IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Performance Analysis And Evaluation Of Deep Learning And Machine Learning Frameworks

N. Sundaravalli 1, Dr. R. Vidyabanu 2

1. Research Scholar, PG & Research Department Of Computer Science, L.R.G Govt. Arts College For Women, Tirupur – 4. India.

2. Assistant Professor, PG & Research Department Of Computer Science, L.R.G Govt. Arts College For Women, Tirupur-4. India.

Abstract: Covid-19 (SARC_CoV-2) instigated by a novel trait coronaviridae has become a universal health catastrophe were leads to significant efforts in early detection through medical imaging. This paper presents a Deep Learning (DL)-based method for automatically identifying Covid-19 from X-ray images of chest using a robust pipeline. The proposed method begins with denoising input images using Efficient Channel and Spatial Attention (ECSA) scheme to improve image quality and drop irrelevant noise. Feature extraction is done using Deep Convolutional Neural Network (DCNN) augmented with Multi-Head Channel Attention (MHCA) which facilitates the model to focus on multiple relevant feature representations simultaneously. For classification, a Modified CNN (MCNN) framework which is optimized for distinguishing amid Covid-19, Normal and Pneumonia cases is employed. Performance of the propounded model is assessed on Kaggle dataset and Curated dataset compiled from multiple public sources. Results demonstrate effectiveness of model with performance assessed based on Accuracy, Recall, Precision and F-measure, showing promising diagnostic capabilities across diverse datasets.

Keywords: Covid-19, Kaggle dataset, Curated dataset, Efficient Channel and Spatial Attention (ECSA), Multi-Head Channel Attention (MHCA), Modified CNN (MCNN), CNN eXtreme Gradient Boost (CNN_XGBOOST), Enhanced Convolutional Neural Network (ECNN), CNN- Random Forest (CNN_RF).

I. INTRODUCTION

Covid-19, a respiratory illness is caused by SARS-CoV-2. It spread very rapidly worldwide, causing global health crisis. The pandemic has significantly affected both individual lives and broader systems. In terms of health, it led to death of millions and severe illnesses, especially among the elderly and those with pre-existing conditions. Hospitals around the world faced unprecedented pressure, with limited resources and overworked medical personnel. In addition to the physical toll, the crisis led to a surge in mental health issues, with people experiencing anxiety, depression and emotional fatigue due to prolonged isolation and uncertainty.

Economically, this pandemic disrupted industries, trade and labour markets. Lockdowns and travel restrictions forced many businesses to shut down, particularly in sectors like hospitality, tourism and retail. Unemployment rates showed a rise, and many families faced financial insecurity. Supply chains were interrupted globally, leading to shortages in goods and rising prices in many areas. At the same time, the need for remote solutions accelerated the adoption of digital technology in work, education and healthcare. Socially, the effects were equally far-reaching

People were forced to alter their routines, stay away from loved ones, and live under strict public health guidelines. This reshaped social interactions and prompted widespread discussion about the importance of resilience, equity and community support during crises. Politically, the pandemic tested leadership and governance across the globe. It led to new public health policies, emergency laws and international cooperation efforts. However, it also revealed gaps in healthcare infrastructure, disparities in vaccine access and dangers of misinformation.

Ongoing research into Covid-19 and its broader impacts is crucial for several reasons. First, understanding long-term impact of virus on health including post-Covid conditions is essential for guiding future medical treatment and health policy. Secondly, the research helps in improving vaccine development, especially in adapting to new variants and ensuring equitable access across all countries. Moreover, studying economic and social consequences of pandemic can inform strategies to better prepare for future global disruptions. This includes designing more resilient healthcare systems, enhancing digital infrastructure for remote work and education, and developing economic safety nets for vulnerable populations. In short, continued research is not just about addressing the current crisis, but about learning from it to build a more prepared, equitable and resilient global society.

1.1 Deep Learning (DL) in Covid-19 Research

DL plays a dominant role in classification of Covid-19 datasets, particularly aiding in prompt detection as well as diagnosis of virus. One of the most significant applications has been in medical imaging, where DL models are trained to identify Covid-19 infections from X-rays and Computed Tomography (CT) scan images of chest. DL models are developed for automatically identifying Covid-19-related Pneumonia from these images, helping Physicians in making quicker and accurate diagnoses. The models can identify subtle patterns that may not be easily visible to the human eye, thereby enhancing early detection and reducing diagnostic delays, especially in resource-limited settings.

Convolutional Neural Network (CNN) which is effective in image recognition tasks is widely adopted for this purpose. These models can distinguish between Covid-19, other types of Pneumonia and healthy lungs by learning complex patterns in imaging data. Pre-trained CNNs such as ResNet, VGG, DenseNet and EfficientNet are often fine-tuned on Covid-specific datasets using Transfer Learning (TL) techniques to improve performance with limited medical data.

