Lung Cancer Detection using ELM Classifier

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*Abstract*—*The detection and classification of lung cancer is a critical task in the area of medical diagnosis. This paper presents an Extreme Learning Machine (ELM) based approach for the detection and classification of lung cancer. ELM is a fast and efficient learning algorithm that has been successfully applied in various fields. The proposed method uses ELM to extract features from lung cancer images and classify them into benign or malignant tumors. The dataset used in this study consists of lung cancer scans collected from different sources. This study proposes a lung cancer detection and classification model using the Extreme Learning Machine (ELM) algorithm. The proposed ELM-based model was evaluated based on a publicly available lung cancer dataset, which consists of Computed Tomography (CT) scans images of lung nodules. The proposed model was able to achieve high accuracy in both lung cancer detection and classification tasks. The performance of the proposed method is evaluated using several performance metrics, such as accuracy, sensitivity, specificity, and F1-score. The experimental results demonstrate that the proposed ELM-based approach achieves high accuracy and outperforms other existing state-of-the-art methods for lung cancer detection and classification. This study suggests that the ELM-based approach can be a promising tool for accurate and efficient lung cancer diagnosis. The experimental results obtained from the model demonstrate the effectiveness of the proposed ELM-based model for lung cancer detection and classification, which could potentially assist medical professionals in early diagnosis and treatment planning for lung cancer patients.*

Keywords—Lung Cancer, CT-Scan, ELM, Accuracy, F1 Score, Sensitivity, Specificity

##### **I INTRODUCTION**

Cancer is a serious and has become one of the most dreadful diseases in the world causing many deaths around the globe. As per the most recent World Health Organization publication, cancer stands as the second primary contributor to worldwide mortality, accounting for approximately 9.6 million fatalities in the year 2018. Within this category of fatal cancers, lung cancer emerges not only as the prevailing form with 2.09 million instances but also as the leading cause of cancer-related deaths, responsible for 1.76 million demises. Early identification and treatment have the potential to curtail the mortality rate of lung cancer patients by 20%. The reported statistics indicate that individuals diagnosed and treated during the initial stage of cancer (when the cancer cells remain confined to the lung) have a 5-year survival rate of 63%. In contrast, those diagnosed at an advanced stage (when cancer cells have disseminated to distant body parts) have a significantly lower survival rate of merely 7%. We can distinguish the cancers generally range from being benign to malignant based on which proper treatment when provided to the patient can cure them. Pulmonary cancer, also known as lung cancer, involves the unregulated growth of abnormal cells in the lungs. These anomalous growths, termed nodules, must be identified in their initial phases to effectively manage the prevention of the cancer cells' subsequent dissemination. This, in turn, has the potential to enhance the survival prospects for patients afflicted by this condition.

Many medical experts and scholars have started to pay attention to the diagnosis and treatment of lung cancer and are provided with more funds in order to encourage them to conduct in-depth research on lung cancer, so that they are able to find or come up with an effective way to find prevention and required treatment. Presently, lung cancer can be categorized into two groups based on the extent of differentiation and morphological attributes: small cell lung cancer (SCLC) and non-small cell lung cancer (NSCLC). Within NSCLC, there exist three subtypes: squamous cell carcinoma, adenocarcinoma, and large cell carcinoma.

Smoking is identified as the primary culprit behind this lethal condition, and established research has unveiled smoking as the principal risk factor for emphysema. Similar investigations have also demonstrated that both the duration and quantity of smoking exert a wide-ranging impact on the progression of the disease. Given the underlying cause of this fatal ailment, it can be further subdivided into three additional types: Para-septal Emphysema (PSE), Centrilobular Emphysema (CLE), and Panlobular Emphysema (PLE). These three subcategories are linked with distinct pathophysiological implications.

