Rotational invariant fractional derivative filters for lung tissue classification

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Abstract
A new and powerful rotation invariant fractional derivative convolution neural network model is proposed for the classification of five categories of interstitial lung diseases. Fractional derivative convolution neural network model employs fractional derivative filters for the texture enhancement of the lung tissue patches instead of the raw image, is given as input directly to the convolution neural network. These FD filters are rotation invariant which solves the problem of rotation invariance of lung tissue patterns caused by pose variations of the patient during CT scanning. Also, the problem of the poor performance of most classifiers such as, support vector machine and K-nearest neighbours caused by an imbalanced dataset is solved, by oversampling the minority categories emphysema and ground glass patches, and under-sampling the majority category, micronodules patches. The experimental results are executed on the publicly available interstitial lung disease database which shows the fractional derivative convolution neural network model performs better than the state-of-art with average F-score and accuracy noted as 93.32% and 93.33% respectively.

1 INTRODUCTION
Interstitial lung diseases (ILD), is a diverse group of disorders found in the tissue between the air sacs of the lungs that leads to fibrosis, or scarring of an interstitium. The scarring of an interstitium makes it difficult for the lungs to receive the oxygen. 15% of all the cases seen by pulmonologists that account for ILD is caused by autoimmune disease, genetic abnormalities, infections, drugs, or long-term exposure to the hazardous materials [1]. Most of the cases, the cause remains unknown and the disease is left as idiopathic. High-Resolution Computerized Tomography (HRCT) imaging is being widely used for visualizing the texture variations of different ILD patterns [2]. However, distinguishing between lung tissue patterns such as Normal, Micronodules, Ground Glass, Fibrosis and Emphysema is a challenging problem because these tissues exhibit similar appearance between different tissue categories and also exhibits great variations within the same categories as shown in (Figure 1). When the radiologists are under heavy workload to manually identify the type of tissue pattern, which is error-prone is difficult. So, it is advised to have an automatic trained system to identify the tissue pattern for interpreting the type of ILD for initial screening.

In this work, we provide the classification of five classes of lung tissue patterns on HRCT images—Normal, ground glass (GG), emphysema, micronodules and fibrosis which are primary among the types of ILDs.

2 RELATED WORK
There exists a wide range of lung tissue classification methods that are broadly classified as hand-crafted features and learned features. In this section, the first part we will mention the approaches that are related to hand-craft features. Next, all the previous works related to learned ones are discussed followed by the recent works on multi-scale rotation variant techniques, and finally, different techniques to solve the problems of the imbalanced data sets are discussed.
2.1 | Hand-crafted features

Medical image classification is carried out in two steps: The first step as feature descriptor extraction based on texture, colour and shape, and the second step labelling the tissue patterns using machine learning algorithms. However, large work is carried out to develop an efficient shape, texture, and colour feature extraction for spatial and frequency-based image analyses. The numerical number of methods for extracting visual features is described by ref. [3]. The intensity properties of tissue patterns are explained by grey level values [4,5]. For additional texture feature extraction, second-order statistic filters such as grey level co-occurrence matrix and RLE [6–10] are employed. Edge features are extracted by Gaussian, Wavelet filters and local binary patterns (LBP) [11–15]. To highlight spatial and shape features [10,13,16], are preferred. Also, to have multivariant, multi-resolution texture descriptors to achieve better results for HRCT imaging are described by the scale invariant feature transform [17,18], and the histogram of oriented gradients [16]. For the given image patch the above-mentioned feature extraction techniques are applied. Figure 2 shows an example of a HRCT lung image with annotated region of interest (AROI).

After obtaining feature descriptors, the next step is to image classification to assign labels to the descriptors. For labelling, the machine learning algorithms are used. In the current work, we focus on supervised approaches. Among them, the most frequently used classification methods are support vector machine (SVM) [10], KNN [9,11,12,15], K-SVD [19], Bayesian classifiers [6], linear discriminant analysis [13,17] and artificial neural network (ANN) [4]. Among these classifiers, SVM gives improved true positive rates and accuracy. Recent work uses unsupervised approaches for extracting learned features from lung tissues to customize the training data. These techniques include sparse representation models [17,20], a bag of features [21] uses k-means, k-SVD to identify the set of textons in the given local patch. RBM [22] used in ANNs produces statistical properties for the given input. Another tool for extracting learned features multiple kernel learning classifier [23] uses class-specific dictionaries minimizes reconstruction error for classification. Albu et al. [24] for estimating the complexity of the model using global motion estimation techniques.

