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Deep learning for lungs cancer detection: a review

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Abstract
Although lung cancer has been recognized to be the deadliest type of cancer, a good prognosis and efficient treatment depend on early detection. Medical practitioners' burden is reduced by deep learning techniques, especially Deep Convolutional Neural Networks (DCNN), which are essential in automating the diagnosis and classification of diseases. In this study, we use a variety of medical imaging modalities, including X-rays, WSI, CT scans, and MRI, to thoroughly investigate the use of deep learning techniques in the field of lung cancer diagnosis and classification. This study conducts a comprehensive Systematic Literature Review (SLR) using deep learning techniques for lung cancer research, providing a comprehensive overview of the methodology, cutting-edge developments, quality assessments, and customized deep learning approaches. It presents data from reputable journals and concentrates on the years 2015–2024. Deep learning techniques solve the difficulty of manually identifying and selecting abstract features from lung cancer images. This study includes a wide range of deep learning methods for classifying lung cancer but focuses especially on the most popular method, the Convolutional Neural Network (CNN). CNN can achieve maximum accuracy because of its multi-layer structure, automatic learning of weights, and capacity to communicate local weights. Various algorithms are shown with performance measures like precision, accuracy, specificity, sensitivity, and AUC; CNN consistently shows the greatest accuracy. The findings highlight the important contributions of DCNN in improving lung cancer detection and classification, making them an invaluable resource for researchers looking to gain a greater knowledge of deep learning's function in medical applications.

Keywords Lungs Cancer · Deep learning · Benign · Malignant · Classification · Segmentation

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1 Introduction

Cancer refers to the growth of abnormal tissues that are unwanted, it's uncontrollable, and it spreads speedily in the body; if it is not treated well at the start, it spreads and affects other body organs also. In the health sector, the use of modern technology has contributed a lot, especially in the detection of lungs cancer. It helps the doctors to identify as well as properly treat a disease. Many deaths occur in the whole world due to lung cancer and due to this, it is one of the deadliest diseases known in the world. In 2020, according to the research, approximately 2.21 million cases were detected, and 1.8 million mortalities were caused by lungs cancer (Sharma 2022). The report presented by the World Health Organization (WHO) in 2020, shows that lungs cancer is the deadliest among all kinds of cancers, that is said according to the death rate that is calculated as 1.80 million (World Health Organization 2022). Figure 1 shows the details of extinction because of cancer in 2020 according to WHO Lungs cancer is one of those diseases in which early-stage diagnosis and disease management play a crucial role in proper treatment.

Just like other cancers, the early detection of lungs cancer is mandatory due to which the chances of survival increase (Pathak et al. 2018). A large number of people affected by lung cancer cannot survive due to the delay in early detection, the overall survival rate of the patient is five years which is less than 20% (Roointan et al. 2019). Age is not a vital prognostic factor when it comes to the survival of patients (Hurria and Kris 2003). Both males and females fall prey to it. Men are more prone to lungs cancer than females According to research, the death rate in men due to lungs cancer is higher than females. (Chen et al. 2016). Factors contributing to increased lungs cancer cases include tobacco, smoke, viral infection, ionizing radiation (Cook et al. 1993; Esposito et al. 2010) air pollution, and unhealthy lifestyle. (Strak et al. 2017) History of chronic obstructive pulmonary disease (COPD) is the main factor that contributes to lungs cancer (Parris et al. 2019). The drastic increase in vehicles and bad smoking habits also play a crucial role. As tobacco is a primary factor, driving lungs cancer trend (Parascandola and Xiao 2019) so, the death toll due to lung cancer can be reduced by controlling tobacco usage (Field et al. 2013).

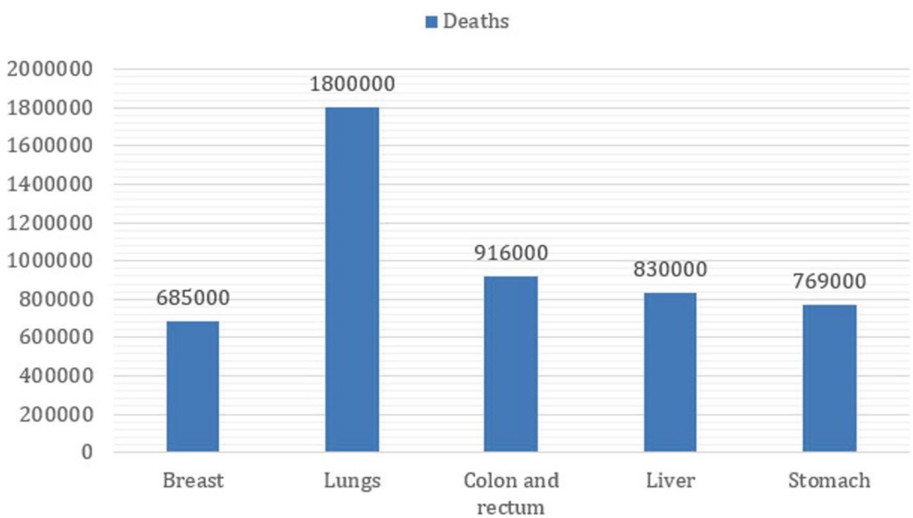

Fig. 1 Global Distribution of Cancer-Related Deaths in 2020

Its symptoms include fatigue, difficulty in breathing, and persistent cough (Corner 2005; Mayo Clinic 2022). Apart from common symptoms, its symptoms vary from person to person, making its diagnosis quite tricky. It might be asymptomatic, and a person may have cancer without any sign (Quadrelli et al. 2015). Lack of symptoms at early stages leads to a late diagnosis of lungs cancer (Goebel et al. 2019). One of the most important cornerstones of human civilization is maintaining one's health, hence modern approaches to medical issues are required. The amount of information available in the form of lab tests, research papers, clinic reports, and other documents has increased due to advancements in the biomedical area (Riad Alharbey et al. 2022).

A lot of research has been performed by many researchers in different fields so that the accurate prediction and classification of lungs cancer can be increased. In recent studies, Initial screening of disease is performed by exhaled breath analysis which is non-invasive and inexpensive (Nardi-Agmon and Peled 2017). Different methods are used for the prediction of lungs cancer. In the detection process X-rays, CT, and MRI& PET scans are most used.

The classification of lungs cancer in its early stages (Basak and Nath 2017), and the chance of survival of the patient is opposite and inversely proportional to the disease. Tumor size determines the cancer stage. The cancer stage is measured by its spread in the body. The more the spread, the higher the stage. Mostly it's not quite visible in the early stages; so, detection in the early stage is difficult (Das et al. 2020). But it's quite easy to deal with it in the early stages as the disease progresses, it becomes complex to cope with it Fig. 2. Depicts the stages of cancer.

Analysis of visual images is an efficient way to investigate the lungs tissues identify the stages of lungs cancer and classify these stages. However, it is difficult to categorize it by stages.However, by the usage of advanced deep learning methods, lungs cancer can be classified accurately. Figure 2 effectively depicts the progression of lungs cancer and categorizes it into stages. Deep learning algorithms are implemented to identify different types of lung cancer and categorize them. The most important and effective method to diagnose and the treatment of lung cancer is made possible by the initial step of disease detection within the lung tissue. Subsequently, various classifiers are used to accurately classify the identified cases into their respective stages Fig. 3. Depicts how classification and prediction of lungs cancer.is performed using deep learning.

Different therapies like chemotherapy and radiotherapy are performed for their treatment, but advanced lungs cancer is quite complex. CT is widely and commonly used for the detection purpose of lungs tumors, but it's been closely observed that small nodules are mostly not predictive for lungs cancer (Horeweg et al. 2014). These are comparatively tricky and complicated to detect and treat. When it comes to classifying benign &

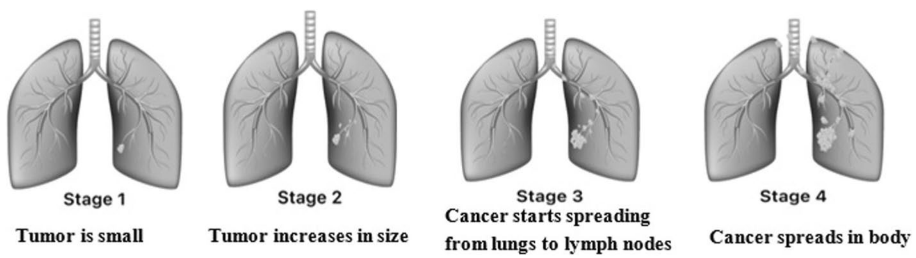

Fig. 2 Progression stages of lung cancer—illustrating the different developmental phases"

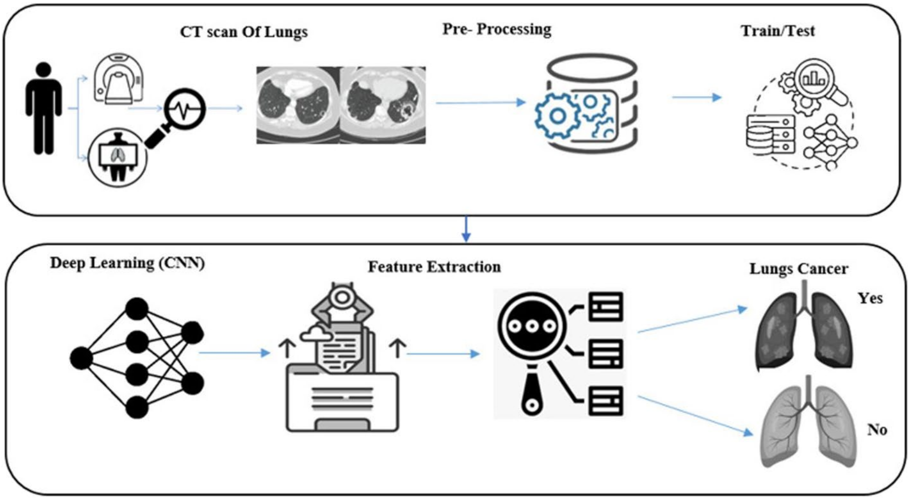

Fig. 3 Deep Learning for the classification and detection of lungs cancer

malignant lesions CT has limited ability (Lardinois et al. 2003) Small lesions, having minimal contact with the chest wall are complicated and dealt with technically (Middleton et al. 2006). Chest wall structure, small blood vessels, airway walls, pulmonary structures (Lu et al. 2015), and tissues that are pretty like nodule makes the detection difficult, so it's rather difficult to perform biopsy that leads to detection. A biopsy is performed for the evaluation of nodules (Lowe et al. 1998). The disease's complexity and poor CT resolution sometimes lead to re-biopsy. Nodules are classified according to their type, size, and growth rate; it's essential because it sets the direction of treatment. Nodules can be classified as the cavity, calcified & non-calcified (El-Baz et al. 2013), or as solid, non-solid, partially solid, and calcified (Massimo 2012). A partially solid tumor is a combination of non-solid and solid, the solidified lung tumors consist of a solid internal core. Lung nodules can also be classified as Benign and Malignant (Dhara et al. 2016; Silvestri MD et al. n.d.; Wu et al. 2020; Zhang et al. 2019)

