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SWIN TRANSFORMER FOR CYSTIC FIBROSIS DETECTION: A NOVEL APPROACH FOR EARLY DIAGNOSIS

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Abstract

Objectives: This study aims to introduce an innovative approach to diagnose cystic fibrosis (CF) utilizing Swin Transformer (Swin-T) technology. The objective is to create a computer vision system that can precisely detect CF in medical imaging examinations such as chest CT scans or X-rays, achieved by training a model with a curated set of labeled medical images.
Methods: Researchers utilized Swin Transformer technology alongside a dataset of annotated medical images to train the CF diagnostic model. Through the application of computer vision techniques, images from chest CT scans or X-rays were analyzed, leading to the development of a classification model capable of differentiating between CF and non-CF conditions. The model's effectiveness was evaluated using various performance metrics including accuracy, precision, recall, F1 score, and ROC curve analysis.
Findings: The study revealed that the proposed method based on Swin-T achieved a detection accuracy of 93.7% on the LUNA16 dataset, surpassing existing algorithms in the early detection and diagnosis of cystic fibrosis. Notably, the model exhibited a consistent capability to identify early stages of CF and distinguish them from non-CF conditions, suggesting its potential for practical implementation in CF diagnosis.
Novelty: The novelty of this research lies in the development of an innovative approach to CF diagnosis employing Swin Transformer technology. By harnessing computer vision techniques and a comprehensive dataset of annotated medical images, researchers successfully trained a model with the ability to accurately identify CF in chest CT scans or X-rays. This study contributes to advancing the field of medical imaging and underscores the promise of deep learning methodologies in enhancing the early diagnosis and detection of hereditary diseases such as cystic fibrosis.

Keywords: Cystic fibrosis, deep learning, Swin transformer, pulmonary diseases, Transformers, Cystic fibrosis transmembrane conductance

1. Introduction

A genetic condition that affects the lungs and digestive tract is called cystic fibrosis (CF). It results in the accumulation of thick, sticky mucus in the digestive system and lungs, which can cause breathing difficulties, poor growth, and stomach issues in addition to recurrent lung infections. Middleton et al. (2019) and Rey et al. (2019) have described CFTR modulators, which are small chemical medicines that target the underlying cause of cystic fibrosis (CF) as a result of the sequencing of the CFTR gene. The main goals of treatment are to control symptoms with medicine, chest physical therapy, and dietary assistance. Despite the lack of a cure, CF patients now live longer and have higher quality of life thanks to medical improvements.

Deep learning algorithms have become increasingly potent tools for medical image processing in recent years, with the potential to improve diagnostic efficiency and accuracy. Of these methods, Swin Transformer (Swin-T), a unique architecture for visual identification tasks, has attracted a lot of attention because to its efficaciousness in capturing contextual information and long-range dependencies inside images. To increase the precision and efficacy of CF diagnosis, this work suggests a unique use of Swin Transformer technology for identifying FC zones in medical imaging data. Main aim is to overcome the shortcomings of conventional techniques and obtain more reliable and accurate FC detection by utilizing the special powers of Swin-T, such as its self-attention mechanism and hierarchical attention mechanism.

The key contributions of proposed work are listed as follows:

- The study presents a novel diagnostic strategy called Swin-T, which stands for the Swin Transformer, a kind of deep learning model created especially for the early diagnosis of cystic fibrosis.
- This is a novel use of sophisticated deep learning architectures in medical picture analysis, with a focus on the CF-affected respiratory system. The stages listed below are used by Swin Transformer in the detection process.
    - ➢ Load the dataset; preprocess it using the necessary format (patches, normalization, etc.).
    - ➢ Launch the Swin Transformer model and load any previously trained weights.
    - ➢ Assemble the model by defining the metrics, loss function, and optimizer.
    - ➢ Train the model on the dataset.
    - ➢ Assess the model using a test or validation dataset.
- The proposed Swin Transformer works well on image classification identification tests and finds regions of cystic fibrosis in medical pictures with accuracy. Compared to the CNN, RNN, DenseNet, and Inception models, it performs substantially better.

