A deep-based compound model for lung cancer detection

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***Abstract*—** X-ray image analysis is primarily performed by medical specialists. Patients expect a correct interpretation of these images regardless of cost. Despite various advantages of chest radiography, the interpretation of Magnetic Resonance Imaging (MRI) has always been a major issue for the physician and the radiologist due to misdiagnosis. According to the World Health Organization, Lung cancer cost around 1.8 million deaths in 2020, which makes it the leading cause of cancer death worldwide. Late diagnosis and lack of means of screening are the main problems. The algorithm can help radiologists accurately estimate the malignancy risk of lung nodules. This paper aims to detect and classify lung cancer using deep learning. We used the Convolutional Neural Network (CNN) algorithm combined with the Faster Regions with CNN (Fast R-CNN). Our model provides very encouraging results compared to those obtained by the work of the literature, which provides a model with a high accuracy rate for medical assistance.

Keywords: *lung cancer, deep learning, nodule detection, classification, convolutional neural networks, computer-aided diagnosis.*

I. Introduction

Artificial Intelligence (AI) is a recent field in science and engineering. After the second world war, researchers invested in this field. The name artificial intelligence was coined in 1956. Historically, four AI methods have been followed involving different people from different backgrounds. The human-centered method must be an empirical method that includes observational and behavioral assumptions. The logical approach includes a combination of mathematics, and these different groups help each other. AI covers several subfields, such as playing chess, social commerce [20], proving mathematical theorems, writing poetry, smart cities [11-16], facial recognition [17-19], service computing [24], computer security [25-30], and diagnosing maladies [21-23]. It is instrumental in mental work. AI research aims to make machines work intelligently. The general problem of creating intelligence has been divided into several sub-problems. These consist of capabilities that the researchers hope an intelligent system can perform. It is truly a global and multidisciplinary field [1].

AI AI image processing has been mainly developed since the 1990s with the introduction of Deep Learning (DL) algorithms based on neural networks and the increase in computing power of computers. Thus, these methods, powerful for detecting objects, have made possible technological advances such as autonomous cars. In the medical field, the clinical applications of these latter approaches on the different imaging modalities are exceptionally vast. They engage in the detection, reconstruction of images, and development of biomarkers for imaging, aid in diagnoses, prognostic evaluation, or prediction of response to detection and classification treatments. In 2010, Gillies et al. [10] introduced the term "radiomics", which refers to translating medical imaging into high-dimensional quantitative data to develop imaging biomarkers. Radiomics is one of the areas of imaging that uses artificial intelligence techniques. Although many works are still in the research stage, many are extremely promising [2].

Among the areas where AI has been concerned is the medical field, especially cancers such as lung cancer which is among the deadliest cancers in the world. To this end, several countries and companies are inventing strategies to detect lung cancer during earlier stages. Detecting lung cancer that appears in malignant lung nodules is a complex task, especially from CT scans. It requires time and effort from radiologists. Computer-Aided Diagnostics (CAD) systems have been proposed to this end. Deep learning methods have recently shown impressive results that have outperformed classical methods for many years. Deep learning techniques are used to increase CAD system performance in lung cancer screening by computed tomography [3].

II. Related works

AI is at the heart of research in the medical field and its applications. This research aims to improve the quality of care for the medicine of tomorrow. AI focuses on the development of assisted operations, individual treatments, remote patient follow-up, help in cancer treatment, ... and further information from mutual insurance companies. The latter helps oncologist doctors make decisions, gives autonomy to patients with diabetes, allows greater precision in medical imaging, and in the long term, will avoid carrying out specific examinations deemed "intrusive" for patients [34]. The AI reads patient files, and thanks to the additional information provided by the doctor, it can now give a diagnosis and establish several treatment proposals. AI-based solutions have helped in the treatment of several types of cancers.

AI, through its algorithms, helps in the development of diagnoses. Indeed, the machine prescribes the same diagnosis as doctors in 99% of cases, and in 30% of cases, it offers a more suitable treatment than specialists. It succeeds in detecting cancers in 89% of cases, while specialists detect them in 73% of cases. The machines are also able to detect heart attacks over the phone. Thus, robotics extends its web to many sectors of medicine. Today, deep learning has taken a big step forward in all fields, especially in the analysis of medical images [4].

DL-based models show promising results in detecting nodules and masses on chest radiographs. The use of DL-

2022 4th International Conference on Pattern Analysis and Intelligent Systems (PAIS) | 978-1-6654-6161-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/PAIS56586.2022.9946875

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based models improves the radiologist performance in detecting nodules.

