

Elevating Cystic Fibrosis Detection in Lungs Using HRCT Images with a Cutting-Edge CNN-Based Approach

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Abstract— The creation of an algorithm for recognizing pathological abnormalities in cystic fibrosis is investigated in this paper using the CNN model with a modified psp-net. Currently, Decision Trees, Random Forests, PSP Nets, and Neural Networks are utilized in the diagnosis of cystic fibrosis. Since convolutional neural networks (CNNs) can process complicated picture data rapidly and efficiently, the goal of this study is to use CNNs for the detection of anomalies associated with cystic fibrosis. The method groups distinct annotated images into a simple and efficient structure, runs the set of images through a multiscale CNN procedure, and precisely locates the lung region affected by cystic fibrosis. The result of this paper demonstrated that differences in the training dataset can impact performance, but annotating CT images and categorizing them in terms of similar pathologies can improve the accuracy of the model. The proposed CNN model achieved an Accuracy of 84 %, Precision of 74%, Recall of 79%, F1-Score of 72%, error rate of 16% Which is better when compared with existing approaches.

Keywords— *CNN, Cystic fibrosis, CF, HRCT images, CT, pathology identification, CFTR*

I. INTRODUCTION

A mutation in both copies of the gene is necessary for cystic fibrosis (CF), a genetic illness that is inherited in an autosomal recessive manner [11][2]. Thick, dirty mucus from CF sufferers accumulates in various places throughout the body, including the airways of the lungs. In addition to serious stomach problems, recurrent lung infections, and other health problems, this mucus plugs the airways, which can be fatal. The CFTR gene mutation that causes cystic fibrosis causes the epithelial cells in the lungs, pancreas, and other organs to become inactive [3][6]. Research has shown that exercise in general and moderate to vigorous physical activity (MVPA) in particular are associated with better health outcomes for children with cystic fibrosis (CF), including increased life expectancy and quality of life. The CFTR gene encodes the Cystic Fibrosis transmembrane conductance regulator protein, which is in charge of the basic pathogenic mechanisms [8].

Variations in the CFTR gene, which is located on chromosome 7, cause the hereditary disease known as cystic fibrosis (CF), which is inherited. The CFTR gene produces a protein that regulates the passage of water and salt into and out of cells, influencing the production of mucus, sweat, and digestive juices. It takes two copies of the defective CFTR gene for a person to have CF, as the condition is autosomal recessive. Usually carrying just one defective copy of the CFTR gene, carriers show no signs of cystic fibrosis. In the event that both parents carry the CFTR gene, the child has a 25% risk of not having a faulty CFTR gene, a 50% probability of being a carrier, and a 25% chance of developing cystic fibrosis.

Multiple studies have investigated different methodologies for diagnosing cystic fibrosis, utilizing machine learning strategies. Marco Artini et al. [1] and Rosa Ma Girón et al. [3] used Longitudinal Random Forest and SVM approaches to analyze patient data. In addition, neural networks and decision trees were leveraged by Clarissa Braccia et al. [2], Rosanna Papa et al. [4], Kate L. Ormerod et al. [5], Ahmed M. Alaa et al. [6], Mayara S. Bianchim et al. [7], Mafalda Bacalhau et al. [8], Abroshan, Mahed et al. [9], and Karamarie Fecho et al. [10] to predict the outcomes and progress of cystic fibrosis. However, while these methods report promise, they may be hindered by issues such as overfitting, generalizability, and sensitivity to data changes. Our work aims to address these issues by introducing a new methodology for using high-resolution CT (HRCT) images, through a deep neural network-based approach (CNN), to increase the accuracy and robustness of cystic fibrosis detection; and thus improve diagnostic reliability and patient outcomes.

Notably, each of the previously cited studies encountered noteworthy challenges, such as overfitting and restricted generalizability, along with high sensitivity to perturbations in the underlying data, which would hinder any potential clinical uses. Accordingly, a Convolutional Neural

Network (CNN) was chosen in this work because it is a state-of-the-art learning algorithm capable of recognizing complex patterns and spatial hierarchies directly from labeled CT images. Furthermore, the CNN architecture offers both image learning capabilities, allowing for more complex features to be captured than most traditional detection methods produce, and is being coupled with ways to mitigate overfitting, such as data augmentation and regularization. Having the ability to tune the architecture to different datasets enables quick adoption and improvements to both generalizability and performance. Ultimately, the CNN architecture yields an accurate and efficient machine learning tool for the detection of cystic fibrosis, improves early patient age diagnosis and management, and provides the basis for future work in machine learning and medical imaging.

