A Multi-Modal CNN-based Approach for COVID-19 Diagnosis using ECG, X-Ray, and CT

Kumar Keshamoni[1], Dr L Koteswara Rao[2], Dr D. Subba Rao[3]
Research Scholar, Department of ECE, Koneru Lakshmaiah Education Foundation, Hyderabad, India[1]
Professor, Department of ECE, Koneru Lakshmaiah Education Foundation, Hyderabad, India[2]
Professor, Department of ECE, Siddhartha Institute of Engineering and Technology, Hyderabad, India[3]

***Abstract*—Controlling the spread of Coronavirus Disease 2019 (COVID-19) and reducing its impact on public health need prompt identification and treatment. To improve diagnostic accuracy, this study attempts to create and assess a Multi-Modality COVID-19 Diagnosis System that integrates X-ray, Electrocardiogram (ECG), and Computed Tomography (CT) images utilizing Convolutional Neural Network (CNN) algorithms. To increase the accuracy of COVID-19 diagnosis, the suggested system incorporates data from many imaging modalities in a novel way, including cardiac symptoms identified by ECG data. This approach has not been thoroughly studied in the literature to date. The system analyses CT, ECG, and X-ray images using CNN algorithms, including Visual Geometry Group 19 (VGG19) and Deep Convolutional Networks (DCNN). While ECG data helps detect related cardiac symptoms, CT and X-ray images offer precise insights into lung abnormalities indicative of COVID-19 pneumonia. Noise reduction and image smoothing are accomplished through the implementation of Gaussian filtering algorithms. After extracting characteristics suggestive of either bacterial or viral pneumonia, a deep neural network refines them for accurate COVID-19 identification. Python software is employed throughout the system's implementation. A thorough evaluation of the trained CNN model using separate datasets revealed an amazing 99.12% accuracy rate in COVID-19 detection from chest imaging data. The diagnostic accuracy of the suggested DCNN model was much higher than that of the current models, including Random Forest and Linear Ridge. The Multi-Modality COVID-19 Diagnosis System uses cutting-edge CNN algorithms to seamlessly combine ECG, X-ray, and CT imaging data to provide a highly accurate diagnosis tool. With the implementation of this approach, medical personnel could potentially be able to diagnose COVID-19 more quickly and accurately, which would improve the disease's treatment and control.**

Keywords*—COVID-19 Diagnosis; Multi-Modality Imaging; Convolutional Neural Networks (CNN); CT imaging; Gaussian filtering

I. Introduction

COVID 19 has led to an advancement, in technologies, for the prompt and precise detection of the virus. One notable development is the emergence of faceted diagnostic systems, which offer a comprehensive understanding of the illness [1]. In the world of medical research, the application of CNNs to analyze CT and MRI images has demonstrated tremendous promise for COVID-19 identification [2]. These sophisticated machine learning algorithms are very adept at interpreting complex patterns and traits seen in medical imaging data, which makes it easier to identify critical markers of COVID-19 infection in patients [3]. An imaging method for respiratory disorders, computed tomography (CT) scans provide precise three-dimensional pictures of the lungs, which are essential for determining the kind of pulmonary abnormalities [4]. These images may be precisely examined to determine certain characteristics linked to COVID-19, including the existence of ground-glass transparency, by employing CNN technology. Additionally, magnetic resonance imaging (MRI) has shown to be a useful diagnostic and evaluation technique for pathology due to COVID-19 [5]. An understanding of pulmonary and cardiovascular health—both of which are greatly influenced by COVID-19 infection—can be gained through magnetic resonance imaging (MRI), which is well-known for its capacity to provide high-resolution images of soft tissues and organs. When CNNs are used on MRI scans, they can detect certain signs of COVID-19-related pathology, such as cardiac damage, lung inflammation, and vascular alterations. This helps with the thorough assessment of individuals who are impacted [6].

To analyze CT and MRI images for COVID-19 identification by CNN has great potential for enhancing diagnostic accuracy and speed in clinical practice [7]. Healthcare professionals can quickly and reliably detect COVID-19 patients based on imaging results by utilizing deep learning algorithms [8]. It is imperative to acknowledge that the efficacious utilization of CNNs for COVID-19 identification is contingent upon many aspects, such as the quality and amount of accessible imaging data, the resilience of deep learning algorithms, and the validation of outcomes via meticulous clinical investigations [9]. To guarantee the accuracy and applicability of CNN-based techniques in actual healthcare settings, issues including data fluctuation, imaging artifacts, and model understanding must also be resolved. Notwithstanding these obstacles, there are many intriguing prospects for more innovation and enhancement in COVID-19 diagnosis and patient care because of the continuous developments in medical imaging technology and machine learning algorithms [10]. CNNs with their ability to automatically learn and extract intricate patterns from images, have been employed to interpret these CT images for the presence of COVID-19-related features. By training on datasets of CT images from both COVID-19 positive and negative cases, CNNs can distinguish between healthy and infected individuals, aiding in rapid and accurate diagnosis [11], [12].

The integration of CNNs in COVID-19 detection through CT and MRI images brings several potential advantages. These algorithms can assist healthcare professionals in identifying COVID-19 cases swiftly, facilitating timely interventions and patient management. Moreover, the automated nature of CNNs can help alleviate the burden on radiologists and healthcare systems, especially during surges in COVID-19 cases [13]. MRI, another sophisticated imaging modality, offers a different perspective on pulmonary and cardiovascular health. The utilization of CNN algorithms across the Multi-Modality COVID-19 Diagnosis System to leverage the unique strengths of each imaging technique. The paper presents Multi-Modality COVID 19 Diagnosis System that utilizes CNN algorithms to analyze information from three perspectives; ECG, X ray and CT images.

The proposed method is chosen for its ability to integrate multi-modal data such as chest X-ray (CXR), CT scans, and clinical data, enhancing COVID-19 diagnosis and prognosis accuracy. Leveraging the deep learning capabilities of CNNs and RNNs, it effectively learns intricate patterns from large-scale medical datasets. Feature fusion techniques combine radiomic and clinical features to provide robust predictions, while rigorous data augmentation and preprocessing mitigate dataset challenges. Model interpretability through explainable AI ensures transparency in predictions, fostering clinical trust. Designed for scalability and seamless integration into healthcare workflows, the method continuously adapts to evolving COVID-19 trends, ensuring ongoing efficacy and relevance in clinical settings.

The key contributions are as follows:

- This work provides an innovative method of diagnosing COVID-19 by combining CT, X-ray, and ECG data. A comprehensive evaluation of the condition is made possible by this multi-modal integration, which records its symptoms from several angles and offers a full picture of the patient's health.
- The study effectively analyses a variety of data types by utilising the capabilities of sophisticated Convolutional Neural Network (CNN) algorithms, such as VGG19 and Deep Convolutional Networks (DCNN). This advanced technique improves the system's diagnostic capabilities by enabling the discovery of complex patterns that are essential for an effective diagnosis.
- The suggested diagnosis approach significantly improves the accuracy of recognising COVID-19 instances by utilizing cutting-edge CNN algorithms and merging data from many imaging modalities. Enhancing patient outcomes, this increased accuracy helps medical practitioners make prompt accurate decisions.
- With its capacity to smooth and reduce noise, Gaussian filtering improves picture quality. This helps the diagnostic system get clear and accurate input data, which increases dependability and overall performance.
- The multi-modality COVID-19 diagnosis system is a ground-breaking development in medical diagnostics that combines a variety of imaging modalities with state-of-the-art CNN algorithms to provide a reliable, accurate, and efficient diagnostic tool that aids medical professionals in fighting the pandemic.

