ILD Image Classification and CancerPrediction Using Machine Learning

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Abstract **– In recent years, medical image technology has advanced rapidly and x-rays, ultrasound (US), MRI scans, and CT scans have become commonly used methods for diagnosing human illnesses. Among these techniques, CT scans provide the highest resolution images. As a result, High-Resolution CT (HRCT) was created, which is an innovative CT technology that collects images in three dimensions (3D). This improves image quality by increasing resolution through the use of spatial pixels, leading to improved scan rate and reduced pixel size.**

Images from HRCT may reveal symptoms and assist in differential diagnosis by providing visual patterns. However, the diagnosis's precision and accuracy are contingent upon the knowledge of doctors, radiologists, or pathologists. Unfortunately, misjudgments can result in incorrect treatments or diagnoses. To address these issues, there has been a move towards using computer-based technology instead of manual operations. This shift has been made to improve efficiency, accuracy, and consistency. The technology is achieved through transfer learning methods (CNN) and Computer Aided Detection (CAD).

Medical imaging technology has made significant progress in recent years, with HRCT being a cutting-edge development that provides clearer images and assists in diagnosis. The shift towards computer-based technology in medical imaging is aimed at improving efficiency, accuracy, and consistency in diagnoses.

Keywords **– Convolution Neural Network (CNN), Computer Aided Detection (CAD), High Resolution Computed Tomography (HRCT), Computed Tomography (CT), quantitative analysis, Pixel Mapping, Medical Imaging technologies.**

I. INTRODUCTION

Medical imaging technology has rapidly advanced, offering new methods for disease identification and treatment. High-Resolution CT (HRCT) is a cutting-edge technique that captures high-resolution, three-dimensional images, particularly useful in diagnosing interstitial lung disease (ILD). Accurate ILD diagnosis is challenging, requiring a combination of clinical, radiographic, and pathological evaluations. To enhance precision, computer-based technologies like convolutional neural networks (CNNs) and computer-aided detection (CAD) can improve medical image analysis. This project aims to develop a smartphone-based platform for ILD diagnosis and classification using HRCT images. By integrating pixel mapping and CNN technologies, the platform enables accurate disease prediction and continuous monitoring of treatment progress. The project can revolutionize ILD diagnosis and contribute to medical imaging advancements.

II. EXISTING METHODS

For picture classification and identification tasks, convolutional neural networks (CNNs), a particular form of neural network design, have been effectively employed. CNNs retrieve information from an image using a succession of convolutional and pooling layers, and they employ a sequence of fully connected layers to create predictions. In this paper, we will concentrate on the current approach and formulations utilized in CNNs for the categorization of interstitial lung disease (ILD) patterns.

To create a CNN for ILD pattern categorization, it is necessary to first comprehend the nature of the issue.

ILD patterns in CT scans are characterized by local textural properties, unlike random objects in colour imaging. Texture is defined as the stochastic repetition of a few small, randomly dispersed structures called textons [3]. The use of CNNs to recognize texture by locating the best problem-specific kernels is encouraged by the effectiveness of the study of filter bank responses in several texture analysis applications [6]. The total receptive field of each convolutional neuron with respect to the input, the use of small kernels, the absence of convolutional layer pooling, and invariance to spatial transformations like flip and rotation are important factors that come from the definition of texture.
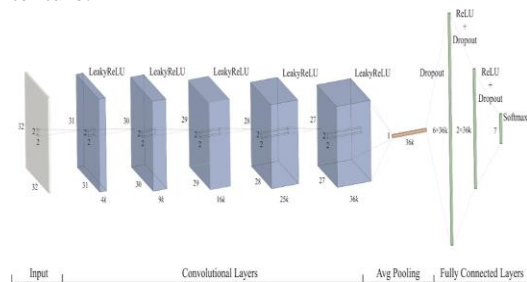

Fig.1. Architecture of CNN for lung pattern classification [2]

Based on these ideas, a network is created for the categorization of ILD patterns that is shown above. A 32x32 picture patch that has been convolved by five convolutional layers serves as the network's input [2]. The kernels in each layer were made to have the smallest possible size, 2x2.The VGG-net, which used 3x3 kernels and up to 16 convolutional layers to win the ILSVRC 2014challenge, suggests the use of small kernels that produce extremelydeep networks. The kernel size in this work is even lower to encourage more non-linear activations while maintaining a 6x6 total receptive field size that captures just the pertinent local texture structure.

