

A Novel Graph Convolutional Neural Networks (GCNNs)-based Framework to Enhance the Detection of COVID-19 from X-Ray and CT Scan Images

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Abstract—The constant need for robust and efficient COVID-19 detection methodologies has prompted the exploration of advanced techniques in medical imaging analysis. This paper presents a novel framework that leverages Graph Convolutional Neural Networks (GCNNs) to enhance the detection of COVID-19 from CT scan and X-Ray images. Hence, the GCNN parameters were tuned by the hybrid optimization to gain a more exact detection. Therefore, the novel technique known as Hybrid NADAM Graph Neural Prediction (NAGNP). The framework is designed to achieve efficiency through a hybrid optimization strategy. The methodology involves constructing graph representations from Chest X-ray or CT scan images, where nodes encapsulate critical image patches or regions of interest. These graphs are fed into GCNN architectures tailored for graph-based data, facilitating intricate feature extraction and information aggregation. A hybrid optimization approach is employed to optimize the model's performance, encompassing fine-tuning of GCNN hyperparameters and strategic model optimization techniques. Through rigorous evaluation and validation using diverse datasets, our framework demonstrates promising results in accurate and efficient COVID-19 diagnosis. Integrating GCNNs and hybrid optimization presents a viable pathway toward reliable and practical diagnostic tools in combating the ongoing pandemic.

Keywords—COVID-19 detection; Graph Neural Networks; X-ray; CT scan images; hybrid optimization; medical imaging analysis; diagnostic tools; pandemic response

I. INTRODUCTION

The COVID-19 virus has spread worldwide, and lung computed tomography (CT) imaging has achieved clinical verification of the diagnosis of COVID-19. [1] The World Health Organization designated COVID-19 as a highly contagious pandemic that began in December 2019. COVID-19, caused by an unfamiliar coronavirus [2], is spread from person to person. Isolating the patients to control this catastrophe requires an accurate diagnosis. [3] Relevant research has demonstrated that lung X-ray and CT imaging data can be crucial for diagnosing COVID-19. However, despite specific automatic detection techniques, their strategies still have a lot of potential for development and rely disproportionately on the knowledge and resources of doctors due to the brief epidemic period of COVID-19 [4].

The local and general characteristics of the lesions serve as a crucial foundation for the COVID-19 diagnosis, which cannot be determined only based on the peculiarities of a particular location. [5] Analyzing and diagnosing CT scans is highly intricate and necessitates doctors' professional expertise and experience. [6] Furthermore, many COVID-19 CT scans morphologically resemble conventional pictures of pneumonia. However [7], the research describes several segmentation techniques designed and used to extract and evaluate the COVID-19 infectiousness from the 2D slices [8]. Using the VGG-UNet, the COVID-19 lesion is removed from the lung CT slice. A pulmonologist or a computer algorithm is used to determine the infection level following extraction. The lung CT slice extracts the COVID-19 lesion using the EfficientNet. The EfficientNet B1 is used for Chest X-ray and EfficientNet B3 is used for CT-Scan. A validation and training procedure is required for the execution of this strategy.

The CNN methodology is employed rather than traditional techniques, Convolutional Neural Network (CNN) segmentation provides a superior outcome. Therefore, several CNN-based segmentation techniques are used to identify and quantify the afflicted area in CT scans. [10] Graph models have recently grown in strength, which has made it possible to apply them to difficult medical situations. In the field of healthcare, [11] graph convolutional neural networks (GCNNs) have become a distinct category of machine learning (ML) models designed to function on graph-structured data due to their ability to accurately capture the intricate relationships between many components of medical pictures. GCNN provides a revolutionary method for deriving insightful information from linked medical entities, facilitating precise forecasts, and carrying out several essential functions for healthcare applications.

The paper proposes a novel framework using Graph Convolutional Neural Networks (GCNNs) to enhance the detection of COVID-19 from X-ray and CT scan images. The research problem addressed is the need for more accurate and efficient methods for diagnosing COVID-19, especially in resource-constrained settings where access to traditional diagnostic tools may be limited. By leveraging the unique

capabilities of GCNNs, the framework aims to improve the accuracy and speed of COVID-19 detection from medical imaging, ultimately aiding in the early and accurate diagnosis of the disease. The paper highlights the potential of GCNNs to analyze the complex relationships within medical images, potentially leading to more reliable diagnostic outcomes compared to traditional methods.

