Artificial Neural Networks in Non-Small Cell Lung Cancer Detection using Computed Tomography Medical Imaging

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***Abstract*— On average, lung cancer is the cancer that kills the most people in the world due to its complex detection and cancer variants such as small and non-small cell cancers, with non-small cell cancers being the most common. The objective of this project is to compare different architectures of convolutional neural networks (CNN) such as: ResNet50, RESNET101, DenseNet201, EfficientNetB4, VGG16 and VGG19, which have been trained with the same database of approximately 1500 computer tomography images (CT) for the detection of the type of non-small cell lung cancer such as: squamous cell, adenocarcinoma and large cell. It was found among all the neural networks that the most reliable for time, space and accuracy is ResNet50, so it seeks to compare the accuracy of the ResNet50 neural network with other investigations, in order to compare the different architectures to see which one has a better accuracy in the detection of lung cancer.**

Keywords*— *Lung Cancer, Convolutional Neural Network, CNN, Machine Learning, Non-Small cell, NSCLC, SCLG

I. Introduction

Cancer has always been the leading cause of human loss over the years. According to the World Health Organization (WHO), cancer is one of the leading causes of death worldwide, with almost 10 million deaths in 2020 [43]. This problem has a high severity because it is fatal in most cases, if not all. It depends a lot on which organ affects so that it kills people more or less quickly. Lung cancer is the aggressive one because it kills around 1.8 million people in 2020, followed by colon and liver cancer. [43]. In Ecuador, lung cancer is the third type of cancer that causes death in both men and women, with these being 1,069 deaths out of 1,185 people detected with cancer, and its risk would range from 0.55 [44]. This interdisciplinary curriculum blends theory with hands-on bioinstrumentation labs, promoting active learning where students independently design, simulate, program, and acquire biomedical signals, fostering their active role in the learning process. [3]

A. *Comparative Analysis of AI Approaches*

There are different configurations made by other researchers when working with neural networks for the detection of lung cancer. The different configurations range from the architecture of the model, the dataset used, the hardware used to train the different networks, the sensitivity used, among others, as we can see in Table 1.

TABLE I. Comparative Table, Between Different Results And Materials Used For Artificial Intelligence Based On ResNet50

Models	***[18]***	***[12]***	***[29]***	***[35]***
Percentages	99,39	97,2	88,1	83,7
Number of images	30,387	5000 x 3	888 + 1397	3442
Hardware	11 GB NVIDIA 32 GB RAM	Google Colaboratory GPU	i7-7700 NVIDIA GeForce RTX	-
Backbone	CDC_Net, ResNet-50, Inception V3, Vgg-19	-	ResNet-50	Pytorch Platform
Method	CDC Net model	Convolutional Neural Network	SC-Dynamic R-CNN	-
Type of Images	Rx and CT	Histoligical	CT	CT
Ratio of training	90.:10	90.:10	-	-
F1-score	98.26	96	-	-
Sensitivity	98.13	-	-	84.4

Table 1 is a comprehensive analysis of the limitations inherent in this research in comparison to others within the same field. The quantity of available data assumes a pivotal role, owing to its profound influence on the development and learning trajectory of the neural network. Additionally, the hardware device employed constitutes a critical aspect that warrants careful consideration, particularly in the context of working with convolutional networks, given its distinct behavior and impact on the overall process.

Lung cancer is the uncontrolled division of cells in a tissue, generally produced by a mutation in the gene that codes for the p53 protein, a protein that is known as the guardian of cells since it controls cell division, but it is mutated. This causes the uncontrolled division of cells [13]. In the lung, cancer occurs in the tissues that line the air passages. There are two main types of lung cancer divided into small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC) [20]. These two types grow differently and are treated differently. Non-small cell lung cancer is the most common type of lung cancer, 85% of all lung cancer cases [24]. Cancer in these types of cells is often difficult to detect even with computed tomography (CT) and is detected when it has already spread to other organs. NSCLC cells are divided into three types, Adenocarcinoma, Squamous Cell Carcinoma, and Large Cell carcinoma. Adenocarcinomas originate in cells that produce mucus and other substances, and generally develop in the peripheral areas of the lung [8]. Squamous cell carcinoma generally forms in the central part of the lungs, specifically in the flat cells that line the interior [6]. Large Cell carcinoma also called undifferentiated carcinoma is formed in any portion of the lung [34]. Differentiating this type of cancer is usually a bit difficult, so nowadays neural networks are being used to help with the detection and differentiation of this type of cancer, in order to reduce the mortality rate thanks to a detection fast, safe, and low-cost. The neural networks that are going to be used will need a training stage, a stage in which computed tomography (CT) images will be used.