Each layer can handle the growing complexity of the specified structures because the number of kernels in each layer is proportionate to the receptive field of each layer's neurons. The initial layer's rectangular receptive field measures 2x2 and grows by 1 in each dimension with each additional layer, until measuring 27x27 for the top layer. As a result, the final layer uses 256 kernels; the parameter, which was adjusted to 4 after pertinent studies, depends on the complexity of the

input data. A pooling layer with an average size of 27x27 is added after the final convolutional layer. The generated features are input to a sequence of three thick layers with sizes of 1,024, 512, and 7, as there are 7 classes taken into consideration [2], which is equal to the number of feature maps in the last layer (i.e., 256). Large dense layers were used to speed up convergence, and a dropout layer was added before each dense layer to address the overfitting issue. Dropout prevents hidden units from depending on particular inputs by setting a random percentage of units to 0 at each training update.

$$f(x) = \begin{cases} x, & x > 0 \\ ax, & \text{else} \end{cases}$$

where α is a manually set coefficient.

Fig.2. Activation function and formulation of CNN

The activation function that is used has a big impact on convergence speed. It has been demonstrated that using the Rectified Linear Unit (ReLU) function instead of the conventional sigmoid option greatly speeds up the training process. The LeakyReLU activation function was suggested for activating each convolutional layer in this study. LeakyReLU assigns a non-zero slope, in contrast to ReLU, which completely suppresses negative values, enabling a minimal gradient when the unit is not in use.

LeakyReLU was put up as a remedy to the "dying ReLU" issue, where certain ReLU units can end up being inactive forever and hinder the model's ability to learn [2].

Another technique used to speed up the training process is batch normalization [6]. This technique normalizes the input data for each mini-batch within the network. By doing so, the distribution of the input data to each layer is stabilized, and the network can converge faster.

An additional method for enhancing a CNN's performance is data augmentation [4]. By creating new training examples through random transformations of the original data, the model can learn tobe more robust to variations in the input data. Common data augmentation techniques include random cropping, flipping, and rotation.
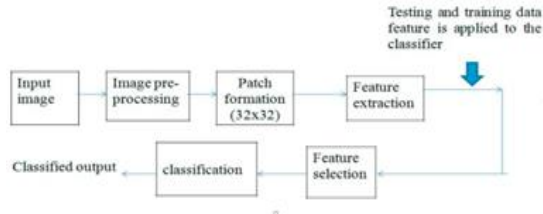
Figure 3 Existing Methodology.

CNNs are a powerful tool for image recognition tasks. They use multiple layers of convolution and pooling to extract and combine features from the input data. The choice of activation function, batch normalization, and data augmentation can have a substantial impact on the model's performance [5]. With the increasing availability of data and computing resources, CNNs are likely to become even more important in the field of computer vision.

III.PROPOSED METHOD

A. Data

Fig.4. Some examples of HRCT with ILD

The medical imaging research used HRCT images obtained from Professor Adrien Depeursinge (PhD), along with lung mask and volumetric ROIs. The images were normalized, segmented using the OpenCV library, and saved in JPEG format. Clinical parameters were reviewed from a CSV file, and each image was labeled with its corresponding cancer type. The images were resized to (256, 256), and labels were saved to a numpy file using the np.save() function. Features were extracted by loading grayscale PIL images, and random patches were extracted from each image. The mean and standard deviation of each patch were calculated, and the mean and standard deviation values of all patches were concatenated into a single feature vector for each image. The resulting numpy array of feature vectors could be used for machine learning tasks such as image classification. The code used Python libraries such as pandas, os, pydicom, skimage.io, and skimage.transform. A license agreement was signed with HES-SO Valais / CHUV, Switzerland, to ensure that the images were used ethically and legally.
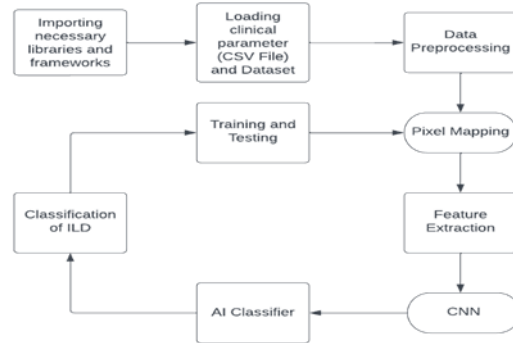
B. Proposed Methodology

