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A novel Covid-19 and pneumonia classification method based on F-transform

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ABSTRACT
Nowadays, Covid-19 is the most important disease that affects daily life globally. Therefore, many methods are offered to fight against Covid-19. In this paper, a novel fuzzy tree classification approach was introduced for Covid-19 detection. Since Covid-19 disease is similar to pneumonia, three classes of data sets such as Covid-19, pneumonia, and normal chest x-ray images were employed in this study. A novel machine learning model, which is called the exemplar model, is presented by using this dataset. Firstly, fuzzy tree transformation is applied to each used chest image, and 15 images (3-level F-tree is constructed in this work) are obtained from a chest image. Then exemplar division is applied to these images. A multi-kernel local binary pattern (MKLBP) is applied to each exemplar and image to generate features. Most valuable features are selected using the iterative neighborhood component (INCA) feature selector. INCA selects the most distinctive 616 features, and these features are forwarded to 16 conventional classifiers in five groups. These groups are decision tree (DT), linear discriminant (LD), support vector machine (SVM), ensemble, and k-nearest neighbor (k-NN). The best-resulted classifier is Cubic SVM, and it achieved 97.01% classification accuracy for this dataset.

1. Introduction

COVID-19 is a virus that transmits from person to person and affects the whole world. This virus, which causes deaths, originally arose in Wuhan, China. However, it later spread to 209 countries [1,2]. The Covid-19 virus is a member of the coronavirus family and is a newly encountered virus, and our body is unable to react because it is not recognized by the human immune system [3]. The virus most often settled in the lungs and multiplies there. Severe respiratory distress indicates because of this virus. For this reason, people face respiratory distress [4].

There are varieties of coronaviruses. The source of these viruses has been identified as musk cats in the acute respiratory syndrome (SARS) outbreak and as the dromedary camel in the middle east respiratory syndrome (MERS) outbreak [5–7]. In the Covid-19 epidemic, the source has not yet been identified. However, its genetic sequence is thought to be bat-derived. Its rapid spreading is an indication that this virus has been transmitted from person to person. In order to prevent the spreading of further Covid-19 virus, countries have blocked international exits [8–11]. At the same time, curfews have been announced within many countries. It is aimed to reduce the transmission rate of the covid-19 virus in countries where going out and contact are reduced as much as possible [12–14]. This virus’s common symptoms include high fever, difficulty breathing, dry cough, fatigue, decreased taste, and smell. In this case, it causes lesions and pneumonia in the lungs. This disease can result in death in the later stages [15,16].

Many studies have been carried out on machine learning and artificial intelligence in the literature [17–21]. Some of these studies have been conducted on disease diagnosis [20,22,23]. In this study, a method for diagnosing Covid-19 disease using the Fuzzy tree and multi-kernel local binary pattern is proposed. Details of the proposed method are presented in the sections below.

1.1. Motivation

Nowadays, the Covid-19 virus affected all humans in the world. The
Covid-19 disease is similar to pneumonia. Our main objective is to differentiate Covid-19 patients from pneumonia patients. Therefore, novel textural features and fuzzy transform-based automated chest images classification method were presented.

