AI-Driven Early Prediction of Pulmonary Fibrosis Using Deep Learning

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***Abstract*— The development of scar tissue (fibrosis) in the lungs is a hallmark of pulmonary fibrosis, a progressive lung disease. impairing its ability to function properly. Progressive nature leading to declining lung function and yearly, 13 to 20 out of 100,00 people effecting by pulmonary fibrosis throughout the world. Present technologies for prediction of pulmonary fibrosis are limited to predictive accuracy, availability of high-quality data and early detection. The recommended technique with a high-resolution computed Tomography (HRCT) scan along with U-Net for better classification of HRCT signals and diagnosis of disease accurately. The results accomplished by this method are remarkable achievements in terms of precision recall, accuracy and F1-Score ranging from 0.96 to 0.98.**

Keywords*— *pulmonary fibrosis, diabetes, deep learning algorithm, u-net, high resolution computed tomography scan, diagnosis, image pre-processing.

. I. INTRODUCTION

Fibrosis of the lungs is a developing lung disorder which are defined thickening and scaring of the lung tissue and indirectly effected by diabetes. This makes difficult for the lungs to function properly by reducing their ability to expand and contrast effectively. As a result, difficulty of breath, coughing, and exhaustion are common symptoms of lung disease that can get worse over time. Although the exact cause of pulmonary fibrosis is frequently unknown, it may be linked to environmental pollutants, specific drugs, or underlying medical disorders. Figure 1 represents the comparison between healthy lungs and lungs effected by Pulmonary fibrosis. Persistent dyspnoea is a common symptom of the illness, particularly in the presence of physical exertion. As the illness worsens, this dyspnoea may become more severe and eventually occur even while the patient is at resting. Another defining feature is a dry, persistent cough in addition to problems with breathing. Reports of exhaustion, inexplicable reduction in weight, and hurting muscles and tendons are also common. Furthermore, in certain instances, clubbing of the fingertips—a condition in which the tips of the fingers swell and round—may transpire.

Diabetes indirectly effecting on lungs which can occur pulmonary fibrosis through several mechanisms, incorporating inflammation, oxidative stress and impaired wound healing and weaken the immune system, making individuals more susceptible to lung infections and exacerbating fibrosis symptoms. Proper management of diabetes is crucial to help alleviate its impact on development of pulmonary progression. Section I dealing with previously existing techniques.

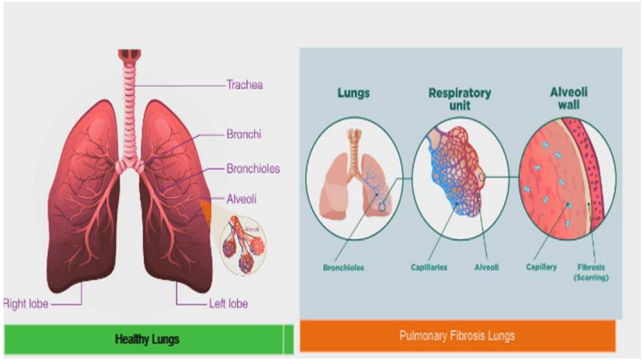

Fig. 1. Comparison between healthy lungs and pulmonary fibrosis

There is no cure for the condition, various approaches can help manage its effects. Medications play a central role in treatment, with corticosteroids and immunosuppressants often recommended to inhibit the immune system's reaction and diminish inflammation, which can help slow the scarring of lung tissue. Additionally, antifibrotic drugs like nonreading and pirfenidone have been approved specifically with relation to idiothetic pulmonary fibrosis (IPF) and are used to slow disease progression by targeting pathways involved in fibrosis. To raise oxygen saturation in the blood and relieve drowsiness especially during physical activity or sleeping, oxygen treatment may be suggested. Pulmonary rehabilitation programs, which combine exercise training, education, and support, can help individuals with pulmonary fibrosis improve their exercise tolerance and overall well-being People with severe disease who have not responded to prior therapies may occasionally be candidates for lung transplantation. Comprehensive management of pulmonary fibrosis also involves regular monitoring by healthcare professionals and lifestyle modifications such as quitting smoking and avoiding exposure to environmental pollutants, which can help slow

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disease progression and optimize treatment outcomes. Proposed AI-Driven Early Prediction of Pulmonary Fibrosis Using Deep Learning, descripted in below sections. Section II handles with various technologies available for prediction of pulmonary fibrosis by various researchers, Section III addresses the introduced method by overcoming the drawbacks of available methodologies, Section IV tackles with process flow and dataset of proposed method, Section V provides results which obtained by using new technique and also compared performance with various technologies, Conclusion follows section VI.