Mainly, the investigation of lung cancer involves the analysis of radiographic images like X-rays, MRI, or Computed Tomography (CT) scans. The efficacy of radiography screening hinges on the ability of radiologists to pinpoint potentially problematic areas in the shape of lung nodules. This demanding responsibility becomes especially vital, particularly for diminutive lung nodules. From existing literature, it is evident that around 68% of lung nodules are accurately identified by a solitary radiologist. Most lung cancers develop from tiny malignant nodules. Radiologists commonly interpret chest CT scans to detect these malignant nodules, examining each slice individually. This method demands significant expertise, focus, and time, and it is both costly and susceptible to the influence of the operator's perspective. The identification of lung nodules in computed tomography (CT) images is a pivotal stage in diagnosing lung cancer. Achieving accurate lung nodule detection outcomes necessitates, and is often dependent on, first segmenting the lung parenchyma. This approach helps eliminate noise interference from areas outside the lung parenchyma by concentrating solely on that region. However, curbing false positive rates becomes more challenging in the absence of lung segmentation. Consequently, most techniques for lung nodule detection execute their analysis within the lung parenchyma that has been isolated using a separate independent method. To the best of our knowledge, no prior research has combined lung segmentation and nodule detection as distinct steps. As separate processes, if the segmentation of the lung parenchyma enclosing the nodules falls short, the potential to achieve accurate nodule detection outcomes diminishes.

Within CT images, pulmonary nodules manifest as rounded or oval-shaped lung tissue masses with a diameter under 30 millimeters. These nodules exhibit considerable diversity in terms of size, density, position, and immediate surroundings. Generally, pulmonary nodules possess a diameter surpassing 3 mm; those with diameters less than 3 mm are termed micro-nodules. Moreover, the rapid expansion of CT-based lung cancer screening has brought about a dramatic surge in the volume of images that physicians need to scrutinize. This surge has significantly augmented their workload, leading to potential diagnostic errors that result in unnecessary patient anxiety or reduced prospects for successful treatment.

In this paper, we propose a novel method and develop one model to discriminate between pulmonary micro-nodules and non-nodules from CT images with the help of ELM (Extreme Learning Model) which is a machine learning algorithm that falls under the umbrella of artificial neural networks. It's used for both regression and classification tasks. This model consists of input layer, hidden layer, output layer. ELM models are known for their computational efficiency and fast training times. They have been applied in various fields such as image and speech recognition, regression tasks, and more. However, the random assignment of hidden layer weights can sometimes make the model more prone to overfitting, depending on the dataset and the model's architecture.

The organization of the paper is arranged as follows: Section-1 will basically provide us with the information regarding the lunger cancer, its causes and detection of lung cancer with the help of CT scans and predicting them using ELM Classifier. Next in Section-2 various literature survey-related works of the pulmonary cancer has been discussed. In Section-3 we discussed about the methodology being used. In Section-4 the dataset we used has been described. In Section-5 the result obtained from the model is being described. In Section-6 conclusion of our paper is provided.

# II LITURATURE SURVEY

In [1]. [Onur Ozdemir](https://ieeexplore.ieee.org/author/37285612700).et.al(2019). have proposed a system that relies entirely on 3D convolutional neural networks, achieving leading-edge results for both lung nodule detection and the classification of malignancy in the given CT scans. Normally, systems for nodule detection are separately designed and refined, but it's crucial to acknowledge the interconnection between the detection and diagnosis aspects. Leveraging this interplay enabled us to create an integrated system that delivers enhanced and more consistent performance, eliminating the requirement for an additional stage to reduce false positives in nodule detection.

In [2]. Shanchen Pang .et.al (2019). have proposed a deep learning model to identify lung cancer type from CT images for patients in Shandong Provincial Hospital. It had a two-fold challenge first, existing artificial intelligence models trained on public datasets fell short of meeting practical demands, and second, the available patient data was limited. To address these two issues, they employed techniques such as image rotation, translation, and transformation to amplify and harmonize the training data. Subsequently, they applied densely connected convolutional networks (DenseNet) to distinguish malignant tumors in images sourced from the collected data. To further enhance classification accuracy, they employed the adaptive boosting (AdaBoost) algorithm to combine multiple classifications. This amalgamation resulted in an improved overall classification performance.

In [3] Sumita Mondal .et.al (2021) have developed a computer-aided technique using the improved deep learning strategy. The initial step involves preprocessing the images through histogram equalization and median filtering. Subsequently, segmentation is achieved using the Fuzzy C Means (FCM) clustering technique. Once segmented, a novel method called Adaptive Local Ternary Pattern (ALTP) is employed to extract pattern descriptors, which are then used for classification purposes. A distinctive contribution lies in the creation of the Parameter Optimized-Faster Region Convolutional Neural Network (PO-FRCNN) to facilitate the diagnostic process. To enhance both pattern recognition and deep classification, the Improved Red Deer Algorithm (IRDA) is applied. IRDA aids in refining significant parameters that positively impact the accuracy of the results.