Several studies are presented in the literature on Covid-19 and Pneumonia disease. Narin et al. [24] proposed a hybrid method, which used ResNet50, InceptionV3, and Inception-ResNetV2 convolutional neural network (CNN) architecture to classify normal chest images and chest images with Covid-19 diagnosis [25]. They achieved a 98.0% accuracy rate for two classes. Jaiswal et al. [26] used Mask-RCNN based model that improved the ResNet101 and ResNet50. They obtained a 99.1% precision value by using NIH CXR14 [27] dataset. Sethy and Behera [28] used the CNN model to classify two classes, and they succeeded 95.38% accuracy rate. Xu et al. [29] used two CNN three-dimensional classification models for two classes of chest images. They obtained 86.7% accuracy with collected data of 2 classes. Wang et al. [30] collected 325 CT images of COVID-19 and 325 CT images. They obtained an 89.5% success rate by using the inception transfer-learning model. Sirazitdinov et al. [31] used an ensemble of two CNN. They utilized the available RSNA Pneumonia Detection Challenge dataset [32] and obtained 79.3% recall rates. Liang and Zheng [33] presented a residual structure for the classification of pediatric pneumonia images. They used the Kermany dataset [34] with 5856 chest X-ray images collected and tagged from children. They achieved a 96.7% accuracy performance rate. Rajpurkar et al. [35] improve a method that can detect pneumonia from chest X-ray images. Their proposed CheXNet method is a 121-layer CNN trained on the ChestX-ray14 database [27] obtained 93.71% value. Ghoshal and Tucker [36] investigated how Dropweights based Bayesian CNN (BCNN) can estimate uncertainty in Deep Learning solutions to develop the diagnostic performance of the human-machine combination using publicly available COVID-19 chest X-ray dataset [37]. Pham [38] suggested a method to diagnose Covid-19 disease using X-ray images. These images are evaluated using convolutional neural networks method. Sallay et al. [39] proposed an approach for Covid-19 disease detection using machine learning techniques. CT and X-ray images were used for different databases in the study. Moreover, the average accuracy value was calculated as 82.88%. Sun et al. [40] proposed a method for diagnosing Covid-19 disease, where Adaptive Feature Selection guided Deep Forest was utilized with 1495 Covid-19 and 1027 pneumonia patients data. Accuracy rate of these data was calculated as 91.79%.

1.2. Novelties and contributions

In this article, a novel examplar chest image classification method was proposed using the proposed F-transform and MKLBP. The novelties are:

- A lightweight multileveled feature extraction method is developed. In this method, a fuzzy transform (F-transform) [41] based on triangle fuzzy sets is proposed and a novel fuzzy tree is constructed using the triangle-based F-transform.
- As we know from literature, F-transforms have been used for image and noise reduction [42]. The proposed fuzzy tree is utilized as a novel operator like convolution.
- Signum and ternary kernels are utilized together to generate features comprehensively because local image descriptor has high performance for feature extraction.
- Highly accurate chest image classification method is developed for Covid-19 detection with a classification rate of 97.01%.

Contributions of this study are:

- In the computer vision applications, discrete wavelet transform, Gabor filters based decomposition, or pooling methods are utilized for decomposition. In order to recommend an effective decomposition model, a new fuzzy tree-based decomposer is presented and successful results have been attained by using this transform.
- Hand-crafted feature generation methods are effective, and they have low computational complexity. Moreover, the implementation of them is easy. However, they cannot solve some computer vision problems since they extract low-level features. Multilayer/multilevel feature generation methods must be created to increase the strength of the hand-crafted feature generators. A multilevel feature generator using the presented fuzzy tree decomposition and multiple kernel local binary pattern is utilized to extract both high-level and low-level features. Further, INCA [43] is utilized as feature selector to choose the optimum number of features for this problem. By using these basic and effective methods, a highly accurate Covid-19 detection method with a short execution time is presented.

2. Backgrounds

The proposed method uses F-transform and MKLBP, which are explained in this section.

2.1. Fuzzy transform (FT)

One of the most efficient methods for image reduction is the fuzzy transform. Martino et al. [42] proposed a concept of fuzzy transform for color image reduction. The image is divided into m x n sizes of non-overlapping blocks to perform this transform. Then, the membership degree of each pixel is calculated. Finally, Eq. (1) is used for reduction.

\[ F_{ij} = \sum_{m=1}^{m} \sum_{n=1}^{n} \frac{P_{ij} - P_{ij}}{A_{ij} B_{ij}} \]  

(1)

where \( p_{ij} \) defines pixel values of the image, \( F \) is fuzzy value, \( A \) and \( B \) are membership degrees of the pixel values.