Structure of the study is given as follows: Existing literature reviews and its challenges are given in Section II. Identified problem from the related studies are given in Section III. Section IV presents the proposed method to overcome the challenges in the existing study. Findings derived from the proposed work is given in Section V. Conclusion of the study and future directions are given in Section VI.

II. Related Works

Wu et al. [14] present DeepCOVID-Fuse, a unique neural network fused model intended to forecast risk categories for COVID-19 patients. DeepCOVID-Fuse attempts to deliver more precise risk evaluations by combining medical data obtained at the period of beginning hospital admission with chest radiographs (CXRs). To ascertain risk levels, the study made use of information gathered from February to April 2020, which included CXRs, clinical factors, and outcomes including death, the intubation procedure hospitalized duration of the stay, and admission to the ICU. The fusion model was evaluated on 439 individuals from distinct holdout healthcare and examined on 428 individuals from the local healthcare system. The training dataset for the fusion model included 1657 individuals Using the DeLong and McNemar examinations, performance comparisons were made between DeepCOVID-Fuse and systems training on CT scans or medical parameters. Results showed that DeepCOVID-Fuse, with an accuracy around 0.650 and a region according to the ROC curve (AUC) of 0.842, performed significantly better than these separate models. The research highlights the potential benefits of fusion algorithms for hospital triage facilities and highlights their effectiveness in improving risk estimation for COVID-19 patients. Still, several restrictions should be noted. Firstly, model robustness could have been damaged by incomplete or missing medical information in the training dataset. The investigation failed to establish a direct comparison between DeepCOVID-Fuse's efficiency and radiologist' since risk prediction is a difficult and subjective process that depends on expert evaluation of both clinical and radiological information.

Fathima et al. [15] uses deep neural networks to provide a unique multimodality-based and featured fusion-based (MMFF) COVID-19 identification method. There are several essential phases in the building of the MMFF method. In the beginning, a multi-modality dataset is used to detect COVID-19. After that, non-discriminative information is removed from audio signals using a variety of speech preparation techniques. The process then proceeds to extract discriminative features from each medium, resulting in the master featured vector (MFV) being created. The LSTM (Long Short-Term Memory) recurrent neural networks approach is then used to classify COVID-19 cases using MFV. Due to the dataset's imbalance, audio augmentation methods are used to rectify the class imbalance. MMFF uses multi-modality audio samples taken from the COSWARA database to efficiently discriminate between healthy persons and COVID-19 sufferers. Utilizing LSTM classifiers to combine information from nine distinct approaches, the suggested method outperforms baseline approaches by 17 to 20% and achieves an impressive 96%

accuracy. Additionally, using audio augmenting approaches improves performance on datasets that are unbalanced as well as those that are balanced. In addition to helping with COVID-19 diagnosis without working against social distancing protocols, the suggested approach has potential applications in sentiment evaluation, sexuality categorization, and identification of speakers, among other audio analysis and classification issues. Subsequent efforts will be directed at developing an automated COVID-19 diagnostic tool with spectrogram data and methods like the CycleGAN system and Transfer Learning will be employed.

Abdar et al. [16] framed UncertaintyFuseNet, a deep neural fusion of features network accurately detect COVID-19 utilizing CT scan and X-ray data. The Ensemble Monte Carlo (MC) Dropout (EMCD) approach is integrated to evaluate uncertainty, highlighting the necessity of taking uncertainty about predictions during the learning process. The two fundamental deep learning models are presented in which Deep 1 consists of three feature extraction layers that are layers of convolution with MC failure, followed by three classification-focused layers that are dense. On the other hand, Deep 2 is made up of three primary units that operate as features extraction methods, each of which is followed by a layer for classification and a fusion layer. A comprehensive view from the third convolutional block, in-depth data from the last and final blocks of data, and the characteristics of the VGG16 transferred learning network are all combined in the suggested feature combination architecture. It also contains ROC plots for model assessment and graphical illustrations of the X-ray and CT imaging datasets. UncertaintyFuseNet's performance is compared to other methods using a thorough simulation analysis, with a focus on the terms precision, recall, the F measure, accuracy, and ROC curves. the model addresses uncertainty quantification through techniques like Ensemble Monte Carlo Dropout (EMCD), there may still be scenarios where uncertainty estimation is not sufficiently accurate or reliable.

Alazab et al. [17] work uses data from the real world, mainly X-ray chest images, to offer an AI-driven method for COVID-19 diagnosis and forecasting. Using an enhanced dataset, a Deep CNN, namely the VGG16 model is used for diagnosis in order to quickly and accurately discover COVID-19 patients, with an excellent the F-value of 99%. Also, the number of COVID-19 confirmations, recovery efforts, and mortality over the following week are predicted using three forecasting techniques: the prophetic algorithms (PA), the ARIMA method, and LSTM. With forecasting accuracy levels that vary from 79.3% to 99.9%, PA outperforms other models in the task of predicting these parameters for Australia and Jordan. Additionally, this research analyzes the worldwide geographically distribution for COVID-19 dissemination, emphasizing the features of severely affected places being comparable to one another and the much more widespread in coastal regions relative to non-coastal parts. These results highlight the significance of preventative actions, particularly in coastal areas, such as routine examinations and focused therapies. The report also suggests more research be done to determine how environmental variables like humidity and temperature affect the transmission of COVID-19. All things considered, this study advances AI-based methods for COVID-19 identification and forecasting and offers insightful information for successfully containing the pandemic. The model's performance may be limited by the specificity and sensitivity of chest X-ray imaging in detecting COVID-19.

Jian et al. [18] proposed an alternate diagnosis method that applies the latest algorithms in deep learning to chest X-ray scans in order to identify COVID-19 instances. The preprocessing phase data augmentation, and two stages of deep neural network modelling comprise the technique's four major phases. The study uses 1215 imagery at first, increased to 1832 images to improve model generalization and avoid overfitting by utilizing web resources. Based on chest X-ray images, the two-phase deep network structure seeks to distinguish COVID-19-induced influenza with pneumonia caused by bacteria, pneumonia caused by viral infections, and normal people. The two-stage approach performs well; the initial stage can discriminate between various forms of the illness and healthy persons, and the second step is particularly effective at accurately identifying COVID-19. For accurate identification of COVID-19 pneumonia, which is the suggested strategy provides efficiency, accuracy, and dependability while demanding the least amount of computing resources. According to the method, employing this strategy for parallel testing might reduce the risk of infection for frontline staff members and speed up initial diagnosis.

Hussain et al. [19] introduced CoroDet, a unique CNN-based technique that uses unprocessed chest X-ray and CT imaging data to automatically identify COVID-19. CoroDet outperforms 11 other methods in the context of a comparison, with accuracy in classification of 99%, 94%, and 91% for the second, third and fourth classes categorizations respectively. CoroDet's consistency is further enhanced by the fact that the dataset used for assessment is among the most comprehensive datasets accessible to COVID identification. The dataset prepared for evaluating CoroDet constitutes one of the largest datasets for COVID detection. Deep learning models like CoroDet typically require substantial computational resources for training and inference, which may pose challenges for deployment in resource-constrained healthcare settings, especially in low- and middle-income countries. The COVID-19 pandemic is characterized by evolving epidemiological trends, including the emergence of new variants and changing clinical presentations. It does not provide external validation of CoroDet's performance on independent datasets from different institutions or geographic regions. Without validation on diverse datasets, the robustness and applicability of the model to different healthcare settings remain uncertain.