Deep learning is contributing tremendously to healthcare (Esteva et al. 2019; Miotto et al. 2018; Mittal and Hasija 2019). Deep learning paves the way for fast and accurate detection and diagnosis of diseases (Mishra et al. 2020), leading to precise and exact treatment. Research shows that the algorithm of deep learning has shown its significance in the prediction, detection, and diagnosis with the classification of lung cancer; pulmonary nodules are closely observed. By incorporating different deep-learning approaches, the tumor, and the nodule features are captured and classified (Wu and Qian 2019). Big Data refers to incredibly massive data collections that are amenable to analysis to identify trends and patterns. Deep Learning is one method for data analysis that can be utilized to discover abstract patterns in large amounts of data (Gheisari et al. 2017). Advanced data representations and knowledge can be extracted with the help of deep learning (DL). Highly efficient DL methods aid in uncovering more buried information (Gheisari et al. 2023). CAD (Computer-aided design) is used for the screening of cancer in the early stages (Traverso et al. 2017). It is proven as a helping hand for doctors and radiologists (Yuan et al. 2006). State-of-the-art methods have been designed to develop automated processes. Coherent Anti-Stroke Raman Scattering (CARS) technique is used for sensitive investigations (Müller and Zumbusch 2007), and is also there to scan the lungs that capture the molecular movement and produce an image that helps to detect diseases accurately. Researchers have defined different classification models to detect & classify lungs cancer automatically (Nasrullah et al. 2019).

Using a deep learning algorithm, other techniques have been made to read and learn data representation from the unorganized (raw) data. Inner body details are examined, and valuable information is extracted from this data. Deep learning models, algorithms, and methods play a tremendous role in increasing accuracy and decreasing error in the classification of lungs cancer. Deep learning-based automatic segmentation is better than manual in many aspects (Liu et al. 2021) Deep learning helps to avoid misclassification, reduces error rate, provides high-quality images, and accurately predicts cancer. False-positive nodules are filtered out using different classifiers (Jiang et al. 2022). Accurate and high-quality images are directly proportional to the radiologist's fast and accurate diagnostic decision. Deep learning methods are also incorporated to predict lungs cancer (Banerjee and Das 2021). Training images are provided, and features are extracted automatically. Comparatively, deep learning costs less than conventional CAD frameworks. Deep learning offers HD representation of the given input data, making the detection and identification process efficient and helping the radiologist. The image's pixel directly contributes to cancer detection, as cancerous and non-cancerous areas are determined on the base of pixels. So, to diagnose accurately and the classification of disease, deep learning assists medical professionals in serving the healthcare system better. It helps to make accurate decisions regarding the disease. CNN design consists of multiple tiers, one of which being Convolutional Layers (CLs). By employing different kinds of convolution filters, the CL layers can extract distinct information from the images of cancer cells that are supplied to them (Manjula Devi et al. 2023). Under the methodology that is being described, the first step in the process is image processing, where preprocessing methods are used to improve the quality of medical images. The improved pictures next go through segmentation, which is an essential stage in identifying pertinent areas within lung imaging. Following identification, the regions are subjected to feature extraction, a process that involves the extraction of significant features to identify crucial patterns suggestive of lung cancer. The classification step, which uses a complex architecture called the Deep Convolutional Neural Network (DCNN), is where the classification process is most centrally located. To dynamically learn hierarchical features, this DCNN is composed of several convolutional layers, each of which has filters, activation functions, and pooling operations. Dense layers known as fully connected layers are another component of the architecture that handles the high-level characteristics that the convolutional layers have learned. The final output shows the findings of the categorization, which differentiates between various lung cancer classifications. The DCNN is an effective technique for accurately classifying lung cancer because its convolutional layers are essential for automatically learning complex patterns.

This study involves the following contributions to the field of medical science especially to the detection of lungs cancer in its early stages:

- Provides the solution for the detection of lungs cancer in the field of healthcare.
- Discussed different existing techniques and procedures.
- Implemented deep learning algorithm and compared with the existing machine learning algorithms and compared the performance with the developed algorithm.
- The designed technique is implemented on a large dataset and shows how to classify the features.

- It shows the usability of Convolutional Neural Networks (CNN) in the field of artificial intelligence.
- For future research it provides useful implementation and development techniques for the early detection of cancer disease.

The other parts of the literature survey are defined in the following sections. Imaging techniques for lungs cancer detection are presented in Section 2. Section 3 includes the latest trends in lungs cancer detection, Section 4 offers the Research methodology of the opted research and the process of selecting research articles is given in Section 4. Section 5 refers to the deep learning contribution towards lungs cancer classification. Section 6 refers to the Literature sources, and the research community's contribution to the current field covering primary techniques and models used to classify, detect, and predict lungs cancer. Results that are obtained from the selected and extracted data are presented in Section 7. Section 8 refers to the conclusion in which the state-of-the-art deep learning contribution towards lungs cancer classification is presented.

2 Imaging techniques for detection of lungs cancer

Different screening approaches are employed for the identification and screening of lung cancer (Schaefer-Prokop and Prokop 2002). These aid in the doctor's ability to see internal bodily processes and to gain an understanding of how internal organs function. To check for lung anomalies. There are several multimodality imaging techniques including positron emission tomography (PET), computer tomography (CT), Ultrasound, chest radiography (X-Ray), and magnetic resonance imaging (MRI) scans (Laal 2013; Tariq Hussain n.d.) Fig. 4 shows a few techniques of Imaging.

3 Latest trends in lungs cancer detection

The primary purpose of the designed research is to demonstrate the methods and strategies employed in the deep learning categorization of lung cancer. Deep Learning algorithm is the most recent technique that helps medical professionals diagnose diseases and helps radiologists find difficult-to-diagnose conditions like lung cancer. The chosen

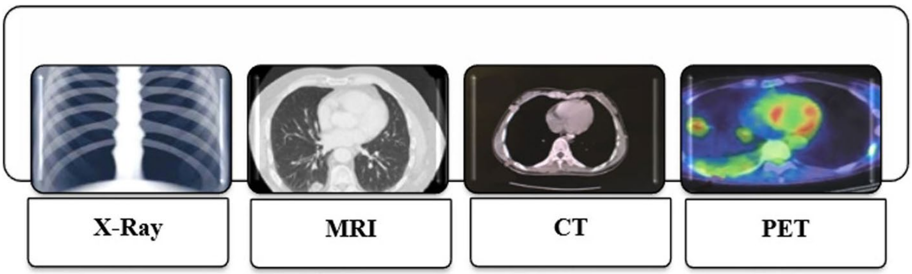

Fig. 4 Modalities in lung cancer detection—a visual exploration of imaging techniques

articles demonstrate the most recent deep learning algorithms and their efficacy in the prediction and categorization of cancer. This paper presents different techniques defined in deep learning algorithms and concepts for this (Fig. 5).

Convolutional Neural Network (CNN) consists of multiple layers. Convolutional layer that extracts features of image pooling layer which selects the feature. The third one is the fully connected or FC layer, its work is to combine those extracted features. Recurrent Neural Network (RNN) is suitable for sequential data and is mostly used for audio, video, and text. Deep Belief Network (DBN) consists of multiple RBMs. These are probabilistic generative models. DBN has many variants. Support Vector Machine (SVM) is a statistical theory-based algorithm. Artificial Neural Network (ANN) is structured just like human brains in which neurons are involved, that's why it is known as a biological-inspired network. Deep Neural Network (DNN) is a new and advanced technique in the field of artificial intelligence, as it can also work for a complex nonlinear relationship. DNA-binding proteins have a close relationship with several human disorders, including AIDS, cancer, and asthma (Ali et al. 2022b). DBP-DeepCNN would be beneficial in developing more promising therapeutic approaches for the management of chronic diseases (Ali et al. 2022a) while patients with chronic depressive illness experience confusion in their social lives (Gheisari 2016). Integrating CC technology with wireless body area networks WBANs systems to create sensor-cloud infrastructure (S-CI) is helping the healthcare industry by enabling early detection of diseases and real-time patient monitoring (Masood et al. 2023, 2018a) while patient privacy should preserved (Masood et al. 2018b). If a deep learning model is developed well, it may help prevent misdiagnosis and waste of time (Javed et al. 2023). Deep machine learning could be applied to the initial processing of images, the segmentation of images to emphasize the diagnostic objects under investigation, and the classification of these objects to ascertain their benign or malignant nature (Jamshaid Iqbal Janjua et al. 2022). It is challenging to predict human diseases, especially cancer, in order to deliver more effective and timely care. Cancer is a potentially deadly disease that affects the human body's many organs and systems (Abbas et al. 2023b)