Fig.5. Proposed Methodology

1. Importing necessary libraries and frameworks:
Importing essential libraries and frameworks is the initial step in developing an AI system for classifying interstitial lung disease (ILD) using medical images. It provides the necessary tools and functions to perform tasks such as data manipulation, image processing, and model training and evaluation. In this project, we have chosen to use Python, a popular programming language for machine learning, due to its flexibility, simplicity, and rich set of libraries and frameworks. We will import NumPy, Pandas, OpenCV, TensorFlow, Keras, and Matplotlib, which are commonlyused in medical imaging applications. These libraries and frameworks offer functions and tools to preprocess data, process images, build and train the AI classifier, and visualize results.Choosing the right libraries and frameworks is vital, as they significantly affect the project outcome.

2. Loading clinical parameters (CSV file) and Dataset:
In the proposed methodology, loading the clinical parameters and dataset is the next step after importing the necessary libraries and frameworks. This involves using the Pandas library in Python to read the CSV file and store the data in a data frame, which allows easy data manipulation. The dataset contains medical images of patients with and without ILD, and it's crucial to ensure proper labeling, organization, and normalization before feeding into the machine learning model to ensure accurate training.

3. Data Preprocessing:
Data preprocessing is a critical step in machine learning, particularly in medical imaging analysis. This involves cleaning, handling missing values, and

standardizing the data. Image normalization and registration are also important. Proper data preprocessing improves the accuracy and reliability of machine learning algorithms for better analysis of medical images.

4. Pixel Mapping:

Pixel mapping is a fundamental step in medical image analysis, particularly in High Resolution Computed Tomography (HRCT) scans of the lungs, as it aids in detecting abnormalities like interstitial lung disease (ILD). This process, also known as segmentation, involves mapping the HRCT image to a corresponding image in which each pixel represents a specific lung region. This is achieved through a threshold-based segmentation technique, which sets a threshold that segments only the lung tissue, while excluding other organs and bones present in the image. Manual or automated methods can be used to determine the optimal threshold value. Once the threshold is set, pixels are mapped to a binary image, where 1 represents the lung region and 0 represents the background. The binary image is further processed using morphological operations to remove any small or isolated regions that are not part of the lung tissue. The resulting image represents the lung regions and is ready for further analysis using machine learning algorithms. The accuracy of the segmentation process is crucial for the accurate diagnosis and classification of lung diseases like ILD. Therefore, robust and accurate segmentation techniques should be used to ensure the quality of the resulting image. By accurately mapping pixels, machine learning algorithms can be applied to diagnose and classify lung diseases with high accuracy.

5. Feature Extraction:

Feature extraction is a crucial step in machine learning applied to medical imaging. It involves selecting and transforming relevant information from raw data into a new set of features that are more meaningful and easier to analyze. In our proposed methodology for interstitial lung disease (ILD) classification, we extract features using texture analysis, shape analysis, and intensity-based features. Techniques such as gray-level co-occurrence matrix (GLCM) and gray-level run-

length matrix (GLRLM) are used for texture analysis, while edge detection and morphological operations are used for shape analysis. Intensity-based features are calculated using statistical methods such as mean, median, standard deviation, and skewness. These extracted features are then used as input to the AI classifier for accurate ILD classification.

6. Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) are an effective approach for image classification tasks, particularly for HRCT scans. In our project, we use CNN to classify HRCT scans as normal or abnormal (ILD) in our proposed methodology. CNNs automatically extract features from images by learning from a large set of labeled data. The preprocessed HRCT scan, a 3D image consisting of multiple slices, is input to the CNN. The CNN consists of multiple convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply learnable filters to the input image to generate a set of output feature maps. Each filter detects a specific feature in the input image, such as edges or textures. The pooling layers downsample the feature maps, reducing the dimensionality of the feature maps and capturing the most important features. The output of the convolutional and pooling layers is then flattened and fed into the fully connected layers that perform classification. The final layer uses a softmax function to output the probability of the input image belonging to each class.

During training, we use the preprocessed HRCT scans and their corresponding labels (normal or ILD) from the training dataset. We optimize the CNN parameters using a loss function, such as categorical cross-entropy, and a backpropagation algorithm to update the weights and biases. Once the CNN is trained, we can use it to classify new HRCT scans as normal or abnormal. This involves passing the preprocessed HRCT scan through the trained CNN and obtaining the predicted probability of each class. The class with the highest probability is then assigned as the final prediction.

