

A distance transformation deep forest framework with hybrid-feature fusion for CXR image classification

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Abstract—Detecting pneumonia, especially COVID-19, from chest X-ray (CXR) images is one of the most effective ways for disease diagnosis and patient triage. The application of deep neural network for CXR image classification is limited due to the small sample size of the well-curated data. To tackle this problem, this paper proposes a distance transformation-based deep forest framework with the hybrid-feature fusion (DTDF-HFF) for accurate CXR image classification. In our proposed method, hybrid features of CXR images are extracted by two ways: hand-crafted feature extraction and multi-grained scanning. Different types of features are fed into different classifiers in the same layer of the deep forest, and the prediction vector obtained at each layer is transformed to form distance vector based on a self-adaptive scheme. The distance vectors obtained by different classifiers are fused and concatenated with the original features, then input into the corresponding classifier at the next layer. The cascade grows until DTDF-HFF can no longer gain the benefits from the new layer. We compare the proposed method with other methods on the public CXR data sets, and the experimental results show that the proposed method can achieve state-of-the-art performance. The code will be made publicly available at <https://github.com/hongqq/DTDF-HFF>.

Index Terms—Classification, Chest X-Ray, COVID-19, Deep Forest, Hybrid Feature Fusion

I. INTRODUCTION

PNEUMONIA is one of the leading causes of death among children and elderly people worldwide, with about 4 million patients at risk of dying each year. According to World Health Organization (WHO), pneumonia accounts for 15% of all deaths in children under five years of age [1]. It is an infection caused by viruses, bacteria or fungi, which will result in inflammation in the lungs and adversely affect the alveoli. Especially in the past year, Coronavirus disease 2019 (COVID-19), caused by a novel corona-virus (SARS-CoV-2), has become the most severe epidemic disease in the world. So far, 215 countries and territories have been affected by the COVID-19 epidemic. **As of December 22, 2022, in the worldwide, more than 650 million cases of COVID-19 have been confirmed, and more than 6 million deaths have been recorded [2].** It has had a severe impact on human's health and global economy.

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Early diagnosis of pneumonia, especially COVID-19, is of great importance in providing the opportunity of performing patient triage in time, planning early interventions, and offering effective treatments. With the continuous development of imaging technology, chest radiography imaging has become a routine tool to estimate whether a patient has pneumonia. Chest computed tomography (CT) and chest X-ray (CXR) have been widely used in clinical practice, which can provide diagnostic basis for screening, diagnosis and differentiation of early pulmonary infection.

Compared to CXR, CT scan has a higher resolution in space and density, which is able to facilitate a quantitative assessment for pulmonary changes. However, CT is not suitable for large-scale screening of pneumonia due to the relatively high cost and high radiation dose [3]. In addition, it requires strict separation of patients with COVID-19 from other general patients to avoid cross infection. With the pandemic of COVID-19, the burden of CT examination in radiology department is increasing along with the potential risk of infection. On the other hand, CXR examination is simple to operate. It requires less imaging time and lower cost. As a supplement to CT, CXR can be utilized to screen patients' initial diagnosis and confirm the priority of patients' treatments, which is helpful for the saturated healthcare system in the pandemic situation [4]. However, CXR images have many very subtle and similar features with low sensitivity, which makes it a cumbersome task for visual inspection. Generally, it is not an easy task to interpret such subtle abnormalities, even for experienced radiologists. Furthermore, the number of suspected infected patients is increasing rapidly, while the number of specialist radiologists is very limited. Hence, it is an urgent need to develop automated methods for identifying those subtle abnormalities in CXR images, which could aid the diagnostic procedure and improve early diagnosis rates with high accuracy. Artificial intelligence (AI) and machine learning solutions are potentially powerful tools for solving such problems [5].

Consequently, researchers in the field of machine/deep learning have been actively exploring approaches to classify CXR images [6]–[13]. At present, deep learning methods used in medical image classification are mostly based on deep neural networks (DNNs). Although DNNs are capable of accomplishing the task well in most cases, it in most time requires a large number of samples for training and consumes a lot of computational resources. DNNs map the original data

1 into the feature space through the convolution layer, pooling
 2 layer and activation function layer. However, DNNs have no
 3 obvious advantage in processing features extracted by tradi-
 4 tional methods. In recent years, as a new deep learning model
 5 integrating trees and forests, deep forest (DF) [14] has been
 6 gradually applied in many fields, which can accomplish the
 7 corresponding tasks under the conditions of fewer required pa-
 8 rameters and computing resources. Compared with the feature
 9 space mapped by the convolution layer and pooling layer in
 10 DNNs, DF can directly handle various types of features. In the
 11 case of COVID-19 pandemic, it is difficult to have a collection
 12 of a large number of filtered CXR data sets. Therefore, under
 13 the condition of limited training data sets, this paper develops
 14 an improved DF framework based on mixed feature fusion and
 15 distance transformation, i.e. DTDF-HFF, to achieve accurate
 16 pneumonia classification on CXR images. Our proposed model
 17 uses the traditional feature extraction method to extract the
 18 image features and uses multi-grained scanning to provide
 19 the image information at different resolutions, enriching the
 20 feature input and enhancing the robustness of the model.

21 The overall process of the method proposed in this paper is
 22 as follows: first, the CXR images are segmented to obtain the
 23 lung mask. Two feature extraction methods are carried out on
 24 the image of the mask part to generate diverse feature subsets:
 25 hand-crafted feature extraction and multi-grained scanning.
 26 Different types of features are fed into different classifiers
 27 in the same layer, and the prediction vectors of each layer
 28 are transformed by a self-adaptive method to form distance
 29 vectors. The distance vectors obtained by different classi-
 30 fiers are fused and concatenated with the original features,
 31 and then feed to the corresponding classifiers at the next
 32 level. Cascading forests are constructed in this way until
 33 they converge. The outputs of the final layer is averaged as
 34 the classification result. This framework can be extended to
 35 classification tasks of various medical images. We compare the
 36 proposed method with other methods on the public CXR data,
 37 and the experimental results show that the proposed method
 38 can achieve superior performance to other state-of-the-art deep
 39 learning methods.