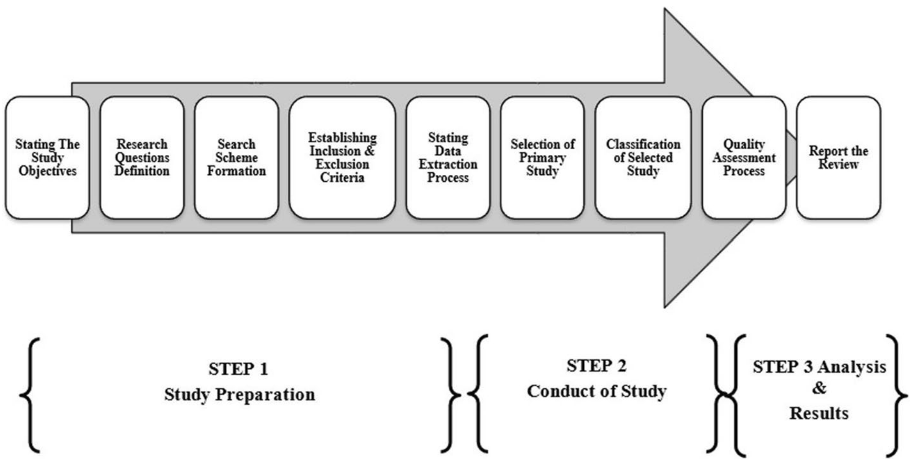

Fig. 5 Sequential process of study execution

4 Research methodology

For the selected research, a mapping study "Classification (lungs cancer)" analysis is chosen as a research methodology. Figure 6 illustrates the mapping process that has been followed. It consists of three steps that are as follows:

Step-I: Study Preparation
Step-II: Conduct of Study
Step-III: Analysis and Results of the Study

In this study, a mapping study methodology is employed to conduct a systematic exploration of the literature on lung cancer classification using deep learning approaches. The mapping process, illustrated in Fig. 5, is structured into three distinct steps: Study Preparation, Conduct of Study, and Analysis and Results of the Study. The main contribution of this paper is described below.

- Conducted a comprehensive Systematic Literature Review (SLR) using deep learning approaches, which included a detailed analysis of pertinent literature in the field of lung cancer.
- Categorized and synthesized the overall methodologies observed in the literature, offering readers a systematic overview of the strategies adopted in the domain of deep learning for lung cancer detection and analysis

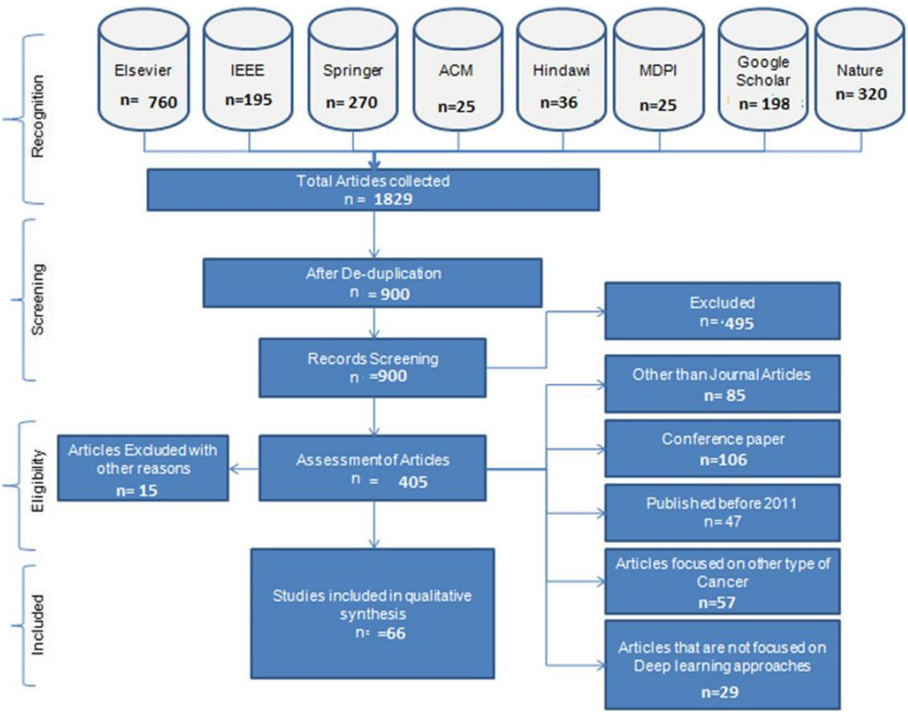

Fig. 6 Visual representation of the systematic article selection process

- Outlined the current state-of-the-art and the latest advancements in deep learning methodologies applied to lung cancer research, providing insights into cutting-edge techniques and emerging trends in the field.
- Conducted a comprehensive Quality Assessment of the approaches used in the examined papers, guaranteeing a strong assessment framework to gauge the validity and dependability of the deep learning methods applied in lung cancer research.
- Provided a comprehensive overview of deep learning methodologies specifically tailored to lung cancer research, consolidating the collective knowledge and advancements in the area for the benefit of researchers, practitioners, and stakeholders.

Study preparation, the first step, entails defining the research's scope, creating inclusion and exclusion criteria, and choosing a search technique. The implementation of the literature search, data extraction, classification, and synthesis of pertinent literature are then included in the Conduct of Study phase. Lastly, analyzing the identified literature, gauging the caliber of the included research, and extracting significant findings to guide the systematic review are all part of the Analysis and Results of the Study phase.

4.1 Research objectives

The main purpose of this research is to provide the scientific community with a systematic step-by-step review of the current research on lungs cancer by using the technique known as deep learning just like the recurrent neural networks (RNN), deep belief network (DBN), support vector machine (SVM), convolution neural networks (CNN) and the deep neural networks (DNN) etc.

4.2 Research questions

As part of this procedure, the questions related to this research are listed in Table 1 and are defined step by step to provide a more thorough understanding of the investigation. These research questions are accompanied by their motivations.

4.3 Search scheme

Following databases and scientific resources have been searched to get and gather the most relevant research papers and articles IEEE Digital Library, Springer, Elsevier, ACM Digital Library, Science Direct, and Google Scholar are the main repositories that were used to get the most relevant research articles.

4.4 Search string

The following search string was used to conduct the automatic search in the selected databases/scientific sources.

> ("Classification" OR "Detection" OR "Prediction" OR "Diagnosis" OR "Analysis") AND ("Lungs Cancer" OR "Lung Cancer" OR "Pulmonary Nodule" OR "Lungs Tumor" OR "Lung Nodule") AND "Deep Learning" also known as "Deep Neural Network" alternate "DNN" also written as "DL"

Table 1 Research questions and motivation

No	Research question	Main motivation
RQ1	What has been addressed on Lungs Cancer in the study?	To understand the world's most death-causing lungs cancer's classification
RQ2	What is the primary issue and how to contribute and solve cancer-related medical issues?	Classification of lungs cancer using deep learning approaches
RQ3	How efficiently do Deep learning methods provide the solution?	Deep Learning methods provide a helping hand for radiologists and doctors by aiding them in the proper detection and classification
RQ4	Which publication channels are the main targets for lungs cancer research?	To classify where lungs cancer classification using deep learning can be devised as well as the best publication sources for future studies

4.5 Study selection procedure

The selection procedure is focused on identifying and recognizing those articles that effectively meet the goal of the study. These articles have been searched and gathered from different sources, so if the article is present in more than one source it is counted just once. After comprehensively investigating and examining titles, abstracts, and keywords, each paper is evaluated and its candidature in a study is determined. The search string is considered in deciding the inclusion and exclusion criteria. Duplicates are removed and articles not observing the search string are excluded.

4.6 Inclusion & exclusion principles for the research studies

For the chosen research Table 2 listed the inclusion and exclusion principles. Articles from journals focused on the classification of lungs cancer where deep learning algorithms, are incorporated, and published between 2015-2024 are collected While Articles that are focused on other types of cancer and do not incorporate deep learning are not included.

Research articles are collected from different geographical locations through a combination of online databases, we gathered articles for our study from various geographic places. Using precise terms and search parameters linked to our research topic, we conducted in-depth searches on academic databases including IEEE, Nature, Google Scholar, etc. Table 3 depicts the geographical locations of the articles selected for the study.

The research process is conducted according to the given flow diagram in Fig. 6, which depicts the steps of gathering the research material, from identifying articles to selecting articles for further analysis.

It starts by gathering articles from well-reputed databases. Then the overall number is calculated. After that, the duplicate articles are removed, and initial screening is performed.

Articles that are not in the English language are excluded, and further assessment is performed in this step different criteria of exclusion are applied. The articles that are not from journals are excluded, conference papers, papers published before 2015, papers that are focused on other types of cancer, and articles that are not focused on deep learning are excluded. After excluding the papers with justification, 66 articles were chosen for further investigation.

Figure 7 displays a graphical depiction of the scientific databases where the search term was used, and articles were chosen.

