A SURVEY ON IMAGE RETRIEVAL SYSTEM FOR IDENTIFICATION AND CLASSIFICATION OF LUNG DISEASES USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The prompt diagnosis and treatment of patients depend heavily on the precise identification and classification of lung illnesses. The development of computer-aided diagnosis systems has drawn more attention as a result of improvements in medical imaging technology. The goal of this review paper is to give a general overview of the architecture of an image retrieval system that uses Artificial Neural Networks (ANNs) to identify and categorize lung illnesses. This Paper examines the various system design elements, such as preprocessing approaches, feature extraction techniques, ANN structures, and assessment measures. The potential to increase the precision and effectiveness of lung disease diagnosis is highlighted as it also explores the difficulties and future directions in this area.

KEYWORDS: *Lung disease, deep learning, CNN, Artificial neural network, classification*

1. INTRODUCTION

Millions of individuals around the world are affected by lung disorders, which also raise morbidity and mortality rates [1]. Infectious diseases (including pneumonia and tuberculosis), chronic obstructive pulmonary disease (COPD), asthma, lung cancer, and interstitial lung diseases are just a few examples of the conditions that fall under this umbrella term. Lung diseases have a considerable negative impact on public health, resulting in lowered quality of life, higher healthcare expenses, and significant socioeconomic consequences.

For prompt diagnosis and effective treatment planning, it is crucial to correctly identify and classify lung disorders. In medical imaging like chest X-rays and computed tomography (CT) scans, different lung diseases show diverse patterns and characteristics [2]. Even for seasoned radiologists, these patterns can be subtle and difficult to correctly interpret. Inadequate or delayed therapy, illness progression, and other serious effects might result from misdiagnosis or delayed diagnosis.

Systems for computer-aided diagnosis (CAD) have become important tools for helping radiologists and doctors analyze medical images and increase diagnostic precision. With the help of cutting-edge technologies like artificial intelligence and machine learning, these systems analyze massive amounts of imaging data and offer automated support for the diagnosis and classification of diseases. CAD systems can efficiently evaluate complicated patterns in lung images, assisting in the identification and characterization of lung disorders. This is accomplished by merging image analysis algorithms and artificial neural networks.

Computer-aided diagnostics systems play a variety of roles in raising diagnostic accuracy. First off, CAD systems can act as a helpful second opinion, giving radiologists new information and lowering the possibility of diagnostic mistakes. They can assess disease severity, identify suspect areas, and aid in differential diagnosis. Additionally, CAD solutions can boost productivity by lessening the radiologist's burden and enabling quicker reporting turnaround times.

Additionally, CAD systems have the potential to improve access to high-quality healthcare, particularly in environments with limited resources. CAD systems can fill the gap between regions with little access to skilled radiologists and the rising need for precise diagnostic services by automating some parts of lung disease diagnosis and classification. Improved patient outcomes can result from early detection, prompt care, and this.

In conclusion, precise diagnosis and treatment of lung disorders depend on the exact identification and classification of those diseases. By utilizing artificial neural networks and image analysis techniques, computer-aided diagnosis systems significantly contribute to increasing diagnostic accuracy. These technologies have the potential to improve access to high-quality healthcare services, decrease diagnostic errors, and improve radiologists' performance. It is possible to advance the management of lung illness by the integration of CAD systems into clinical practice, which will ultimately lead to better public health outcomes.

2. FEATURE EXTRACTION METHODS

2.1 Handcraft Features: - Texture, Shape and Intensity based features

In order to identify and categorize diseases, handcrafted features refer to manually created features that capture particular properties of lung pictures. These characteristics are frequently discovered by examination of the texture, shape, and intensity patterns found in the photographs. The descriptions of each type of handcrafted feature are as follows:

2.1.1 Texture features: The spatial arrangement of pixel intensities in an image is referred to as texture. Texture characteristics are designed to record the changes in texture patterns that are suggestive of particular lung conditions. Typical textural characteristics include:

• Gray Level Co-occurrence Matrix (GLCM): GLCM analyzes the connections between adjacent pixels to derive the statistical characteristics of pixel intensities.

• Local Binary Patterns (LBP): Based on binary patterns, LBP records the connections between a pixel and its neighbors, revealing details about texture patterns.

• Haralick features: Derived from the GLCM, these features quantify texture properties like contrast, homogeneity, entropy, and energy.