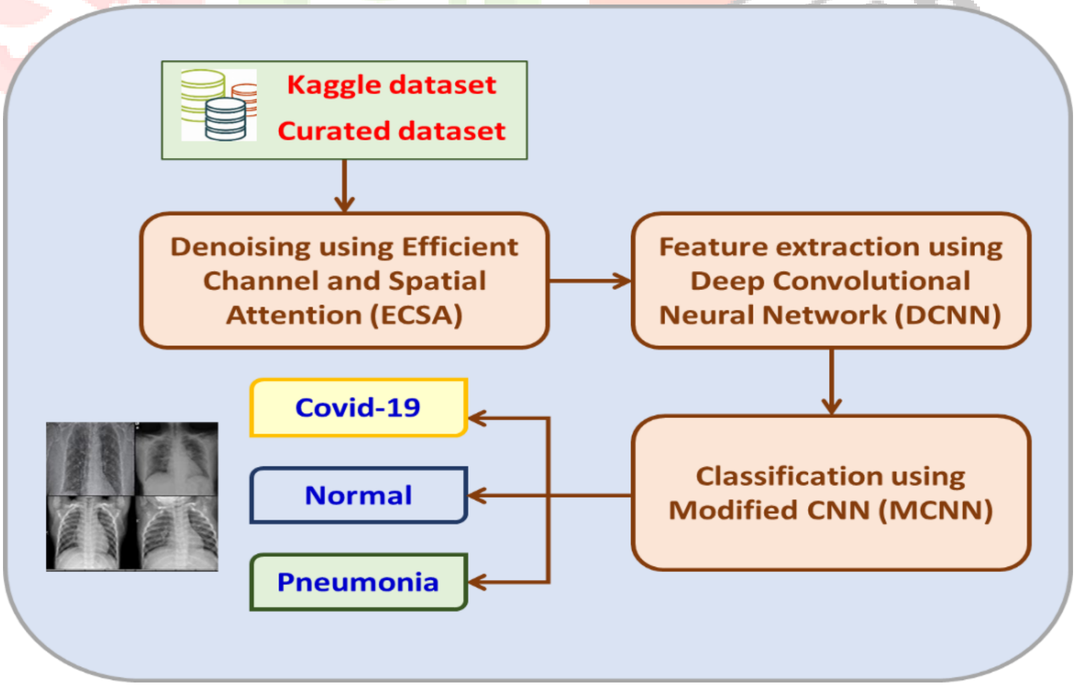

Figure 1: Proposed System

In addition to image-based diagnosis, DL is applied to structured clinical datasets containing patient demographics, symptoms, comorbidities and laboratory test results. Models such as Multi-Layer Perceptron (MLP) and Recurrent Neural Networks (RNN) are utilized to classify patient conditions, predict disease severity or assess likelihood of hospitalization or ICU admission. These approaches enable healthcare providers to make informed decisions about resource allocation and patient care. Further, hybrid models that integrate both imaging and clinical data offer even greater diagnostic accuracy by combining multiple sources of information. Overall, DL has become a powerful tool in managing Covid-19 pandemic by enabling faster and more accurate disease classification.

In this paper, Kaggle and Curated Covid-19 datasets are considered. Denoising of input images is performed using Efficient Channel and Spatial Attention (ECSA) scheme, followed by feature extraction using deep CNN augmented with Multi-Head Channel Attention (MHCA) strategy. Further classification is performed using Modified CNN (MCNN) architecture. Performance is analysed based on Precision, Accuracy, Recall and F-measure. Figure 1 gives a view of the work done in this paper.

II. RELATED WORK

Mansour et al (2021) [7] have designed Unsupervised DL based Variational Autoencoder (UDL-VAE) framework for both diagnosis as well as classification of Covid-19 from X-ray images. The proposed model incorporates adaptive Wiener Filtering (WF) to improve image quality, employs Inception v4 architecture with Adagrad optimizer for effective feature extraction and utilizes VAE for unsupervised classification. Evaluated on a dataset comprising various pulmonary conditions, including Covid-19, the UDL-VAE model offers improved accuracy rates for binary and multi-class classification outperforming several existing methods. The model's reliance on unsupervised learning may limit its ability to capture nuanced distinctions between similar pulmonary conditions, potentially affecting classification precision.

Shankar & Perumal (2021) have offered Fusion Model with Hand-Crafted Features and DL Features (FM-HCF-DLF), a fusion-based approach which combines hand-crafted as well as DL features for diagnosing Covid-19 using X-ray images. The model's operations commence with Gaussian filtering to lessen noise in images. Feature extraction is performed by merging Local Binary Patterns (LBP) for capturing texture-based hand-crafted features and Inception v3 CNN for DL features. The Inception v3 model's performance is enhanced using Adam optimizer involving a learning rate scheduler. Finally, a MLP classifier is used for categorising images. The propounded model offers better accuracy, specificity, F1-score, sensitivity, precision and kappa value indicating its effectiveness in classifying Covid-19 from other pulmonary conditions. The model's dependence on a relatively small dataset may limit its applicability to larger, more diverse populations.

Kumar et al (2022) have introduced multi-modal fusion framework for timely diagnosis as well as precise categorization of Covid-19 patients by integrating X-ray images and processing of speech signals. The framework utilizes DL models for determining features from X-ray images as well as audio samples of cough, employing a weighted sum rule fusion technique for integrating modalities. The system offers improved recognition accuracy, specificity and sensitivity. The fusion approach is capable of imaging and audio data for effective Covid-19 diagnosis. The reliance on publicly available datasets for cough audio samples may limit model's generalizability across diverse populations and real-world scenarios.

Althaqafi et al (2023) have introduced Self-Configured Optimized Deep Learning with Dual-Dimensional Classification (SCODL-DDC) model, an advanced AI framework for Covid-19 detection and categorisation by using X-ray images. The model integrates EfficientNet for feature extraction, optimized through Sine Cosine Optimization (SCO) algorithm and employs Quantum Neural Network (QNN) for classification, with its parameters fine-tuned using Equilibrium Optimizer (EO). This multi-faceted approach aims at enhancing diagnostic accuracy and efficiency in identifying Covid-19 cases from radiographic data. Inclusion of complex optimization techniques and quantum neural networks increases computational demands, potentially limiting the model's practicality in resource-constrained clinical environments.

Bhosale & Patnaik (2023) have proposed PulDi-Covid, an ensemble deep CNN. The network model is designed to classify different pulmonary conditions including Covid-19 and Chronic Obstructive Pulmonary Diseases (COPDs) using X-ray images. The system integrates pre-trained CNNs using Snapshot Stacked

Ensemble (SSE) approach for improving diagnostic accuracy and reducing classification bias. Trained on diverse datasets from multiple public sources, the model achieves high classification accuracy. The study also introduces a user-friendly graphical interface for potential deployment in clinical decision-making to reduce severity and mortality rates among patients with overlapping respiratory conditions. The model's near-perfect accuracy for some classes suggests overfitting, which may hinder its generalizability on unseen data.

Ullah et al. (2023) have introduced DeepLungNet, a DL framework designed for classification of diverse lung diseases using Chest Radiographic Images (CRIs). The model includes 20 learnable layers, including 2 Fully Connected (FC) layers and 18 convolutional layers, and incorporates architectural features such as Leaky ReLU activation functions, fire modules, batch normalization, group convolution and max pooling layers, and shortcut connections. DeepLungNet is evaluated on 2 datasets involving different classes like tuberculosis, viral and bacterial Pneumonia, Normal, Covid-19 and lung opacity, offering an improved accuracy. The study highlights model's potential in aiding prompt detection as well as classification of lung diseases, thus enhancing outcomes and reducing the spread of infectious illnesses. Performance of the model is validated in real clinical settings, which limits its applicability in practical healthcare environments.

Nawaz et al (2024) have introduced DL-based Covid-ECG-RSNet model designed to categorise Covid-19 and other cardiac conditions using ECG images. The model enhances traditional ResNet architecture by incorporating the Swish activation function, which improves gradient flow and learning efficiency. Trained on a dataset with several images, the proposed scheme offers improved accuracy, precision and recall demonstrating its effectiveness in distinguishing between Covid-19, myocardial infarction, abnormal heartbeats and normal heart conditions. However, the model's reliance on a relatively small and potentially homogeneous dataset may limit its generalizability to diverse patient populations and real-world clinical scenarios.