The paper's remaining content is structured as follows: Section 2 reviews recent related state-of-the-art research. Section 3 provides a detailed description of the proposed Swin-T technology Section 4, proposed approach is tested, compared with alternative methods. Lastly, Section 5 summarizes the findings and scope of the study.

2. Related works

Although it was always thought to be a childhood condition, cystic fibrosis is now progressively becoming an adult condition. According to Hughan et al. (2019), the move to an adult care center is now a significant milestone for patients and their families, and new factors in illness management must be considered, such as employment, desire for marriage, and parenting. According to Vekaria et al. (2019), there has been a gradual rise in the number of pregnancies and paternities linked to CF patients. As a result, evaluating the safety of CFTR modulator therapy during pregnancy and lactation has become more difficult. There are various methods for estimating survival in cystic fibrosis (CF), and the medical community, as well as patients and their families, frequently find the language employed in this sector to be convoluted and perplexing. Nonetheless, in order to give patients the right information, doctors must be able to distinguish between the various measurements. Keogh and Stanojevic (2018) have released a very thorough guide to help standardize the presentation of survival data in CF patient registry reports and to make it easier to evaluate the projected median age of survival in cystic fibrosis. Regretfully, not all patients with CF may take use of these extremely potent modulator medications because their (rare) mutation is not covered by insurance. A number of pharmaceutical companies are developing modulator therapy at this time. In addition, 16 different nations are participating in a European study known as "Human Individualized Treatment for CF" (HIT-CF). By evaluating the mini-guts (organoids) of these patients in vitro and forecasting their clinical medication response, the initiative aims to deliver modulator medicines to pwCF with (ultra)-rare mutations (Lammertyn et al., 2020). For up to 90% of people with pwCF, the introduction of these CFTR modulators will be a lifesaver.

The general increase in life expectancy presents new difficulties and necessitates the development of fresh approaches to long-term problem prevention. For example, it is well recognized that pwCF has a comparatively high prevalence of anxiety and depression, and that beginning a modifying medication may exacerbate symptoms even when overall health improves. Thus far, research by Taylor and Jain (2021) suggests that modulators can be used safely, but additional information is required. Dietary recommendations also need to be modified. When using a modulating medication, pwCF has significant weight gain, which should raise awareness of the obesity issue. As people with CF age, there will be a greater chance of intestinal cancer and cardiovascular problems, which will necessitate the development of early therapies and preventive screening programs (Burton et al., 2021; Kartal et al., 2020). A two-year research comparing the results of non-responders and short-term responders to the pre-treatment baseline was conducted. This provided compelling evidence that ivacaftor is advantageous even in the absence of observable short-term increases in ppFEV1 and/or BMI. According to Heltshe et al. (2018), the greatest result was a 50% decrease in pulmonary exacerbations before and after ivacaftor treatment. After 5.5 years of ivacaftor by Guimbellot, long-term data in a G551D population demonstrates a sustained effect on numerous outcome levels, including lung function (2020).

Additionally, there is proof that ivacaftor medication improves hepatic statuses in those with liver illness due to cystic fibrosis and insulin secretions in those with impaired glucose tolerance. The European Medicines Agency (EMA) reduced the minimum age to four months in September 2020. An important study conducted in a ferret model revealed that medication administered in utero could partially halt the progression of illness until the treatment was stopped.A Swin-PANet model with dual supervision and a coarse-to-fine approach was presented by Liao et al. in 2022. It is made up of a hybrid transformer network and a prior attention network. Direct learning is carried out by the hybrid transformer network with increased attention blocks, while intermediate supervisory learning is carried out by the swin transformer-assisted prior attention network. Additionally, the encoder and decoder of the hybrid transformer network are connected via a skip link. Zhang et al.'s (2021) goal was to extend the capabilities of vision transformers so that they could be applied as a reliable feature learner for 3D CT COVID-19 diagnosis. Li et al. (2020) developed a framework that consists of two main stages: lung segmentation and image classification utilizing Swin transformer as a foundation. This approach was motivated by the success of Swin vision transformer and CT classification work by Wang et al. (2020). Using a pre-trained Unet, lung segmentation in CT scans is done in the first stage. This results in a lung mask that limits learning to certain lung regions. A max-pooling layer is used to aggregate the features from each 2D CT slice into 3D volume level features after a Swin vision transformer has extracted the features from each slice. Nevertheless, it's important to note that, based on the validation dataset findings; the framework using the core of EfficientNetV2-M provides a good speed-accuracy tradeoff. This suggests that in further research, a simple increase in model size could lead to an improvement in categorization.