Inverse fuzzy transform is described in Eq. (2) [42].

\[ p_{ij} = \sum_{m=1}^{m} \sum_{n=1}^{n} F_{ij} A_{ij} B_{ij} \]  

(2)

In this paper, a novel FT is presented for image reduction. In the presented method, triangle fuzzy sets are selected for image reduction, and this method is explained in Section 3.

2.2. Multi kernel local binary pattern

MKLBP is an improved version of the LBP [44] and LTP [45]. LBP and LTP use 3 × 3 sized overlapping blocks and the same pattern. The main difference between these feature extractors is the used kernel (binary feature generation) function. While LBP uses the signum function as the kernel, LTP uses the ternary function. Equations of function are given in Eqs (3) and (4).

\[ s(P_c, P_l) = \begin{cases} 0, & P_c - P_l < 0 \, , \, L = \{1, 2, ..., 8\} \\ 1, & P_c - P_l \geq 0 \end{cases} \]  

(3)

\[ t(P_c, P_l, d) = \begin{cases} 1, & P_c - P_l > d \\ 0, & |P_c - P_l| < d \\ -1, & P_c - P_l < -d \end{cases} \]  

(4)

where \( s_{(.,.)} \) and \( t_{(.,.,.)} \) define signum and ternary functions respectively. PC is the center pixel of the 3 × 3 sizes block, PLs are neighbor pixels of the center pixel, \( d \) represents threshold value, and generally, this value is user-defined. Eqs. (5) and (6) define bit extraction from ternary value.

\[ b_{ij}^{lower} = \begin{cases} 0, & t > -1 \\ 1, & t = -1 \end{cases} \]  

(5)
The proposed MKLBP generates three feature images named signum, upper, and lower. The length of the histogram of each image is 256. Hence, MKLBP generates 768 features. The procedure of the MKLBP is shown in Fig. 1.

As seen from the procedure, lines 09–11 extract binary features, and these binary features are converted to decimal values in these lines. Histogram extraction is given in line 18. A mathematical description of the histogram extraction is indicated below.

\[
\text{histogram} = \text{zeros}(1, 256) \\
\text{histogram}(\text{value}(i, j)) + +, i = \{1, 2, ..., W - 2\}, j = \{1, 2, ..., H - 2\}
\]

A graphical demonstration of the MKLBP method is given in Fig. 2.

3. Material

There may be some rules that cannot be well found by the less experienced doctor’s eye on the X-ray images. Chest X-ray images of patients infected with COVID-19 are just one of these images. In COVID-19 patients, chest X-ray images show mostly bilateral involvement abnormalities [46].

3.1. Dataset

In this study, chest X-ray images were used to detect the COVID-19. The used database is composed of the publicly available datasets. 135 X-ray images with COVID-19 diseases were collected from GitHub [47]. 46 of these patients are female, and 64 are male, and 25 of them are not determined. While 17 patients were between 25 and 49 years old, 118 patients were over 50 years old. To increase the reliability of the proposed method, normal and pneumonia diagnosis images were downloaded from the Kaggle platform. Due to the scarcity of COVID-19 diagnosed X-ray images, only 150 normal and pneumonia chest X-ray images were selected from Kaggle [48]. Posterior anterior (PA) images were chosen to increase the visibility of the spotting. Our experiments are based on a data set of 135 COVID-19, 150 pneumonia patients and 150 normal (total 435 images) chest X-ray images. In Fig. 3, COVID-19, normal, and pneumonia patient’s chest X-ray images are presented.
4. The proposed image classification method

A novel chest image classification method is implemented by using the proposed F-transform and MKLB. The stages of this method are given below.

- Feature extraction
- Feature selection
- Classification.

A graphical outline of this method is presented in Fig. 4.

In Fig. 4, the graphical presentation of the proposed fuzzy MKLB and INCA based method is shown. The novelties of the proposed method are the utilization of the fuzzy tree and INCA feature selection approach. By using the fuzzy tree, a multilevel feature extraction method is created. In this work, MKLB is utilized for feature extraction and INCA is chosen for feature selection. In the classification phase, 16 classifiers are used to show the general success of the proposed exemplar MKLB and INCA based feature extraction and feature selection.