Pulmonary fibrosis is a complicated lung disease which is affected by type 2 diabetes. But its treatment is not accurate. Junfeng Guo, et al, [1] presented A Chinese remedy called Bu Yang Huan Wu Decoction (BYHWD) exhibits an effective treatment for pulmonary fibrosis. The ingredients of BYHWD taken from SymMap2 and the TCMSP (Traditional Chinese Medicine Systematic Pharmacology Database). One chronic developing illness that raises the death risk is pulmonary fibrosis. Saqib H. Baig, et al, [2] aimed to compare the effects of chronic diseases by using NIS database. They surveyed with people more than 60 years and predict the idiopathic pulmonary fibrosis. And the death rate. Finally, they resulted, out of 4975 patients with AE-IP. Fibrosis of the lungs is a one kind of developing lung illness which leads to lose of lung function. Medium IPF patients have a medium survival rate of three to five years. Introduced two drugs that nonreading with pirfenidone to treat pulmonary fibrosis. Jie Ma, et al, [3] concluded that outline of existing and upcoming medication inventions. For lung fibrosis that is idiopathic (IPF) discharged exosomes (exos) and Malignant mesenchyme stem cells (MSCs) are linking to change pulmonary fibrosis. Exosome microRNAs (miR) can monitor the plentiful disease. Liang Zhu, et al, [4] introduced that The MIR 30b plays a crucial part in the root cause and management of IPF. Ross Summer et al. [5] examined the plasma samples of 300 IPF patients enrolled in the IPRV research and determined that moving levels of metabolites associated with the existence of IPF. Angelo ziellu, et al, [6] focused to evaluate the predictive efficacy of ischemia modified albumin (IMA), a recently developed indicator of oxidative stress and ischemia, in a cohort of 56 idiopathic patients who were recruited in 2015.
Yi sun, et al, [7] reviewed about iron homeostasis is, a biochemical and physiological process of lungs. Imbalance iron result in causes a surplus of iron, which exacerbates oxidative stress and the intensity of colonization by bacteria. Iron -dependent cell death leads to pulmonary fibrosis. Concluded that a technology. Seba Hassan Attita, et al, [8] reviewed about the drugs available for treatment for pulmonary fibrosis and their adverse effects. Wenhong Wang, et al, [9] concluded that the pharmacokinetics, pharmacological mechanisms, toxicity, and both in vitro and in vivo effects of PTS provide information for the therapy of fibrosis. Mihai Lazar, et al, [10] examined that post-covid-19 fibrosis offers an important challenge because of its complex pathogenesis which are involve a cascade of cellular effectors and fibrosis mediators. ShumeiLv, et al, [11] evaluated the fibrosis which defined fibrosis deposition and remodelling of tissue. PKM2, a central enzyme in glycolysis, orchestrates metabolic shifts crucial for fibrosis development, indicating its potential as therapeutic target. And proposed a unique treatment for mitigating fibrosis across different organs. Uzma yaseen, et al, [12], targeted to improve the knowledge of KLF10's multifaceted function in fibrosis and inspire more investigation into its potential as a target in the fight against fibrotic disease. Manoj V. Maddali, et al [13] introduced a method with deep learning convolution neural network which takes input from CT scans. Trained the CNNs to predict the existence of disease. applied the poll data to evaluate the precision of all algorithmic methods for diagnosing pulmonary fibrosis that are currently available. recommended early diagnosis of pulmonary fibrosis using deep learning algorithm for prediction of disease [14].