In [4] Patrice Monkam .et.al (2019) ,have proposed a system to differentiate between micro-nodules and non-nodules in CT images by an ensemble learning of multiple-view 3D-CNNs.The pulmonary nodule candidates are cropped with five different sizes including 20 × 20 × 3, 16 × 16 × 3, 12 × 12 × 3, 8 × 8 × 3 and 4 × 4 × 3. Subsequently, five separate 3D-CNN models are constructed and applied to a specific set of nodule candidates. An extreme learning machine (ELM) network is employed to integrate the outputs of these five 3D-CNNs, resulting in the ultimate classification outcomes. These achievements far surpass the results achieved by 2D-CNNs, a single 3D-CNN model, and even the outcomes of state-of-the-art methods that were implemented using the same dataset. In terms of the ensemble approach, ELM outperforms majority voting, averaging, the AND operator, and autoencoder techniques. The amalgamation of multiple-view 3D-CNNs with ensemble learning significantly contributes to the exceptional identification accuracy, suggesting the potential for creating other dependable clinical decision support systems.

In [5] Anum Masood .et.al (2019),have developed a novel computer-aided decision support system for lung nodule detection based on a 3D Deep Convolutional Neural Network (3DDCNN) for assisting the radiologists. Their diagnostic aid system offers an additional perspective to radiologists during the process of making lung cancer diagnoses. To tap into the 3D details present in Computed Tomography (CT) scans, they utilized median intensity projection and a multi-Region Proposal Network (mRPN) to automatically identify potential regions of interest. This demonstrated the capabilities of deep learning, coupled with cloud computing, for precise and streamlined detection of lung nodules using CT imaging. Such advancements could potentially assist medical professionals and radiologists in effectively managing lung cancer patients.

In [6] Shouliang Qi et.al. (2019) have presented a comprehensive analysis of the CNN methods and their performances. Initially , they provide a concise introduction to the basic concepts of Convolutional Neural Networks (CNNs) and explain the rationale behind their effectiveness in analyzing medical images. Following this, a succinct depiction of diverse medical image datasets and the necessary infrastructure for conducting lung nodule investigations through CNNs is presented. Additionally, they offer detailed summaries of recent advancements in employing CNNs for the analysis of pulmonary nodules. Lastly, they address the current obstacles and potential avenues for enhancing the utilization of CNNs in medical image analysis, with a particular focus on assessing pulmonary nodules.

In [7] Imdad Ali .et.al. (2020), they proposed transferable texture Convolutional Neural Networks (CNN) to improve the classification performance of pulmonary nodules in CT scans. They have integrated an Energy Layer (EL) into the architecture, which is responsible for capturing texture characteristics from the convolutional layer. This addition of the EL component results in a reduction in the network's count of trainable parameters, subsequently leading to decreased memory needs and a less intricate computational process. The model they propose consists of solely three convolutional layers and one EL, replacing the conventional pooling layer.

In [8] Weihua Lui .et.al (2020) have proposed a deep multi-task learning (MTL) approach to integrate tasks for better lung nodule detection. Three new ideas lead to proposed approach. Initially, lung parenchyma segmentation is employed as the attention mechanism and is merged with nodule detection within a singular deep network. Subsequently, nodule detection in an anchor-free approach is executed by splitting it into two components: the identification of nodule centers and the regression of nodule sizes. Lastly, a new pyramid dilated convolution block (PDCB) is introduced to capitalize on the benefits of dilated convolution while addressing its issue of producing a grid-like pattern, thus enhancing the quality of lung parenchyma segmentation.

In [9] Yutong Xie .et.al. (2019), have proposed a multi-view knowledge-based collaborative (MV-KBC) deep model to separate malignant from benign nodules using limited chest CT data. The approach involves capturing the 3D attributes of lung nodules by breaking down a 3D nodule into nine predetermined perspectives. For each of these perspectives, a collaborative sub-model based on knowledge (KBC) is established. These nine KBC sub-models collectively participate in classifying lung nodules, employing an adaptable weighting technique learned during error back propagation. This mechanism allows the MV-KBC model to be trained holistically in an end-to-end fashion.