40 To the best of our knowledge, our DTDF-HFF is the
 41 first framework to exploit DF in the task of CXR image
 42 classification. The main contributions of this paper are as
 43 follows:

44 1. A new deep forest framework (DTDF-HFF) based on
 45 hybrid-feature fusion and distance transformation is proposed
 46 for accurate classification of CXR images. This framework can
 47 be extended to classification tasks of various medical images.

48 2. Multiple types of features are fed to different classifiers,
 49 and the sliding window is used to get multi-resolution image
 50 features to avoid global information loss under single reso-
 51 lution. Therefore, hybrid features support the high diversity
 52 among different classifiers, so as to enhance the discriminative
 53 ability of the proposed model.

54 3. A new distance transformation scheme is designed for the
 55 DF framework. It replaces the augment vector in the original
 56 DF with the distance vector transformed by the adaptive
 57 method, aiming to accelerate the convergency.

II. RELATED WORK

A. Machine learning techniques for medical image classifica- tion

During the past few years, a considerable amount of ma-
 chine learning techniques have been proposed for medical
 image classification. Most of these methods can be roughly
 classified into two groups: classical machine learning-based
 methods and deep learning-based methods.

Generally, the classical machine learning based methods
 require two stages for the classification task. In the first stage,
 multiple features of medical images are extracted, and then the
 features are fed to classifiers, such as support vector machine
 (SVM), Markov random fields, random forests (RF), neural
 networks, in the second stage for classification [15]–[19].

Under the influence of the COVID-19 pandemic, recent
 studies have mostly focused on the automatic diagnosis of
 pneumonia using chest radiography images. Zargari et al.
 [20] used global features of the whole CXR images to build
 machine learning classifier. The model is able to distinguish
 COVID-19 cases from non-COVID-19 cases with high accu-
 racy and sensitivity. Dey et al. [21] employed the ensemble
 feature scheme (EFS) for pneumonia detection in CXR, which
 combined the hand-crafted features with the deep features and
 tested in different classifiers.

Recently, more and more studies have focused on medical
 image classification based on the deep learning technique,
 which has the strong representation learning ability via training
 multi-layer artificial neural networks [8], [10], [22]–[26]. Punn
 et al. [27] proposed a loss function approach for transfer learn-
 ing on binary classification of posteroanterior CXR images.
 Rajpurkar et al. [28] developed a deep learning network termed
 as Chexnet based on ChestX-ray14 for pneumonia detection.
 The model achieved state of the art results on all 14 diseases
 in Chest X-rays. Nour et al. [29] proposed deep convolutional
 neural network (CNN) model which was trained from scratch
 to extract discriminative features on CXR images. Rubin et al.
 [30] proposed a novel DuaNet for processing both frontal and
 lateral CXR images. Their model improved performance in
 recognizing findings in CXR images. Lakhani et al. [31] built a
 model that integrated the AlexNet and GoogleNet for detecting
 tuberculosis in CXR. Wang et al. [32] utilized natural language
 processing method to mine disease image tags, demonstrating
 that these common chest diseases can be detected by a unified
 weakly supervised multi-label image classification and disease
 localization framework.

On account of the COVID-19 pandemic, more researchers
 have been applying deep learning to pneumonia diagnosis.
 Ozturk et al. [33] presented the DarkCovidNet for automatic
 COVID-19 detection in CXR images. Chen et al. [34] designed
 a system based on CT for diagnosis of COVID-19 pneumonia.
 Xu et al. [35] established a deep learning models for the early
 screening of COVID-19 on CT datasets. Oh et al. [4] proposed
 a patch-based convolutional neural network approach with a
 relatively small number of trainable parameters for COVID-19
 diagnosis. The Covid-Net, an open source deep convolutional
 neural network platform, was proposed in [36] for detecting
 chest radiographs of COVID-19 cases. Ozturk et al. [33] pro-

posed a model for automatic detection of COVID-19 for binary classification diagnosis. Jadon et al. [37] proposed a custom few-shot learning method to detect COVID-19 using Siamese networks. Chaddad et al. [38] fed GMM-CNN features into a robust classifier to distinguish COVID-19 from other cases of pneumonia. CoVIRNet was proposed by Almalki et al. [39] to automatically diagnose the COVID-19 patients from CXR images. Dong et al. [40] proposed a learning model called RCoNet, which can distinguish COVID-19 from ordinary pneumonia more accurately and robustly. Irfan et al. [41] proposed a hybrid deep neural network (HDNNs) to predict the risk of developing COVID-19 in patients using computed tomography (CT) and X-ray imaging. A deep uncertainty-aware transfer learning framework was proposed by Shamsi et al. [42] for the detection of COVID-19 infected patients using CT and CXR images.

Despite more other works in literatures [43]–[49] report a excellent performance in detecting COVID-19, most deep learning techniques for medical image classification are based on deep CNNs, which generally require a large number of training samples or pretrained models. Currently, collecting sufficient data samples with proper annotations is still one of the main challenges for effective training of deep neural network models.

B. Deep forest (DF)

Inspired by the layer to layer of DNNs which abstract information layer by layer, Zhou and Feng [14] put forward a novel decision tree-based ensemble deep learning framework with layers of cascade structure. Each layer contains two different types of forests with the aim of enhancing the diversity. Although the structures similar to DNNs, DF does not rely on back propagation. Compared with DNNs, DF requires much less training data, and is easier to be trained with fewer parameters.

A number of studies have begun to develop variant models based on DF, including the deep multi-feature fusion for hyperspectral image feature fusion and classification [50], the Deep-Resp-Forest for the classification of the anti-cancer drug response [51], the multi-label based deep forest (MLDF) for the multi-label problems [52], the weighted deep forest for Schizophrenia data classification [53], and the adaptive feature selection guided deep forest for COVID-19 classification with chest CT [54]. These studies have demonstrated that DF can well handle a set of challenges in a variety of fields [55]–[58]. Given the limited medical image data sets, this study tries to develop the DF with hybrid feature fusion, aiming to improve the diagnostic accuracy of lung diseases.