2.2 | Learned features

The major drawback of machine learning algorithms is that they do pixel classification without considering the local dependency of labels. To account for this, one can employ CNN. Recent works on Deep learning techniques and especially CNN’s achieved impressive results in the field of medical image classification [23]. Unlike the approaches are discussed previously CNN’s learn features and train the network at the same time by minimizing the loss function. Firstly, shallow architectures are used for lung tissue classification. In AlexNet [23], VGG-Net [25] and LeNet [26] was used for classification. The input is a colour image with size 224 x 224, so the authors should resize their image patch into three dimensional by applying various Hounsfield unit (HU) windows. Later in ref. [21] the pre-trained CNN [23] was used for lung tissue classification. Song et.al [27] designed three types of deep neural networks CNN, DNN and SAE for lung cancer calcification. Zhang et al. [28] designed a 3D-CNN for the classification of pulmonary nodules into benign or malignant. Bermejo-Pelaez et al. [29] incorporate two, two-and-half three dimensional CNN’s to extract discriminant features for ILD classification. Polat et al. [30] designed a new 3D-hybrid CNN for the detection of lung cancer from the CT scan images. Ajin et al. [31] hybrid kernel-based SVM classifier gave a good classification of ILD compared to CNN and ANN. Aliboni et al. [32] CNN for ILD pattern recognition and evaluated their correlation to functional data. Wáng et al. [33] integrated spherical semi-supervised K- means clustering and convolutional neural networks for ILD classification.
2.3 | Multi-scale rotation-invariant convolution neural network

During CT scanning slight variation in the pose of the patient may cause rotation variation of lung tissue pattern. Also, breathing affects the volume of the lung, ultimately at different scales, different lung details are displayed. Multiscale rotation-invariant features can represent lung tissue patterns rather than raw data given directly to CNN [34]. Lyu et al. [35] designed a multi-level convolution neural network for determining the type of malignancy of lung nodules. Considering this, we propose rotation invariant discrete fractional derivative filters (FDCNN) to get texture details in eight directions [36] after which the image is given to CNN. The silent features of rotation invariant FD filters are: i) In smooth regions it preserves low-frequency details, ii) when variations in grey level are insignificant, it enhances textures features and iii) when variations are considerable, it preserves high-frequency marginal details. Six discrete FD filters [37], which prove an outstanding performance compared to the traditional differential, integral based operators by experimentally and theoretically analysing filters. Eight FD filters [38] using Srivatava-Owa fractional operator, and by varying statistical power parameters he proved the performance is better than the canny edge operator.

2.4 | Imbalanced data distribution

When classifying ILD tissue patterns we face a common problem with an imbalanced number of samples with the database [39], which results in the underrepresentation of most models and causes low classification accuracy. Consider KNN [17], SVM [14], [40] and CNN [15] on the same database have a lower classification performance on minority class because the majority class dominates the neighbourhood of a test sample by considering distance measures. There are very a smaller number of methods to solve this problem. Of them, synthetic minority over-sampling technique (SMOTE) [41] introduces an oversampling method for the minority class, by adding synthetic examples to the feature maps instead of performing rotation and skew operations for increasing the training data set. MOC-SSVM [42] designed a cost-sensitive SVM classifier by optimizing intrinsic parameters, feature set, and misclassification cost of the classifier. Adaptive synthetic minority oversampling method [43] solves the problem of an overgeneralization, by clustering the minority class and lack of flexibility, by using the technique multi trails and feedback in the SMOTE method. By changing the overlapping size between the patches [34] designed a balanced dataset. Gu et al. [44] used weighted support vector machine and calculated Gmean to avoid poor prediction accuracy for the minority class.

