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GLCMs Based multi-inputs 1D CNN Deep Learning Neural Network for COVID-19 Texture Feature Extraction and Classification

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Keywords

Quantization, GLCM, PCA, 1D CNN, COVID-19

RESEARCH PAPER

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Abstract

Coronavirus disease 2019 epidemic (COVID-19) is an infectious disease that appeared because of the newest version of discovered coronavirus. The advent and rapid spread of this disease over the world necessitated a concerted effort to contain and eradicate it. Computer Tomography (CT) imaging and X-Ray images are considered as one of the important medical examinations used for disease diagnosis. To speed up and confirm the correctness of the medical diagnosis, many artificial intelligence techniques and machine learning methods are proposed. In this paper, a new and efficient proposed system is introduced to extract appropriate and meaningful features for CT scans and X-Ray COVID-19 images. The proposed method depends on extracting statistical texture features of the images using the GLCM method. The GLCMs matrices are extracted from different three quantized versions of the original image in different distances and directions. New multi-inputs 1D CNN architecture of the deep neural network is implemented to extract the effective features directly from GLCMs matrices after reducing its dimensions using the PCA technique. Three datasets are used to evaluate our method that includes SARS-CoV-2 CT-scan, COVID-CT, and DLAI3 Hackathon COVID-19 Chest X-Ray datasets. The proposed system achieved a classification improvement in terms of accuracy, F1 score, and AUC metrics compared with other methods and exceeds 98%, 89%, and 93% for three datasets, respectively.

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1. Introduction

Coronavirus disease 2019 epidemic (COVID-19) is one of the recent virus diseases spread and caused many injuries and deaths in all world. Computer Tomography (CT) scans and X-Ray images consider as non-invasive (potentially bedside) tools to test and monitor the progress of the disease [1]. Many teams and researchers collect datasets and use Artificial Intelligent (AI) techniques to help hospitals and medical scientific research centres for a correct and rapid diagnosis [2]. One of the most useful AI techniques and is the texture feature extraction algorithms that identify the best features to represent the image and contain fewer parameters [3]. Feature extraction Using Grey Level Co-occurrence Matrix (GLCM) method can be expressed a useful and meaningful image features, therefore, a fast and successful classification task [4]. GLCM is a popular and powerful structural texture-based feature extraction approach. The GLCM represents the second-order statistical textural relationship between image pixels usually two [5]. The GLCM contains the appearance of two adjacent pixels brightness values in a specific distance as (d = 1, 2, 3 …) and specific direction (angle Θ = any angle value is possible) [6]. The result of GLCM is represented as a two-dimension squared matrix where the number of rows and columns are equal to the number of image grey levels. If the grey levels of the image are large, the dimension of the resulting GLCM matrix will be quite large and therefore it

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will be time and memory-consuming during its process [7]. For this reason, in this study, we use a quantization method as a pre-processing step for the processed image.

Quantization is considered as a pre-processing method used in many applications and image processing tasks to perform more fast performance and efficient results with large datasets. Also, there are applications such as image retrieval that have a good effect if it contains a quantization as a pre-processing [8–10]. Quantization is a process of reducing the number of the original image grey levels into a desired limited number of intensities and producing a new quantized image [11]. The reduction of grey levels consists of dropping the bits number needed to characterize each pixel in the image. If the number of grey levels is L, then there are log2L = N (L = 2 N) bits are required for each pixel [12]. There are several categories of quantization approaches developed across successive decades as Uniform quantization, k-mean clustering, Dithering, and Halftoning quantization methods [12–14]. In this paper, we use a new quantization method proposed in our previous work to construct three versions for each dataset image with a different number of grey levels. There are many properties that can be computed from the GLCM matrix and represent the GLCM as a whole e.g. energy, dissimilarity, homogeneity, and so on. The extracted properties can be used to represent the image and entered into the classification task [4]. In this study, we extract the image feature from the GLCM matrix itself using 1D CNN deep neural network and not depend on GLCM properties. There are many GLCMs matrices that can be constructed from each image depending on specific distance and direction. Therefore, there are stacked GLCMs matrices for each quantized image.

Principle component analysis (PCA) is one of the widely used dimensionality reduction methods that present its effectiveness with many applications and algorithms. PCA aims to compute the directions of maximum variance in high dimensional data and project it onto a new subspace with equal or fewer dimensions than the original one [15]. PCA has many steps started by standardizing the dataset dimension, creating the covariance matrix then decomposing it into its eigenvectors and eigenvalues. Then sort the eigenvalues in decreasing order to rank its eigenvector and select the k eigenvectors that have k largest eigenvalues, where k is the new data dimension. Finally, transform the original dataset with d dimension using the projected w matrix constructed from the k eigenvectors [16].

Image feature extraction using Convolution neural networks (CNNs) considers as one of the recent and powerful methods that are used in many image processing applications. Deep CNN captures the low-level features in the earlier convolution layer and progresses to get the high-level features in later convolution layers. CNN uses many filters with different sizes consisting of the neural weights also called kernel. The CNN architecture contains many layers of convolutions cascaded followed by down-sampling pooling layers. Also, the architecture contains a non-linearity activation function usually used ReLU function [17]. There are many types of CNN networks according to the filter dimension used; 2D, 1D, and 3D CNN. 2D CNN is the standard type of CNN that contains a filter with 2D and slides the data in 2 dimensions and it required a large number of parameters to train the network and is usually used with 2D image data. In 3D CNN, the filters have 3 dimensions slide the data in 3 dimensions and the number of trainable parameters is more than one in 2D CNN. This type of CNN is usually used with video data. 1D CNN contains 1D filters that slide the data in one dimension and have a lower number of trainable parameters compared with other CNN types. 1D CNN is used usually with audio and one dimension serial data [18,19]. Fig. 1 shows an example of the three types of CNN.