II. RELATED WORK

A. A Few Recent Associated Works are Described as Follows

Fan X et al. [12], a new framework using Transformer and Convolutional Neural Network (T-CNN) is proposed for detecting COVID-19 from CT images [9]. This method uses Transformer's global feature extraction and CNN's local feature extraction capacity. A bidirectional feature fusion structure is created by fusing features from two branches and branch parallel structures, enhancing Accuracy. This approach also advances the field's ability to diagnose lung diseases in real-time, potentially saving lives. It has limitations due to relying on one CT image with fewer features and incomplete patient diagnosis output.

Jia H et al. [13], a novel module called pixel-wise sparse graph reasoning (PSGR) for CT image segmentation of COVID-19 infected areas. Global contextual information modelling is improved by the PSGR module, which is placed between the network's encoder and decoder. It projects pixel characteristics to create a network, transforms it into a sparsely linked graph, and then applies global reasoning. Three datasets were used to assess the segmentation structure and to contrast it with other models. Results show that the suggested module outperforms competing models in properly segmenting and successfully captures long-range relationships despite its high computational cost.

Fritz C et al. [14], to forecast local COVID-19 instances, this study employs semi-structured deep distributional regression (SDDR) as a multimodal learning framework. Neural networks and structured additive distributional regression are combined in SDDR, where the statistical regression model is embedded within the neural network. It applies latent characteristics discovered by deep neural networks to the additive predictor of each distributional parameter. An orthogonalization cell is utilized to distinguish between structured and unstructured model portions.

Lu S et al. [15], the research created a computer-aided diagnostic system that utilizes artificial intelligence to recognize COVID-19 in chest computed tomography pictures. Transfer learning lets the system obtain novel, neighbouring aware representation (NAR) and image-level representations (ILR). The neighbouring familiar graph neural network (NAGCNN) is designed and validated. The results demonstrated its superior generalization capacity over all state-of-the-art approaches, indicating its effectiveness for clinical diagnosis.

Xing X [16], this paper introduced an advanced multi-level attention graph neural network (MLA-GCNN) for predicting and diagnosing diseases. In particular, weighted correlation network analysis converts omics data into co-expression graphs. Multi-level graph features are then created, and to

perform predictions, they are fused using a carefully thought-out multi-level graph feature entirely fusion module. A unique full-gradient graph saliency method is designed for model interpretation to determine the genes associated with the disease. Regarding proteomic data from coronavirus disease 2019 (COVID-19)/non-COVID-19 patient sera, GCNN performs at breaking point.

The key contributions of this work are described as follows

- Initially, the Kaggle dataset is collected and trained in a Python program.
- With the necessary characteristics for detecting COVID-19, the novel NAGNP is introduced.
- Thus, the NADAM function is used in optimization and CNN is used in Feature analysis to extract the relevant and necessary features from the dataset.
- GNN accomplishes the prediction process, and classification is carried out.
- At last, the detection process is completed, and performance metrics, including F1 score, Accuracy, recall, and precision, are computed and compared to other models.

III. PROPOSED METHODOLOGY

A novel Hybrid NADAM Graph Neural Prediction (NAGNP) system was introduced in this study for forecasting the COVID-19 affection from the lung's CT scan data. Preprocessing is performed to rid the data of the noisy components. Following that, the method of extracting the features for COVID-19 feature prediction is carried out. The CNN is used to extract features. Henceforth, prediction is accomplished by GNN. Lastly, COVID-19 prediction has been carried out, and performance metrics are assessed.

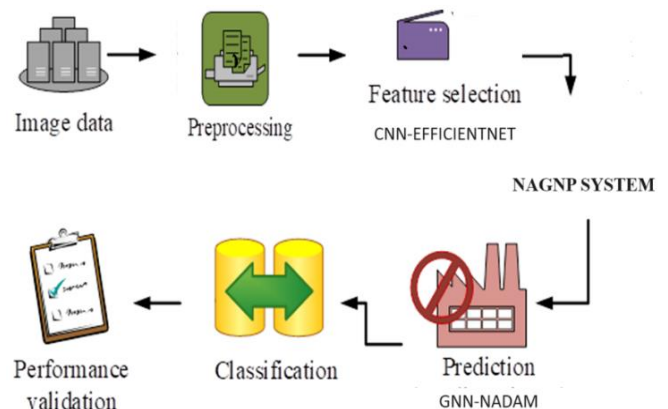


Fig. 1. Proposed methodology.