In clinical practice, it is often difficult for radiologists to detect nodules and differentiate between benign and malignant ones. It is why radiologists must pay particular attention to the shape and marginal properties of the nodules. The detection method is region-level classification, while the segmentation method is pixel-level classification. The segmentation method can provide more detailed information than the detection method. Pixel-level classification also makes tracking changes in lesion size and shape easier, as the shape can be used as a reference during detection [5].

Several works exist in the literature that uses different DL techniques, such as DNN, CNN+DCT, EKNN, and CNN3D.

Kuruvilla and Gunavathi [6] proposed an artificial neural network based on texture features to detect and classify lung cancer. The accuracy rate of the proposed model is 93.30%. Enhancing the model with shape features could improve this accuracy.

El Hassani al. [7] used Discrete Cosine Transform (DCT) with Convolutional Neural Network (CNN) to classify lung nodules. The accuracy rate of this model is 96.51%.

Thamilselvan et al. [8] suggest a model to detect and classify malignant and benign cancerous tissue in magnetic resonance lung cancer images. The authors used the nearest neighbor K-means algorithm to identify lung cancer images. The proposed model provides an accuracy of 96.57%.

Albert et al. [9] proposed deep convolutional networks for lung cancer detection. The proposed system used a linear classifier as a reference, vanilla 3D CNN, and 3D CNN based on Google net. The detection of pulmonary nodules in CT images uses CNNs. They propose the detection and classification of lung cancer with a 3D-CNN. The proposed method provides an Accuracy of 97%.

According to the results, the research in this area is new and open. We can move towards more improved and developed methods in detecting and classifying lung cancer.

III. A SMART COMPOUND APPROACH FOR LUNG CANCER DETECTION

Our approach comprises two tasks: the detection task and the classification task. First, we present the detection task.

Early detection of lung nodules is essential for diagnosing and screening lung cancer. Due to superior performance, most lung nodule detection models are based on regional and Faster R-CNN. We offer an Assisted Detection System (ACD) based on the Faster RCNN model for detecting pulmonary nodules. The proposed model was trained and tested on a large, publicly available Kaggle dataset on lung cancer, see Figure 1.

The classification model uses different input images. This model, which we describe in detail in the following section, must respond to the various concerns of diagnostic errors relating to the interpretation of chest X-rays performed daily in hospitals under various vital medical conditions of patients.

A. Detailed process

In order to build a deep learning model for classification with CNN that can classify tumors accurately, we propose the CNN based setup of Figure 2.

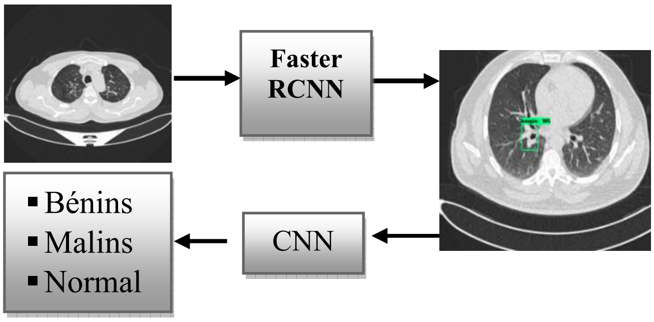

Fig. 1. General view

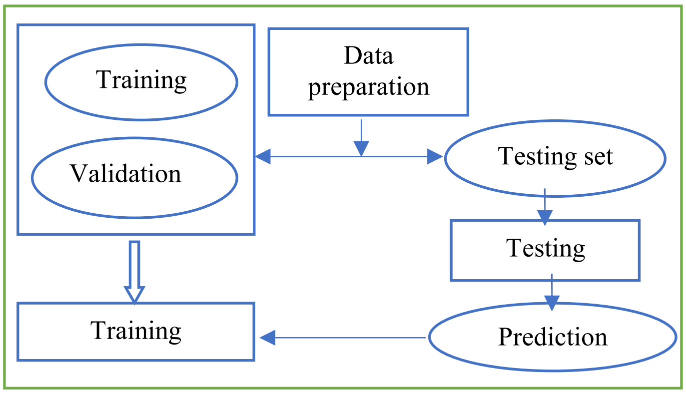

Fig. 2. Detailed CNN process

B. Data preparation

Dataset: We used a public Kaggle lung cancer database. Each patient has X-ray images. In this retrospective study, radiologists randomly selected 1097 chest X-rays from three participating centers, including 416 regular exams and 561 with a malignant lung nodule, and 120 with a benign lung nodule, confirmed by CT or CT scan and anatomopathological examination. A second group of radiologists, including three from each facility, interpreted the selected chest radiographs with and without cancerous nodules.