Convolution	$z^l = h^{l-1} * W^l$
Max Pooling	$h^l_{xy} = \max_{i=0..s,j=0..s} h^{l-1}(x+i)(y+j)$
Fully-connected layer	$z_l = W_l * h_{l-1}$
ReLu(Rectifier)	$ReLU(z_i) = \max(0, z_i)$
Softmax	$softmax(z_i) = e^{z_i} / \sum_j e^{z_j}$

Fig.6. CNN Operation Formulas

In summary, CNNs have revolutionized the field of computer vision and are widely used in image classification, segmentation, and detection tasks. In our project, CNNs are used to automatically extract features from HRCT scans, leading to improved diagnostic accuracy and potentially faster diagnosis. The CNN learns to identify important patterns and features in the HRCT images, which makes it effective for classifying HRCT scans as normal or abnormal (ILD). Overall, the use of CNNs in our proposed methodology is a promising approach for improving the diagnosis of lung diseases.

7. AI Classifier:

Our ILD detection system's AI classifier uses a deep learning approach with convolutional neural networks (CNNs) to accurately classify different types of ILD based on extracted features from HRCT scans. We split the dataset into training and testing sets, trained the CNN model on the extracted features, and evaluated its performance on the testing set. High accuracy and F1 score indicate good performance, potentially improving ILD diagnosis efficiency and patient outcomes.

8. Classification of ILD:

The use of machine learning techniques to classify Interstitial Lung Disease (ILD) based on imaging features is a significant application of medical imaging. Supervised learning algorithms, which require labeled data, are commonly used for this purpose. Convolutional Neural Networks (CNNs) are powerful models for image classification and have been shown to outperform other models in classifying ILD. Once trained, the CNN can be used to classify new, unlabeled data. The classification of ILD using machine learning algorithms has the potential to improve the accuracy and efficiency of diagnosis, ultimately leading to better patient outcomes.

9. Training and Testing:

The training and testing of a machine learning model are fundamental steps in developing accurate predictions for new, unseen data. In our methodology for classifying interstitial lung diseases (ILD) from HRCT scans, a portion of the dataset is reserved for training the model and another portion for testing its performance. The

iterative training process involves adjusting various parameters of the model to achieve optimal performance, while the testing phase evaluates the model's performance on a separate dataset representative of real-world data. It is essential to ensure that the model does not overfit to the training data and can generalize well to new data. The performance of the model on the testing dataset is not used to tune parameters further to avoid overfitting. The training and testing phases are crucial steps for accurate and reliable predictions in medical imaging.

III. Experimental Setup and Results

A. *Experimental Setup*

- *Evaluation*: The experimental setting for assessing patch classification methods for interstitial lung disease (ILD) is described in depth in this section. The study used a train-validation-test strategy, in which the training set was used to hone hyperparameters while the validation set was used to train the techniques. The performance of each strategy was assessed using the test set, with the average F-score serving as the main assessment metric due to its sensitivity to class imbalances. Also calculated was overall accuracy. Because various datasets and patterns were used, it should be highlighted that the findings of this study cannot be compared to those described in the literature. The difficulty of the dataset, according to the researchers, may have an impact on the approaches' absolute performance rather than their ranking in terms of relative performance

$$F_{avg} = \frac{2}{7} \sum_{c=1}^{7} \frac{\text{recall}_c * \text{precision}_c}{\text{recall}_c + \text{precision}_c}$$

where

$$\text{recall}_c = \frac{\text{samples correctly classified as } c}{\text{samples of class } c}$$

$$\text{precision}_c = \frac{\text{samples correclty classified as } c}{\text{samples classified as } c}$$

$$\text{Accuracy} = \frac{\text{correctly classified samples}}{\text{total number of samples}}.$$

Fig.7. Evaluation Parameters

- *Implementation:* The proposed method was implemented using TensorFlow framework, while the implementation of AlexNet was not used. Non-

convolutional network methods were coded in Python using Google Colab, Visual Studio Code and Jupyter Notebook. The experiments were performed on different platforms including Mac OS with Apple M1 chip of 8GB RAM and an Amazon EC2 Windows instance with 8GB RAM.