B. Role of Convolutional Neural Networks (CNNs) in Lung Cancer Detection

CT images are a type of modern medical image based on a method of radio graphic imaging that can determine the density and atomic makeup of objects that are not transparent [31]. That is, lung cancer is detected by a contrast image and a brightness that comes from cancer cells [23]. The way in which these detection works is based on the fact that doctors introduce a substance that will generate a high contrast with non-cancer cells, so this ink that they add to the patient's blood flow allows them to visualize cancer in an easier way. Some of the patients who have to do these CTs have to make them annually to control their well-being, so the computerized tomography of low doses is the solution so that they do not acquire any disease due to the amount of radiation that must be made to be exposed annually [17]. In the early stages and with several images of computerized tomography to review, doctors may or may not identify cancer cells. It must be taken into account that for each CT there are approximately 250 images [15], so it takes a long time for doctors to identify cancer among all those images, so for this process to be faster, an AI is carried out as a solution for greater accuracy and faster detection of cancer cells because for some nonpriority patients, the results of their CT scans could take up to several days, and for the most priority patients it could take a day, or in the best case, hours. The doctor with the implementation of artificial intelligence could do this work of days in less than seconds [39].

C. Advantages of Convolutional Neural Networks (CNNs) in Medical Imaging

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm inspired by the structure of the human visual cortex that has been extensively used in the field of computer vision [32]. CNNs are composed of multiple layers that extract features from the input data and pass them on to the next layer, allowing them to learn complex patterns and features that traditional machine learning algorithms struggle to identify [4]. They have been successfully applied in various image-related tasks such as object recognition, image segmentation, and facial recognition. In medical imaging, CNNs have shown remarkable accuracy in detecting and diagnosing lung cancer and other diseases, making them an invaluable tool for early diagnosis. They can recognize subtle patterns in tissue structure or texture, which may not be apparent to the human eye, allowing for improved accuracy and detection rates. Additionally, CNNs can process large amounts of data quickly and efficiently, making them an ideal choice for medical imaging applications. These advancements in medical imaging using CNNs offer great promise for early diagnosis and treatment of lung cancer and other diseases, potentially improving patient outcomes [16].

D. Exploring Different Neural Network Architectures

Different types of neural networks were used for the work, among which there are:

- ResNet-50: Enhancing Depth and Structure ResNet-50 is a convolutional neural network having a depth of 50 layers. Resnet 50 is a neuronal network of deep application, based on its predecessor Resnet 34 using a concept similar to the "shortcuts" between layers arriving at omitted information of some layers by modifying a natural network in a residual network [41].
- DenseNet-201: Layer Accumulation Model DenseNet-201 is a convolutional neural network that is 201 layers deep. The DenseNet system is a network learning model based on feedback on its results. In each layer, the results of the anterior layer would be used as an input and its output was used as an input for the posterior layers. It is an accumulation of results for the next layer, starting with just an entrance and ending with two hundred entries for its 201 layers.[37].
- VGG16 and VGG19: Distinctive Architectures VGG16 is a convolutional neural network trained on a subset of the ImageNet dataset, a collection of more than 14 million images belonging to 22,000 categories. The VGG networks are a proposal of convolutional networks, these are distinguished by their architecture since although they work with layers you are when they progress in the training they will be reducing their size during this showing only the information to discriminate within the pixels that present [38], This is one of the networks that gave one of the results that we used, even if it was not very precise, it helped to understand the system. VGG19 is a variant of the VGG model which in short consists of 19 layers (16 convolution layers, 3 Fully

connected layers, 5 MaxPool layers and 1 SoftMax layer). There are other variants of VGG like VGG11, VGG16 and others. VGG19 has 19.6 billion FLOPs [14]. This has been one of the best networks and has been highly effective in the first tests carried out with the program.