The steps of this method are given below.

**Step 1:** Load image.
**Step 2:** Create a fuzzy tree. Triangle F-transform is proposed to create this tree. The steps of the triangle F-transform method given below.

In this article, three levels of the fuzzy tree are proposed. In the tests, variable levels of the fuzzy tree and the optimum results were achieved by using three levels of the fuzzy tree.

**Step 2.1:** Extract the histogram of the image.
**Step 2.2:** Divide the histogram into two parts.

\[ H_1 = H(1 : 128) \]
\[ H_2 = H(129 : 256) \]

where \( H \) is the histogram of the image, \( H_1 \) and \( H_2 \) parts of the histogram, \( \mu_a \) and \( \mu_b \) represent membership degrees of the A and B sets, \( pv \) describes pixel value.

By using these membership degrees, novel images are created. The procedure of the fuzzy tree-based image generation is given in Fig. 6.

NCA [48] is one of the commonly preferred feature selection methods. It calculates positive weights for each feature. Firstly, NCA assigns a weight for each feature randomly. It calculates the correlation of the features and target by using a city block distance-based fitness function. By using stochastic gradient descent optimization, optimum weight values are set. The main problem of the NCA is the selection of the optimal number of features. Because the whole weights of the NCA are positive. Therefore, redundant features cannot be assigned, and feature selection is implemented parametrically. Iterative NCA is developed to solve this problem. In the INCA, a loss value calculator is also needed. So
**Fig. 4.** Graphical outline of the F-transform, MKLBP, and INCA based chest image classification method.

**Fig. 5.** Pseudocode of the peak value (threshold value) calculation.

**Procedure: Peak value calculation**

**Input:** Histogram pieces, $H_1$ and $H_2$ with size of 128

**Output:** Threshold points, $t_1$ and $t_2$

01. Calculate maximum points of the pieces. $m_1 = \max(H_1)$, $m_2 = \max(H_2)$
02. for $i$=1 to 128 do
03. if $H_1(i) = m_1$ then
04. $t_1 = i$
05. end if
06. if $H_2(i) = m_2$ then
07. $t_2 = i$
08. end if
09. end for
10. $t_2 = t_2 + 128$

**Fig. 6.** The fuzzy tree-based image generation.

**Procedure: Fuzzy tree based image generation**

**Input:** Image I with size of $W \times H$

**Output:** Feature images $F_k$ with size of $W \times H \times 15$, $k\in\{1,2,3\}$

01. Load image I
02. count=1;
03. [$A B = \text{f(t)}(I)$] is triangle fuzzy transform
04. $F^I = I; \ F^A = A; \ F^B = B; \ // \text{Assign images to } F$
05. [$F^A \ F^B = \text{f1}(A)$]
06. [$F^B \ F^C = \text{f2}(B)$]
07. for $i=1$ to 4 do
08. $[F^3 \ F^3 = \text{f3}(C)]$
09. count = count + 2;
10. end for

**Step 2.3:** Calculate indices of the maximum points of the $H_1$ and $H_2$ and these points are used to create triangle fuzzy sets. The pseudocode of this calculation is given in **Fig. 5**.

**Step 2.4:** Create triangle fuzzy sets using $t_1$ and $t_2$. A and B sets are created using these points.

**Step 2.5:** Calculate membership degrees of each pixel using Eqs. (11) and (12).

$$\mu_A(pv) = \begin{cases} \frac{pv}{t_1}, & pv \leq t_1 \\ \frac{255 - pv}{255 - t_1}, & pv > t_1 \end{cases}$$  \hspace{1cm} (11)

$$\mu_B(pv) = \begin{cases} \frac{pv}{t_2}, & pv \leq t_2 \\ \frac{255 - pv}{255 - t_2}, & pv > t_2 \end{cases}$$  \hspace{1cm} (12)

