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Detection and Classification of Lung Diseases for Pneumonia and COVID-19 using Deep Learning Techniques

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Abstract: Rapid advancements in medical imaging technologies have increased the need for sophisticated diagnostic instruments that can reliably and quickly identify lung diseases. The primary goal of this research is to develop and apply deep learning or machine learning methods for the diagnosis and classification of COVID-19 and pneumonia, two dangerous respiratory infections. The research investigates the potential of artificial intelligence in analyzing medical imaging data, such as X-rays and CT scans, using state-of-the-art computational models and algorithms to distinguish between healthy and diseased lung tissues. Using large datasets with a variety of COVID-19 and pneumonia case examples, machine learning or deep learning models are trained using the selected methodology. These respiratory disorders can be accurately identified and classified thanks to the models' ability to learn complex patterns and features. The study also aims to explore the robustness and generalization capabilities of the models across different imaging modalities and populations. The results of the study offer a quick and non-invasive method for diagnosing lung conditions, which has important ramifications for medical diagnostics. The utilization of cutting-edge healthcare technologies has the potential to improve diagnostic precision, reduce staff workload, and enable timely interventions, especially when it comes to respiratory illnesses. The research's conclusions and insights reinforce current initiatives to use artificial intelligence to enhance healthcare outcomes and solve issues with respiratory disease diagnosis and treatment.

Keywords: *Computed Tomography, Machine Learning (ML) and Deep Learning (DL), Convolutional Neural Networks.*

1. Introduction

At the beginning of 2020, the world was hit by a pandemic of COVID-19 (Sars-Cov-2), which has so far infected a total of 672 million people and caused 6.85 million deaths. This outbreak, which began in the city of Wuhan, China, devastated Europe in March 2020, collapsing the Italian healthcare system and causing 12,399 deaths in March of that year alone. In Brazil, the peak of confirmed deaths in 2020 occurred between the months of May and August, totaling 30,435 deaths in the month of June alone. During the same period, several countries on different continents registered cases of COVID-19 in their territories and closed their borders. Preventive measures, such as lockdown and high testing rates, applied early helped countries reduce the number of deaths, infections and collapse of the health system.

The method commonly used to diagnose COVID-19 is reverse transcription polymerase chain reaction (RT-PCR), which has high specificity, but is slow in producing results and has a high financial cost. In 2022, the costs for carrying out these exams varied between R$200 and R$400, according to Valor Investe magazine.

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AI is now utilized in all facets of controlling and preventing epidemics. Artificial Intelligence (AI) image processing can reduce scanning and post-processing times, increase productivity, and save a significant amount of money on medical supplies. People located and identified two anti-COVID-19 compounds that are present in palmatine and sochidone using DL and structure-based screening techniques. These two substances have a strong affinity for the COVID-19 Main Protease (Mpro) enzyme, which allows them to form a stable complex that inhibits the enzyme's activity. The fields of drug research, development, and innovation have benefited greatly from this discovery; Artificial Intelligence (AI) is also required for tracking and predicting epidemics.

On the other hand, chest x-rays are widely available and easily accessed by hospital institutions, and their cost is lower than that of the RTPCR exam, varying between R$37 and R$70 depending on the number of incidences, according to the institution Pro Exame. X-ray images are often used by healthcare professionals to detect pneumonia, as these images can be considered crucial in medical diagnoses as they contain important information about the patient's situation. Only a small percentage of patients will still have residual GGO. In the early stage, GGO can be seen in either the unilateral or bilateral lower lobes of the lung; in the advanced stage, patients frequently have diffused GGO in both pulmonary lobes; in the severe stage, pulmonary consolidation will be more common, accompanied by GGO with thickened interlobular septa. When physicians manually diagnose COVID-19 patients from a vast number of imaging images, it takes a lot of time and effort, and the high-stakes nature of the work can lead to errors in image interpretation and judgment. Within a few seconds, AI technology can locate lesions with great power. The effort required of physicians to meticulously identify and assess lesions from imaging scans can be significantly reduced. Researchers are now using AI in medical imaging research as a result of the advancements in AI in the medical field.

The basic characteristics of large-scale and rapid spread of infectious diseases place extremely high requirements on the comprehensiveness and effectiveness of medical response. Entering the 21st century, the world has encountered three coronavirus epidemics: severe acute respiratory syndrome (SARS) in 2003, Middle East respiratory syndrome (MERS) in 2015, and novel coronavirus pneumonia (COVID-19) in 2019. At present, the COVID-19 epidemic is still spreading in many places around the world. It is having a serious and far-reaching impact on many aspects of global politics, economy, society, etc. It has also posed a huge challenge to some developing countries with poor medical response capabilities. Existing research shows that my country's national strategy of "Internet + Healthcare" has played a major role in the prevention and control of the COVID-19 epidemic, and the achievement of relevant results is inseparable from the advanced layout and continuous construction of artificial intelligence (AI) in my country's hospitals. The construction and application of AI in hospitals in my country lasted more than 10 years and is divided into three main stages: ① System integration and data exchange stage (2009-2014), which basically eliminated the medical "information island" phenomenon; ② Closed-loop reengineering and "Internet +" In the construction stage (2015-2018), the construction of the medical data center has been basically completed; ③ in the development stage of big data center and AI application scenarios (2019-), explore and practice the implementation of multiple types of AI platforms, and gradually transform and improve hospital diagnosis and treatment The activities focus on solving long-term pain point problems faced in hospital management decision-making, clinical, medical research and other scenarios. The severe situation of COVID-19 epidemic prevention and control at home and abroad indicates that hospital AI applications can play a more important role in building a healthy China. At the same time, the COVID-19 epidemic has created a negative impact on hospital capacity building: AI applications have enhanced hospital users' sense of gain and participation, and the application effects have improved medical staff's acceptance of AI products; epidemic prevention and control has prompted hospital information Professionals in the medical field learn medical knowledge. Under the current situation, the public, government, institutions and related industries have significantly increased their awareness of hospital AI construction. Therefore, it is time to implement strategic-level planning and quickly deploy hospital AI construction. Taking this as a starting point for research, this article sorts out the current status and progress of AI applications in hospitals in China, highlights the experience summary of COVID-19 epidemic prevention and control, clarifies the shortcomings of hospital AI applications in ethics, efficiency, data, etc., and proposes the construction of AI in hospitals in my country. Objectives, structure and development recommendations.