3. Methodology

A recent development in the realm of deep learning is the Swin Transformer, which was created expressly to overcome the shortcomings of conventional Transformers when it came to processing massive amounts of image data. Due to its effectiveness and efficacy, the Swin Transformer is a particular kind of transformer model that has been modified for vision applications, such as picture classification, and it has been gaining popularity. The Swin Transformer uses the transformer design to photos by first splitting the image into patches and then processing these patches through a series of transformer blocks, in contrast to standard transformer models that are applied directly to text sequences.

One of the main innovations of this architecture is the "Shifted window," which is represented by the "Swin" in Swin Transformer. Compared to applying self-attention throughout the image, it drastically lowers computational complexity by dividing the image into windows and applying self-attention within these windows. Moreover, it moves these windows in later layers, facilitating cross-window relationships and improving the model's ability to represent the world context. The section discusses the methodology for swin-T based Cystic Fibrosis Detection that involves several key steps.

3.1 Preprocessing of Dataset

The reduction of image acquisition artifacts and the standardization of images throughout a data set are the primary objectives of medical image preprocessing. Denoising, intensity normalization, and background removal are examples of preprocessing procedures.

3.1.1 Background Removal

Segmenting the area of interest from the image background is the first step in background removal. By restricting the image to the area of interest, target workflow's accuracy and efficiency is increased. Applying a mask of the region of interest that construct using morphological operations or other segmentation approaches is usually how background removal is done. These background removal approaches ensure consistency and make it easier to extract useful information related to different medical disorders, such as cystic fibrosis identification, from medical images before further analysis.

3.1.2 Smoothing filter

The primary purposes of smoothing filters are to minimize blurring and noise in images. Before extracting features, the image's unnecessary information is blurred out. In this work, blood vessel spots in the image are reduced using smoothing filters, such as median filters. Equation (1) represents the median function.

$$(x, y) = \frac{1}{2\pi\sigma} e^{\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

The pixel intensity value that is situated inside the kernel at s and t coordinates is represented by the symbol g(s, t). The intensity value located on the x and y coordinates is represented by the xy notation.

3.1.3 Intensity Normalization

By standardizing the range of picture intensity values throughout a data collection, intensity normalization is achieved. There are two steps to doing this. First, reduce the range of intensities. Second, set the clipped intensity range to match the picture data type range, e.g., [0, 255] for unit or [0, 1] for double. Equation (2) defines the Histogram Equalization (HE) function that is applied to an image having a k-bit grayscale.

$$K_O = round(\frac{C_i.(2^k-1}{w.h}) \tag{2}$$

Ci is the cumulative distribution of the grayscale values of the original image on i-pixel, and Ko is the outcome of the histogram equalization. The function round will rounds to the next whole number. W and H stand for the image's width and height, respectively. This method separates the pertinent anatomical data from the surrounding context in an efficient manner. The accuracy and speed of diagnostic processes can be improved by properly identifying the region of interest linked with lung structures. This allows for the emphasis of following computer analyses, such as cystic fibrosis identification, on the clinically significant areas.