In [10] Linqin Cai .et.al. (2020), for the detection and segmentation of pulmonary nodule 3D visualization diagnosis were proposed based on Mask Region-Convolutional Neural Network (Mask R-CNN) and ray-casting volume rendering algorithm. The Mask R-CNN utilized resnet50 as its foundational architecture and incorporated the Feature Pyramid Network (FPN) to comprehensively analyze multiscale feature maps. In addition, the Region Proposal Network (RPN) was employed to suggest potential bounding boxes for candidates. Moreover, the mask matrices were combined with the original medical image sequences, yielding predicted sequences of pulmonary nodules. Ultimately, a ray-casting volume rendering algorithm was utilized to produce 3D models of the pulmonary nodules.

In [11] Chi Chong Nguyen .et.al. (2021),they propose a novel Computer Aided Detection (CAD) system based on Faster R-CNN model with adaptive anchor box for lung nodule detection. Their approach utilizes actual nodule sizes from the training dataset to create adaptable anchor box dimensions for Faster R-CNN. These learned anchor dimensions are then employed as a hyper-parameter to enhance the detection capabilities of Faster R-CNN. To mitigate the occurrence of false positives in the output of Faster R-CNN, they introduce a residual convolutional neural network.

In [12] Gai Li .et.al. (2020), They introduce a novel technique known as wavelet dynamic analysis to extract and enhance the lung parenchyma, thereby eliminating disruptive noise beyond the lung parenchyma. This algorithm aids in pinpointing lung nodules with increased precision. Subsequently, they employ both a convolutional neural network (CNN) optimized via genetic algorithm and a conventional CNN to extract features from CT images of pulmonary nodules. These distinct features among different images are automatically differentiated. Ultimately, the genetically optimized CNN is employed to identify and categorize the existing pulmonary nodule images, offering valuable guidance for the advancement of pulmonary nodule CT image detection technology.

##### III PROPOSED METHODOLOGY

1. Problem Statement

The detection and classification of pulmonary conditions through medical imaging are critical aspects of modern healthcare. Traditional diagnostic approaches often rely on manual interpretation of images, which can be time-consuming, subject to human error, and challenging to standardize. This project addresses these limitations by proposing an innovative solution that leverages cutting-edge image analysis techniques and machine learning algorithms to automate the detection and classification of various pulmonary conditions from pulmonary CT scan images.

1. Proposed System

The system used in this research consists of 5 main modules, namely pulmonary CT scans as the input image, pre-processing, segmentation, feature extraction and classification.

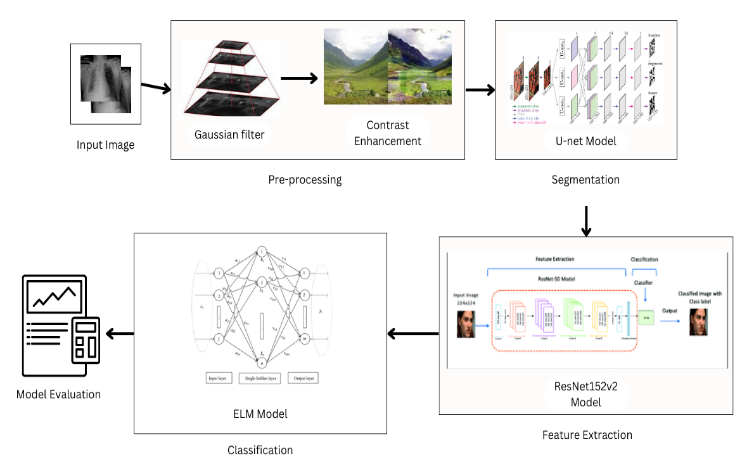


Figure 1

1. Load Images

This module is responsible for the initial step of importing and loading images into the system. It prepares the raw image data for further processing. This involves reading images from the files, and converting them into a format that can be manipulated by the subsequent modules.