Preprocessing: Before providing the data to CNN, it is necessary to apply some image processing techniques to prepare the data and build an efficient DL model. In our work, the preprocessing step consists of a resizing operation since we used it to build a learning model.

Database division: The most used dataset splitting strategy in DL is to split the dataset into a training set and a test set. Generally, we have 70% training, 20% testing, and 10% validation.

C. Classification models

In this work, we tested two classification models, CNN and VGG16, on the same database.

The CNN model: We used a supervised Deep Learning model (CNN) to specify the classification problem.

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Before we can start training the network, the details of the hyper parameters used in this study are described in Table 1.

TABLE I. CNN HYPERPARAMETER TABLE

Loss fonction	Sparse_categorical_crossentropy
Optimizer	Adam
Initialisation	Xavier
Epoch	10
Batch size	8
Fonction d'activation	Soft max (dense), ReLU (conv 2D)

CNN architecture: The architecture of the CNN and stacking several convolution layers. It enables the analysis of the images supplied as input and detects the presence of a set of characteristics (features) with a succession of filters, such as max pooling. Max pooling reduces the size of images while preserving their most essential characteristics. The ReLU correction layer makes it possible to replace all the negative values received as inputs with zeros And fully connected.

Each image received as input will be filtered, reduced, and corrected several times to form a vector finally.

The VGG16 Model: The VGG16 architecture consists of 16 convolution layers with uniform architecture. It only has 3x3 convolutions but lots of filters. It is currently the preferred choice in the community for extracting features from images. The VGG16 weight configuration is publicly available and has been used in many other applications and challenges as a base feature puller.

Before starting to train the network, the details of the hyper parameters used in this study are described in Table 2.

TABLE II. VGG16 HYPER PARAMETER TABLE

Loss fonction	categorical_crossentropy
Optimizer	Adam
Initialisation	Xavier
Epoch	20
Batch size	32
Fonction d'activation	Sigmoid

VGG16 Architecture: The input to the network is an image of dimensions (224, 224, 3). The first two layers have 64 channels of a 3*3 filter size and the same padding. Then, after a maximum stride layer (2, 2), two convolution layers of 256 filter size and filter size (3,3). It is followed by a stride layer (2, 2) which is the same as the previous layer. Then there are two filter size convolution layers (3, 3) and 256 filters, see figure 20.

IV. RESULTS OBTAINED

In this part, we will see the performance of our model (CNN): Loss, Accuracy, confusion matrix, and prediction.

A. *Presentation of the performances obtained*

To visualize the performance of our DL CNN over time during training, we created the following:

- A graph of "Accuracy" on the train dataset "acc" on training epochs.
- A graph of "Loss" on the train dataset "Loss" over the training epochs.

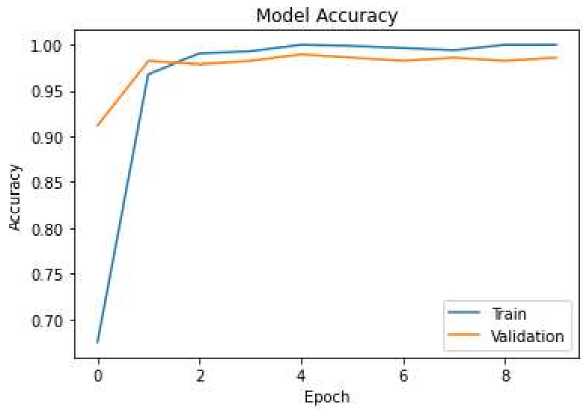

Fig. 3. CNN Model Accuracy

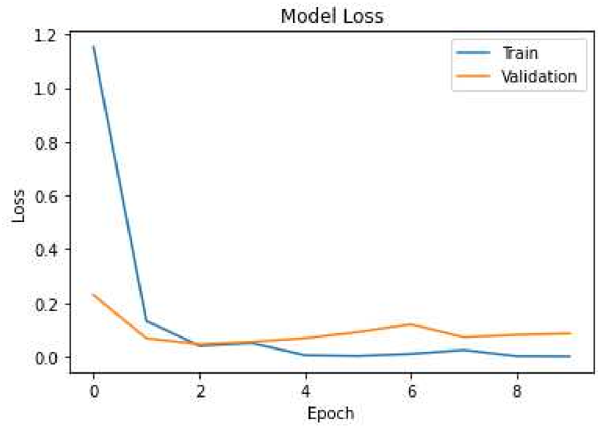

Fig. 4. CNN Model Loss

In DL, checkpoints are the stored weights of the model when there is an improvement in classification accuracy on the validation dataset. These weights can be used to make predictions or as a basis for continuing education. In our case, the best value of validation accuracy (Val-accuracy) is in epoch number 8.