III. PROPOSED METHOD

The overall architecture of the proposed method is shown in Fig. 1. The CXR images are firstly preprocessed and segmented by FC-DenseNet [59] to generate the mask of lung regions, which is subsequently processed by two feature extraction schemes: hand-crafted feature extraction and multi-grained scanning. These features are fed to the distance transformation DF with hybrid-feature fusion (DTDF-HFF), which

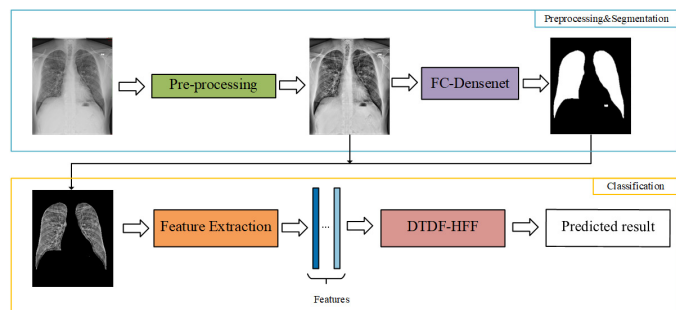


Fig. 1. Overall architecture of the proposed method. (1) The CXR images are preprocessed and segmented to generate the mask of lung regions. (2) Multiple types of features are extracted and input into our DTDF-HFF for classification.

is a new framework for accurate CXR image classification. The details are given as follows.

A. Preprocessing and Segmentation

CXR images mainly contain left lung, right lung, heart, and background. The segmentation technique is used to extract the lung region to remove the negative impact from the irrelevant features based on FC-DenseNet103. Since the original images collected from different datasets under various conditions, the data sets are processed and normalized to ensure that the images can be normally segmented:

- ① Adopt the contrast-first adaptive histogram equalization algorithm (CLAHE) to make the histogram strength of data uniform.
- ② Adjust all images to the same size before inputting into FC-DenseNet103 for image segmentation.
- ③ Detect the contour shape after image segmentation and calculate the contour area.
- ④ Keep the top two contour images in area size and remove the rest contours with noise in the image.

B. Hybrid feature extraction

Owing to the rich information of pathological features in CXR images, multiple features obtained from different processing techniques are applied to mine image features and their rich internal information fully [55]. The common hand-crafted features obtained from discrete wavelet transform (DWT) and gray level difference method (GLDM), as well as multi-grained scanning features are applied in our framework.

(1) Hand-crafted Feature

There is no texture information in the masked image except for the lung areas. Therefore, it is necessary to reduce the use-less information of these untextured regions in the extraction of hand-crafted features. As shown in Fig. 2, we clip most of the untextured areas around the lung areas and scale the image to a uniform size, and then extract features respectively for the upper and lower parts of the left and right lungs.

The features of the low frequency components, horizontal high frequency components, vertical high frequency components and diagonal high frequency components are obtained

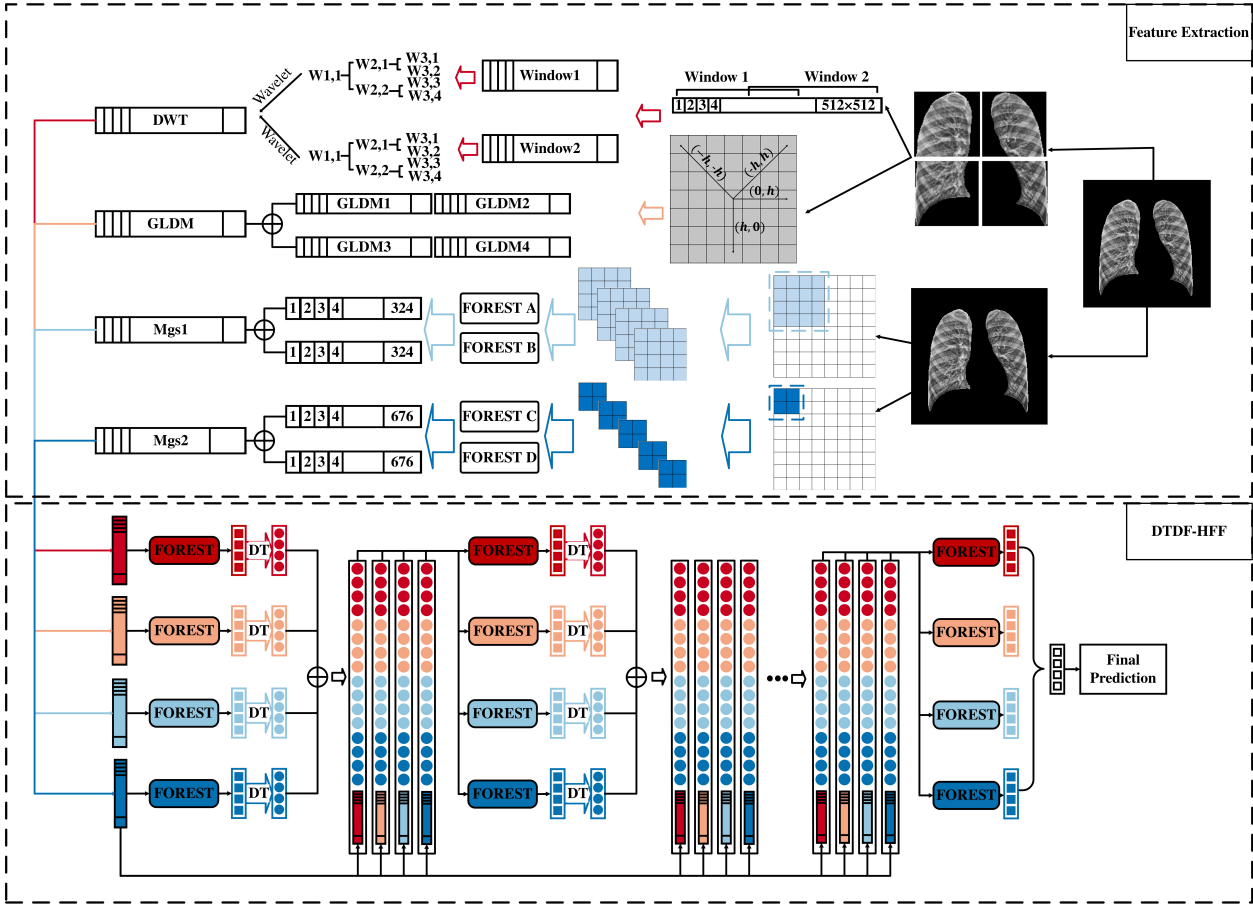


Fig. 2. The structure of our DTDF-HFF. (1) We extract hand-crafted features respectively for the upper and lower parts of the left and right lungs and generate multi-grained scanning features for the feature re-representation. (2) Different colors represent different input features. (3) Distance transformation vector is calculated by distance transformation (DT) of the prediction probability. (4) The inputs in the second and subsequent layers are concatenation of feature and distance transformation vectors.

