

# Evolutionary RNN framework for Precise Lung Nodule detection from CT scans

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**Abstract:** Radiologists find it challenging and time-consuming to recognize and evaluate nodules of lung using CT scans that are malignant. Because of this, early lung growth prediction is necessary for the inquiry technique, which raises the likelihood that the treatment will be successful. Computer-aided diagnostic (CAD) tools have been used to help with this issue. The primary goal of the work is to identify if the nodules are cancerous or not and to deliver more accurate results. The RNN [Recurrent] which is a type of neural network model that includes a feedback loop. In this paper, evolutionary algorithms are examined using the MATLAB Tool, including the Grey Wolf Optimization Algorithm and Recurrent Neural Network (RNN) Techniques. Additionally, statistical characteristics are generated and examined in comparison to other RNNs using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) combinations. Comparing the suggested approach to other state-of-the-art techniques, it yielded results with extremely high accuracy, sensitivity, specificity, and precision. In the past few years, there has been a substantial increase for evolutionary algorithms in the field of feature selection due to their simplicity and potential for global search capabilities. The suggested solutions have outperformed classical approaches employed across various fields, showing excellent results. Determining whether lung nodules will become malignant or not will be made easier with early identification.

**Keywords:** Optical Character Recognition (OCR), Classification, Digital Image Processing.

## I. INTRODUCTION

Several different sectors make up the health industry. People want the best treatment and services available, no matter how much it costs, in this high-priority industry. While it takes up a considerable part of the budget, the assumption was neither socially nor economically beneficial. Results are often reviewed by a medical specialist. There is very little human professional interpretation of images because of subjectivity, visual complexity, and significant differences between Tiredness and numerous interpreters. Comprehensive learning is now recognized as a vital System for upcoming health-related applications and offers interesting medical imaging solutions since it has proven successful in another real-world use.

The primary causes of a high lung cancer death rate are a lack of initial analysis and a deficient prediction. Approximately 58% of cases of lung cancer were documented originating from less developed countries. With the lowest success rate upon diagnosis and an annual spike in fatalities, lung cancer is regarded as a distinct kind of the deadliest tumours worldwide. Regardless of the quantity of researchers utilizing machine learning frameworks, this problem persists. Regaining the same degree of success is impossible due to the numerous factors that must be meticulously developed to determine the greatest performance.

Information about diagnosis of lung cancer and classification is provided in this article. The huge images produced by modern medical imaging modalities, which are very challenging to manually interpret and might necessitate a significant amount of processing time to locate lung nodules, led to the evolution of the issue formulation in this work. Consequently, this work bridges the knowledge gap from previous works where deep learning algorithms were only used to solve temporal problems rather than spatiotemporal issues by addressing the issue of classifying lung nodules as cancerous or not by combining various intermediate stages of image processing with state-of-the-art Optimization and classifier based on deep learning for easy analysis. Furthermore, the accuracy parameter, which determines the percentage the worth of accurate cancer region of interest classification rate, is improved in this work. GLCM is utilized

for feature extraction in post-processing, whereas the median filter with a weighted value is utilized in pre-processing to reduce noise in pictures. Ultimately, the sickness is detected using Grey Wolf Optimization (GWO) in conjunction with a Recursive Neural Network (RNN) classifier.

This method's primary contribution is to easily see the type of cancer by classifying it and optimizing and extracting the data features. Finding and categorizing anomalies will be simplified as a consequence. This will make it feasible to detect and evaluate lung cancer early in the prevention process, which would enable appropriate monitoring of known risk factors and timely treatment when necessary.

Two knowledge gaps in identifying lung cancer through the utilization of deep learning algorithms as opposed to standard classifiers were found after a thorough assessment of the literature. First, methods in deep learning exclusively address temporal difficulties; in contrast, spatial-temporal problems that arise in. Several contemporary datasets are not included [30]. This study uses a blend of RNN and Grey

Wolf Optimization. It's a standard supervised spatio-temporal problem which exemplifies the novelty of our approach. This work considers both the accuracy and sensitivity of detecting the precise tumour location, as well as the second gap during the processing time. The suggested work's classification capability gets around the time parameter problem as accuracy and sensitivity increase.

