Deep Learning with Radial Basis Sigmoid Function based Classification COVID -19 Chest X- Rays

[1]Aman Yadav, [2]Ankita Tiwari and [3]Nitya Khare,
[1]Research Scholar, [2]Assistant Professor, [3]Head and Professor
[1,2,3]Department of CSE, Sagar Institute of Research & Technology - Excellence, Bhopal, India

Abstract-The episode of the Covid infection 2019 (Coronavirus) caused the passing of an enormous number of individuals and pronounced as a pandemic by the World Wellbeing Association. A great many individuals are tainted by this infection and are as yet getting contaminated consistently. As the expense and called for investment of traditional Converse Record Polymerase Chain Response (RT-PCR) tests to distinguish Coronavirus is uneconomical and over the top, analysts are attempting to utilize clinical pictures like X-beam and Registered Tomography (CT) pictures to recognize this illness with the assistance of Man-made brainpower (artificial intelligence)- based frameworks, to help with computerizing the checking method. In this paper, we surveyed a portion of these recently arising man-made intelligence-based models that can recognize Coronavirus from X-beam or CT of lung pictures. We gathered data about accessible examination assets and investigated a sum of 80 papers till June 20, 2020. We investigated and dissected informational collections, preprocessing procedures, division strategies, highlight extraction, grouping, and trial results which can be useful for finding future exploration headings in the area of programmed determination of Coronavirus sickness utilizing simulated intelligence-based structures. It is likewise mirrored that there is a shortage of explained clinical pictures/informational indexes of Coronavirus impacted individuals, which requires improving, division in preprocessing, and space transformation in move learning for a model, creating an ideal outcome in model execution. This review can be the beginning stage for a fledgling/novice scientist to deal with Coronavirus characterization.

Keywords: *COVID-19, Deep learning, medical image, Survey, AI, CT scan, X-ray.*

I. INTRODUCTION

The global COVID-19 pandemic has placed unprecedented pressure on healthcare systems, demanding rapid and accurate diagnosis to mitigate the spread of the virus. One of the key diagnostic tools for COVID-19 is medical imaging, particularly chest X-rays, which can provide critical insights into the presence of lung abnormalities associated with the virus. Chest X-ray imaging is widely available, cost-effective, and non-invasive, making it an essential tool in the early detection of COVID-19, especially in resource-limited settings.

However, manual interpretation of chest X-rays by radiologists can be time-consuming and prone to human error, particularly under high patient volumes. The advent of deep learning techniques, specifically convolutional neural networks (CNNs), has revolutionized medical image analysis by automating the classification and interpretation of radiological images. These techniques allow for rapid, accurate, and scalable identification of COVID-19, helping to prioritize patients and improve clinical workflows.

In this context, the classification of COVID-19 chest X-rays using deep learning is a critical area of research. By training deep learning models on large datasets of chest X-ray images, AI systems can learn to distinguish between COVID-19, pneumonia, and normal lung conditions. The goal is to develop systems that not only provide fast and reliable results but also support healthcare professionals by offering decision-making insights, thereby enhancing overall diagnostic accuracy.

Despite the promising applications, the process of classifying COVID-19 chest X-rays with deep learning presents several challenges, such as limited and imbalanced datasets, data quality issues, and the need for model interpretability. To address these, researchers are exploring novel solutions including data augmentation, transfer learning, and hybrid models that combine traditional image processing with deep learning.

The significance of this research extends beyond COVID-19 diagnosis. The methods developed for classifying COVID-19 chest X-rays can be applied to other respiratory diseases, such as pneumonia and tuberculosis, making them valuable tools in the broader field of medical image analysis. As deep learning techniques continue to evolve, the potential for AI-powered diagnostic systems to transform healthcare systems worldwide remains immense. This paper explores the challenges, solutions, and future directions of deep learning approaches for classifying COVID-19 chest X-rays, highlighting their potential to revolutionize medical diagnostics.

