CNN architecture in the second stage. The suggested TSCNN architecture provided competitive detection performance, according to experimental results.

This paper [3] proposes a convolutional neural network called 3D-Res2UNet, and offers a method for segmenting lung nodules in CT images using 3D-UNet and Res2Net. An asymmetrical hierarchical connection network in 3D-Res2Net allows for effective multi-scale feature extraction. It increases the receptive field of each layer of the network and allows the network to convey multi-scale information with finer granularity. The network is less likely to experience gradient disappearance and explosion issues, which increases the precision of segmentation and detection. The method's dice coefficient index achieved 95.30% and the recall rate reached 99.1%, showing that it performs well for segmenting images of lung nodules.

In [4], a pipeline for detecting lung nodules in chest X_Ray images is proposed and analyzed, which includes lung area segmentation, potential nodule localization, and nodule candidate classification. a method for classifying nodule candidates with a CNN trained from scratch is presented. The effectiveness of the method relies on the selection of data augmentation parameters, the design of a specialized CNN architecture, the use of dropout regularization on the network, inclusive in convolution layers, and addressing the lack of nodule samples compared to background samples balancing mini-batches on each stochastic gradient descent iteration. The experiments showed that CNNs were capable of achieving competitive results when compared to state-of-the-art methods.

For the accurate diagnosis of the malignant nodules, a novel deep learning-based model comprising several techniques is proposed in [5]. For lung nodule identification and classification, two deep three-dimensional (3D) customized mixed link network (CMixNet) designs have been used. Faster R-CNN was used to detect nodules using recently-learned features from CMixNet. The developed 3D CMixNet structure's learned characteristics were used to classify the nodules using a gradient boosting machine. Better results were obtained compared to the existing approaches thanks to the proposed system, which produced findings with a sensitivity and specificity of 94% and 91%, respectively.

The effectiveness of deep learning algorithms for diagnosing lung cancer on issues involving medical image analysis is addressed in this research [6]. In order to perform binary classification tasks on medical images with high classification accuracy and little variance, a new deep learning architecture was presented. The proposed deep convolution neural network's initial discriminant compact features are meant to be learned.

The main objective of the work [7] is to detect cancerous lung nodules and classify lung cancer and its severity. To detect the location of the cancerous lung nodules, this work uses novel deep learning methods and top feature extraction techniques such as Histogram of oriented Gradients (HoG), wavelet transform-based features, Local Binary Pattern (LBP), Scale Invariant Feature Transform (SIFT), and Zernike Moment. After extracting texture, geometric, volumetric, and intensity features, Fuzzy Particle Swarm Optimization (FPSO) algorithm is applied for selecting the best feature. Finally, these features are classified using Deep learning. From the experimental results, it is shown that novel FPSOCNN performs better than other techniques.

Due to the variety of lung nodules and the similarity of visual characteristics between nodules and their surroundings, a robust segmentation of nodules becomes a challenging problem. In study [8], a Dual branch Residual Network (DB ResNet) was developed. The approach integrates two new schemes to improve the generalization capability of the model: 1) The proposed model can simultaneously capture the multi-view and multi-scale features of different nodules in CT images; 2) the features of the intensity and the convolution neural networks (CNN) are combined. Experimental results show that the DBResNet achieves superior segmentation performance with an average dice score of 82.74%, which is 0.49% higher than that of human experts. This proves that the proposed method is as good as the experienced radiologist.

In order to categorize the various forms of lung nodule malignancies, a novel structure called a multi-level cross-residual convolutional neural network (ML-xResNet) is developed in [9]. To extract multi-scale features from the inputs, ML-xResNet is built using three-level parallel ResNets with varying convolution kernel sizes. The residuals also form a crossover relationship with not just the current level but also other levels. Based on the outcomes of the experiments, the suggested ML-xResNet gets the best results, with a ternary classification accuracy of 85.88% and a binary classification accuracy of 92.19%, without the use of any additional custom preprocessing algorithms.