- ResNet-101: Amplified Depth for Enhanced Results ResNet-101 is a convolutional neural network having a depth of 101 layers. Like the systems already presented by Resnet, Resnet 101 is a system that is based in the same way to be a system of residual neural networks. Taking the same principle as its predecessors but amplifying its depth ratio and optimizing its results giving a system, in theory, more stable [42].

E. *Comparative Insights from AI Studies*

Figure 1 shows some of the most accurate artificial intelligence for lung cancer detection using Resnet50, some of them use bigger amounts of data for the phase of training the IA, so that might be why some of them have really high accuracy. Also, the most accurate [18] is not based on results of cancer detection or lung cancer detection, but the authors mention that this method and algorithm used for this purpose could be applied for early cancer detection. It is based on results obtained with CT images for covid-19 detection in the lungs, that's why they have the biggest accuracy of those four methods. Also, the second most accurate [12] does not uses CT images it uses histological images from the lungs combined with a CNN gives a great result for cancer detection. The rest [35] [30] are very similar to the models that are going to be used in the paper because both use CT images for cancer detection and have an accuracy of the percentages indicated on the graphic.

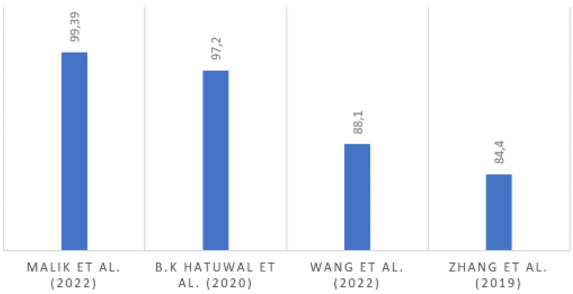

Fig. 1. Comparison between some of the most accurate artificial intelligence for lung cancer detection.

F. *Project Objective and Importance*

The objective of this project is then, through neural networks, to choose the best artificial intelligence which learns to distinguish CT images of non-small cell lung cancer and differentiate them quickly so that the patient can receive early treatment. This is done because by selecting the best neural network from the mentioned neural networks, one is chosen and can be used to detect cancer in its early stages when it is most treatable. Also, the chosen neural network can reduce the amount of time and resources needed to diagnose cancer, making it more efficient.

II. Materials and Methods

A. *Database*

For the project, a large number of CT images of lung cancer were needed since these will be used to train the neural networks. It is estimated that we have 1500 images to train the neural network and 500 images to validate the neural network. An example of images to be used for lung cancer specifically of the chest is shown in Figure 2.

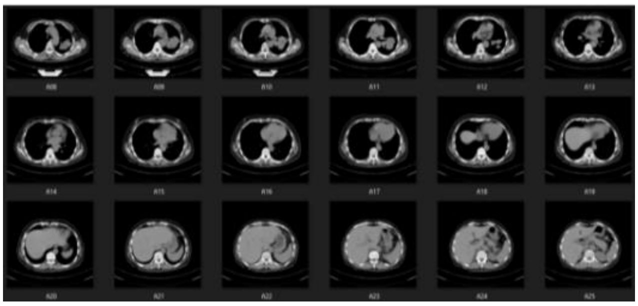

Fig. 2. Pictures used as the database, downloaded from the free Kaggle.com website

B. *Carcinoma Classification and Learning Process*

The images that are in our database are divided into three different types of lung carcinomas: squamous carcinoma, adenocarcinoma, and large cell carcinoma. We searched for different types of carcinoma and classified them to see how the neural network works in the learning process, which of these types of lung cancer is easier or more difficult to detect. The training process will be the longest due to the number of images that must be processed in order to issue a result with a high degree of veracity [11]. It will also be a long process to collect these images as they will need to meet certain requirements for us to facilitate machine learning.

C. *Understanding and analysis of the collected Dataset*

This investigative research endeavor will commence by embarking on an information retrieval journey and meticulous data acquisition. This will encompass the selection of relevant images that will support the AI learning process.. Notably, the data will be sourced from reputable databases such as Physionet, Scopus, and ENCBI. The research's focal point will center on amassing images germane to lung carcinoma.

Once the compilation of images is accomplished, the subsequent phase entails the implementation of the program within the Python software framework. Upon achieving program completion, the initiation of the learning phase will follow suit. To facilitate this process, the amassed information will be harnessed as a foundation, enabling the program to engage in a self-learning trajectory marked by iterative self-improvement.