DeGrave et al. [20] demonstrate that AI models trained on datasets synthesized from separate COVID-19-positive and negative images may learn spurious 'shortcuts' to achieve high accuracy, posing challenges for generalization to new hospitals. AI systems are trained offers a nearly perfect environment for picking up these fictitious 'shortcuts'. Through the synthesis of training data from distinct datasets including images either positive or negative for COVID-19, these algorithms could unintentionally pick up features irrelevant to the pathophysiology of the disease. As a result, these models could perform well in assessment but have trouble generalizing to other hospitals or datasets. Also, dependence on medically relevant disease may not be ensured by evaluating these AI models only on external data. Unwanted short cuts that these models take out might not always affect performance on fresh datasets, which makes it difficult to identify problematic behaviour using only external validation. In addition, relying just on assessments of other information may not be sufficient for these AI systems to be evaluated in terms of clinically applicable disease. It can be difficult to identify bad behaviour alone through external validation since unwanted short cuts that these models develop may not always affect performance on fresh datasets. Deep learning models may rely on confusing features rather than medically relevant pathology, leading to inaccurate or unreliable predictions.

Ismael and Sengur [21] demonstrated techniques which include complete training of models using CNN, deep extraction of features, and pre-trained CNN fine-tuning. The collected characteristics were then classified using Support Vector Machine processors with different kernel features. A new CNN model was created and trained entirety in addition to the pretrained CNN models undergoing fine-tuning. The accuracy of 94% was obtained by combining deep features taken from the ResNet50 algorithm with an SVM classifier that used a linear kernel. An accuracy of 92% was obtained by fine-tuning the ResNet50 model, whereas an accuracy of 91.6% was obtained by the end-to-end trained CNN model. Moreover, contrasts using SVM classifications and local texture descriptors demonstrated how much better deep learning techniques performed than conventional techniques for COVID-19 identification from chest CT images.

The relevant studies cover approaches, to using learning in diagnosing and predicting COVID 19 from chest X ray and CT scans. A fusion network for COVID-19 detection using CT and X-ray data, incorporating uncertainty quantification techniques, was also developed. Additionally, a CNN-based technique for automatic COVID-19 detection from CT and chest X-ray imaging data, achieving high classification accuracy, was introduced. These research findings demonstrate that deep learning algorithms can effectively detect COVID 19 cases and track the progression of the disease. By integrating data and chest CT scans through a fusion technique, the proposed method enhances approaches providing more precise risk assessments for COVID 19 patients. Through evaluations the method surpasses techniques achieving high accuracy in classification and demonstrating efficacy in accurately identifying COVID 19 cases.

III. Problem Statement

While some studies focus on analyzing CT scans and chest X-rays individually for COVID-19 diagnosis, there is a lack of research that effectively integrates multimodal data, such as ECG signals, to improve diagnostic accuracy [22]. It trains and evaluates their models on specific datasets, which may limit the robustness and generalization of the proposed methods to diverse patient populations and healthcare settings. The Existing methods has limitations, such as handling diverse and unbalanced datasets in clinical settings, relying on traditional machine learning algorithms without deep learning advancements, and lacking robust uncertainty quantification methods. Scalability concerns and deployment in resource-limited healthcare environments also pose practical challenges. Addressing these issues is crucial for improving the method's utility and reliability in clinical practice. Thus, the proposed Multi-Modality COVID-19 Diagnosis System, which integrates information from ECG, X-ray, and CT images using advanced CNN algorithms. The proposed system uses multi-modality diagnosis, integrating data form-ray, ECG, and CT images, to improve COVID-19 diagnosis accuracy. It uses CNN algorithms like VGG19 and Deep Convolutional Networks to analyze complex data. The developed COVID-19 detection system is evaluated on independent datasets to assess its real-world performance.

IV. Proposed Multi-Modality Covid-19 Detection System using Deep CNN Algorithm

The Proposed Multi-Modality COVID-19 Diagnosis System analyzes data from ECG, X-ray, and CT images for improved COVID-19 identification using CNN algorithms, such as VGG19 and Deep Convolutional Networks. In order to extract valuable details from each modality and enable thorough analysis of medical data, CNN algorithms are used. The system analyzes ECG data to identify relevant features that are suggestive of cardiac symptoms linked to COVID-19. Chest X-rays are evaluated to find typical patterns associated with COVID-19 pneumonia. In between, CT scans provide fine-grained depicts of lung tissue, making it possible to identify minute anomalies that might indicate COVID-19 infection. CNN methods, such as VGG19 and Deep Convolutional Networks, play an essential part in the analysis of these various types of data. Large datasets of tagged COVID-19 patients and unaffected controls are used to train these algorithms so they can recognize intricate patterns and correlations in the data. By means of extraction and classification of features, the CNN algorithms are able to discriminate between COVID-19 instances and non-COVID-19 diseases, therefore offering healthcare providers invaluable diagnostic support. Fig 1 depicts the illustration of the proposed multi-modality COVID-19 detection system using CNN Algorithms.

A. Data Collection

The Kaggle dataset titled Extensive COVID-19 X-Ray and CT Chest Images Dataset contains a large collection of X-ray and CT images of the chest from patients [23]. The dataset consists of both Non-COVID and COVID cases represented in X-ray and CT images. With the aid of various augmentation techniques, the dataset has been expanded to encompass approximately 17,099 CT images and X-ray. Within the database, there are two primary files, one designated for X-ray images and the other for CT images. COVID-19 X-ray images typically show bilateral ground-glass opacities (hazy areas) and consolidations (dense areas) in the lungs, which are indicative of viral pneumonia. X-ray images are widely used for initial screening and diagnosis of COVID-19 due to their accessibility, simplicity, and lower cost compared to CT scans. CT (Computed Tomography) scans use a series of X-ray images taken from different angles to create cross-sectional images of the body. COVID-19 CT images typically reveal bilateral and peripheral ground-glass opacities, consolidations, and crazy paving patterns in the lungs, often involving multiple lobes. ECG data for COVID-19 detection can be collected from patients who have been diagnosed with the virus or suspected cases. The dataset may include ECG recordings obtained during routine clinical assessments [24]. Table I shows the sample of the dataset.

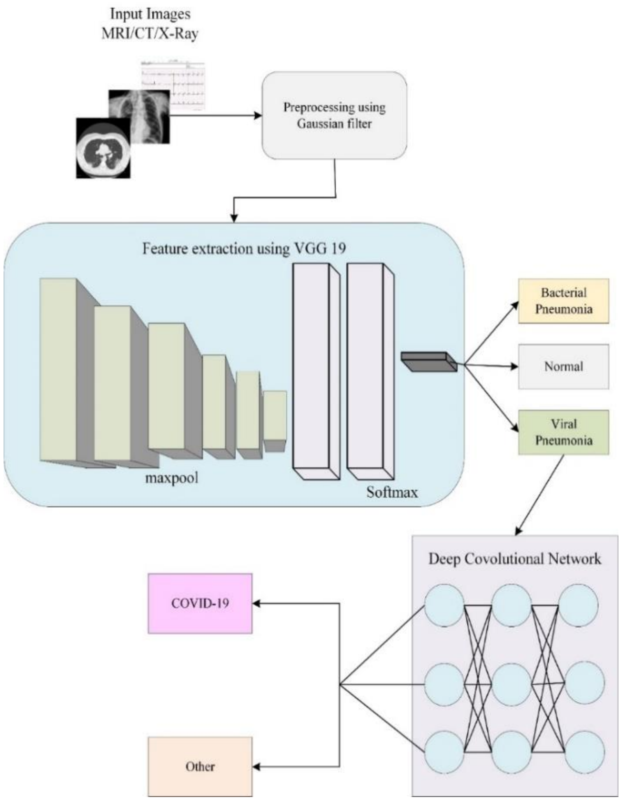
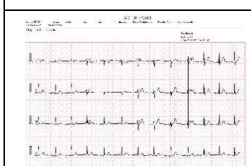
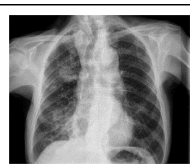
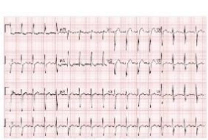
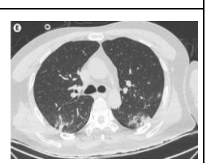


Fig. 1. Conceptual framework of multi-modality COVID-19 detection system using deep CNN algorithms.