3.1.4 Segmentation

The technique of dividing an image into several sections in order to distinguish interesting structures from the background is known as segmentation. Segmentation techniques are utilized to isolate the lungs or particular regions within the lungs in the context of cystic fibrosis detection. Thresholding, region growth, and edge-based approaches are examples of common segmentation techniques.

3.2 Cystic fibrosis detection using a Swin Transformer

The Swin Transformer algorithm uses a hierarchical framework to analyze images in a patch-based fashion. The major steps of the Swin-T algorithm are as follows:

3.2.1 Patch Partitioning

Consider the following: H is the height, W is the width, and C is the number of channels (RGB channels) in the input image. Separate the input image into patches that don't overlap. Initially, the RGB CT scan image is divided into a number of distinct, non-overlapping patches. Each patch in the Swin Transformer arrangement is 4 × 4 in size, and since each pixel has RGB three channel values, each patch has a dimension of 4 × 4 × 3. A linear embedding layer then converts each patch into a C dimensional feature matrix. Every patch has a fixed P×P size. N patches are produced by the division of the image into a grid of patches, where N = (H/P) x (W/P). By stacking multiple blocks, the second stage block captures deep properties. To learn picture features, four attention blocks are repeated. The designated space is projected with the processed patches. The input feature was first split using linear embedding into the C dimension before being passed to the Swin Transformer Block.

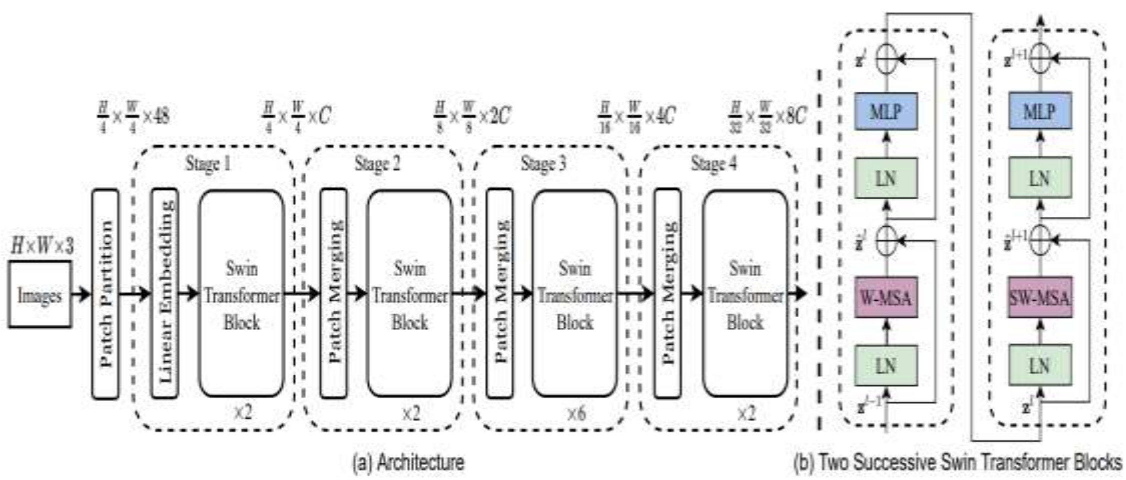

Figure 1. *The architecture of a Swin Transformer (Swin-T); (b) two successive Swin Transformer Blocks*

Two cascading Swin Transformer modules combine to form a single, whole block, as seen in Figure 1. The LayerNorm layer (LN), multi-head self-attention module (MSA), multilayer perception (MLP) with non-linearity activation function, and twice residual link between LN are visible components of each Swin Transformer module. Next, patches in the local 2 × 2 range are stitched using the Patch Merging process. This results in a feature dimension of 4C and a number of patch blocks of H/8 × W/8.

The Swin Transformer block receives 4C after it has been compressed into 2C using the same linear embedding technique as in stage 1. A layered representation with the same feature mapping resolution as a typical convolutional network is produced by combining these pieces. Through the use of this mechanism, swin-T is able to process localized information within each patch, which makes it easier to analyze the chest CT image thoroughly and identify patterns that may be indicative of cystic fibrosis or other medical issues.