II.METHODOLOGY

Present available techniques for detection of pulmonary disease in early stage is crucial. Many technologies are been introduced to overcome the problems in detection of tumours. Even though current landscape of technologies for prediction pulmonary fibrosis is marked by different notable drawbacks. While imaging techniques such as x-rays and CT scans are commonly used, their accuracy in predicting disease progression remains limited, often leading to challenges in early stage [15]. Many diagnostic procedures, including lung biopsies, are invasive and carry inherent risk for patients, making them less desirable for predictive purpose. Cost and time associated with certain diagnostic tests and image procedures pose barriers to widespread adoption and accessibility, hindering early prediction efforts. Furtherly, the subject interpretation of imaging results and pulmonary function tests introduces variability in diagnosis leading to inconsistent performance. Current available bio makers may lack the necessities like specificity, sensitivity of accurate diagnosis. Addressing these challenges necessities advancement in non-invasive diagnostic techniques.

For deep understanding and early prediction, introduced a unique method to overcome the problems using U-Net algorithm and high-resolution computed tomography (HRCT) scan.

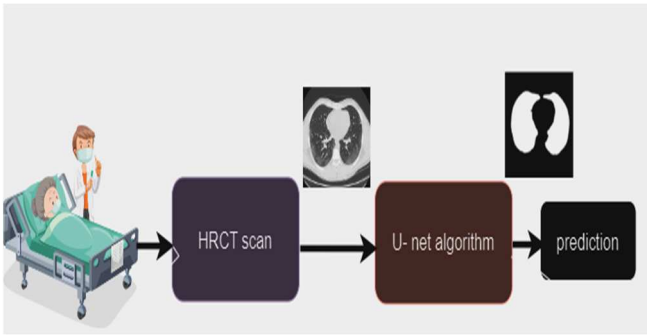

Fig. 2. Proposed method for prediction of pulmonary fibrosis

The proposed method shown in figure 2 for early diagnosis of pulmonary fibrosis using U-Net algorithm used patient's demographic data and clinical laboratory tests from the HRCT scan for the prediction of a disease. A sophisticated imaging method called A high-re Computed Tomography (HRCT) produces a finely precise cross-sectional picture of the lungs and surrounded structures. HRCT scans have high resolution and thinner slice thickness, allowing for more precise visualization of anatomical structures and pathological changes [16]. During the process of HRCT scan, the patient lies on a motorized bench that passes through a doughnut-shaped scanning device during the HRCT scan procedure.

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Multiple angles are used to send X-ray beams into the body, and sensors quantify the quantity of radiation that enters the tissue. HRC is particularly useful in segmentation and monitoring lung disease characterized by abnormalities, such as fibrotic changes, ground-glass opacities, and modules. Result which are obtained from HRCT scan applied to novel method (U-Net) for further processing and prediction of disease existence.

A. Data Description:

In this, the goal is to forecast the decline severity in a patient's lung function using an imaging test on their lungs. A spirometer, which gauges the forcefully vital capacity (FVC), or the amount of air breathed, is used to assess lung function. Each patient's initial chest CT scan and associated clinical information are included in the dataset [17]. Every patient gets an image captured at Week = 0 and has their FVC recorded at many follow-up appointments over a period of one to two years as shown in the figure 3. A hidden baseline HRCT scan and the whole history of FVC values are included in the training set. In the test set, you are provided with a baseline HRCT scan and only the initial FVC measurement. There are approximately 200 instances in the public and private test sets combined. This is divided roughly 15-85 between public and private.

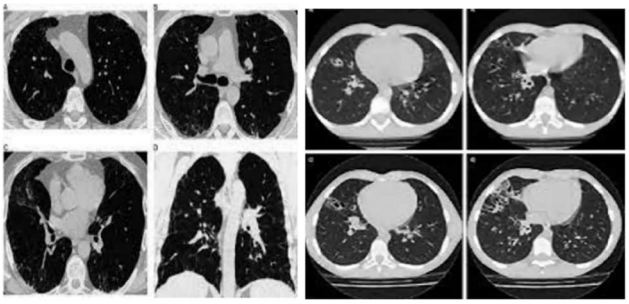

Fig. 3. Samples of lungs from HRCT scan

B. Pre-processing

In order to provide consistent input for the network, U-Net pre-processing entails normalizing the pixel values of the images being used to a specified range, such as [0, 1]. Furthermore, data augmentation methods like as flipping, scaling, and rotation are used to enhance model generalization and diversify the training sample [18].

