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A Comparative Study of Image Classification Models using NN and Similarity Distance

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***Abstract*— The following paper presents a comparative analysis based on two algorithms for Covid-19 image classification. Both of them use wavelet coefficients forming image features vector but they differ in the way the vectors are treated for the purpose of classification. The first algorithm uses the mechanism of similarity distance computation using Euclidean distance. The second model uses neural networks for the process of classification. The comparative analysis on the base of the two models is performed on accuracy, precision and recall performance measures. The obtained results show the advantages and disadvantages of both models for the analyzed parameters.**

Keywords—wavelet, wavelet coefficients, image decomposition, image feature vectors, wavelet transform, neural network, similarity distance, image classification

I. Introduction

A new disease called Covid-19 and reported by the World Health Organization has spread over the world for a short period of time. It is a part of the coronavirus family which is evaluated as dangerous pathogens because of the respiratory, neurological, cardiac complications. The disease spreads among people, affecting their health to varying degrees. Two types of tests are used for Covid-19 diagnosing: real-time polymerase chain reaction (RT-PCR) and medical imaging tools and methods. The two main disadvantages of RT-PCR is the option of error occurrence and time consuming to identify the disease. On the other hand, medical imaging provides clear evidence for disease occurrence and enables its treatment.

The two main approaches used for image classification are based on similarity distance computation and neural networks (NN). In both cases image features are extracted using a specified technique. Then the generated feature vectors are used for either similarity distance evaluation or processing by NN for classification task. The image features vectors can be generated on the base of such primitives as texture, color and shape. Discrete Wavelet Transform [1], Gabor Wavelet Transform [2], [3], [4], Dual-Tree Complex Wavelet Transform [5], Contourlet Transform [6], [7], Curvelet Transform [8], 3D Fourier Transform [9] are most often used for texture extraction and orientation recognition. On the other hand, to generate feature vectors by color widely used are color histogram [10], [11], [12], color moments [13] and correlogram [14]. For the cases of shape recognition typical techniques are: Harris Corner Detector [15], Barnard Detector [16], Contour-based shape features [17], [18], [19], Hough Transform [20]. To compute similarity in the algorithms and systems for image classification distance measures is applied. Such measures are Manhattan distance, Mahalanobis distance, Canberra distance, Euclidean distance, etc.

Another technique for image classification is artificial neural networks (ANN). ANN are designed on the model of natural neural networks and the performance of functions of the human brain. The neural network (NN) is made up of a finite number of neurons connected to each other in a certain order and model to perform a specific task. This approach is used to classify data on the base of extracted feature vectors in advance performing deep learning to learn the neural network for a new classification task [21], [22].

In addition, neural networks are designed to solve a wide range of tasks such as human face detection, user image classification, biological data identification [23], object recognition, disease assessment based on medical images for diagnosis and appropriate treatment. Gancheva and Georgiev [24] propose a system for learning and knowledge extraction including patterns from a collection of input data or past experience. Generally, the system processes knowledge in three phases: features extraction and training the system for identifying specific patterns; detecting and classifying a possible pattern; execution of Machine Learning (ML) algorithm to determine the most appropriate model to represent the behavior or the pattern of the data.

On the other hand, the problem of healthcare data security and privacy remains one of the hottest issues facing medical science. It was reported that in 2016 the increase of hacking attacks achieved 320% [25]. In their quest to find solution of cyberattacks and threads, the scientists and software developers propose strategies and methods for data protection against phishing attacks [26], spam, malicious links [27] and network and software-based attacks [28], such as authentification, encryption, data masking, monitoring and auditing, etc.

The following paper presents a comparative analysis on the base of two algorithms for Covid-19 image classification using similarity distance computation and NN respectively. It is organized as follows. Section 2 indroduces the Dual-Tree Complex Wavelet Transform used for image feature vectors generation. Section 3 presents the proposed algorithm with the use of NN for the case study of Covid image classification and experimental results based on the comparative analysis on the described algorithm and the one using image feature vectors generated through the Dual-Tree Complex Wavelet Transform and Euclidean distance to define the similarity distance. Section 4 concludes the paper.