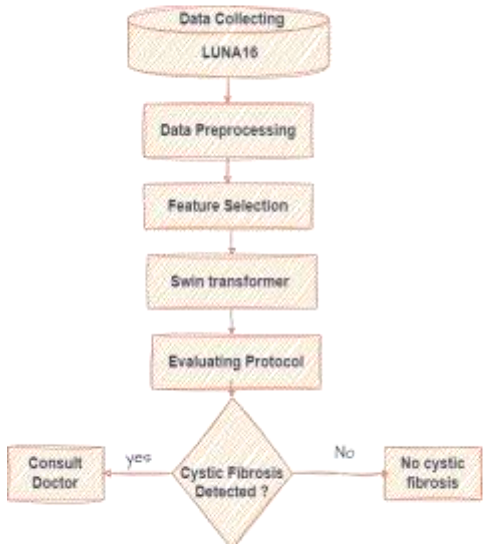

Figure 2. *Architecture of proposed method*

3.2.2 Self-awareness in windows without overlapping

Self-attention within local windows is estimated for effective modeling. The windows are positioned so that they don't overlap and divide the image equally. The computational complexity of a global MSA module and a window-based one based on an image of h × w patches, assuming each window has M × M patches, are as follows:

$$\Omega(MSA) = 4hwC^2 + 2(hw)^2C \quad (3)$$

$$\Omega(W - MSA) = 4hwC^2 + 2M^2hwC \quad (4)$$

where the latter is linear when M is fixed (set to 7 by default), and the former is quadratic to patch number hw. For a big hw, global self-attention computation is typically pricey, whereas window-based self-attention is scalable.

3.2.3 Shifted window partitioning in successive blocks

Cross-window connections are added because the modeling capabilities of non-overlapping windows are definitely limited by the lack of information flow between them. The key distinction is that the second Swin Transformer module uses shifted window-based multi-head self-attention (SW-MSA) instead of the window-based multi-head self-attention (W-MSA) module used in the first. Drawing from a pair of subsequent transformer blocks featuring both conventional and shifted window partitioning mechanisms, the Swin transformer block's attention learning process can be expressed as follows:

$$\hat{Z}^l = W - MSA\left(LN(Z^{l-1})\right) + Z^{l-1} \quad (5)$$

$$Z^l = MLP\left(LN(\hat{Z}^l)\right) + \hat{Z}^l \quad (6)$$

$$\hat{Z}^{l+1} = SW - MSA\left(LN(Z^l)\right) + Z^l \quad (7)$$

$$Z^{l+1} = MLP\left(LN(\hat{Z}^{l+1})\right) + \hat{Z}^{l+1} \quad (8)$$

where $\hat{Z}^l$ and Z^lrepresent the outputs of theW-MSA of the lth layer or the SW-MSA of the(1-l)$_{th}$ layer, and the MLP of the l$_{th}$ layer.

3.2.4 Window-based self-attention

Ultimately, Swin Transformer employs segmentation and classification as its two downstream tasks. The number of classifications (there were two categories for the identification of cystic fibrosis, with and without nodules) is the output dimension for the classification mission. The output is then passed through softmax to determine the final classification probability. Semantic segmentation serves as the foundation for extracting picture features in this segmentation endeavor. The move from Transformer to swin makes advantage of a window-based self-attention technique. This formula is used to compute it:

$$\text{Attention}\,(\mathrm{Q},\mathrm{K},\mathrm{V}\,) \;=\; \text{softmax}\left(\frac{QK^T}{\sqrt{D}}+B\right)V \quad (Q,K,V \in R^{M^{2+d}}) \tag{9}$$

where B, the relative position parameter, is introduced in a manner akin to that of Transformer's position embedding. The size of d, which balances the sizes of QKT and B, is the dimension corresponding to each head. Q, K, V calculation: after a linear layer, the corresponding query, key, and value values are derived for the incoming window information.