**Step 3:** Resize the generated 15 images to $256 \times 256$ sized images.

**Step 4:** Extract 768 features from each image by using MKLBP.

**Step 5:** Divide images into $128 \times 128$ sized exemplars.

**Step 6:** Extract 768 features from each exemplar.

**Step 7:** Concatenate the features and obtain a final feature vector with a size of $768 \times 75 = 57,600$.

**Step 8:** Apply INCA to extracted 57,600 features and select 616 most valuable features.

$k$-NN classifier with 10-fold cross-validation was used as a loss value calculator. The steps of the proposed INCA are shown below.
Step 8.1: Apply min-max normalization to extracted 57,600 features. Because NCA is a distance-based feature selector. Min-max normalization phase should be used to use effectiveness of the NCA [49].

\[
X^N(i, : ) = \frac{X(i, : ) - X(i, : )_{\text{min}}}{X(i, : )_{\text{max}} - X(i, : )_{\text{min}}}
\]

(13)

where \(X(:, i)\) is ith feature and \(X^N\) denotes normalized features.

Step 8.2: Apply NCA weight generation function to normalized features.

[weights index] = NCA\(X^N, \text{target}\);

(14)

Step 8.3: Set an upper and lower range value to iteratively calculate loss value. The range is from 40 features to 1040 features.

Step 8.4: Select features.

\[
fs_{\text{t}}( :, t) = X(:, \text{index}(t)), \quad t = 1, 2, \ldots, 40 + g, \quad g = 0, 1, \ldots, 1000
\]

(15)

\(fs_t\) is \(t\)th selected feature vector.

Step 8.5: Calculate the loss values of the selected feature vectors.

\[
\text{loss}(k) = k\text{NN}\big(f_{\text{fs}}(k), \text{target}, 10, \text{CB}, 1)\big)
\]

(16)

where loss is calculated loss value, \(k\text{NN}\) is \(k\)-NN [50] function, which is calculated loss value. Parameters of the loss function are the, features, target, \(k\)-fold validation (10-fold CV is selected), distance metric (\(\text{CB}\) represents city block) and \(k\) (\(k\) value is chosen as 1) value respectively.

Step 8.6: Find the minimum loss of valued features and indices of it.

\[
\text{[minimum indice]} = \text{min(loss)}
\]

(17)

Step 8.7: Select the minimum loss of valued features using Eq. (18).

\[
fs_{\text{final}}( :, t) = X(:, \text{endex}(t)), \quad t = 1, 2, \ldots, 39 + \text{indice}
\]

(18)

where \(fs_{\text{final}}\) final selected feature vector.

Step 9: Use the final selected feature vector as the input of the selected 16 classifiers with 10-fold cross-validation. The details of the used classifiers are given in the experimental results section.

Further, the pseudocode of the presented F-transform and MKLBP based exemplar feature generation and INCA feature selection based model is also given below.

Algorithm 1. Pseudo code of the presented F-transform and MKLBP based exemplar feature generation and INCA selector based automated Covid19 detection model.

| Input: Covid image dataset (DB) with a size of D (number of images). |
| Output: Results |
| 00: Load Covid19 chest image dataset. |
| 01: for \(k\)=1 to \(D\) do |
| 02: Read image (\(lm\)) |
| 03: Apply F-transform based image generation (It is defined in Figure 6) |
| 04: Obtain 15 F-transformed images |
| 05: Resize F-transformed images into 256 x 256 sized images. |
| 06: Divide these images into exemplars with a size of 128 x 128. |
| 07: Generate features from these images and original image using MKLBP. |
| 08: Merge the extracted features and obtain feature vector with a length of 57,600. |
| 09: end for |
| 10: Apply INCA to the extracted feature vector and select the most discriminative features. |
| 11: Feed the chosen features to conventional classifiers and obtain results. |

5. Experimental results

In this section, the results of the proposed fuzzy MKLBP and INCA based approach are given. This method is implemented on MATLAB (2019b) programming environment. The used exemplar fuzzy MKLBP