After the COVID-19 epidemic emerged, China's determination, speed and efficiency in fighting the epidemic left a deep impression on countries around the world. Driven by the mission of building a community with a shared future for mankind, China has actively contributed to the global fight against the epidemic, not only dispatching medical teams and donating supplies, but also sharing medical diagnosis and treatment experience, especially AI technology to fight the epidemic.

The COVID-19 outbreak directly drives the use of AI technology and products in hospitals. For example, Huoshenshan Hospital and Leishenshan Hospital in Wuhan, Hubei Province launched "cloud supervision". During the quarantine period, local governments used cloud platforms to observe the resumption of work and production, etc., which improved the efficiency of epidemic prevention and control and production recovery. The First Affiliated Hospital of Zhejiang University School of Medicine and Shulan (Hangzhou) Hospital are on the front line in the fight against the COVID-19 epidemic. They have used a variety of AI applications to fight the epidemic and achieved good results. Despite this, it is still necessary to summarize front-line application experience in a timely manner, analyze the technical shortcomings faced by the actual needs and condense the "stuck" problems, and do a good job in overall planning and top-level design before large-scale implementation of hospital AI construction; focus on moving the intervention barrier forward , change the passive response situation, and create necessary conditions to prevent possible large-scale acute respiratory infectious diseases in the future.

AI image reading technology can quickly and quantitatively evaluate the patient's condition. During the COVID-19 outbreak, due to the scarcity of medical personnel and the need to wear protective clothing when entering the isolation ward, many inconveniences were caused. AI technology was used to quickly evaluate the results of pulmonary medical imaging examinations, and to judge the clinical diagnosis and disease progression of COVID-19. of great value. During the epidemic, the average daily examination volume of each CT machine in designated hospitals once exceeded 1,000, which greatly exceeded the manual reading capabilities of doctors. After adopting AI scanning software provided by multiple companies, with its assistance, doctors in a relatively short period of time, we completed the formation, scope, density and quantitative analysis of characteristic lesions on key images of a large number of COVID-19 patients, as well as the screening and quantitative evaluation of imaging data. The quantitative data provided by AI reading software directly supports doctors in diagnosis and therapeutic evaluation, significantly improving the efficiency of COVID-19 diagnosis and treatment. This observation is consistent with the conclusions of early studies. The following are this paper's primary contributions: (1) Overview (1) A hole space pyramid pooling module is designed to capture the multi-scale information of COVID-19 lesions; (2) The squeeze and attention modules are used to improve the attention of pixel grouping; (3) The generalized dice loss function is introduced to solve the small area segmentation problem, reducing the correlation between lesion size and Dice loss. Novel coronavirus infection (coronavirus disease 2019, COVID-19) seriously threatens human health. The currently circulating Omicron variant has significantly lower pathogenicity and increased infectivity than the original strain. In October 2022, an outbreak in Hohhot, Inner Mongolia was caused by immunity. The COVID-19 epidemic caused by Omicron BF.7 with stronger escape ability and transmissibility.

Epidemic prevention and control in my country "moved forward" and entered a period of normalized prevention and control in December 2022 after scientific adjustments were made. During this period, there was a sudden increase in the number of infections in medical institutions and a notable rise in the number of severe patients. turn into the main priority for the medical staff. Important assurances for lowering mortality include prompt COVID-19 patient screening, identifying patients at high risk of serious illness, and enhancing critical illness identification skills. CT chest exams are quick and effective. It is one of the most effective ways to combat COVID-19 and is frequently used to diagnose, assess the severity, and determine the prognosis of the virus.

The domestically independently developed lung computer-aided diagnosis software and epidemic monitoring system, as well as the enhanced AI system for COVID-19, have been used on the front lines of COVID-19 epidemic prevention and control. The lung computer-aided diagnosis software and epidemic monitoring system use AI algorithms to evaluate the degree of lung infection in patients and can quickly form an initial diagnosis report, which provides great convenience for doctors to formulate accurate diagnosis and treatment plans; it can also be used according to the degree of abnormality in the patient's lungs. Prioritize and guide intelligent triage; AI only takes 2 to 3 minutes to interpret a CT chest X-ray, which is 4 to 5 times faster than manual interpretation, saving valuable energy and a lot of time for doctors who are overloaded during the epidemic. The enhanced AI system for COVID-19 has the ability to detect signs similar to COVID-19. It can intelligently classify various signs of pneumonia and provide quantitative analysis of consolidation and ground-glass opacity to assist doctors in determining the stage and severity of pneumonia. gives early warning tips for suspected pneumonia diseases, and automatically generates a structured graphic report for COVID-19 diagnosis under the intervention of a doctor.