The dataset consists of images of pulmonary CT scans which need to be classified into their respective classes. In this module, the system takes raw pulmonary CT scan images and prepares them for further processing and analysis. CT scan images are a type of medical imaging that provides detailed cross-sectional views of the body, making them valuable for diagnosing and monitoring various conditions, including pulmonary diseases. In this study the images used are the images of a patient’s pulmonary CT scan. The image is of the type png. Figure 2 is an example of the image used in this section.

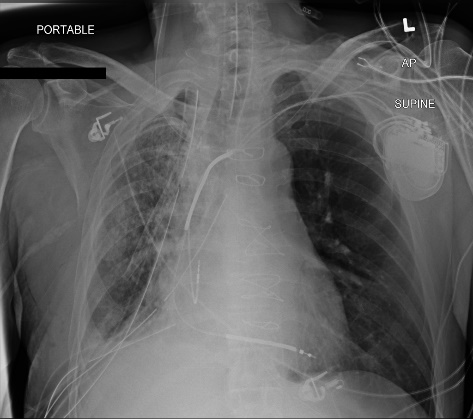


Figure 2

1. Pre-processing

The pre-processing module takes the loaded images and prepares them for segmentation. This step might involve various tasks such as resizing, noise reduction, contrast enhancement, and colour normalization. The goal is to improve the quality of the images and make subsequent tasks more effective and accurate.

Pre-processing is a crucial step in our system, as it lays the foundation for accurate and effective segmentation, feature extraction, and classification. In our system, pre-processing

involves two key techniques: Gaussian filtering and contrast enhancement.

1. *Gaussian Filter*

Gaussian filtering is a common image processing technique used to reduce noise and smooth out variations in pixel intensities. Noise can arise from various sources such as sensor limitations, compression artifacts, or environmental factors. The Gaussian filter works by convolving the image with a Gaussian kernel, which is a two-dimensional bell-shaped function. This has the effect of reducing high-frequency noise while preserving the overall structure of the image.

When applied, the Gaussian filter assigns higher weights to nearby pixels and lower weights to pixels farther away. This averaging effect helps to blur out random noise while maintaining the edges and important features in the image.

1. *Contrast Enhancement*

Contrast enhancement is a technique used to improve the visual quality of an image by increasing the distinction between different intensity levels. This is particularly important in cases where certain features of interest might be difficult to discern due to low contrast. By enhancing the contrast, you can make these features more prominent and easier to analyse.

Contrast enhancement techniques stretch or compress the intensity values of the image to make use of the full available range. Histogram equalization is a popular method for achieving this. It redistributes the pixel intensities in such a way that the resulting histogram is as uniform as possible, leading to improved contrast.

In our system, the pre-processing module plays a critical role in ensuring that the images are prepared for further analysis in a way that maximizes the effectiveness of subsequent modules. By applying Gaussian filtering and contrast enhancement, we are setting the stage for more accurate and robust segmentation, feature extraction, and classification, leading to more reliable results and insights.

**Benefits of Pre-processing with Gaussian Filter and Contrast Enhancement are many some of them are:**

1. **Noise Reduction:** Gaussian filtering effectively reduces noise in the image, which can lead to clearer segmentation and more accurate feature extraction.
2. **Smoothing:** The smoothing effect of Gaussian filtering can help eliminate small variations and irregularities in the image, resulting in a more uniform appearance.
3. **Improved Feature Detection:** Contrast enhancement makes subtle details and features more noticeable, enabling better detection of objects and regions during subsequent stages of analysis.
4. **Enhanced Visual Quality:** The combination of these techniques enhances the overall visual quality of the image, making it easier for human observers to interpret and analyse.
5. Segmentation

Segmentation is the process of dividing an image into meaningful and distinct regions or objects. It plays a fundamental role in image analysis and computer vision by isolating specific areas of interest for further processing, measurement, or analysis. In your system, segmentation is the third module, following image loading and pre-processing, and preceding feature extraction and classification.

A U-net model is used for the segmentation process. The U-Net architecture is specifically designed for semantic segmentation tasks. It is named after its U-shaped architecture, which consists of an encoding path (contracting path) and a decoding path (expansive path). The U-Net model excels at capturing both local and global context while preserving spatial information, making it well-suited for segmenting images with fine details, like medical images.