D. *MATLAB Technique for Glaucoma Diagnosis*

The project aimed to develop a computational technique using MATLAB for early diagnosis of glaucoma, improving accuracy and accessibility. The method achieved a 94.61% accuracy, demonstrating its feasibility for glaucoma detection.[1]. This study presents a systematic review of the literature on the use of photoelasticity technique to analyze stresses and deformations in shoulder joints with arthroplasty. It highlights the need for further research on reverse arthroplasty, a common treatment for various pathologies. [2]

E. *Materials used for the training of machine learning*

For the machine learning to learn in the most appropriate way, we have performed the learning process on a computer with 12GB of RAM, a 512 GB NVMe, a Ryzen 7 5000 series processor with 8 cores and 16 threads and a 6 GB Nvidia RTX 3060 graphics card. All this is accompanied by a windows 11 operating system, where we had installed Pyton 3.11.1 Keras 2.11 and Tensor-Flow 2.0.

F. TensorFlow and Keras for Neural Networks

TensorFlow is a library of code used to learn across a variety of areas, and was discovered by Google to meet their needs for systems capable of inputting neural networks to detect and describe correlated patterns, analogous to human learning and reasoning, while Keras is an Open Source Neural Network library written in Python, capable of running on top of TensorFlow, Microsoft Cognitive Toolkit or Theano [19].

G. Creating a Convolutional Neural Network

What we are looking to do specifically is to create a convolutional neural network so that our algorithm can identify each of the images that we send it and give us back if there is any type of cancer or not. This will work in a way that our image will be divided into pixels and each of the pixels will be a neuron of our neural network, then this neuron will pass through at least two other reducing layers and at least one classifier layer so that our algorithm is able to identify each of these pixels and identify some kind of anomaly in it [5]. We will also look for our neural network to have an effectiveness greater than 98%.

H. Convolutional Neural networks in Action

A convolutional neural network (CNN) is a type of artificial neural network that is primarily used in computer vision applications, such as image recognition and object detection [10]. The main feature of a CNN is that it uses convolutional layers to extract relevant features from input images, rather than relying on specific features that must be manually selected. These convolutional layers are able to detect patterns in the input image, such as edges, textures and shapes, at different levels of abstraction [7]. Convolutional neural networks have been shown to be very effective in a variety of tasks, such as object recognition in images, object tracking in videos, medical image classification, and facial feature identification. In addition, CNNs have also proven useful in other areas, such as natural language processing and speech recognition [9].

Fig. 3. Architectural model of the neural network VGG19

I. Technical implemetation and Data preparation

We will start writing the code, where as we mentioned before we will use Python in its version 3.11 to start programming. First, we must import all the libraries that we are going to use, among these are TensorFlow, we will also import the architectures that we are going to use to make the comparison of which one is better and which one will have better results. Finally, we will also import other important libraries, which will help us to better visualize our data and to manipulate them in an easier way. Among these libraries, numpy stands out, which will help us to visualize our data in the form of shades, or pandas, which is useful for data management, analysis and processing.

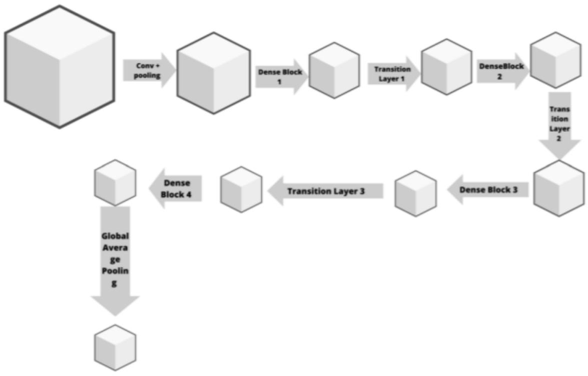

Fig. 4. DenseNet201 Architectural Model

J. Leveraging Transfer Learning for Improvement

Finally, we start with the training part of our first neural network model, for this training process, performing it on the machine with the characteristics previously specified, it took a learning time of about 22 minutes. Now we will begin to train our artificial intelligence, in different architectures, starting with ResNet50, where the same process that was applied for the previous architecture is applied, where the data is manipulated so that the learning process takes less time, with this architecture the learning process took about 87 minutes.