II. BACKGROUND

The classification of COVID-19 chest X-rays has emerged as a critical area of study in medical imaging, catalyzed by the global impact of the pandemic and the pressing need for accurate diagnostic tools. Numerous studies have applied deep learning methods to differentiate COVID-19 from other pulmonary conditions based on chest radiographs, reflecting a convergence of medical imaging and artificial intelligence (AI) techniques. The integration of convolutional neural networks (CNNs) into COVID-19 classification has shown considerable promise. For instance, Wang et al. (2020) introduced COVID-Net, a neural network architecture designed specifically for COVID-19 chest X-ray detection, demonstrating its ability to achieve over 90% accuracy when validated on benchmark datasets. Their findings align with earlier efforts by Narin et al. (2020), who utilized transfer learning with pre-trained CNNs such as ResNet50, yielding similarly high levels of diagnostic precision.

The reliance on publicly available datasets has also shaped the field significantly. Studies such as those by Apostolopoulos and Mpesiana (2020) employed datasets like the COVIDx dataset, achieving enhanced performance by combining data augmentation and ensemble learning methods. However, dataset limitations, including small sample sizes and class imbalance, have posed challenges. Zhang et al. (2020) highlighted that such biases could lead to overfitting, underscoring the need for more diverse and representative datasets.

A comparative analysis of machine learning (ML) algorithms has further illuminated their relative effectiveness in COVID-19 chest X-ray classification. Khalifa et al. (2021) benchmarked multiple approaches, including support vector machines (SVMs), random forests, and deep learning models, concluding that CNNs consistently outperformed traditional ML methods due to their superior feature extraction capabilities. Similarly, Sethy and Behera (2020) combined CNN-based feature extraction with SVM classifiers, revealing a synergistic effect that improved the robustness of predictions.

Attention mechanisms have also been a focal point in recent research. Studies such as those by He et al. (2021) introduced attention-based CNNs that adaptively focus on regions of radiographic images most indicative of COVID-19 pathology. These methods align with the work of Li et al. (2020), who proposed an attention-guided approach to enhance model interpretability, ensuring that diagnostic decisions are clinically explainable. This interpretability is critical in bridging the gap between automated diagnostic tools and their adoption in clinical settings.

The application of ensemble learning strategies has further advanced the accuracy and reliability of classification models. Ghoshal and Tucker (2020) explored Bayesian optimization to combine predictions from multiple CNN models, achieving a consensus-based output that reduced variance and enhanced reliability. The study by Ozturk et al. (2020) also demonstrated the efficacy of combining multiple deep learning frameworks to achieve superior classification performance.

The integration of cross-modality imaging data has been another noteworthy trend. While chest X-rays provide valuable diagnostic information, incorporating data from computed tomography (CT) scans, as explored by Harmon et al. (2020), has shown potential to improve sensitivity and specificity in differentiating COVID-19 from other respiratory infections. This approach mirrors the findings of Bai et al. (2020), who combined chest X-rays and CT images to develop multimodal deep learning models capable of leveraging complementary information from different imaging modalities.

The impact of explainable AI (XAI) on this field has been significant. Researchers such as Tolkachev et al. (2021) emphasized the importance of integrating saliency maps and Grad-CAM visualizations into classification models, enabling clinicians to better understand the decision-making processes of AI systems. These tools enhance trust and transparency, as echoed by Singh et al. (2021), who underscored their role in fostering clinical adoption.

Despite these advancements, challenges persist in terms of generalizability and robustness. Farooq and Hafeez (2020) highlighted that model performance often deteriorates when tested on external datasets, revealing the need for standardized protocols in dataset creation and evaluation. Furthermore, the ethical implications of deploying AI in healthcare, as discussed by Roberts et al. (2020), require careful consideration to address potential biases and ensure equitable access to diagnostic tools.

III. PROBLEM IDENTIFICATION

The distinguished issue in existing work is as per the following:

i. The possibilities of distinguishing proof of Coronavirus patients might need because of low accuracy.
ii. The forecast of Coronavirus patients might need because of low review.
iii. The precision of Coronavirus patient recognizable proof might debase because of low exactness.

IV. RESEARCH OBJECTIVES

The research objectives as per identified problem in existing work are as follows:

i. To improve precision for proper identification of COVID-19 patients.
ii. To improve recall for effective prediction of COVID-19 patients.
iii. To recover the accuracy of COVID-19 for exactness identification of patients.