Ullah et al (2024) have designed ChestCovidNet, a lightweight and robust DL model for classification into lung opacity and Pneumonia by using Chest Radiograph Images (CRIs). The architecture comprises 11 learnable layers, comprising of 8 convolutional layers and 3 FC layers, and incorporates features such as Leaky ReLU activation functions, group convolutions, ShuffleNet units, and batch normalization and cross-channel techniques. Trained as well as tested on a dataset, the proposed scheme offers improved classification performance demonstrating its effectiveness and efficiency in detecting multiple lung conditions from CRIs. The model's performance has not been validated in real-world clinical settings, which may limit its applicability in practical healthcare environments.

Balasamy & Seethalakshmi (2025) have introduced Hybrid Classification Optimization using Recurrent Learning and Fuzzy (HCO-RLF), a hybrid optimization model designed for classification that combines Recurrent Learning (RL) and Fuzzy Logic (FL) for detecting Covid-19 from CT images. The model includes RNNs for capturing temporal patterns in imaging data and applies fuzzy logic to handle uncertainties inherent in medical imaging. This hybrid approach aims at enhancing diagnostic accuracy and reliability in identifying Covid-19 cases. Integration of RNNs and FL increases the model's complexity, potentially leading to higher computational demands and longer processing times, which may hinder its applicability in real-time clinical settings.

III. DENOISING USING EFFICIENT CHANNEL AND SPATIAL ATTENTION (ECSA)

ECSA is used for denoising CXR images. This method aids in preserving complex anatomical details like hemi-diaphragm edges, and offers enhanced classification for Covid-19 detection. It includes channel as well as spatial attention enabling the network to aim at texture information in '$C \times R$' images and lessen number of parameters.

Channel attention aims at enhancing or suppressing specific channels in feature maps to enhance performance of image denoising, particularly for images of shape '$C \times R$'. To achieve this, the mechanism models relative importance of every feature channel. Given input feature maps '$M_C = R^{H \times W \times C}$', Global Average Pooling (GAP) is applied on compressing spatial dimensions and producing compact channel-wise descriptor '$d \in R^{1 \times 1 \times C}$'. Traditionally, this descriptor is passed through 2 FC layers to facilitate lessening of dimensions and capturing cross-channel dependencies. Nevertheless, this dimension reduction can introduce a loss of information, adversely affecting the quality of channel attention prediction.

To overcome this, FC layers are replaced with a 1D convolution operation using a kernel of size of 5 and padding of 2. This maintains the channel dimension while enabling local cross-channel interaction with a significantly lower computational cost. Next, the feature descriptor is passed through sigmoid activation function for producing attention weights '$\hat{d} \in R^{1\times1\times C}$', which are then used to reweight the original input feature maps via element-wise multiplication:

$$\text{Output} = M_c \odot \hat{d} \tag{1}$$

This approach avoids the drawbacks of dimension reduction while preserving inter-channel relations effectively and efficiently, leading to notable improvements in denoising performance.

The spatial attention component is responsible for emphasizing relevant regions in a feature map. Starting with a feature tensor ($M_S = R^{H\times W\times C}$), pooling operations like GAP and Global Max Pooling (GMP) are applied independently across channel axis. These operations extract spatial cues that capture the distribution of features from different perspectives.

$$F_{avg}^{c} = \text{GAP}(F) \in R^{C\times1\times1} \tag{2}$$

$$F_{max}^{c} = \text{GMP}(F) \in R^{C\times1\times1} \tag{3}$$

These are passed through shared MLP.

$$M_c = \sigma\left(W_2.\delta\left(W_1.F_{avg}^{c}\right) + W_2.\delta(W_1.F_{max}^{c})\right) \tag{4}$$

Where:

- $W_1 \in R^{\frac{C}{r}\times C}$ and $W_2 \in R^{C\times\frac{C}{r}}$ are learned weights (with reduction ratio r)
- δ - ReLU activation
- σ - Sigmoid function
- $M_c \in R^{C\times1\times1}$ - Channel Attention Map

Outputs of pooling operations are then stacked along channel dimension, producing a combined tensor '$F_S = R^{H\times W\times 2}$'. This tensor is fed into convolutional layer. Sigmoid activation which yields spatial attention map $(\hat{F}_S = R^{H\times W\times 1})$ highlighting important spatial regions follows the convolutional layer.

Finally, attention map is multiplied element-wise with original input 'M_S', producing spatially attended features. The ECSA module integrates both channel and spatial attention in a residual block structure to improve feature refinement, particularly for tasks like image restoration or denoising. The process begins with a convolution layer (kernel size '3×3') for extracting initial low-level features, followed by PReLU activation function for introducing non-linearity. Next convolution layer (also '3×3') is then applied to enhance the features before attention mechanisms are introduced. The output is split and passed through two parallel branches: A channel attention branch, where channel-wise significance is computed using global pooling and a lightweight 1D convolution to capture inter-channel dependencies without dimensionality reduction.

Spatial attention branch captures key spatial features through pooling and convolution. The outputs from both branches are integrated along channel axis to fuse refined information from both attention perspectives. A final '3×3' convolution layer processes this concatenated output to extract residual information. This residual is then added to the module's original input, forming a skip connection and completing the residual block:

$$\text{Final Output} = \text{Input} + \text{Conv}_{3\times3}([\text{Channel Output} \| \text{Spatial Output}]) \tag{5}$$

This design allows the network to focus on both where and what to emphasize in the feature maps, leading to improved performance with minimal additional computational burden.

IV. FEATURE EXTRACTION USING MULTI-HEAD CHANNEL ATTENTION (MHCA) IN DEEP CNN

This attention module introduces a novel mhca strategy, specifically designed to boost feature learning and classification accuracy in medical imaging applications. It operates on feature tensors output by convolutional layers, which represent abstract, high-level features extracted from input images.

- **Channel Compression via Weighted Pooling:** Weighted Global Average Pooling (WGAP) operation is applied, compressing spatial dimensions of input while retaining original quantity of channels. This step converts the input feature map into a single-channel descriptor for each feature map, maintaining essential channel-wise context.
- **Attention Head Structure:** At the heart of the block is its multi-head design, where multiple attention heads are used in parallel to capture various types of channel relationships. Each head independently learns to assign importance to different channels, enhancing the model's flexibility and interpretability. The number of heads is set to 16 by default. Each head performs the following operations:
  - ✓ The first dense layer reduces channel dimension based on tunable reduction ratio (chosen empirically). ReLU activation follows for introducing non-linearity.
  - ✓ The second dense layer aids in restoring the original dimension. It uses a sigmoid function for computing attention scores that indicate the significance of each channel.
  - ✓ These attention scores are multiplied element-wise with the pooled channel descriptor, producing a weighted output that emphasizes relevant channels.
- **Aggregation and Further Processing:** The outputs from all attention heads are aggregated to combine the different learned perspectives. This combined feature is then reshaped to ensure compatibility with subsequent layers in the model. A final FC layer is used to further refine representation, facilitating capture of more abstract and complex patterns in the data.
- **Impact and Use Case:** By enabling the network to evaluate feature channels from multiple viewpoints, this mechanism increases model's capability for focusing on critical information while filtering out irrelevant or noisy features. This is predominantly valuable in complex classification tasks like identifying Covid-19 from CT scan images, where precision and attention to detail are essential.