2. Literature Review

Cui and associates [2019] According to theories, Finding the natural host and intermediate host and determining the route of infection are the core issues in controlling the source of infection and cutting off the route of transmission. Many domestic research teams rely heavily on AI algorithms and technology to build mathematical models to predict the host of the 2019 novel coronavirus (2019-nCoV). The Peking University research team applied BiPathCNN technology to predict the host of 2019-nCoV. The Wuhan Institute of Virology, Chinese Academy of Sciences, compared the genome sequence of 2019-nCoV and found that bats may be the host of 2019-nCoV.

According to Huang et al. [2020], that pangolins may be one of the intermediate hosts of 2019-nCoV. The research team of the China Centre for Animal Health and Epidemiology tested more than 4,800 samples of pigs, poultry, dogs, cats and other animals collected in recent years, and all were negative for 2019-nCoV. Based on this, it can be preliminarily ruled out that 2019-nCoV originated from poultry and livestock. possibility. The prediction research results of these virus host directly point out the direction for the epidemic prevention and control of governments at all levels, that is, the implementation of emergency legislation, prohibiting the trade and indiscriminate eating of wild animals, and controlling the source of 2019-nCoV infection to cut off the transmission route.

According to Shi et al. [2020], Following a 2019-CoV infection, common symptoms include fever, exhaustion, dry cough, and gradually worsening breathing. Severe or subtle symptoms may also manifest. According to the most recent data, 2019-nCoV can spread both between humans and animals. It also spreads swiftly. In order to stop the epidemic from spreading further, it is essential to identify patients who are infected with the virus as soon as possible and to cut off the virus's path of transmission. Viral nucleic acid detection has a very high specificity and is currently the best method of confirming 2019 CoV infection; however, its sensitivity is poor and heavily dependent on the sampler and the sampling site. Furthermore, we discovered that numerous cases with viral pneumonia imaging abnormalities during the first CT screening were ultimately diagnosed with negative viral nucleic acid tests following multiple sampling tests.

According to Nyirenda et al. [2019], imaging screening—particularly chest thin-section CT scans—is now a necessary test item for clinical diagnosis and is crucial for the early detection and diagnosis of 2019-nCoV. The first responders to the pandemic are now imaging technicians. Nonetheless, my nation's imaging departments operate in a very subpar environment. Due to the limitations of the traditional model, patients are frequently held in cramped waiting areas or computer rooms, where there is a high risk of cross-infection. The theoretical knowledge of infection control, isolation, and operational training that is taught to domestic imaging technicians in schools is almost non-existent, and survey results from international scholars indicate that the knowledge of infection control and practical operation scores of imaging technicians are subpar. As part of the recommended training and assessment materials for infection control management in the imaging department, seven infection control topics—sterility, disinfection, hand hygiene, personal hygiene, and personal protective equipment—should be covered.

By extracting nucleic acid sequences from the blood of suspected cases through nucleic acid testing, and comparing them with 2019-nCoV, we can basically determine whether there is a pathogenic infection. This is an important testing method for confirming the diagnosis of COVID-19. Whole-genome sequence analysis and comparison of virus samples from suspected cases is time-consuming and labour-intensive, but with the help of AI, the preliminary screening work can be completed quickly, greatly improving the efficiency of COVID-19 detection. Computing power and algorithms are extremely critical for the large-scale implementation of the above detection process, and are therefore regarded as key supports for COVID-19 epidemic prevention and control. Since January 2020, many domestic innovative research institutions have opened up the Linear Fold linear algorithm for free, which is used to predict the ribonucleic acid (RNA) structure of the entire sequence and entire genome, achieving a comprehensive acceleration of RNA structure prediction; providing computing power support Assisted in the completion of domestic drug screening research to combat COVID-19; in response to the COVID-19 research needs of global public scientific research institutions, AI computing power is freely available to promote the rapid progress of global research.

Zhang et al [2020] analysed Lung function recovery after serious surgery is crucial, as it is one of the organs most susceptible to infection in patients. According to one month's statistics from the ICU (that is, the intensive care unit) of a tertiary hospital, 87.6% of the cases of severe pulmonary infection after surgery have occurred, and 100% of serious cases have some degree of pulmonary infection after surgery. More than 38.7% of cases are aggravated by lung infection. It can be seen from this that performing lung function exercises after surgery for serious illness and collecting and analysing the data of lung function exercises will help doctors scientifically diagnose lung infections and provide an important reference for prescribing symptomatic anti-inflammatory drugs. Various medical cases reflect the importance of postoperative pulmonary care for seriously ill patients, and how appropriate pulmonary care can effectively suppress pulmonary infection.

According to Sun et al. [2020], as of March 2, 2020, at 24:00, there were 25,352 confirmed cases of new coronavirus pneumonia nationwide (including 5,952 severe cases), 52,045 cases that had been cured and released, 3,012 deaths, and 80,409 confirmed cases—including suspected cases—that had been reported. Nationwide, 522 new cases of coronavirus pneumonia have been identified.

Almomani, et al [2020] explained the system APP must first implement the "login" and "register" functions to ensure the uniqueness and security of each user account. It must ensure information security while also ensuring that information is not recorded repeatedly. Next is the upload data function, which records the detailed information of the data that needs to be uploaded, especially the upload time, duration and vital capacity, etc., to ensure accuracy. Then the doctor checks the patient's information and clicks on the information that the patient can see, including discharge time, surgery or healing time, number of lung exercises, time of each exercise and the effect of exercise, etc. Finally, a series of functions such as dialogue and communication between patients and doctors are realized, allowing doctors to decide whether to continue prescribing medicine or going to the hospital for review based on the patient's recovery.

Khuntia et al [2020] illustrated merge the account number and password into a list for storage. The difference is that the two identical texts of the account number and the account number are merged and stored before saving the list. In this way, the "not equal to" in "Logic" can be used to determine whether to register. If it has been When registering, a dialog box will pop up prompting "Account Already Registered". If not, it will prompt "Registration successful". Such a user can only log in with a unique password [7]. At the same time, this method also has disadvantages, that is, if a user stores data twice, the database usage will be twice that of before.