V. METHODOLOGY

1. we need some input data; specifically, we need a picture as x and a label as y for our CXR actual photos. y = "typical," "pneumonia," and "COPD-IV-19."

2. Information provided as output Normal, pneumonia, or COVID-19 may be reported for output label y.

3. During the preprocessing stage, a 512 x 512 pixel resolution is applied to the CXR pictures.

For m steps of training, the number of iterations is as follows:

i. Take a sample of m random numbers from the noise prior Pg(z);

ii. take a sample of m random numbers from the distribution of generated examples Pdata(x). The true picture is sent to the discriminator in step

iii. Using the transfer model, the discriminator is updated by increasing its stochastic gradient.

Conclusion for (i) The noise prior Pg(z) is sampled in a minibatch of size m, and the discriminator is updated by minimizing its stochastic gradient. The countdown has reached 5! In the testing step, a label y is produced as the output.

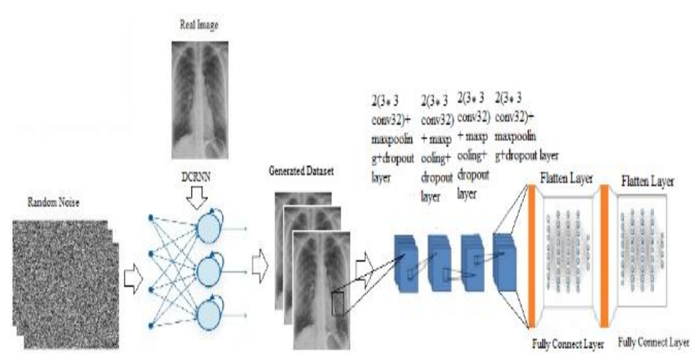

Figure 1: Architecture of proposed CNN+DCRNN model.

VI. RESULTS AND ANALYSIS

The following observations are collected during the process of the proposed model on the patient X-Ray dataset. Precision, Recall, and Accuracy parameters are calculated as follows:

Table 1: Summary of results.

Dataset	Number of images	Model	Training accuracy	Testing accuracy
COVID-19 X-ray [1]	188	AlexNet [1]	90.2	92.2
		GoogLeNet [1]	89.4	91.4
		DCGAN-CNN [1]	93.8	94.8
		Proposed DCRNN-CNN	95.3	96.8
COVID Chest X-ray [1]	803	AlexNet [1]	92.5	93.5
		GoogLeNet [1]	88.5	90.5
		DCGAN-CNN [1]	94.6	96.6
		Proposed DCRNN-CNN	96.2	97.5
COVID-19 Radiography [1]	5910	AlexNet [1]	96.3	96.7
		GoogLeNet [1]	94.5	95.5
		DCGAN-CNN [1]	98.4	98.5
		Proposed DCRNN-CNN	99.2	99.6

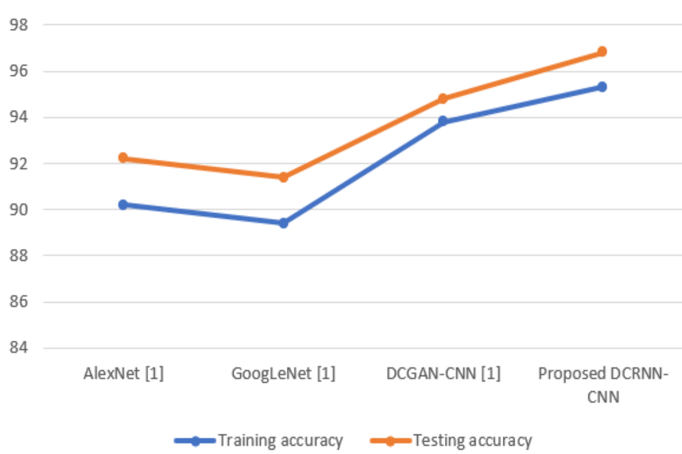

Figure 2: Graphical analysis of training and testing accuracy for COVID-19 X-Ray [1] dataset

The above graph show that the proposed model gives better training and testing accuracy as compare than AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] respectively. When use Covid X-Ray Dataset [1] then then training accuracy improve by 5.6%, 6.5%, 1.6% and testing accuracy improve by 4.9%, 8.7%, 2.1% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] respectively.

