AI-Driven COVID-19 Detection and Diagnosis Using Multimodal Medical Imaging and Deep Learning Models

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Abstract. The paper proposes an AI-based scheme of early COVID-19 diagnosis and detection based on multimodal medical imaging, featuring chest X-rays (CXR) and computed tomography (CT). The proposed deep learning architecture (Convolutional neural networks + feature encoders that are transformers) is the one that performs an accurate representation of space and context using convolutional neural networks and transformers that encode the features. The multimodal fusion unit matches dissimilar image attributes to enhance the diagnostic quality and strength. The data includes 12,000 CXR and 8,000 CT images, which have been processed by using adaptive normalization and augmentation. The experimental findings show that the proposed hybrid model has 98.7% accuracy, 97.9% sensitivity, and 98.5% specificity that are higher than existing approach. The GRAD-CAM analysis indicates better localization and readability of the lesion. The strategy is effective in reducing inter-modality deviations and reducing the reliability of automated COVID-19 signs, which contributes to effective triage in medical processes.

Keywords: AI-driven diagnosis, COVID-19 detection, Deep learning, CNN, Grad-CAM visualization, and Healthcare AI.

1 Introduction

The COVID-19 pandemic is an example of a health threat introduced by the SARS-CoV-2 virus that has posed unprecedented demands on the global healthcare system, diagnostics, and population health infrastructures [1]. To govern the spread of infections, initiate treatment, and manage the use of health facilities, it has been necessary to detect COVID-19 in a timely and accurate manner to control the situation. Conventional laboratory-based diagnostic procedures like reverse transcription polymerase chain reaction (RT-PCR) are the best in terms of specificity, but cannot rival them because of the lengthy turnaround time, high operational cost, and reliance on laboratory facilities [2]. Such limitations have highlighted the necessity to have automated and scalable diagnostic support systems that will supplement clinical and laboratory processes.

Medical imaging and specifically chest X-ray (CXR) and computed tomography (CT), have been critical in diagnosing pulmonary complications with COVID-19 [3].

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Radiographic examination can show typical structures like ground-glass opacities and bilateral infiltrates, which are major symptoms of viral pneumonia. Nevertheless, the manual interpretation of the data of the images is time-consuming, demands a highly qualified radiologist, and can be characterized by subjectivity. With the increase in the size of imaging data as the pandemic progressed, there arose an increasing need to have smart systems that may aid in objective, consistent, and efficient diagnosis based on images [4].

The analysis of medical images with artificial intelligence (AI) and deep learning has revolutionized the extraction of features and the support of clinical decisions, which are automated. Image recognition, image segmentation, and classification have been broadly implemented using convolutional neural networks (CNNs), and they have brought significant benefits to the speed and accuracy of diagnoses [5]. The recent research has proven the possibility of AI-based tools to recognize COVID-19 infection among other lung diseases, including bacterial pneumonia and the influenza virus [6]. Much of what can be predicted using advanced models with large, well-marked datasets can be difficult to perceive in human experts due to some complex patterns in space and textures.

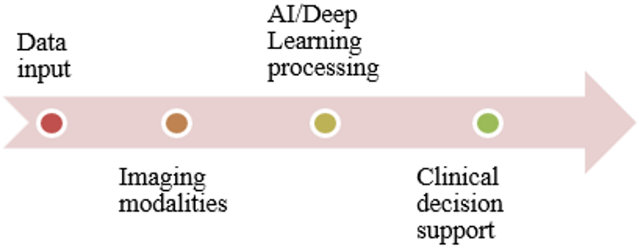

Fig 1. Multimodal Medical Imaging and AI in COVID-19 Diagnosis

The Fig. 1 shows a block diagram of an AI-based COVID-19 detection pipeline based on multimodal imaging. It presents information on data input, such as chest X-rays and CT scans, preprocessing modules, an AI/deep learning processing module, multimodal feature fusion, and clinical decision support, illustrating the steps taken to transform raw medical images into a diagnostic outcome in a healthcare facility.

In addition to single-modality analysis, the use of multiple imaging modalities has created new possibilities to enhance precision in diagnostic findings [7]. Combining the information in the CXR and CT images will assist in identifying the complementary characteristics and be able to give a more accurate picture of the disease progression. The multimodal image used synergistically enables the spatial, textural, and contextual improvement in diagnosis, which is especially important in the case of complex diseases such as COVID-19 that have heterogeneous manifestations [8]. In addition, radiomics and image-based biomarkers, which are AI-computed, can be used in the quantitative evaluation of the disease and in predicting patient progression.