Normalization: Normalization is essential to scale the pixel value of image to a standard range, typically [0,1] or [-1,1].

Min-Max Normalization:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (1)$$

Where, I is the original pixel value, I_{min} is the minimum pixel value and I_{max} ia the maximum pixel value.

Z-Score Normalization:

$$I_{std} = \frac{I - \mu}{\sigma} \quad (2)$$

Where, σ is the standard deviations, while μ is the pixel value mean.

Resizing: Resizing this image to a fixed size suitable for the U-Net architecture is necessary because neural networks typically require a consistent input size.

$$x_t = (\frac{x}{W})\, x\, W_t \quad (3)$$

$$y_t = (\frac{y}{H})\, x\, H_t \quad (4)$$

If the original image size is (H,W) and the target size is (W_t and H_t), each pixel's new coordinates (x_t and y_t) can be computed in Eq (3) & (4).

Data Augmentation: By using randomized transformations, this approach adds variation to the training data.

Rotation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (5)$$

Translation:

$$x' = x + t_x \quad (6)$$

$$y' = y + t_y \quad (7)$$

Where, t_x and t_y are the translation distances.

Scaling:

$$X = S_x * x \quad (8)$$

Patch Extraction**:** if the patch size is (P_H , P_W) and the stride is (S_H , S_W) then the coordinates of the top-left corner of each patch (i,j) can be expressed as:

$$(i, j) = m^* S_H , n^* S_W \quad (9)$$

Where, m and n are the integers such that 0<=i<=H - P_H and 0<=j<=W - P_W.

One-Hot Encoding of Labels: for segmentation task, each pixel need to be assigned to a specific class, often encoded in a one-hot manner.

One-Hot Encoding: for C classes, the one-hot encoded vector y for a class c is:

$$y_i = \begin{cases} 1 & if\ i = c \\ 0 & otherwise \end{cases} \quad (10)$$

Where, I in range from 1 to C.

By performing these pre-processing steps, the images become more suitable for inclusion in the U-Net model, boosting the effectiveness from the training process and improving the segmentation results.

C. *U-Net Algorithm*

The U-Net algorithms is a deep learning structure initially proposed for the segmentation of biological images, has gained prominence across various domains for its remarkable efficacy in precise image segmentation task

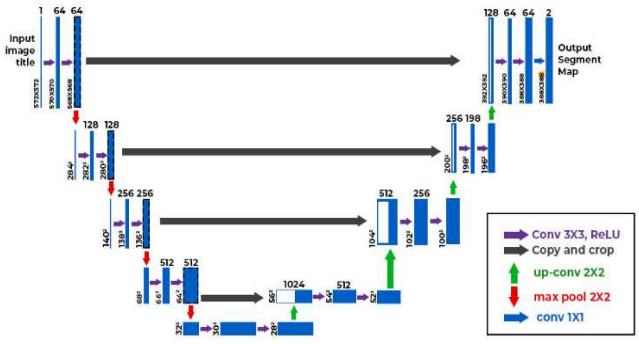

Fig. 4. Architecture of U-Net

It is distinctive construction of the encoder-decoder, coupled with bypass connections, enables accurate delineation object boundaries and fine details within image. Figure 4

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shown how the U-Net network converts a grayscale feed picture with dimensions of 572×572×1 into a 388×388×2 binary segment result map. Since no padding is used, the output size is less than the input size. Padding, however, allows us to maintain the input size. The input picture gradually loses width and height as the number of channels increases in the contracting route. As the network progresses down the path, the rise in channels allows it to collect the highest-level characteristics. A last convolution action at the bottleneck creates a feature map with a 30x30x1024 structure. The map of features from the bottleneck is then taken by the expansive path, which uses expanding layers to transform it back into an image the same size as the original input. These layers reduce the number of the channels in the feature map while increasing its spatial accuracy. The contracting path's skip connections help decoding layers find and hone the image's characteristics. In the end, every pixel in the output image denotes a label that corresponds to a certain class or item in the initial image.