The research [10]suggests a Deep Deconvolutional Residual Network (DDRN) based method for lung nodule segmentation from CT images. This strategy is founded on two important realizations. The 2D set of the CT images is sent into the suggested deep deconvolutional residual network, which is trained from beginning to end and can recognize a wide range of nodules. The spatial information lost during the pooling procedure is preserved and the full-resolution features are captured by the summation-based long skip connection from the convolutional to the deconvolutional component of the network. Results show that the approach can divide nodules into distinct parts and generate an average Dice score of 94.97%.

in the table below 2.2 we summarize the works we have discussed before

PAPER	MODEL	DATASET	RESULT
Enhui Lv et al [1]	novel deep convolutional network approach to classify the benignity and malignancy of lung nodules	LIDC dataset	accuracy of 96%
Haichao Cao et al [2]	A two-stage convolutional neural network (TSCNN) : UNet & 3D CNN	LIDC IDRI dataset	sensitivity of 84.8%
Juan Lyu et al [3]	multi-level cross residual convolutional neural network (ML-xResNet)	LIDC IDRI dataset	85.88% accuracy for ternary classification and 92.19% accuracy for binary classification
Julio Mendoza and Helio Pedrini.[4]	CNN trained from the scratch for classifying nodule candidates	LIDC IDRI dataset	sensitivity value of 73.1%
Jun Sang at al[5]	a novel deep learning-based model with multiple strategies	LIDC IDRI dataset	sensitivity (94%) and specificity (91%)

Table 2.1: state of the art

PAPER	MODEL	DATASET	RESULT
Bahram Lavi at al[6]	a new deep learning architecture	Kaggle Data Science Bowl 2017 (KDSB17) dataset	87% for Sensitivity, 99% for specificity and 95% for the f1-score
Zhitao Xiao at al [7]	a new convolutional neural network (3D-Res2UNet) Based on 3D-UNet and Res2Net	LUNA16 public dataset	the dice coefficient index reached 95.30% and the recall rate reached 99.1%
A Asuntha and Andy Srinivasan.[8]	This work uses feature extraction techniques And classified using deep learning.	LIDC IDRI dataset	The accuracy obtained is 97.213%, Sensitivity is 97.853%, Specificity is 97.513%
Enmin Song at al[9]	Dual branch Residual Network (DB ResNet) which is a data driven model.	LIDC IDRI dataset	segmentation performance with an average dice score of 82.74% on the dataset.
Ganesh Singadkar [10]	Deep Deconvolutional Residual Network based approach for the lung nodule segmentation.	LIDC IDRI dataset	segmentation performance with an average dice scores of 94.97%, and Jaccard index of 88.68%.

Table 2.2: state of the art

In conclusion, the chapter on related work emphasizes the critical need to develop effective methods for the classification and segmentation of lung nodules. The development of such methods is crucial as it aids radiologists in making accurate diagnoses and reduces the labor-intensive and time-consuming nature of this task. Throughout the chapter, we have summarized more than ten articles that specifically address the challenges faced by these applications. By reviewing and analyzing the existing literature, we gain insights into the current state of research and identify gaps that our own study aims to address. The collective efforts presented in these articles highlight the importance of advancing the field of lung nodule analysis and pave the way for further advancements in the accurate detection and characterization of these nodules.

Chapter 3

method

Machine learning: Machine learning (ML) is an umbrella term that refers to a broad range of algorithms that perform intelligent predictions based on a data set. These data sets are often large, perhaps consisting of millions of unique data points.
Pattern recognition which is a type of machine learning is a scientific discipline whose goal is the classification of objects into several categories or classes. Depending on the application, these objects can be images, signal waveforms, or any type of measurement that needs to be classified.
We devote this chapter to explaining in detail our proposed methods that are for lung nodule classification and segmentation using CNN and Unet based on CT scans. Along with transfer learning or the use of pretrained models in our lung image classification study. Each model possesses its own unique architecture and characteristics, enabling them to capture and learn features for accurate classification. We provide a concise definition of each model, highlighting its key attributes.

3.1 classification

Medical image classification plays a crucial role in the field of healthcare, enabling accurate diagnosis, treatment planning, and disease management. With the advancements in imaging technology, large volumes of medical images, such as X-rays, CT scans, and MRIs, are generated daily. Efficient and accurate classification of these images has the potential to significantly impact patient care. In the specific context of lung images, classification tasks aim to distinguish between different conditions, including lung cancer, benign tumors, and healthy lung tissue. The classification process involves training machine learning models to recognize patterns and features within the images that are indicative of specific lung conditions.

These models learn from labeled datasets, where each image is annotated with its corresponding class.