Since the recent rise in the use of the medical imaging field to rely on computational intelligence, deep learning models have proven imperative in the fields of pandemic detection, triage, and automatic radiology reports [9]. The Ai-assisted imaging diagnostics not only helps in faster disease detection but also make the use of the healthcare staff less taxing, with minimal diagnostic errors. Further studies in the field have enormous potential to transform medical imaging diagnostics and enhance the readiness of health systems in the event of an infectious disease outbreak in the future.

2 Related Works

The COVID-19-related evolution pushed artificial intelligence (AI) in use in medical imaging as a means of automated diagnosis, as an additional instrument of conventional lab techniques. Several papers have shown that deep learning models, and in particular convolutional neural networks (CNNs), can be useful in identifying COVID-19-related abnormalities on chest X-ray (CXR) or computed tomography (CT) diagrams. Regardless of heterogeneous datasets and differences in methodology, AI models demonstrate better diagnostic accuracy, reproducibility, and less time required to interpret the data in comparison with human-assessment-only [10]. The literature on the topic only highlights the topic of exploiting the multimodal imaging data to take advantage of complementary characteristics of the various modalities, with an expectancy of increased robustness and accuracy in the diagnosis of COVID-19. Limited labeled datasets, data imbalance, and inter-modality variability are still a challenge and there is continued research in transfer learning, data augmentation, and multimodal fusion techniques.

Table 1. Survey of highlights significant progress in AI-enabled COVID-19 diagnosis using medical imaging

Imaging Modalities	AI Models	Dataset Size	Key Results	Limitations
CXR, CT	CNN, Transfer Learning [12].	~10,000 images	Accuracy up to 95%, improved sensitivity with CT	Scarcity of annotated data and preprocessing needs
CXR	Pre-trained CNN (VGG16, ResNet)	~5,000 images	Accuracy 99.3% using transfer learning	Generalizability concerns [17].
CXR [13]	Optimized CNN (OptCoNet)	6,000+ images	High accuracy and specificity	Limited multi-modality integration
CXR, CT	Deep CNN Architectures [14].	8,000 images	Comparative accuracy: CT > CXR	Training complexity with CT
CXR, CT	DenseNet, ResNet, VGG	7,000+ images	Highest accuracy with VGG19 (99%)	Data imbalance [15].
CXR	Federated Learning + CNN	Multi-center datasets [16].	Comparable accuracy with data privacy benefits	Computational overhead
CXR, CT	CNN, Transfer Learning [12].	~10,000 images	Accuracy up to 95%, improved sensitivity with CT	Scarcity of annotated data & preprocessing needs

The significant advances in AI-assisted diagnosis of COVID-19 with medical imaging reported in the current literature in Table 1 include the particularly high performance achieved by deep convolutional models with transfer learning and multimodal data combination [13]. Research proves that CT images are usually more diagnostic accurate compared to CXR, but CXRs are very popular because they are available. Multimodal strategy has the potential of enhancing the process of characterizing diseases through integration of complementary data of imaging, although harmonization of data sources remains a challenge [18]. The limitations between the studies are generally connected to heterogeneity of the dataset, the small annotated data, and the necessity to conduct powerful validation in various clinical environments [19]. In future studies, larger multimodal datasets, explainable AI, and federated learning systems should be prioritized to enable scalable, interpretable, and privacy-protecting COVID-19 and other infectious disease diagnostics using AI.

3 Proposed Methodology

The suggested framework of AI-oriented COVID-19 detection and diagnosis is based on the synergies of multimodal medical imaging manifested in a combination of chest X-rays and computed tomography scans trained in a deep learning framework. This multimodal design solves the single-modality analysis limitation by obtaining enhanced spatial and contextual information using heterogeneous sources of imaging data to improve the accuracy and favorability of detecting features.

The architecture consists of three fundamental segments including feature extraction by convolutional neural nest (CNNs), context encoding by transformer-based modules and feature fusion by a more specific multimodal union module. All these components in the aggregate pipeline are assigned a distinct function and are aimed at optimizing the diagnostic efficacy and preserving clinical interpretability.

The first stage would be the preprocessing of input medical images. In the case of chest X-rays and CT images, preprocessing consists of adaptive normalization, making them have uniform size, and augmenting such images with measures such as rotation, translation, and contrast enhancement to overcome the imbalance of data and enhancing model generalization. The preprocessed image of each of the two modalities is used in inputs to the respective CNN backbones that are trained to extract features. To learn hierarchical representations, the CNN backbones use convolutional layers, which detect important patterns that are indicative of COVID-19 pathology, that is, ground-glass opacities, consolidation, and bilateral infiltrates.