D. Model Training

The Adam method was used to optimize the model, which was developed by utilizing the Dice coefficient as a losing function. To get the best results, hyperparameters like batch size and learning rate were adjusted.
Dice Coefficient: A statistical metric used to assess how similar two sets are is the Dice coefficient, sometimes called the Sørensen–Dice index. It is frequently used to assess how well the expected segmentation and the ground truth overlap in picture segmentation tasks. The definition of the dice coefficient D is:

$$D=\frac{2|X\cap Y|}{|X|+|Y|} \quad (11)$$

Where, X is the set of predicted elements (or pixels in the case of image segmentation), Y is the set of ground truth elements, |X| and |Y| are two cardinalities (sizes) for the respective sets and also $|X\cap Y|$ is the number of elements common to both sets. This loss function helps in optimizing the model to maximize the Dice coefficient, thereby improving the accuracy of segmentation tasks.

Adam Optimization Algorithm:

One well-liked and efficient technique for deep neural network model training is the Adam optimization method. It combines the benefits of Root Mean Square Propagation (RMSProp) and Adaptive Gradient Algorithm (AdaGrad), two further expansions of the stochastic gradient descent (SGD). Adaptive Moment Estimation is what Adam stands for
Initialize Parameters:

m_0=0 (Initialize the first moment vector)

v_0=0 (Initialize the second moment vector)

t=0 (Initialize the time step)

updated parameter at each step

t=t+1

$$m_t = \beta_1 m_{t-1} + (1-\beta_2) g_t$$

$$v_t = \beta_2 m_{t-1} + (1-\beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$\theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t}+\epsilon}$$

this case, g_t is the gradients at timestep t, β_1 and β_2 are the moment estimates' exponentially decaying rates, α is the learning rate, and ϵ is a tiny constant that keeps division by zero from happening.
Tuning hyperparameters:
Rate of Learning: The size of the steps the optimizer undertakes to update the model values is determined by the learning rate α. Overshooting the ideal values might occur from a learning rate that is too high, while a very sluggish convergence could occur from a learning rate that is too low
Typical Values: 10^{-1} *to* 10^{-5}.
Batch Size: Batch size is the quantity of samples for training utilized in a single training cycle.

- Small Batch Size: Enhances generalization and has a regularizing impact, although it may provide noisier gradient estimations.
- Large Batch Size: Offers a more precise gradient estimate, but it uses greater amounts of memory and may cause overfitting.
- Typical Values: Powers of 2 (e.g., 16, 32, 64, 128)
- Tuning Methods: Grid search or empirical testing based on memory constraints and training stability

Figure 5 illustrates the work flow of our proposed model "AI-Driven Early Prediction of Pulmonary Fibrosis Using Deep Learning". Included various methods for prediction of disease by analyzing the images through preprocessing, Training and Tuning.

Fig. 5. Workflow for prediction of pulmonary fibrosis using the U-Net Algorithm

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E. Performance metrics

When using the U-Net algorithm to predict lung diseases, a number of performance metrics, including recall, accuracy and F1-score, can be used to assess the efficacy and accuracy of predictions. These metrics include true negative (TN true positive (TP), false positive (FP), and false negative (FN).

TABLE I. PERFORMANCE METRICS FOR TESTING AND VALIDATION DATASETS

	Testing	Validation
Accuracy	0.98	0.975
Precision	0.965	0.975
Recall	0.975	0.972
F1-score	0.965	0.97

While precision and recall provide information on the model's capacity to accurately identify positive instances and steer clear of false negatives or false, accuracy offers an overall measure of correct predictions. The F1-score strikes a compromise between these two metrics.