V. CONCLUSION

Thanks to Deep Learning, the future of artificial intelligence is bright. Image analysis and computer vision are essential in many fields, such as the medical field. In this work, we studied the use of deep neural networks, particularly convolutional neural networks, for classifying and detecting pulmonary radiological images. We have focused on predicting lung cancer.

We have introduced different deep CAD systems and models to alleviate the work of radiologists in detecting pulmonary nodules. It turns out that deep learning has reached a level of precision that allows for implementation, not just as a second opinion in diagnosis but as a powerful tool that doctors can consider in their work. Thoughtful work

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shows that deep learning techniques have led to high performance in detecting lung cancer using CT scans.

In the context of our contributions, we identify several avenues that must be explored to complete and extend our work. Indeed, we can cite three main possible perspectives:

- Increase lung cancer detection and add other types of lung disease to the CNN model.
- Using another data set for training, validation and testing.
- Consideration of privacy through the use of security techniques and approaches.

REFERENCES

[1] H. Wang, B. Raj, and E. P. Xing, "On the origin of deep learning," arXiv preprint arXiv: 1702.07800,2017.

[2] AShimazaki, D Ueda, A Choppin, a Yamamoto… - Scientific reports, 2022 - nature.com.

[3] H. Chen and W. WuH. Xia, J. Du, M. Yang, and B. Ma, "Classification of pulmonary nodules using neural network ensemble," Advances in Neural Networks, Springer, Guilin, China.

[4] Jiang, Y., Yang, M., Wang, S., Li, X., & Sun, Y. (2020). Emerging role of deep learning-based artificial intelligence in tumor pathology. Cancer communications, 40(4), 154-166.

[5] Yasaka K, Abe O (2018) Deep learning and artificial intelligence in radiology: Current applications and future directions. PLoS Med 15(11): e1002707.

[6] J. Kuruvilla and K. Gunavathi, "Lung cancer classification using neural networks for CT images," Computer Methods and Programs in Biomedicine, vol. 113, no. 1, pp. 202–209, 2014.

[7] Abdelhamid EL HASSANI, Brahim AIT SKOURT, Aicha MAJDA: Méthode efficace de classification des nodules pulmonaires à l'aide de neurones convolutifs Réseau (CNN) et transformée discrète en cosinus (DCT). International Journal of Advanced Computer Science and Applications,Vol. 12, No. 2, 2021.

[8] Thamilselvan, P., & Sathiaseelan, J. G. R. (2016). Detection and classification of lung cancer MRI images by using enhanced k nearest neighbor algorithm. Indian Journal of Science and Technology, 9(43). https://doi.org/10.17485/ijst/2016/v9i43/104642

[9] Aishwarya Kalra, Brijmohan singh,Himanshu Chauhan, une Approche pour la classification de cancer de poumon, International Journal of Engineering and Technologie(IRJET)9/sep/2020

[10] Gillies, R. J., Anderson, A. R., Gatenby, R. A., & Morse, D. L. (2010). The biology underlying molecular imaging in oncology: from genome to anatome and back again. *Clinical radiology*, *65*(7), 517-521.

[11] Abdelatif, S., Derdour, M., Ghoualmi-Zine, N., & Marzak, B. (2020). VANET: A novel service for predicting and disseminating vehicle traffic information. *International Journal of Communication Systems*, *33*(6), e4288.

[12] Sahraoui, A., Makhlouf, D., & Roose, P. (2018). Smart Traffic Management System for Anticipating Unexpected Road Incidents in Intelligent Transportation Systems. *International Journal of Grid and High Performance Computing (IJGHPC)*, *10*(4), 67-82.

[13] Abdelatif, S., Makhlouf, D., & Roose, P. (2017). Extended iCanCloud simulation framework for VANET-Cloud architectures. In *3rd International Conference on Networking and Advanced Systems*.