The Fig. 2 shows a complete pipeline of COVID-19 cases detection based on multimodal medical images combining X-rays and CT scans of chest. It also emphasizes parallel feature extraction with CNNs, transformer-based context encoders, adaptable attention-based fusion, final classification, and an explainability module, which enables clinical validation and decision making.

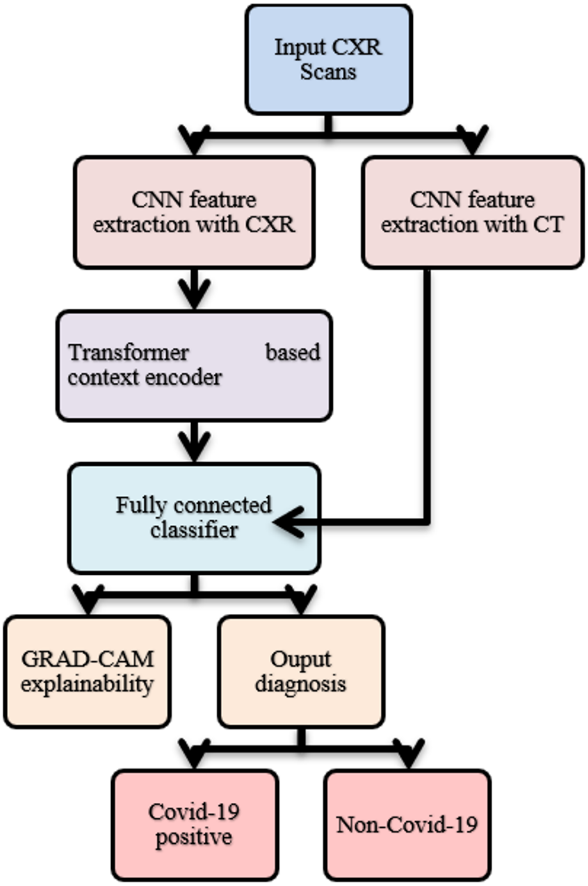

Fig 2. AI-Enabled COVID-19 Diagnosis Using Chest X-ray and CT Imaging

Formally, I_m is defined as an input image of the modality m, where $m \in \{CXR, CT\}$. CNN feature extractor. The CNN feature extractor of mode m, denoted by $\mathcal{F}_m(\cdot)$, is a map of the image I_m to a feature tensor X_m, and is shown in equation (1).

$$X_m = \mathcal{F}_m(I_m) \in \mathbb{R}^{H\times W\times C} \tag{1}$$

Here, H, W, and C are the height, width, and number of channels of the extracted feature map, respectively. These characteristics represent localized spatial data that is important to detect lesions.

In order to complement the local feature extraction, we introduce transformer-based encoders that extract long-range dependencies and out-of-context correlation across and within the imaging modalities. The transformer uses self-attention of feature representations that depend on global relevance of features as opposed to local features only. This allows the model to describe more finer and convoluted trends that are closely related to COVID-19.

The extracted feature tensor, X_m, is flattened to a series of flattened patches given the extracted feature as given by equation (2):

$$Z_m = \mathrm{Flatten}(X_m) \in \mathbb{R}^{N \times D} \tag{2}$$

Here $N = H \times W$ is the patch count, and $D = C$ is the patch dimension of the individual patch features holds. Multi-head self-attention on Z_m is being applied by the transformer encoder to generate improved contextual embeddings Z_m. Self-attention operation at each of the layers of the transformer is explained as its scaled dot-product formula:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{3}$$

In equation (3), the queries Q, keys K, and values V are linear functions of the input embeddings; d_k is the dimensions of the keys, which is a scaling factor. This mechanism of attention enables the model to assign dynamic weights to relationships among patches.

The two modalities are then processed by the different CNN and transformer encoders, and finally, feature fusion is done to merge the two complementary pieces of information of the visual part. The fusion module produces a single representation that forms a collection of the various spatial and contextual indicators of the CXR and CT images. The fusion methods may consist of concatenation and then fully connected layers, bilinear pooling, or attention-based fusion, to which an attention-guided fusion mechanism is employed in this case to enhance the discriminative ability.