2.1.2 Shape characteristics: Shape characteristics describe the geometric features of lung lesions or regions of concern. These characteristics record data on the size, shape, and symmetry of lung anomalies. Shape aspects include, for example:

• Area, perimeter, and circularity: These characteristics categorize and quantify lung lesions' dimensions and forms.

• Eccentricity and elongation: These characteristics define the eccentricity and elongation of lung anomalies.

• Contour-based characteristics: These features depict the irregularity and geographic distribution of lesion borders.

2.1.3 Intensity-based features: These features concentrate on the lung image's pixel intensity values. These characteristics describe the statistical characteristics and distribution of pixel intensities. Common traits based on intensity include:

• Features based on histograms: These characteristics explain how an image's pixel intensities are distributed.

• Statistical moments: The statistical properties of pixel intensities are quantified by moments like mean, variance, skewness, and kurtosis.

Traditional machine learning algorithms have used a lot of hand-crafted features, but their efficacy significantly depends on feature engineering and domain knowledge. Due to its capacity to automatically discover useful features from raw data, deep learning-based techniques have drawn a lot of interest in recent years, negating the need for manual feature extraction.

2.2. Deep Learning Based feature extraction: Convolutional Neural Network (CNNs)

Deep learning architectures known as convolutional neural networks (CNNs) have completely changed feature extraction and picture analysis. Without explicitly constructing handcrafted characteristics, CNNs are excellent at learning hierarchical representations from unprocessed image data.

They are made up of several layers, including pooling, convolutional, and fully linked layers.

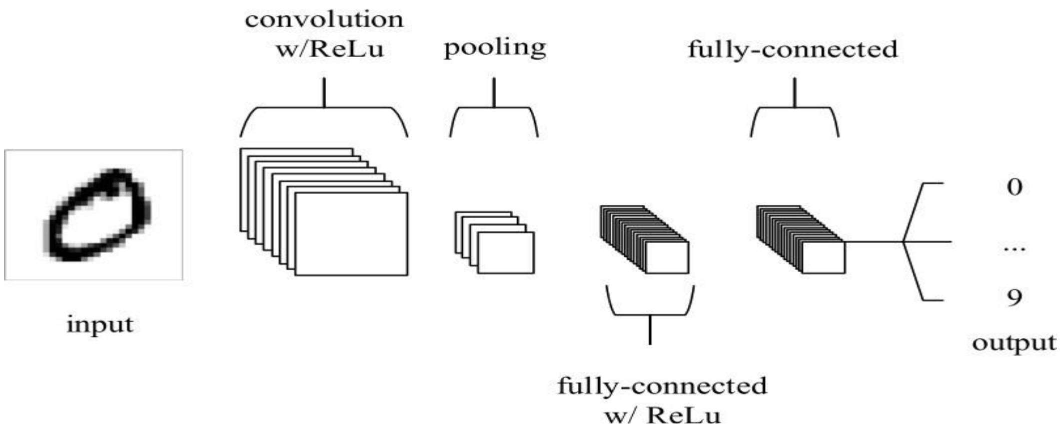

Fig 1 An Example of a CNN working structure.

By convolutional layering (also known as kernel convolution) filters over the input pictures, CNNs learn features hierarchically. At various sizes, the filters extract regional patterns and features. The feature maps are down-sampled by the next pooling layers, which reduce spatial dimensions while keeping pertinent data intact. Fully connected layers then receive the learnt information from numerous convolutional and pooling layers for classification.

In a variety of image-related tasks, such as the identification and categorization of lung diseases, CNNs have demonstrated extraordinary performance. CNNs can detect minute details and nuanced correlations in lung pictures by learning complex patterns and features directly from the raw pixel data. CNNs can successfully distinguish between various lung illnesses thanks to this feature.

A significant amount of labeled data is needed to train a CNN for the categorization of lung diseases. The CNN is taught using a supervised learning method, where it discovers how to associate the illness categories that match to the input lung images. Forward propagation, backpropagation, and gradient-based optimization techniques are used throughout the training process to modify the weights and biases of the network in order to reduce the classification error.

Researchers have obtained cutting-edge performance in lung disease categorization tasks by utilizing CNNs. CNNs can potentially learn highly discriminative features automatically, minimizing the need for manually created features and feature engineering.