3.2.5 Loss Function

The loss function for the classification mission is as follows:

$$L = \frac{1}{N}\sum_i L_i = \; -\frac{1}{N}\sum_i \sum_{c=1}^{M} y_{ic}\log(p_{ic}) \tag{10}$$

where y_{ic} is the symbolic function (0 or 1) and M is the number of categories. Take one if the sample I's true category is equal to two; take zero otherwise. The expected probability that the observed sample I falls into category 2 is represented by pij. The attention directing decoder's parameter change will be overseen by the computed loss. Subsequently, the enhanced attention network will incorporate the attention predictions from the previous attention network to facilitate the final segmentation stage. This tactic can improve the functionality and interpretability of the Transformer attention mechanism and offer a method for directing attentional learning in Transformer that is understandable to humans. Utilizing the Transformer Encoder with Windows based self-attention mechanism is essential for comprehending intricate patterns linked to cystic fibrosis.

4. Results and discussion

4.1 Experimentation and dataset

The Lung Image Database Consortium-Image Database Research Initiative (LIDC-IDRI) database, which is available at the National Biomedical Imaging Archive, contains a subset called LUNA16 that has had its heterogeneous scans filtered according to several criteria. For the purpose of developing CAD systems for CT images, the Cancer Imaging Archive was established. The LIDC-IDRI statistics were gathered from a number of US locations. There are 1018 CT images from 1010 distinct patients in the LIDC-IDRI dataset. 888 CT scans are chosen for the LUNA16 grand challenge from the LIDC-IDRI database. The LUNA16 dataset is perfect for the investigation carried out in this work since it includes a significant number of CT scans with various slice thicknesses. CT scans with uneven slice spacing or slices thicker than 3 mm were not included. Four thoracic radiologists with extensive experience annotate images in two stages. Initially, every radiologist divides the results into three groups: nodule ≥ 3 mm, nodule ≤ 3 mm, and non-nodule ≥ 3 mm. Subsequently, in the second phase, every radiology examines their own classification as well as the anonymous classifications made by the other radiologists. Thus, each of the four radiologists reviews each nodule annotation on their own.

4.2 Performance analysis

The performance of the suggested method is evaluated against an existing algorithm with an emphasis on statistical measures, including F1 score, Precision, Recall, and Accuracy. Precision is defined as the percentage of positive, correct predictions made relative to all positive predictions. Recall is the percentage of positive right predictions made compared to all positive actuals. The weighted harmonic average of Precision and Recall is known as the F1-score. Accuracy is the percentage of accurate predictions the model produces. The performance of the suggested and current models (CNN, RNN, DenseNet, and Inception) in terms of accuracy, precision, recall, and F1 score is shown in Figure 3, Table 1. The following is the calculating formula:

$$Accuracy = TP + TN/TP + FP + FN + TN \tag{11}$$

$$Precision = TP/TP + FP \tag{12}$$

$$Recall = TP/TP + FN \tag{13}$$

$$F1\,score = 2 * (Recall * Precision) / (Recall + Precision) \tag{14}$$

True positive (TP) indicates the proportion of true cases that are also classified as true; false negative (TN) indicates the proportion of false cases that are classified as false; false positive (FP) indicates the proportion of false cases that are classified as true; and false negative (FN) indicates the proportion of true cases that are classified as false. Table 1 and Figure 3 show accuracy performance results, in which the proposed method achieves the highest value of 93.7% compared to other models. A larger Accuracy indicates the better performance of the model.