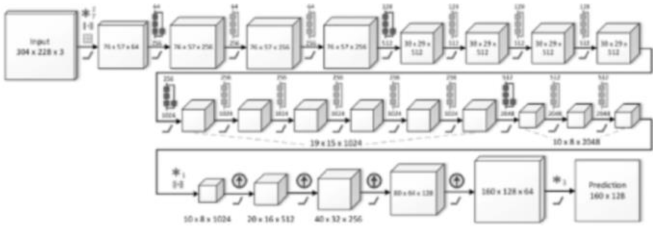

Fig. 5. ResNet50 Architecture Model [45]

K. Insight into Model Architectures

The process is repeated with the architectures VGG16, ResNet 101, VGG19, DenseNet201, and EfficientNetB4, with a learning waiting time of 37, 39, 62, and 91 minutes respectively. In order to transfer our model to other architectures that can perform much better, we will apply a deep learning transfer process. Transfer learning in deep learning refers to a technique where a pre-trained model developed for a particular task is used as the starting point for a new but, related task. Instead of starting from scratch, transfer learning enables us to leverage the knowledge learned by the pre-trained model to train a new model with fewer data and computational resources [21].

L. Insight into Model Architecture

If we analyze the diagrams of each of the model architectures, we can see that they have several layers of simple neurons, together with complex neurons for the different pixels. The simple neurons analyze small pieces of the images, while the complex neurons take several results from the simple neurons in order to create a complete image, previously trained in our neural network.

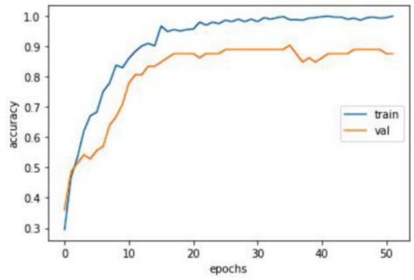

Fig. 6. EfficientNetB4 architectural model [36]

III. Results

As a result of, the environment of the first architecture of the convolutional neural network we have that our neural network learns very well, having an effectiveness of almost 100%, but at the time of performing real exercises, our neural network remains with an effectiveness of 70%, a range too low for the detection of something as important as lung cancer.

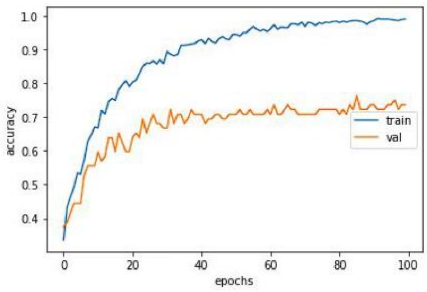

Fig. 7. Results of our proposed architecture

We continue with ResNet50, performing a quick analysis we see that it has an accuracy of 89.5%. Next architecture to testing is VGG16 that has an accuracy of 50% apart, which takes a long time in the training process. The next one is ResNet 101 that has an accuracy of 59.6%, but it also takes too long to train the artificial intelligence. The next is VGG19 this architecture has an accuracy of 56.5%, and also takes a long time to train the data.

The next is DenseNet201, that has a great improvement over the rest, obtaining an accuracy of 81.9% despite the fact that its training was also slow. Finally, we test EfficientNetB4, that had an accuracy of 85.4%, even better than DenseNet201, but takes on average 20 minutes longer to train.

TABLE II. TABLE OF THE DIFFERENT ARCHITECTURE MODELS, WITH THEIR RESULTS AFTER TRAINING

Architecture Type	*Accuracy*	*Packet Lose*	*Time of Train (min)*
Our Architecture	53.3%	1.164	22
Resnet 50	89.5%	0.315	87
VGG16	50.0%	1.157	37
ResNet 101	59.6%	1.157	39
VGG19	56.5%	1.135	62
DenseNet 201	81.9%	0.546	91
EfficientNetB4	73.3%	0.658	65

As evident from the data presented in the provided table, the architectural models that exhibit the most promising success rates include ResNet50, DenseNet201, and EfficientNetB4. Upon a thorough examination of the statistics related to the proportion of lost data packets, a notable correlation becomes apparent with the success percentages. Specifically, there exists a strong inverse relationship: higher success rates correspond to fewer lost packets.