In conclusion, prior machine learning algorithms for lung disease categorization have extensively leveraged handcrafted features such texture, shape, and intensity-based features. However, deep learning-based methods, in particular CNNs, have become potent instruments for automatically extracting features from unprocessed lung pictures. The accuracy and effectiveness of tasks involving the identification and categorization of lung diseases are increased by CNNs' ability to learn intricate patterns and features straight from the data.

3. ARTIFICIAL NEURAL NETWORK ARCHITECTURES

3.1 Overview of ANNs and their suitability for lung disease classification

The structure and operation of biological neural networks serve as the basis for computing models known as artificial neural networks (ANNs). Artificial neural networks (ANNs) are made up of linked artificial neurons or nodes arranged in layers. To produce an output, each neuron receives input signals, computes them using a weighted formula, and then applies an activation function. Weights are assigned to the connections between neurons and are modified throughout training to enhance the functioning of the network.

Due to their capacity for learning intricate patterns and correlations from huge datasets, ANNs are highly suited for classifying lung diseases. They are able to identify minor characteristics and fluctuations that are suggestive of various lung diseases because they can capture both linear and non-linear correlations within the data. ANNs are excellent at automatically removing pertinent features from the unprocessed input data, doing away with the requirement for laborious feature engineering.

For the classification of lung diseases, various ANN models have been used, each with an own architecture and set of properties. Popular ANN architectures and their uses in this situation are outlined in the following sections.

3.1.1. Feedforward neural networks (FNNs):- commonly referred to as multilayer perceptrons (MLPs), are the most basic type of artificial neural networks (ANNs). A hidden layer or layers, an output layer, and an input layer make them up. Information moves unidirectionally through the hidden layers and output layer in FNNs, starting at the input layer. Every neuron in the network is linked to every other neuron in the layer below it. The categorization of lung diseases using structured data, such as clinical features or manually created image features is a good application for FNNs.

3.1.2. Convolutional Neural Networks (CNNs): CNNs are created specifically for the analysis of grid-like data, such as photographs. Tasks involving image processing, such as identifying lung diseases, have been transformed by CNNs. Their distinct architectural features, including convolutional layers, pooling layers, and fully linked layers, serve as distinguishing features. In order to execute local convolutions over the input data and identify spatial patterns, convolutional layers need filters (kernels). Downsampling the feature maps by pooling layers reduces the spatial dimensions while retaining crucial data. Then fully linked layers are used to classify the learned characteristics. CNNs are excellent at identifying complex spatial patterns and characteristics in lung pictures, producing findings for illness classification that are incredibly accurate.

3.1.3. Recurrent Neural Networks (RNNs): Recurrent Neural Networks (RNNs) use feedback connections between neurons to process sequential data. They possess memory-like characteristics that allow them to retain knowledge of earlier inputs. RNNs are appropriate for jobs involving sequential data, such as time series data or sequential medical records, in lung disease classification. RNNs can recognize temporal linkages and enduring patterns in sequential data because to recurrent connections.

3.1.4 Hybrid Architectures: To take advantage of each ANN type's unique characteristics, hybrid architectures mix them. Combining CNNs and RNNs can be used to create hybrid architectures for classifying lung diseases. With this pairing, the network may take use of the spatial and temporal dependencies included in sequential data and lung pictures, respectively. In the classification of lung diseases, hybrid architectures have demonstrated promise in obtaining thorough information and achieving high accuracy.

In conclusion, categorization of lung diseases is a good application for ANNs, such as Feedforward Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks, and hybrid architectures. These architectures can recognize and classify diseases accurately by learning intricate patterns and correlations in lung pictures and other pertinent data sources. The type of input data and the precise specifications of the task for classifying lung diseases determine which ANN architecture should be used.

4. EVALUATION METRICS

4.1 Common evaluation metrics for assessing the performance of lung disease classification models: - Accuracy, sensitivity, specificity, precision, and F1-score are common evaluation measures for evaluating the effectiveness of lung disease classification algorithms. These metrics can be used to assess the efficiency of the image retrieval system and offer insights into many facets of model performance.