In Fig. 1, the proposed approach is described. It uses a CT scan image to anticipate the COVID-19. Performance metrics were computed, including the F1 score, Accuracy, recall, and precision. The following portions display the process of the proposed model in brief.

3.1 Data importing and preprocessing.

The detection data importing function's primary step is executed by Eq. (1). Based on the initialization principle of the hybrid optimization model, the initialization process was activated and done successfully.

$$F(T) = T\{1,2,3,\dots,n\} \quad (1)$$

Here, T it determines CT scan data, defines the data training variable, and describes the n number of trained CT images.

After the training phase, the critical module in the forecasting framework is preprocessing, which is executed to neglect the noisy pixel range from the imported image data. Also, the proper filtering function has helped to earn the needed Accuracy in the prediction function. Consequently, the preprocessing function is processed by Eq. (2).

$$D = \frac{T(H - n)}{T(P)} \quad (2)$$

Here, P is the total pixel and $T(P)$ denotes the entire pixel in the trained data. Moreover, D the preprocessing variable, the highest pixel, and the noisy pixel are available in the imported database.

B. Feature Selection

The process feature selection is the chief processing module to get the forecasting outcome expected. According to the dataset there were two models proposed one for X-ray and one for CT-Scan. Both models use CNN. The feature extraction is done by Transfer Learning Architecture EfficientNet B1 for X-ray and EfficientNet B3 for CT-Scan. The meaningful features like spatial and temporal are extracted using Principal Component Analysis. The PCA projects data onto a lower-dimensional subspace while maximizing variance. Eq. (3)

$$\text{var}(Z) = \sum(\lambda_i * (z_i)^2) \quad (3)$$

where Z is the projected data,

λ_i are the eigen values and

z_i are the principal components.

C. Prediction and Classification

The COVID region prediction is an intricate process for medical professionals. It has affected a wide range of people. It is predicted by applying the NADAM optimization in GCNN. The proposed model NAGNP shows better performance in feature extraction. To optimize the GCNN's performance, an optimizer like NADAM is employed. It builds upon Adam (Adaptive Moment Estimation) by incorporating momentum for faster convergence. NADAM updates weights (θ) based on estimates of the first and second moments of gradients (m_t, v_t) using specific decay rates (β_1, β_2). Mathematically, Eq. (4) the update rule might involve:

$$m_t = \beta_1 * m_{(t-1)} + (1 - \beta_1) * g_t,$$

$$v_t = \beta_2 * v_{(t-1)} + (1 - \beta_2) * g_t^2, \quad (4)$$

where, g_t is the current gradient. The weights are then adjusted using these moment estimates and estimated noise (η).

By combining classification with GCN architecture and NADAM optimization, the model learns to effectively map features to class labels, enabling accurate predictions for unseen chest X-rays

The prediction is executed by Eq. (5).

$$P_r = F_{TAL} > P_r \left(\frac{F_s}{C,N} \right) \quad (5)$$

P_r represents the prediction variable, the trained stored feature, and the Covid and Non-Covid. The Fitness predicts the COVID cases, and Eqn 6 does classification.

$$C = \begin{cases} \text{if}(P_r = 0) & \text{Non Covid} \\ \text{if}(P_r = 1) & \text{Covid} \end{cases} \quad (6)$$

C denotes the classification variable. The value 0 indicates the Non-Covid affected, and 1 represents the COVID affected. The Flowchart for the proposed NAGNP model is displayed in Fig. 2.

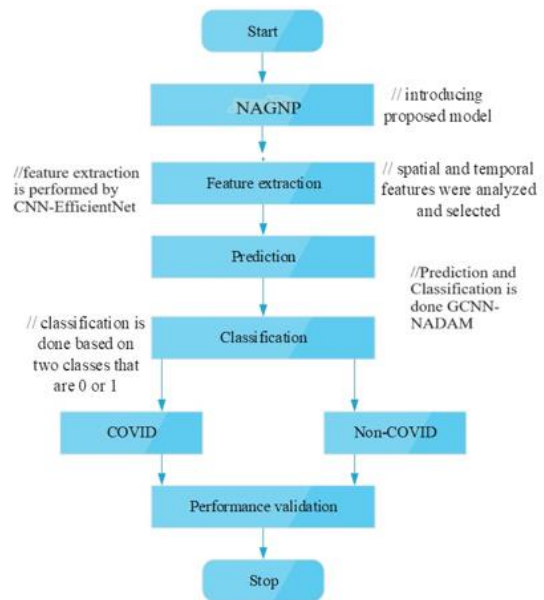


Fig. 2. The Flowchart for the proposed NAGNP model.