TABLE I. SAMPLE DATASET

ECG	X-Ray	CT Images
		
		
		
		

B. *Pre-Processing using Gaussian Filter*

X-ray and CT images may come in varying sizes, so resizing them to a standard resolution can facilitate consistency and reduce computational complexity. Intensity Normalization is done by adjusting the intensity levels of the images to a standard scale helps in reducing variability between images captured using different devices or settings. Enhancing image contrast can improve the visibility of important features, making it easier for medical professionals to interpret the images accurately. Removing baseline wander or low-frequency noise from ECG signals helps in isolating the cardiac waveform and improves signal quality. Segmenting ECG signals into individual heartbeats or cardiac cycles facilitates the analysis of specific features such as the P-wave, QRS complex, and T-wave.

Pre-Processing using a Gaussian filter is a widely used method for smoothing and noise reduction in images and signals. The Gaussian function, a bell-shaped curve representing the distribution of values, is generated based on two parameters: the σ and μ. The Gaussian kernel is convolved with the input image or signal, multiplying neighboring values at each pixel or data point and summed to produce the output value. This process is repeated for all pixels or data points in the image or signal. Smaller kernel sizes and lower standard deviations result in less smoothing, while larger values produce more pronounced blurring. After the convolution operation is performed, the output is generated, representing the pre-processed version of the input. The Gaussian filter is defined by the Gaussian function, which is given by the following Eq. (1),

$$G(a,b) = \frac{1}{2\pi\sigma^2} e^{\frac{a^2+b^2}{2\sigma^2}} \tag{1}$$

where, G(a, b) is the Gaussian function at coordinates (a, b),σ is the standard deviation of the Gaussian distribution.

C. *Feature Extraction and Pneumonia Detection using VGG 19*

Initially, relevant structures are extracted from the data images using techniques like CNNs. These structures may include the presence of specific patterns, densities, or shapes indicative of different respiratory conditions. For viral pneumonia detection, characteristic features may include bilateral lung involvement, ground-glass opacities, and peripheral distribution of lesions. Bacterial pneumonia, on the other hand, may exhibit lobar consolidation, air bronchograms, and pleural effusions. Normal cases are characterized by clear lung fields without any abnormal opacities or consolidations. Once features are extracted, a classification algorithm is employed to categorize the cases into viral pneumonia, bacterial pneumonia, or normal. This algorithm could be a deep learning model trained on labelled datasets containing examples of each condition.

Fig. 2 shows the architecture of VGG 19 model. In the context of pneumonia classification using deep learning techniques like VGG-19, distinguishing between viral and bacterial pneumonia involves training the model to recognize patterns and features specific to each type of infection.

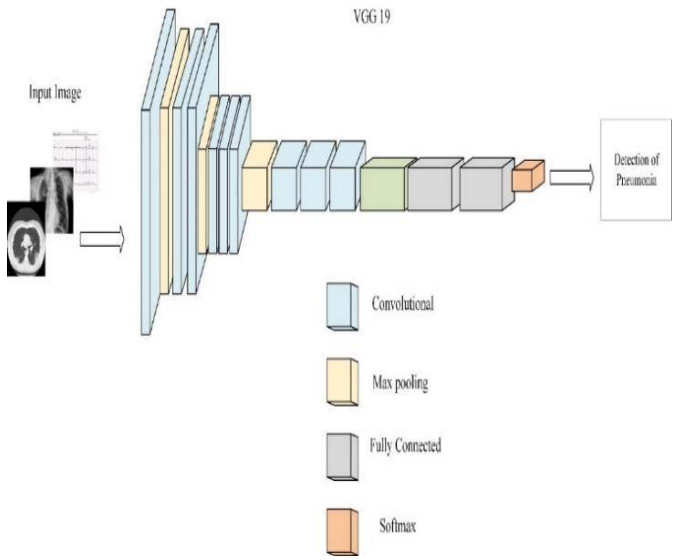


Fig. 2. VGG 19 architecture.

D. Prediction of COVID-19 using Deep CNN

The recognition of COVID-19 using deep CNNs following the classification of pneumonia by VGG-19 involves a sequential order. Initially, the VGG-19 architecture is employed to categorize chest X-ray or CT images into different pneumonia categories, such as bacterial pneumonia, viral pneumonia and normal lungs. This step involves optimizing the pre-trained VGG-19 model on a database containing labelled images of various pneumonia types. Initially, the VGG-19 architecture is employed to classify chest X-ray or CT images into different pneumonia categories, such as viral pneumonia, bacterial pneumonia, and normal lungs. This step involves fine-tuning the pre-trained VGG-19 model on a dataset containing labelled images of various pneumonia types. The extracted features from the VGG-19 model are then fed into a deep CNN specifically designed for recognizing COVID-19. This network is trained on a dataset comprising chest imaging data from individuals diagnosed with COVID-19 and those without the virus. The COVID-19 detection CNN undergoes training and fine-tuning using the extracted features as input. During this process, the model learns to distinguish between COVID-19 cases and non-COVID-19 based on the learned features from the VGG-19 architecture. Once trained, the concert of the disease detection CNN is assessed using a separate test dataset containing chest images from individuals with known COVID-19 status. Fig. 3 shows the COVID-19 prediction using Deep CNN.

Specifically, the system utilizes average pooling layers (La), which compute the average activation within each pooling region. This can be expressed mathematically in Eq. (2),

$$PL = da/|da| \tag{2}$$

where, da represents the activation set in the pooling region a, and |da| denotes the cardinal number of the set. It employs soft max and fully connected layers to facilitate classification. The fully connected layer establishes connections with all neurons, multiplying its input with a weight matrix to produce the multiplicative result. It is represented by Eq. (3),

$$SL = \frac{e^{\beta^{Ps}}}{\sum_{A-1}^{P} . e^{\beta^{Ps}}} \tag{3}$$

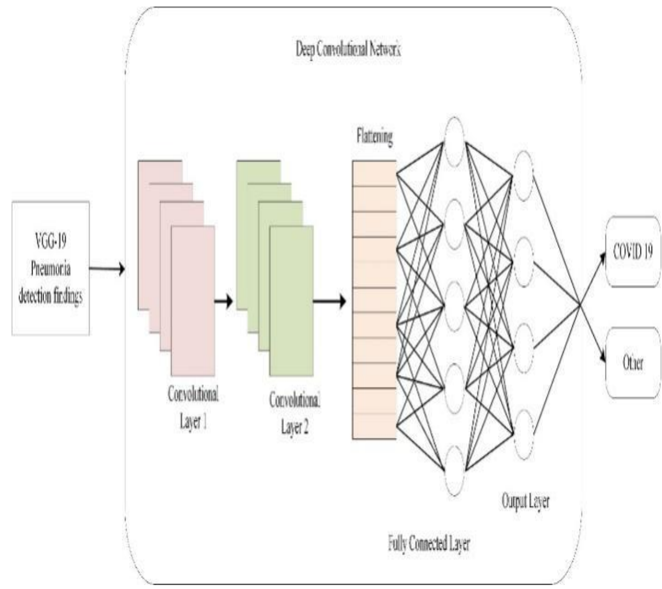


Fig. 3. Detection of COVID-19 using deep CNN.