by two-dimensional DWT. Assuming that $\psi(r)$ is a wavelet centered at $r = 0$. Let

$$\psi_{a,b}(r) = \frac{1}{\sqrt{a}} \psi\left(\frac{r-b}{a}\right) \quad (1)$$

where a and b are scale factors and shift factors defined discretely respectively. And according to certain given base scale factor a_0 and shift factor b_0 , a and b are defined as: $a = a_0^\alpha, a_0 > 0, \alpha \in \mathbb{Z}; b = \beta b_0 a_0^\alpha; b \in \mathbb{R}, n \in \mathbb{Z}$. More specifically, for each pair of (α, β) , the corresponding wavelet is:

$$\psi_{\alpha,\beta}(r) = a_0^{-\frac{\alpha}{2}} \psi(a_0^{-\alpha} r - \beta b_0) \quad (2)$$

The DWT of a function $f(r)$ is defined as

$$\text{DWT}(\alpha, \beta) = \int_{\mathbb{R}} f(r) \psi_{\alpha,\beta}(r) dr \quad (3)$$

The features based on the GLDM are block-based localized features, which are derived from the P function [60]. These features are calculated by the P function for eight gray levels

in four different directions. For any given displacement vector $h = (dx, dy)$, the probability density function of gray level g of image I is defined as:

$$P(g | h) = \text{Prob}(\text{diff}(\theta, \rho) = g) \quad (4)$$

where $\text{diff}(\theta, \rho) = |I(\theta, \rho) - I(\theta + dx, \rho + dy)|$.

GLDM features are extracted from 4 directions of each part and DWT features are extracted from 8 wavebands of each part. The features obtained from each part are calculated by statistical methods, including Mean, Std, Skewness, Kurtosis, Energy, Entropy, Max, Min, Mean Deviation, Median, Range, RMS, Uniformity, MeanGradient, and StdGradient. Eventually, 448-dimensional features are extracted from DWT and 224-dimensional features are extracted from GLDM, and they are concatenated to form a 672-dimension vector for each sample.

(2) *Multi-grained scanning features (Mgs)*

Besides the extracted hand-crafted features, the sliding window scanning is deployed for feature re-representation. As

shown in the bottom half of Fig. 1, the images are processed by the sliding windows to input Extra-Trees (ETs). The feature dimension G generated for each ET is:

$$G = C \times \left(\left\lceil \frac{z_l - w}{s} \right\rceil + 1 \right) \times \left(\left\lceil \frac{z_w - w}{s} \right\rceil + 1 \right) \quad (5)$$

where C is the class number, and z_l, z_w are the image length and width dimensions; w is the size of a scan window, and s is the length of stride.

In this way, our proposed framework accommodates four different types of features, which are fed to different classifiers to enrich the flexibility and versatility of the model.

C. Distance transformation scheme

The distance transformation (DT) scheme is designed to enhance the discriminative ability of the DF framework, as shown in Fig. 2.

In the original cascading structure, different classifiers in the same layer receive the same features as inputs. Their outputs are combined to form the augment vector, which is fused with the original feature set to form the input for the next layer. While in our algorithm, hybrid features are input to train the corresponding ETs, so as to enhance the diversity among them. As shown in Fig. 2, the four ETs in each layer output four probability vectors, which are combined as the augment vector.

After the preprocessing, there would still exist noise in the image data, so that the probabilities corresponding to different classes could still be biased towards the major classes. Furthermore, the inconspicuous lesions as well as characterization of different diseases may have similar appearance on some regions of the samples. As a result, the probability values of two classes in the prediction vector may not be of great difference. When the output probabilities of different classes of the model are close, the diseases represented by the images may be misclassified.

To optimize the information from the probability vector, the confusion matrix is deployed to measure the correlation strength of various classes by a self-adaptive method. The confusion matrix reflects the relationship between the ground-truth labels and the prediction results. Assume that for the classification task of C classes, the identification data set S contains n samples. Let $cm_{i,j}$ represent the number of samples of class i judged by the m_{th} ET as class j . Then, the confusion matrix CM of ET m is a $C \times C$ matrix:

$$CM(S, m) = \begin{bmatrix} cm_{1,1} & \cdots & cm_{1,j} & \cdots & cm_{1,C} \\ cm_{2,1} & \cdots & cm_{2,j} & \cdots & cm_{2,C} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ cm_{i,1} & \cdots & cm_{i,j} & \cdots & cm_{i,C} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ cm_{C,1} & \cdots & cm_{C,j} & \cdots & cm_{C,C} \end{bmatrix} \quad (6)$$

The main steps of the distance vector mapping are given as follows:

① Generate the output probability vectors with the corresponding ETs. Suppose there are M ETs in the l_{th} layer, and

T trees in each ET, then the probability vector of the n_{th} sample is:

$$v_{m,l}^n = \frac{1}{T} \sum_{t=1}^T p_{m,l}^{n,t} \quad (7)$$

where $p_{m,l}^{n,t}$ is the prediction probability of the n_{th} sample in tree t of the m_{th} ET in layer l .

② Calculate the distance between each row of the normalized confusion matrix $CM(S, m)$ and the probability vector $v_{m,l}^n$. The distance evaluation method adopted here is Euclidean distance, and the distance between the probability vector and a row vector C_n of the normalized confusion matrix is calculated by:

$$d_{m,l}^{n,c} = \sqrt{\sum_{k=1}^C (v_{m,l}^{n,k} - cm_{c,k})^2} \quad (8)$$

③ Generate the input vectors for the corresponding classifiers of the next layer. After calculating the distance, the N -dimensional enhancement vectors are fused and concatenated with the corresponding original features and input to the corresponding classifiers of the next layer. Let $D_{m,l}^n = (d_{m,l}^{n,1}, \dots, d_{m,l}^{n,C})$ be the n_{th} sample's distance transformation vector of m ET in l_{th} layer. Let $V_l^n = (D_{1,l}^n, \dots, D_{M,l}^n)$ be the concatenation vectors of distance vectors. The training feature of sample n_{th} for ET m in the next layer is:

$$X_{m,l}^n = (S_m^n, V_l^n) \quad (9)$$

where S_m^n is the m_{th} feature of n_{th} sample.