The main problem solved in this work is how can increase the accuracy of COVID-19 medical images classification. This problem can solve by finding more efficient and meaningful features to represent the image datasets. This paper introduces a proposed system for GLCM and deep learning neural network-based images feature extraction for the COVID-19 medical images. The system extracts the statistical texture features by generating the GLCMs matrices from three quantized versions of each original CT or X-Ray COVID-19 image. The texture statistics GLCMs matrices dimensions are reduced using the PCA technique. The resultant three vectors are entered into the new 1D CNN architecture to train and finally used the trained model to extract the appropriate features to represent the dataset. This study aims to build an effective system that depends on texture image features and extract efficient high-level features using a 1D CNN model that provides high success results outperforms the previous and state of art methods.

There are many contributions that aim to solve the main problem of the research and increase the classification accuracy that can be summarized as follow:

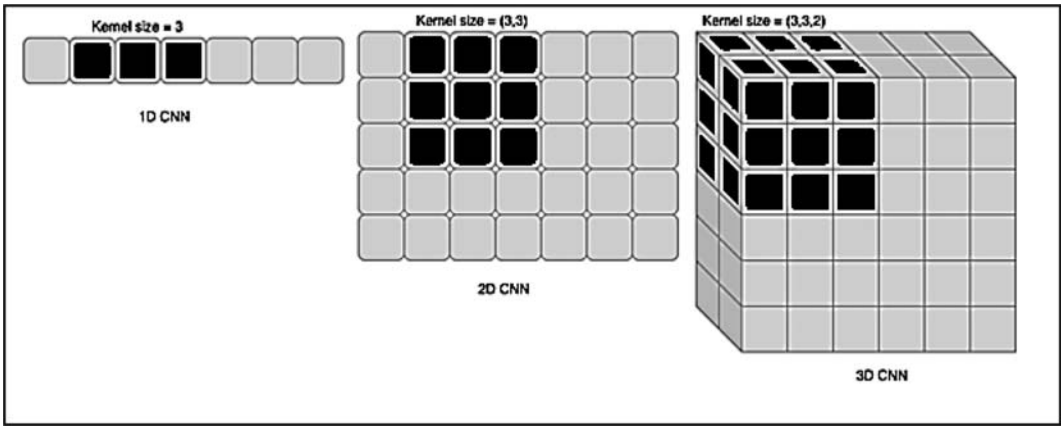

Fig. 1. 1D CNN, 2D CNN, and 3D CNN.

- The system extracts meaningful and perfect texture features using GLCMs matrices constructed in three different distances and many different directions.
- Using a new 1D CNN architecture with three different input layers that required a little number of parameters and trained on the image statistical features only to produce good represented features for classification tasks.
- The system used three varied types of datasets of the more recent challenge image datasets for COVID-19 CT and X-Ray images without any data augmentation process and gets high performance on it.
- The proposed system achieves improvement in results compared with the pre-trained deep neural networks (DNNs) and state-of-art approaches in terms of accuracy and F1 score metrics as explained in the results section.

The rest of this paper is organized: section 2 introduces the related works in texture feature extractions and CNN models test the COVID-19 images. Section 3 explains the proposed system in detail. The datasets, evaluations metrics, comparisons, experiment results, and discussions are explained in section 4. Section 5 contains the conclusions.

2. Related works

In the context of using GLCM texture features to represent the medical and the COVID-19 CT and X-Ray images, many researchers deal with this field and introduced methods to process it.

Saban and Bayram [20] used many texture features extraction methods such as GLCM, LBP, LBGLCM, GLRLM, and SFTA and compared the classification results using these algorithms. They used large-size histopathological images and partition them into pieces with smaller sizes. They used the GLCM properties like entropy, homogeneity, and dissimilarity as texture features as well as the other texture features methods as LBP, LBGLCM, GLRLM, and SFTA. Their method collects all features from these methods in one feature matrix and evaluates its efficiency using many classification methods like SVM, KNN, LDA, and Boosted Tree approaches. The GLCM extracted features are and do not look to the GLCM matrix as a whole as is used in this paper.

K. Shankar et al. [21] introduced a method to classify chest X-Ray COVID-19 dataset using handcraft feature extraction approaches. Weiner filtering enhancement method was used as a preprocessing for the dataset images. They fused features extracted using three types of texture feature extraction techniques are GLCM, GLRM, and LBP after selecting the optimum set using the salp swarm algorithm. The collected features are classified using a traditional neural network (ANN) to distinguish infected and healthy patients.

Saban Ozturk et al. [22] analyzed the X-ray and CT scan images using two steps of image enhancement. They used the data augmentation technique to treat the deficient and unbalanced in the dataset. To analyze the images, they used handcraft features extraction methods such as GLCM, LBGLCM, GLRLM, and SFTA approaches and combined these features in one feature vector then used synthetic minority over-sampling technique as the second step of enhancement. PCA and stacked autoencoder are used to reduce the dimension of the feature vector and finally classify it using the SVM technique.

All these three works above used GLCM properties to extract the dataset images' texture features and don't utilize the raw GLCM statistics to feature extraction purposes. In the context of using deep learning neural networks (DNNs) to implement feature extraction COVID-19 dataset images, there are diverse methods introduced and presented to this task.

Asmaa Abbas et al. [23] used a CNN network called Decompose, Transfer, and Compose (DeTraC) model to extract features of COVID-19 X-Ray dataset images. They constructed the DeTraC model in three stages: used a pre-trained model to generate the image deep local features then reduce these features' dimensionality using the PCA technique. Second, they used a sophisticated gradient descent optimization approach to train the resulting data. Finally, they used the composition layer to implement decision-making classification for the image dataset.