The proposed CNN

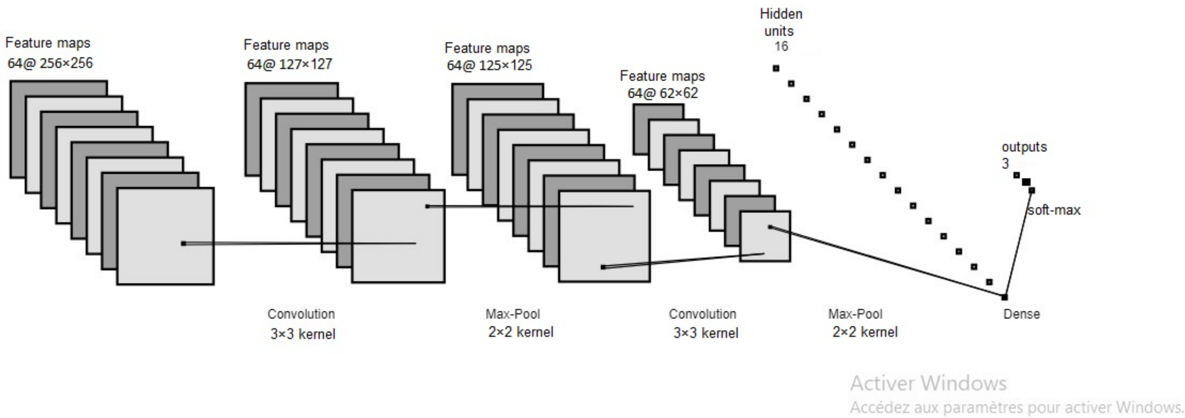


Figure 3.1: Scheme of our proposed CNN architecture.

The proposed CNN architecture mainly consists of the following layers: two convolution layers that followd by a max-pooling layer each, and two fully connected layers with one softmax unit as shown in figure 3.1. The network begins with one convolution layer which takes as input an image of size 254 * 254 pixels. It consists of 64 feature maps with the convolution kernel of 3 * 3. The kernel size for max pooling layers is 2 * 2 and the stride of 2 pixels, and the fully-connected layer generates an output of 16 dimensions. These 16 outputs are then passed to another fully connected layer containing a softmax unit. which represent the probability that the image belongs to a class from the three classes we have. Note that each convolution layer in our CNN model is followed by a rectified linear unit (ReLU) layer to produce their outputs.

3.1.1 Loss function used

A s aloss measure, we employed Sparse categorical crossentropy which computes the cross-entropy loss between the labels and predictions. It is a loss function that is used when having a single-label with multi-class classification problem. The labels are mutually exclusive for each data, meaning each data entry can only belong to one class.

3.1.2 Activation functions used:

Rectified Linear Unit: As an activation function, we used Rectified Linear Unit ReLU. It is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. As shown in the figure 3.2.
ReLU has significant effects on back-propagation during training. It implies that computing the gradient of a neuron requires little computational effort. On the contrary, non-linear activation functions such as the Sigmoidal functions don't often have this characteristic.

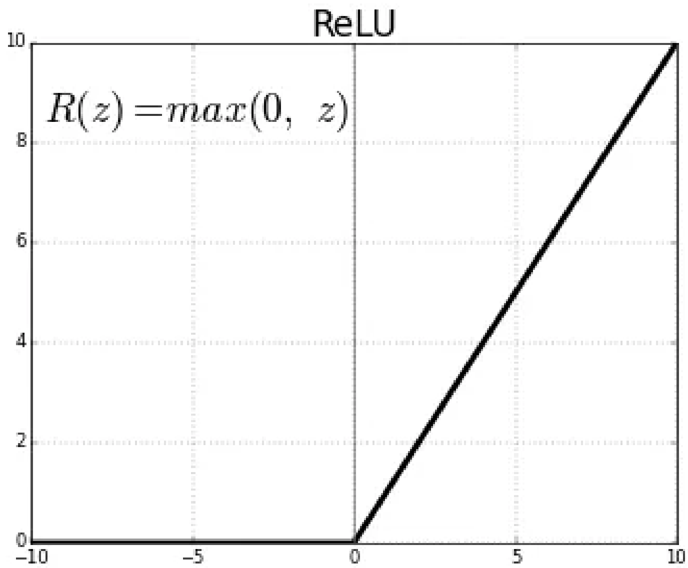


Figure 3.2: RELU function

From the figure 3.2 above, we can see that the function is half rectified, which reduces the model's capacity to effectively fit or train from the data. This means that any negative input to the ReLU activation function immediately becomes zero, and when several neurons only output a value of zero, the dying ReLU problem occurs.