**Key Components of U-Net:**

1. **Encoder (Contracting Path):** This part of the network captures and compresses the input image's features, reducing spatial dimensions and increasing feature abstraction. It consists of convolutional layers, followed by downsampling operations such as max-pooling or strided convolutions.
2. **Bridge:** The bridge connects the encoder and decoder. It typically includes several convolutional layers that capture high-level semantic features, enabling the model to understand the context of the input.
3. **Decoder (Expansive Path):** The decoder takes the high-level features from the bridge and gradually upsamples them to produce a segmentation mask of the same size as the input image. This part of the network involves transposed convolutions (also known as deconvolutions or upsampling) and concatenation with feature maps from the corresponding encoder stage.
4. **Skip Connections:** U-Net employs skip connections between encoder and decoder stages. These connections enable the decoder to leverage information from multiple scales, helping in accurate localization and handling of fine details.

In our proposed system, the segmentation module uses the U-Net model to process the pre-processed pulmonary CT scan images and create pixel-wise segmentation masks. Each pixel in the mask is classified as belonging to a specific region, such as lung tissue, blood vessels, or potential lesions.

**Benefits of U-Net for Segmentation:**

1. **Semantic Understanding:** U-Net's architecture helps capture semantic understanding by combining local and global context, which is crucial for accurate segmentation.
2. **Localization:** Skip connections allow U-Net to precisely localize features, making it effective for identifying and delineating regions of interest.
3. **Adaptability:** U-Net can adapt to different levels of image detail, making it suitable for segmenting structures of varying sizes, such as small nodules and larger lung areas.
4. **Efficiency:** U-Net reduces the risk of undersegmentation (missing details) and oversegmentation (over-detailed results) due to its skip connections and multi-scale feature aggregation.
5. Feature Extraction

Feature extraction is the process of transforming raw image data into a set of relevant and meaningful features that capture the essential characteristics of the objects or regions in the image. These features serve as input for the subsequent classification step.

Feature extraction is a pivotal module in our system. We are utilizing a Multi-head Attention-based ResNet152v2 for this purpose.

**ResNet152v2:**

ResNet (Residual Networks) is a type of deep neural network architecture that introduced the concept of residual learning. Residual learning involves using shortcut connections, or skip connections, to allow the network to learn residual mappings instead of attempting to learn the full desired mappings directly. This architecture has proven highly effective in training very deep networks while mitigating the vanishing gradient problem.

ResNet152v2 is an extended version of the original ResNet architecture with 152 layers. It is a powerful and deep convolutional neural network (CNN) that has demonstrated exceptional performance in various computer vision tasks, including image classification, object detection, and segmentation.

**Multi-head Attention:**

Attention mechanisms are inspired by human visual attention and enable the network to focus on specific parts of the input data while ignoring irrelevant information. Multi-head attention is an extension of this concept, where multiple attention mechanisms are run in parallel, allowing the model to capture different types of relationships between features.

**Integration of Multi-head Attention and ResNet152v2:**

Integrating multi-head attention with a deep architecture like ResNet152v2 can yield several benefits:

1. **Enhanced Feature Learning:** Multi-head attention allows the model to focus on different aspects of the image simultaneously, capturing both local and global relationships. This can lead to more robust and representative feature extraction.
2. **Contextual Understanding:** Attention mechanisms enable the model to consider the context of each feature in relation to others, leading to a richer understanding of the image's content.
3. **Better Discriminative Features:** The combination of multi-head attention and ResNet152v2 can result in the extraction of features that are highly discriminative for distinguishing between different classes.
4. **Complex Patterns:** Deep architectures like ResNet152v2 excel at capturing intricate patterns in images, and integrating attention mechanisms can help in understanding the hierarchies and relationships within these patterns.

In our proposed system, the feature extraction module, driven by the Multi-head Attention-based ResNet152v2, takes segmented regions from the previous step and transforms them into a compact representation of key features. These features encode the distinctive attributes of each region, which are essential for accurate classification. By utilizing a Multi-head Attention-based ResNet152v2 for feature extraction, your system is poised to extract rich, contextually aware, and highly discriminative features from segmented regions, which can significantly contribute to the accuracy and effectiveness of subsequent classification tasks.

