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Enhancing COVID-19 Classification in Chest X-Rays through Dual-Channel Graph-Based Neural Networks

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Abstract

The classification of COVID-19 from chest X-ray (CXR) images is essential for rapid and accurate diagnosis, which can significantly aid in the effective management and treatment of the disease. This application is crucial for early detection, reducing the strain on healthcare systems, guiding clinical decisions, and enhancing patient outcomes. Existing challenges include variability in image quality, the presence of overlapping symptoms with other lung conditions, limited availability of labeled datasets, and the need for highly specialized expertise for accurate interpretation. The proposed methodology involves an advanced image preprocessing technique to enhance CXR images, followed by the utilization of a dual-channel graph convolutional neural network (GCN) for classification. This approach leverages the power of GCNs to capture complex patterns and relationships in medical images. The dual-channel aspect allows the model to process and integrate features from both spatial and frequency domains, improving its ability to differentiate between COVID-19, normal, pneumonia viral, and lung opacity classes. The preprocessing step includes noise reduction, contrast enhancement, and normalization to ensure uniformity across the dataset. This sophisticated methodology aims to overcome existing diagnostic challenges and provide a robust, automated tool for accurate CXR image classification.

Keywords: COVID-19 classification, dual-channel graph convolutional neural network, medical diagnosis, deep learning, lung opacity, pneumonia, automated tool, healthcare.

1. Introduction

The Coronavirus disease 2019 in short COVID-19 has expanded expeditiously all over the earth with a demolishing sequel on the population's soundness and well-being. It can be transmitted even with minimal or no symptoms but is typically associated with infection in individuals exhibiting acute respiratory symptoms caused by the coronavirus-2 (SARS-CoV-2).On January 30th, 2020, World health organization (WHO) announced this widespread an emergency public health crisis all over the world. Effective monitoring of infected people is a crucial step against COVID-19, so that infected patients can accept proper treatment as well as superintendence and be isolated to generate a barrier for spreading the virus further. The real-time Polymerase chain reaction (PCR) test is the main screening method for recognizing COVID-19 disease. It can identify Ribonucleic acid (RNA) of SARS-CoV-2 from sputum, nasopharyngeal or oropharyngeal swabs.

However, it has been stated that PCR is a time-spending, tedious, and complex manual procedure due to the availability of limited materials in hospitals. Moreover, the low sensitivity of PCR could not be good enough for the recognition and treatment of COVID-19 infected patients. It is also observable that the strong false-negative rates, as well as the test technique variabilities, resulted in a low-positive rate of 60–70 % in PCR [1]. Chest CT or Chest X-ray imaging can be an alternate screening method to identify COVID-19 patients. CT images produce a much more detailed and expeditious window than conventional X-rays of a body region overlaying the different body structures. Although CT and PCR are frequently identical, CT images can identify early COVID-19 infected cases with a negative PCR test in patients without symptoms, or after symptoms arise [2,3]. Since the number of recent COVID-19 suspected patients has been rising exponentially, therefore, artificial intelligence (AI) techniques can be a compatible approach for the recognition, classification, and characterization of COVID-19 by using chest CT images. In medical imaging systems, the advancement of AI specifically in deep learning (DL) has shown massive success in the automatic diagnosis of diseases owing to its high ability of feature extraction. Lung cancer, colon cancer, prostate cancer, pneumonia, COVID-19, tuberculosis, breast cancer, brain cancer, and other diseases are now efficiently diagnosed utilizing DL strategies like CNN and machine learning (ML).