④ Calculate the final prediction result at the last layer. The layer obtaining the highest performance on the validation set is deployed as the output layer. And after obtaining the prediction vectors of all ETs in the last layer, the n_{th} sample is assigned to the class corresponding to the maximum value of the averaged prediction vector, as given below:

$$V^n = \frac{1}{M} \sum_{m=1}^M (v_{m,l}^n) \quad (10)$$

Algorithm 1 presents the process of training and prediction based on our distance transformation deep forest with hybrid-feature fusion (DTDF-HFF). The data set S is divided into the training set $S_{Tr} = (S_{Tr}^1, \dots, S_{Tr}^M)$ and the test set $S_{Test} = (S_{Test}^1, \dots, S_{Test}^M)$. Samples in S_{Test} are regarded as unknown samples. At the training phase, after each layer is generated, the overall performance of the model is calculated to determine whether the cascade forest continues to grow. At the testing phase, the outputs of the last layer are combined together as the output vectors, and the corresponding unknown sample in the test set is assigned to the class represented by the highest probability in the averaged output vector. The performance of our algorithm is verified in the following experiments.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Data source and processing

The pandemic of COVID-19 has put limited medical resources under serious and continuous strain, making the pneumonia related diseases diagnosed to become an urgency. In

Algorithm 1 Distance transformation deep forest with hybrid-feature fusion (DTDF-HFF)

```

1:  $V_l^{X_{Tr}} = \square, V_l^{X_{Test}} = \square$ 
2: //Training stage
3: for  $l = 1 : L$  do
4:   if  $i = 1$  then
5:     let  $X_{Tr} = S_{Tr}$ 
6:   else
7:     let  $X_{Tr} = \text{concat}(S_{Tr}, V_{l-1}^{X_{Tr}})$ 
8:   end if
9:   for each  $m = 1 : M$  do
10:    train  $ET(m)$  using  $X_{Tr}$  to get the  $V_{m,l}^{X_{Tr}}$  and
11:     $CM(X_{Tr}, m)$ 
12:    calculate  $D_{m,l}^{X_{Tr}}$  by formula 8
13:   end for
14:    $V_l^{X_{Tr}} = \text{concat}(D_{1,l}^{X_{Tr}}, \dots, D_{m,l}^{X_{Tr}})$ 
15: end for
16: //Testing stage
17: for  $l = 1 : L - 1$  do
18:   if  $i = 1$  then
19:     let  $X_{Test} = S_{Test}$ 
20:   else
21:     let  $X_{Test} = \text{concat}(S_{Test}, V_{l-1}^{X_{Test}})$ 
22:   end if
23:   for each  $m = 1 : M$  do
24:    feed  $X_{Test}$  into  $ET(m)$  to get the  $V_l^{X_{Test}}$  and
25:     $CM(X_{Tr}, m)$ 
26:    calculate  $D_{m,l}^{X_{Test}}$  by formula 8
27:   end for
28:    $V_l^{X_{Test}} = \text{concat}(D_{1,l}^{X_{Test}}, \dots, D_{m,l}^{X_{Test}})$ 
29: end for
30: if  $l = L$  then
31:   for each  $m = 1 : M$  do
32:    feed  $X_{Test}$  into  $ET(m)$  to get  $v_{m,L}^{X_{Test}}$ 
33:   end for
34:   calculate  $V^{X_{Test}}$  by formula 10
35:    $Y_{Test} = \text{argmax}(V^{X_{Test}})$ 
36: end if

```

general, most community-acquired pneumonia (CAP) patients suffered from bacterial infection. Studies have shown that *Streptococcus pneumoniae*, *Haemophilus influenzae* and virus pneumonia are the common causes of CAP. Even in the case of the COVID-19 pandemic, the incidence of bacterial pneumonia and tuberculosis remains high. Therefore, in order to distinguish between common lung diseases and COVID-19, we have conducted experiments based on the public CXR datasets as shown in Table I.

The JSRT [61] and SCR [62] datasets are considered for segmentation network training. Corresponding segmentation masks were collected from the SCR dataset. To compare COVID-19 with normal and different lung diseases, the CXR images were also collected from different data set sources, such as NLM [63], CoronaHack [64], and Cohen et al. [65], which are fully open to any research community. These images have different dimensions and are resized to 1024 pixels. In our experiments, CXR images are divided into four

TABLE I
THE PUBLIC CXR DATASETS USED IN EXPERIMENTS

Datasets	Class	Number	Mask
JSRT/SCR	Normal/Nodule	227	Left lung and right lung
NLM	TB	58	—
CoronaHack	bacteria/virus /normal/covid	426	—
Cohen et al	bacteria/covid	216	—

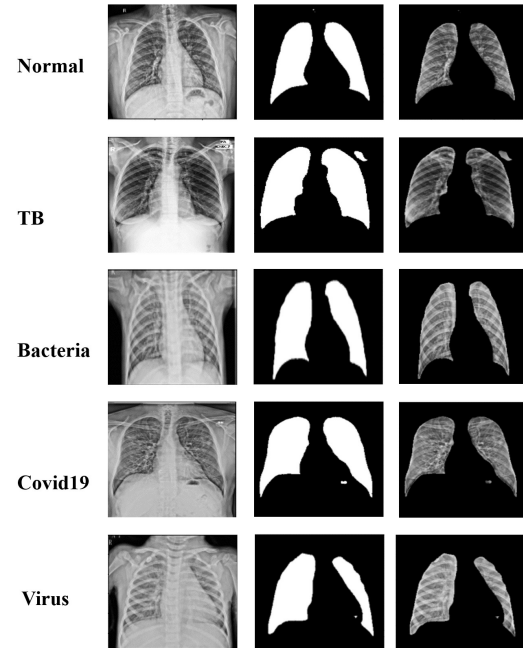


Fig. 3. An example of the preprocessed images (left), together with their corresponding segmentation results (middle), and the extracted lung areas (right) for different categorical classes of CXR images.