Table 2 Inclusion and exclusion principles

Inclusion method	Exclusion method
IC1-Articles presenting Concepts related to the classification of Lungs cancer	**EC1**- Articles that are focused on the Classification of other types of cancer
IC2-Articles focused on the classification of lungs tumor by using deep-learning algorithm	**EC2**- Articles focused on the classification of lungs tumor and defined by other approaches other than deep learning
IC3-Research articles from well-reputed studies	**EC3**- Articles from conferences
IC4-Articles from any geographical location from 2015–2024	**EC4**- Articles that are published before 2015

Table 3 Geographic distribution of selected articles

Country	No of articles selected
Bosnia and Herzegovina	1
Egypt	5
Germany	2
Ireland	5
Netherlands	7
New Zealand	1
Switzerland	2
UK	19
US	24

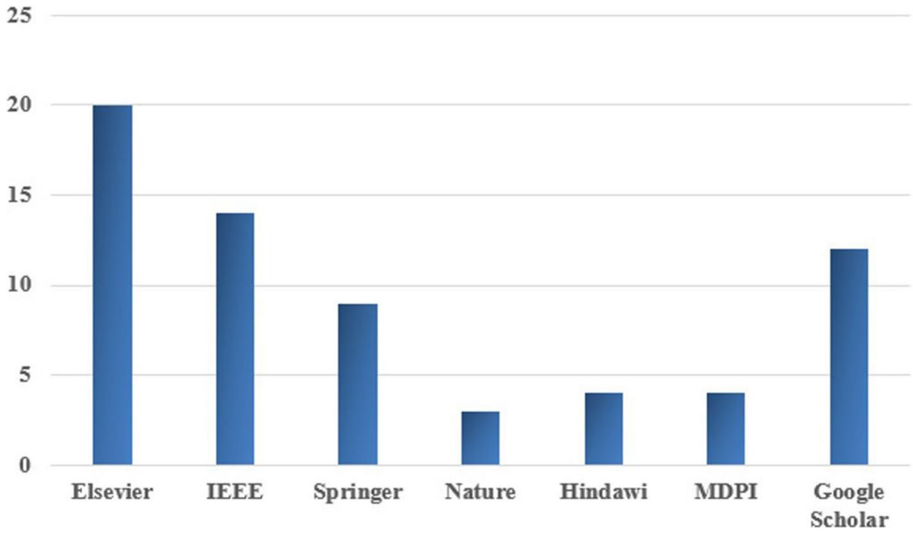

Fig. 7 Distribution of articles selected from scientific databases

5 Quality assessment of study

Quality assessment is important in systematic reviews of literature as it determines the quality of the study that is included.

1) The solution to the problem is presented clearly in the paper. The answer could be yes (+ 1), No (0), somehow (0.5)
2) The contribution of the paper regarding the issue “Classification of lung cancer using deep learning is presented clearly. The answer could be yes (+ 1), No (0), somehow (0.5)
3) Limitations and future study are presented and defined clearly the answer could be yes (+ 1), No (0), somehow (0.5)

4) Result parameters are presented clearly, the answer could be yes (+ 1), No (0), somehow (0.5)

Table 4 presents a detailed Quality assessment score. In which selected articles along with their reference number are presented. These are evaluated based on the solution of the problem, contribution, limitation, future work, and results. Each question possesses one score. A total of 4, each article is evaluated and graded.

Table 5 presents a summary of the total scores. There is one paper that possesses a score of 2, 7 articles with 2.5. There are 13 articles with a score of 3, 25 articles with a score of 3.5, and 20 articles with a score of 4

6 Literature sources

To look over and explore the detection, classification, and prediction of lung cancer using deep learning, 66 relevant articles published by reliable sources were examined.

To ensure the credibility of the systematic literature review, credible journals are selected as sources and data collection. Moreover, a large number of adequate literature surveys exist for that kind of review Fig. 8 portrays the year-wise detail of collected articles.

It's evident that the selected articles are from 2015 to 2024 and the chart represents that 2020 is the maximum contributing year because the maximum number of articles falls in 2020.

The nature of the review was to present the work done on the topic of the classification of lungs cancer using different deep-learning methodologies. According to the collected data, it is observed that the most frequently used method is the convolutional Neural Network) CNN. Convolution neural networks (CNN) is also a technique used to solve deep learning problems; it consists of multiple layers. CNN is contributing a lot to Image processing and computer vision (Liu et al. 2019a). It is to be noted that the article review was quite prejudiced to the articles published (2015–2024), and the articles that have "Deep Learning" used in titles. It is observed that multiple data sets have been used in research.

This shows that many diversities in data when it comes to training and testing on CNN. MRI, thoracic surgery data, X-ray, CT, PET image data, CARS images, breathing data, thoracic MR images, Whole Slide Imaging (WSI), Lymph Node Slides, H & E slides, and Histopathological. Table 6 presents the summary of the selected research articles. The datasets used in the research, and their descriptions are presented. The parameters that decide the form of classification, applied method or approach, and the feature extraction techniques used are provided after thoroughly examining the selected research articles.

Cancer image data is collected and presented in forms. It is observed that a CT scan is the most frequently used type of data.

The management of input image sizes is a critical consideration in deep learning field for lung CT-scan processing. Some models require a specific input size, which calls for preprocessing operations like scaling or cropping to fit the data into this preset dimension. Such modifications, however, run the danger of information loss or image distortion, which reduces the model's effectiveness. In contrast, to solve these problems more advanced and sophisticated methods are developed. Models can adjust to different image sizes using techniques like padding or spatial pyramid pooling, but they may also introduce noise or artifacts. The idea of picture pyramids also produces numerous image copies at varying

Table 4 Quality assessment

Author	Quality assessment				T. score
	1	2	3	4	
(Wani et al. 2023)	1	1	1	1	4
(Kumar Swain et al. 2024)	1	1	0	1	3
(Shah et al. 2023)	1	1	1	1	4
(Said et al. 2023)	1	1	0.5	1	3.5
(Siddiqui et al. 2023)	1	1	1	1	4
(Wankhade and Vigneshwari 2023)	1	1	1	1	4
(Pandit et al. 2022)	1	1	1	0.5	3.5
(Lanjewar et al. 2023)	1	1	0.5	1	3.5
(Abbas et al. 2023a)	1	1	1	1	4
(Shakeel et al. 2022)	1	1	1	1	4
(Liu and Yao 2022)	1	1	0	1	3
(Masud et al. 2021)	1	0.5	0	1	2.5
(Kumar and Bakariya 2021)	1	1	0.5	1	3.5
(Gu et al. 2021)	1	1	1	1	4
(Wang et al. 2021)	1	0.5	1	1	3.5
(Cui et al. 2022)	1	0.5	1	1	3.5
(Sui et al. 2021)	1	0.5	1	0	2.5
(Oh et al. 2021)	0.5	0	1	1	3
(Jena et al. 2021)	1	1	1	1	4
(Sori et al. 2020)	1	1	1	1	4
(Tian et al. 2021)	1	1	0	1	3
(Obulesu et al. 2021)	1	1	1	1	4
(Heuvelmans et al. 2021)	1	1	0	1	3
(Chaunzwa et al. 2021)	1	1	1	1	4
(Asuntha and Srinivasan 2020)	1	1	0.5	1	3.5
(Elnakib et al. 2020)	1	1	1	1	4
(Doppalapudi et al. 2021)	1	0.5	0	1	2.5
(Guo et al. 2021)	1	1	0.5	1	3.5
(Hu et al. 2021)	1	0.5	1	1	3.5
(Savitha and Jidesh 2020)	1	1	1	1	4
(Zhao et al. 2020)	1	0.5	0.5	1	3
(Li et al. 2020)	1	0.5	0.5	1	3
(Yu et al. 2020)	1	0.5	0.5	1	3
(Zhang and Kong 2020)	1	0.5	0.5	1	3
(Wang et al. 2020a)	1	0.5	1	1	3.5
(Lin and Li 2020)	1	1	0.5	1	3.5
(Shakeel et al. 2020)	1	0.5	0	1	2.5
(Ozdemir et al. 2020)	1	1	1	1	4
(Affonso et al. 2020)	1	1	0.5	1	3.5
(Ardila et al. 2019)	0.5	0.5	1	1	3
(Liu et al. 2019a)	1	0.5	0	1	2.5
(Lang et al. 2019)	1	0	0.5	1	2.5
(Liu et al. 2019b)	1	0.5	0.5	0	2
(Shakeel et al. 2019)	1	0.5	0	1	2.5

Table 4 (continued)

Author	Quality assessment				T. score
	1	2	3	4	
(Hoang Ngoc Pham et al. 2019)	1	1	1	1	4
(Chae et al. 2020)	1	1	0.5	1	3.5
(Wang et al. 2020b)	1	1	0.5	1	3.5
(Li et al. 2019)	1	1	0	1	3
(Tran et al. 2019)	1	1	1	1	4
(Xu et al. 2019)	1	1	0.5	1	3.5
(Hussein et al. 2019)	1	1	0.5	1	3.5
(Nam et al. 2019)	1	1	1	1	4
(Naqi et al. 2018)	1	1	0.5	1	3.5
(Xie et al. 2019)	1	1	0.5	1	3.5
(Lakshmanaprab et al. 2019)	1	1	1	1	4
(Tan et al. 2019)	1	1	1	1	4
(Jung et al. 2018)	1	1	0.5	0.5	3
(Coudray et al. 2018)	1	1	0.5	1	3.5
(Ciompi et al. 2017)	1	1	0.5	1	3.5
(Weng et al. 2017)	1	1	0.5	1	3.5
(Song et al. 2017)	1	1	1	1	4
(Abbas 2017)	1	1	0.5	1	3.5
(Nibali et al. 2017)	1	1	0.5	1	3.5
(Jiang et al. 2017)	1	1	0.5	1	3.5
(Park et al. 2016)	1	0.5	0.5	1	3
(Yu-Jen Chen et al. 2015)	1	1	0.5	1	3.5

scales, facilitating feature capture at varied levels of detail. Fully Convolutional Networks (FCNs) are also specially designed to support arbitrary input sizes. The decision between these methods depends on the particular deep learning architecture and the actual requirements of the task of medical image analysis, taking into account elements like computational complexity and the requirement to adapt to various input dimensions.

The process of lungs cancer/nodules detection or classification goes as follows: -

Pre-Processing: it is the first step which is used to take inputs in the form of MRI, Thoracic Surgery Data, X-ray, CT, PET Image Data, Breathing Data, Thoracic MR Images, Whole Slide, Imaging (WSI), Lymph Node Slides, Histopathological Cancer Images, CARS Images, H&E. Different Image processing/ feature extraction techniques are applied on the Input. Table 7 lists the various data types used in the reviewed studies.