Steps involved in MHCA

- **Channel-Wise Feature Descriptor:** To compute channel attention, a descriptor is often obtained using GAP.

$$f_c = GAP(F) \in R^C \tag{6}$$

- **Multi-Head Mechanism:** For multi-head attention, let there be 'h' heads. Each head learns an independent transformation of the channel-wise descriptor:

$$M_j = \sigma\left(W_j^2 . \delta\left(W_j^1 . f_c\right)\right), j = 1,2 \dots h \tag{7}$$

  - ✓ $W_j^1 \in R^{\frac{C}{r} \times C}$ and $W_j^2 \in R^{C \times \frac{C}{r}}$ - Learnable weights
  - ✓ δ - ReLU activation function
  - ✓ σ - Sigmoid activation to scale attention weights between '0' and '1'
  - ✓ r - Reduction ratio for compression of dimensionality
- **Attention Aggregation:** Attention is aggregated from all heads by averaging or concatenation followed by transformation.

$$M = \frac{1}{h}\sum_{j=1}^{h} M_j \tag{8}$$

$$M = FC([M_1, M_2, .. M_h]) \tag{9}$$

Where 'FC' is a fully connected layer if concatenation is used

- **Feature Recalibration:** The final attention vector '$M \in R^{C}$' is applied back to the original feature map:

$$F' = M \odot F \tag{10}$$

Where:

✓ $\odot$ - denotes channel-wise multiplication (broadcasting M across H and W).

V. CLASSIFICATION USING MODIFIED CNN

To classify medical images, a Modified CNN (MCNN) is developed using Keras library. The model is defined through a function called make_model, which accepts two parameters: input_shape and num_classes. Rather than collecting additional data, the model leverages data augmentation techniques to diversify the training samples. This includes rescaling input images to a 0-1 range, which improves training efficiency.

The network architecture includes multiple convolutional layers which are followed by ReLU activation, batch normalization, max pooling for reducing spatial dimensions and dropout layers for preventing overfitting. The architecture is specifically tuned, employing varying filter sizes and increasing dropout rates across layers to improve learning capability and generalization.

Global average pooling layer follows convolutional blocks for reducing the quantity of trainable parameters and simplifying the model. This is succeeded by a FC (dense) layer with ReLU activation and dropout rate of 0.5 for further mitigating overfitting. The output layer is dynamically selected based on classification type: Sigmoid activation (binary) and softmax activation (multi-class).

The model is optimized using Adam optimizer with less learning rate to ensure stable convergence. It uses sparse categorical cross-entropy as loss function. During training, callbacks such as early stopping are applied to halt training if the validation loss stagnates, and a learning rate scheduler is employed to progressively decrease learning rate over time, improving training dynamics.

MCNN is specifically tailored for classifying medical images like identifying Pneumonia and Covid-19. It utilizes advanced augmentation schemes like random horizontal flips, small-angle rotations and zooming to improve generalization and robustness. Convolutional layers use filter sizes of 32, 64, 128 and 256 for extracting features at different abstraction levels. Dropout layers (in the range 0.3 to 0.5) and max pooling further help control overfitting and reduce computational overhead.

A dense layer with 256 neurons processes the pooled features before final classification step. The combination of these design elements enables MCNN to learn discriminative features, generalize across different data distributions, and perform reliably across varying classification scenarios. The model achieves improved validation accuracy and validation loss, indicating better performance in both learning from training data and classifying unseen cases.

Additionally, the model's architecture is supported by a pseudocode structure which outlines the specific layer configurations and training steps implemented.

Pseudocode of CNN model architecture

```
Make_Model(shape, num_class)
input = keras.Input(input_shape)
x = data_augment(input)
x = layer.experiment.preprocess.rescale(1.0/255)(x)
# Adding more convolutional layers and adjusting filter sizes
for filters in {32, 64, 128, 256}
        x = layer.Conv2D(filters, 3, padding='same', kernel_regularizer=l2(0.01))(x)
        x = layer.Batch_Normalise()(x)
        x = layer.Activation("relu")(x)
        x = layer.Max_Pool2D()(x)
        x = layer.Dropout(0.3)(x) # Increased dropout rate
        x = layer.GAP_2D()(x) # Using
        GlobalAveragePooling2D before the dense layer
        x = layer.Dense(256, activation='ReLu', kernel_regularizer=l2(0.01))(x)
        x = layer.Dropout(0.5)(x)
        if (num_class==2)
                activation = 'sigmoid'
                units = 1
        else
              activation = 'softmax'
              units = num_class
              output = layer.Dense(units, activation)(x)
        return (keras.Model(inputs, outputs))
end function
```

VI. DATASETS USED

In this section, details of datasets used for study are included.

6.1 Kaggle Dataset

The dataset comprising Chest X-Ray (CXR) images of Covid-19, normal and other lung infections has been released in multiple phases. Initially, it included 219 images of Covid-19 cases, 1341 normal cases, and 1345 cases of viral pneumonia. In the first update, the number of Covid-19 images was expanded to 1200. A second update further enlarged the dataset to 3616 confirmed Covid-19 cases, 10192 normal cases, 6012 cases of lung opacity (non-Covid lung infections), and 1345 viral pneumonia cases, each accompanied by corresponding lung masks. The dataset will continue to be updated as new Covid-19-related X-ray images become available. [16].

6.2 Curated Dataset

This dataset is a curated collection of Covid-19 X-ray images compiled from 15 publicly accessible sources. The initial compilation includes 1,281, 3,270, 1,656 and 3,001 X-rays of Covid-19, normal, viral Pneumonia and bacterial Pneumonia. To create a more comprehensive resource, all gathered datasets are merged into a single integrated repository, resulting in a total of 4,558, 5,403, 4,497 and 5,768 X-rays of Covid-19, normal, viral Pneumonia and bacterial Pneumonia. Duplicate images are identified using similarity analysis which reveals 1,379, 1,476, 2,690 and 2,588 redundant X-rays of Covid-19, normal, viral Pneumonia and bacterial Pneumonia. The duplicates were subsequently removed to ensure dataset integrity. [17].