classes: normal, tuberculosis (TB), COVID-19, and pneumonia (bacteria and virus), and the COVID-19 label is distinguished from other pneumonia. The combined dataset includes 218, 58, 204, and 220 images for normal, TB, pneumonia (bacteria and virus), and COVID-19, respectively. All our experimental data are based on the ten-fold cross-validation. That is, the data set is divided into training set and test set, and test set in each fold is one-tenth of the total data, which is a conventional division way for small datasets. In the training phase, cross-validation will be conducted after the generation of a new layer. In other words, part of the data in the training set will be used as the validation set to generate evaluation indicators to determine whether DTDF-HFF continues to grow. The training data used in the segmentation are all JSRT/SCR data sets. The other data sets are segmented by the trained FC-Densenet model, and the obtained images after applying the mask are used for the training and test of the classification model. After segmentation, the mask is restored to the same original size of CXR images. Fig. 3 shows an example of the preprocessed images, together with their corresponding segmentation results, and the extracted lung areas for different

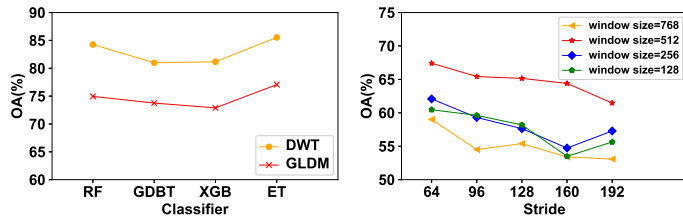


Fig. 4. (Left) The accuracy of GLDM and DWT on different base classifiers. (Right) The accuracy of different sliding window sizes on ET.

classes of CXR images.

B. Performance metrics and experimental environments

For the performance comparisons, six measurements are used based on true-positive (TP), true-negative (TN), false-positive (FP), false-negative (FN), as given by follows:

$$1) Accuracy = (TN + TP) / (TN + TP + FN + FP) \quad (11)$$

$$2) Precision = TP / (TP + FP) \quad (12)$$

$$3) Recall = sensitivity = TP / (TP + FN) \quad (13)$$

$$4) F1score = 2(Precision \cdot Recall) / (Precision + Recall) \quad (14)$$

$$5) Specificity = TN / (TN + FP) \quad (15)$$

$$6) YoudenIndex = Recall + Specificity - 1 \quad (16)$$

The experimental environments in this paper are as follows: DTDF-HFF and other decision tree-based methods run on the 32 Intel(R) Xeon(R) CPU E5-2665 0 @ 2.40GHz, and DNN-based methods run on VGA compatible controller: NVIDIA Corporation GP102 [GeForce GTX 1080 Ti].

C. Feature extraction and base classifier selection

Since the size of each sample fed into the DTDF-HFF needs to be the same, multiple statistical indicators such as the mean, maximum, and minimum values of the DWT and GLDM features are calculated and concatenated as the input features. The accuracy of these features on different base classifiers is observed in Fig. 4 (left), which shows that ET achieves the best performance compared with other base classifiers, such as XGBoost (XGB), RF, and gradient boosting decision tree (GDBT).

As for the multi-grained scanning, the window size may affect the generation of features, and the accuracy is observed by using ET to determine the relevant parameters. Two multi-grained scanning features with different parameters (consistent with the number of hand-crafted features) are selected for the training of our proposed model. The features obtained by two sliding window sizes reflect the image information under different resolutions. However, as shown in Fig. 4 (right), the accuracy using the features with different stride of 768 window sizes is low, so the features with higher accuracy corresponding to other window sizes are selected to participate in our model training. The sliding window sizes of the two types of features are set to 512, 256 respectively, and the

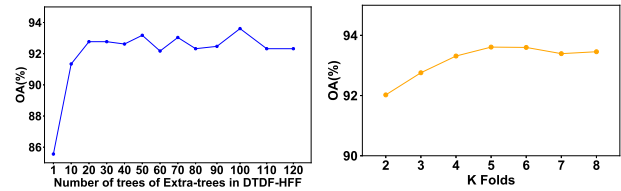


Fig. 5. (Left) The impact of the number of ETs on the performance of DTDF-HFF. (Right) K-value of the k fold cross validation of ET in DTDF-HFF.

TABLE II
HYPERPARAMETERS OF DTDF-HFF

Hyperparameter	value
Number of ET in each layer	4
Number of trees in each ET	100
K-Fold cross validation	5
Early stop rounds	3

stride sizes are both set as 64. The corresponding feature dimensions generated by multi-granularity scanning are 648 (Mgs1), 1352 (Mgs2). It should be noted that, when the image resolution is high and the stride size is small, the operation of sliding window is kind of memory consuming. However, it is not necessary to use very small stride size of sliding window for high resolution image, which has little influence on the performance of the proposed framework.

D. Hyperparameter analysis

As the advantage of the DF framework, the number of hyperparameters of DTDF-HFF is smaller than those of neural networks, which are summarized in Table II. As the analysis above, ET is adopted as the base classifier in our model for training and prediction. The number of trees in each ET is a key parameter. The accuracy is observed with the changes of tree numbers in each ETs of DTDF-HFF. As shown in Fig. 5 (left), the accuracy generally increases with the increasing of the tree number. When the number of trees in the ETs is less than 20, the performance of the model is obviously poor. This is because the learning ability of the model is greatly limited by the small scale of ETs. When the number of ETs is greater than 50, the performances of the model do not vary much. It is observed that the accuracy of DTDF-HFF with 110 ETs is even slightly lower than that using 100 ETs, and more ETs means higher computational cost. Thus, the number of ETs in our model is set to 100.