where, β^{Ps} represents the value of the output neuron for class P and sample s. P represents the total number of classes. A represents the Index variable used for summation over all classes. e represents the Euler's number, approximatelyequalto2.71828. To prevent overfitting, we incorporate dropout layers, which randomly deactivate neurons during model training, and rectified linear units (ReLU) to efficiently handle gradient-based training. It is given by the Eq. (4).

$$Relu\ Function = max(0, \alpha) \tag{4}$$

where, α represents the Input value to the ReLU function. The ReLU function outputs the maximum of either 0 or the input value α. If α is negative, the ReLU function outputs 0; otherwise, its outputs α.

This process involves the expansion and training of a specialized CNN architecture tailored specifically for detecting COVID-19 from chest imaging data. The CNN architecture is trained using the labelled training dataset to learn the patterns and features associated with COVID-19 in chest imaging data. As the CNN trains on the chest imaging data, it automatically learns to extract relevant features and patterns from the input images. These features capture important characteristics indicative of COVID-19 infection, such as ground glass opacities, consolidation, and other abnormalities typically observed in chest imaging of COVID-19 patients. Once training is complete, the CNN is evaluated on the database to evaluate its concert and recognize latent problems such as underfitting. Finally, the trained CNN is tested on an independent dataset (the testing set) to evaluate its real-world performance.

Algorithm for the Proposed Multi-Modality COVID-19 Diagnosis System

Input: ECG data, X-ray images, CT images

Output: COVID-19 diagnosis

Start

Load the Input Images

Pre-Processing using Gaussian Filter

Resize CT images and X-ray to a standard resolution

Normalize intensity levels of images

Enhance image contrast

Apply Gaussian filtering for image smoothing and noise reduction

Feature Extraction and Pneumonia Detection using VGG19

Load pre-trained VGG19 model

Extract features from input images using VGG19

Classify features into pneumonia categories (viral, bacterial, normal)

Prediction of COVID-19 using Deep CNN

Optimizing pre-trained VGG19 model for COVID-19 detection

Train specialized CNN architecture for COVID-19 identification

Evaluate trained CNN on independent datasets

Output

COVID-19 diagnosis based on analysis of ECG, X-ray, and CT data

End

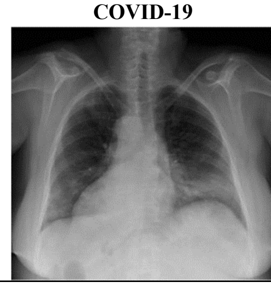
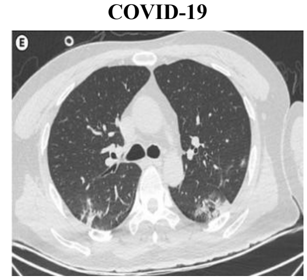
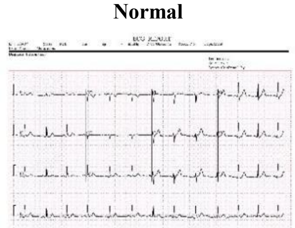
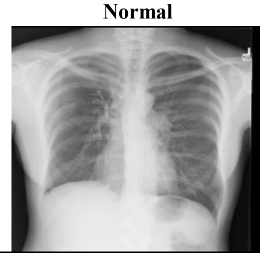
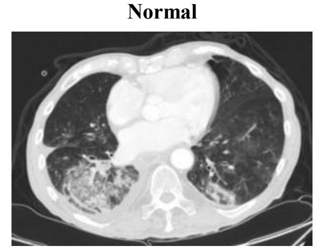
V. Results and Discussion

The Multi-Modality COVID-19 Diagnosis System, integrating ECG, X-ray, and CT data, demonstrated robust performance in enhancing COVID-19 diagnosis. The study's approach of implementing each dataset separately underscores its meticulous and thorough methodology in evaluating the performance of the proposed multi-modality COVID-19 diagnosis system. By analysing each dataset independently, the study ensures a comprehensive understanding of the system's effectiveness across various medical imaging modalities, including ECG, CT scans, and X-rays. Feature extraction and pneumonia detection using VGG19 facilitated the recognition of specific patterns indicative of viral or bacterial pneumonia, further enhancing COVID-19 diagnosis accuracy. The deep CNN, fine-tuned on extracted features from VGG19, effectively detected COVID-19 cases. Employing various neural layers ensured robust classification and regularization of the model. During training, the COVID-19 detection CNN iteratively adjusted parameters based on error, learning to extract relevant features suggestive of disease infection from input data. Implemented in Python software, the COVID-19 detection system achieved an impressive accuracy of 99% when evaluated on dataset. Implemented in Python software, the COVID-19 detection system achieved an impressive accuracy of 99.12% when evaluated on the Extensive COVID-19 X-Ray and CT Chest Images Dataset. Through iterative parameter adjustments based on error during Deep CNN training, the system learns to extract relevant features indicative of COVID-19 infection from chest imaging data. The evaluation on independent datasets, including the dataset, showcases anotable accuracy of 99.12% in detecting disease.

A. Dataset Comparison

Table II shows that the ECG abnormalities in Covid-19 patients could be attributed to myocardial damage, inflammation, or arrhythmias. A typical chest X-ray reveals clean lung fields, well-defined lung structures, and no evidence of infection or consolidation. It acts as a benchmark for comparison. Covid-19 pneumonia is often characterized by bilateral ground-glass opacities or consolidations on chest X-rays. A typical CT scan of the chest shows clear lung tissue and blood arteries, with no evidence of infection or inflammation. Covid-19 CT findings include bilateral GGOs, crazy-paving patterns, and consolidations.

TABLE II. Comparison of Dataset

ECG	X-Ray	CT Images
COVID-19 	**COVID-19** 	**COVID-19** 
Normal 	**Normal** 	**Normal** 

B. Evaluation of Performance for VGG 19 in Pneumonia Detection

Table III and Fig. 4 gives the comparison of VGG 19 with other existing models. The proposed VGG-19's precision is 99.4%. This indicates that the technique correctly predicts pneumonia 99.4% of the time. The proposed VGG-19 has a recall of 98.7%, which means it properly detects 98.7% of all cases of pneumonia. The proposed VGG-19 has an excellent F1 score of 99.32%. The proposed VGG-19 has an accuracy of 99%, demonstrating a high level of accuracy in pneumonia diagnosis. The proposed VGG-19 has superior precision, recall, F1-score, and accuracy in identifying pneumonia. Its outstanding performance makes it an attractive contender for use in clinical settings.