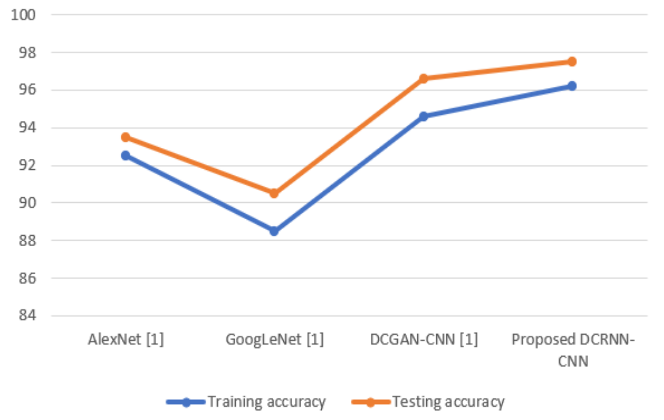

Figure 3: Graphical analysis of training and testing accuracy for COVID-19 Chest X-Ray [1] dataset

When use Covid Chest X-Ray Dataset [1] then then training accuracy improve by 4%, 1.6%, 1.6% and testing accuracy improve by 4%, 4.2%, 0.9% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] respectively.

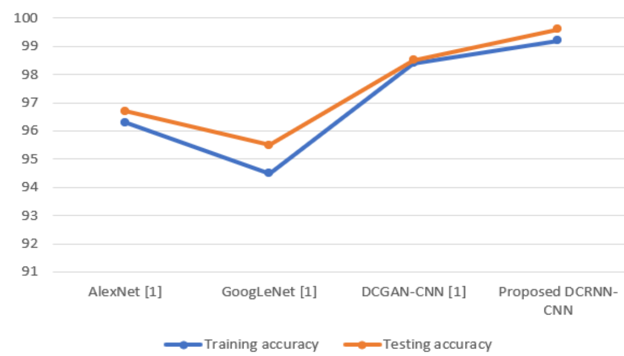

Figure 4: Graphical analysis of training and testing accuracy for COVID-19 Radiography [1] dataset

When use Covid Radiography Dataset [1] then then training accuracy improve by 4%, 4.8%, 0.8% and testing accuracy improve by 3%, 4.3%, 1.1% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] respectively.

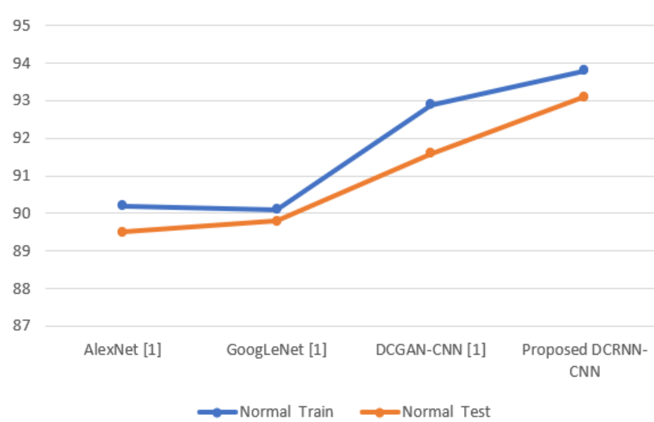

Figure 5: Graphical analysis of train and test class accuracy in Normal cases for COVID-19 X-Ray [1] dataset

Table 2: Accuracy per class

Dataset	Model	Normal		Pneumonia		COVID-19	
		Train	Test	Train	Test	Train	Test
COVID-19 X-ray [1]	AlexNet [1]	90.2	89.5	89.2	88.5	90.6	91.8
	GoogLeNet [1]	90.1	89.8	90.3	91.5	91.3	92.5
	DCGAN-CNN [1]	92.9	91.6	93.4	91.9	95.6	94.3
	Proposed DCRNN-CNN	93.8	93.1	94.7	92.7	96.7	95.4
COVID Chest X-ray [1]	AlexNet [1]	91.6	90.8	87.6	90.8	92.3	93.6
	GoogLeNet [1]	90.5	89.5	89.5	88.5	92.2	91.1
	DCGAN-CNN [1]	93.6	92.4	94.6	93.4	93.5	94.3
	Proposed DCRNN-CNN	94.6	93.2	95.3	94.2	94.3	95.1
COVID-19 Radiography [1]	AlexNet [1]	95.6	94.8	93.6	94.3	94.5	94.9
	GoogLeNet [1]	94.5	93.8	92.5	91.8	91.4	91.6
	DCGAN-CNN [1]	98.2	97.9	97.4	98.2	95.7	96.8
	Proposed DCRNN-CNN	99.1	98.5	98.5	98.9	96.2	97.3