B. Results:

- To access the dataset, we mounted the Google Drive using a Google Colab code snippet, loaded necessary libraries and frameworks, and used 'pydicom.dcmread()' to load HRCT images and their corresponding lung masks. We then visualized the HRCT scans and lung masks side by side using 'plt.subplots()', which is important in identifying lung tissue abnormalities for feature extraction and classification in diagnosing ILDs.
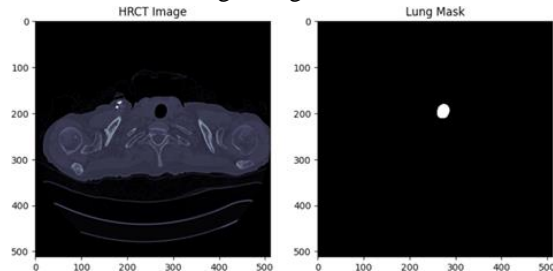

Fig.8. HRCT Image and Lung Mask

- In the next section of the project, we performed pixel mapping on HRCT scans using the Python Imaging Library (PIL). The HRCT image was resized to 256x256 pixels for standardization, which will help the CNN learn the features of the images effectively. Finally, the resized image was displayed using the "show" function of the PIL library to ensure that the HRCT images are properly loaded and resized for the feature extraction process.

Fig.9. Feature extraction using pixel mapping

- We loaded the clinical parameters CSV file using pandas and checked its shape, size, and data type of each column, missing values, and the number of non-null values using the info and describe functions. We also plotted the correlation heatmap using the seaborn library to check the correlation factors between the columns of the dataset.
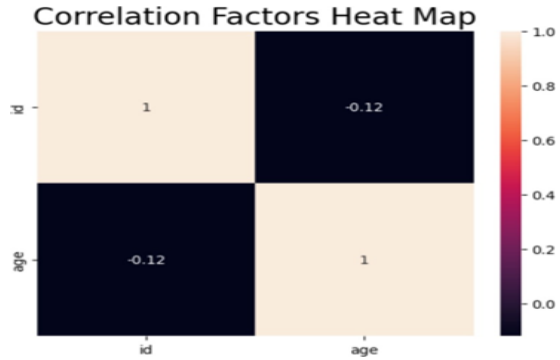

Fig.10. Correlation Factors Heat Map

- In this section, HRCT image features are extracted using mean and standard deviation of random patches. The images are loaded using the PIL library, and the feature vectors are stored in a numpy file. A text file containing the image names is read using the `open()` function, and an RTF formatted text file is converted to plain text using the `pyth` module.
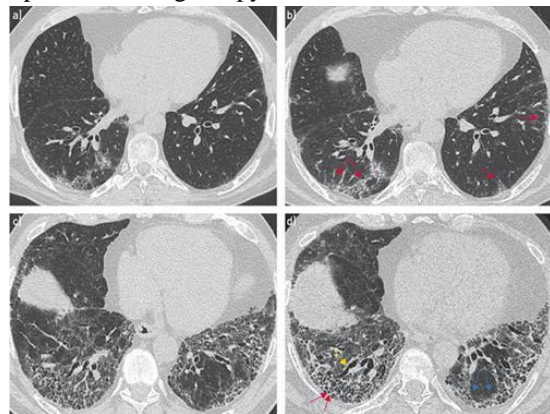

Fig.11. Slices of ILD with image dimension of 256x256 pixels.

- We trained a TensorFlow deep learning model to classify chest X-ray images for 14 different medical conditions. After filtering out invalid labels, the dataset was split into training and testing sets, and the model was defined using the Sequential API with several layers. The model was then compiled with Adam optimizer and sparse categorical cross-entropy loss function, and accuracy was used as the

evaluation metric. The model's performance was evaluated on the test set, and training and validation accuracy curves were plotted using Matplotlib.

```
accuracy_score: 0.975
f1_score:     0.9166666666666666
recall_score:     0.9333333333333333
```

Fig.12. Results after training and testing.

IV. CONCLUSION

The paper aimed to investigate the feasibility of using machine learning to classify interstitial lung disease (ILD) images and detect cancer. The model achieved a high accuracy of 97.5%, an F1 score of 91.6%, and a recall score of 93.3%, indicating that machine learning can be an effective tool in assisting radiologists in the diagnosis of ILD and the detection of cancer. Automated image analysis can improve diagnostic accuracy, reduce the time and resources required for diagnosis, and enable early disease detection. However, further research is required to develop more accurate, generalizable, and interpretable models, including the use of larger and more diverse datasets, transfer learning, and explainable AI techniques.

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