TABLE III. EVALUATION OF PERFORMANCE

Methods	Precision (%)	Recall (%)	F1- Score (%)	Accuracy (%)
Res Net 50[25]	95	95.3	96	95.6
Image Net[25]	98.2	97	97.4	97.68
Proposed VGG 19	99.4	98.7	99.32	99

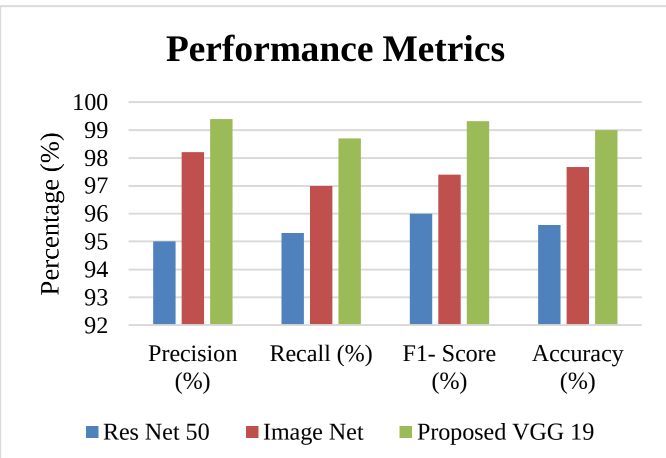


Fig. 4. Comparison of VGG performance with existing methods.

TABLE IV. COMPARISON OF THE PROPOSED VGG 19'S PERFORMANCE IN ECG,CTS AND X-RAY IMAGES

Proposed VGG 19	Accuracy (%)	Recall (%)	Precision (%)	F1 Score (%)
ECG	99.1	98.4	98	98.9
CTs	99	98.9	99.23	98.34
X-Ray	99.12	99.34	99.02	98.07

Fig. 5 and Table IV shows the accuracy of the proposed VGG 19 model. The suggested VGG-19 has an amazing 99.1% accuracy in categorizing ECG images. This high level of precision suggests that the model is good in detecting aberrant heart beats and patterns in ECG data. The proposed VGG-19 retains a high accuracy of 99% when identifying CT images. CT scans are critical for identifying a variety of illnesses, and the accuracy of the model provides repeatable findings. The Proposed VGG-19 obtains 99.12% accuracy on X-ray images. This precision is critical in diagnosing lung abnormalities, fractures, and other disorders evident on X-rays. The proposed VGG-19 performs consistently and robustly across multiple medical imaging modalities, making it an important tool for correct diagnosis and treatment of patients.

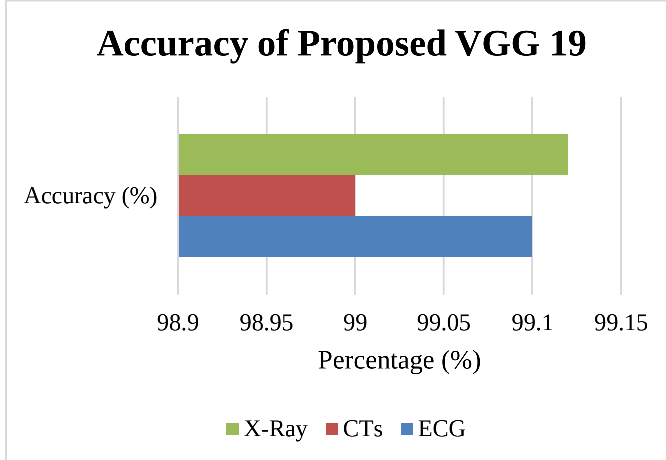


Fig. 5. Accuracy of proposed VGG 19.

C. Training and Validation Accuracy

As shown in Fig. 6, the training accuracy measures the efficiency with which the trained model responds to training data for every epoch. Training precision increases substantially with an increasing number of epochs. In the beginning, after 10 epochs, the model obtains a training accuracy of 0.41, indicating underfitting.

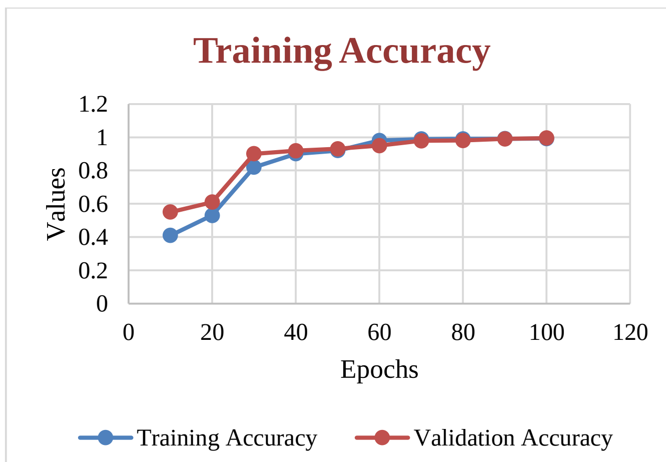


Fig. 6. Training accuracy of deep CNN.

But as training goes on, accuracy gradually improves. At 60 epochs, the training accuracy is 0.98. At 100 epochs, it has improved to 0.992. This pattern indicates that a model is acquiring information from the training information and getting more effective. Validation accuracy assesses how effectively the model extends to new data (validation set). Validation accuracy, like training accuracy, increases as epochs increase. The validation accuracy at ten epochs is 0.55. By the 100th epoch, it has reached an amazing 0.995, showing that the framework operates effectively with new information. The growing validation accuracy indicates that the prediction model has minimal overfitting and may generalize successfully. As the algorithm trains, the accuracies of both training and validation improve regularly. The model's performance maintains at roughly 100 epochs, indicating that more training could not considerably increase accuracy. It is critical to establish a balance between training for sufficient time to understand patterns while minimizing overfitting.

D. *Training and Validation Loss*

The training loss is the difference between both model's predicted and real desired outcomes at each epoch. As shown in Fig. 7, reduced training loss implies that the model is well fitted to the training data. In the supplied data, the training loss is 0.98 after 10 epochs. The training loss lowers continuously as the epochs advance, reaching 0.36 after 60 epochs. At 100 epochs, it drops to an excellent 0.16. This pattern indicates that the algorithm is absorbing information from training data and increasing its forecasting abilities. The validation loss indicates how effectively the model applies to previously unidentified information (validation set). Like training loss, smaller validation loss suggests higher adaptation. In the presented data, the validation loss is 0.89 after 10 epochs. By 100 epochs, it has dropped significantly to 0.11. The reduction in validation loss indicates that the algorithm has limited overfitting and will function well with new data. As the model learns, both training and validation losses gradually reduce. The gradual reduction of training and validation losses indicates that the algorithm is learning efficiently and without overfitting from occurring. The right quantity of epochs for training can be determined through observation of the loss curve. The Deep CNN has a positive loss curve, suggesting excellent learning and adaptation. Model training requires improving hyperparameters and ending quickly due to validation loss.

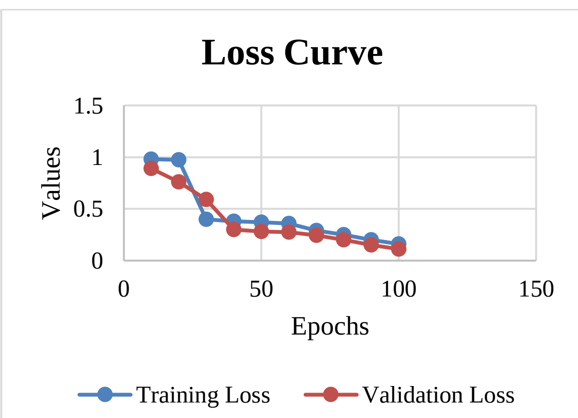


Fig. 7. Loss curve of deep CNN.