These are the study's principal contributions: To enable more thorough model testing and training, we first assembled a sizable dataset of high-resolution CT scans that have been specially annotated for cystic fibrosis (CF). Second, we created a brand-new Convolutional Neural Network (CNN) architecture [11] specifically designed to detect cystic fibrosis (CF), utilizing cutting-edge pooling techniques to boost the accuracy of diagnosis and improve the representation of disease-specific features. Third, we compared the performance of the suggested CNN to the techniques that were already in use, and the results were better in terms of accuracy, sensitivity, specificity, and robustness.

This document's remaining sections are arranged as follows: Insightful graphical representations are used to enhance the text as it delves further into the materials and techniques covered in Section 2. In Section 3, the findings are presented along with a detailed analysis of their implications. The article concludes with a summary of the major discoveries, an examination of their wider ramifications, and a thorough list of references for additional research.

II. MATERIALS AND METHODOLOGIES

A. 2.1 Dataset Description

The It's a set of HRCTs (High-Resolution Computed Tomography), courtesy of the radiology dept. In the nearby hospital, and the series has 312 pictures. Those are post training numbers, well at phase 1, there were 128 of the 200 CF patients in the database. These results from the empirical model have been tested for statistical significances using the Kruskal-Wall's test. The only way to diagnose from a CT scan (Computed Tomography) with CAD (Computer-Aided Diagnosis). That was determined by comparing the former to the continuous and the dichotomous variables. The entire testing phase contained 42 repetitions over 5 distinct test case samples. So that when each of the test case samples are analyzed separately, they were scaled to an order of about 63 CT images for each sample.

B. 2.2 Feature Engineering

The aforementioned feature engineering is based on a multi-scale CNN to extracting intricate and hierarchical attributes from high-resolution computed tomography (HRCT) [3][6] images. The CNN is trained to extract [11]

facets of the image features including textures, edges, shapes and patterns with images in possessing relevant characteristics of cystic fibrosis Characteristics. The movement of images during the feature extraction performance will convolve the input image through several layers in a way that the high resolutions of the images as well as the low resolutions of the images will be obtained.

C. 2.3 Proposed CNN Architecture for Cystic Fibrosis

This is a flowchart of a Convolutional Neural Network (CNN) used for detecting cystic fibrosis in lung CT scans. The process begins with the input of a HRCT scan into the CNN, which then outputs a feature map. The feature map is pooled to reduce the dimensions, and is then processed through a series of duplicate convolutional layers that split the feature map into sub-regions of varying sizes, including two-by-two (2 x 2), three-by-three (3 x 3), and six-by-six (6 x 6). These multi-scale features are then up sampled, combined, and concatenated to form a final feature map at the end of the CNN. The feature map is run through one last convolutional layer to result in an accurate prediction of cystic fibrosis, tapping into features at many different scales to help with making the diagnosis.

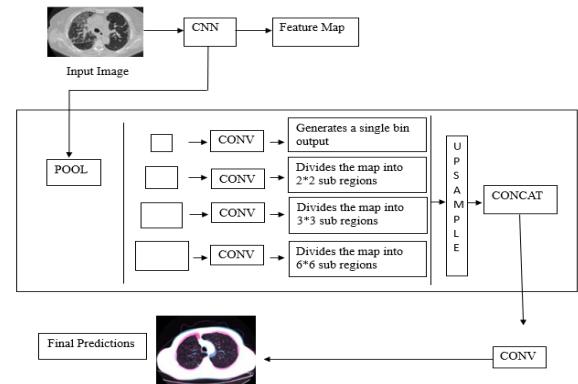


Figure 1. CNN incorporated with PSP -NET to detect CF.

Stage 1 commences with the input of medical images that are subject to pixel manipulation, which may include preprocessing steps such as normalization or enhancement to prepare the images for the next phase of analysis. A multi-scale Convolutional Neural Network (CNN) then extracts the appropriate features from the images, and annotations are post-applied to mark regions of interest into the images. Next, the images are pieced into different sized portions, which permits finer analysis.