SoftMax function: The softmax function is a more generalized version of logistic activation function, that is used for multiclass classification most of the time in the last layer. which returns the probability of the sample belonging to each class.

3.1.3 Layers

convolutional layer: The convolutional layer is the most important part of the CNN design. It is made up of a number of convolutional filters (also known as kernels). The output feature map is produced by convolving the input image with the filter, which is expressed as N-dimensional metrics.Later, this feature map is given to other layers.[13]

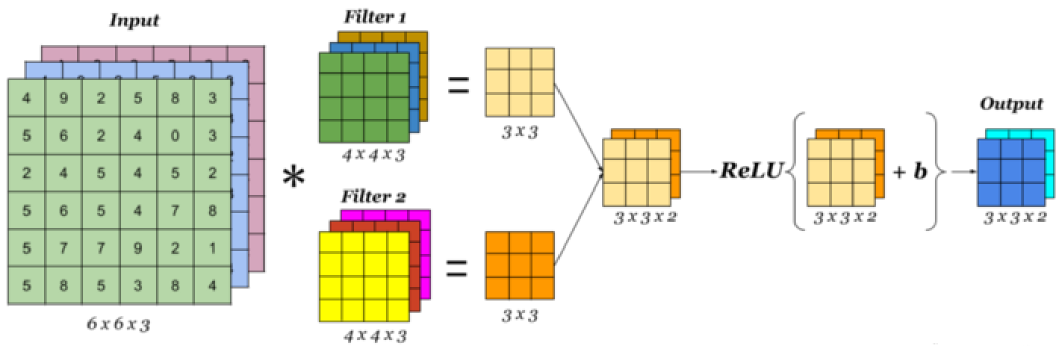


Figure 3.3: convulotional layer

Pooling Layer: The main task of the pooling layer is the sub-sampling of the feature maps. These maps are generated by following the convolutional operations. In other words, this approach shrinks large-size feature maps to create smaller feature maps. Concurrently, it maintains the majority of the dominant information (or features) in every step of the pooling stage. The most familiar and frequently utilized pooling methods are max, min, and GAP pooling. Figure 3.4 illustrates these three pooling operations.[13]

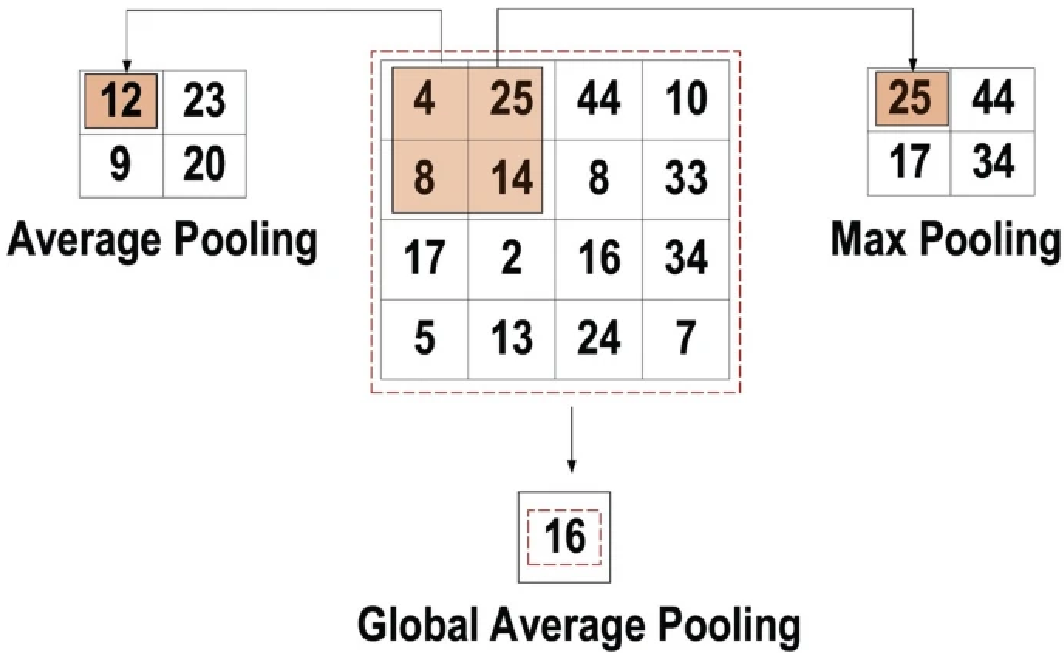


Figure 3.4: Three types of pooling operations

in max pooling, the maximum element from the region of the feature map that is covered by the filter is selected as shown in 3.5.