The cascade structure is key to the excellent performance of deep learning methods. The early stop parameter of the DTDF-HFF is set to 3. That is, the training process terminates when the accuracy of the i_{th} layer is not larger than that of the $(i-3)_{th}$ layers. Then the number of layer is set to i . This accuracy is based on the training set. As shown in Fig.5 (right), our DTDF-HFF can achieve the best classification performance, when the five-fold cross-validation is adopted in the training phase. When K is greater than 5, increasing the number of K folds increases the training time of the model, but does not improve the classification performance significantly. Cascade forest evaluates whether the model will continue learning or

TABLE III
THE ACCURACY OF DIFFERENT DECISION TREE-BASED METHODS

Feature	RF	GDBT	XGB	ET	DF	DTDF-HFF
Mgs1	65.79	64.26	65.94	67.42	71.39	73.05
Mgs2	61.73	60.63	59.89	61.57	64.66	65.25
DWT	84.26	80.99	81.17	85.53	86.48	86.91
GLDM	74.95	73.75	72.89	75.98	77.06	81.02
Mgs1+Mgs2 +DWT+GLDM	86.64	86.81	86.51	88.37	88.49	93.61

TABLE IV
CLASSIFICATION RESULTS OF DIFFERENT DECISION TREE-BASED METHODS

Method	Accuracy	Preci-sion	Recall	F1 score	Specifi-city	Youden Index
RF	86.64	89.31	87.82	87.88	95.28	83.10
GDBT	86.81	89	87.76	87.41	95.34	83.09
XGB	86.51	89.44	87.80	87.84	95.20	83.00
ET	88.37	89.63	89.29	89.06	95.89	85.18
DF	88.48	90.41	89.32	89.32	95.76	85.08
DTDF-HFF	93.61	95.01	93.66	93.93	97.74	91.40

not based on pre-set evaluation indicators, which are derived from the training set. Therefore, when evaluating whether DTDF-HFF continues learning or not, evaluation indicators is calculated through five-fold cross validation. Usually the number of layers increases, the accuracy of the model is improved. The observation of experimental results shows that our model grows no more than 5 layers in most cases.

E. Comparison with different decision tree-based methods

In order to verify the effectiveness of model optimization, hand-crafted features and multi-grained features are fed to original DF and other decision tree-based methods (including RF, GDBT, XGB and ET) for comparison.

Table III shows the accuracy of single and fused features on different decision tree-based methods. In accord with the previous observation, the performance of ET for a single feature is slightly lower than that of DF and our method, but superior to other decision tree-based methods. Therefore, ET is selected as the classifier of each layer in our model. As showed in the table, the results obtained using DWT is the best in each model when compared with those using a single type of feature. And it is obvious that the results based on the ensemble methods are much better than those using a single learner, and the performance of DF and our model are much better than that of other methods.

As for the results obtained based on the hybrid features, since except for our model, other models cannot handle multiple types of features at the same time, different types of features are concatenated to serve as their inputs. It can be seen that the change of inputs offer slightly higher discriminative ability. On the other hand, the input of multiple features to our model greatly improve its performance. To some extent, the diversity of these features maintain high generalization ability of our model.

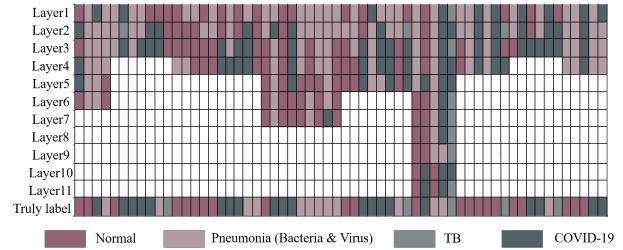


Fig. 6. The typical training results in different layer of DTDF-HFF without the distance transformation.(The colored area represents the predicted result of the corresponding layer sample, and the white area represents the stop of the model.)

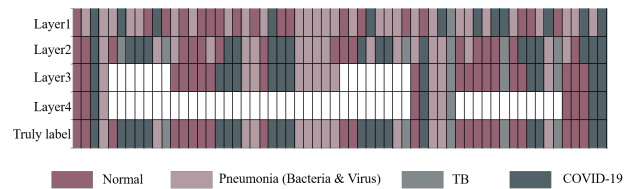


Fig. 7. The typical training results in different layers of DTDF-HFF with the distance transformation.(The colored area represents the predicted result of the corresponding layer sample, and the white area represents the stop of the model.)

Although it can be seen from the comparison of the single feature based classification performances of DF and DTDF-HFF in Table III, the distance transformation DF has achieved better accuracy. But the effect is not significant and is not compared in the case of multiple features. Hence, in order to verify the optimization effect of the predicted probability vector, we compare and visualize the predicted results of model with and without the self-adaption method layer by layer. Fig. 6 shows the prediction results of the samples at different layers without the self-adaption method in the DTDF-HFF. By comparing the prediction results with the self-adaption method in Fig. 7, it can be seen that the self-adaption method gets the correct prediction at earlier levels. In other words, the enhancement vector can optimize the training of the model, and the distance transformation vector corrects the misclassified samples of the previous layer in the training process of the subsequent layers. In addition, it is obvious that the model trained by distance vectors can converge earlier.

Besides accuracy, other performance metrics of the different decision tree-based methods are presented in Table IV, which shows that the proposed DTDF-HFF can achieve the best performances when compared with other decision tree-based methods.

F. Comparison with other SOTA methods

The performance of DTDF-HFF is compared with other state-of-the art (SOTA) approaches, and the overall performances of the proposed method and the other SOTA approaches on the above data sets are presented in Table V.

TABLE V
CLASSIFICATION RESULTS OF DIFFERENT SOTA METHODS

Method	Accuracy	Preci-sion	Recall	F1 score	Specifi-city	Youden Index
Resnet34	88.12	89.55	89.57	88.84	95.44	85.01
CovidCXR	88.99	90.66	90.34	89.99	96.19	86.53
Covid-classifier	83.33	85.97	82.86	83.31	82.14	65.02
DTDF-HFF	93.61	95.01	93.66	93.93	97.74	91.40

TABLE VI
THE DETAIL CLASSIFICATION PERFORMANCES OF EACH CLASS OF THE PROPOSED METHOD AND THE OTHER SOTA APPROACHES

Methods	Categories	Preci-sion	Recall	F1 score	Specifi-city	Youden Index
Resnet34	Normal	86.55	72	76.74	95.63	68.63
	Bacteria & virus	76.29	89	88.41	92.09	81.09
	TB	93.58	100	96.52	96.75	96.75
	COVID-19	98	94.28	93.39	97.3	91.57
Covid CXR	Normal	87.41	80	83.86	94.89	74.89
	Bacteria & virus	83.16	87	84.07	92.51	79.52
	TB	96.6	100	98.18	99.33	97.33
	COVID-19	96.39	94.36	94.82	98	92.364
Covid-classifier	Normal	88.89	80	84.21	85.71	60.13
	Bacteria & virus	80	80	80	95.23	71.04
	TB	100	71.4	83.33	71.42	95.34
	COVID-19	75	100	85.71	76.19	77.60
DTDF-HFF	Normal	96.89	85.82	90.57	98.58	84.41
	Bacteria & virus	91.27	93.09	91.91	95.94	89.0
	TB	99.09	97.14	97.85	99.84	96.98
	COVID-19	92.8	98.56	95.37	96.60	95.16