VII. RESULTS AND DISCUSSION

Inclusion of attention mechanisms significantly improves model's capability for isolating and focusing on diagnostically relevant areas in X-ray images. ECSA aids in pre-processing by reducing noise and highlighting key features, while MHCA ensures comprehensive feature learning. The proposed MCNN performs efficiently with minimal overfitting and reveals strong generalization. Performance is analysed based on Accuracy, Recall, Precision and F_Measure for Kaggle and Curated datasets. Initially, the results obtained for Kaggle dataset are discussed.

Figure 2 shows the Accuracy obtained for Kaggle dataset. The proposed MCNN offers 4% and 1% better Accuracy in contrast to CNN_RF and CNN_XGB respectively, and 2% lesser Accuracy when compared to Ensemble CNN (ECNN).

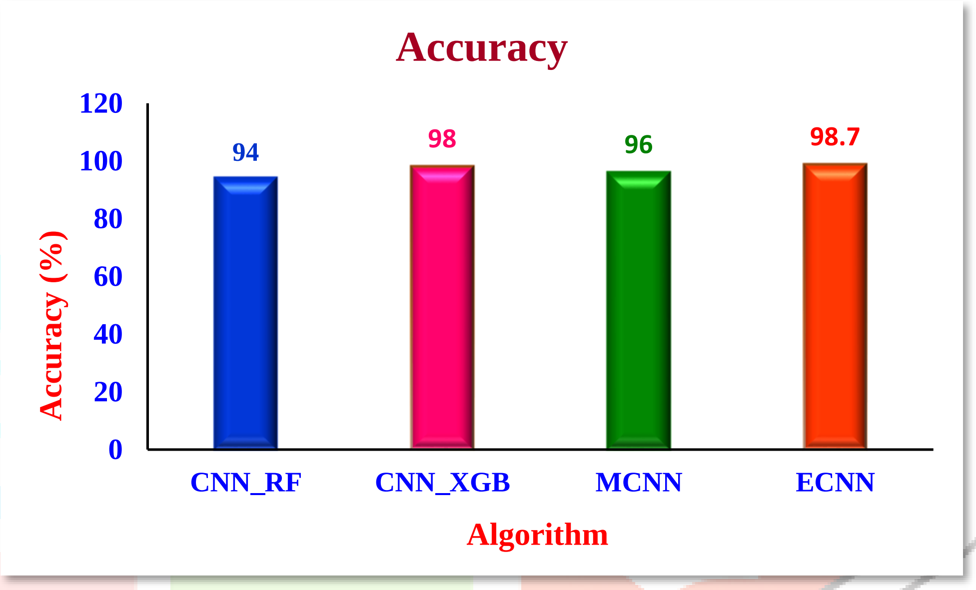

Figure 2: Accuracy for Kaggle Dataset

Figure 3 shows the Precision obtained for Kaggle dataset. The proposed MCNN offers 5% and 4% better Precision when compared to CNN_RF and CNN_XGB respectively, and 1% lesser Precision in contrast ECNN. Figure 4 shows the Recall obtained for Kaggle dataset. The proposed MCNN offers 3% and 2% better Recall in contrast to CNN_RF and CNN_XGB respectively, and 2% lesser Recall when compared to ECNN. Figure 5 shows the F-Measure obtained for Kaggle dataset. The proposed MCNN offers 4% and 3% better F-Measure when compared to CNN_RF and CNN_XGB respectively, and 2% lesser F-Measure in contrast ECNN.