3 | OUR CONTRIBUTION

In this paper, we present a joint discriminate power of using rotation invariant fractional derivative (FD) filters and convolution neural network (CNN) to design a new and robust FDCNN model for the classification of the lung tissue pattern more accurately. Our major contributions are detailed as follows.

Construction of rotation invariant filters using fractional-order derivatives and apply those filters for the texture enhancement of the lung tissue pattern.

Design of a CNN model and apply the texture enhanced image patches to CNN for classification instead of raw data as input. Compare the performance of the proposed FDCNN model with the state-of-art.

Also, we solve the problem of an imbalanced dataset that causes low classification accuracy in which most of the classifiers face by under-sampling the majority classes and over-sampling minority classes in the dataset.

4 | METHODS

The overall framework for classifying the lung tissue patterns by FDCNN model is illustrated in (Figure 3). At the very outset, we introduce Fractional-order Derivatives to derive rotational invariant filters [36], for the texture enhancement of the lung tissue pattern. Second, we describe how the proposed FDCNN model accurately classifies the lung tissue patterns by incorporating the rotational invariant texture features as input to CNN rather than raw grey-level images.

4.1 | Discrete fractional derivative filter

FD filters preserve low-frequency contours in the smooth areas for the lung tissue pattern. Since textures are characterized by low-frequency components, these rotation invariant FD filters are employed for texture enhancement. It is defined mathematically [36] as follows:

$$D_z^\alpha f(z) = \frac{(\mu + 1)^\alpha}{\Gamma(1 - \alpha + m)} \left( \frac{d}{dz} \right)^{\mu + 1} \int_0^z \xi^\mu f(\xi)(\xi^{\mu + 1} - \xi^\mu + 1)^{\alpha - \mu - 1} d\xi$$

(1)

The image patch is processed in discrete form. So, using Equation (1) is divided into n equal parts in the interval [0, z], z is real. For each part, the differential is calculated and combined. The FD operator in discrete form is given by Equation (2).

$$D_z^\alpha f(z) = \frac{(\mu + 1)^\alpha}{\Gamma(1 - \alpha + m)} \left( \frac{d}{dz} \right)^{\mu + 1} \sum_{j=1}^n \int_0^z \xi^\mu f(\xi)(\xi^{\mu + 1} - \xi^\mu + 1)^{\alpha - \mu - 1} d\xi$$

$$= \frac{(\mu + 1)^\alpha}{\Gamma(1 - \alpha + m)} \sum_{j=1}^n \left( \frac{d}{dz} \right)^{\mu + 1} \times \xi^\mu f(j)(\xi^{\mu + 1} - \xi^\mu + 1)^{\alpha - \mu} \sum_{j=1}^n$$
The filter coefficients are designed in eight directions [36] using Equations (5) and (6). The texture enhanced image is obtained by convolving the image patch with the FD filter defined as follows:

$$b(x,y) = \sum_{m=-h}^{h} \sum_{t=-h}^{h} w(m,t)f(x+m,y+t).$$

where $f$ represents pixel value in the image patch, $w$ represents filter coefficients as shown in (Figure 4), and $s = t = n$ (size of the filter). These filters are rotation invariant and located on the positive $y$-coordinate, left upward diagonal, negative $x$-coordinate, right upward diagonal, negative $y$-coordinate, right downward diagonal and positive $y$-coordinate and left downward diagonal respectively. By varying statistical values as $0 < \alpha \leq 1$, $\mu \geq 0$ and $\rho \in \mathbb{R}$ (real), the degree of enhancement can be varied.