## **II. LITERATURE SURVEY**

Lung cancer research stands as a paramount area of focus within the therapeutic sector, with the early detection of the condition holding significant potential for reducing mortality rates. However, this task is labour-intensive, relying heavily on operator availability for precision. Numerous studies in the literature aim to distinguish and categorize lung cancer protuberances, employing both traditional and deep learning methods.

In a study presented[1], the researchers have introduced Healthcare-As-A-Service (HAAS), a novel concept in automated diagnosis of lung cancer employing Convolutional Neural Networks (CNNs)(CNN)-based classifiers. The proposed HAAS service, accessible globally through cloud technology, addresses the crucial aspect of usability, often neglected in current research. Artificial intelligence (AI) has been an intensely researched subject in recent years and thoracic imaging has particularly benefited from the development of AI and in particular deep learning.

The objective of this article [2], was to review the current applications and perspectives of AI in thoracic oncology. Conventional machine learning and deep learning techniques have been applied in pulmonary nodule segmentation allowing nodule volumetry and pulmonary nodule characterization. In another study [3], A proposal for computer-aided diagnosis (CAD) approaches utilizing deep learning for the detection and classification of lung cancer. This study covers pre-processing, segmentation, false positive reduction, and retrieval. However, challenges such as over-fitting, interpretability issues, and limited annotated data persist.

The study [4] investigates the potential of blood-based screening for the early detection of lung cancer among Chinese patients. Employing an innovative interdisciplinary approach that integrates metabolomics and machine learning, the research identifies specific plasma metabolites as diagnostic biomarkers. Naïve Bayes is recommended as a potent tool for the early prediction of lung tumour. This study not only provides backing for the feasibility of blood-based screening but also provides a more accurate, rapid, and integrated diagnostic tool for the early detection of lung cancer. The interdisciplinary approach suggested in this research holds promise for adaptation to other types of cancer beyond lung cancer.

The study [5] introduces an optimal methodology for the timely identification of lung cancer through image processing, deep learning, and metaheuristic techniques. A novel convolutional neural network, enhanced by the Marine Predators Algorithm, is designed for improved accuracy achieving about 93.4% accuracy.

This paper [6] presents an exploration of state-of-the-art deep-learning-based lung nodule screening and analysis techniques focusing regarding their performance and clinical applications, aiming to help better understand the current performance, the limitation, and the future trends of pulmonary nodule analysis. In [7], aimed to validate the Lung Cancer Prediction Convolutional Neural Network (LCP-CNN). The LCP-CNN is adept at producing a malignancy score for individual nodules based on CT data, achieving a notable sensitivity of 99.0%. This implies that malignancy can be confidently excluded in 22.1% of the nodules, leading to a potential 18.5% reduction in the need for follow-up scans among patients.

The authors of the research [8] proposed a novel approach for non-invasive identification of lung cancer pathological types through CT images, addressing the invasiveness of traditional histopathological examinations. Utilizing a residual neural network with a medical-to-medical transfer learning strategy, pre-training on the luna16 dataset and fine-tuning on a proprietary lung cancer dataset, the model achieves an impressive 85.71% accuracy.

The study [9] addresses the crucial necessity for timely identification of lung cancer, a highly lethal cancer type. Utilizing artificial intelligence, a computer-aided system is proposed for lung cancer detection in a dataset sourced from Iraqi hospitals. The convolutional neural network, employing AlexNet architecture, distinguishes patient cases as normal, benign, or malignant. This research emphasizes the potential of AI-driven systems in significantly improving early diagnosis and outlook for individuals with lung cancer, thereby enhancing survival rates.

The article [10] focuses on improving entity subtyping in lung cancer for effective therapy stratification. Morphological evaluation, crucial for subtyping, often involves subjective decisions on whether to use immunohistochemistry (IHC), which is not universally accessible. To address this, the study evaluates CNNs for classifying common variants of lung cancer. Various architectures of CNN are trained, with InceptionV3 in classifying the entities. A quality control metric identifies cases requiring IHC for definitive subtyping, highlighting the capabilities and constraints of CNNs in distinguishing tumours.