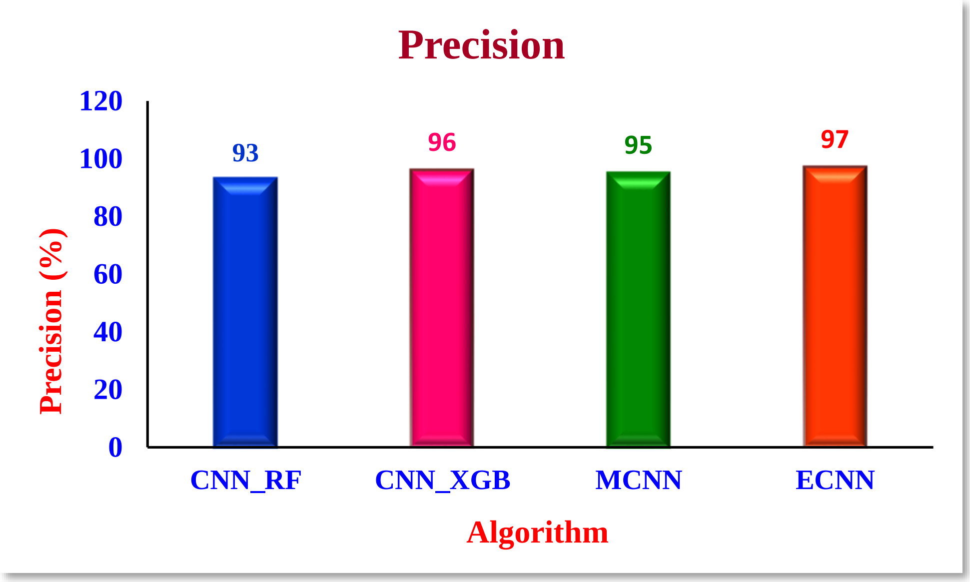

Figure 3: Precision for Kaggle Dataset

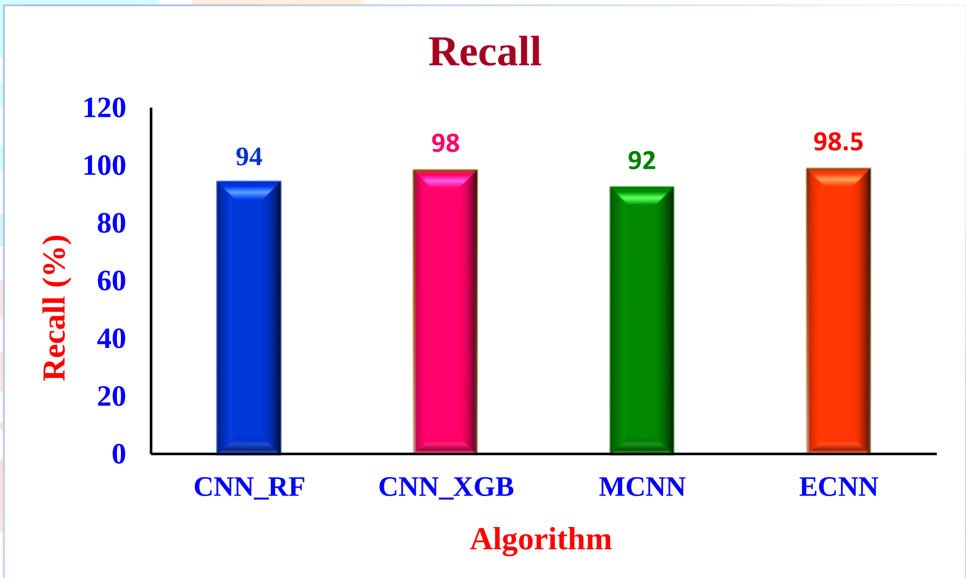

Figure 4: Recall for Kaggle Dataset

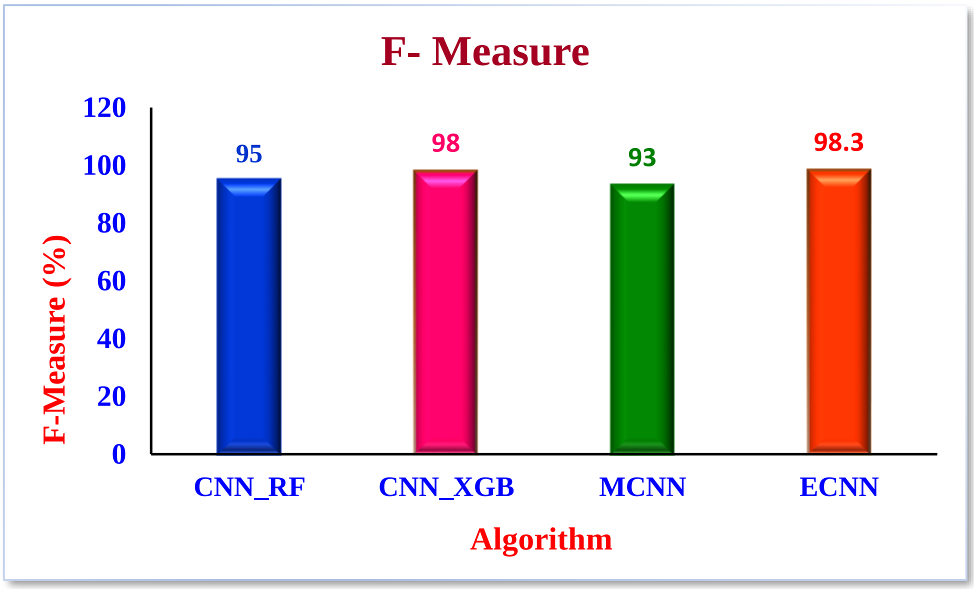

Figure 5: F-measure for Kaggle Dataset

Figure 6 shows the Accuracy obtained for Curated dataset. The proposed MCNN offers 5% and 4% better Accuracy in contrast to CNN_RF and CNN_XGB respectively, and 3% lesser Accuracy when compared to Ensemble CNN (ECNN). Figure 7 shows the Precision obtained for Curated dataset. The proposed MCNN offers 5% and 3% better Precision when compared to CNN_RF and CNN_XGB respectively, and 2% lesser Precision in contrast ECNN.