Pedro Silva et al. [24] introduced a DNN method to classify the COVID-19 CT scan image dataset based on a voting approach. They utilized the pre-trained EfficientNet weights by copying them into a new model and adding an additional layer on the top of the model. Then, they train the model with randomly initialized to learning process according to loss function and optimization method. They reconstructed two COVID-19 CT scan datasets using a voting method and used it to evaluate the DNN model.

Eduardo Soares et al. [25] collected the SARS-CoV-2 CT scan dataset and used eXplainable DNN (xDNN) to evaluate the dataset and provided baseline results to it.

Matteo Polsinelli et al. [26] introduced a DNN model to classify the COVID-19 CT scan dataset by building a custom CNN model based on SqueezeNet pre-trained DNN that has many squeeze convolution layers called fire modules. They added the Transpose Convolutional layer to the last fire module and expand the feature maps 4 times. Then, concatenated these feature maps with the second custom fire module followed by weighted sum, convolution layer, and global average pooling layers.

In this paper, we present a new texture feature extraction method based on generating multi GLCMs matrices and a 1D CNN model with a specific quantization pre-processing method.

3. The proposed method

The proposed system in this paper contains a newly proposed method for medical image feature extraction with an appropriate preprocessing stage. Fig. 2 illustrates the stages of the proposed system. The system contains many stages to find efficient features to represent the medical image (in our case we use COVID-19 CT and X-Ray medical images). The first stage contains three steps: 1) quantization technique, 2) GLCMs matrices, 3) PCA technique. The output of the first stage is entered to the second stage that is the feature extraction stage. This stage contains a new architecture of the 1D CNN to extract the appropriate and more meaningful features that represent the input images data. The efficiency of the extracted features is examined using the classification process represented in the third stage of the proposed system. In the rest of this section, we explain the system stage in more detail.

3.1. Preprocessing stage

The preprocessing stage contains many steps as illustrated in Fig. 3. Each image in the dataset is entered to this stage as a gray image with 255 Gy levels and different sizes depending on the

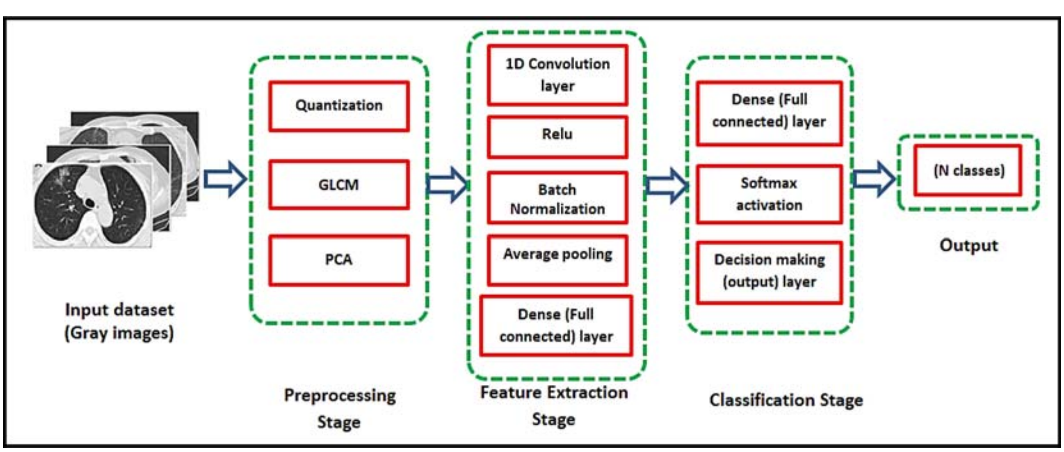

Fig. 2. Block diagram of the proposed system.