II. The Dual-Tree Complex Wavelet Transform

In 1998 Nick Kingsbury introduced an effective Complex Wavelet Transform (CWT) method called the Dual-Tree Complex Wavelet Transform (DT CWT). It is CWT based on complex valued scaling function and complex-valued wavelet:

$$\Psi_c(t) = \Psi_r(t) + j\Psi_i(t) \quad (1)$$

where $\Psi_r(t)$ - real and even part, $j\Psi_i(t)$ - imaginary and odd part, $\Psi_c(t)$ - analytic signal;

Kingsbury's idea was to develop a transform which produces analytic signal on the analogy of Fourier transform and which possesses the following properties:

- smooth non-oscillating magnitude;
- nearly shift-invariant magnitude;
- significantly reduced aliasing effect;
- directional wavelets in higher dimensions;

For the DT CWT realization Kingsbury uses two Discrete Wavelet Transforms (DWTs) performed on two different binary wavelet trees A and B (Fig.1) for each. Thus he designs the real and the imaginary part of DT CWT to produce the analytic signal.

Fig. 1 illustrates graphically the 1-D DT CWT analysis filter bank (FB) structure.

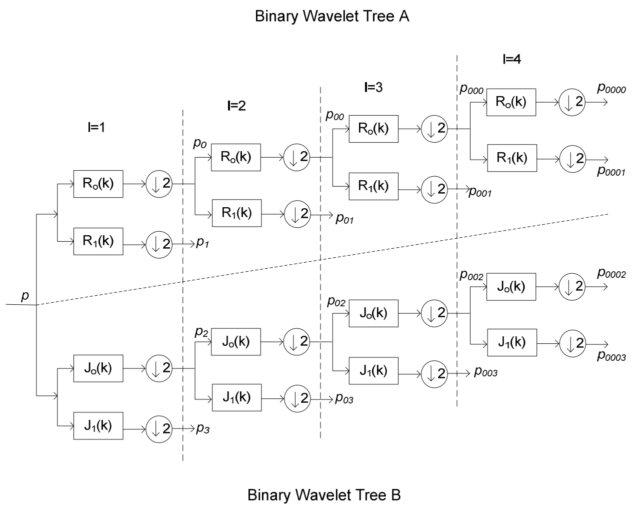

Fig.1. The 1-D DT CWT analysis filter bank (FB) structure

The input signal p is decomposed by the lowpass filters $R_0(k)$ for the real part and $J_0(k)$ for the imaginary one and decimated by 2:1 generating its lowpass components p_0 and p_2. The highpass filters $R_1(k)$ and $J_1(k)$ and decimation by 2:1 produce the highpass components p_1 and p_3 of the signal p. This process continues as far as required for levels $l=1, 2, 3, 4$. The final result of the decomposition of p is: p_1, p_{01}, p_{001}, p_{0001} for the real part and p_3, p_{03}, p_{003}, p_{0003} for the imaginary part. The filters used for DT CWT are chosen to be linear-phase satisfying the Perfect Reconstruction (PR) condition [14] and are joined so that the final result of the transform is approximately analytic:

$$\Psi(t) := \Psi_R(t) + j\Psi_J(t) \quad (2)$$

where: $\Psi_R(t)$, $\Psi_J(t)$ - wavelets generated by the two DWTs.

In addition, both low-pass filters $R_0(k)$ and $J_0(k)$ have to be designed to possess a property so as the corresponding wavelets to form an approximate Hilbert transform pair:

$$\Psi_J(t) \approx H\{\Psi_R(t)\} \quad (3)$$

where:

$$\Psi_R(t) = \sqrt{2}\sum_k R_1(k)\Phi_R(t) \quad (4)$$

$$\Phi_R(t) = \sqrt{2}\sum_k R_0(k)\Phi_R(t) \quad (5)$$

For this goal one of the two lowpass filters has to be nearly half-sample shift to the other:

$$J_0(k) \approx R_0(k-0.5) \Rightarrow \Psi_J(t) \approx H\{\Psi_R(t)\} \quad (6)$$

This half-sample delay leads to nearly shift-invariant wavelet transform.

Besides one-dimensional application, DT CWT may be used for two dimensional tasks through 2-D DT CWT relying on the M-D dual-tree wavelets properties to be approximately analytic and oriented. Thus, it is suitable for edge and surface detection in image processing. The process of filtering is performed by two different groups of filters providing two 2-D separable DWTs and six subbands: two HL, two LH, and two HH subbands.

2-D DT CWT finds application in image segmentation [29], motion estimation [30], texture analysis and synthesis [31], feature extraction [32], [33].