1. Classification

Classification is the final step in our system’s pipeline, where the system assigns a label or category to each segmented and feature-extracted region. The goal is to accurately determine the class or category of the objects or regions within the images.

The classification module of our system, utilizes an Extreme Learning Machine (ELM) for making predictions based on the extracted features.

**Extreme Learning Machine (ELM):**

Extreme Learning Machine is a machine learning algorithm that falls under the umbrella of neural networks. ELM is particularly known for its efficiency and simplicity in training. Unlike traditional gradient-based methods that iteratively adjust weights, ELM randomly initializes input weights and analytically calculates the output weights, which leads to a faster training process.

**Benefits of using an ELM for Classification:**

An ELM in our system for classification offers several advantages:

1. **Efficiency:** ELM's training process is typically faster than traditional iterative optimization algorithms, making it well-suited for real-time or resource-constrained applications.
2. **Single Hidden Layer:** ELM uses a single hidden layer, simplifying the architecture and potentially reducing the risk of overfitting.
3. **Universal Approximator:** ELM has been proven to be a universal approximator, capable of approximating complex functions with a relatively small number of hidden units.
4. **Non-linearity:** ELM can effectively capture non-linear relationships between features and class labels, allowing it to handle intricate and nonlinear classification boundaries.

In the proposed system, the classification module takes the high-dimensional feature representations generated by the Multi-head Attention-based ResNet152v2 and uses them as input for the ELM algorithm. ELM learns the relationships between the features and the corresponding class labels based on a labelled training dataset.

##### IV DATASET DISCRIPTION

The dataset is a comprehensive collection of 5606 medical images, specifically CT scans, covering a wide spectrum of diagnostic possibilities across 14 distinct classes. These classes encompass a diverse range of pulmonary conditions, including Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural Thickening, Pneumonia, and Pneumothorax.

The dataset is accompanied by two key files: "Sample\_labels.csv" and "data.csv." "Sample\_labels.csv" provides essential information regarding the labels assigned to each image within the dataset, offering a valuable reference for accurate classification. Meanwhile, "data.csv" offers additional insights into the classification attributes of each image, further enhancing the dataset's potential for rigorous analysis.

With its extensive collection of X-ray images and comprehensive label information, the dataset forms a foundation for in-depth research and development in the field of medical image analysis. The diverse classes and sizable image count provide ample opportunities for training, validating, and fine-tuning algorithms that can aid in the accurate and early detection of a range of pulmonary conditions. The availability of detailed class information enhances the dataset's suitability for building robust classification models, and its potential to contribute to advancements in diagnostic accuracy and patient care is substantial.

##### V RESULT

Measuring the performance of a model lies at the heart of assessing the effectiveness of its predictions and guiding the refinement process. In the realm of data science, where algorithms aim to make informed decisions based on data, evaluation metrics serve as the yardstick by which the model's accuracy and reliability are gauged. These metrics provide quantitative insights into how well a model aligns with the actual outcomes it seeks to predict. By examining various aspects of a model's performance, such as its ability to correctly classify instances, minimize errors, and adapt to different scenarios, practitioners gain a comprehensive understanding of its strengths and limitations. This critical evaluation ensures that the models are not only developed but also fine-tuned to deliver actionable and trustworthy results in real-world applications.

##### VI CONCLUSION

In this paper, we have proposed the detection of the pulmonary cancer detection from the given CT images. Firstly, the given datasets are extracted using multihead attention based ResNet152v2 which will help to extract the features required. Then the ELM Classifier is used to process the given dataset and further classify it which would enable to efficiently detect the pulmonary nodules from the given images. We carried out the experiment from the obtained dataset and the experiment results show that our model achieved a better classification result over the given set of images where the accuracy was of 98.0%, F-score of 92.20%. Based on these values we can say that our model can detect pulmonary cancer more accurately which can assist the radiologists to obtain the diagnosis results more easily, simplify the long procedure for lung cancer diagnosis, improve their accuracy of prediction and furtherly reduce any misdiagnosis being done.

##### Acknowledgments

“Acknowledgment(s)” is spelled without an “e” after the “g” in American English.

As you can see, the formatting ensures that the text ends in two equal-sized columns rather than only displaying one column on the last page.

This template was adapted from those provided by the IEEE on their own website.

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