### 4.2 Convolution neural network

Recently, the CNN was used in medical image classification since it extracts features and performs classification at the same time giving outstanding results. CNN consists of four layers such as the convolution layer, pooling layer, activation and fully connected layer. The convolution layer [26,45] consists of kernels into which the signals are to be convolved is applied to obtain feature maps. The feature maps are joined to the past layers with the weights of the kernel. To upgrade the properties of the input layer the values to the weights are assigned during the training phase. In general convolution layer have fewer weights compared to the last dense fully connected layers to make CNN easy for training. For easy convergence of the network, the weights are assigned by backpropagation during
training. Backpropagation gradients will vanish if the network fails to converge during training. To maintain activations and gradients in control levels initialization is done. At each output of the unit, a non-linear activation is applied. This function is responsible for the speed of convergence of the network. Rectifier linear units (ReLU), defined as

$$f(x) = \max(0, x).$$  \hspace{1cm} (8)

This function gave better results [23] more than hyperbolic tangent and classic sigmoid functions, and speed up training. The function assigns a constant 0 value which results in the elimination of all negative values. By the introduction of the leaky rectifier linear unit (LeakyReLU) the limitations of Equation (8) are overcome. This function introduces a small slope on the negative part of the function. LeakyReLU activation function is defined as

$$f(x) = \max(0, x) + \alpha \min(0, x).$$  \hspace{1cm} (9)

The edge features [40] are enhanced by convolving all features from the initial layers. Pooling is used to spatially combine nearby features [40] to reduce the computational load of the next stages. It is of two types: Max-pooling and average pooling. In maximum pooling, the value is replaced by the maximum value defined in the kernel. In average pooling, the value is replaced by the average value defined in the kernel. Regularization prevents overfitting by applying L1 and L2 regularization. Because of this, we can bind the absolute values of kernel weights. Another regularization method introduced is Dropout [40]. In this method, we can stochastically add noise to hidden layers by multiplying probability value $P$ (e.g. 0 or 0.5), to each unit during the training process. This helps the network to learn the features on their own. Data augmentation can be used to increase the size of training sets either by translation or rotation and reduce overfitting [23]. Since the classification of the patch is obtained by the central voxel, we restricted the data augmentation to rotating operations. In ref. [23] author considered image translations, but for segmentation, this could result in the wrong classification of the patch. So, by rotating the original image patches in multiples of $90^\circ$ we generated a new data set. CNN is trained by minimizing the following cost function. We used the categorical cross-entropy as in Equation (10).

$$H = - \sum_{j \in \text{voxels}} \sum_{k \in \text{classes}} C_{j,k} \log(\hat{C}_{j,k}).$$  \hspace{1cm} (10)

where $\hat{C}_{j,k}$ represents the probabilistic predictions.

## 5 Experimental Setup

### 5.1 Dataset

The proposed method is executed on the standard Talisman suit provided by university hospitals of Geneva (HUG). The HUG gives 2D and 3D annotated lung tissue patterns to examine multiple cases of ILD. Different tissue patterns are drawn by 15 to 20 years of experienced radiologists for 108 image slices of $512 \times 512$ pixels/slice. The 2D AROIs for the image slices are examined to indicate altogether 17 different lung tissue patterns. In the dataset, 113 sets of image slices and AROIs of 1458 are given for classification. In our study, we classify five classes of lung tissue patterns such as, normal, ground glass, emphysema, micronodules and fibrosis out of 17 tissue patterns. The
TABLE 1 Overview of the database

| Class          | Normal ($C_N$) | Emphysema ($C_E$) | Ground glass ($C_G$) | Fibrosis ($C_F$) | Micronodules ($C_M$) |
|----------------|----------------|-------------------|----------------------|-----------------|---------------------|
| Visual aspect  | ![Image](image1) | ![Image](image2)  | ![Image](image3)    | ![Image](image4) | ![Image](image5)    |
| Images         | 15             | 9                 | 35                   | 35              | 18                  |
| AROIs          | 157            | 108               | 416                  | 479             | 298                 |
| Unbalanced patches | 6934          | 1474              | 2974                 | 4456            | 7893                |
| Balanced patches | 4195          | 5385              | 5567                 | 3819            | 5139                |

ROI drawn is divided into $32 \times 32$ image patches with 70% of pixels that must fall inside the annotated ROI. In ref. [39], the adjacent patches overlapping size is $16 \times 32$, which leads to an imbalanced dataset with relatively fewer patches for categories emphysema and ground glass. SVM, KNN is sensitive to imbalanced data set, which would cause low classification accuracy. So, we changed the overlapping size between adjacent patches, to design a cost-sensitive classifier. Here, [34] increased the overlapping size to $23 \times 32$, to get more samples to the categories namely, emphysema and ground glass. Similarly, for micronodules, we decreased the overlapping size to $9 \times 32$, to get fewer samples. The balanced dataset for the five lung tissue patterns after oversampling the adjacent patches is given in Table 1.