In the user login interface, enter the password in the password text box and the user name in the user name text box, according to Liu et al.'s [2020] analysis. Simply click "Login" to access the system's main interface if the user name and password match those in the database. A prompt will appear if the entered information is incorrect.

In 2020, Chen et al. clarified Hospitals in many provinces and cities across the country have sent medical teams to Hubei to take over hospitals or wards related to COVID-19 in Wuhan, Hubei, playing a decisive role in the rapid and precise prevention and control of the epidemic. Remote consultation teams in hospitals thousands of miles apart make full use of mobile communication networks for convenient data transmission, and combine AI technology to carry out remote video consultations and remote guidance exchanges; isolation wards and imaging examination rooms are equipped with cameras, microphones, stethoscopes and other equipment, combined with network information transmission With remote diagnosis, the potential risk of infection by medical staff due to direct contact with patients is significantly reduced. Intelligent equipment such as isolation ward robots and throat swab taking robots for nucleic acid testing have been deployed on a large scale in front-line hospitals and are undergoing clinical application testing. Smart outpatient pre-examination can classify medical patients according to their risk of infection, which not only avoids cross-infection in the hospital, but also reduces the load of hospital fever clinics and saves medical protective materials, which has a good protective effect during the outbreak stage. The new coronavirus infection self-test and evaluation system installed on smartphones is used to intelligently analyze the infection risks of testers and provide medical advice. This plays an important role in alleviating social panic during the spread of the epidemic and guiding residents to seek medical treatment rationally. The intelligent epidemic prevention and control systems adopted in various places automatically report key information to community terminals to realize dynamic monitoring of the epidemic situation in the community and ensure the accuracy and efficiency of epidemic prevention and control. The AI monitoring system for COVID-19 recovered people provides comprehensive and accurate monitoring services for recovered and isolated groups.

Ling et al. [2020] reported that the World Health Organization estimates that as of June 2022, the novel coronavirus will have caused the deaths of about 6.31 million people worldwide, with over 539 million cases diagnosed. One of the distinguishing characteristics of COVID-19 is interstitial pneumonia, for which chest Computed Tomography (CT) scan images have been shown to be the Basic method. Deep learning-based computational imaging technology has promising future development for detecting positive cases of novel coronavirus infections. SARS-CoV-2 can lead to serious lung damage and COVID-19 infection. It is possible to differentiate COVID-19 infection from other respiratory infections, such as community-acquired pneumonia (CAP), and bacterial pneumonia with chest imaging. Critical decisions revolve around control, diagnosis, and treatment.

CNN models have been proposed by numerous researchers worldwide to identify or categorize COVID-19 positive patients using a variety of medical data. Research has been conducted and numerous formats have been made publicly available by scientific research organizations worldwide in an effort to use computer technology to better understand and treat this illness. Utilizing Artificial Intelligence (AI), particularly Deep Learning (DL) models, is one of the research's primary technologies for detecting COVID-19 from chest X-rays and CT scans.

Jiang and associates [2020] Three categories exist for CT images of new coronavirus infections: influenza A viral pneumonia, health, and new coronavirus infection. The 618 images in the data set are divided into 219 images of newly diagnosed coronavirus infections, 224 images of A-virus infections, 224 images of influenza virus pneumonia patients, and 175 images of healthy individuals. The photos were classified using a three-dimensional deep learning model, and the overall classification accuracy was 87.6%.

In order to classify new coronavirus infections and CAP based on chest CT images, Sun et al. [2020] proposed a feature selection method in conjunction with a deep forest model. The experimental results demonstrate that this method performs better when compared to other popular machine learning techniques. Literature performed thin-section CT scans on 1,027 patients with CAP lung disease and 1,658 patients with new coronavirus infections. All images were pre-processed to obtain the segmentation of lung and infection areas, which was used to After extracting features from particular locations, the Infection Size-Aware Random Forest method (ISARF) was put forth. Initially, the subjects were automatically divided into groups based on the size range of infected lesions. Within each group, random forests were used for classification.

In 2020, Harjoseputro et al. The hospital uses AI technology for body temperature measurement and face recognition to quickly, efficiently and in batches complete the temperature screening and identity recognition of COVID-19 patients. Epidemic prevention personnel carry out non-contact body temperature detection and personal information identification to promptly detect fever and suspicious patients, significantly reducing the labor input of medical staff and avoiding the risk of contact infection. AI technology has significantly improved the traffic efficiency in many scenarios, such as hospitals, stores, airports, stations, etc., and supports epidemic prevention investigators to conduct online investigations and clarify the flow trajectories of patients and suspicious patients through health screening. The mobile dual-light rapid temperature measurement intelligent identification system developed by domestic institutions combines infrared thermal imaging and face recognition technology to conduct fast and accurate non-contact body temperature monitoring of passing personnel; the number of monitoring personnel per minute exceeds 200, and the measurement People with abnormal body temperature can be immediately detected within a distance of 5 m, thereby minimizing the potential risk of 2019-nCoV transmission. The use of facial recognition algorithms and thermal imaging intelligent temperature measurement technology can also realize automatic identification and management of personnel body temperature, mask wearing, personnel identity, etc., and complete the unified presentation and automatic archiving of information in real time.