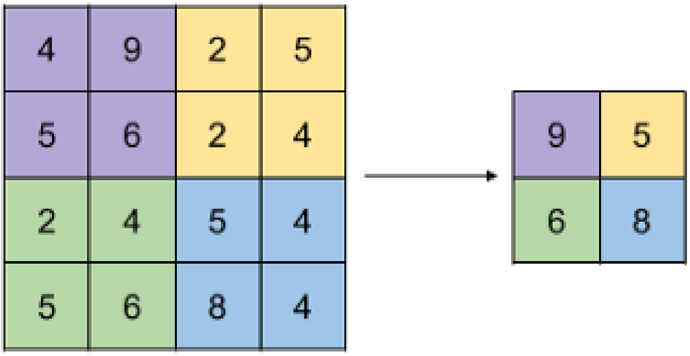


Figure 3.5: Maxpooling process

Flatten layer:flattening converts the 2-dimensional output of the convolutional layer into a one-dimensional linear vector to be used as input for a dense layer as illustrated in 3.6.

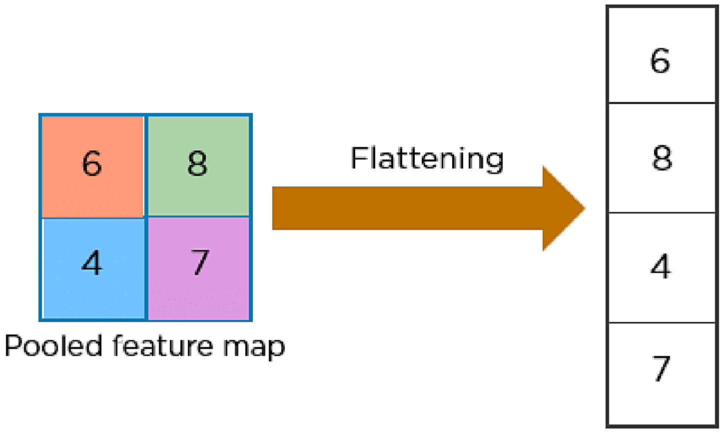


Figure 3.6: flattening process

Dense layer: The last stages of the neural network use a layer known as a dense layer, also known as a fully connected layer. This layer helps in changing the output's dimensionality from the preceding layer so that the model can easily establish the relationship between the values of the data it is working with.

3.2 Transfer learning

In our study, we place significant emphasis on the use of transfer learning techniques to leverage the power of pre-trained models for lung image classification. Transfer learning involves using knowledge learned from one task or dataset and applying it to a different but related task or dataset. This approach has gained prominence in medical image analysis due to its ability to overcome limitations posed by small datasets or limited labeled data and computationally expensive training processes also it helps prevent overfitting, as the pre-trained models have already learned useful general features from a large and diverse dataset. This regularization effect allows the models to generalize better to new lung images and make accurate predictions. Lung image classification is a challenging task that requires the identification and differentiation of various lung conditions, including diseases such as lung cancer, benign tumors, and normal lung tissue. However, due to the limited availability of annotated lung image datasets, training accurate deep-learning models from scratch becomes a challenging and resource-intensive process. Transfer learning addresses this challenge by using pre-trained models, such as ResNet (Residual Neural Network) and VGG (Visual Geometry Group) networks, which have been trained on large-scale image classification datasets like ImageNet. These pre-trained models have learned rich and generic features from diverse images, enabling them to extract meaningful representations of lung images as described in figure3.7.