III. RESULT & DISCUSSION

In our study focusing on the prediction of pulmonary fibrosis using U-Net algorithm, observed promising results indicative of model's efficiency in detecting fibro regions with scan images of lungs which are obtained by high resolution computed tomography.

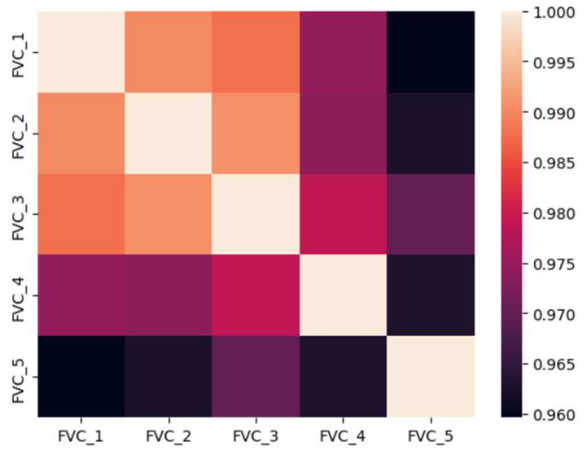

Fig. 6. Correlation Matrix of FVC Variables

Figure 6, illustrates the correlation matrix for different FVC (Forced Vital Capacity) measurements, labelled FVC_1 to FVC_5, which are crucial in predicting the progression of pulmonary fibrosis. High correlation values, ranging from 0.960 to 1.000, signify strong positive relationships between these measurements. Lighter colours represent higher correlations, indicating strong linear relationships, while darker colours show slightly lower correlations. This high degree of correlation suggests that the FVC measurements are consistent and reliable over time. Such consistency is essential for developing accurate predictive models for pulmonary fibrosis progression. These models help clinicians track disease progression effectively, leading to better patient management and treatment planning. Understanding these correlations allows for more precise monitoring and intervention strategies in managing pulmonary fibrosis.

A model's performance metrics on testing and validation databases are shown in table I, recall, accuracy, precision, and F1-score are all included. High overall performance is shown by the testing accuracy of 0.98 and the validation accuracy of 0.975. Precision is slightly higher in validation (0.975) compared to testing (0.965), suggesting the model is more precise in validation. Recall is comparable in both datasets, with 0.975 for testing and 0.972 for validation. The testing and validation scores for F1-, which balance accuracy and recall, are 0.965 and 0.97, respectively, indicating consistent results over datasets.

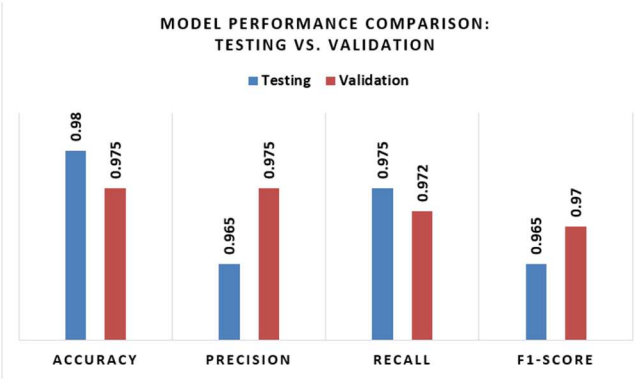

Fig. 7. Model Performance Comparison Testing vs. Validation

The graphical representation of comparison of model performance metrics on testing and validation datasets shown in Figure 7. The accuracy is slightly higher for testing (0.98) compared to validation (0.975). Precision is higher in validation (0.975) than testing (0.965), while recall is nearly equal for both (0.975 for testing and 0.972 for validation). Consistent performance across both datasets is indicated by the F1-score, which strikes a compromise between accuracy and recall, which is 0.965 for testing and slightly greater at 0.97 for validation.