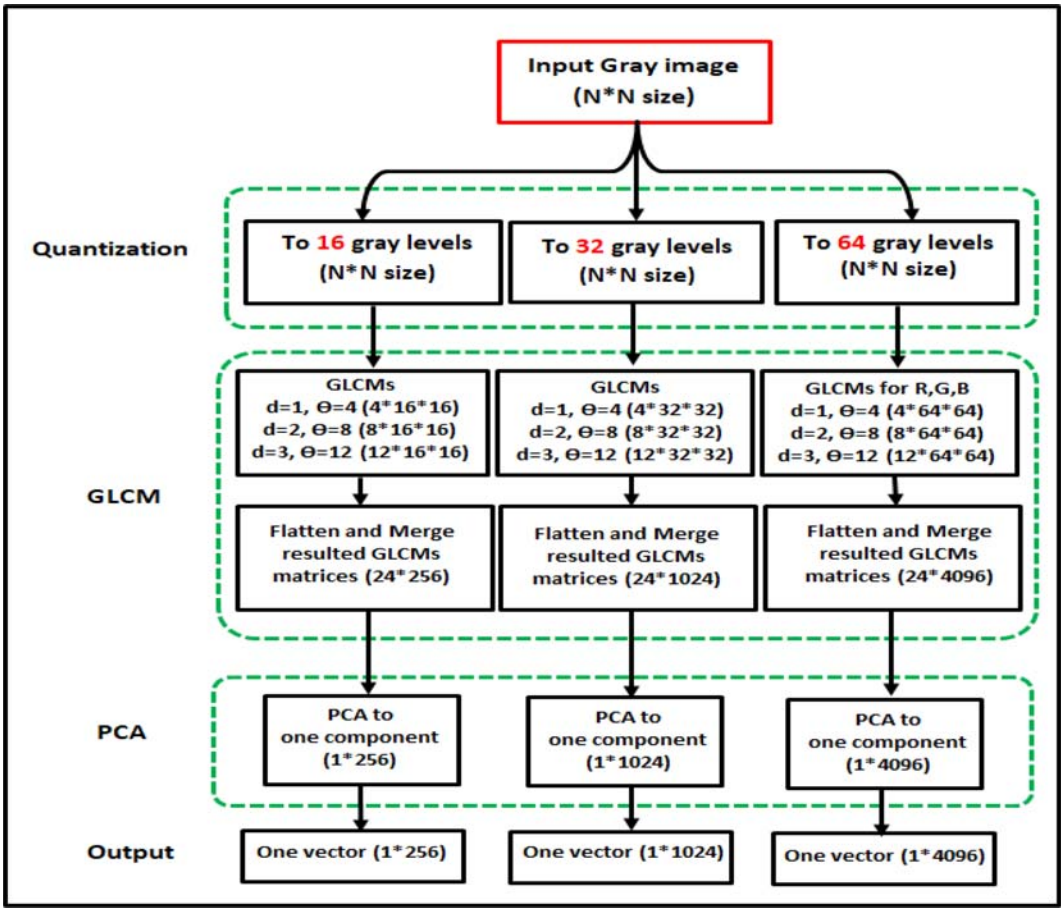

Fig. 3. Block diagram of the Preprocessing stage.

experimented dataset. The output of this stage will be three different dimension vectors that are used as input to the next stage.

3.1.1. Quantization step

At the beginning of the preprocessing stage, our new quantization method presented in our previous work is used. The reason for using this method of quantization, the resultant quantized image have more information from the original image and less distortion compared with other traditional methods as K-mean or uniform quantization methods. In the quantization process, the input grey images are quantized to three different numbers of grey levels 16, 32, and 64. This grey level reduction is considered as a very efficient step to increase the resulted classification accuracy as well as its impact to reduce the GLCMs dimension in the next step as explained later. The quantization process reduces the number of grey levels of the original image from 255 to the desired number of grey levels determine in this paper in three numbers 16, 32, and 64. The three resultant quantized images have different texture features as well as provide different GLCMs matrices. The resulting quantized image contains grey levels that are generated as threshold values by separating the original range of grey levels depending on optimizing the PSNR metric for the quantized image. First, the divide and conquer strategy is used to find the threshold values, then, in each division, apply the PSNR metric on the resulting quantized image with the threshold value to find the optimum threshold value that is selected as grey level in the quantized image. Fig. 4 illustrates the quantization process that used in this work.

Each grey image in experiment datasets is inserted into the three quantized quantization processes and resulted in three quantized images with 16, 32, 64 grey levels values. Each version of the resulting images has features that are different from each other depending on the number of grey levels.

3.1.2. Grey level Co-occurrence matrix (GLCM) step

In the GLCM step, we find many GLCM matrices in three different distances and different directions in each distance. These matrices are considered as

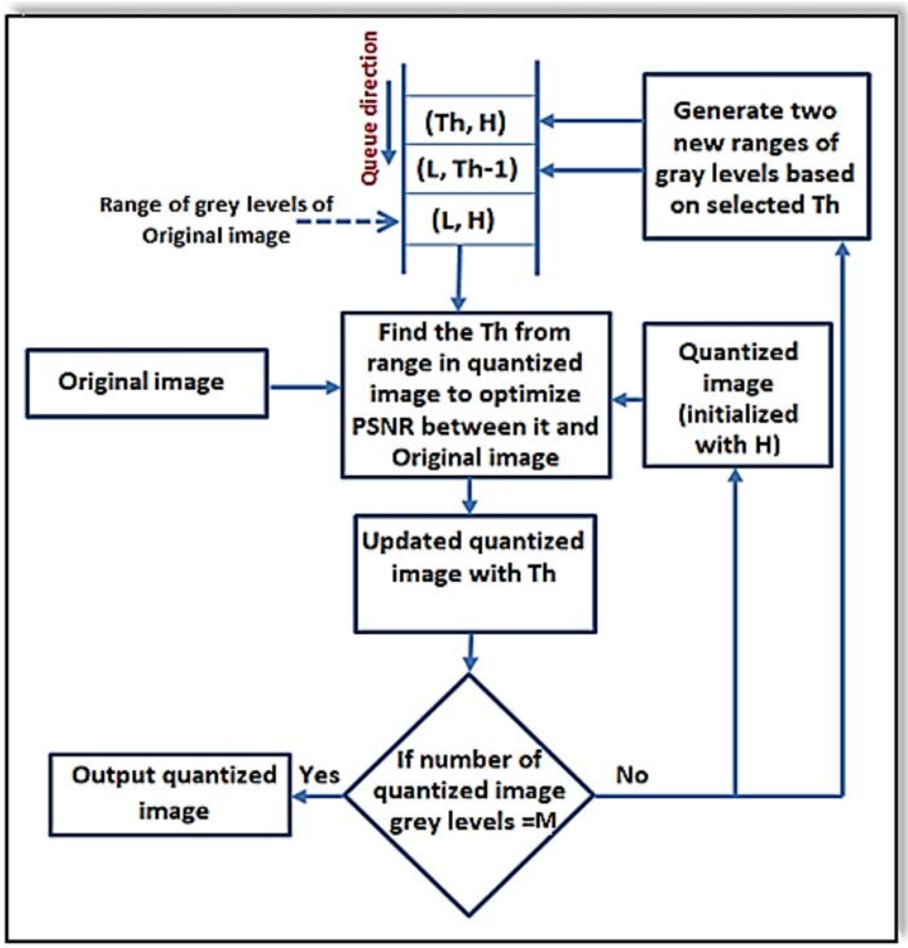

Fig. 4. Block diagram of the quantization process.

second-order statistical features that can find a relation between two pixels almost be neighbours in the image. The powerful and activate as well as the simplicity of GLCM matrices in the way we use is the reason behind using this method instead of other methods. As is known, GLCM is a square matrix and its dimensions depend on the number of gray levels of the input image. For that, in this paper, the dimension of generated GLCM matrices depends on the three different quantized images constructed in the previous step (quantization step). Fig. 5 illustrates the construction of GLCM matrices for one quantized image with N gray levels values.