In the research [11], Leveraging CT(Computed Tomography) scans, aims to detect cancerous pulmonary nodules and classify lung cancer severity. Innovative deep learning methods, including a novel FPSOCNN (Fuzzy Particle Swarm Optimization Convolutional Neural Network), are employed for accurate detection. The work utilizes advanced feature extraction techniques like HoG, wavelet transform-based features, LBP, SIFT, and Zernike Moment. Fuzzy Particle Swarm Optimization optimizes feature selection, enhancing computational efficiency. Histological pictures of biopsied tissue from lungs that may be contaminated are used by medical practitioners to make diagnoses. It takes lots of efforts and is often prone to error to diagnose different forms of lung cancers. Convolutional neural networks can be used to swiftly identify and classify different forms of lung cancer. This work yields training and validation accuracy percentages for the CNN model of 96.11 and 97.2.

ANN model is used to identify whether lung cancer exists in the human body or not. The results of the evaluation demonstrated that the ANN model has a 96.67% accuracy rate in detecting the of lung cancer[13].

In the research [14],intends to look into a fast image segmentation technique for medical imaging to cut down on the time doctors need to spend evaluating images from CT scans. Large, very depressing images are produced by modern medical imaging technologies and are complex to manually analyse. The study examined the effectiveness of five different optimisation algorithms in extracting the tumour from the lung image. Particle swarm optimisation, k-means clustering, inertia-weighted particle swarm optimisation, and guaranteed convergence particle swarm optimisation (GCPSO) are some of these approaches. It was discovered that the GCPSO had the highest accuracy, at 95.89%.Numerous computer-assisted methods that make use of machine learning and image processing have been studied and put into practice. It assesses the many computer-aided methods, examines the best method already in use to determine its shortcomings, and then proposes a fresh model that improves on the most effective model in use right now. The process involved ranking and classifying lung cancer detection methods according to how accurate they were at detecting the disease[15].

The research [16], has three major phases: segmentation, nodule candidate detection and malignancy classification. This allows efficient training and detection and more generalise ability to other cancers. Extensive preprocessing techniques to get accurate nodules to increase the accuracy. Classification of lung cancer is intended to be addressed by different types of deep neural networks, namely CNN, DNN, and SAE. These networks are modified and fed to the job of lung nodules classification on CT medical image into benign and malignant. The LIDC-IDRI database used to assess those networks. The CNN network performed the best out of the three, archiving an accuracy of 84.15%, sensitivity of 83.96%, and specificity of 84.32% [17].

In [18], The lung images are identified using the Enhanced K Nearest Neighbour (EKNN) method. One crucial strategy for data mining algorithms is the k closest neighbour method. It follows pre-processing, feature extraction, classification, and cancer tissue detection. Morphological processing is used in preprocessing stage to remove noisy, irrelevant data from images. The photos are extracted in the second step using a discriminator algorithm and statistical analysis and classifying and identifying the malignant tissues in MRI images using the enhanced k Nearest Neighbour

(EKNN) approach. To categorise benign and malignant tissues, the experimental study using the improved k closest neighbour algorithm yields better and more promising classification results.

The research in [19] consists of four phases. The processes include lung extraction, lung region segmentation, feature extraction, and lung categorization into normal, benign, and malignant conditions. Using the trained data, it examines and determines the categories. It is frequently to diagnose illnesses. To classify the extracted features, SVM kernels are used. Real-time computer tomography pictures are used perform the experiment.

Medical imaging can provide a non-invasive visual representation of the distinct phenotypic characteristics found in human tumours. Based on these results, it appears that radiomics can identify a generic prognostic trait that is present in both head and neck cancer and lung cancer. This may have a clinical impact as imaging is routinely used in clinical practice, providing an unprecedented opportunity to improve decision-support in cancer treatment at low cost [20].

### III. PROPOSED METHODOLOGY

The proposed methodology, as illustrated in Fig. 1, encompasses a series of steps aimed at achieving precise lung nodule detection. Each step is designed to enhance the accuracy of the detection process.

Step 1: Image Acquisition and Database Retrieval.

Lung CT medical images are imported from a medical database as the initial step in the process.

Step 2: Preprocessing for Noise Reduction.

The pre-processing step is introduced to mitigate noise and aberrations introduced during image acquisition. The Median filter is applied, replacing pixel values with the median of grey levels in their vicinity.

$$\hat{f}(x, y) = \text{median}_{(s, t) \in S_{xy}} \{g(s, t)\}$$

Where:

$\hat{f}(x, y)$  is the filtered image.

$g(s, t)$  is the received image with artifacts.