TABLE I. COMPARISON OF PROPOSED MODEL AND OTHER MODELS

models	Accuracy		Precision		Recall		F1-Score	
	Test	Val	Test	Val	Test	Val	Test	Val
	0.94	0.92	0.94	0.94	0.93	0.95	0.94	0.94
Li [19]	0.90	0.92	0.94	0.92	0.95	0.89	0.93	0.94
Zhu[20]	0.91	0.91	0.94	0.91	0.93	0.93	0.94	0.92
Cui [21]	0.92	0.91	0.96	0.91	0.93	0.95	0.90	0.87
Xu [22]	0.90	0.85	0.93	0.84	0.94	0.92	0.79	0.81
Proposed method	0.98	0.975	0.965	0.97	0.975	0.972	0.965	0.97

Further comparative analysis with baseline methods underscored the superior performance of the U-Net approach, obtained outstanding performance as compared to other proposed models. Table I, Analysed that exceptional performance obtained by using U-Net algorithm in terms of recall, precision, accuracy and F1-Score with 0.96 to 0.98.

IV. CONCLUSION

Concluded that, our study on diagnosis of pulmonary fibrosis using U-Net algorithm demonstrating promising outcomes indicative of its effectiveness in identifying fibrotic regions within lung images. Through comprehensive

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evaluation encompassing various performances metrics incorporating F1-Score, recall, accuracy, and precision. Which are spanning from 0.965 to 0.98. We observed consistently high levels of predictive accuracy. Comparative study using baseline techniques revealed the superior performance for U-Ne contact, showcasing its capacity as a robust tool for diagnosis of pulmonary fibrosis. Moreover, discussion surrounding the algorithm robustness and generalization capabilities suggest promising prospects for real -world clinical application

REFERRENCE

[1] Junfeng Gu, Yuwei Zhang, Rui Zhou, Yanwei Hao, Xuanyu Wu, Ganggang Li, Quanyu Du, "Deciphering the molecular mechanism of Bu Yang Huan Wu Decoction in interference with diabetic pulmonary fibrosis via regulating oxidative stress and lipid metabolism disorder", Journal of Pharmaceutical and Biomedical Analysis, 2024, vol: 234, pp: 116061.

[2] Saqib H. Baig, Erika J. Yoo, "The Impact of Chronic Comorbidities on Outcomes in Acute Exacerbations of Idiopathic Pulmonary Fibrosis", 2024.

[3] Jie Ma , "Comprehensive review of potential drugs with anti-pulmonary fibrosis properties", Biomedicine & Pharmacotherapy, 2024, vol173.

[4] Liang Zhu, Yun Xu, Jianqing Wang, Yi Zhang, Jiawang Zhou & Huaxiang Wu, "Mesenchymal stem cells-derived exosomes carrying microRNA-30b confer protection against pulmonary fibrosis by downregulating Runx1 via Spred2", Molecular Genetics and Genomics, 2024, vol: 299.

[5] Ross Summer, Jamie L. Todd, Megan L. Neely, L. Jason Lobo, Andrew Namen, L. Kristin Newby, Shirin Shafazand, Sally Suliman, Christian Hesslinger, Sascha Keller, Thomas B. Leonard, Scott M. Palmer, Olga Ilkayeva, Michael J. Muehlbauer, Christopher B. Newgard & Jesse Roman, "Circulating metabolic profile in idiopathic pulmonary fibrosis: data from the IPF-PRO Registry", Respiratory Research, 2024, vol:25.

[6] Angelo Zinellu,Stefano Zoroddu, Simona Fois, Sabrina Mellino, Chiara Scala, Erika Virdis, Elisabetta Zinellu, Salvatore Sotgia, Panagiotis Paliogiannis, Arduino A. Mangoni, Ciriaco Carru, Pietro Pirina and Alessandro G. Fois, "Ischemia-Modified Albumin (IMA) Is Associated with Poor Survival in Patients with Newly Diagnosed Idiopathic Pulmonary Fibrosis (IPF): A Pilot Study", 2024.

[7] Yi Sun, Yu Ren, Li-yun Song, Yin-ying Wang, Tian-gang Li, Ying-li Wu, Li Li, Zhong-shan Yang, "Targeting iron-metabolism:a potential therapeutic strategy for pulmonary fibrosis", Biomedicine & Pharmacotherapy, 2024, vol: 172.