Table 1

| Group | Classifier | Parameters |
|-------|------------|------------|
| Tree [51-53] | Fine | Number of splits: 100, Criteria: Gini |
| Medium | Number of splits: 20, Criteria: Gini |
| Discriminant [54] | Linear Discriminant | Covariance structure is full. |
| SVM [55] | Cubic | Kernel: Cubic (3rd degree polynomial), C: 1, Multiclass: 1 vs 1 |
| Quadratic | Kernel: Quadratic (2nd degree polynomial), C: 1, Multiclass: 1 vs 1 |
| Gaussian | Kernel: Gaussian, C: 1, Multiclass: 1 vs 1 |
| Linear | Kernel: Linear, C: 1, Multiclass: 1 vs 1 |
| k-NN [50] | Fine | k=10, Distance: Euclidean, Weight: Equal |
| Medium | k=10, Distance: Euclidean, Weight: Equal |
| Coarse | k=100, Distance: Euclidean, Weight: Equal |
| Cosine | k=10, Distance: Cosine, Weight: Equal |
| Cubic | k=10, Distance: Cubic, Weight: Equal |
| Weighted | k=10, Weight: Squared inverse Distance: Euclidean, |
| Ensemble [56] | Bagged Tree | Method: Bag, Splits: 434, Learners: 30 |
| Learner type: Decision tree, |
| Subspace | Subspace domain: 308, Method: Subspace, Learners: 30, Learner type: Discriminant |
| Subspace k-NN | Subspace domain: 308, Method: Subspace, Learners: 30, Learner type: k-NN, |
and INCA feature selection are coded on MATLAB M files. MATLAB Classification Learner Toolbox (MCLT) was used for classification. 16 classifiers in 5 groups were utilized as classification methods. These classifiers and their attributes were listed in Table 1. 616 features were forwarded to these classifiers.

In the literature, accuracy, geometric mean, Precision, and recall parameters have been widely used to evaluate models. Testing and training observations are selected randomly. Therefore, tests of each classifier were repeated 100 times to obtain general results. The obtained results were shown in Table 2, and mathematical notations of the used evaluation parameters were given as below [23,57].

\[
\text{Accuracy} = \frac{tps + tns}{tps + tns + fps + fns}
\]
Recall $=$ $\frac{tps}{tps + fns}$ (20)

Precision $=$ $\frac{tps}{tps + fps}$ (21)

Geometric mean $=$ $\sqrt[\text{fps} * \text{tns}]{\frac{tps * \text{tns}}{(tps + fns) * (tns + fps)}}$ (22)

where $tps$, $tns$, $fps$, and $fns$ are true positives, true negatives, false positives, and false negatives, respectively.

As it can be seen in Table 2, experimental studies on 16 classifiers were carried out. In each experiment, 10-fold cross-validation was used, and accuracy, geometric mean, Precision, and recall parameters were calculated. Maximum, minimum, mean, and standard deviation values of these parameters were obtained by running each classifier 100 times. When the results obtained in the experimental studies are examined, it is seen that the accuracy of the SVM classifier is at the highest rates with 97.01% and 96.78% values. After these accuracy values, the Ensemble Subspace k-NN classifier has become the highest accuracy value of 96.55% ratio. The highest values in the study were obtained using the SVM Cubic classifier. The maximum accuracy rate of 97.01%, a minimum accuracy of 95.17%, an average accuracy of 96.23% were obtained with this classifier. The standard deviation is only 0.42%. The small standard deviation indicates that the results obtained with this classifier are close to each other. It is seen that these classifiers give the highest Geometric mean, Precision, and Recall values. The results obtained from the experimental results show that the proposed method is successful in diagnosing COVID-19.

### 6. Discussions

The objective of this paper is to accurately classify chest X-ray images of the Covid-19, pneumonia, and healthy subjects. Our model consists of fuzzy image construction, exemplar MKLB feature generation, and feature selection with INCA. These methods are explained in sections 2 and 4. The fuzzy tree is applied as a novel operator like convolution. In the feature generation phase, 57,600 features are extracted. INCA is applied to these features to select discriminative ones. INCA solves the automatic optimal feature selection problem of the NCA. A range of the number of features are defined to decrease computational cost. The plotting of the calculated loss values was also shown in Fig. 7.