5.2 Evaluation metrics

We compare the proposed rotation invariant FDCNN model by the standard evaluation metrics for the given database. The performance of lung tissue classification is estimated with a four-fold cross-validation setup in terms of recall, precision, F-score and accuracy.

\[
\text{Recall} = \frac{TP}{TP + FN}. \tag{11}
\]
\[
\text{Precision} = \frac{TP}{TP + FP}. \tag{12}
\]
\[
\text{F-score} = \frac{2TP}{2TP + FP + FN}. \tag{13}
\]
\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{14}
\]

where TP is number of true positive for the classification of lung tissue patterns. Similarly, FP—false positive, TN—true negative and FN—false negative. The 3D AROIs are excluded for image patch classification.

5.3 Set up

The proposed FDCNN model is as shown in (Figure 3). As the first step, fractional-order derivative (FD) filters of size $3 \times 3$ are designed in eight orientations: $0^\circ$, $45^\circ$, $90^\circ$, $135^\circ$, $180^\circ$, $225^\circ$, $270^\circ$ and $315^\circ$. These filters are located on the positive y-coordinate, left upward diagonal, negative x-coordinate, right upward diagonal, negative y-coordinate, right downward diagonal and positive y-coordinate and left downward diagonal respectively. All these eight FD filters are summed together to form the rotation invariant FD filter. The statistical parameter values [36] are set as $\alpha = 0.1$, $\mu = 0.05$ and $\rho = 6$ for calculating the coefficients of the filters. The texture enhanced image is represented by convolving the grayscale image patch with the rotation invariant FD filter. After that, the 2D rotation invariant FD enhanced $32 \times 32$ image patch is applied as input to the CNN.

CNN consists of altogether 3 convolution layers with filters of size $5 \times 5$ and the number of filters increased to 16, 32 and 64 respectively. The output of the convolution layer is followed by maximum pooling with kernels of size $2 \times 2$ that reduces the size of the image patch by half. Activation functions are followed to speed up the process of convergence. The Leaky ReLu activation function used solves the dying ReLu problem and has the mean activation function close to zero which makes training faster. The default value for leaky parameter $\alpha$ as 0.01 is changed to 0.3, to increase the speed of convergence. The proposed CNN is to classify five categories of lung image patches, so the last fully connected layer is designed for 5 outputs with a dropout of 0.5%. The training of CNN is done by properly tuning the hyperparameters as shown in Table 2. In the present work, Adam optimizer [38] is used to minimize cross-entropy. Adam optimizer [38] is a first-order gradient method that minimizes the cross-entropy by tuning three parameters such as learning rate, exponential decay rates for gradient, and squared gradient. These parameters are updated by using lower-order moments to optimize the stochastic objective function. After many observations, the default values for the three parameters are set to 0.001, 0.99 and 0.9 respectively.
### TABLE 2  Hyper parameters for training CNN

| Stage         | Hyper parameter | Value   |
|---------------|-----------------|---------|
| Initialization| Bias            | 0.1     |
|               | Weights         | Xavier  |
| Leaky ReLU    | $\alpha$        | 0.3     |
| Drop out      | $P$             | 0.5     |
| Training      | Learning rate   | 0.001   |
|               | Max epochs      | 50      |
|               | Momentum        | 0.9     |
|               | Minimum batch size | 64    |

### TABLE 3  Confusion matrix for image patch classification

| Actual classes | Prediction in (%) | $C_E$ | $C_F$ | $C_G$ | $C_N$ | $C_M$ |
|----------------|-------------------|------|------|------|------|------|
| $C_E$          |                   | 85   | 0    | 0    | 6.67 | 8.33 |
| $C_F$          |                   | 1.67 | 96.67| 1.67 | 0    | 0    |
| $C_G$          |                   | 0    | 0    | 96.67| 1.67 | 1.67 |
| $C_N$          |                   | 3.33 | 0    | 0    | 96.67| 0    |
| $C_M$          |                   | 3.33 | 0    | 1.67 | 3.33 | 91.67|