First, four GLCMs are generated by finding the occurrence of pixel P with green pixels in Fig. 5 with distance d = 1 and directions ϴ= (0°, 45°, 90°, 135°). These matrices are stacked in one matrix with dimensions (4, N, N). Second, eight GLCMs are constructed with d = 1 and ϴ= (0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135°, 157.5°) and then stacked in one matrix with dimension (8, N, N). Finally, we generate 12 GLCMs with d = 3 and ϴ= (0°, 15°, 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, 165°) and grouped in one matrix with dimension (12, N, N). After GLCMs generation, we need to prepare the resulted data for the next step (PCA). For that, the resulted matrices for each quantized image are merged and flatted to produce one dimension matrix. This is done by merging and reshaping the GLCM matrices (4, N, N), (8, N, N), and (12, N, N) to one dimension matrix with length (24, N*N). This step is repeated for three quantized images resulted from previous step (quantization). Where the three quantized images with input dimensions (16, 16), (32, 32), and (64, 64) and the resulted matrices from GLCMs step are 2D matrices that are (24, 16*16), (24, 32*32), and (24, 64*64), respectively.

3.1.3. Principal Component Analysis (PCA) step

As shown in the previous step, the dimension of resultant 2D GLCMs matrices is (24, 16*16), (24, 32*32), and (24, 64*64) or (24, 256), (24, 1024), and (24, 4096). Whereas, these matrices have high dimensions to be the input layer to the next feature

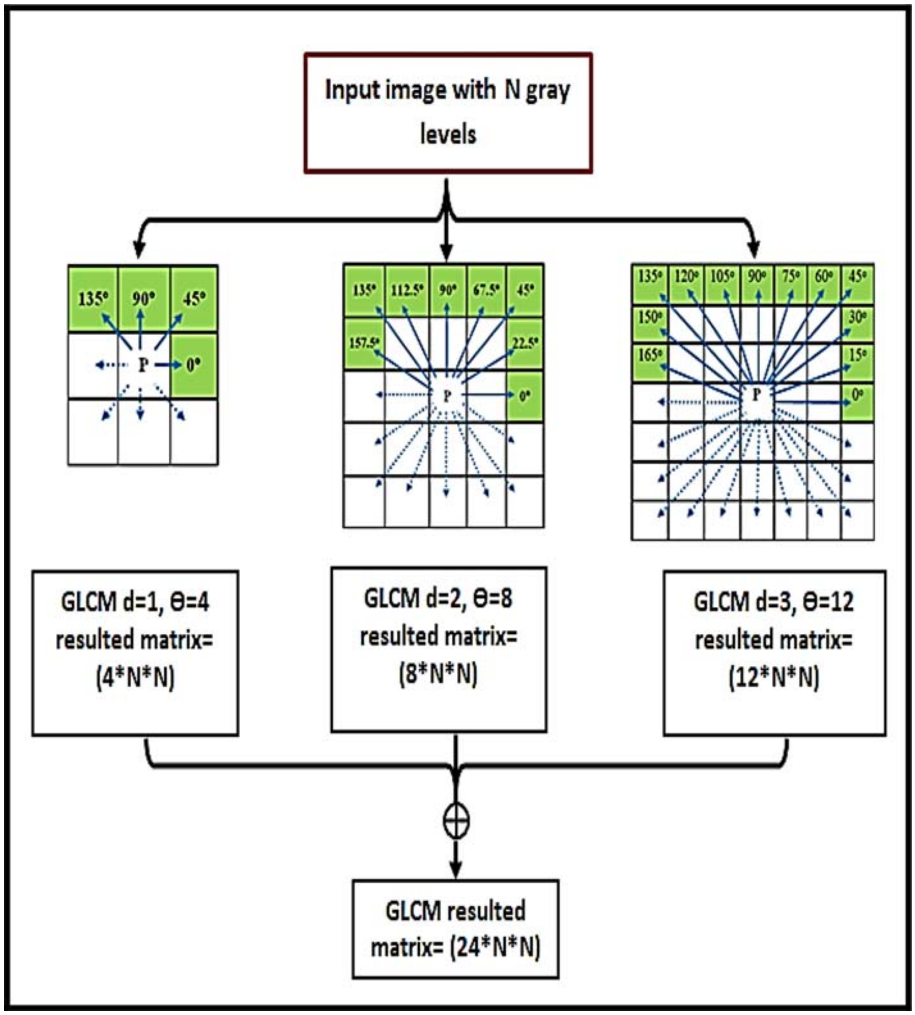

Fig. 5. GLCM step for one quantized image.

extraction stage. Also, the natural of GLCM is a sparse matrix that contains a lot of zero values. It is very useful and efficient to use one of the dimension reduction methods to reduce the matrices dimensions that will be as an input layer to the next stage and decrease the computational complexity as well as getting a more effective feature extraction process. In this paper, Principal Component Analysis (PCA) is used as an efficient dimension reduction method to extract the most significant values of data and reduce the 2D GLCMs matrices. In this step, the merged GLCM matrix with (24, N*N) dimension is entered into the PCA procedure and one principal component is selected. The output of the PCA procedure is one vector with (1, N*N) dimension. For three merged 2D GLCMs matrices (24, 16*16), (24, 32*32), and (24, 64*64), the resultant one principal component will be vectors with (1, 16*16), (1, 32*32), and (1, 64*64) dimensions, respectively.