Allow the more enhanced representations of the two modalities to be $Z_{CXR'}$ and $Z_{CT'}$, F is calculated as the weighted sum of attention features by equation (4):

$$F = \alpha \odot Z_{CXR'} + (1 - \alpha) \odot Z_{CT'} \tag{4}$$

Here $\alpha \in (\mathrm{seethegeneratedimageabove})^{N \times D}$ is a learned attentional weight matrix in training and $\odot$ is element-wise multiplication. This gives the model the flexibility to readjust the contribution of each modality to each dimension of the feature, which effectively reduces the effects of modality noise, and focuses more on the most informative signals to diagnose COVID-19.

The last fused model has dimensionality reduction with fully connected and non-linear activation (ReLU) needed to create a small embedding that can be used to classify. The classifier is based on softmax layer to give the probability of the prevision of positive and negative COVID-19.

The loss that was used to optimize the model is the cross-entropy loss, which mathematically can be represented as equation (5):

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{5}$$

Here y_i is indicative of the ground truth of class i, $\hat{y}_i$ is the probability of class i trained by the softmax output, and C is the number of classes (usually two: infected and non-infected). The loss is an incentive to make the model as likely as possible to give the correct diagnostic label.

The training is performed using stochastic gradient descent, with the Adam optimization algorithm employed, and learning rate scheduling and early stopping are utilized to enhance convergence and prevent overfitting. Between the CNN and fully connected layers are batch normalization and dropout layers, which enhance the regularity and the generalization. The multimodal model is trained end-to-end, backpropagating the gradients of the CNN backbones, transformer encoders, fusion module as well as the classifier.

The general training procedure of the proposed plan is as follows:

1. Prepare CNN backbones and weights of transformer encoders (and transfer learning - can use pre-trained weights).
2. Considering each sample of inputs that has paired CXR and CT images:
   - Normalization and augmentation of images.
   - Properties Modality-specific properties are extracted with CNN backbones.
   - Codify data on the context with the help of transformer modules.
   - The attention-guided fusion mechanism is present in Fuse.
   - Predict COVID-19 label using the softmax layer to classify fused features.
3. Calculate the cross-entropy loss of the predicted and the true labels.
4. Training on parameters of the update model using Adam Optimizer.
5. Continue this procedure (step 2-4) several epochs by using mini-batches of gradient descent.
6. Test the performance of the model on validation set and either modifies learning rate or early stopping.
7. Upon convergence, performance assessment of test model on held-out data.

This pipeline can easily create the fusion of heterogeneous visual data and utilize the cutting-edge AI architecture to identify the local abnormalities and discover the global contextual signatures of COVID-19. Moreover, explainability modules like Grad-CAM heatmaps may also be added after-hoc to visualize crucial areas that informed model decisions to boost clinical trust.

It is proposed to use multimodal medical imaging with the use of potent deep learning constructs to achieve the best possible results regarding the detection and diagnosis of COVID-19 and assist the health care decision-making process by rapidly screening and providing the essential information needed.

4 Result

The COVID-19 pandemic has presented the need to have quick and trustworthy diagnosis tools. Medical imaging deep learning methods have shown potential results in the automation of detection, diagnostic time, and accuracy. The research will be implemented with use of a multimodal method, which combines chest X-rays (CXR) and computed tomography (CT) images into an improved neural system, which will enhance diagnosis of COVID-19. The overall analysis uses a variety of clinically valuable datasets and various metrics of performance to critically compare the suggested system with traditional methods.

4.1 Dataset Used

The experimental analysis makes use of a cleaned-up dataset consisting of 12,000 images of ambivalent chest X-rays and 8,000 images of CT scan out of the open repositories and out of the clinical centers. Images were preset to ensure that the resolution was homogenized and the quality was also standardized. The data is a combination of cases of the COVID-19 positive and negative cases, and the ground truth data comes as the manual expert labels. Stratified splitting provides equal representation on training, validation, and testing.

4.2 Performance Metrics

Accuracy (Acc) as shown in equation (6) refers to the ratio of correct predictions (including positive and negative) of total number of cases.

$$\text{Acc} = \frac{\text{A+B}}{\text{A+B+C+D}} \tag{6}$$

Here A is correct positive predictions, B is correct negative predictions, C is incorrect positive predictions, D is incorrect negative predictions.