Hu and associates [2020] This paper solves the problem by adding a reweighted layer, which effectively uses channel dependencies to enable the network to obtain a more robust feature representation to improve classification accuracy. SENet offers a novel system and focuses on channel relationships. Compression and excitation block, or SE block, is the structural unit that models the interdependence between channels explicitly and adaptively recalibrates the channel feature map. A channel descriptor is created by aggregating the spatial dimension H×W feature map through the compression operation. This descriptor allows information from the network's global receptive field to be utilized by its lower layers by embedding the global distribution of the channelized feature response. In order to generate the channelized implemented in response, global average pooling is used.

3. MATERIALS AND METHODS

The methodology incorporated statements addressing distinctions between genders in aspects like labor costs, productivity, workplace behavior, and job attributes. Respondents were tasked with expressing their agreement levels, and these statements were chosen based on their frequent mention in business circles. The goal was to capture prevailing beliefs about gender in the professional realm, either aligning with common assertions or challenging persistent stereotypes. This selection aimed to offer insights into prevalent attitudes surrounding gender dynamics at work.

3.1 Data collection

Prospectively, the ultrasound images of 3,966 patients who had ultrasound examinations from June to September 2020 at Shanghai Pulmonary Hospital Affiliated to Tongji University were gathered. Pleural effusion, lung consolidation, A-line, and B-line were measured. Every component has 1,500 ultrasound pictures. The following criteria are used to exclude images: (1) There are two or more lung signs present in a single image; (2) There is a bone occlusion that leaves part of the image missing. Ultimately, 1,384 pleural effusion images, 1,388 A-line images, 1,375 B-line images, and 1,398 lung consolidation images were chosen. Using the LOGIQ E9 color Doppler ultrasound diagnostic system (GE Company, USA) with a convex array probe and a frequency range of 2.8 to 5.0 MHz, a focus and depth adjustment (8 to 10 cm) and optimal acoustic window selection were used to perform a lung ultrasound examination. Show the intended image.

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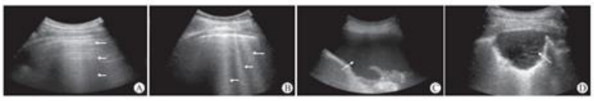

Fig 1. Ultrasound Images of 4 Common Lung Signs

A: Arrows in an A-line. High echo artefact that is transverse, equidistant, and has a decreasing echo intensity, and it is parallel to the pleural line. B: The B-line (arrows). a breath-moving, vertical laser beam from the pleural line that stretches unabated to the screen's edge and moves back and forth. C: Arrows indicate pleural effusion. Anechoic region separating the visceral and parietal pleura, with enhanced echo behind. Within the effusion is a sizable mass of compressed lung tissue floating around. D: Lung enlargement (arrows). When lung tissue condenses into large areas, the consolidated lung tissue exhibits liver parenchymal-like soft tissue echoes. The "fragmentary sign," also known as irregular fragmentary strong echo, is a characteristic of the consolidation of small lung pieces.

3.2. Image Design

Fig 2 depicts the image pre-processing procedure. It mainly consists of three steps: (1) Pre-process the original image and crop out some useless information. (2) Perform data enhancement processing to expand the data set. (3) In order to ensure the relative independence between data samples and the independence between data sets, the data sets are randomly divided.

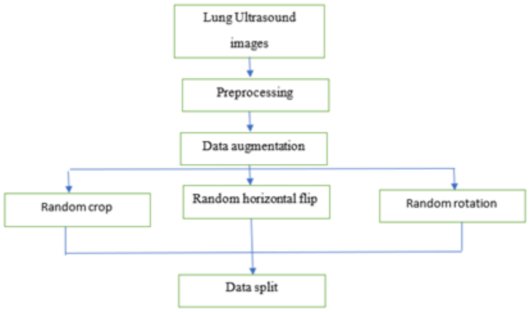

Fig 2. Pre-Processing Procedure of Lung Ultrasound Images

The lung ultrasound images collected by the hospital contain information such as collection date, time, machine model, etc. This information is useless for online learning. In order to avoid the model learning useless features, the image is pre-processed first. The original image is uniformly cropped, retaining only the useful information in the image.

Data enhancement and data partitioning are performed on the cropped images before being sent to model training. The data augmentation methods used in this study include post-fill cropping, probabilistic horizontal flipping, and random rotation. The images were randomly divided into 60% training set (3433 images), 20% validation set (1056 images) and 20% test set (1056 images).

Classify four types of lung ultrasound sign maps based on the end-to-end deep residual network ResNet152. In order to improve the generalization ability of the classification model and prevent over-fitting, the experimental data is processed through image pre-processing, data enhancement, normalization and other methods. Before the model started training, in order to prevent overfitting and improve the robustness of the model, data enhancement was performed: (1) the image was randomly cropped after filling around it; (2) the image was flipped horizontally with a 50% probability; (3) the image was randomly Rotate a certain angle.

During the data collection and saving process, the two adjacent images are very similar. In order to avoid using a large number of highly similar images as training sets and verification sets respectively, which would lead to high scores on the verification set during model training, this study used the method of randomly dividing the data set for verification, and based on a certain proportion from the validation set was randomly selected from the entire dataset. Randomly sample 20% of the images from the cropped image set as the validation set, 20% as the test set, and the rest as the training set.

The steps of the classification method for four signs of lung ultrasound in the network ResNet152 are as follows: (1) Pre-process the lung ultrasound images and perform data enhancement to prevent overfitting; (2) Complete the design of the residual network based on the image; (3) The weights of each layer in the network are accumulated to achieve classification. Deep learning networks are mainly divided into connection modes, nonlinear modules, optimizers, loss functions and hyperparameters.