3.2. Feature extraction and classification stages

In this stage, feature extraction and classification processes are implemented by proposed a new multi inputs 1D CNN model. The main objective of the proposed model is to extract the most important features from three different raw reduced GLCMs vectors and classify the input images depending on these extracted features. The proposed model contains three pipelines according to the three inputs GLCM vectors. The model is consists of many layers that done different functions depending on the particular objective of each layer. The proposed architecture of each pipeline in the model depends on the input GLCM vector that represents the input layer to the model and its dimension. Fig. 6 illustrates the model architecture and the dimension depth of data in each layer.

Since the input layers are one dimension vectors, there is very effective in this model to use 1D

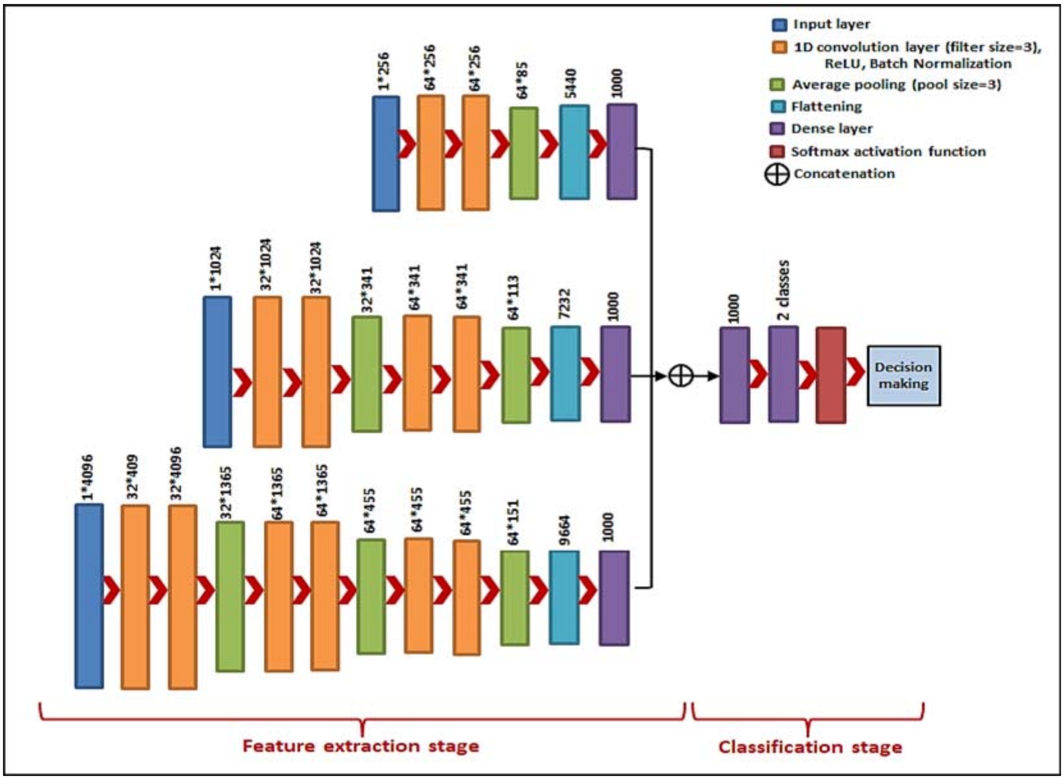

Fig. 6. Feature Extraction and Classification stage.

Convolution (1D Conv) layers instead of 2D convolution layers. All the 1D CNN layers with a filter size (3*1) followed by non-linear activation function that represented by Rectified Linear Units (ReLU) function and then batches normalization layer. Each two 1D Conv followed by one average pooling layer with pool size 3*1. The average pooling layer, as known, is used to reduce the data dimension by downsampling the input layer data with the pool size factor. After cascading the 1D Conv and pooling layers, fattening and Dense (fully connected) layers are used to appropriate the extracted features of three input layers to fuse in one resulted feature vector. The resulted features are fused represented by the concatenate to the resulted three vectors from three model pipelines.

To classify the resulted concatenated vectors, Dense fully connected and Softmax layer is used. The Softmax layer is considered as an activation function that used a normalized exponential function to normalize the network output and find a probability distribution over predicted output classes.

4. Results and discussions

To present the efficacy of our proposed method as a feature extraction process, we extensively evaluate the system. In this section, the experimental results of applying our system on three types of COVID-19 CT and X-Ray images datasets. The results are compared with transfer learning methods that used pre-trained deep neural networks. Also, the system results are compared with state of art methods that introduce and use the same datasets.

4.1. Datasets description

In this paper, to prove the efficiency of our proposed method, three datasets are considered. The first dataset is called SARS-CoV-2 CT-scan dataset [27] contains 2482 CT scan images belonging to 120 patients, 1252 CT scan images are infected with COVID-19, and 1230 CT scan images with no COVID-19, but have other lung infections. Data was composed by Sao Paulo hospitals in Brazil and it is available at https://www.kaggle.com/plamenedua rdo/sarscov2-CT scan-dataset. The dataset images sizes are different and ranged between 104 × 153 pixels for the smallest size to 484 × 416 for the largest one.

The second dataset that is used in this paper is the COVID-CT dataset [28] CT scan images that contain a total of 746 CT scan images, 349 CT scan images with COVID infection and 397 CT scan images are no COVID-19. The dataset is collected from scientific articles published in the medRxiv and biRxiv impactful journals. Also, some images were donated by hospitals (http://medicalsegmentation.com/COVID-19/). The dataset contains Metadata collected manually for these images: patient age, gender, location, medical history, scan time, the harshness of COVID-19, and medical report. The COVID-CT dataset is available at https://github.com/UCSD-AI4H/COVID-CT. The images in this dataset are very different in size that ranged in heights between 153 and 1853 pixels with 491 pixels as an average and ranged in widths between 124 and 1458 pixels as an average.