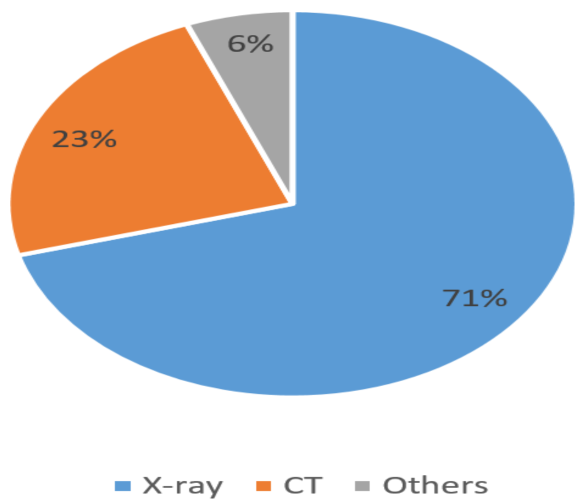

Fig 2 the deep learning image type used in recent years for lung illness identification.

4.2 Accuracy, sensitivity, specificity, precision and F-1 score

4.2.1 Accuracy: - Accuracy gauges how accurately the classification outcomes are overall. It determines what portion of the total cases (lung pictures) were correctly classified. When dealing with imbalanced datasets, where the number of examples in various illness classifications varies dramatically, accuracy alone might not be sufficient.

4.2.2 Sensitivity (Recall): The proportion of positive cases (lung pictures with the disease) that are correctly detected by the model is referred to as sensitivity, also known as recall or true positive rate. It measures how well the system can identify the existence of lung conditions. A low rate of false negatives is indicated by a high sensitivity.

4.2.3 Specificity: Specificity indicates the percentage of events that the model properly classifies as negative (lung pictures free of illness). It shows how well the system can recognize situations that don't have lung illnesses. A low percentage of false positives is indicated by a high specificity.

4.2.4 Precision: Out of the instances that the model predicted as positive, precision determines the percentage of accurately identified positive occurrences (true positives). It illustrates how precisely the technology can spot cases of lung illness. When false positives can result in costly or unneeded invasive procedures or treatments, precision is especially crucial.

4.2.5 F1-score: The harmonic mean of recall and precision is known as the F1-score. It offers a fair assessment of model performance by taking into account both precision and recall. The F1-score is helpful when there is a trade-off between false positives and false negatives or when the dataset is unbalanced.

4.3 Receiver operating characteristic (ROC) curve and analysis

When choosing evaluation metrics, it's crucial to take the unique context and requirements of the work of classifying lung diseases into account. To evaluate model performance thoroughly, additional metrics, such as the area under the receiver operating characteristic (ROC) curve or the precision-recall curve, may occasionally be utilized.

Researchers can learn more about the image retrieval system's ability in precisely recognizing and classifying lung disorders by analyzing it using these assessment measures. These metrics aid in determining the system's advantages and disadvantages, direct future developments, and enable comparisons with other models or research.

5. CONCLUSIONS

More studies on deep learning-based lung disease diagnosis have been published over time. On the current state of research and application, there was, unfortunately, no systematic survey available. In order to provide an exhaustive survey of lung disease diagnosis using deep learning, this document was created. Especially on COVID-19, lung cancer, pneumonia, and tuberculosis, and published from September 2016 to September 2020. 98 publications on the subject in total were taken into account when creating this survey.

Based on the survey of the works taken into consideration, a taxonomy of state-of-the-art deep learning aided lung illness detection was created. It summarizes and organizes the important concepts and focus of the present work on lung disease detection using deep learning. On the basis of the taxonomy's defined attributes, analyses of the trend in current works on this subject are also provided. According to assessments of the works' distribution, both CNN and transfer learning are often used.

With the exception of the ensemble characteristic, all of the taxonomically recognized qualities in the surveyed study showed a linear increase in average over time. The remaining problems and the path of deep learning for lung illness diagnosis were then identified and described. Deep learning lung disease detection problems were broken down into four categories: data imbalance, handling large image size, dataset availability, and high error correlation when utilizing ensemble approaches. To address the observed problems, it is suggested that four potential approaches be used for lung disease diagnosis using deep learning: making datasets available to the public, using cloud computing, employing more features, and using the ensemble.

In order to ensure that future research stays on the right road and enhance the effectiveness of illness detection systems, it is crucial to look into how deep learning was used in the detection of lung diseases. Other scholars could plan their research contributions and activities using the taxonomy that has been offered. The indicated probable future course could boost the effectiveness and broaden the range of applications for deep learning-assisted lung disease detection.

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