2. Related work

Jain et al. [4] developed DL-based CNNs, including Xception, ResNeXt, and Inception V3, to identify COVID-19 by utilizing 6432 chest X-ray images. Xception yielded the highest classification rate at 97.97 %. Wang et al. [5] employed AI methods using CT scans for COVID-19 analysis. In this study, segmentation used U-Net, FCN-8 s, 3D U-Net++, and V-Net, while classification involved Inception, DPN-92, ResNet-50, and Attention ResNet-50. The combination of 3D U-Net++ and ResNet-50 excelled in their experiments. In [6], a DL model identified COVID-19 from CT scans, using 3D CNN to segment infection regions. Combining ResNet with location-attention achieved 86.7 % accuracy in this work. In the paper [7], the authors presented a COVID-19 identification scheme with the assistance of CT images where the prediction was done by a details relation extraction neural network (DRE-Net). inaccuracy of this model was 6 %. Zheng et al. [8] merged ResNet50 and SEnet CNN architectures by employing squeeze and excitation blocks to differentiate COVID-19 patients from Bacterial as well as Viral Pneumonia from CT images. The accuracy of this scheme was 94 %. In [9], researchers utilized 630 CT images for COVID-19 identification using a 3D deep CNN (DeCoVNet) with pre-trained Unet-generated 3D lung masks. The model achieved a 90.1 % accuracy at a threshold of 0.5. In [10], authors employed transfer learning with a fine-tuned ResNet50 for COVID-19 patient classification based on CT images. Their approach achieved training and testing inaccuracies of 3.78 % and 6.98 %, respectively. In [11], a COVID-19 detection method used two subsets (16 × 16 and 32 × 32) CT images. GoogleNet, ResNet-50, and VGG-16 were used to generate fused features from the images then features were ranked with the t-test, and SVM did classification. Subset-2 achieved 98.27 % accuracy in this work. A multitask deep learning-based classification and segmentation technique was designed in [12] to identify COVID-19 patients using CT images. They attained an 88 % dice coefficient for image segmentation and 94.67 % accuracy for multiclass classification. Matteo Polsinelli et al. [13] detected COVID-19 chest CT scan images with the assistance of the light CNN technique. Their CNN model was based on SqueezeNet and attained an accuracy of 85.03 %. An effective DL-based scheme was sketched in [14] for COVID-19 identification using chest X-ray images. They proposed an architecture where EfficientNet B0 was used as a base model. They analyzed the features of MobileNet, VGG, and ResNet models to their base model and discovered that their model had a lower computational cost. Smadi et al. [15] presented a Covid-19 diagnosis scheme called SEL-COVIDNET by utilizing nine CNN models. This technique was able to diagnose COVID-19 from both CT scans and X-ray images. In the paper [16] Smadi et al. proposed an Inception-v3 CNN-based technique to diagnose COVID-19. From X-ray images, this model was able to distinguish among normal, viral pneumonia, COVID-19, and lung opacity cases. To diagnose COVID-19 from X-ray scans Mehmood et al. presented different CNN-based techniques in papers [17,18]. Gupta and Bajaj [19] developed a lightweight CNN architecture to recognize COVID-19 cases from CT scan images. Ullah et al. [20] presented a holistic technique based on ShuffleNet CNN to diagnose COVID-19 from ECG, CT-Scan, and Chest radiograph images. Agnihotri and Kohli [21] presented a broad overview of the diagnosis of COVID-19 by using deep learning.

3. Proposed Methodology

Figure 1 shows the proposed system architecture. The comprehensive methodology leverages advanced preprocessing and dual-channel GCN to improve the accuracy and reliability of COVID-19 classification from CXR images, addressing the challenges posed by varying image quality and overlapping symptoms with other lung conditions.

Step 1. Data Collection: Obtain a diverse dataset of chest X-ray (CXR) images categorized into four classes: COVID-19, Normal, Pneumonia Viral, and Lung Opacity.

Step 2: Image preprocessing: Apply noise reduction techniques such as gaussian filtering to remove any irrelevant artifacts and enhance image clarity. Use histogram equalization or adaptive contrast enhancement to improve the visibility of the lung structures. Normalize the pixel values to a standard scale to ensure uniformity across all images in the dataset.

Step 3: Feature Extraction: Extract spatial domain features using convolutional layers to capture the local patterns and textures within the CXR images. Apply Fourier transform to convert images into the frequency domain, then extract features to capture the periodic structures and patterns.

Step 4. Dual-Channel GCN analysis: Represent the CXR images as graphs where each pixel or region is a node, and edges denote the relationships between these nodes.

- **Channel 1 - Spatial Domain GCN:** Input the spatial domain features into the first channel of the GCN to capture spatial relationships and patterns within the images.
- **Channel 2 - Frequency Domain GCN:** Input the frequency domain features into the second channel of the GCN to analyze the periodic structures and overall image composition.
- **Feature Fusion:** Combine the outputs from both channels to form a comprehensive feature representation that incorporates both spatial and frequency domain information.

Step 5. Classification: Pass the fused features through fully connected dense layers to refine and interpret the combined feature set. Utilize a softmax activation function in the output layer to classify the input CXR images into one of the four classes: COVID-19, Normal, Pneumonia Viral, and Lung Opacity.