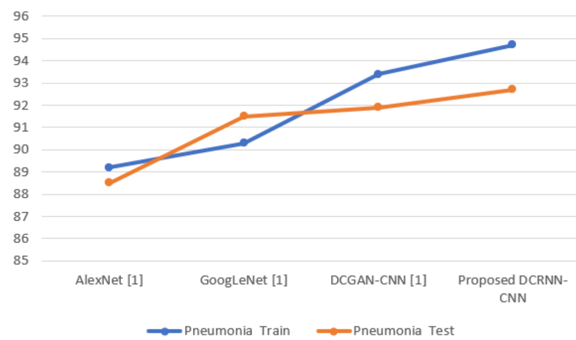

Figure 6: Graphical analysis of train and test class accuracy in Pneumonia cases for COVID-19 X-Ray [1] dataset

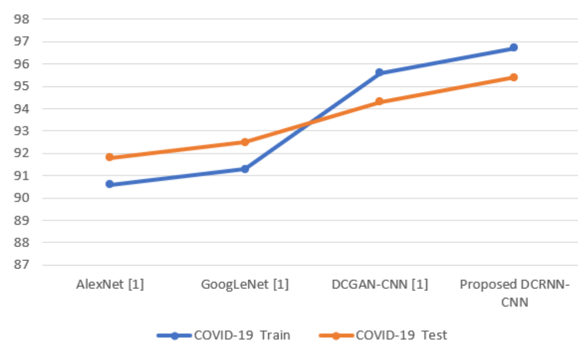

Figure 7: Graphical analysis of train and test class accuracy in Covid-19 cases for COVID-19 X-Ray [1] dataset

The above graph show that the proposed model gives better train and test class accuracy as compare than AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] respectively. When use Covid X-Ray Dataset [1] then train class accuracy improve by 6.7%, 5.9%, 1.1% and test class accuracy improve by 3.9%, 3.1%, 1.2% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] in Covid-19 cases.

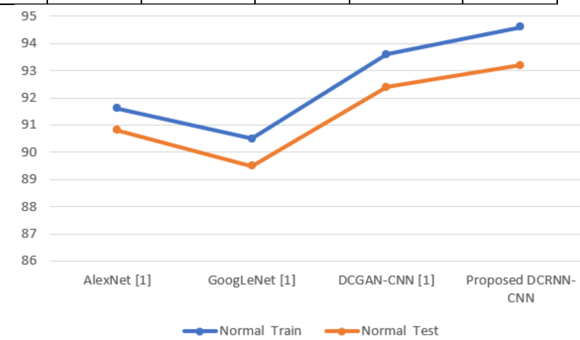

Figure 8: Graphical analysis of train and test class accuracy in Normal cases for COVID-19 Chest X-Ray [1] dataset

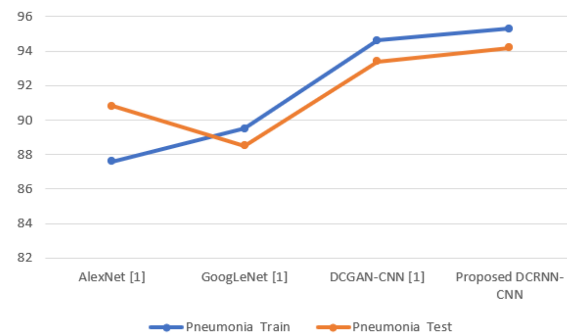

Figure 9: Graphical analysis of train and test class accuracy in Pneumonia cases for COVID-19 Chest X-Ray [1] dataset