IV. RESULTS AND DISCUSSION

The planned novel solution is verified in the Python environment version 3.10 and running in the Windows 10 environment. The dataset is collected from the Kaggle site. The noisy parts are removed using preprocessing to extract the significant features from the gathered photos. CNN is then used for feature extraction. The GNN predicts COVID-19. As a result, the necessary metrics for the proposed NAGNP are evaluated. The execution parameters are described in Table I.

TABLE I. EXECUTION PARAMETERS

Metrics	Specification
Operating System	Windows 10
Version	3.7.14
Program platform	Python
Dataset	Kaggle
Optimization	NADAM
Network Architecture	CNN-GNN

A. Case Study

The purpose of the study is to comprehend the proposed NAGNP model process. The images used come from Kaggle's website. Datasets are used for training and testing to determine the designed model. Table II shows the predicted image.

The prediction result describes the region affected by COVID-19. Blue represents the affected region, light blue indicates the low-affected region and dark blue shows the heavily affected area.

B. Performance Analysis

Performance was validated by evaluating chief metrics like error rate, F1-score, Accuracy, recall and precision. The existing paradigms, which are obtained for the comparative validation is Xception Model (XM) [17], Inception V3 Model (IV3M) [17], VGG16 [17], ResNet 50 (RN50)[17], VGG 19 [17] and DenseNet (DN) [17].

Moreover, the positive scores in the forecasting function are measured with the help of precision metrics; the formulation is revealed in Eq. (6).

$$Precision = \frac{Tp}{FP + TP} \tag{6}$$

Here, *TP* it denotes the true positive and *FP* false positive samples. Hence, to know the mean performance in the cases of both sensitivity and precision score, the F-measure validation metrics were evaluated using Eq. (8).

$$F_score = \frac{2 \times recall \times precision}{recall + precision} \tag{8}$$

The precision and F-score rate for the Covid detection of the proposed NAGNP is made a comparison with the prevailing models is displayed in Fig. 3.

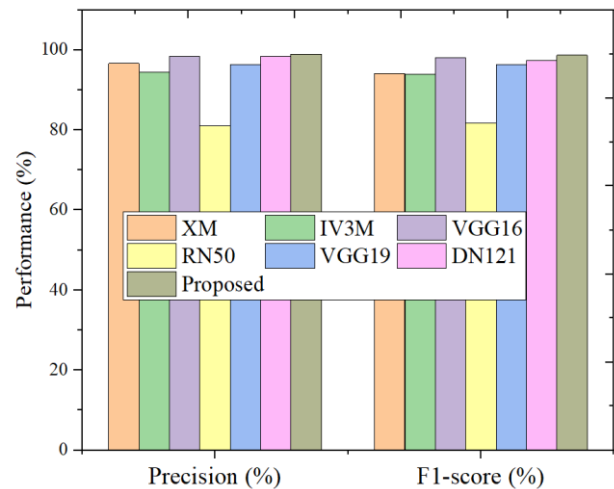


Fig. 3. Precision and F1 score comparison.

TABLE II. PREDICTION RESULTS

Input image	Ground Truth	Prediction

Here, Precision rate for the existing models, XM gains 96.6 %, IV3M gains 94.4 %, VGG16 gains 98.4%, RN50 gains 81 %, VGG19 gains 96.41 % and DN121 gains 98.37%. Meanwhile, the proposed model NAGNP gains 99%. Similarly the F1 score obtained by the prevailing models XM, IV3M, VGG16, RN50, 4.2.1 Precision and F1 score VGG19, DN121 obtained 94.07%, 94%, 98%, 81.73%, 96.41%, 97.38 % respectively and the proposed model obtained 98.7%. This shows better performance of the proposed model.