An intriguing aspect that warrants investigation pertains to the training duration of these models. Remarkably, the two most efficacious models, namely ResNet50 and DenseNet201, coincide with the lengthiest training periods. Additionally, a noteworthy observation can be made regarding EfficientNetB4. Although its success rate is superior to the mean, it falls short in efficiency compared to ResNetB4 and DenseNet101. Nevertheless, its advantage lies in a reduced training time, which is nearly equivalent to that of VGG19.

Consequently, with the intention of further enhancing the results achieved by the three aforementioned neural networks and simultaneously expanding the dataset, a decision has been made to proceed with the training of ResNet50, DenseNet201, and EfficientNetB4.

Upon implementing these enhancements to ResNet50, a noteworthy accuracy of 91.7% is attained. Additionally, a compelling trend becomes evident as the learning curve aligns closely with the real test curve. This convergence signifies a favorable outcome, as it indicates that the neural network within this architecture is acquiring knowledge from practical instances, underscoring its proficiency in genuine data analysis as opposed to merely making conjectures for subsequent data points.

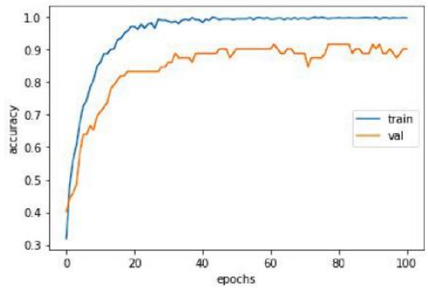

Fig. 8. Graphic of training and value process of ResNet50

We continue with DenseNet201, where we have an accuracy of 90.1%, where there is a much faster learning curve, and in turn we also find a curve in real values that grows faster and starts with more and more constant training for longer time.

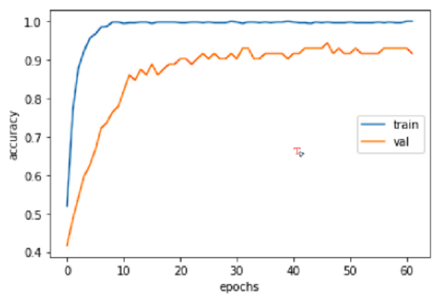

Fig. 9. Graphic of training and value process of DenseNet201

Finally, we have EfficientNetB4 where we achieved an accuracy of 89.5%, also in this graph we find a growth almost at par, the learning curve, along with the curve of real exercises.

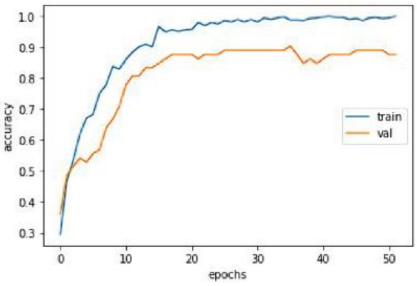

Fig. 10. Graphic of training and value process of EfficientNetB4

Each of the neural networks with the increase of datasets, took approximately twice as long to train, but we also managed to see a substantial improvement towards the same. In this case, both DenseNet 201 and ResNet 50 are the best architectures that can be used for the detection of lung carcinoma.

Finally, of the 4 types of carcinomas in which the neural network was trained, in the case of healthy lungs the neural network had an accuracy of 98 %, in the case of adenocarcinomas it had an accuracy of 91%, in the case of squamous cell carcinoma it had an accuracy of 92% and finally in the case of large cell carcinoma, it had an accuracy of 94%.

IV. Discussions

With these results, we can make a comparison to see how these architectures have performed on other items compared to ours.

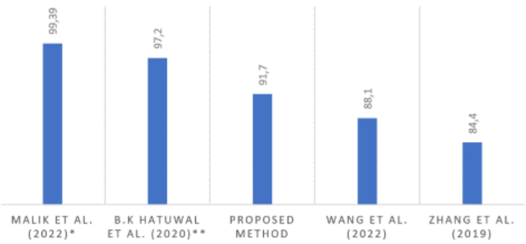

Fig. 11. Comparison between some of the most accurate artificial intelligence for lung cancer detection

As we can see in Figure 11, our architecture of ResNet50 with our database was the third in terms of percentage of effectiveness, only surpassed by the architectures made by [18] [12]. One of the reasons why this may happen is that our architecture performs learning from CT scans, while Hatuwal, uses CT images, and Malik performs its analysis from images of patients with COVID 19, and that according to the author may have uses in lung cancer.