Computed Tomography is used most of the time, because it's been frequently used in our review techniques used for preprocessing includes FPSOCNN, Wavelet-Transform-Based Features, SIFT, LBP, ABF Zernike Moment, and HE, inceptionv3, LDA, ODNN, Novel Nodule Candidate Detection Method, Single-level discrete Two-Dimensional Wavelet Transform (2D-DWT), Fractional-Order Darwinian Particle Swarm Optimization, Two-Dimensional Discrete Fourier transform (2D-DFT), U-Net, Back-Propagation, Deep Learning Architectures, Gradient Descent, SIFT + LBP, Swarm Algorithms, Bipartite Undirected Graphical Models (RBMs), including Alex, Deep (ConvNet),Intensity features + SVM Support Vector Machines, Transfer Learning Networks, Hybrid Geometric Texture Feature

Table 5 Summary of quality assessment (QA) scores

Ref	T. Score
(Liu et al. 2019b)	2
(Masud et al. 2021), (Sui et al. 2021), (Doppalapudi et al. 2021),, (Shakeel et al. 2020), (Liu et al. 2019a), (Lang et al. 2019), (Shakeel et al. 2019)	2.5
(Oh et al. 2021), (Tian et al. 2021), (Heuvelmans et al. 2021), (Zhao et al. 2020), (Li et al. 2020), (Yu et al. 2020), (Zhang and Kong 2020), (Ardila et al. 2019), (Li et al. 2019), (Jung et al. 2018), (Park et al. 2016), (Kumar Swain et al.2024), (Liu and Yao 2022)	3
(Kumar and Bakariya 2021), (Wang et al. 2021), (Cui et al. 2022), (Asuntha and Srinivasan 2020), (Guo et al. 2021), (Hu et al. 2021), (Wang et al. 2020a), (Lin and Li 2020), (Affonso et al. 2020), (Chae et al. 2020), (Wang et al. 2020b), (Xu et al. 2019), (Hussein et al. 2019), (Naqi et al. 2018), (Wang et al. 2021), (Cui et al. 2022), (Asuntha and Srinivasan 2020), (Guo et al. 2021), (Hu et al. 2021), (Wang et al. 2020a), (Lin and Li 2020), (Affonso et al. 2020), (Chae et al. 2020), (Wang et al. 2020b), (Xu et al. 2019), (Hussein et al. 2019), (Naqi et al. 2018), (Xie et al. 2019), (Coudray et al. 2018), (Ciompi et al. 2017), (Weng et al. 2017), (Abbas 2017), (Nibali et al. 2017), (Jiang et al. 2017), (Yu-Jen Chen et al. 2015), (Said et al. 2023), (Pandit et al. 2022), (Lanjewar et al. 2023)	3.5
(Gu et al. 2021), (Jena et al. 2021), (Sori et al. 2020), (Obulesu et al. 2021), (Chaunzwa et al. 2021), (Elnakib et al. 2020), (Savitha and Jidesh 2020), (Ozdemir et al. 2020), (Hoang Ngoc Pham et al. 2019), (Hoang Ngoc Pham et al. 2019), (Tran et al. 2019), (Nam et al. 2019), (Lakshmanaprab et al. 2019), (Tan et al. 2019), (Song et al. 2017), (Shah et al. 2023), (Siddiqui et al. 2023), (Wankhade and Vigneshwari 2023), (Abbas et al. 2023a), (Shakeel et al. 2022), (Wani et al. 2023)	4

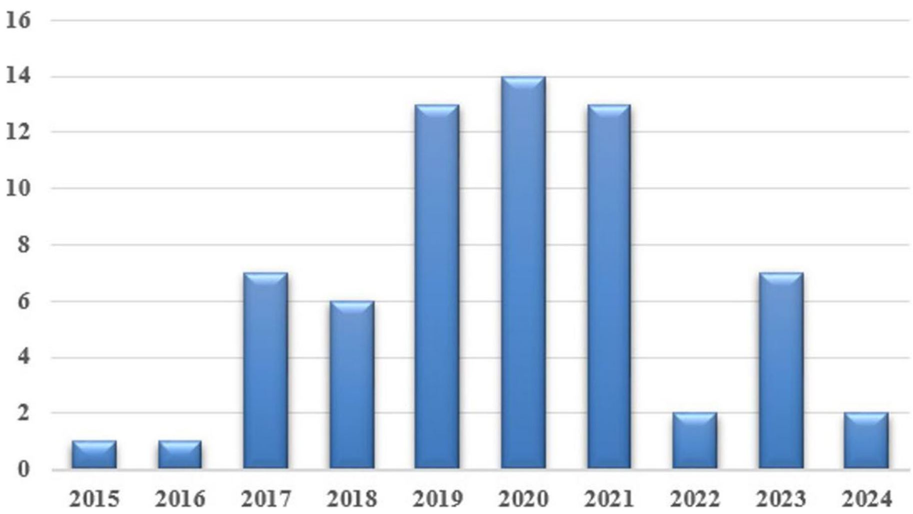

Fig. 8 Annual article selection overview (2015–2024)

Descriptor, FODPSO CARS, VGG16,Wiener Filter, VGG19, Three-Dimensional (3D) CNN model, CNN Region-Of-Interest (ROI), Median Filter, Gaussian Filter, Gabor Filter, Knowledge-Based Collaborative (KBC) sub-mode, ResNet-50 networks, ProNet, RadNet, UB open-source software ITK-Snap, 3D Stereoscopic Planning System, IMR, Maximum Intensity Projection Technique, Based On Lung-RADS version 1.1, Three Reconstruction

Table 6 Overview of approaches assessed in the study

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Wani et al. 2023)	-	Survey Lung Cancer	Lungs Cancer	CNN	Hybrid Deep Learning-based technique ConvXGB
(Kumar Swain et al. 2024)	CT	LC25000 dataset	Lung Cancer	DL	Sparse Neural Network
(Shah et al. 2023)	CT	LUNA 16 Grand challenge dataset with 200 Images of each CT	Nodule Detection	CNN	Deep Ensemble 2D CNN
(Said et al. 2023)	CT	Decathlon lung dataset consisting 96 sets of segmented 3D CT scans	Malignant Benign	UNETR neural network	self-supervised neural network
(Siddiqui et al. 2023)	CT	LIDC-IDRI and LUNA-16 datasets	Benign Malignant	DBN	deep belief network with Gabor filters
(Wankhade and Vigneshwari 2023)	CT	Lung and colon cancer histopathological image dataset (lc25000)	Lungs Cancer	DL	Lung Cell Cancer Detection (DL-LCCD) method
(Pandit et al. 2022)	CT	-	Lungs Cancer	CNN	convolution neural network and Adam Algorithm
(Lanjewar et al. 2023)	CT	Kaggle chest CT-scan images dataset	Normal Small cancer Squamous Carcinoma Adenocarcinoma	DL	DenseNet201 model
(Abbas et al. 2023a)	Text File	Lung cancer dataset by staceyinrobert kaggle	Lungs Cancer	DELM	Federated deep extreme machine learning
(Shakeel et al. 2022)	CT	-	Lungs Cancer	DNN	Deep Neural Network & ensemble classifier
(Liu and Yao 2022)	-	TCGA dataset and ICGC dataset	Lungs Cancer	DNN	Deep learning with KL divergence gene selection

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/preprocessing
(Masud et al. 2021)	Histopathological Cancer Images	LC25000 dataset from James A. Haley Veterans' Hospital 25,000 color images categorized into five types including colon tissues and lung (15000Lungs)	Adenocarcinoma Benign Squamous Cell Carcinoma	CNN	Digital Image Processing (DIP) DL-Based Supervised Learning Method Discrete Fourier Transform (2D-DFT)
(Kumar and Bakariya 2021)	CT	LIDC-IDRI dataset 244,527 screening images	Benign Malignant	DCNN	Median Filter Gaussian Filter Gabor Filter Alex Net GoogleNet DNN
(Gu et al. 2021)	CT	LUNA16, LIDC, DSB2017, LIDC-IDRI, NLST, Tian-Chi, and ELCAP	Nodules Non-Nodules Benign Malignant	DL	CADe and CADx systems
(Wang et al. 2021)	CT	Department of Medical- Imaging in National Taiwan-University- Hospital 40 keV dataset	Absence of Nmet on Primary Tumors Presence of Nmet on Primary Tumors	DL Nmet	Novel-Deep-Prediction Methods, Size-Related Damper Block Core-Ring Blocks Residual Estimation (Nmet) Identification
(Cui et al. 2022)	CT	(LDCT) screening study was conducted at the Tianjin-Medical University180 individuals	Solid Nodule Part-Solid Non-Solid Detection in LDCT Lung Cancer Screening	DL	DL-CAD

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Sui et al. 2021)	CT	Non-Small-Cell-Lung Cancer (NSCLC) from Cancer Archive 211 subjects from an NSCLC	Transformation of Genomic Data onto Tumor Images	DL	Prognosis and (GSEA) Gene-Set Enrichment Analysis GVAE-GAN Correlation Analysis Algorithm
(Oh et al. 2021)	PET/CT	Chonnam-National-University-Hwasun- Hospital in South Korea 2685	Features Related to Survival Time	CNN	DenseNet using CoxPH CNN model ImageNet Score-CAM Maximum intensity projection (MIP)
(Sanjukta Rani Jena et al. 2021)	CT	Lung-Image Database Consortium (LIDC-IDRI) 1018-Cases Thoracic-CT-Scans	Benign Malignant	CNN	Deep-Gaussian-Mixture-Model, Region-Based CNN [DGMM-RBCNN] Gaussian And Wiener Filter
(Sori et al. 2020)	CT	Kaggle-Data-Science Bowl 2017 challenge (KDSB), LUNA 16	Cancer Non-Cancer	CNN	Hounsfield Unit (HU) Residual-Learning- Denoising Model (DR-Net) Feature Fusion Strategy DCA
(Tian et al. 2021)	CT	Lung CT-Diagnosis Database f 61 Patients' CT Images	Benign Malignant	DL	CSAR Algorithm optimized with Fuzzy C-ordered means (DSARFCM)
(Obulesu et al. 2021)	Thoracic Surgery Data	National Lung Cancer Registry 470 Instance	Disease Prediction	DL Network	WS-GDL Method, Signed-Rank-Gain Preprocessing Algorithm
(Heuvelmans et al. 2021)	CT	US NLST Dataset scans containing 2106 Nodule Lung Cancer Detection by Using Artificial Intelligence and Big Data (LUCINDA)	Benign Malignant	CNN	Lung Cancer Prediction Convolutional Neural Network (LCP-CNN)