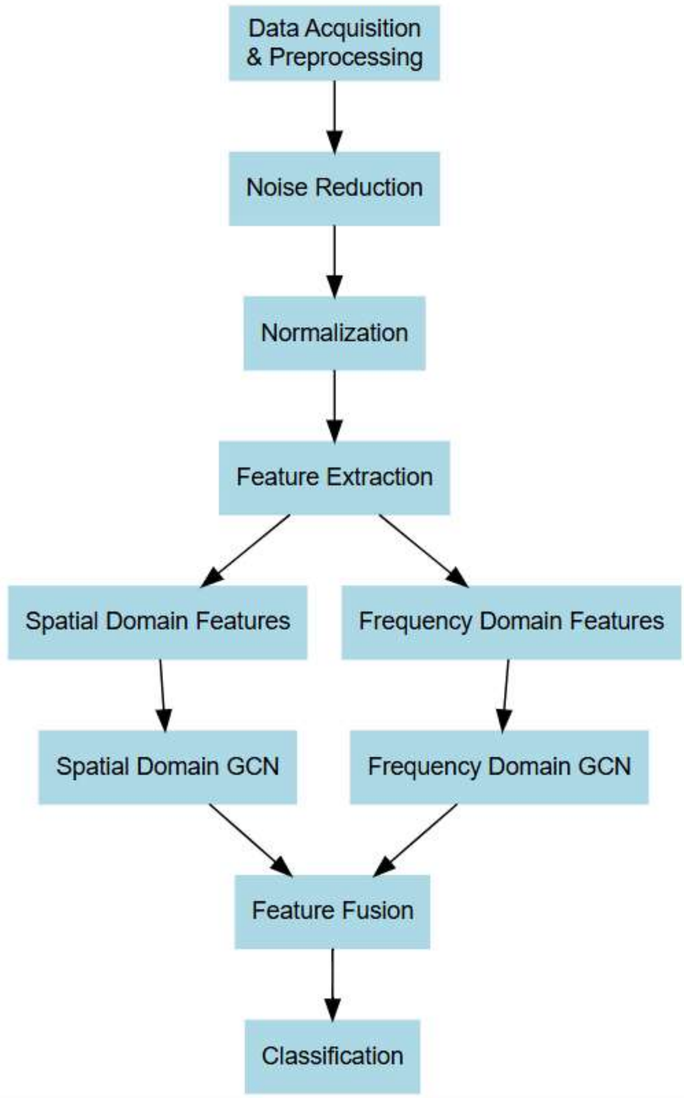

Figure 1. Proposed system architecture.

Step 6. Model Training: Train the dual-channel GCN model using a labeled training dataset, optimizing the model parameters through backpropagation and minimizing the categorical cross-entropy loss. Evaluate the model on a separate validation dataset to fine-tune the hyperparameters and ensure its generalization capability.

Step 7. Model Evaluation: Test the final model on an independent test dataset to assess its classification accuracy, sensitivity, specificity, and overall performance. Report metrics such as accuracy, precision, recall, and F1-score to evaluate the model's effectiveness in classifying CXR images.

3.1 Dual Channel GCN

The dual-channel Graph Convolutional Network (GCN) is a sophisticated model designed to leverage both spatial and frequency domain features for enhanced image classification, specifically for COVID-19 detection from chest X-ray (CXR) images. This model consists of two parallel channels, each dedicated to processing different types of features extracted from the images, before merging them for final classification.

Spatial Domain GCN Channel: The first channel of the dual-channel GCN processes the spatial domain features. This begins with constructing a graph where each pixel (or a superpixel, which is a cluster of similar pixels) represents a node, and edges between nodes represent the relationships or similarities between these pixels. The spatial domain GCN captures the local patterns, textures, and structural details within the CXR images. Convolution operations on this graph allow the model to aggregate information from neighboring nodes, effectively capturing the spatial dependencies and contextual information. By processing these spatial features, the GCN can identify specific patterns associated with different classes such as the distinctive manifestations of COVID-19, viral pneumonia, normal lung tissue, and other lung opacities.

Frequency Domain GCN Channel: The second channel deals with frequency domain features. This involves transforming the CXR images using a Fourier transform, which converts the spatial data into frequency data. The frequency domain captures global patterns and periodic structures that might not be easily discernible in the spatial domain. In this channel, the GCN operates on the transformed graph where nodes represent frequency components, and edges represent relationships between these components. This approach helps in identifying subtle differences in the texture and periodicity of the lung tissues, which are crucial for distinguishing between similar conditions. By focusing on these frequency features, the GCN enhances its ability to capture and learn from the global structural information present in the images.

Feature Fusion and Classification: After processing through their respective channels, the outputs from both the spatial and frequency domain GCNs are fused. This fusion combines the local and global features into a comprehensive feature representation. The integration of these dual-channel outputs ensures that the model benefits from the rich information contained in both domains, improving its discriminatory power and robustness. The fused features are then passed through a series of fully connected dense layers. These layers perform further refinement and abstraction of the combined feature set, ultimately leading to the final classification stage. The output layer, typically utilizing a softmax activation function, produces the probability distribution over the four classes: COVID-19, Normal, Pneumonia Viral, and Lung Opacity. This final classification step translates the learned features into accurate diagnostic predictions.