[8] Seba Hassan Attia, Sara F. Saadawy, Samaa M. El-Mahroky & Mahitab M. Nageeb, "Alleviation of pulmonary fibrosis by the dual PPAR agonist saroglitazar and breast milk mesenchymal stem cells via modulating TGFß/SMAD pathway", Naunyn-Schmiedeberg's Archives of Pharmacology , 2024.

[9] Wenhong Wang, Ke Li, Dandan Bai, Jiabin Wu & Weihua Xiao, "Pterostilbene: a potential therapeutic agent for fibrotic diseases", Inflammopharmacology, 2024.

[10] Mihai Lazar, by Mihai Lazar, Mihai Sandulescu, Ecaterina Constanta Barbu, Cristina Emilia Chitu-Tisu, Darie Ioan Andreescu, Andreea Nicoleta Anton, Teodora Maria Erculescu, Alexandru Mihai Petre, George Theodor Duca, Vladimir Simion, Isabela Felicia Padiu, Cosmina Georgiana Pacurar, Ruxandra Rosca, Teodor Mihai Simian, Constantin Adrian Oprea and Daniela Adriana Ion, "The Role of Cytokines and Molecular Pathways in Lung Fibrosis Following SARS-CoV-2 Infection: A Physiopathologic (Re)view", 2024.

[11] Shumei Lv, Mengfei Cao, Jie Luo, Kewei Fu & Wei Yuan, "Search progress of pyruvate kinase M2 (PKM2) in organ fibrosis", 2024. vol:51.

[12] Uzma Yaseen, Soonjae Hwang, Sangbin Park, Soo-Bin Kim, Ho-Jae Lee and Ji-Young Cha, "New Insights into the Role of KLF10 in Tissue Fibrosis", 2024.

[13] Maddali Manoj V. Maddali, Angad Kalra, Michael Muelly, Joshua J. Reicher, "Development and validation of a CT-based deep learning algorithm to augment non-invasive diagnosis of idiopathic pulmonary fibrosis", Respiratory Medicine, 2023, vol: 219, Pp:107428.

[14] Nelson, M., Rajendran, S., Khalaf, O.I. and Hamam, H., 2024. Deep-learning-based intelligent neonatal seizure identification using spatial and spectral GNN optimized with the Aquila algorithm. AIMS Mathematics, 9(7), pp.19645-19669.

[15] Balamurugan, K.S., Ramesh, T., PJ, S.K., Surendran, R. and Tamilvizhi, T., 2024, November. Development of Cancer Drug Targets and Potential Anti-Cancer Agents using Deep Learning and Screening Processes. In 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI) (pp. 787-791). IEEE.

[16]`Thanarajan, T., Alotaibi, Y., Rajendran, S. and Nagappan, K., 2023. Eye-Tracking Based Autism Spectrum Disorder Diagnosis Using Chaotic Butterfly Optimization with Deep Learning Model. Computers, Materials & Continua, 76(2).

[17] Vineetha, B., Surendran, R. and Madhusundar, N., 2024, November. Enhancing Accuracy in Obesity Prediction and Nutrition Guidance through KNN and Decision Tree Models. In 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI) (pp. 757-762). IEEE.

[18] Khalid, M., Deivasigamani, S., V, S. and Rajendran, S., 2024. An efficient colorectal cancer detection network using atrous convolution with coordinate attention transformer and histopathological images. Scientific Reports, 14(1), p.19109.

[19] Li D, Liu Y, Wang B, "Identification of transcriptomic markers for developing idiopathic pulmonary fibrosis: an integrative analysis of gene expression profiles", Int J Clin Exp Pathol 2020;13(7):1698–706.

[20] Zhu K, et al. "Integrated analysis of the molecular mechanisms in idiopathic pulmonary fibrosis", Int J Med Sci 2021;18(15):3412–24.

[21] Cui Y, et al. "Identification of key candidate genes involved in the progression of idiopathic pulmonary fibrosis" Molecules, 2021;26:4.

[22] Xu Z, et al. "Using bioinformatics approach identifies key genes and pathways in idiopathic pulmonary fibrosis", Medicine 2020;99:36.

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