3.3 Convolutional Neural Network

The deep residual network that this study suggests is predicated on This study used the deep residual network ResNet152, which uses residual design to overcome the deep neural network's depth limit. In residual design, identity mapping is used instead of several layers for concatenation, and the output is added to the residual function's output. By doing this, the issues with gradient vanishing and gradient explosion brought on by adding more neural network layers can be successfully avoided. It will not add more parameters or make the network's computation more complex while maintaining its depth. Deep learning is referred to as a "black box" due to its end-to-end features and its opaque learning process. The model is visually presented in this study to enhance its interpretability. The deep residual network ResNet152's fundamental network is called the ResNet portion (Fig 3).

Each residual network ResNet (such as ResNet18, ResNet50, ResNet152) has 4 layers. ResNet152 is a deep network composed of "Bottleneck" structures, in which each layer is composed of several layers. The chemical layer refers to the different chemical generalization used, which can achieve the same systemaccess and control of different sizes. The original processing operation defines the size of the cliff area in advance, and the size of the cliff area is defined in advance. The modified image is just the weighted summation of the weights corresponding to the special images in each layer based on the original image, and finally superimposition on the original image. The area where you can kill the enemy is the area where you can punish the city.

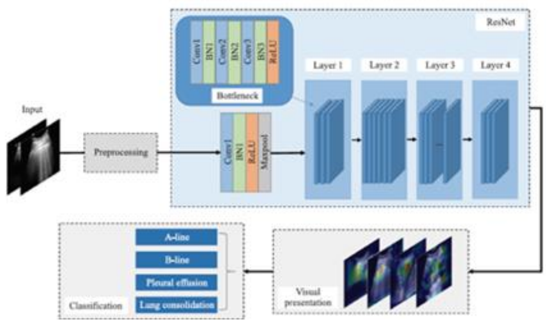

Fig 3. Diagram of Overall Network Architecture

3.4 Classification Evaluation Criteria

The precision rate, accuracy, specificity, recall rate, and F1 index were computed to assess the classification performance of the classification model using the sonographer's classification results as the gold standard. Precision rate (%) is the total number of true positive images divided by the total number of false positive images; accuracy (%) is the total number of true positive images divided by the total number of images × 100%; specificity (%) is the total number of true negative images divided by the total number of true negative images and the number of false positive images; recall rate (%) is the total number of true positive images divided by the total number of true positive images and the number of false negative images divided by the number of true positive images; F1 index (%) is equal to 2 × precision rate × recall rate / (precision rate + recall rate).

Indicators such as accuracy are mostly used for binary classification. Multi-classification is based on calculating the corresponding value for each category based on the binary classification, and then performing a weighted average calculation result. In addition to the above traditional statistical calculation classification model classification performance, the following indicators that directly define and measure the multi-classification effect are also calculated. The Kappa coefficient (1). The Kappa coefficient is a consistency test indicator and a model evaluation parameter that is computed using the confusion matrix. The Kappa coefficient typically falls between 0 and 1. The consistency is higher when the value is nearer 1. Very low consistency is denoted by a Kappa coefficient of 0.00 to 0.20, average consistency by 0.21 to 0.40, and moderate consistency by 0.41 to 0.60. High consistency is indicated by 0.61⁝0.80, and almost complete consistency is indicated by ≥0.81. The model's classification accuracy rises with the value of the Kappa coefficient. computed in the manner described below:

$$Kappa = \frac{p_0 - p_e}{1 - p_e}$$

Among them, the overall classification accuracy is denoted by p_0, which is the number of correctly classified samples in each of the four categories divided by the total number of samples. p_e is the ratio of the total number of samples to the product of the number of real samples in each class and the number of samples that are predicted for that class? The following is the calculation formula:

$$p_e = \frac{\sum a_i \times b_i}{n \times n}$$

where n is the total number of samples; and is the number of real samples of each category; b is the predicted number of samples of each category; i is the number of categories (in this study, i = 4).

2) Confusion matrix. Confusion matrices are a visual aid that can accurately depict the model's classification outcomes. In the confusion matrix, each row denotes the actual category label, each column the category prediction, and the sum of each row the actual number of samples in the category, and the sum of each column the number of samples predicted for the category. Number: The more samples the corresponding class correctly predicts, the darker the colour on the diagonal.

4. Result

This study records the real labels and the actual prediction results of the model, summarizes them in the form of a matrix, and uses this information to evaluate the deep learning model and reflect the classification performance. Table 1 displays the deep classification model's accuracy, specificity, F1 index, and Kappa coefficient for the classification of lung consolidation, pleural effusion, A lines, and B lines. Among them, the recall rates are 90.38%, 86.97%, 94.25%, and 91.18%, and the accuracy rates of this deep classification model for classifying four signs of A-line, B-line, pleural effusion, and pulmonary consolidation are 97.51%, 87.31%, 85.42%, and 93.70%, respectively. Following training, the model's final accuracy was 90.70%, with the classification accuracy of lung consolidation, pleural effusion, A-line, and B-line being 96.02%, 93.66%, 94.41%, and 96.77%, respectively. This deep classification model's Kappa coefficient is 0.873 7, which shows that the trained model and manual classification have good consistency.