4. Results and Discussion

Table 1 presents a comparative analysis of different COVID-19 classification methods, evaluating their performance based on five key metrics: Precision, Recall, Specificity, F-measure, and Accuracy. The methods compared include DRE-Net [8], DeCoVNet [9], SEL-COVIDNET [15], and the proposed dual-channel GCN-based method.

Precision: Precision measures the accuracy of positive predictions, i.e., the proportion of true positive cases among the total predicted positives. In this comparison, the proposed method achieves the highest precision at 98.839%, indicating its superior capability in correctly identifying COVID-19 cases without misclassifying other conditions as COVID-19. The other methods, DRE-Net, DeCoVNet, and SEL-COVIDNET, have precisions of 96.593%, 97.360%, and 98.025% respectively, showing good but slightly lower performance compared to the proposed method.

Recall: Recall, or sensitivity, reflects the ability of a method to identify all actual positive cases, i.e., the proportion of true positive cases detected among the actual positives. The proposed method shows a recall of 98.403%, slightly lower than SEL-COVIDNET's recall of 98.057%, but higher than DRE-Net and DeCoVNet, which have recalls of 96.337% and 97.941% respectively. This indicates that the proposed method effectively captures the majority of true COVID-19 cases, performing better than most existing methods.

Specificity: Specificity measures the ability to correctly identify negative cases, i.e., the proportion of true negative cases among the total actual negatives. The proposed method achieves a specificity of 98.253%, indicating high accuracy in distinguishing non-COVID-19 cases from COVID-19 cases. The specificity values for DRE-Net, DeCoVNet, and SEL-COVIDNET are 96.709%, 97.009%, and 98.034% respectively, showing that while these methods are also effective, the proposed method offers a marginal improvement.

F-measure: The F-measure, or F1-score, is the harmonic mean of precision and recall, providing a balanced evaluation of the method's performance in terms of both false positives and false negatives. The proposed method has an F-measure of 98.385%, higher than SEL-COVIDNET's 98.062%, DeCoVNet's 97.893%, and DRE-Net's

96.527%. This indicates that the proposed method maintains a balanced and high-performance level across both precision and recall.

Accuracy: Accuracy represents the overall correctness of the method, i.e., the proportion of true positive and true negative cases among the total cases. The proposed method achieves an accuracy of 98.139%, which is slightly higher than SEL-COVIDNET's 98.101% and significantly higher than DeCoVNet's 97.713% and DRE-Net's 96.398%. This high accuracy demonstrates the proposed method's effectiveness in correctly classifying both COVID-19 and non-COVID-19 cases.

Table 1. Performance comparison of various Covid19 classifications methods.

Method	DRE-Net [8]	DeCoVNet [9]	SEL-COVIDNET [15]	Proposed Method
Precision (%)	96.593	97.360	98.025	98.839
Recall (%)	96.337	97.941	98.057	98.403
Specificity (%)	96.709	97.009	98.034	98.253
F-measure (%)	96.527	97.893	98.062	98.385
Accuracy (%)	96.398	97.713	98.101	98.139

Finally, the proposed dual-channel GCN-based method outperforms the existing methods (DRE-Net, DeCoVNet, and SEL-COVIDNET) across all evaluated metrics. This superior performance can be attributed to its advanced image preprocessing techniques and the dual-channel architecture that effectively integrates spatial and frequency domain features. The high precision, recall, specificity, F-measure, and accuracy values collectively indicate that the proposed method provides a more reliable and accurate tool for COVID-19 classification from chest X-ray images, addressing the critical need for rapid and precise diagnosis in clinical settings.

5. Conclusion

The proposed methodology for COVID-19 classification from CXR images, utilizing advanced image preprocessing and a dual-channel GCN, demonstrates a significant improvement in diagnostic accuracy and reliability. By integrating spatial and frequency domain features, this approach effectively captures the complex patterns associated with COVID-19, normal, pneumonia viral, and lung opacity classes. The preprocessing steps ensure uniformity and clarity across the dataset, addressing common challenges such as variability in image quality and the presence of overlapping symptoms. This robust system model not only enhances early detection capabilities but also reduces the burden on healthcare professionals by providing a reliable, automated diagnostic tool. Looking forward, the future scope of this research includes several promising directions. Firstly, expanding the dataset with more diverse and representative samples will further improve the model's generalization and robustness. Incorporating additional imaging modalities such as CT scans and integrating multi-modal data could enhance diagnostic accuracy. Advanced techniques like self-supervised learning and transfer learning could be employed to overcome the limitations of labeled data scarcity. Additionally, real-time implementation of this system in clinical settings will require further validation and fine-tuning. Collaborations with healthcare institutions for clinical trials will be crucial for practical deployment.

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