### EXPERIMENTAL RESULTS AND DISCUSSION

#### 6.1  Patch level classification

Here we analyse the patch-wise lung tissue classification results using our proposed FDCNN model. Table 3 shows the confusion matrix calculated for the five categories. It measures an average true positive rate of 93.34% which shows better performance when compared with the existing popular techniques [17,25,34]. 1.67% of ground glass (GG) image patches are falsely identified as Normal because they are highly dense. Micronodules and normal image patch background intensities are high and become difficult to distinguish as a result 3.33% of them are misclassified. The low accuracy of the emphysema image patch is because of its similarity with other categories as seen in (Figure 1).

The Emphysema image patches are fewer compared with the other class patches. The deep learning model will not work well if training samples are not enough to train the model. This is a little bit worse condition that limits the performance of the proposed FDCNN model. We provide additional information about the performance of the proposed method as in (Figure 5) in terms of loss and accuracy during the training of the proposed CNN. The red descending curves correspond to the loss function values for the training and validation sets during training. The blue ascending curves correspond to the accuracy values for the training and validation sets during training. The two curves start to diverge from one another to nearly around 100 epochs. However, validation loss continues to descend approximately up to 500 epochs. The time complexity for the proposed model is 54 ms.

Table 4 summarizes the classification recall, precision, and F-score for all five lung tissue categories. The results show relatively high performance among the tissue patterns, which proves the reduction in the classification difficult between low range inter-class divergence and high-level intraclass divergence.

#### 6.2  Comparisons with the existing hand-crafted features

The main characteristics of the rotation invariant FDCNN model are to remove the rotation variance of lung tissue patterns by applying rotation invariant fractional-order derivative (FD) filters to the image patches instead of applying raw image directly as input to the CNN. In this section, we discuss the most popular handcraft techniques used for the classification of lung tissues and we compare the performance of our FDCNN model with the existing techniques in terms of precision and recall as shown in (Figure 6). The existing techniques are 1) MRCNN [34], designed a multiscale rotation invariant CNN architecture using Gabor filters, LBP instead of the raw image given as input to the CNN, 2) patch-adaptive sparse approximation (PASA) [17], constructed two feature vectors namely the rotation-invariant Gabor-local binary patterns texture descriptor and multi-coordinate histogram of oriented gradients gradient descriptor and classification is done by a new data-adaptive and non-parametric approach, namely PASA method, 3) LF [14], constructed feature vector by combining gray level histogram and wavelet-based texture features, followed by SVM classifier, 4) LSRE [46], uses ensemble classifiers with fused data-adaptive distribution, and approximation-based weights for the datasets are generated by hierarchal clustering using the affinity matrix.

Our FDCNN model exhibits better performance for the categories of ground glass and fibrosis and comparative performance for normal and micronodule tissues. Due to the misclassification of other classes, the recall of emphysema is less compared to other approaches. This is because, Locally-constrained Sub-cluster representation Ensemble [46] method, higher fusion weights are assigned to the minority class emphysema and PASA [17] method, the classifier labels are assigned with minimum reconstruction error.

#### 6.3  Evaluation of different balanced data distribution

Most of the classification methods are affected by the imbalanced data set [39] since these datasets cause poor performance of the model even though it is efficiently designed. To solve this problem in this section, we first discuss different balanced data distribution methods, and next, we evaluate the proposed FDCNN model with the above methods. Table 5 gives an overview of the balanced dataset generated after sampling.
FIGURE 5  (a) Accuracy and (b) loss curves during the training of the network.