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Chaunzwa et al. 2021)	CT	Dataset comprising 311 Early-stage NSCLC Patients	Adenocarcinoma Squamous Cell Carcinoma (SCC)	CNN	Transfer Learning Approach Vgg-16 NN Architecture VGG Architecture K-NN SVM On CNN
(Asuntha and Srinivasan 2020)	CT	Real-time dataset from Arthi Scan Hospital Digital Imaging Communication Medicine (DICOM) images 1000 lung images	Benign Malignant	CNN	HoG Wavelet Transform-Based Feature, LBP, SIFT, ZM, FPSOCNN
(Elnakib et al. 2020)	CT	320 LDCT Images the International-Early -Lung-Cancer-Action Project, I-ELCAP, Online Public DB	Cancerous Non-Cancerous	CNN	Alex VGG16 VGG19 Networks Genetic Algorithm (GA) Feature Optimization CADe
(Doppalapudi et al. 2021)	Set of ASCII Text Files	Lung's Cancer Section, Surveillance, Epidemiology, and Results (SEER) cancer registry. SEER Dataset 702,411 records	Early Survival Period Prediction	DL	ANN RNN CNN
(Guo et al. 2021)	CT	Dataset comprised 920 Patients	Adenocarcinomas Squamous Cell Carcinomas Small Cell Lung Cancers (SCLC)	3D DL	ProNet RadNet UB open-source-software ITK Snap

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Hu et al. 2021)	H&E Slides	Lung Cancer H&E Slides 55 Collected-independently	Identification of Patients who might benefit from Immunotherapy, such as anti-PD-1	CNN	Multi-scale LBP, AP algorithms Transfer Learning using the Xceptionmodel Affinity Propagation (AP) Algorithm
(Savitha and Jidesh 2020)	CT	LIDC / IDRI dataset 888 CT scans	Sub solid Part-Solid Nodules Benign Malignant	DL	DCNN and CRF
(Zhao et al. 2020)	CT	501 Lung -Adenocarcinoma Patients	Predict LN Metastasis in T1 Lung Adenocarcinoma	Cross-Modal- 3D-NN	DensePriNet 3D CNNs
(Li et al. 2020)	WSI	200 H&E-Stained Slide 150 Training Images 50 Test Images of 200 Patients	Small Cell Lung Cancer Small Cell Carcinoma Adenocarcinoma	DL	Pixel-level Co-teaching algorithm Transfer Learning Multi-Model-Method Single-Model-Method FCN Multi-Model based Pixel-wise Segmentation
(Yu et al. 2020)	CT	http://diagnijmegen.nl/	Absence of Lungs Cancer Presence of Lungs Cancer	DNN	Adaptive Hierarchical Heuristic Mathematical Model (AHHMM) Modified K-means Algorithm
(Zhang and Kong 2020)	CT	LIDC / IDRI is a public data set of 1018 CTfrom 1010 patients	Identification System for Lung Nodules	CNN	MSDLF by the vesselness filter

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Wang et al. 2020a)	CT	LIDC database Low-Dose CT	Nodule Non-Nodule	DL CNN	CNN Residual Network Integrated DL Algorithms Incorporating into 6G-enabled IoMT ReLU activation function Region Growth Algorithm LSTM algorithms
(Lin and Li 2020)	CT & X-ray	National Cancer Institute 16,471 Images	Benign Malignant	CNN	Taguchi-based CNN
(Shakeel et al. 2020)	CT	(CIA) Dataset consisting 5043 CT	Predicts Cancer	IDNN	Hybrid-Spiral-Optimization intelligent-generalized rough set approach ensemble classifier
(Ozdemir et al. 2020)	CT	Kaggle-DataScience Bowl 2017 challenge (KDSB) contains 2,101 labeled Data and LUNA 16	Lung Nodule Detection Malignancy Classification Benign Malignant	CNN	CADe/CADx system LUNA16 pulmonary nodule annotations
(Affonso et al. 2020)	CT	(LIDC-IDRI) databases 250,000 medical images of CT	Cancerous Non-Cancerous	Swarm Intelligence Algorithms CNN	Swarm Algorithms U-Net Back-Propagation Gradient Descent
(Ardila et al. 2019)	CT	6,716 National Lung Cancer Screening cases NLST Dataset 42,290CT Dataset from a US Academic Medical Center1,739 cases LUNA	Overall Malignancy Prediction Localization for Predicted Cancerous Nodules Cancerous Non-Cancerous	CNN	LUMAS system

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Liu et al. 2019a)	CT	IMR of 60 patients	Healthy Lung Sick Lung	CNN	Model-Based Iterative Recombination Technique (MBIR) Three-Dimensional Stereoscopic Planning System IMR Statistical Model "Forced Image Smoothness
(Lang et al. 2019)	MRI	MRI Database of 61 Patients	Lung Cancer Other Tumors	CNN	Radiomics-based Analysis Hot-Spot ROI-based DCE Kinetic Analysis Radiomics Using DCE Histogram Parameters and Texture DCE-MRI
(Liu et al. 2019b)	CT		Lung Cancer Detection	Deep Reinforcement Learning Models	Value-based Deep-Reinforcement-Learning Model Deep-Q-Network Deep-dueling-Q-network Hierarchical Deep Q-Networks
(Shakeel et al. 2019)	CT	CIA Dataset 5043 Images	Predicting-Lung- Cancer	DITNN	Weighted Mean Histogram Equalization IPCT DITNN
(Hoang Ngoc Pham et al. 2019)	WSI	349 LNS 101 Lung Cancer patients from Nagasaki University Hospital, Japan	Tumor Non-Tumor Lymphoidfollicile Tumor Other	CNN	HALO-Tissue-Classifier-Analysis-Module Random-Forest-Algorithm. HALO AI CNN, VGG Network

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Chae et al. 2020)	CT	173 Whole non Enhanced-Chest CT Images from (Chonbuk National University Hospital)	Benign Malignant	CNN	Convolutional Neural Network (CT-lungNET) FC/Softmax
(Wang et al. 2020b)	WSI	WSI's Dataset from TCGA 939 WSIs		CNN	Fully Convolutional Network (FCN) OTSU Algorithm Avgfeat, Weighted feat, and Maxfeat Patch Based CNN Weakly Supervised Learning Methods Context-Aware Feature Selection & Aggregation
(Li et al. 2019)	MRI Scans	142 T2-Weighted MRfrom Hospital of Guangzhou Medical University 142 T2W-MR scans	Lung Nodule Detection	CNN	Region Proposal Network (RPN) Residual Network (ResNet) VGG16 ResNet50 ResNet101 R-CNN
(Tran et al. 2019)	CT	LIDC/IDRI Dataset extracted by the LUNA16 888 Thoracic CT scans	Nodule Non-Nodule	CNN	LdcNet-FL Novel 15-layer 2D Deep CNN Architecture Hyperparameter Tuning

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Xu et al. 2019)	CT	Brigham-and-Women's/ Dana-Farber Cancer Center Dataset A consists of 179 Patient Dataset B, comprising 89 Patients	Low Mortality Risk Group High Mortality Risk Group	DL	Transfer learning CNN's merged with an RNN ResNet
(Hussein et al. 2019)	CT & MRI	LIDC-IDRI Dataset Consisting 1018 CT & 171 MR from Lung Image Database Consortium	Benign Malignant	3D CNN	Supervised and Unsupervised Learning Approaches Graph Regularized Sparse MTL
(Nam et al. 2019)	CT& X-ray	43292 Chest Radiograph Seoul National University Hospital	Detection of Malignant Pulmonary Nodules	DL based- Automatic- Detection- Algorithm	DLAD
(Naqi et al. 2018)	CT	LIDC–IDRI Total 888 CT Scans	Nodule Candidate Detection Nodules Non-Nodules	DL	FODPSO Hybrid Geometric Texture Feature Descriptor
(Xie et al. 2019)	CT	LIDC-IDRI dataset	Benign Malignant	MV KBC DNN	Knowledge-based Collaborative (KBC Sub mode ResNet-50 Networks OA HVV HS Patches Extraction
(Lakshmanaprab et al. 2019)	CT	50 low dosage CT	Normal Benign Malignant	DNN	ODNN LDA

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Tan et al. 2019)	CT	LIDC-IDRI database	Nodules Non-Nodules Juxta-Pleural Pulmonary Nodules	CNN	Vector Quantization 185 (VQ) Algorithm Self-Adaptive Online VQ Algorithm Histogram of Oriented Gradients (HOG) Feature CADs tool CNN
(Jung et al. 2018)	CT	LNS 2016 (LUNA16) challenge 888 CT-Scans out of a total of 1018 CT (LIDC-IDRI)	Nodules Non-Nodules	DCNN	Deep CNN with Shortcut and Dense Connections Augmentation Methods 3-D structure of DCNN
(Coudray et al. 2018)	WSI	NCI Genomic Data Commons Dataset of 1,634 WSITCGA Research Network	LUAD LUSC Adenocarcinoma Squamous cell Carcinoma Gene Mutation	CNN	Inception V3 Convolutional Neural Network Googlenet Architecture
(Ciompi et al. 2017)	CT	MILD trial 943 DLCST 468	Solid Calcified Partially solid Perifissural Speculated	Multi-Stream Convolutional Network Architecture	Convolutional Networks (Convnet) Triplets Of 2D Patches Intensity Features + SVM support Vector Machines E-T-Distributed-Stochastic-Neighbor-Embedding(T-SNE) Algorithm
(Weng et al. 2017)	CARS Images	CARS Images on Human Lung Tissues larger dataset (7926	Normal Small cancer Squamous Carcinoma Adenocarcinoma	Deep CNN	Coherent Anti-Stokes Raman Scattering (CARS)