Table 1. Classification Performance of Deep Learning Model For 4 Signs on Lung Ultrasound Images

Classification	**Precision/%**	**Specificity/%**	**F1score/%**	**Recall/%**	**Accuracy/%**	**Kappa**
A-line	96.51	98.37	92.68	89.38	95.97	
B-line	84.31	95.09	86.19	85.97	92.66	
Pleural effusion	83.42	93.07	88.52	93.25	93.41	
Lung consolidation	92.70	96.85	90.92	90.18	95.02	
Total	90.99	95.85	89.50	89.70	89.70	0.8637

The confusion matrix used by the deep learning model to classify the four signs of lung ultrasound is shown in Figure

4. In the first row, 237 pictures were predicted as line A by the model, 16 pictures of line A were incorrectly predicted as line B, and 11 pictures were mistakenly predicted as line B. The A-line was wrongly predicted as pleural effusion. As shown in the confusion matrix, the prediction effect of B-line is worse than that of the other three categories, that is, the B-line category may be predicted as the other three categories. However, A-line will not be predicted as pulmonary consolidation, and pleural effusion and pulmonary consolidation will not be predicted as A-line, that is, the three categories of A-line, pleural effusion, and pulmonary consolidation are more independently separable.

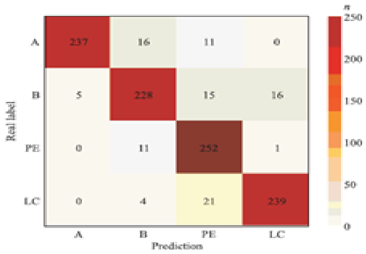

Fig 4. Confusion Matrix of Deep Learning Model For classification of Signs of Lung Ultrasound

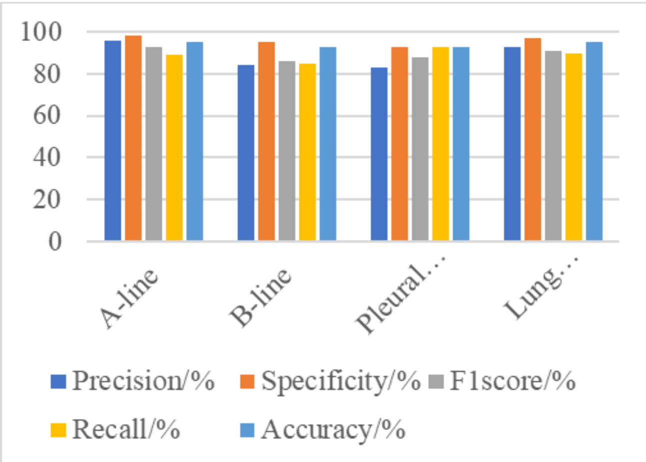

Fig 5. Classification Performance of Deep Learning Model For 4 Signs on Lung Ultrasound Images

A-line maintains its accuracy with a robust precision (96%) and specificity (98%), underlining its proficiency in correctly identifying positive and negative cases. B-line demonstrates enhancements across all metrics, particularly in precision (84%) and specificity (95%), leading to a more balanced overall performance. Pleural effusion sustains a steady performance, showcasing a consistent interplay between precision (83%) and recall (93%), resulting in a well-rounded F1 score (88%).Lung consolidation upholds its efficacy with sustained high precision (93%) and specificity (97%), coupled with improved recall (90%) and F1 score (91%). A-line and Lung consolidation continue to deliver a commendable accuracy of 95%, affirming their effectiveness in comprehensive classification. B-line maintains a respectable accuracy of 93%, indicating its continued effectiveness despite a lower precision compared to A-line and Lung consolidation. A-line's recall of 89% underscores its aptitude for correctly identifying positive instances, contributing to its balanced F1 score (93%). Pleural effusion maintains a balanced performance, as reflected in its F1 score of 88%, showcasing an effective equilibrium between precision and recall. B-line, with an F1 score of 86%, presents a reliable balance between precision and recall, positioning it as a trustworthy choice for classification. Overall, A-line and Lung consolidation persist as robust choices for scenarios prioritizing high precision and recall, while B-line and Pleural effusion offer balanced performances catering to different classification needs.

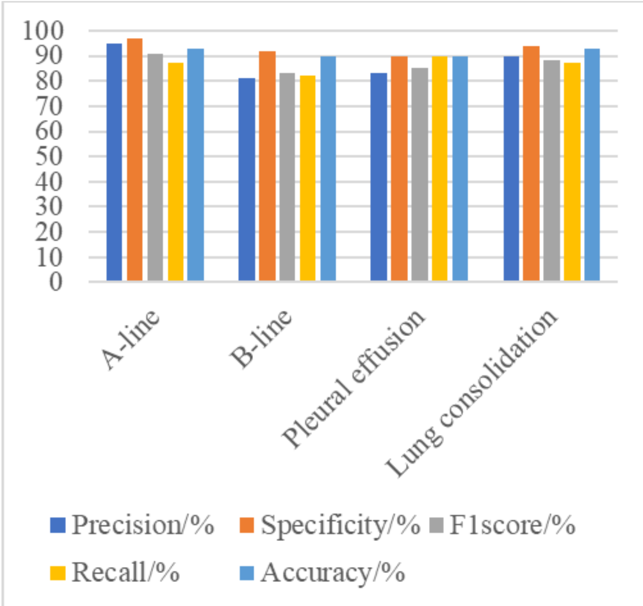

Fig 6. Classification Performance of Deep Learning Model For 4 Signs on Lung CT Scan Images

A-line exhibits the highest precision (95%) and specificity (97%), showcasing its accuracy in correctly identifying positive and negative instances. B-line demonstrates relatively lower precision (81%) and specificity (92%) compared to A-line, indicating some challenges in accurately classifying both positive and negative cases. Pleural effusion and Lung consolidation share similar specificity (90%) but differ in precision and recall, with Pleural effusion having slightly higher precision (83%) and recall (90%).Lung consolidation shows the highest F1 score (88%), highlighting a balanced performance between precision and recall, contributing to its effectiveness in classification. A-line and Lung consolidation share similar accuracy (93%), suggesting their overall effectiveness in correctly classifying instances. Pleural effusion exhibits a balanced performance with an F1 score of 85%, reflecting its ability to strike a good trade-off between precision and recall. B-line's F1 score of 83% indicates a fair balance between precision and recall, despite lower values in both metrics compared to A-line and Lung consolidation. A-line and Lung consolidation show higher recall values (87%), emphasizing their ability to correctly identify positive instances. B-line, while having a lower precision and recall, still maintains a respectable accuracy of 90%, showcasing its overall effectiveness in classification. Overall, the choice between these lines depends on the specific priorities – A-line and Lung consolidation for higher recall, B-line for balanced accuracy, and Pleural effusion for a balanced precision-recall trade-off.