III. Proposed Algorithm and Experimental Results

A. Image Classification Algorithm Using DT CWT and NN

The proposed algorithm for Covid-19 image classification is illustrated in Fig. 2. Its task is to determine if a submitted image has the affiliation of positive or negative Covid group and to enable diagnosing. The presented model of algorithm consists of two stages consistently performed. The first stage comprises image decomposition and the process of wavelet generation which form the image features vectors. The stage itself is divided into six individual phases. In the first phase greyscale test image database is loaded. In the second phase image preprocessing is performed. It includes image scaling to 256 x 256 pixels. On that base DT CWT is performed and wavelet coefficients forming image feature vectors are generated. They are submitted to the NN where the training is performed. The second stage concerns the processing of the submitted query-image following the same order of phases as described for stage 1. The generated feature vector of the query-image is submitted to the NN and classified into Covid positive (1) or Covid negative (0) group and the result is displayed.

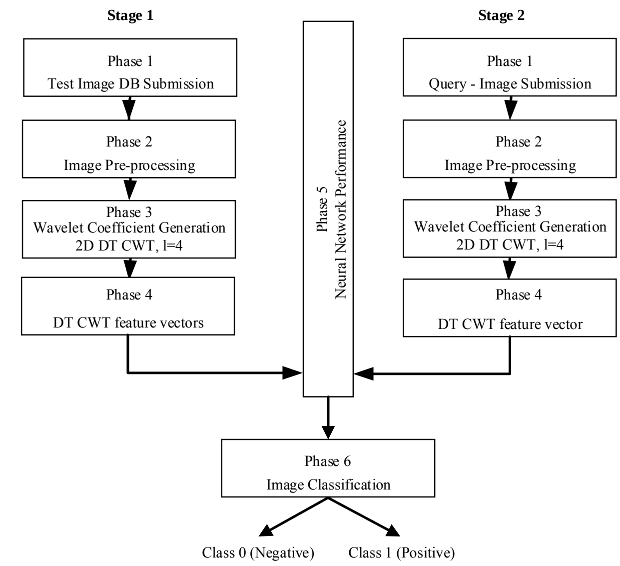

Fig.2. Covid-19 images classification using DT CWT and NN

B. *Experimental Results*

For the verification of the proposed algorithm for Covid-19 image classification a Covid image database is used. It consists of 758 images in greyscale color space in JPEG and PNG format. They are classified into two groups for positive and negative cases respectively as shown in Fig. 3 and Fig. 4.

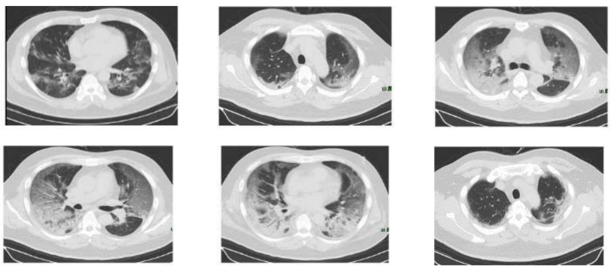

Fig. 3. Covid-19 positive image database

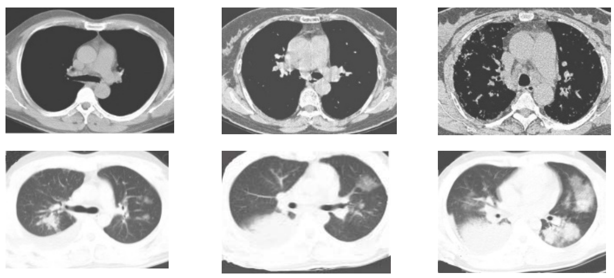

Fig. 4. Covid-19 negative image database

To realize and verificate the algorithms, the software for mathematical and engineering computation Matlab is used.

For the analysis and evaluation of the proposed model with neural network, a comparative analysis is performed. It includes the described algorithm and another one using DT CWT for generating image feature vectors to describe the images performed in the same processing order as it runs for the algorithm with NN. When a query-image is submitted it is processed following the same steps. The similarity between the query-image and the image database is computed through Euclidean distance. For the comparative analysis such performance metrics as classification accuracy, precision and recall defined as (1), (2), (3) respectively are analyzed:

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

where:

- TP (True Positives) – an indicator of the cases when the actual output and the prediction parameter match and both have YES value;
- TN (True Negatives) – an indicator of the cases when the actual output and prediction parameter match and both have NO value;
- FP (False Positives) – an indicator of the cases when the prediction expectations are evaluated negative (NO) and the prediction result doesn't match having value YES;
- FN (False Negatives) – an indicator of the cases when the prediction expectations are evaluated as positive (YES) and the prediction result doesn't match having value NO.