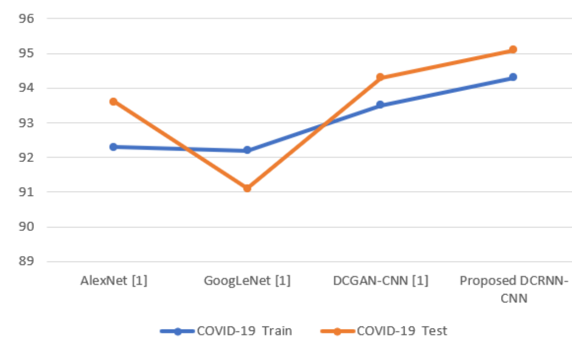

Figure 10: Graphical analysis of train and test class accuracy in Covid-19 cases for COVID-19 Chest X-Ray [1] dataset

When use Covid Chest X-Ray Dataset [1] then train class accuracy improve by 2.1%, 2.3%, 0.8% and test class accuracy improve by 1.6%, 4.3%, 0.85% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] in Covid-19 cases.

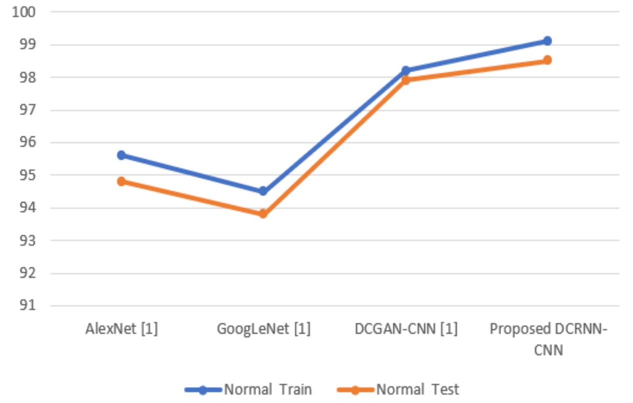

Figure 11: Graphical analysis of train and test class accuracy in Normal cases for COVID-19 Radiography [1] dataset

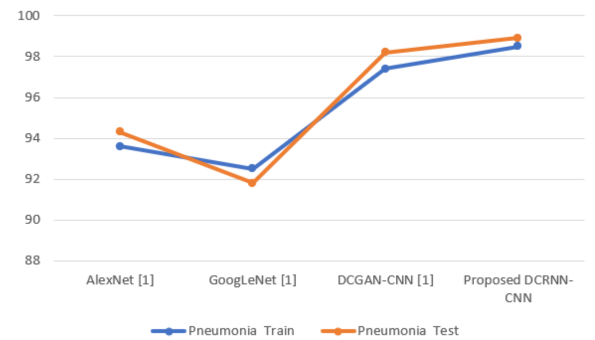

Figure 12: Graphical analysis of train and test class accuracy in Pneumonia cases for COVID-19 Radiography [1] dataset

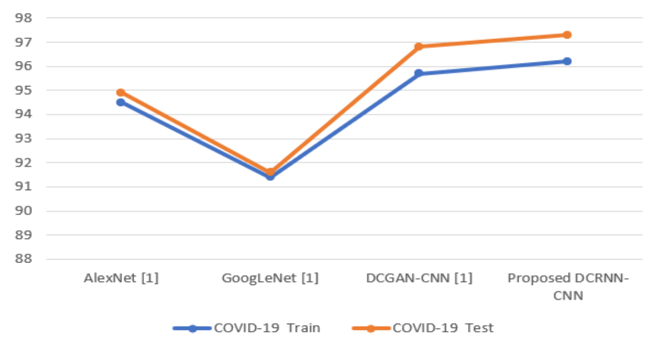

Figure 13: Graphical analysis of train and test class accuracy in Covid-19 cases for COVID-19 Radiography [1] dataset

When use Covid Radiography Dataset [1] then train class accuracy improve by 1.8%, 5.2%, 0.7% and test accuracy improve by 2.5%, 6.2%, 0.5% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] in Covid-19 cases. Similarly, improvement of train and test class accuracy in normal and pneumonia cases.