Table 1. *Performance of the proposed algorithm on LUNA16 dataset*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
CNN	79.5	61.4	64.3	62.1
RNN	86.6	63.7	71.6	67.5
DenseNet	86.3	70.2	77.8	69.2
Inception	90.5	77.8	80.1	78.6
Proposed Algorithm	93.7	79.3	84.9	80.9

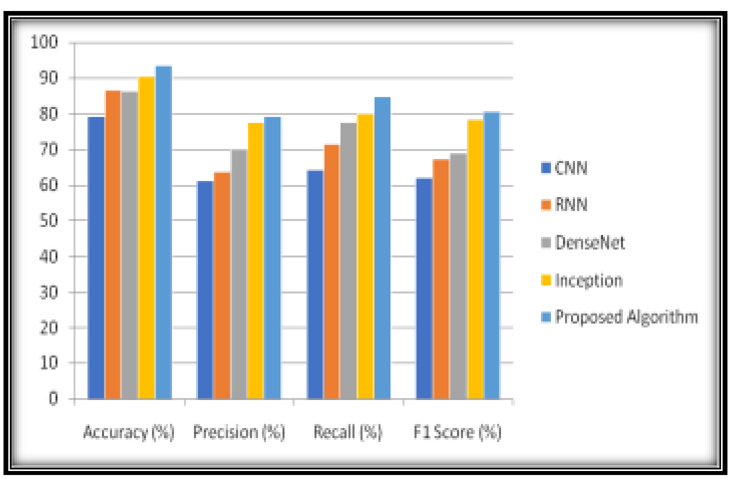

Figure 3. *Accuracy, Precision, Recall, and F1-score for various methods*

Another method for evaluating machine learning models is the receiver operating curve (ROC), which is used to calculate the percentage or degree to which the model can distinguish between distinct classes of dataset instances. Figure 4 illustrates the ROC curve for proposed model. The presentation estimation for grouping problems at various edge settings is the AUC-ROC curve. The link between the deep learning model's sensitivity and specificity is displayed via ROC. It indicates the degree to which the model is capable of class recognition. The model's ability to distinguish between patients who have the illness and those who do not improves with a higher AUC. Plotting the TPR against the FPR, with TPR on the y-pivot and FPR on the x-pivot, yields the ROC curve.

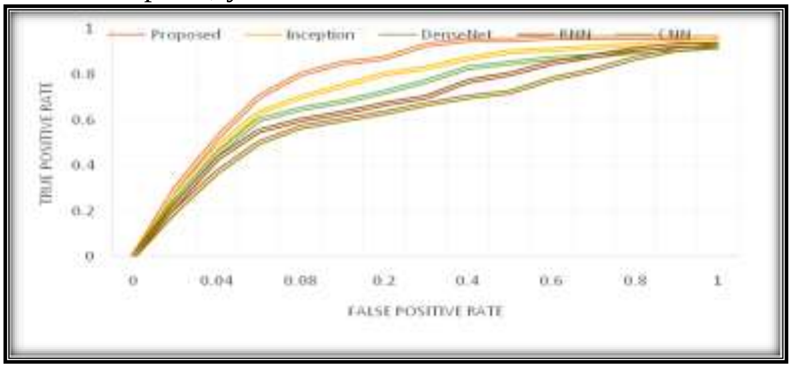

Figure 4. *ROC curve for proposed framework with existing models using LUNA16 dataset*

5. Conclusion

Enhancing cystic fibrosis detection through the use of cutting-edge technology like the Swin Transformer presents exciting opportunities. Researchers and doctors can increase the precision and efficacy of screening techniques and identify CF cases early by utilizing Swin-T's capabilities. Improving patient outcomes and starting prompt therapies depend on this early detection. The Swin-T method outperformed previous methods with an astounding accuracy of 93.7% during thorough examination. Furthermore, the F-measure (80.9%), recall (84.9%) and precision (79.3%) statistical results showed that the Swin-T technique was superior in identifying CF instances early on.

Furthermore, the detection procedure may be streamlined by incorporating Swin-T into current diagnostic protocols, which would lessen the strain on healthcare systems and increase accessibility to screening programs. Subsequent investigations ought to concentrate on enhancing and verifying this methodology in more extensive and varied datasets to guarantee its suitability for various demographics and environments. In the end, Swin-T's incorporation into clinical practice has a lot of potential to enhance the quality of life and results for CF patients.

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