1) *Recall and accuracy*: Besides, the scalability of the executed model in the presence of a forecast fall ratio is found using recall metrics. Their formulation is given in Eq. (7), it can give the average performance by incorporating positive and negative classes.

$$Recall = \frac{Tp}{Tp + FN} \tag{7}$$

The correctness of the prediction process is found using Eq. (5) here, the exact forecasting is validated from the entire COVID detection performance.

$$Accuracy = \frac{exact \text{ Forecast}}{total \text{ prediction}} \tag{5}$$

The Accuracy and Recall measure of the proposed NAGNP is made a comparison with the existing models is displayed in Fig. 4.

Here, Accuracy gained for the existing models, XM 94.2 %, IV3M 93.96 %, VGG16 98%, RN50 81.29%, VGG19 96.38% and DN121 97.38%. Meanwhile, the proposed model NAGNP gains 98.5%. Similarly, the Recall measure obtained by the prevailing models XM 91.6%, IV3M 93.6 %, VGG16 97.61 %, RN50 82.87 %, VGG19 96.41 %, DN121 96.41% and the proposed model obtained 98.5%. This demonstrates

that the proposed model performs better. The overall comparison is depicted in Table III.

C. Discussion

The accuracy value of the proposed NAGNP is higher than that of the current techniques. This demonstrates the top performance across all parameters, including recall, Accuracy, precision, and F-score. It provides a 98.5% accurate forecast. Table IV shows the proposed approach performs. The overall effectiveness of the proposed NAGNP approach suggests that NADAM and ant NADAMfitness optimization provide superior feature extraction and prediction. It leads to increased precision.

Limitations: The effectiveness of GCNNs relies heavily on the availability and quality of labeled data. Limited or biased datasets could impact the model's performance and generalizability. GCNNs can be computationally intensive, requiring substantial resources for training and inference. This could be a limitation in resource-constrained environments or for real-time applications.

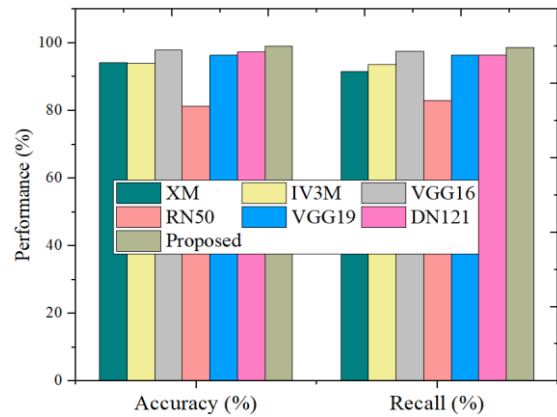


Fig. 4. Accuracy and recall comparison.

TABLE III. OVERALL COMPARISON STATISTICS

Metrics	XM	IV3M	VGG 16		RN50	VGG 19	DN 121	EfficientNet
Precision	96.6	94.4	98.4		81	96.41	98.37	99
F1-score	94.07	94	98		81.73	96.41	97.38	98.7
Accuracy	94.2	93.96	98		81.29	96.38	97.38	98.5
Recall	91.6	93.6	97.61		82.87	96.41	96.41	98.5

TABLE IV. NAGNP PERFORMANCE

Metrics	X-ray (EfficientNet B1)	CT-Scan(EfficientNet B3)
Accuracy	97.5 %	98.5 %
Precision	99 %	99 %
Recall	97 %	98.5 %
F1-score	97.92%	98.64%

V. CONCLUSION

The NAGNP framework for detecting COVID-19 is described in this study. The Python program is used to execute it, and the results are described. Initially, the Kaggle site is used to gather data for COVID-19 detection, and preprocessing is used to eliminate noisy elements. Subsequently, the CNN does the feature extraction technique, and the ant NADAM fitness performs the prediction, yielding a superior prediction outcome. The feature extraction procedure takes the critical features from the data and predicts COVID-19. Finally, the suggested model's performance is verified using several metrics, including F1-score, Precision, Accuracy and Recall. The outcome revealed that the proposed model performs better. The designed model gains an accuracy of 98.5 %, a precision of 99 %, A recall of 98.5 %, and an F1-score of 98.7 %, resulting in better performance. Compared to the current models, the accuracy of the proposed NAGNP model is improved by 1% to 2%. However, future work is needed to detect and segment in real time.

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