[14] Sahraoui, A., Derdour, M., & Marzak, B. (2018). A Multi-Objective ACO to Solve the Daily Carpool Problem. *International Journal of Strategic Information Technology and Applications (IJSITA)*, *9*(2), 50-60.

[15] Abdelatif, S., Makhlouf, D., Roose, P., & Becktache, D. (2016, August). Loop speed trap data collection method for an accurate short-term traffic flow forecasting. In *International Conference on Mobile Web and Information Systems* (pp. 56-64). Springer, Cham.

[16] Abdelatif, S., Makhlouf, D., Ahmim, A., & Roose, P. (2020). Vehicular-cloud simulation framework for predicting traffic flow data. *International Journal of Internet Technology and Secured Transactions*, *10*(1-2), 102-119.

[17] Khaldi, Y., Benzaoui, A., Ouahabi, A., Jacques, S., & Taleb-Ahmed, A. (2021). Ear recognition based on deep unsupervised active learning. *IEEE Sensors Journal*, *21*(18), 20704-20713.

[18] Khaldi, Y., & Benzaoui, A. (2021). A new framework for grayscale ear images recognition using generative adversarial networks under unconstrained conditions. *Evolving Systems*, *12*(4), 923-934.

[19] Khaldi, Y., & Benzaoui, A. (2020, November). Region of interest synthesis using image-to-image translation for ear recognition. In *2020 International Conference on Advanced Aspects of Software Engineering (ICAASE)* (pp. 1-6). IEEE.

[20] Dembri, A., & Gharzouli, M. (2020, November). Graph-based Model for Negative e-WOM Influence in Social Media. In *2020 5th International Conference on Cloud Computing and Artificial Intelligence: Technologies and Applications (CloudTech)* (pp. 1-6). IEEE.

[21] Imane, K., Abbas, M., Miloudi, A., & Meftah, M. C. E. (2022). A CNN Model for Early Leukemia Diagnosis. *International Journal of Organizational and Collective Intelligence (IJOCI)*, *12*(1), 1-20.

[22] Gasmi, M., Derdour, M., & Gahmous, A. (2022). Transfer Learning for the Classification of Small-Cell and Non-small-Cell Lung Cancer. In *International Conference on Intelligent Systems and Pattern Recognition* (pp. 341-348). Springer, Cham.

[23] Gasmi, M., Derdour, M., Gahmousse, A., Amroune, M., Bendjenna, H., & Sahraoui, B. (2021, September). Multi-Input CNN for molecular classification in breast cancer. In *2021 International Conference on Recent Advances in Mathematics and Informatics (ICRAMI)* (pp. 1-5). IEEE.

[24] Merabet, F. Z., & Benmerzoug, D. (2021). Qos prediction for service selection and recommendation with a deep latent features autoencoder. *Computer Science and Information Systems*, (00), 54-54.

[25] Tolba, Z., Derdour, M., Ferrag, M. A., Muyeen, S. M., & Benbouzid, M. (2022). Automated Deep Learning BLACK-BOX Attack for Multimedia P-BOX Security Assessment. *IEEE Access*, *10*, 94019-94039.

[26] Tolba, Z., & Derdour, M. (2022). Deep Neural Network Based TensorFlow Model for IoT Lightweight Cipher Attack. In *International Conference on Artificial Intelligence and its Applications* (pp. 112-121). Springer, Cham.

[27] Tolba, Z., & Derdour, M. (2021, October). Deep learning for cryptanalysis attack on IoMT wireless communications via smart eavesdropping. In *2021 International Conference on Networking and Advanced Systems (ICNAS)* (pp. 1-6). IEEE.

[28] Tolba, Z., Derdour, M., & Menassel, R. (2021, September). Towards a Novel Cryptanalysis Platform based Regions Of Interest Detection via Deep Learning models. In *2021 International Conference on Recent Advances in Mathematics and Informatics (ICRAMI)* (pp. 1-6). IEEE.

[29] Azzaoui, H., Boukhamla, A. Z. E., Arroyo, D., & Bensayah, A. (2022). Developing new deep-learning model to enhance network intrusion classification. *Evolving Systems*, *13*(1), 17-25.

[30] Azzaoui, H., & Boukhamla, A. (2020, June). Two-Stages Intrusion Detection System Based On Hybrid Methods. In *Proceedings of the 10th International Conference on Information Systems and Technologies* (pp. 1-7).

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