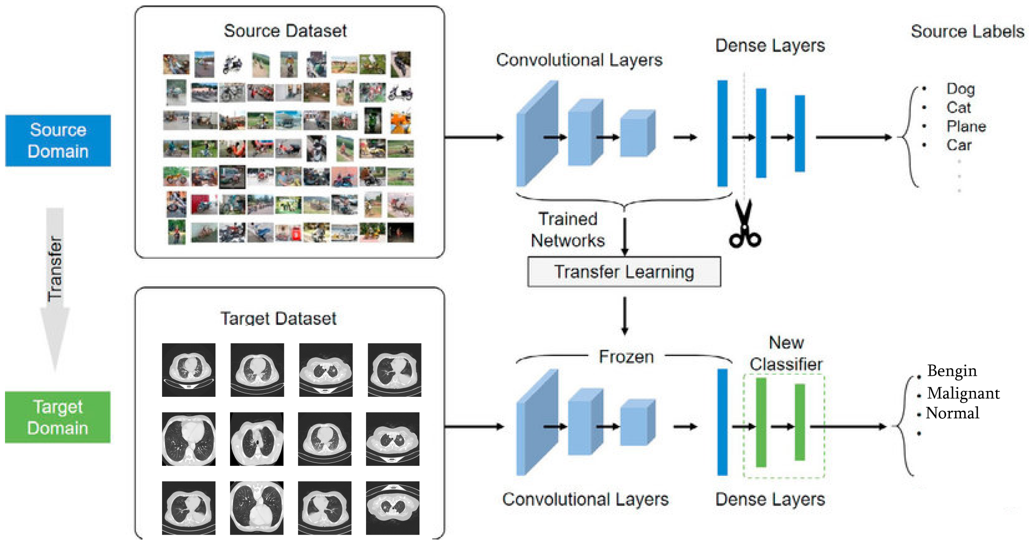


Figure 3.7: Graphic representation of transfer learning

VGG16 is a convolutional neural network (CNN) architecture proposed by the Visual Geometry Group (VGG) at the University of Oxford. The "16" stand for the number of weight layers in the model (convolutional layers), primarily composed of convolutional layers followed by max-pooling layers. VGG16 is known for its uniform architecture, utilizing small 3x3 convolutional filters throughout the network as we can see in figure 3.8 below. The model's deep structure enables it to capture intricate details and complex patterns within the lung images, contributing to its classification performance.

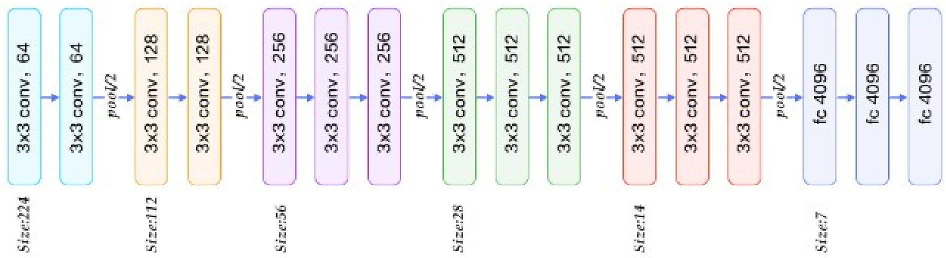


Figure 3.8: VGG16 architecture

ResNet50 is another variant of the ResNet architecture but with 50 layers. Like ResNet50V2, it incorporates residual connections to alleviate the vanishing gradient problem. ResNet50's deeper architecture enables it to capture more complex and abstract features from the lung images. The model has shown promising performance in various computer vision tasks, including image classification.

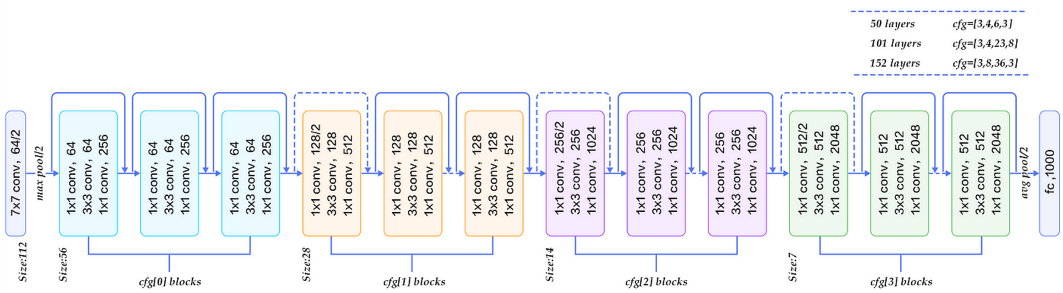


Figure 3.9: resnet50 architecture

ResNet50V2 is an extension of the ResNet (Residual Neural Network) architecture. It addresses the degradation problem encountered in very deep neural networks by introducing residual connections. These connections allow information to bypass certain layers, facilitating the flow of gradients and enabling the network to learn more effectively. ResNet50V2 consists of 50 layers, including convolutional layers, batch normalization layers, and fully connected layers. The model's ability to capture both local and global features makes it suitable for lung image classification tasks.