Table 6 (continued)

Author	Dataset	Dataset Description	Parameters	Algorithm/Methodology	Feature Extraction Technique/ preprocessing
(Song et al. 2017)	CT	LIDC-IDRI Database 4581 Images of Lung Nodules	Benign Malignant	CNN	CNN DNN SAE Multi-scale Convolution Image Feature
(Abbas 2017)	CT	(LIDC-IDRI) 3250CT	Nodule Pattern Honeycomb GGlass BCho Empmlk Normal	DL	CNN &RNN Softmax Classifier Lung Deep System
(Nibali et al. 2017)	CT	LIDC/IDRI Dataset CT scans for 1010 Patients	Benign Malignant	DL	Combining DRL, CL, and Transfer Learning Rival CNN models (Setio-CNN and Over Feat)
(Jiang et al. 2017)	ThoracicMR Images	LIDC/IDR LIDC/IDRI 1018 Helical-Thoracic CT-Scans obtained from 1010 different patients	Nodule Detection	CNN	Vascular Elimination Frangi Filter Four-Channel (CNN) Model
(Park et al. 2016)	Breathing Data	The Intra-Fractional Variation Dataset contains 130 databases, and the Inter-Fractional Variation, Dataset contains 32 Database	Tumor Movement	FDL	Intra-and-Inter-Fractional Variation Of Multiple Patients IIFDL
(Yu-Jen Chen et al. 2015)	CT	Lung Image Database Consortium dataset 2,545	Malignant Benign	DBN	CNN + DBN

Kernels. Multi-Scale Dilated Residual Representation Block Size-Related (SR-DiRes) &Multi-Mask Convolution Representation Block (ConvRB), Multi-Scale LBP, AP Algorithms, Affinity Propagation (AP) Algorithm, Deep Convolution Neural Network (DCNN) Architecture, Radiomics-Based Analysis, Hot-Spot ROI-based DCE Kinetic Analysis, Deep Dueling Q-network, Hierarchical Deep Q-Networks, Radiomics Deep Q-Network, Weighted Mean Histogram Equalization, Dense PriNet, Multi-and single model method, Pixel-Wise Segmentation based On FCN ,Multi-Model, Weakly Supervised Learning Methods, HALO Tissue Classifier Analysis Module (Random Forest Algorithm), HALO AI (CNN, VGG network),Context-Aware Feature Selection And Aggregation, Graph Regularized Sparse MTL,K-means Algorithm, Extensive Data Augmentation,LUNA16 Pulmonary Nodule Annotations, Multi-Group Patch-Based Learning System, Diffusion (VED) and a Vessel filter, Integrated Deep Learning , Region Growth Algorithm, fuzzy logic and a NN, HE hybrid learning algorithm, ACC, VEL, Correlation Analysis Algorithm, PCA, (GSEA)Gene-Set Enrichment Analysis, ReLU Activation Function, CVAE-GAN, DenseNet using CoxPH, CNN model, ImageNet, Score-CAM Maximum Intensity Projection (MIP).,Multi-Scale Convolution Image Feature, Novel 15-Layer 2D Deep CNN architecture Hyperparameter Tuning, vector Quantization(VQ) algorithm, Gaussian noise model-based collaborative Wiener Filtering (GNM-CWF),Self-Adaptive Online VQ algorithm Residual Learning Denoising Model (DR-Net),Feature fusion strategy called DCA, Curriculum Learning, And Transfer Learning, Rival Convolutional Neural Network Models (setio-CNN and Over Feat), Taguchi-based CNN, combination of Deep Residual Learning, The Trial And Error Method, ACL algorithm, Converged Search and Rescue (CSAR) Algorithm, Novel Wilcoxon Signed-Rank Gain Preprocessing, Hybrid Spiral Optimization Intelligent-Generalized Rough Set approach, AI-based noninvasive radiomics biomarkers, SVM Principal Component Analysis (PCA), Multilevel Brightness-Preserving approach,. Numerous segmentation methods and approaches are then applied.

Segmentation contributes to the feature extraction process; it prepares the extracted data for classification.

Classification: - Classification is the phase where the prepared, feature extracted and segmented data is classified into different categories that may be abnormal or normal, benign, or malignant, LUAD or LUSC. After the detection of cancer nodules or pulmonary nodules which confirm that the disease is present or not of lungs cancer further classification is performed to classify these nodules into solid, calcified, partially solid, perifissural, and speculated.

Several classifiers are used in our study which includes; Fuzzy Particle Swarm Optimization (FPSO),Confusion matrix, Forest Classifiers, Back-Propagation, SVM or Naïve Bayes classifiers, Cross Entropy loss and Transfer Learning, RMS Prop-optimization method, Modified Gravitational Search Algorithm (MGSA),Multi-Channel CNN, Deep Learning and Swarm Intelligence, DBN and CNN Deep Learning, Convolutional Network Architecture, FODPSO, CARS & Deep learning, GoogleNet Inception v3 CNN architecture, Deep Learning Approach Based On Stacked Autoencoder and Softmax, CADe systemVGG19architectureand SVM classifier, Multi-View Knowledge-Based Collaborative (MV-KBC) Deep Model, Long Short-Term Memory/LSTM, Recurrent Neural Network/RNN,CNN Cancer Risk Prediction Model, triplet, DCNN AlexNet, watershed segmentation Banarization, Auto Encoder/AE &General Adversarial Networks/GAN, Deep Belief Network/DBN, Random Forest Classifier, Deep Quality Model, GG-net architecture, Convolutional Neural Networks with a U-net architecture, Recurrent Neural Networks (RNN), 3D Deep Learning and Radiomics, Core-Ring Blocks Residual Estimation with size-related damper block deep prediction model, GG-net architecture, Conditional

Table 7 Data types employed in reviewed studies

Data type	Number of articles
MRI	2
Thoracic Surgery Data	1
X-Ray	1
CT	52
PET Image Data	1
Breathing Data	1
Thoracic MR Images	1
Whole Slide Imaging (WSI)	2
Lymph Node Slides	1
Histopathological Cancer Images	2
CARS Images	1
H& E	1

Random Framework, SVM anti-PD-1 response prediction by H&E,DCNN CAD system, DCE Kinetic Parameters, Convolutional Long Short Term Memory (CLSTM) Network, DCE-MRI,Value-based Reinforcement Learning Approach, DSRL, Deep Successor Q-Network, Profuse Clustering Technique (IPCT),Deep. Learning Instantaneously Trained Neural Network (DITNN), deep Q-network and hierarchical deep Q-network, Explosion-Trained Deep Learning Neural Network (DITNN),CADe / CADx models, Deep Learning Classifier (Lymphoid Follicle CNN - LFCNN),3D Neural Network, Fully Convolutional Network (FCN),FCN, ScanNet, proportion-SVM, Adaptive Hierarchical Heuristic Mathematical Model (AHHMM),K-mean algorithm, 3D fully CNN based on the V-Net architecture, Four-Channel CNN, corrective lung contour, Wilcoxon Signed Generative DL (WS-GDL)Hyper-Parameter Tuning Algorithm, Multi-Scene Deep Learning Framework (MSDLF),Normalized Spherical Sampling, LSTM algorithms, NFNet, Fast R-CNN, Intra- And Inter-Fraction Fuzzy Deep Learning (IIFDL),deep learning-based radiogenomic framework-net, EfficientNet, CoxPH and CoxCC, LdcNet, Converged Search and Rescue Algorithm, Deep Gaussian Mixture Model in region-based CNN[DGMM-RBCNN], Lung-Deep System, Novel Nodule CADeCNN, INC classification, (DFD-Net), Two-path CNN with feature fusion DFD-Nets, Curriculum learning, 3D (DCNNs), Taguchi-based CNN, Fuzzy C-Ordered Means (FCOM) with ECN, Enhanced Capsule Networks (ECN), Lung Cancer Prediction (LCP-CNN), Generative Deep Learning, Survival Neural Network model, machine learning peculated known as k-nearest, KNN neighbors and SVM on CNN Ensemble Classifier and Improved DNN.

7 Literature synthesis: unveiling patterns and insights

Deep Convolutional Neural Networks (DCNN) is the best technique to detect lungs cancer in the field of machine learning. The highest levels of accurate lung cancer case classification were continuously attained using DCNN. The ability to make accurate diagnoses, a critical component in healthcare, is shown by this improved accuracy. Additionally, DCNN demonstrated exceptional specificity, reducing the incidence of false positives. In healthcare contexts, this precision is crucial since it lessens the possibility of misdiagnosing non-cancerous patients as cancer. The remarkable sensitivity of DCNN enabled the identification of sizable actual lung cancer cases. The potential for early identification and intervention, which are essential for enhancing patient outcomes, is increased by this high sensitivity. Finally, DCNN demonstrated impressive accuracy in detecting lung cancer. Finally, DCNN demonstrated remarkable accuracy in diagnosing lung cancer, reducing the possibility of incorrect diagnosis. These findings demonstrate how well DCNN performs in automatically extracting complex patterns from medical images, which helps in the accurate and reliable identification of lung cancer. DCNN stands out as the leading machine learning technology, to improve the accuracy and reliability of lung cancer detection in clinical practice due to its exceptional performance in accuracy, specificity, sensitivity, and precision. To promote medical diagnostics in this crucial area, we encourage continued investigation and development of DCNN-based techniques.