Here, the k-NN classifier is used as a loss value (loss value $= 1$-accuracy) generator. INCA is an iterative feature selector. Here, the initial and end iteration variables are selected as 40 and 1040. Hence, 1000 feature vectors are generated utilizing the iterative feature selection. The k-NN classifier is employed to the selected each feature vector in the iteration, and 1000 loss values are generated. The plot of the calculated

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### Table 3

| Classes            | Healthy-Covid19 | Healthy-Pneumonia | Covid19-Pneumonia |
|--------------------|-----------------|-------------------|-------------------|
| p-values           | 7.0569e-42      | 5.6981e-31        | 0                 |

### Table 4

| Method               | Accuracy |
|----------------------|----------|
| AlexNet [58]         | 93.56    |
| GoogLeNet [59]       | 93.79    |
| ResNet18 [60]        | 94.71    |
| ResNet50 [60]        | 95.17    |
| ResNet101 [60]       | 94.94    |
| VGG16 [61]           | 94.02    |
| VGG19 [61]           | 95.63    |
| InceptionNet v3 [62] | 93.56    |
| DenseNet201 [63]     | 95.86    |
| MobileNet [64]       | 93.79    |
| Our Method           | 97.01    |
loss values is denoted in Fig. 7, and as seen in Figs. 7 and 616 features were selected by using INCA. These features were forwarded to 16 classifiers and results were listed (See Table 2). The presented F-transform and MKLBP generator and INCA selector model attained successful results on the used 16 shallow classifiers, and it is denoted the discriminative feature generation ability of the proposed approach. To show the discriminative ability of the created and selected features, statistical analysis (t-test) is applied to features of a couple of the classes. The boxplot of the generated p-values of the features of a couple of the classes p-values are shown in Fig. 8.

Moreover, the calculated p-values are listed in Table 3. Table 3 demonstrates that p-value of the Covid19-Pneumonia is found as 0. The confusion matrix of the presented model (See Fig. 9) was proved these results.

We also utilize the pre-trained convolutional neural networks, which are AlexNet [58], GoogLeNet [59], Residual Networks (ResNet18 ResNet50, ResNet101) [60], Visual Geometry Group Networks (VGG16, VGG19) [61], InceptionNet version 3 [62], DenseNet201 [63] and MobileNet [64]. These networks are utilized as feature extractors, and Cubic SVM (our best classifier) is utilized as a classifier. Comparatively, results were listed in Table 4. Table 4 demonstrates that the proposed fuzzy MKLBP and INCA based chest X-ray image classification method has achieved better success rate than the pre-trained feature extraction techniques. Pre-trained feature extraction models are used with the SVM classifier, and the good classification accuracies are obtained. Therefore, SVM is selected as a classifier for comparison, and their best results are listed in Table 4.

Our study also compared with the COVID-19 detection and classification studies from X-ray images in literature so far. Table 5 shows the comparison of the previous studies in the literature to verify the validity of the proposed F-transform based method.

As seen in Table 5, deep learning models were used to obtain high performance on this problem. Our model uses a hand-crafted feature generator and an SVM classifier. The presented F-transform and MKLBP based image classification model attained 97.01% accuracy by using SVM classifier. The presented F-transform is utilized for both noise reduction and decomposition. By applying MKLBP, the salient features