MobileNet is a lightweight convolutional neural network architecture specifically designed for mobile and resource-constrained devices. It focuses on achieving a good balance between model size and accuracy. MobileNet utilizes depthwise separable convolutions, which decompose the standard convolution operation into depthwise and pointwise convolutions. This significantly reduces the computational complexity and model size while preserving the ability to capture important features. MobileNet is well-suited for scenarios where computational resources are limited, making it an efficient choice for lung image classification tasks on mobile devices or edge computing platforms.

InceptionV3 also known as GoogLeNet, is a deep convolutional neural network architecture that has achieved remarkable performance in various computer vision tasks. It introduces the concept of inception modules, which consist of multiple parallel convolutional operations of different sizes. This allows the network to capture both local and global features effectively. InceptionV3 employs a combination of 1x1, 3x3, and 5x5 convolutions, as well as max pooling and bottleneck layers, to extract rich spatial information from the input data. This architecture has demonstrated excellent performance in lung image classification, enabling accurate and discriminative feature representation.

NASNetLarge short for Neural Architecture Search Network Large, is an architecture designed using neural architecture search (NAS) methods. NASNetLarge is a highly complex and deep neural network architecture that surpasses human-designed models in terms of performance. It utilizes a cell-based architecture, where cells are repeated multiple times to construct the network. NASNetLarge leverages a reinforcement learning algorithm to automatically search for the optimal architecture that maximizes accuracy. It has demonstrated state-of-the-art results in various computer vision tasks, including lung image classification. NASNetLarge excels in capturing intricate patterns and features, making it a powerful model for accurate and high-performance lung image classification tasks.

3.3 Segmentation

In order to give an accurate lung CT image analysis, such as lung cancer detection, lung CT image segmentation is a prerequisite step for lung image analysis. In this study, we suggest segmenting lung CT images using the U-net architecture, one of the most popular deep learning image segmentation architectures. The architecture consists of a path that contracts to extract high-level information and a path that expands symmetrically to restore the required information. This network outperforms many others and can be trained end-to-end from a small number of pictures.

The use of the UNET

The U-Net architecture is a popular deep learning model widely used for medical image segmentation tasks, including lung cancer segmentation. It was originally proposed by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015. The U-Net architecture is specifically designed for tasks that require precise pixel-wise segmentation of images.
The U-Net architecture consists of an encoder-decoder network with skip connections. The encoder part captures the context and extracts high-level features from the input image, while the decoder part reconstructs the segmented output by upsampling and combining the feature maps from the encoder. The skip connections, which connect corresponding layers between the encoder and decoder, helping to preserve fine-grained spatial information during the upsampling process. Ronneberger et al [14]. proposed an architecture, U-net (see Figure 3.10), based on the FCN architecture, the basic elements of the U-net can be viewed as an association of convolution layers in the contracting path and deconvolution layers in the expansive path. The contracting path is like a classic architecture of a convolutional neural network that consists of Convolution layers with Rectified Linear Units and Max-pooling layers. On the other side, the expansive path, it consists of an upsampling of the feature map followed by up-convolution and convolution layers with ReLU. Due to the loss of border pixels at every convolution, it is necessary to crop a corresponding feature map from the extracting path and concatenate it with corresponding layers in the expansive path [15].

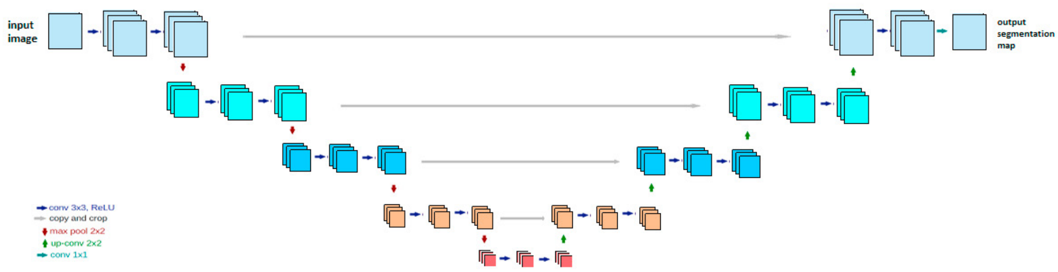


Figure 3.10: the UNET architecture

The u-net architecture used in [14]. Consists of two paths: the left path consists of two convolutions with the same padding followed by ReLU and a 2*2 max-pooling with stride 2, this operation is repeated four times on this path, and the right path consists of an up-convolution of the feature map from the left side and two 3*3 convolutions followed by ReLU, this operation is repeated four times in this path. Between the two paths, it is necessary to crop and concatenate corresponding feature maps from the left side with their corresponding in the other path due to the loss of border pixels in convolution layers.