In the study, 66 research articles were carefully examined and their methods were analyzed. In Table 8, the results of this evaluation procedure are collated and summarized. Important details including reference numbers, research methodology, and performance measures like the F1 score, accuracy, precision, sensitivity, and AUC are included in this table. Table 8 is a useful tool for comparing and assessing the research findings because these metrics are significant indicators of the efficacy and dependability of the various methodologies covered in the examined papers. The major limitation of current studies is mostly the size of the data sets. There is potential for improvement because there isn't a finished product or global standard for cancer detection and prediction. To ascertain the accuracy of these models, researchers need to gather up-to-date and new data, employ various deep learning and machine learning techniques, and combine new and old data. Early cancer detection can benefit millions of people. To detect cancer, there is no established standard or finished product. While deep learning has promising opportunities for lung cancer detection, there are important gaps that need to be filled. The generalizability of current findings is frequently problematic while accurate feature extraction is also crucial to be handled. Certain populations in the actual world may not respond well to models that were trained on their particular datasets. Furthermore, characterization may be eclipsed by an emphasis on detection. Some models are quite good at detecting nodules, but they may not give information about the tumor, which makes it more difficult to diagnose patients early and accurately. In addition, the "black box" nature of sophisticated deep learning models and worries about data security and privacy persist, making it challenging to comprehend how these models make decisions. Most of the research frequently runs into issues with feature extraction, making it difficult to identify pertinent elements that are essential for accurate prediction. These restrictions make it more difficult to do the thorough study needed to produce accurate and trustworthy detection results. In order to advance deep learning models' efficacy and dependability in lung cancer detection and eventually enhance patient outcomes and diagnostic accuracy, it is imperative that these issues be resolved. Despite these shortcomings, scientists are working hard to fill in the gaps Closing the existing gaps is critical to the future of deep learning for lung cancer detection. Researchers are focusing on tumor characterization rather than merely detection, enhancing generalizability through transfer learning, and advanced approaches. Strong data security protocols and resolving any biases in training data are also essential. Lastly, to stay up to date with the changing features of cancer, ongoing learning will be crucial. Deep learning has the potential to transform lung cancer detection and result in earlier diagnoses and better patient outcomes by overcoming these obstacles.

Table 8 Comprehensive overview and comparative results

Results

Author	Method	Accuracy	Sensitivity	Specificity	Dataset
(Lang et al. 2019)	CLSTM	0.75–0.84	0.75	0.968	MRI
(Shah et al. 2023)	CNN	0.95	-	-	CT
(Pandit et al. 2022)		0.995	-	-	CT
(Jena et al. 2021)		0.8779	-	-	CT
(Sori et al. 2020)		0.878	-	0.891	CT
(Heuvelmans et al. 2021)			0.99	0.221	CT
(Chaunzwa et al. 2021)		0.686	0.375	0.829	CT
(Asuntha and Srinivasan 2020)		94.97	96.68	95.89	CT
(Elnakib et al. 2020)		0.9625	0.975	0.95	CT
(Zhang and Kong 2020)		98.7	-	-	CT
(Lin and Li 2020)		99.6	0.999	0.993	CT
(Ozdemir et al. 2020)		-	0.965	-	CT
(Affonso et al. 2020)		0.9371	0.9296	0.9852	CT
(Ardila et al. 2019)		-	0.815	0.95	CT
(Liu et al. 2019a)		100	-	-	CT
(Chae et al. 2020)		0.73	0.6	0.87	CT
(Tran et al. 2019)		0.972	0.96	0.973	CT
(Tan et al. 2019)		-	0.88	-	CT
(Song et al. 2017)		84.15	0.8396	0.8432	CT
(Masud et al. 2021)		0.9633	-	-	WSI
(Hoang Ngoc Pham et al. 2019)		0.945	1	0.965	WSI
(Wang et al. 2020b)		0.973	-		WSI
(Coudray et al. 2018)		0.961	-	-	WSI
(Hu et al. 2021)		-	-	-	H&E Slides
(Hussein et al. 2019)		91.26	0.7785	0.7828	MRI
(Wani et al. 2023)		0.9743	0.9871		N/A
(Oh et al. 2021)		0.95	-	-	PET
(Li et al. 2019)		-	0.852	-	MRI
(Jiang et al. 2017)		-	0.94	0.918	ThoracicMR
(Zhao et al. 2020)	Cross-Modal 3D Neural Network	0.876	0.857	0.883	CT
(Siddiqui et al. 2023)	DBN	0.99424	0.98497	0.98319	CT
(Yu-Jen Chen et al. 2015)		-	0.734	0.822	CT
(Kumar and Bakariya 2021)	DCNN	1	1	1	CT
(Jung et al. 2018)		-	-	-	CT
(Wang et al. 2020a)		0.9032	0.912	0.8944	CT
(Weng et al. 2017)		0.892	0.987	1	CARS Images
(Savitha and Jidesh 2020)		0.8948		-	CT

Table 8 (continued)

Results					
Author	Method	Accuracy	Sensitivity	Specificity	Dataset
(Liu et al. 2019b)	Deep Reinforcement Learning Models	-	-	-	CT
(Abbas et al. 2023a)	DELM	-	-	-	Text
(Shakeel et al. 2019)	DITNN	0.9842	-	0.972	CT
(Guo et al. 2021)	DL	0.716	-	-	CT
(Kumar Swain et al. 2024)		98.29	96.66	99.12	CT
(Said et al. 2023)		0.9877	-	-	CT
(Wankhade and Vigneshwari 2023)		0.953	-	-	CT
(Lanjewar et al. 2023)		0.95	-	-	CT
(Gu et al. 2021)		75.01% to 97.58%	61.61% to 98.10%,	-	CT
(Cui et al. 2022)		-	0.901	-	CT
(Sui et al. 2021)		-	-	-	CT
(Tian et al. 2021)		0.9665	-	-	CT
(Xu et al. 2019)		-	-	-	CT
(Naqi et al. 2018)		0.969	0.956	0.97	CT
(Abbas 2017)		-	0.88	0.8	CT
(Nibali et al. 2017)		0.899	91.07	88.64	CT
(Li et al. 2020)		0.95	0.9	0.95	WSI
(Doppalapudi et al. 2021)		0.7118	-	-	Text
(Nam et al. 2019)		-	0.807	0.952	Xray
(Obulesu et al. 2021)		0.86	-	-	Thoracic
(Wang et al. 2021)	DLNmet	0.86	0.9	0.83	CT
(Shakeel et al. 2022)	DNN	0.972	-	-	CT
(Yu et al. 2020)		0.9667	-	-	CT
(Lakshmanaprab et al. 2019)		0.9456	0.962	0.942	CT
(Shakeel et al. 2020)		0.962	-	0.984	CT
(Liu and Yao 2022)		-	-	-	N/A
(Park et al. 2016)	FDL	Intrafunctional0.33 Inter-functional 0.38	-	-	Breathing Data
(Ciompi et al. 2017)	Multi-Stream Convolutional Network Architecture	0.729	-	-	CT
(Xie et al. 2019)	MV-KBC DNN	75.62	87.22	64.32	CT

Different algorithms used for classification and detection purposes perform differently in terms of performance CNN surpasses the others.

8 Conclusion

Lung cancer is a serious and sometimes fatal disease that necessitates early discovery to effectively treat it. This work emphasizes how deep learning—specifically, the application of Convolutional Neural Networks, or CNN—is essential to changing the face of medical diagnosis. Deep learning techniques reduce the workload of healthcare professionals by automating the identification and categorization of lung cancer. This technological advancement improves the precision and efficacy of diagnosis. In the context of lung cancer research, this paper offers an extensive Systematic Literature Review (SLR) that makes use of deep learning approaches. It benefits researchers, practitioners, and stakeholders by classifying and synthesizing methodologies, outlining the state-of-the-art, conducting a thorough Quality Assessment, and offering a customized overview of deep learning approaches for lung cancer research. Our thorough analysis examines the several deep learning methods used in the identification and categorization of lung cancer across a range of imaging modalities, including MRIs, CT scans, and X-rays. Notably, we ensure a current overview by concentrating on the years 2015 to 2024 and obtaining information from credible journals. The study highlights the critical function that Deep Convolutional Neural Networks (DCNN) fulfill in the field of deep learning techniques. In particular, DCNN is the recommended method in the Convolutional Neural Network (CNN) architecture because of its unique multi-layered architecture, which makes direct feature learning from lung nodule images possible. The main reason why DCNN is so effective at obtaining the best accuracy is that it has the innate capacity to learn weights automatically. These models can significantly boost the efficiency and accuracy of lung cancer classification by the automatic learning of pertinent features, which improves diagnostic procedures in clinical settings. The research thoroughly assesses several performance measures, such as AUC, sensitivity, specificity, accuracy, and precision. When it comes to the classification of lung cancer, DCNN frequently performs more accurately than other algorithms. Even with these noteworthy successes, there are still difficulties, especially when managing large-volume datasets. This study presents the classification process on multiple data sets and multiple classifiers are used. The focus of the study is to present different deep learning algorithms and approaches to classify lungs cancer Nevertheless, there are still some challenges that still exist, most of them are related to the size of datasets. This study will help the researchers to better understand the existing deep-learning techniques and procedures to classify lungs cancer. This work lays the groundwork for future advancements in the field by providing a comprehensive grasp of the state-of-the-art deep learning methods for the categorization of lung cancer. Lung cancer diagnosis could be revolutionized by deep learning, however there remain obstacles because of the scale of data sets and the absence of an international standard. Current data must be gathered, deep learning and machine learning methods must be used, and both new and old data must be combined. Generalizability, characterization, data security, and privacy issues are lacking, nonetheless. Notwithstanding these obstacles, researchers are concentrating on tumor characterization, improving generalizability via transfer learning, and addressing biases in training data in an effort to close these gaps. Continual learning is also crucial to stay updated with changing cancer features.

Author contributions Rabia and Ali Haider have written a major part of the paper under the supervision of Tahir and Ali Daud. Tahir and Ali Daud have helped design and improve the methodology and wrote the paper initial draft with Rabia and Ali Haider. Riad and Amal have helped in improving the paper sections, such as, review methodology, datasets, performance evaluation and challenges and future directions. Ali, Amal and Riad have improved the technical writing of paper. All authors are involved in revising the manuscript critically and have approved the final version of the manuscript.

Declarations

Competing interests The authors declare no competing interests.

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