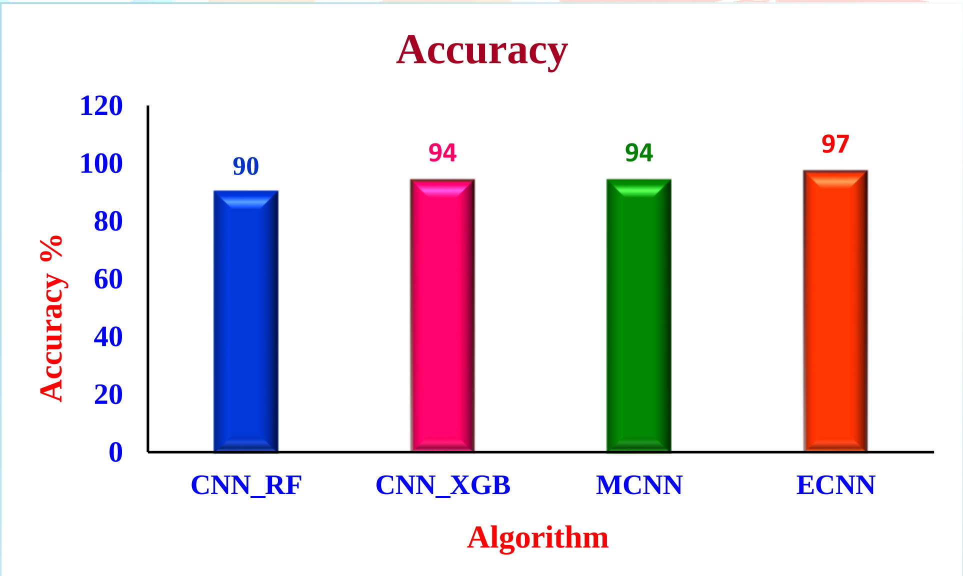

Figure 6: Accuracy for Curated Dataset

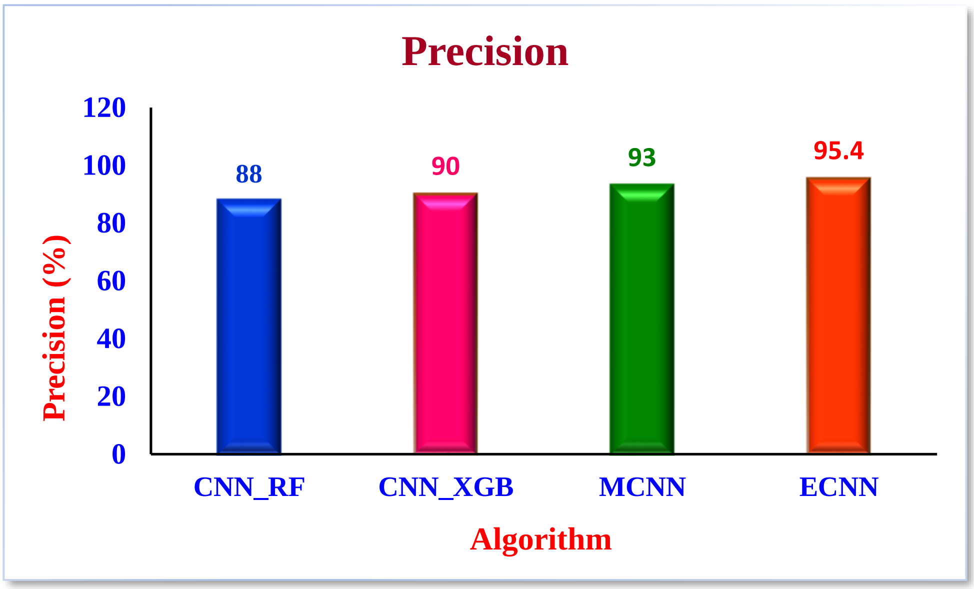

Figure 7: Precision for Curated Dataset

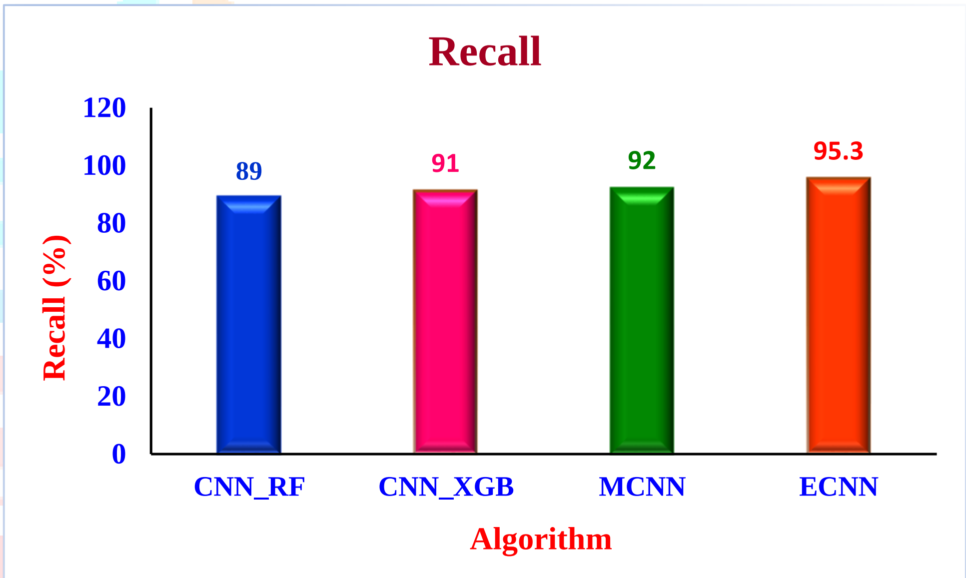

Figure 8: Recall for Curated Dataset

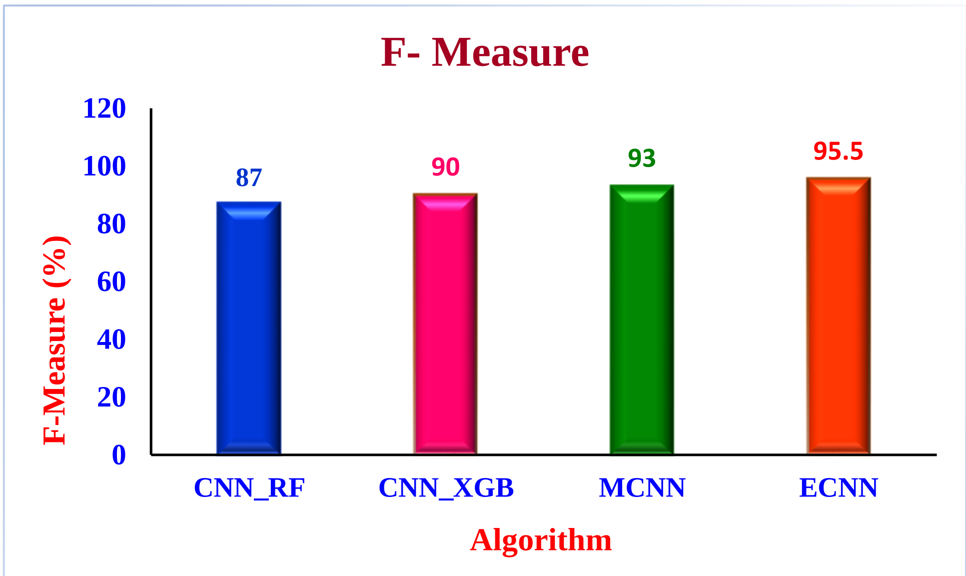

Figure 9: F-measure for Curated Dataset

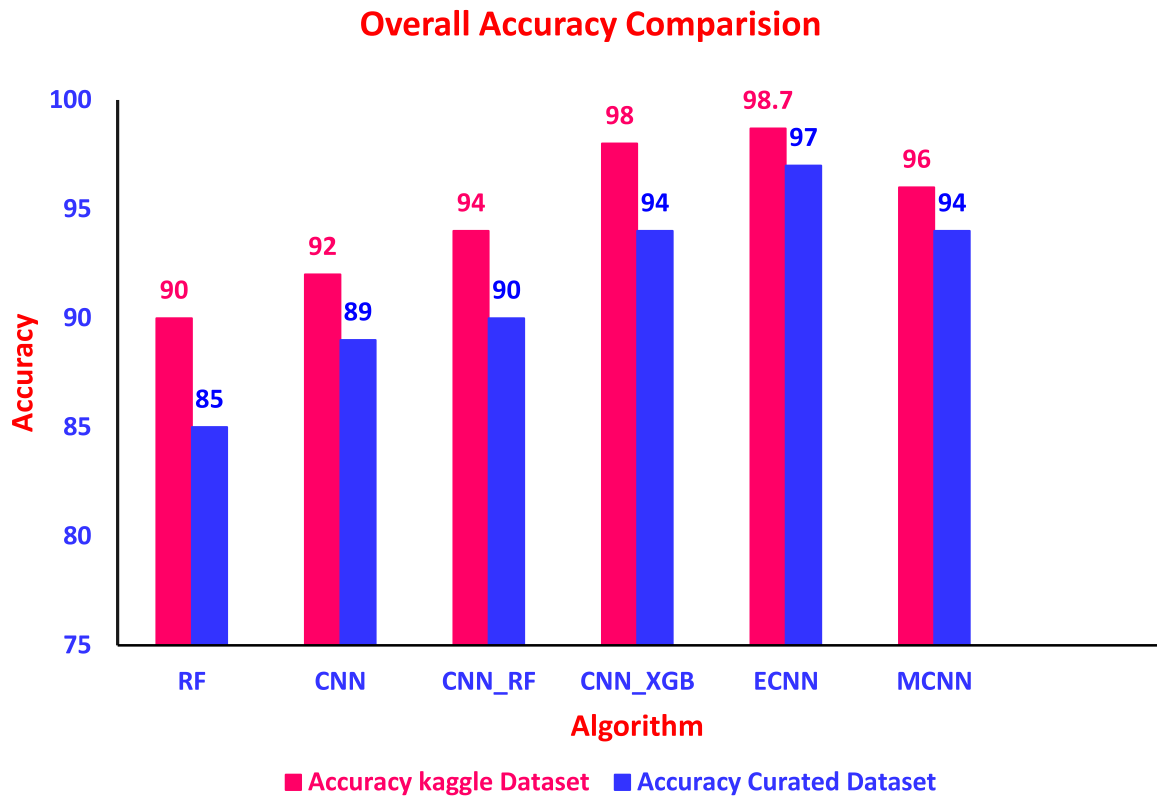

Figure 10 : Overall Accuracy Comparision

Figure 8 shows the Recall obtained for Curated dataset. The proposed MCNN offers 3% and 1% better Recall in contrast to CNN_RF and CNN_XGB respectively, and 2% lesser Recall when compared to ECNN. Figure 9 shows the F-Measure obtained for Curated dataset. The proposed MCNN offers 6% and 3% better F-Measure when compared to CNN_RF and CNN_XGB respectively, and 2% lesser F-Measure in contrast ECNN. Figure 10 shows the Kaggle dataset obtained better accuracy of RF 5%, CNN 3%,CNN_RF 4%, CNN_XGB 4%,ECNN 1.7% and MCNN 2%than Curated dataset. It is obivious that the proposed comprehensive overall accuracy of ECNN offers better result obtained in kaggle dataset than in curated dataset.

VIII. CONCLUSION

In this paper, a comprehensive deep learning framework is propounded for Covid-19 detection from X-ray images, integrating denoising, advanced feature extraction and classification into a unified pipeline. The Efficient Channel and Spatial Attention (ECSA) mechanism significantly improves input quality, while Multi-Head Channel Attention (MHCA) in Convolutional Neural Network (CNN) architecture enhances extraction of discriminative features across channels. The final classification using an ECNN model achieves high performance, validated through extensive testing on both Kaggle and curated datasets. Performance is analysed in terms of Recall, Accuracy, Precision and F-measure to confirm model's robustness and generalizability. It is obivious that the proposed comprehensive overall accuracy of ECNN offers better result obtained in kaggle dataset than in curated dataset. These results show the potential of attention-driven DL models in supporting fast and reliable Covid-19 diagnosis from radiographic images particularly in resource-limited environments.

REFERENCES

[1] Ciotti, M., Ciccozzi, M., Terrinoni, A., Jiang, W. C., Wang, C. B., & Bernardini, S. (2020). The COVID-19 pandemic. Critical reviews in clinical laboratory sciences, 57(6),365-388.

[2] Shi, Y., Wang, G., Cai, X. P., Deng, J. W., Zheng, L., Zhu, H. H., ..& Chen, Z. (2020). An overview of COVID-19. Journal of Zhejiang University. Science. B, 21(5), 343.

[3] Velavan , T. P., & Meyer , C. G. (2020) . The COVID - 19 epidemic . Tropical medicine & international health, 25(3), 278.

[4] Suryasa , I. W., Rodríguez - Gámez , M., & Koldoris , T. (2021) . The COVID - 19 pandemic International Journal of Health Sciences, 5(2), 572194.