5. Discussion

The lungs are gas-rich organs that have historically been regarded as a restricted area for ultrasound examinations due to their ability to block the transmission of ultrasonic waves. Nonetheless, research has shown that ultrasonography can distinguish between the symptoms of pathological and normal lungs [4]. This phenomenon is thought to be caused by variations in the air-liquid ratio that occur in the lungs under various pathological circumstances. The clinical diagnosis of numerous lung diseases, such as pneumothorax, cardiogenic pulmonary edema, pulmonary infection, and pulmonary tumours, has made extensive use of the four common signs of lung ultrasonography: A-lines, B-lines, pulmonary consolidation, and pleural effusion. It is highly sensitive and specific for conditions like acute massive pulmonary embolism and post-traumatic hemorrhage. Sonographers' subjective perception is currently the primary factor used for image classification and interpretation of lung ultrasonography signs. This work achieves high feature classification accuracy and suggests a novel and efficient way to automatically interpret features based on lung ultrasonography images. This can successfully lessen reliance on medical expertise and minimize variations in interpretation amongst physicians.

When paired with the BLUE protocol, the study's suggested method can assist clinicians in promptly and precisely determining the cause of acute dyspnea. This work classifies lung ultrasonography images using deep learning. Data analysis reveals that the model developed using the deep learning approach has excellent specificity and accuracy. Sonographers can receive diagnostic assistance from the deep learning model. In this study, deep learning models are trained using physician classification results as labels. The deep learning method's overall classification accuracy is higher than that of professional doctors' image reading classification. Simultaneously, deep learning models are able to automatically select features by using operations like convolution and pooling to extract pixel-level feature information from training data. Auxiliary deep learning technology can help save professional imaging physicians from tedious and complex work, optimize workflow, and increase productivity by mitigating the impact of the ultrasound physician's experience on diagnostic outcomes and serving as a reference for clinicians' diagnosis classification. The ResNet152 network structure was used in this study; it achieves good network effects and very deep network layers through the use of a residual structure design. In the process of extracting features from neural networks, residual design can somewhat augment the available data without increasing the number of parameters or computational complexity of the network. Numerous fields that deal with image classification use this network.

The following are the limitations of this study: (1) The design of this study is single-centre. Variations in the ultrasound equipment and scanning techniques used can result in varying image quality. Deep learning will eventually need to be validated using image data sets from various centres and quality levels. Technique execution. (2) Every image examined in this study only includes one lung ultrasonography feature; other common features are not covered, and more work needs to be done on improving this in the future. (3) Other signs may still be crucial for the diagnosis of particular diseases, even though the four lung ultrasonography signs included in this study comprise the majority of lung ultrasonography signs. (4) Ultrasound video sequences may contain more information than the single static image used in this investigation. (5) The study excluded the clinical information of the patients and only classified images of four typical lung ultrasonography signs in an initial manner. To address clinical issues, more thorough research plans must be created in the future.

Transfer learning techniques or better network parameters (like utilizing different loss functions) can be applied in the future to enhance the model's inventiveness in terms of deep learning algorithms. Use three-dimensional convolutional neural networks to extract both spatial and temporal feature information from videos. Simultaneously, the model is trained and learned using data gathered by various ultrasonic instruments in order to enhance its generalization capabilities. To sum up, this research investigates the potential and worth of deep learning when it comes to using lung ultrasonography images. In classifying four signs of lung ultrasonography, the deep learning model based on neural networks has achieved impressive results with good prediction accuracy. Good classification outcomes. The ability of clinicians to diagnose lung diseases can be narrowed down by computer-assisted technology, which can also increase diagnostic efficiency and offer a new way to achieve homogeneous, high-quality diagnosis.

6. Conclusion

To sum up, this study demonstrates the great potential and effectiveness of using deep learning and machine learning methods for lung disease classification and diagnosis, with a focus on COVID-19 and pneumonia. The application of advanced algorithms to the interpretation of CT and X-ray data in medicine has demonstrated the possibility of accurately identifying and classifying respiratory conditions.

The created models have powerful diagnostic capabilities due to their remarkable capacity to identify complex patterns and traits suggestive of pneumonia and COVID-19. The models' reliability in practical situations has increased thanks to the analysis of large and varied datasets, which has also enabled them to generalize across various demographics and imaging modalities. This study adds to the increasing amount of data that supports the use of artificial intelligence in medical diagnostics by offering a quick and simple way to help medical professionals make decisions that are accurate and timely. The results of this study have clinical setting applications that go beyond research boundaries. The application of deep learning and machine learning techniques to lung disease diagnosis has the potential to transform healthcare procedures, enhance patient outcomes, and expedite the diagnostic process. With the ongoing COVID-19 pandemic and other respiratory health issues, the data from this study supports continued efforts to improve diagnosis accuracy and healthcare effectiveness. Further research in this area will be necessary to ensure the models' scalability, adaptability to changing healthcare environments, and optimization. As technology develops, the full potential of machine and deep learning for lung disease detection and classification will only be realized with the combined efforts of researchers, medical professionals, and technology developers.

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