The third dataset that used in this paper is called DLAI3 Hackathon COVID-19 Chest X-Ray [29]. The dataset is downloaded from the Kaggle website that introduced a DLAI3 Hackathon COVID-19 Chest X-Ray challenge and it is available at https://www.kaggle.com/c/dlai3/data. The dataset contains 1084 X-Ray images with COVID and Non-COVID (normal) divided into train and test sets. Train set contains 125 X-Ray images for COVID infection and 551 X-Ray images for Non-COVID states. The test set contains 118 X-Ray images for COVID infection and 290 X-Ray images for Non-COVID states. The size of images is different and it is varying in contrast and brightness. The larger dataset was from the CSC532 Machine Learning project of Puttipong Thammachart & Vasin Virasak. Also, a part of this dataset is from https://github.com/ieee8023/covid-chestxray-dataset.

To evaluate our proposed system, there are three performance metrics used: Accuracy, F1 score, and Area Under the Receiver Operating (AUC) metrics. Accuracy is the ratio between the number of true positive and true negative classified points to the total number of points and it is defined as follow:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where, TP, TN, FP, and FN represent the true positive, true negative, false positive, and false negative, respectively. F1 score is the harmonic mean of precision and recall and is defined as:

$$F1\ score = \frac{2*precision*recall}{precision + recall} \tag{2}$$

where, precision and recall defined as:

$$precision = \frac{TP}{TP + FN} \tag{3}$$

$$recall = \frac{TP}{TP + FP} \tag{4}$$

AUC is defined as a plot of true positive rate versus false positive rate [24,30].

4.2. Experiments and discussions

The proposed system is implemented in Python 2021.1.3 with Tensorflow 2 on an 8G RTX 2070 machine. The 1D CNN model is trained with a learning rate of 0.001, a momentum of 0.9, epochs of 40, and a batch size of 16. The optimizer is used in our CNN architecture is a gradient descent (with momentum) (SGD) optimizer with a learning rate of 0,001, the momentum of 0.9, and decay rate of (learning rate/epochs). It is worth noting that no data augmentation is used in the system. As we see in sub-section 4.1, we use three datasets that are different in images types, size as well as using different introduced methods that evaluated on it. Then, due to different evaluation conditions and to a fair comparison, we evaluate the performance and efficiency of our proposed system with other methods using each dataset separately.

4.2.1. System evaluation on SARS-CoV-2 CT-scan dataset

To evaluate the method, we compare our proposed system with other pre-trained (black-box) deep neural network approaches like ResNet, GoogleNet, VGG-16, and Alexnet networks. Also, we compared our method with the xDNN algorithm introduced by Soares et al. [27]. We use the protocol presented in [27] to divide the dataset randomly in training (80%) and test (20%) partitions. The size of images when applied our method in this experiment is (448 × 448) pixels. Table 1 shows the results of a comparison between our method and other state-of-art methods using accuracy, F1 Score, and AUC metrics. Fig. 7 shows these results in visual form.

From the experiment results in Table 1, it is clear that our method outperforms the other previous methods. The proposed method presents enhanced results of accuracy, F1 score, and AUC metrics with an increasing range of (1.1%−6.7%), (1.6%−6.7%), and (1.05%−6.6%), respectively.

Table 1. Proposed method results compared with other pre-trained DNNs and state-of-art approaches applied on SARS-CoV-2 CT-scan Dataset.

methods	Accuracy	F1 score	AUC
ResNet-50	94.96%	95.03%	94.98%
GoogleNet	91.73%	91.82%	91.79%
VGG-16	94.96%	94.97%	94.96%
AlexNet	93.75%	93.61%	93.68%
xDNN [27]	97.38%	97.31%	97.36%
Our	**98.387%**	**98.387%**	**98.405%**

Bold font illustrates the best results.

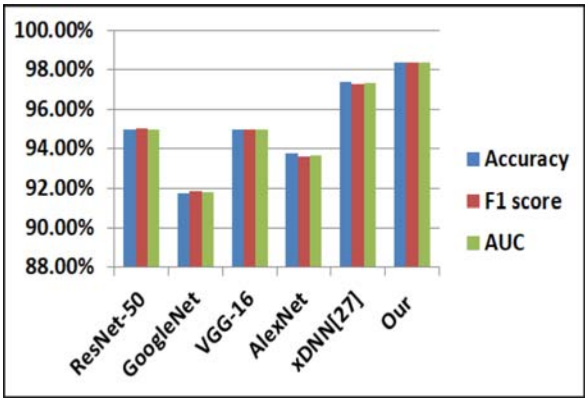

Fig. 7. Proposed method results compared with other pre-trained DNNs and state-of-art approaches applied on SARS-CoV-2 CT-scan Dataset.

4.2.2. System evaluation on COVID-CT dataset

The COVID-CT dataset is considered a more challenging and popular dataset that is used by many researchers for evaluation purposes. We use the same protocol used in [30] of the division dataset and divide the dataset to 85% train and validation, and the rest for test purposes. The experiment results of our proposed method on this dataset are compared with the pre-trained deep neural networks on large-scale datasets, including ImageNet and the Lung Nodule Malignancy (LNM) dataset and its results presented in [30] that included VGG16 [31], ResNet18 [32], ResNet50 [32], DenseNet-121 [33], DenseNet-169 [33], EfficientNet-b0 [34], and EfficientNet-b1 [34]. Also, the results of our method are compared with other state-of-art approaches included methods presented by Mobiny et al. [30], Polsinelli et al. [26], He et al. [30], and Pedro Silva et al. [24]. It is important to note that some of the previous methods as in [26,30] use a data augmentation and merge more than one dataset that increases the number of images in the train set and therefore causes different accuracy results. Table 2 illustrates the results of our mothed compared with the other methods in terms of accuracy, F1 score, and AUC performance metrics. Fig. 8 shows these results visually.