[5] Ciotti, M., Angeletti, S., Minieri, M.,Giovannetti, M., Benvenuto, D.,Pascarella, S., & Ciccozzi,M. (2020).COVID-19 outbreak: an overview. Chemotherapy, 64(5-6),215-223.

[6] Baloch, S., Baloch, M.A., Zheng, T., & Pei, X. (2020).The coronavirus disease 2019 (COVID-19) pandemic. The Tohoku journal of experimental medicine, 250(4), 271-278.

[7] Mansour, R. F., Escorcia-Gutierrez, J., Gamarra, M., Gupta, D., Castillo,O., & Kumar, S. (2021). Unsupervised deep learning based variational autoencoder model for COVID - 19 diagnosis and classification. Pattern Recognition Letters, 151, 267-274.

[8] Shankar, K., & Perumal, E. (2021). A novel hand-crafted with deep learning features based fusion model for COVID-19 diagnosis and classification using chest X-ray images. Complex & Intelligent Systems, 7(3), 1277-1293.

[9] Kumar, S., Chaube, M. K., Alsamhi, S. H., Gupta, S. K., Guizani, M., Gravina, R., & Fortino, G (2022) . A novel multimodal fusion framework for early diagnosis and Accurate classification of COVID-19 patients using X - ray images and speech signal processing techniques. Computer Methods and programs in biomedicine, 226, 107109.

[10] Althaqafi,T.,Al-Ghamdi, A.S. A.M., & Ragab, M.(2023). Artificial intelligence based COVID-19 detection and classification model on chest X-ray images. In Healthcare, Vol . 11, No. 9, p. 1204.

[11] Bhosale, Y. H., & Patnaik, K. S. (2023). PulDi-COVID : Chronic obstructive pulmonary (lung) diseases with COVID -19 classification using ensemble deep convolutional neural network from chest X-ray images to minimize severity and mortality rates. Biomedical Signal Processing and Control, 81, 104445.

[12] Ullah, N., Marzougui, M., Ahmad, I., & Chelloug, S. A. (2023). Deeplungnet : An effective dl - based approach for lung disease classification using cris. Electronics, 12(8), 1860.

[13] Nawaz, M., Saleem, S., Masood, M., Rashid, J., & Nazir, T. (2024). COVID - ECG - RSNet : COVID -19 classification from ECG images using swish - based improved ResNet model. Biomedical Signal Processing and Control, 89, 105801.

[14] Ullah, N., Khan, J. A., Almakdi, S., Alshehri, M. S., Al Qathrady, M., Anwar,M. S., & Syed, I. (2024).Chestcovidnet: An effective dl-based approach for covid-19, lung opacity, and pneumonia detection using chest radiographs images. Biochemistry and Cell Biology

[15] Balasamy, K., & Seethalakshmi, V. (2025). HCO-RLF : Hybrid classification using recurrent learning and fuzzy for COVID-19 detection on CT images. Biomedical Signal Processing and Control, 100, 106951.

[16] https://www.kaggle.com/datasets/prashant268/chest-xray-covid19-pneumonia/data

[17] Sait, U., Lal, K., Prajapati, S., Bhaumik, R., Kumar, T., Sanjana, S., & Bhalla, K. (2020). Curated dataset for COVID-19 posterior-anterior chest radiography images (X-Rays). Mendele Data, 1(J).