It is imperative to acknowledge and scrutinize potential threats to the validity of this study to ensure the robustness and meaningfulness of the findings. One prominent consideration is the representativeness and diversity of the dataset employed for training and testing the neural network models. Ensuring that the dataset captures a wide spectrum of CT images from different demographics, lung conditions, and image qualities is crucial to enhance the model's generalization to various real-world scenarios. Furthermore, the potential bias inherent in the dataset, as well as the generalizability of the models to populations not adequately represented in the dataset, warrant careful examination. Additionally, while accuracy serves as a fundamental evaluation metric, a comprehensive assessment encompassing sensitivity, specificity, and ROC analysis would provide a more nuanced evaluation of the model's diagnostic capabilities. Beyond the algorithmic aspects, the clinical relevance and impact of the proposed solution within medical practice require meticulous exploration. By addressing these potential threats to validity and delving deeper into their implications, this study endeavors to offer a more comprehensive understanding of the practical implications and limitations of utilizing neural network architectures for early lung cancer detection.

With respect to the volume of data at our disposal, when juxtaposed against the research materials employed as points of reference, as succinctly outlined in Table 3, a discernible pattern emerges: both the precision and sensitivity metrics exhibit a linear growth as the volume of images in question expands. Equally critical is the need to take into account the proportional dynamic between the quantity of images and the resulting accuracy. This phenomenon is underscored by the circumstance that our dataset's extent is contracted to a mere one-third in comparison to the data quantum spearheading the aforementioned table.

TABLE III. Related Works and Proposed Method

Models	***Accuracy %***	***Number of images***	***Characteristics***
Proposed Method	91.7	5900	**Hardware:** HRyzen 75700hx NVIDIA, GeForce, Rtx 3060hq **Method:** SuperPower Model **Training Ratio:** 90:10 **Sensitivity:** 92.0
Malik et al. (2022) [18]	99.3	30,387	**Hardware:** 11 GB, NVIDIA GPU, 32 GB, RAM **Method:** CDC Net Model **Training Ratio:** 90:10 **Sensitivity:** 98.1
B.K Hatuwal ***et al. (2020)*** *[12]*	97.2	5000 x 3	**Hardware:** Google Colaboratory, GPU **Method:** CNN **Training Ratio:** 90:10
Wang et ***al. (2022) [29]***	88.1	888 + 1397	**Hardware:** i7-7700 CPU, NVIDIA, GeForce, RTX 2080 **Method:** SC-Dynamic R-CNN
Zhang et al. (2019) [35]	83.7	3442	- **Sensitivity:** 84.4

Nevertheless, it is important to acknowledge that adjustments in hardware and training images could potentially impact the outcomes and their applicability across various clinical scenarios and datasets. Consequently, further assessment and experimentation across diverse conditions are advisable prior to practical implementation.

V. Conclusions

This neural network, unlike the others mentioned, was able to reach an almost perfect detection, thus having an accuracy of 99.8% as observed both in comparative tables 1 and 3. We can then conclude that Resnet50 is a tool that could be used in hospitals for the detection of detection of lung cancer and other lung diseases in the most effective, cheapest and fastest way. It is worth mentioning that Resnet50 is only a neural network architecture but when developed as a web application, for example, this would be a great complement that is very useful in hospitals for use in the detection of non-small cell lung cancer, lung cancer, which kills 1.8 million people a year.

Despite showing different hardware configurations, these do not affect the performance of artificial intelligence, since these are determined more by the number of images we have of the dataset, and by the architectural model of artificial intelligence that we use. For this reason, the article by Malik [18] is so effective since it contains many images for validation, training and verification.

Finally, the ResNet50 neural network has all the necessary resources for its operation from the learning source to its programming model, turning it into an efficient source of its work, the software will have at its disposal the images that it will require for its analysis and will be able to have a steady job. Generated the detection application with this neural network architecture, a person could have their CT image results immediately, leaving behind a process of several hours since the program would take this process and reduce it to empirical information in seconds. All this would not be possible without the network system used in this program.

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[45] Figure 2.6: ResNet-50 architecture (encoder-decoder) proposed by[5], ResearchGate, https://www.researchgate.net/figure/ResNet-50-architecture-encoder-decoder-proposed-by5_fig7_341671113