Table 2. Our proposed method results of COVID-CT Dataset compared with other pre-trained DNNs and state-of-art approaches.

methods	Accuracy	F1 score	AUC
VGG-16	76%	76%	82%
ResNet-18	74%	73%	82%
ResNet-50	80%	81%	88%
DenseNet-121	79%	79%	88%
DenseNet-169	83%	81%	87%
EfficientNet-b0	77%	78%	84%
EfficientNet-b1	79%	79%	84%
Mobiny et al. [30]	87.6%	87.1%	**96.1%**
Polsinelli et al. [26]	84.56%	83.98%	–
He et al. [30]	86%	85%	94%
Pedro et al. [24]	87.6%	86.19%	90.5%
Our	**89.26%**	**89.18%**	89.38%

Bold font illustrates the best results.

Although the pre-trained DNNs are trained on large datasets and have deeper and complex architectures, our proposed method gets better performance than these networks. The proposed method is provided with an improvement with pre-trained DNNs in terms of accuracy and F1 score metrics with a nearly increasing range of (6.26%–15.26%) and (8.18%–16.18%), respectively. As shown in Table 2, our method outperforms the other state-of-art previous methods in [24,26,30,31] in terms of accuracy and F1 score with an improved range of (1.66%–4.7%) and (2.08%–5.2%), respectively.

4.2.3. System evaluation on DLAI3 Hackathon Dataset

As explained in section 4.1, this dataset is obtained from the Kaggle website that introduced a DLAI3 Hackathon COVID-19 Chest X-Ray challenge [29]. The DLAI3 Hackathon COVID-19 Chest X-Ray challenge introduced a baseline of 92% for accuracy metric. In this section, we evaluate our proposed method by comparing the accuracy and F1 score results with the baseline DLAI3 Hackathon challenge and with the pre-trained DNNs included VGG16, AlexNet, VGG19, Dense-169 networks as shown in Table 3. Fig. 9 shows these results visually.

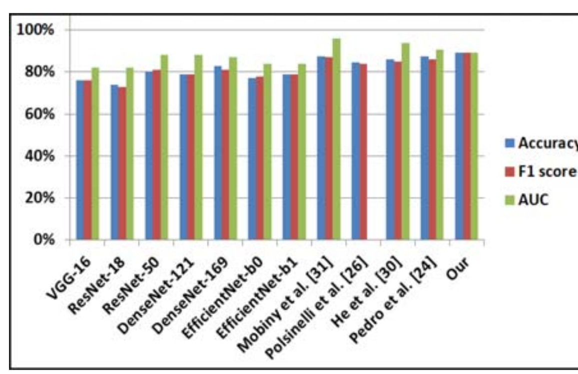

Fig. 8. Our proposed method results of COVID-CT Dataset compared with other pre-trained DNNs and state-of-art approaches.

Table 3. Our proposed method results of DLAI3 Hackathon Dataset compared with other pre-trained DNNs and state-of-art approaches.

methods	Accuracy	F1 score
VGG-16	86.27%	82.95%
VGG-19	78.92%	76.85%
DenseNet-121	90.17%	88.08%
DenseNet-169	90.08%	87.41%
Baseline [29]	92%	–
Our	**93.38%**	**93.06%**

Bold font illustrates the best results.

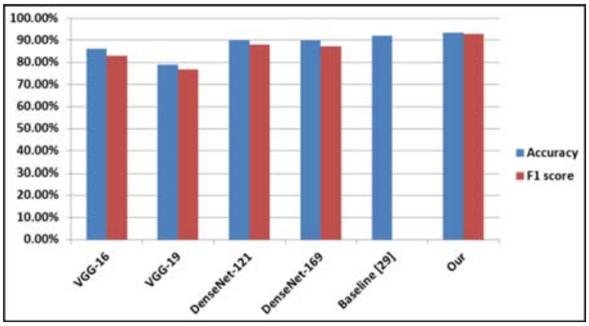

Fig. 9. Our proposed method results of DLAI3 Hackathon Dataset compared with other pre-trained DNNs and state-of-art approaches.

As shown in Table 3, the proposed method outperforms the baseline accuracy and other pre-trained DNNs networks. Our method gets better results and exceeded the pre-trained DNNs networks in terms of accuracy and F1 score metrics with an increasing range of (3.21%−14.46%) and (4.98%−16.21%), respectively. Also, the proposed system provides an improvement in terms of accuracy metric compared with baseline [29] with increases of 1.38%.

5. Conclusions

This paper introduces a new Texture feature extraction method for the three different CT and X-Ray image datasets depending on constructing diverse GLCMs matrices generated in many distances and directions. The dimensions of GLCMs matrices are different from each other depending on the number of grey levels for the quantized images generated in the pre-processing stage. The proposed system reduces the dimensions of GLCMs matrices using PCA, therefore, reduces the dimensions of input layers of the DNN network. Also, this paper proposed a new 1D CNN architecture with multi inputs layers each one having one pipeline in the proposed model. The extracted features from the three pipelines in the model are concatenated in one representative vector that defines the high-level texture features for the input image. The efficiency and strength of the system are presented in the improved results and provide an outperformance compared with many pre-trained DNN models and state of art methods.

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