Stage 2 involves using the aforementioned segments as input for the next model, which is named Pyramid Scene Parsing Network (PSPNet). To improve the utilization of image segmentation in depth, PSPNet adds a pyramid pooling module. By now, the output is a refined result of classification or division that proves cystic fibrosis exists and makes the illness observable for research or identification.

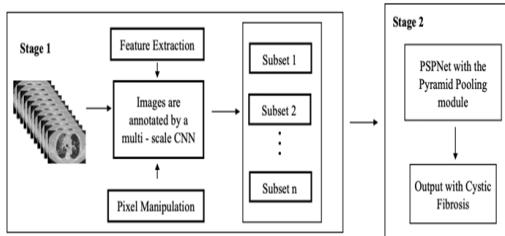


Figure 2. There are two phases to the system's structural operation:

- Stage 1: A multi-scale CNN is used to annotate HRCT images.
- Stage 2: PSP Net is used in conjunction with the pyramid module to identify CF.

III. RESULTS & DISCUSSIONS

A. Accuracy of Proposed Method CNN with Various Existing Methods

The ratio of correctly predicted by the model is called accuracy. Table 1 shows how accuracy and CNN model are compared. It is evident that the suggested CNN model, which has an accuracy of 84%, is accurate when compared to other models like Decision Tree, Neural Networks, PSP Net, Random Forest, and is graphically shown in Figure 2.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Table 1: Accuracy Comparison of existing model with proposed CNN approach

S. No	Model Name	Accuracy (%)
1.	CNN [11]	84
2.	Decision Tree [16]	78
3.	Neural Networks [18]	77
4.	PSP Net [11]	82
5.	Random Forest [21]	75

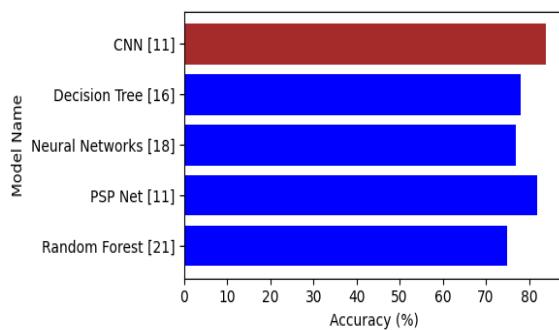


Figure 2. Accuracy comparison if existing models with proposes CNN approach

B. Precision of Proposed Method CNN with Various Existing Methods

The ratio of genuine positives to all of the model's positive predictions is known as precision. Table-2 illustrates the

comparison of the precision and CNN model. It is clear that the proposed CNN model with precision of 74% is accurate when compared with other models such as Decision Tree, Neural Networks, PSP Net, Random Forest and depicted in the figure 3 graphically

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Table 2: Precision Comparison of existing model with proposed CNN approach

S.NO	Model Name	Precision (%)
1.	CNN [11]	74
2.	Decision Tree [15]	70
3.	Neural Networks [18]	70
4.	PSP Net [11]	72
5.	Random Forest [18]	68

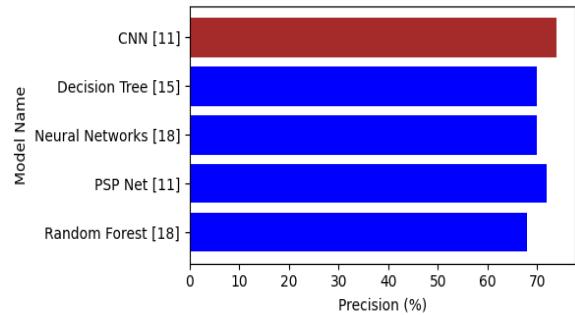


Figure 3. Precision comparison if existing models with proposes CNN approach

C. Recall of Proposed Method CNN with Various Existing Methods

The ratio of genuine positives to actual positives is known as recall. Table-3 illustrates the comparison of the recall and CNN model. It is clear that the proposed CNN model with recall of 79% is accurate when compared with other models such as Decision Tree, Neural Networks, PSP Net, Random Forest and depicted in the figure 4 graphically