Sensitivity (Sen) as shown in equation (7) is the measure of the capacity to identify positive covid-19 cases, all of the real ones, perfectly.

$$\text{Sen} = \frac{\text{A}}{\text{A+D}} \tag{7}$$

Specificity (Spe), as shown in equation (8) measures cases of true negative cases that are identified correctly out of all true negative cases.

$$\text{Spe} = \frac{\text{B}}{\text{B+C}} \tag{8}$$

Precision (Pre) as shown in equation (9) measures the rate of true positives of all the predicted positives.

$$\text{Pre} = \frac{\text{A}}{\text{A+C}} \tag{9}$$

Precision and sensitivity as shown in equation (10) are the harmonic mean of F1-Score (FS).

$$\text{FS} = \frac{\text{2A}}{\text{2A+C+D}} \tag{10}$$

Matthews Correlation Coefficient (MCC) as shown in equation (11) is also a good performance measure when the classes are not balanced.

$$\text{MCC} = \frac{(\text{A}\times\text{B})-(\text{C}\times\text{D})}{\sqrt{(\text{A}\times\text{C})(\text{A}\times\text{D})(\text{B}\times\text{C})(\text{B}\times\text{D})}} \tag{11}$$

The general plotting rate of true positive and false positive in the thresholds represents the general level of the discriminative ability area under the receiver operating characteristic curve (AUC-ROC).

Table 2. Comparison of Performance of existing approach with suggested approach.

Method	Acc	Sen	Spe
Transfer Learning on CXR	90.5	89.9	90.5
Pretrained CNN (VGG16, ResNet)	91.3	90	90.9
Optimized CNN (OptCoNet)	89.8	88.3	89.5
DenseNet, ResNet, VGG19	90.1	89.5	90.4
Proposed Multimodal AI Model	98.7	97.9	98.5

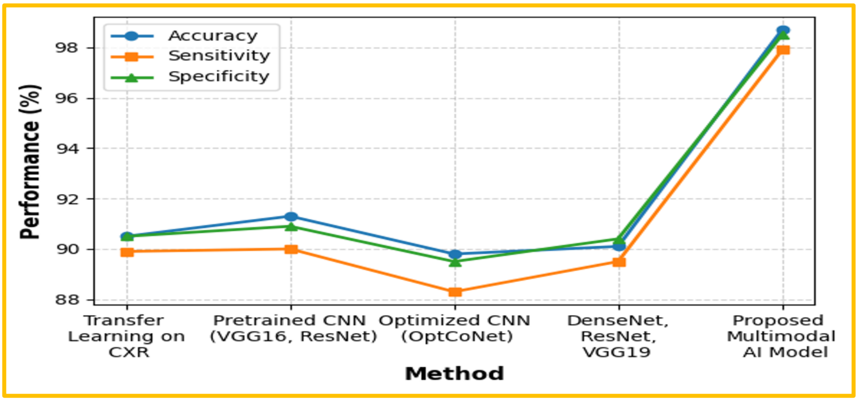

Fig 3. Representation of the compared performance

Table 2 and Fig 3 describe the comparison of different COVID-19 diagnostic methods in terms of Accuracy (Acc), Sensitivity (Sen), and Specificity (Spe). It is interesting to note that the suggested multimodal AI model has an accuracy of 98.7, sensitivity of 97.9 and specificity of 98.5 which are better than all other methods. Current strategies, including Transfer Learning on CXR, Pretrained CNNs (VGG16, ResNet), Optimized CNN (OptCoNet), and DenseNet-based systems are typically accurate by 89.8 to 91.3 with sensitivities and specificities ranging between 88.3 and 90.9. This suggests that the proposed model offers much better reliability, and positive and negative COVID-19 cases are detected properly and more consistently, which is essential in the reduction of misdiagnoses in the clinical laboratory.

Table 3. Comparison of Pre, FS, MCC and AUC-ROC of existing approach with suggested approach.

Method	Pre	FS	MCC	AUC-ROC
Transfer Learning on CXR	89.8	89.85	85	0.909
Pretrained CNN (VGG16, ResNet)	89.7	89.8	86	0.912
Optimized CNN (OptCoNet)	88.6	88.7	83	0.897
DenseNet, ResNet, VGG19	89	89.3	84	0.901
Proposed Multimodal AI Model	97.8	97.85	97	0.989