In the training phase, the input images and their corresponding masks are used to train the U-net, and in the test phase, we give an image as input to generate the corresponding mask as output as shown in Figure3.11. And then, we apply the mask to the corresponding image to segment the area of interest, i.e. the lung nodule in our case.

The ground truth of the lung nodule was provided by manual segmentation, and before performing our experimentation in the dataset, we did a pre-processing step that consists of cropping the images to simply remove any information that does not belong to the area of study.[15]

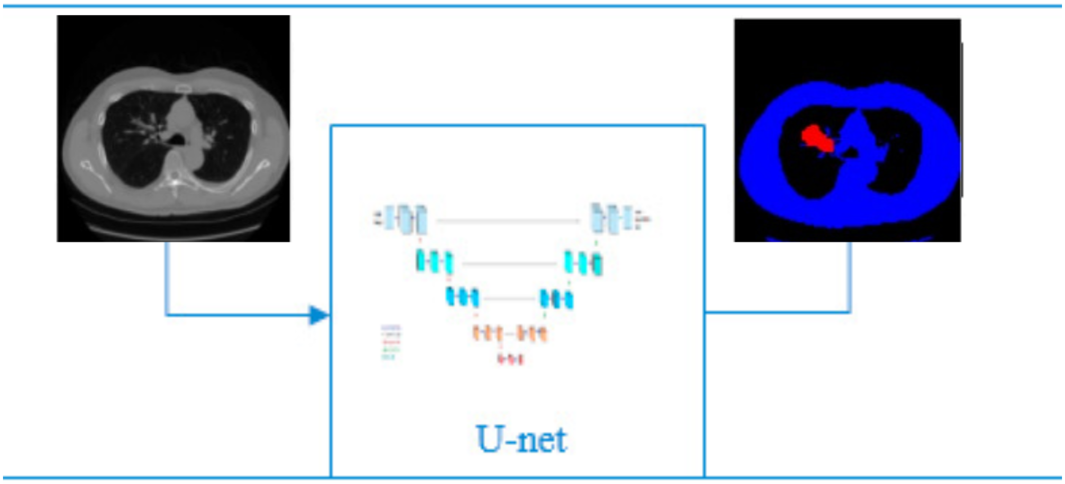


Figure 3.11: the way that U-net architecture works is that it takes the input image and generate the corresponding map for segmentation.

We received a variety of findings from our most recent work with CNN and UNET, some positive and some negative, which we will discuss in more detail in the following chapter.

The details of the experimental findings will be covered in more depth in the following chapter, together with a description of the materials and data used and a discussion of the results attained for each contribution.

Chapter 4

Experimentation

Coclusion

A lot of research is being done on the application of artificial intelligence (AI) in diagnostic medical imaging. AI has demonstrated outstanding sensitivity and accuracy in identifying imaging abnormalities, and it has the potential to improve tissue-based detection. AI and ML in medical imaging can be used for cancer diagnosis. We chose two primary approaches in this study—a convolutional neural network (CNN) for classification and we used UNET to improve the early detection and classification of lung nodules. We were motivated by the significant impact AI is having on the medical profession.

In this work we presented a lung nodule classification model by developing a CNN architecture from scratch, our model was implemented in the (IQ-OTH/NCCD) dataset we found on Kaggle and we obtained a classification accuracy of 0.98. Then we tried many pretrained CNN architectures like VGG16, RESNET50, InceptionV3, and others on the same data to compare our model results and performance.

On another hand, we tried the segmentation using the U-net architecture implemented on the DECATHLON dataset and we obtained an accurate segmentation with a 0.7 Dice-coefficient index. It was difficult to find a segmentation dataset for lung nodules because of the lack of data and the existing ones were private.

The training took some time and the process required better materials than our available ones. We kindly think that the use of ML in the medical field is still in its infancy, that more and more advantageous upgrades are being developed, and that the future impact of the resource shortage won't be felt because all the new machines are really powerful.

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