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

Table 3: Recall Comparison of existing model with proposed CNN approach

S.NO	Model Name	Recall (%)
1.	CNN [11]	79
2.	Decision Tree [16]	74
3.	Neural Networks [10]	76
4.	PSP Net [11]	77
5.	Random Forest [18]	70

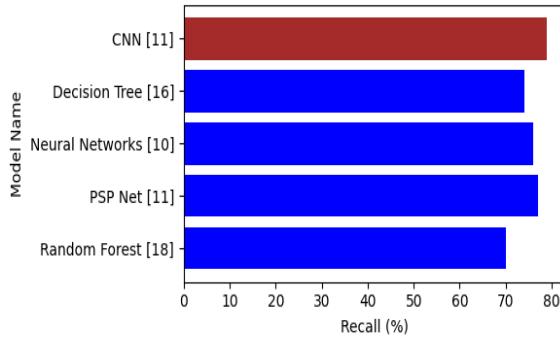


Figure 4. Recall comparison if existing models with proposes CNN approach

D. F1-Score of Proposed Method CNN with Various Existing Methods

An indicator that can counterbalance the accuracy-recall trade-off is the F1-Score. The comparison between the CNN model and the F1-Score is shown in Table 4. When the suggested CNN model is compared against various models, including Decision Tree, Neural Networks, PSP Net, Random Forest, and is graphically shown in Figure 5, it is evident that the CNN model with an F1-Score of 72% is correct.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Table 4: F1-Score Comparison of existing model with proposed CNN approach

S.NO	Model Name	F1-Score (%)
1.	CNN [11]	72
2.	Decision Tree [13]	68
3.	Neural Networks [25]	66
4.	PSP Net [11]	70
5.	Random Forest [18]	66

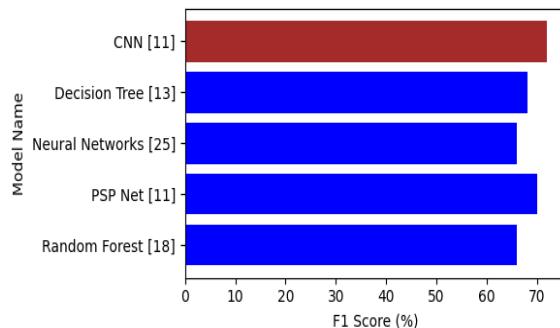


Figure 5: F1-Score comparison if existing models with proposes CNN approach

E. Error Rate of Proposed Method CNN with Various Existing Methods

The error rate is a measure of how often a model makes incorrect predictions. Table 5 illustrates the comparison of the Error Rate and CNN model. It is clear that the proposed CNN model with Error Rate of 16% is accurate when

compared with other models such as Decision Tree, PSP Net, SVM, Recurrent Neural Network, and depicted in the figure graphically.

$$\text{Error Rate} = \frac{FP + FN}{TP + TN + FP + FN} \quad (5)$$

$$\text{Error rate} = 1 - \text{Accuracy}$$

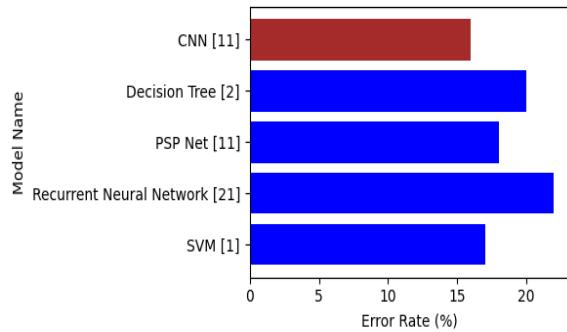


Figure 6. Error Rate comparison if existing models with proposes CNN approach

F. Matthews Correlation Coefficient of Proposed Method CNN with Various Existing Methods

A confusion matrix's four variables are TP, TN, FP, and FN. The comparison between the CNN and MCC models is shown in Table 6. The proposed CNN model, which has an MCC of 71%, is clearly more accurate than other models, including Decision Tree, Neural Networks, Random Forest, SVM, and the graphic representation of the model in Figure 7.