The accuracy is an evaluation technique suitable mainly for the cases when images for the positive and negative cases are approximately equal number. For a complex and accurate analysis and evaluation we added the metrics precision and recall. Precision (2) determines the percentage of the relevant results and is useful for the cases when the cost of the false positive is very high while the cost of the false negative is low:

$$\Pr ecision = \frac{TP}{(TP + FP)}, \quad (2)$$

On the other hand, Recall (3) determines the percentage of actual positives. It is a useful measure for the cases when a false negative is high. It is an indicator of the number of prediction expectations evaluated by the classification model as positive:

$$\operatorname{Re} call = \frac{TP}{(TP + FN)}, \quad (3)$$

Both wavelet features-based algorithms are designed for an image classification system. For the evaluation of the algorithm with similarity computation using Euclidean distance evaluation experiments are performed in the following order:

1. To reduce the influence of any running system processes, each image from the image test database is submitted as a classification query-image;
2. Image features are extracted through 2D DT CWT;
3. The similarity distance is computed using Euclidean distance.

On the other hand, for the proposed in the paper algorithm using NN another three steps are followed:

1. The NN model is trained using the generated with 2D DT CWT feature vectors for the case study of Covid-19;
2. In order to achieve a truthful evaluation, the test images are submitted for classification in class Positive (1) and class Negative (0);
3. The computed results are displayed.

In Table 1 the results of five experiments are listed. The last row presenits the average of the analysed evaluation measure. Judging by the average values of accuracy, precision and recall, the results for both techniques differ. With regard to accuracy, NN-based algorithm demonstrate higher results compared to the similarity distance algorithm with 16,6%. In terms of precision, the similarity distance-based algorithm produces a better result than the NN-based algorithm with 1,4%. Therefore, it is suitable for the cases when the cost of a false positive is very high while the cost of the false negative is low. Comparing the results for Recall, NN-based model demonstrates higher result than the similarity-based one with 26,4 % reaching 87,8% against 61,4% for the latter. The results show that the NN-based model is suitable for the cases when a false negative is high.

TABLE I. RESULTS OF THE ALGORITHMS USING EUCLIDEAN DISTANCE AND NN

Experiment	**Accuracy (%)**		**Precision (%)**		**Recall (%)**	
	NN-based	**Similarity distance-based**	**NN-based**	**Similarity distance-based**	**NN-based**	**Similarity distance-based**
Exp. 1	95%	76%	84%	100%	86%	79%
Exp. 2	93%	70%	96%	85%	92%	62%
Exp. 3	98%	78%	99%	97%	81%	55%
Exp. 4	96%	87%	100%	86%	87%	53%
Exp. 5	94%	82%	87%	91%	93%	58%
Total	95,2%	78,6%	93.2%	91,8%	87.8%	61,4%

In Fig. 5, 6 and 7 the obtained results for experiment 1, 2, 4 are graphically presented.

Submitted Classification Image	Classified Image with NN-based Algorithm	Classified Image with Similarity Distance-based Algorithm

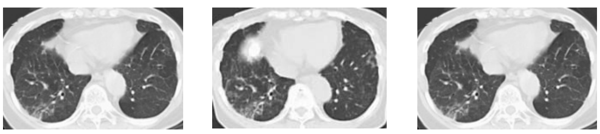

Fig. 5. Image classification result for experiment 1

Submitted Classification Image	Classified Image with NN-based Algorithm	Classified Image with Similarity Distance-based Algorithm

Fig. 6. Image classification result for experiment 2

Submitted Classification Image	Classified Image with NN-based Algorithm	Classified Image with Similarity Distance-based Algorithm

Fig. 7. Image classification result for experiment 4

IV. CONCLUSION

The presented report deals with a comparative analysis between two algorithms for Covid-19 image classification. The first one uses wavelets coefficients generating feature vectors and similarity distance computation through Euclidean distance. The second model also uses feature vectors and NN in addition. Comparative analysis on the base of the two models is performed on accuracy, precision and recall performance measures. The analysis show that the NN-based model has better ability to classify than the similarity distance-based algorithm. Furthermore, on the base of recall results, it is recommended for the cases when a false negative is high. On the contrary, the similarity distance – based is useful for the cases when the cost of a false positive is very high while the one of the false positive is low.

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