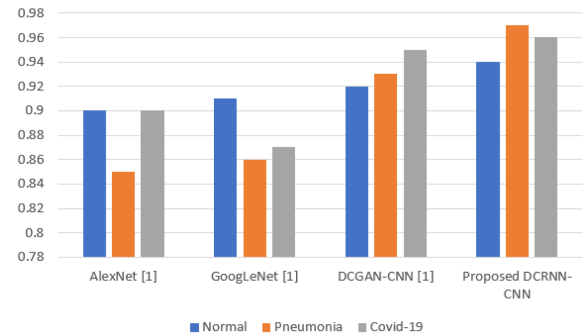

Figure 14: Graphical analysis of recall in Normal, Pneumonia and Covid-19 cases for COVID-19 X-Ray [1] dataset

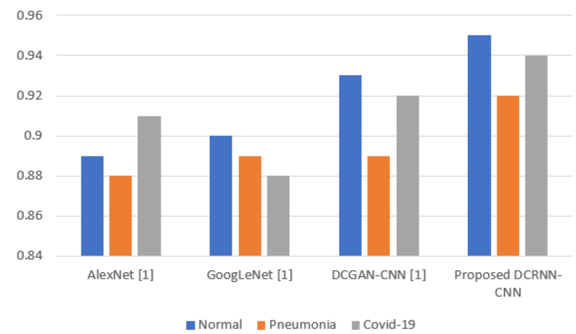

Figure 15: Graphical analysis of precision in Normal, Pneumonia and Covid-19 cases for COVID-19 X-Ray [1] dataset

The above graph show that the proposed model gives better recall and precision as compare than AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] respectively. When use Covid X-Ray Dataset [1] then recall improve by 6.7%, 10.3%, 1.05% and precision improve by 3.3%, 6.8%, 2.2% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] in Covid-19 cases.

Table 3: Recall and precision per class

Dataset	Model	Normal		Pneumonia		COVID-19	
		Recall	Precision	Recall	Precision	Recall	Precision
COVID-19 X-ray [1]	AlexNet [1]	0.9	0.89	0.85	0.88	0.9	0.91
	GoogLeNet [1]	0.91	0.9	0.86	0.89	0.87	0.88
	DCGAN-CNN [1]	0.92	0.93	0.93	0.89	0.95	0.92
	Proposed DCRNN-CNN	0.94	0.95	0.97	0.92	0.96	0.94
COVID Chest X-ray [1]	AlexNet [1]	0.91	0.88	0.84	0.87	0.89	0.9
	GoogLeNet [1]	0.9	0.86	0.89	0.86	0.92	0.91
	DCGAN-CNN	0.93	0.92	0.94	0.91	0.92	0.94
	Proposed DCRNN-CNN	0.95	0.94	0.96	0.95	0.94	0.96

COVID-19 Radiography [1]	AlexNet [1]	0.94	0.9	0.92	0.9	0.93	0.94
	GoogLeNet [1]	0.93	0.91	0.92	0.93	0.89	0.91
	DCGAN-CNN [1]	0.96	0.95	0.94	0.94	0.95	0.96
	Proposed DCRNN-CNN	0.98	0.96	0.97	0.96	0.97	0.97

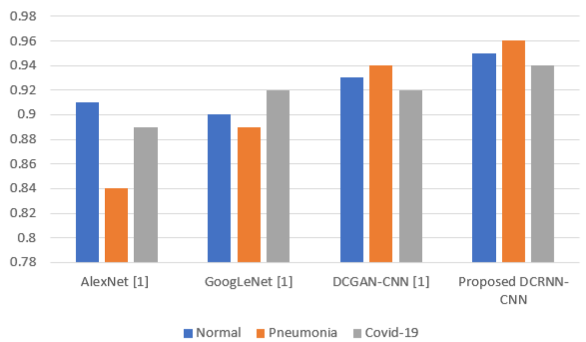

Figure 16: Graphical analysis of recall in Normal, Pneumonia and Covid-19 cases for COVID-19 Chest X-Ray [1] dataset

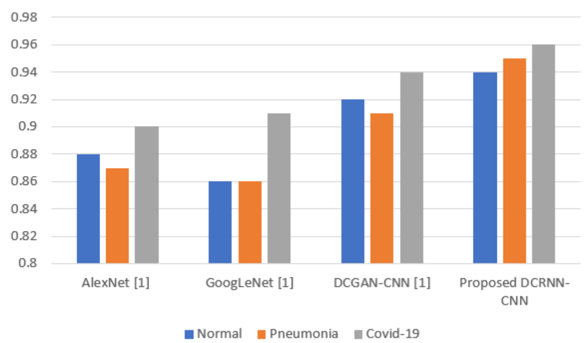

Figure 17: Graphical analysis of precision in Normal, Pneumonia and Covid-19 cases for COVID-19 Chest X-Ray [1] dataset

When use Covid Chest X-Ray Dataset [1] then recall improve by 3.2%, 8.7%, 2.2% and precision improve by 6.7%, 5.5%, 2.1% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] in Covid-19 cases.