$S_{xy}$  is the neighbourhood of pixel  $(x, y)$ .

Step 3: Feature Extraction using GLCM.

Feature extraction is done using the Gray Level Co-Occurrence Matrix (GLCM) approach. GLCM determines pertinent features representing pixel appearance and movement.

Step 4: Grey Wolf Optimization (GWO) Algorithm used for Optimisation.

The features extracted are given as an input into the GWO algorithm to attain an optimal solution. The GLCM assesses pixel frequency, and directions of GLCM are represented.

$$M^n = M \times M \times \dots \times M$$

Where:

$M$  is the integers.

$Mn$  is the universal set.

$X$  is an  $(n)$ -tuple representing a pixel in  $(Mn)$ .

Step 5: Iterative RNN Classification.

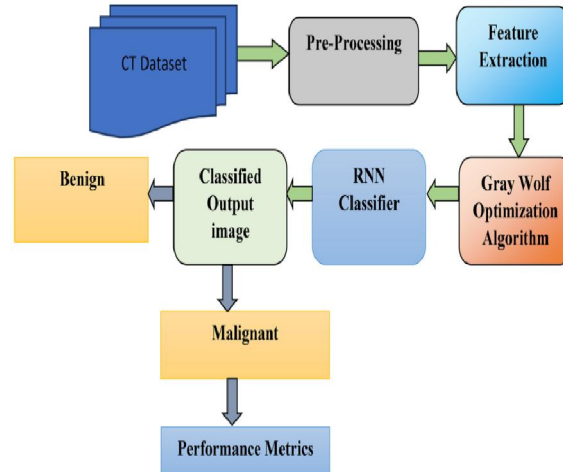
An iterative Recurrent Neural Network (RNN) classification technique is employed to classify tumours for malignancy. This step utilizes the optimal solution derived from the GWO algorithm.

Step 6: Performance Metrics Computation.

Various performance metrics are computed to facilitate a more precise interpretation of the findings. These metrics provide numeric measures of the algorithm's effectiveness in lung nodule detection.

**IV. BLOCK DIAGRAM**

The block diagram visually represents the sequential flow of the proposed methodology. It starts with image acquisition, followed by pre-processing, feature extraction, optimization using GWO, iterative RNN classification, and concludes with the computation of performance metrics. Each block represents a distinct stage in the process, showcasing the structured and systematic nature of the proposed lung nodule detection method.



**FIG. 1: SYSTEM ARCHITECTURE**

**V. CONCLUSION**

In conclusion, the proposed Evolutionary RNN framework for precise lung nodule detection using CT scans presents a comprehensive and systematic approach to address the associated challenges with identification of cancerous nodules accurately. The methodology, depicted in Fig. 1 and outlined in a stepwise manner, integrates advanced techniques from image processing, feature extraction, optimization algorithms, and iterative neural network classification.

Median filter in the pre-processing step effectively is used which reduces noise and artifacts introduced during image acquisition, enhancing the overall quality of the lung scans. Feature extraction through the Gray Level Co-Occurrence Matrix (GLCM) provides relevant information about pixel appearance and movement, contributing to a more comprehensive analysis.

Grey Wolf Optimization (GWO) algorithm is integrated in the optimization stage allows for the determination of optimal solutions based on pixel frequencies and directions. This synergy between GLCM and GWO contributes to the algorithm's ability to discern intricate patterns associated with malignant lung nodules.

The iterative Recurrent Neural Network (RNN) classification technique further refines the classification of tumours for malignancy, leveraging the optimal solutions obtained from the GWO algorithm. This iterative approach enhances the model's capacity to capture temporal dependencies difficult for accurate detection of lung nodule.

The proposed methodology is depicted in a system Architecture (Fig. 1), visually illustrating the coherent flow of the sequential stages. From image acquisition to performance metrics computation, each step contributes to lung nodule detection system. The systematic approach, encompassing pre-processing, feature extraction, optimization, and classification, sets the base for a robust and efficient detection of lung cancer system.

As a result, the proposed Evolutionary RNN framework helps in advancing the state-of-the-art in lung nodule detection, offering a nuanced and technologically sophisticated solution to enhance the accuracy of early cancer diagnosis. The integration of evolutionary algorithms and RNN signifies a notable step towards enhancing the capabilities of computer-aided diagnostic systems in medical imaging.



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