TABLE 4  Results of image patch classification

| Metric   | $C_E$ | $C_F$ | $C_G$ | $C_N$ | $C_M$ | Avg |
|----------|-------|-------|-------|-------|-------|-----|
| Precision| 91.07 | 100   | 96.67 | 89.2  | 90.16 | 93.42 |
| Recall   | 85    | 96.67 | 96.67 | 96.67 | 91.67 | 93.34 |
| F-score  | 87.93 | 98.3 | 96.67 | 92.8  | 90.91 | 93.32 |

FIGURE 6  Shows the comparison performance of our proposed fractional derivative convolution neural network model with other popular handcraft features in terms of (a) recall and (b) precision.
The methods used are 1) Original method, the overlapping size between neighbouring patches is $16 \times 32$ which yields 9619 micronodule patterns, 1157 emphysema, and 1187 ground glass patterns respectively. The resulting is an imbalanced dataset. 2) Resample method, micronodules are large in number compared to the remaining four categories in the original dataset, 2800 of these patterns are under-sampled during every training process. And also, we alleviate the minority classes emphysema and ground glass patches by re-sampling extra 1672 patches for each class respectively. 3) SMOTE [41] introduces an over-sampling method for the minority class, by adding synthetic examples to the feature maps instead of performing rotation and skew operations for increasing the training data set. The synthetic examples are generated by multiplying a random number between 0 and 1 to the difference taken between the test sample and its KNN. Depending upon the sampling required, neighbours are created randomly from the KNN along the same line segment. 4) Proposed method, the overlapping size between adjacent patches is changed, micronodules are under sampled by reducing the overlapping size to $9 \times 32$ to get fewer samples, and emphysema and ground glass patterns are oversampled by increasing the overlapping size to $23 \times 32$ to get more samples.

We evaluate the performance of the rotation invariant FDCNN model for the imbalanced data and the balanced dataset as shown in Table 5. (Figure 7) shows the Recall and Precision values of the five lung tissue patterns for original, resample, SMOTE and proposed method.

SMOTE method shows a tremendous decrease in both recall and precision for all the categories, this may be because in this method minority patches are generated without considering neighbouring patches, which increases the overlapping between patches. Although considering 2800 samples out of 9619 of micronodules in the resampling method, the classification recall is slightly affected. By changing the overlapping size between adjacent patches, our FDCNN model learns discriminant features for the five categories which show high classification recall and precision, which reduces the overfitting problem in the Resample method and overgeneralization problem in the SMOTE method.

### 6.4 Comparison with other standard convolution neural network’s

Table 6 provides a comparison of the proposed CNN with other standard CNNs. Li [15] is the first CNN with 3 convolution layers and 3 dense layers. It is the shallow architecture that prevents the network from learning non-linear features results in low accuracy.
TABLE 6 | Comparison of proposed CNN with other CNN’s

| Method         | $F_{avg}$ | Accuracy |
|----------------|-----------|----------|
| Li [15]        | 0.6657    | 0.6705   |
| LeNet [26]     | 0.6783    | 0.6790   |
| AlexNet [23]   | 0.7031    | 0.7104   |
| VGG-Net [25]   | 0.7804    | 0.7800   |
| Anthimopoulos [47] | 0.8547    | 0.8561   |
| FDCNN model    | 0.9332    | 0.9333   |

TABLE 7 | Classification accuracy

| Rotation invariant methods | Accuracy (%) |
|----------------------------|--------------|
| Local binary pattern (LBP)| 86.7         |
| Gabor                      | 89.7         |
| Gabor + LBP                | 90.1         |
| FD filters                 | 93.3         |

7 | CONCLUSION

A new rotation invariant FDCNN model is presented in this paper for the classification of five categories of lung tissue patterns on publicly available ILD database. In this method, instead of a raw image applying to the CNN, a texture enhanced rotation invariant image is given as input to the CNN. This improves the classification performance for the reasons such as Fractional-order Derivative (FD) filters produce rotation-invariant features by properly defining the statistical parameters for the construction of filters, and compared to the other feature learning models, CNN along with FD filters optimizes the feature maps and classification. Finally, unlike the traditional methods that suffer from unbalanced data distribution with the tissue pattern Emphysema and Ground Glass, we solved this problem by under-sampling the majority classes and oversampling the minority classes. Our experimental results on the publicly available ILD database shows that this rotation invariant learned features are effective for lung tissue classification. In the future, we will apply this model to multispectral images.

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