| Study | Attributes of dataset | Feature extraction and classification methods | Type of Images | Accuracy (%) |
|-------|-----------------------|---------------------------------------------|----------------|--------------|
| [65]  | 125 COVID-19, 500 Healthy 500 Pneumonia | DarkCovidNet Images | X-ray | 87.02 |
| [66]  | 25 COVID-19, 25 Healthy | COVIDX-Net Images | X-ray | 90.0 |
| [67]  | 224 COVID-19, 504 Healthy 700 Pneumonia | VGG-19 Images | X-ray | 93.48 |
| [68]  | 777 COVID-19, 708 Healthy | DRE-Net Images | CT | 86 |
| [69]  | 25 COVID-19, 25 Healthy | ResNet50+ SVM Images | X-ray | 95.38 |
| [70]  | 313 COVID-19, 229 Healthy | UNet3D Deep Network Images | CT | 90.8 |
| [46]  | 53 COVID-19, 5526 Healthy | COVID-Net Images | 92.4 |
| [71]  | 219 COVID-19, 175 Healthy 224 Pneumonia | ResNet þ Location Attention Images | CT | 86.7 |
| [30]  | 195 COVID-19, 258 Healthy | M-Inception Images | CT | 82.9 |
| [72]  | 449 patients with COVID-19, 425 normal ones, 98 with lung cancer, 98 with lung cancer | Multitask learning CT | 94.67 |
| [73]  | 320 COVID-19, 320 Healthy | Deep convolutional neural network Images | CT | 93.64 |
| [74]  | 100 COVID-19, 200 Healthy | Convolutional neural network Images | X-ray | 95.74 |
| [75]  | 322 Pneumonia 80 COVID-19, 72 Healthy 78 Pneumonia | Convolutional neural network Images | CT | 96.2 |
| Our Proposed method | 135 COVID-19, 150 Healthy 150 Pneumonia | F-transform, MKLBP and SVM Images | X-ray | 97.01 |

Table 5: Comparison of the proposed method with previous studies.
are generated, and INCA selects the most appropriate/discriminative features. Therefore, high classification rates are obtained using a conventional classifier. The developed method has shown that it can assist to expert radiologists in diagnosing COVID-19. However, the proposed method can be made more robust and accurate with the increase of COVID-19 data. The confusion matrix of our best result was also shown in Fig. 9.

The benefits of the proposed fuzzy MKLBP and INCA based chest image classification method are given below.

- A novel fuzzy-based transformation is proposed similar to convolution.
- Normally, X-ray image patterns of Covid-19 and pneumonia diseases are similar. Therefore, these X-ray images are difficult to differentiate. The proposed fuzzy MKLBP and INCA based method classified these diseases successfully (See Fig. 8).
- A high accurate classification performance is achieved by the proposed approach.
- Comprehensive results are obtained by using 16 classifiers (See Table 2).
- The proposed approach is a cognitive method because there is no need to set millions of parameters as deep learning networks.
- The proposed approach has achieved higher classification accuracy than ten pre-trained deep learning networks (See Table 4).
- A small dataset is used with the presented model. Bigger datasets or more chest related disorders can be used.

7. Conclusions

The covid-19 pandemic has affected all of the world. Therefore, it has become one of the most important and hot-topic research area. To contribute Covid-19 researches, a novel automated chest X-ray image classification method is proposed. This method consists of fuzzy tree creation, exemplar MKLBP based feature extraction, INCA based feature selection, and classification procedures. By using the fuzzy tree, a novel F-transformation is proposed, and this transformation is used as an image operator, and 15 variable images are obtained from each chest X-ray image. MKLBP generates features from these chest X-ray images and exemplars of these images. INCA solves the automated optimal feature selection problem of the NCA. The obtained feature vector is tested on 16 classifiers with five groups. According to the results, Cubic SVM has achieved 97.01% classification accuracy. The obtained results are compared to the transfer learning based feature extraction model, and previous studies in Tables 3 and 5. The presented results reveal that the proposed framework is successful for Covid-19 detection using chest X-ray images. Covid-19 and pneumonia show similar characteristics. Therefore, their chest X-ray images are similar. The proposed fuzzy MKLBP and INCA based approach has the ability of discrimination of these diseases successfully.

As a future work, a real time automated Covid-19 detection system can be created using the proposed MKLBP and fuzzy transform-based model. The architecture of our planned future is summarized in Fig. 10. Moreover, generation binary pattern-based deep models and F-transform based decomposers can be recommended.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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