E. *ROC Curve*

Fig. 8 shows the Receiver Operating Characteristic Curve for the Deep CNN based on the provided True Positive Rate and False Positive Rate data. The ROC curve is an illustration of a classifier's efficiency at various classification levels. It compares the TPR (sensitivity or recall) to the FPR (1-specificity) when the value of the threshold for identifying positive and negative examples changes. The information being given demonstrates the TPR and FPR at different thresholds (0 to 0.6). At the lowest possible threshold (0), both TPR and FPR are zero, indicating that the model forecasts no positive events (either true or false positives). As the value of the threshold is raised, TPR gradually rises, showing that the model correctly recognizes more positive events. PR also rises, but at lower rates, implying that the model has produced certain false positive forecasts. At 0.6, the TPR is 0.991, indicating that the model accurately identifies 99.1% of positive cases. The FPR is also 0.991, meaning that the model mistakenly labels 99.1% of negative instances as positive.

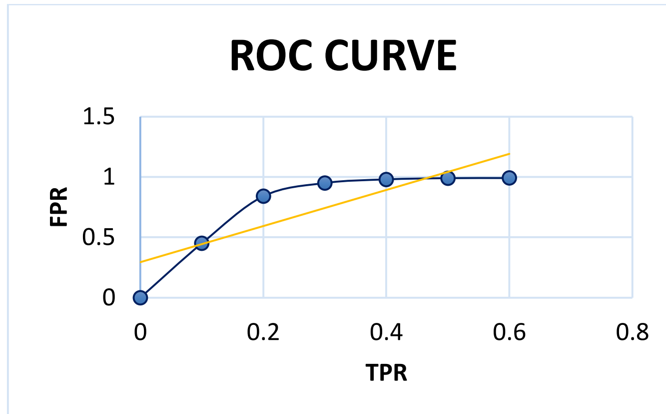


Fig. 8. ROC curve of DCNN.

F. *Comparison of the Proposed Deep CNNs Performance with Existing Methods*

The Deep CNN performed successfully, exceeding both Random Forest and Linear Ridge techniques. As shown in Fig. 9 and Table V, its high precision (99%), recall (99.1%), and F1-score (98.8%) suggest appropriate Covid-19 classification. The proposed CNN utilizes transferable learning and pre-trained structures, making it useful for medical imaging despite the low availability of information. The proposed Model achieves a high accuracy of 99.12%, which is comparably high with RF and Linear ridge methods.

G. *Discussion*

The results from the multi-modality COVID-19 diagnosis system, integrating ECG, X-ray, and CT scan data, enhancing the accuracy and performance of COVID-19 analysis. By leveraging VGG19 for feature extraction and pneumonia detection, the machine demonstrates robust performance in figuring out specific patterns indicative of viral or bacterial pneumonia, thereby augmenting the accuracy of COVID-19 prognosis [25]. The best-tuning of deep CNNs on extracted functions in addition complements the system's capability in detecting COVID-19 instances, making sure a complete method to disease identity.

TABLE V. COMPARISON OF PERFORMANCE IN COVID-19 CLASSIFICATION USING DEEP CNN

Methods	Precision (%)	Recall (%)	F1- Score (%)	Accuracy (%)
Random Forest [26]	58.8	56.3	57.3	56
Linear Ridge [26]	54.4	53.3	53.6	53.6
Proposed Deep CNN	99	99.1	98.8	99.12

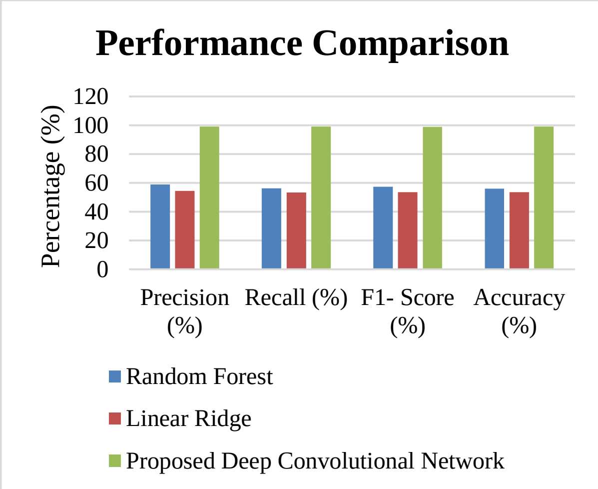


Fig. 9. Comparison of performance in COVID-19 classification using deep CNN.

The evaluation of the proposed VGG19 version's performance against present techniques highlights its superiority in precision, recall, F1-score, and accuracy in figuring out pneumonia throughout distinct imaging modalities. With precision achieving 99.4% and an accuracy of 99%, the proposed VGG19 version showcases good performance in pneumonia diagnosis, underscoring its ability for medical application [26]. Additionally, the version's constant and strong performance across numerous clinical imaging modalities, which include ECG, CT scans, and X-rays, emphasizes its versatility and reliability in helping accurate diagnosis and treatment selection-making.

The training and validation processes of the deep CNN elucidate the model's dynamics and generalization competencies. The determined patterns of growing training and validation accuracies imply the model's effective learning from the data at the same time as minimizing overfitting. The integration of training and validation losses similarly validates the model's efficient mastering method without conceding its capability to simplify to new data. The ROC curve evaluation affords insights into the version's sensitivity and specificity, showcasing its efficiency in categorizing positive instances while minimizing false-fine predictions. Overall, the contrast of the proposed deep CNNs overall performance with existing strategies underscores its efficacy in COVID-19 type, signifying its capacity as a valuable tool in clinical settings for correct disease diagnosis.

VI. Conclusion and Future Work

The multi-modality COVID-19 diagnosis system created in this work uses deep Convolutional Neural Network (CNN) algorithms to analyse CT, X-ray, and ECG images, which is a major breakthrough in medical diagnostics. The extraction of complementary information is made possible by the integration of many imaging modalities, which improves the overall efficiency and accuracy of diagnosis. Capturing the different patterns linked to COVID-19 in medical images, the CNN algorithms employed in this system are skilled in feature extraction and classification. Additionally, the ability to detect cardiac abnormalities—which are commonly seen in COVID-19 patients—enhances the diagnosis procedure when ECG data is included. Healthcare workers' diagnostic load is lessened by this automated, quick analysis capabilities, which makes processing massive amounts of medical data more effectively possible. The outcome of the study show that this technology has the potential to greatly enhance patient outcomes and diagnostic accuracy. However, further actions are required before its potential could be realized in clinical practice. To guarantee the system's dependability and efficacy across a range of patient demographics and healthcare contexts, validation via comprehensive clinical studies and real-world application is essential. Subsequent investigations have to concentrate on many crucial domains to augment the system's relevance and influence. Primarily, broadening the dataset to encompass a more diverse array of patient demographics and imaging modalities would enhance the system's resilience and generalizability. Through the implementation of cutting-edge machine learning techniques, the multi-modality COVID-19 diagnosis system shows great promise for revolutionizing COVID-19 diagnoses by increasing accuracy and efficiency. The problem identified in this paper include the complexity of integrating multi-modality data, the computational demands of training deep neural networks, and the need for extensive and diverse datasets to ensure the robustness of the system. Additionally, addressing potential biases in the training data and ensuring the generalizability of the model across different populations are critical challenges that need to be addressed in future research. This approach has the potential to be a vital weapon in the global fight against COVID-19, improving patient outcomes and healthcare delivery around the globe, if the previously indicated future research directions are addressed.

References

[1] M. Asif, Y. Xu, F. Xiao, and Y. Sun, "Diagnosis of COVID-19, vitality of emerging technologies and preventive measures," *Chem. Eng. J.*, vol. 423, p. 130189, Nov. 2021, doi: 10.1016/j.cej.2021.130189.