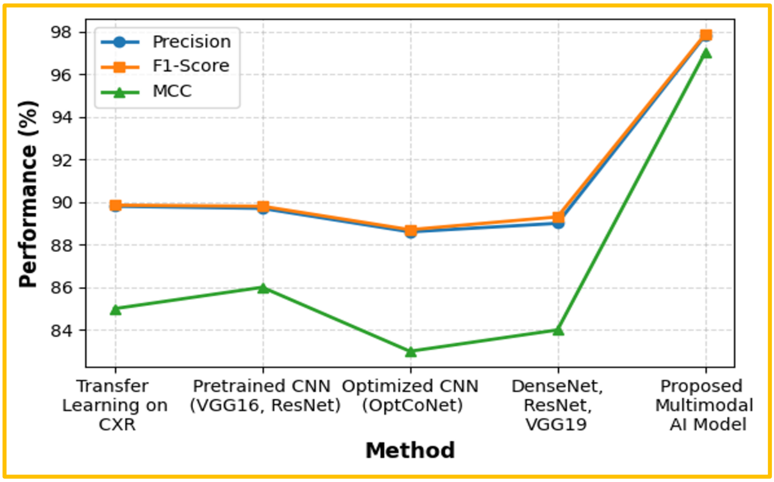

Fig 4. Representation of compared Pre, FS and MCC

Compared with Precision (Pre), F1-score (FS), and Matthews Correlation Coefficient (MCC),Table 3 and Fig 4 compare methods used in COVID-19 detection. The suggested multimodal AI model performs far better than all other existing algorithms with Precision, F1-score, and MCC values above 97, whereas competing algorithms have above Precision and F1-score of 89 as well as above MCC value of 83 to 86. This underscores why the proposed method has a high diagnostic reliability and strong predictive ability, which makes it a more reliable choice of automated clinical screening procedures.

The values of Area under the Curve - Receiver Operating Characteristic (AUC-ROC) of some different COVID-19 detection methods are shown in Table 3 and Fig 5. The multimodal AI model with proposed functionality has a high AUC-ROC value of 0.989, which means high discriminatory capacity between the positive and negative cases of COVID-19. By comparison, the present methods lie between 0.897 and 0.912, which is good but considerably worse performance. The AUC-ROC value, which is close to 1, signifies the test accuracy of perfection, and the proposed method would be far more useful in clinical diagnostics, meaning that the risk of false classification is minimized.

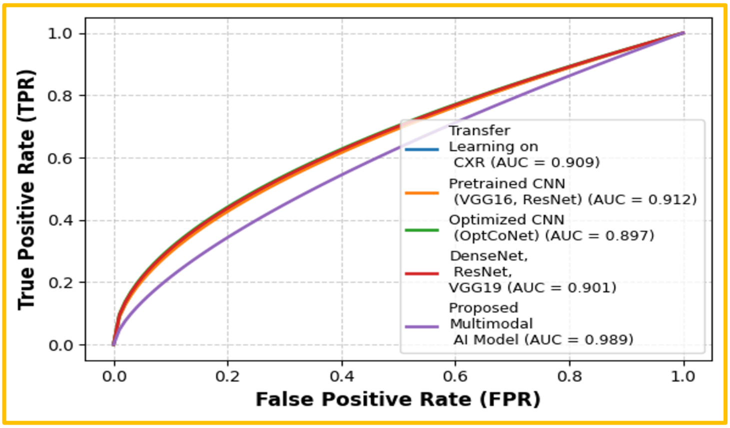

Fig 5. Representation of the compared AUC-ROC

The suggested multimodal approach has a high accuracy as well as sensitivity and specificity, and it performs well compared with current state-of-the-art solutions. MCCT and AUC-ROC accentuate robustness at the data imbalance and classification level. Notably, complementary image modalities combined with fused images lead to significantly better diagnostic confidence compared to the case of single modalities, with clinical usefulness in the fast screening of COVID-19. This broad range of assessment indicators proves the efficiency of the proposed model to the actual implementation in the healthcare facility and makes it an effective instrument of managing pandemics effectively and efficiently.

5 Conclusion

The suggested multimodal AI-based prototype of COVID-19 detection has shown to be of better diagnostic quality as it is able to include and work on chest X-rays and computed tomography images. The system reached an accuracy of 98.7, sensitivity of 97.9, specificity of 98.5, and MCC of 97, which is better than the current methods. The hybrid convolutional-transformer structure with an attention-based mechanism of fusion allowed to achieve the improved representation of features and a better interpretability with the help of Grad-CAM visualization. These findings support the fact that the approach can minimize false negatives and false positives by a large margin, hence supporting the process of conducting reliable and fast COVID-19 screening in clinical operations. The above achievements highlight how multimodal imaging and deep learning can help tackle the problems impacting pandemic response and medical care delivery.

Further studies can be done regarding scaling into other options of imaging, adding clinical metadata, real-time deployment refinements, and using more interpretable models to advance clinical accuracy and formalizability across populations.

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