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (6)$$

Table 6: MCC Comparison of existing model with proposed CNN approach

S.NO	Model Name	MCC (%)
1.	CNN [11]	71
2.	Decision Tree [13]	67
3.	Neural Networks [23]	65
4.	Random Forest [18]	64
5.	SVM [23]	63

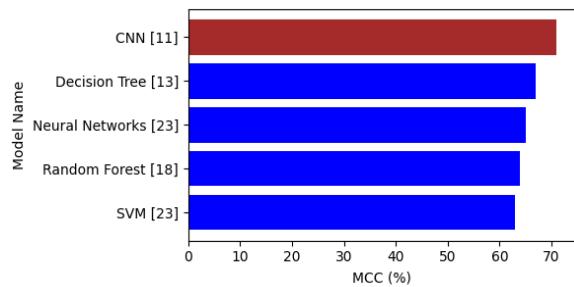


Figure 7. MCC comparison if existing models with proposes CNN approach.

G. Specificity of Proposed Method CNN with Various Existing Methods

A high specificity indicates that the model can detect non-positive situations with some degree of accuracy. This is especially useful when trying to minimize those false positives. Table 7 illustrates the comparison of the Specificity and CNN model. It is clear that the proposed CNN model with Specificity of 76% is accurate when compared with other models such as Decision Tree, Neural Networks, PSP Net, Random Forest, and depicted in the figure 8 graphically

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (7)$$

Table 7: Specificity Comparison of existing model with proposed CNN approach

S.NO	Model Name	Specificity (%)
1.	CNN [11]	76
2.	Decision Tree [16]	72
3.	Neural Networks [18]	70
4.	PSPNet [11]	74
5.	Random Forest [18]	68

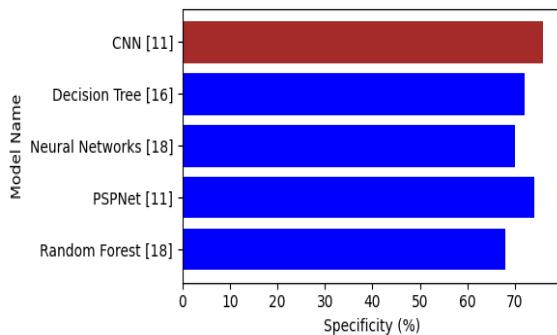


Figure 8. Specificity comparison if existing models with proposes CNN approach

IV. CONCLUSION

The variety of input from different data sets can cause fluctuations in training and therefore model performance. But, by marking up CT images, and training the model to recognize them by similar pathologies, it does recognize Cystic Fibrosis. Then the generated subset groups are fed through the PSP Net and CNN, which has a pyramid pooling module in it. It turns out this module uses alternate scaling methods to improve the recognition of pathology without compromising the model's ability to pick up on Cystic Fibrosis. The CNN is very important here, because it can find very intricate patterns in the CT images and these patterns are needed to differentiate between normal and abnormal tissue. The deep layers of the CNN can learn high-level features, which are very important for accurate classification, and the pyramid pooling module further enhances these features by considering them at different scales, so the network is more robust to changes.

Moreover, this model's design and methodology pave a path for future studies on locating lung-related pathologies in CT images to identify serious diseases like COVID-19. By

adjusting the pipeline proposed, this model can be applied to wider applications for medical imaging that help to analyze life-threatening diseases in their early stage and improve diagnosis.

The CNN plays an integral role here as its deep layers are capable of detecting complex patterns in the CT images, delineating normal tissue structures from abnormal ones. The deep architecture provides an avenue for the CNN to learn different high-level features, critical for making this classification decision. The pyramid pooling module also further refines those features by pooling information at multiple scales which aids in increasing the versatility of the model, allowing it to adjust to different types of data.

With an accuracy of 84, precision of 74, recall of 79, and F1 score of 72, this two-stage procedure significantly outperforms other existing techniques. It is worth noting that the model yielded an error rate of 16 -- a significant decline in the error rate compared to other approaches. This demonstrates notable performance in detecting cystic fibrosis, particularly analyzing sensitivity versus specificity for particular datasets done reliably. The combination of CNN's deep feature extraction and the PSPNet's multi-scale pooling generates a more robust and accurate approach to cystic fibrosis detection yielding a new contribution to medical imaging evaluation.

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