The CovidCXR method segments the lung area from CXR image first, and then focuses on the random patches of the lung area for model training. The covid-classifier directly uses a variety of hand-crafted features for the training process. As shown in Table V, our method is superior to the other SOTA methods. In detail, compared with Resnet34, CovidCXR [4], and covid-classifier [20], our method gets higher scores with 5.49%, 4.62% and 10.28% accuracy scores, and 5.09%, 3.94%, and 10.62% F1-score scores. As the accuracy results indicate the overall performance of the method on all test samples, and the F1-score results reveal the balance between the Precision and Recall measurements, these higher results confirm that the performance of our method is much better than other SOTA method in general. The confusion matrices for CovidCXR (left) and DTDF-HFF (right) are shown in Fig. 8, which verifies that our method can better recognize the COVID-19 samples.

The detail results of different classes are tabulated in Table VI. It is observed that, our method is able to achieve remarkable classification performances in most metrics of each class. Especially, compared with Resnet34, CovidCXR, and covid-classifier, the proposed DTDF-HFF has got higher scores with 1.98%, 0.55%, and 9.66% F1-score scores on the COVID-19

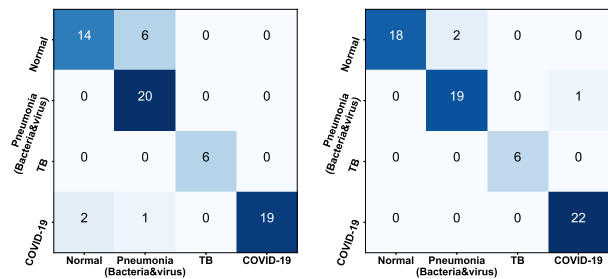


Fig. 8. Confusion matrices for CovidCXR (Left) and DTDF-HFF (Right).

TABLE VII
COMPARISON OF SENSITIVITY OF COVIDCXR AND DTDF-HFF

Methods	Normal	Bacteria&virus	TB	COVID-19
CovidCXR	0.8	0.87	1	0.94
DTDF-HFF	0.86	0.93	0.97	0.99

class.

In addition, DTDF-HFF has performed well in terms of the sensitivity on different classes. Table VII presents the comparison of sensitivity between CovidCXR and DTDF-HFF. Although the sensitivity to the TB class of our model is slightly lower than that of CovidCXR, our method has significantly improved the sensitivity to the other three classes when compared to CovidCXR.

Since our proposed method is a decision tree-based architecture without the back propagation algorithm, our method spends less than half the time required by CovidCXR (Table VIII). In short, our method has achieved excellent results on the public CXR data sets, when compared to other SOTA methods. The structure of our proposed method can not only bring advantages in reducing computational cost, but also guarantee the high performance on the small datasets.

TABLE VIII
COMPARISON OF RUNNING TIME OF COVIDCXR AND DTDF-HFF

Methods	Feature extraction	Classification
CovidCXR	–	56 m52 s
DTDF-HFF	15 m36 s	7 m94 s

G. Clinical application

We are conducting a case study of deploying the proposed framework for the assessment and detection of pneumonia in clinical application. Figure 9 presents a typical clinical application scenario of this study. Firstly, the proposed framework is trained with well-curated data. Then, the trained model is deployed in hospitals using a web server remotely. The new X-ray images obtained from the patients will be sent to the server and input into the trained model on the server. The model will make a prediction of the pneumonia type for the patient and send a report to the user on the client.

V. CONCLUSION

In this paper, a new method named DTDF-HFF has been proposed for accurate CXR image classification, which ex-

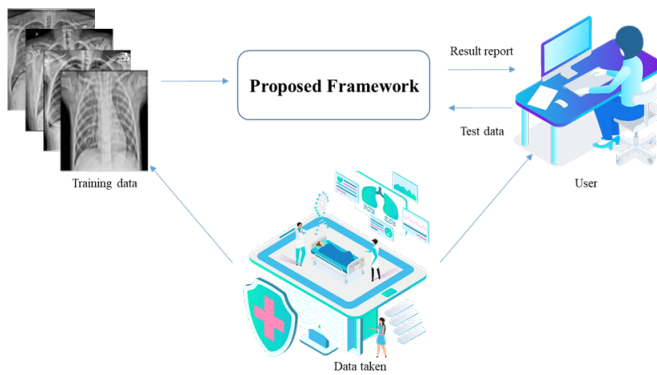


Fig. 9. A typical clinical application scenario of this study for the assessment and detection of pneumonia in clinical application.

tends the structure of the original DF model to make better use of fusion feature information. The hybrid features are input into the proposed method to increase the diversity of feature information among different forests in the model. In our framework, in order to take full advantage of output information at each layer, the output vectors are transformed through the self-adaptive method and combined with the original input characteristics to create enhanced features. The performance of our method is verified on the public available data sets. And the experimental results confirm that our DTDF-HFF can achieve superior performance to other SOTA deep learning methods. Furthermore, unlike the neural network-based deep learning techniques, our method requires much less computational cost.

Generally, our method can achieve high accuracy in the case of small training samples. If another epidemic pneumonia breaks out next time, it would be quite difficult to collect a large number of well-curated data in a short time to train DNN-based models. However, our framework can be easily extended to the new classification tasks in the case of limited training data.

Although our proposed method has achieved remarkable performance on CXR images classification, there is some research work remaining to be done in the future. First, the feature size deployed in our model is still relatively large, which may result in kind of memory consuming. Hence, the feature reduction techniques can be employed to reduce the feature size, especially the redundancy of the multi-grained scanning information. Secondly, the hierarchical structure of DTDF-HFF is inspired by the deep neural network, but there is no strategy to utilize the error for the modification of the generated structure, which may limit the performance of our model. Therefore, our future work will focus on the design of new strategies for feeding the errors to the previous layer or forests, aiming to improve the performance of the overall structure.

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