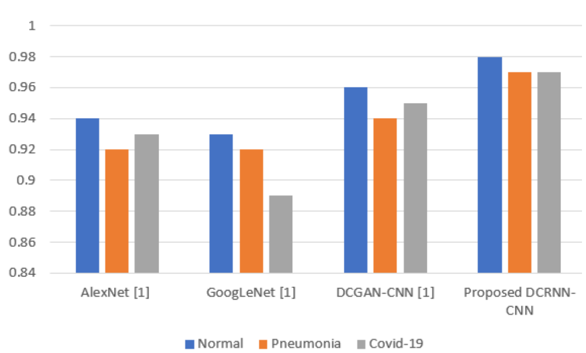

Figure 18: Graphical analysis of recall in Normal, Pneumonia and Covid-19 cases for COVID-19 Radiography [1] dataset

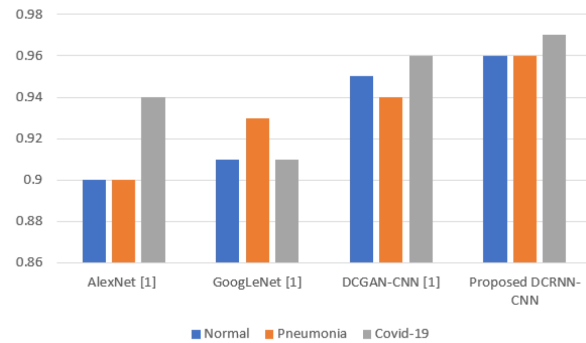

Figure 19: Graphical analysis of precision in Normal, Pneumonia and Covid-19 cases for COVID-19 Radiography [1] dataset

When use Covid Radiography Dataset [1] then recall improve by 4.3%, 8.9%, 2.1% and precision improve by 3.2%, 6.5%, 1.04% for AlexNet [1], GoogLeNet [1] and DCGAN-CNN [1] in Covid-19 cases.Similarly, improvement of recall and precision in normal and pneumonia cases.

CONCLUSION

These are supposed to have conclusions, and this one do:

(1) AlexNet [1], GoogLeNet [1], and DCGAN-CNN [1] all saw increases in training accuracy of 5.6%, 6.5%, and 1.6%, and in testing accuracy of 4.9%, 8.7%, and 2.1%, respectively.

(2) For Covid-19, AlexNet [1], GoogLeNet [1], and DCGAN-CNN [1] each show gains of 6.7%, 5.9%, 1.1% in train class accuracy and 3.9%, 3.1%, 1.2% in test class accuracy, respectively.

(3) The proposed model outperforms AlexNet [1], GoogLeNet [1], and DCGAN-CNN [1] in terms of recall and accuracy. AlexNet [1], GoogLeNet [1], and DCGAN-CNN [1] all perform better on the Covid X-Ray Dataset [1], with recall increasing by 6.7%, 10.3%, and 1.05% and precision increasing by 3.3%, 6.8%, and 2.2% in the Covid-19 instances, respectively. Recall and accuracy have also increased in both non-pneumonia patients and those with pneumonia.

Therefore, the suggested system, DCRNN-CNN (Deep Convolution Recurrent Neural Network with CNN), is more effective in classifying X-Ray pictures for normal, pneumonia, and Covid-19 illness symptoms.

The diagnostic precision and treatment efficacy are both enhanced by the approach we offer. Future improvements must evaluate accuracy with new datasets and use other AI methods to verify precision calculations. Due to the massive quantity of data needed for performance estimation of train data, the proposed model has a processing time restriction. In the future, the same algorithms will be used to data in real time to estimate the system's efficacy.

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