[2] "Deep insight: Convolutional neural network and its applications for COVID-19 prognosis," *Biomed. Signal Process. Control*, vol. 69, p. 102814, Aug. 2021, doi: 10.1016/j.bspc.2021.102814.

[3] "Advances in artificial intelligence for accurate and timely diagnosis of COVID-19: A comprehensive review of medical imaging analysis," *Sci. Afr.*, vol. 22, p. e01961, Nov. 2023, doi: 10.1016/j.sciaf. 2023.e01961.

[4] I. S. Farahat*et al.*, "The Role of 3D CT Imaging in the Accurate Diagnosis of Lung Function in Coronavirus Patients," *Diagnostics*, vol. 12, no. 3, Art. no. 3, Mar. 2022, doi: 10.3390/diagnostics12030696.

[5] "Magnetic resonance imaging features of coronavirus disease 2019 (COVID-19) pneumonia: The first preliminary case series," *Clin. Imaging*, vol. 69, pp. 261–265, Jan. 2021, doi: 10.1016/j.clinimag.2020.09.002.

[6] N. N. Khanna *et al.*, "Vascular Implications of COVID-19: Role of Radiological Imaging, Artificial Intelligence, and Tissue Characterization: A Special Report," *J. Cardiovasc. Dev. Dis.*, vol. 9, no. 8, Art. no. 8, Aug. 2022, doi: 10.3390/jcdd9080268.

[7] "A deep transfer learning-based convolution neural network model for COVID-19 detection using computed tomography scan images for medical applications," *Adv. Eng. Softw.*, vol. 175, p. 103317, Jan. 2023, doi: 10.1016/j.advengsoft.2022.103317.

[8] A. Rehman, T. Sadad, T. Saba, A. Hussain, and U. Tariq, "Real-Time Diagnosis System of COVID-19 Using X-Ray Images and Deep Learning," *IT Prof.*, vol. 23, no. 4, pp. 57–62, Jul. 2021, doi: 10.1109/MITP.2020.3042379.

[9] K. M. N. K. Khalif, W. Chaw Seng, A. Gegov, A. S. A. Bakar, and N. A. Shahrul, "Integrated Generative Adversarial Networks and Deep Convolutional Neural Networks for Image Data Classification: A Case

Study for COVID-19," *Information*, vol. 15, no. 1, Art. no. 1, Jan. 2024, doi: 10.3390/info15010058.

[10] M. Azeem *et al.*, "Neural Networks for the Detection of COVID-19 and Other Diseases: Prospects and Challenges," *Bioengineering*, vol. 10, no. 7, Art. no. 7, Jul. 2023, doi: 10.3390/bioengineering10070850.

[11] R. Grassi *et al.*, "COVID-19 pneumonia: computer-aided quantification of healthy lung parenchyma, emphysema, ground glass and consolidation on chest computed tomography (CT)," *Radiol. Med. (Torino)*, vol. 126, no. 4, pp. 553–560, Apr. 2021, doi: 10.1007/s11547-020-01305-9.

[12] M. Moitra, M. Alafeef, A. Narasimhan, V. Kakaria, P. Moitra, and D. Pan, "Diagnosis of COVID-19 with simultaneous accurate prediction of cardiac abnormalities from chest computed tomographic images," *PLOS ONE*, vol. 18, no. 12, p. e0290494, Dec. 2023, doi: 10.1371/journal.pone.0290494.

[13] T. Goel, R. Murugan, S. Mirjalili, and D. K. Chakrabartty, "OptCoNet: an optimized convolutional neural network for an automatic diagnosis of COVID-19," *Appl. Intell.*, vol. 51, no. 3, pp. 1351–1366, Mar. 2021, doi: 10.1007/s10489-020-01904-z.

[14] Y. Wu, A. Dravid, R. M. Wehbe, and A. K. Katsaggelos, "DeepCOVID-Fuse: A Multi-Modality Deep Learning Model Fusing Chest X-rays and Clinical Variables to Predict COVID-19 Risk Levels," *Bioengineering*, vol. 10, no. 5, Art. no. 5, May 2023, doi: 10.3390/bioengineering10050556.

[15] N. Fatima, R. Jahangir, G. Mujtaba, A. Akhunzada, Z. Hussain Shaikh, and F. Qureshi, "Multi-Modality and Feature Fusion-Based COVID-19 Detection Through Long Short-Term Memory," *Comput. Mater. Contin.*, vol. 72, no. 3, pp. 4357–4374, 2022, doi: 10.32604/cmc.2022.023830.

[16] M. Abdar*et al.*, "UncertaintyFuseNet: Robust uncertainty-aware hierarchical feature fusion model with Ensemble Monte Carlo Dropout for COVID-19 detection," *Inf. Fusion*, vol. 90, pp. 364–381, Feb. 2023, doi: 10.1016/j.inffus.2022.09.023.

[17] "ijcisim_1.pdf." Accessed: Feb. 19, 2024. [Online]. Available: https://www.softcomputing.net/ijcisim_1.pdf

[18] "A deep learning approach to detect Covid-19 coronavirus with X-Ray images," *Biocybern. Biomed. Eng.*, vol. 40, no. 4, pp. 1391–1405, Oct. 2020, doi: 10.1016/j.bbe.2020.08.008.

[19] E. Hussain, M. Hasan, M. A. Rahman, I. Lee, T. Tamanna, and M. Z. Parvez, "CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images," *Chaos Solitons Fractals*, vol. 142, p. 110495, Jan. 2021, doi: 10.1016/j.chaos.2020.110495.

[20] A. J. DeGrave, J. D. Janizek, and S.-I. Lee, "AI for radiographic COVID-19 detection selects shortcuts over signal," *Nat. Mach. Intell.*, vol. 3, no. 7, pp. 610–619, May 2021, doi: 10.1038/s42256-021-00338-7.

[21] A. M. Ismael and A. Şengür, "Deep learning approaches for COVID-19 detection based on chest X-ray images," *Expert Syst. Appl.*, vol. 164, p. 114054, Feb. 2021, doi: 10.1016/j.eswa.2020.114054.

[22] N. Nasir *et al.*, "Multi-modal image classification of COVID-19 cases using computed tomography and X-rays scans," *Intell. Syst. Appl.*, vol. 17, p. 200160, Feb. 2023, doi: 10.1016/j.iswa.2022.200160.

[23] "COVID 19 XRay and CT Scan Image." Accessed: Feb. 24, 2024. [Online]. Available: https://www.kaggle.com/datasets/ssarkar445/covid-19-xray-and-ct-scan-image-dataset.

[24] "COVID-19-ECG-Classification/covid19_ECG at main · mkfzdmr/COVID-19-ECG-Classification," GitHub. Accessed: Feb. 24, 2024. [Online]. Available: https://github.com/mkfzdmr/COVID-19-ECG-Classification/tree/main/covid19_ECG.

[25] W. N. Ismail, H. A. Alsalamah, and E. A. Mohamed, "Genetic-efficient fine-tuning with layer pruning on multimodal Covid-19 medical imaging," *Neural Comput. Appl.*, vol. 36, no. 6, pp. 3215–3237, Feb. 2024, doi: 10.1007/s00521-023-09194-5.

[26] Y. Wu, A. Dravid, R. M. Wehbe, and A. K. Katsaggelos, "DeepCOVID-Fuse: A Multi-Modality Deep Learning Model Fusing Chest X-rays and Clinical Variables to Predict COVID-19 Risk Levels," *Bioengineering*, vol. 10, no. 5, p. 556, May 2023, doi: 10.3390/bioengineering10050556.