The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

Automatic Detection of Covid-19 from Chest X-ray Images using Corona Net

D. L. Asha Rani[1*], P. Anishiya[2], T. Pramananda Perumal[3]
[1]Presidency College, Triplicane, Chennai-600 005, Tamil Nadu, India
Email: aancy35@gmail.com
[2]Anna University, CEG Campus, Guindy, Chennai- 600 025, Tamil Nadu, India
Email: anishiya04@gmail.com
[3]Presidency College, Triplicane, Chennai-600 005, Tamil Nadu, India
Email: pramanandaperumal@yahoo.com
*Corresponding author

Abstract

The most devastating pandemic to ever infiltrate humans is COVID-19. An automatic detection system is an instantaneous diagnosis option to prevent COVID-19 transmission. The objective of this research work is to propose a novel CNN (Convolutional Neural Network) based Covid-19 detection system to classify the radiological (chest X-ray) images into binary classes (Covid-19 and Non-Covid-19) and three (multi) different classes (Normal Lungs, Lungs infected by Covid-19 and Lungs infected by Pneumonia). The efficiency of the proposed CNN(CoronaNet) model is compared with six existing pre-trained models (AlexNet, GoogleNet, VGG-16, SqueezeNet, Inception-V3 and ResNet-50) for identifying Covid-19 from radiological images. The computer experimental results demonstrate that the proposed CoronaNet model has achieved an overall accuracy of 96.4% for binary-class classification (Covid-19 and Non-Covid-19) and 94.4 % for multi- class classification (Normal, Covid-19 and Pneumonia). The proposed technique could be a useful tool for radiologists to diagnose and treat Covid-19 patients promptly.

Keywords: Covid-19, CNN, Deep Learning, Chest X-ray images classification

1. Introduction

COVID-19 has exploded into a global public health disaster, putting massive burden on healthcare systems around the world. According to the medical study, Covid-19 symptoms include an initial fever, respiratory infection with dry cough, dyspnea (shortness of breath), loss of smell and taste, fatigue /weariness and myalgia (muscle pain) [1]-[3]. Around 15–20% of patients have severe illness, with a mortality rate of around 2-3% [4]. It can be diagnosed using a variety of laboratory tests, such as Real-Time Polymerase Chain Reaction (RT-PCR) or Sequencing, nasopharyngeal aspirate and oropharyngeal aspirate [3]-[5]. For diagnosing Covid-19, RT-PCR test is the gold standard method [6] and it requires atleast 4-6 hours to give out the results from sample collection [7]. RT-PCR has a number of disadvantages, including a lack of test kits, time consuming, possibility of false negative results and a sensitivity of 60–70% [8]-[9]. Covid-19 can also be detected through various medical imaging technologies such as Computed Tomography (CT) scan and chest X-ray images [9]-[13].

Recently, the Convolutional Neural Networks (CNNs) (a type of 'Deep Learning Algorithms') are used to detect diseases from mammogram images [14], MRI scan images [15], X-ray images [6], CT scan images [16], Ultrasonography [17], microscopic images and so on. However, deep learning models can extract relevant features from the data, without any human supervision [32].

CNNs have been widely used for image classification and segmentation. Several studies have shown that COVID-19 may be detected using chest X-ray and CT scan images [18]-[28]. T. Ozturk et al. [18] have introduced DarkNet model to detect Covid-19 from chest X-Ray images and the model has 19 convolutional layers with different filters in each layer. It has achieved an accuracy of 87.02% for three-class classification.

Linda Wang et al. [19] have introduced COVID-Net model that has yielded the highest accuracy of 93.3% for three-class classification. M. Polsinelli et al. [20] has used SqueezeNet model to detect Covid-19 from CT scan images. The dataset which has consisted of 453 Covid-19 images, 497 normal images, achieving 85.03% accuracy for binary class classification. M. M. Mijwil and E. A. Al-Zubaidi [21] have classified Covid-19 images from chest X-ray images by applying GoogleNet architecture, with an elapsed time of 74 minutes and 37 seconds and has achieved an accuracy of 82.14% for training the dataset.

Lourdes Duran-Lopez et al. [22] have designed a novel deep learning based system and called COVID-XNet for Covid-19 detection from chest X-ray images. A 5-fold cross-validation method has been used to train and validate the system and it has yielded the highest accuracy of 94.43% for two(binary) class classification. Prabira Kumar Sethy et al. [23] have applied ResNet-50+SVM classifier to classify Covid-19 images from chest X-ray images and the model has achieved an accuracy of 95.33%.

Ezz EI-Din Hemdan et al. [24] have implemented seven pre-trained CNN models such as VGG19, DenseNet121, ResNetV2, InceptionV3, Incepetion-ResNet-V2, Xception and MobileNetV2 for classification of Covid-19 from Normal cases. VGG19 and DenseNet121 have achieved the highest accuracy of 90% for binary class classification. X. Xu et al. [25] have used CT chest scan images to train ResNet50 model which has achieved an accuracy of 86.7% for binary class classification. M. Rahimzadeh and A. Attar [26] have proposed concatenation of Xception and ResNet50V2. It has yielded the highest classification accuracy of 91.4% for three class classification.

T. Mahmud et al. [27] have presented a new CNN model called CovXNet which has used chest X-ray images to diagnose Covid-19 automatically. It has yielded the highest classification accuracy of 94.7% for binary class classification and 89.6% for three class classification.

K. Medhi et al. [28] have used data acquisition, pre-processing (noise removal), segmentation, feature extraction and classification model to detect Covid-19 from chest X-ray images. It has yielded the highest classification accuracy of 93% for two class classification.

The literature survey shows that the prior models are using limited samples and the data are typically unbalanced. Also, it should be emphasized that binary class classifications are used by most of the prior models. However, limited models have used multi-class (three or four class) classifications. The main objective of our proposed study is to build an efficient CNN-based network model for automatic detection of Covid-19 infection from chest X-ray images using binary class and multi-class classifications.

This paper is organized as follows. In section 2, we briefly describe the details of proposed study such as dataset and its augmentation, convolutional neural network, proposed CoronaNet model and its implementation process. In section 3, we present our results and discussion on CoronaNet model for (a) dropout (b) batch size (c) epoch (d) performance of different optimizers (e) graphics of training accuracy and validation loss (f) confusion matrix of CoronaNet model and (g) comparison of proposed CoronaNet model with other existing studies. In section 4, we highlight the principal outcome of the study.

2. Details of Proposed Study

The proposed model intends to classify the chest X-ray images into multi-classes (Normal, Covid-19 and Pneumonia) and binary classes (Covid and Non-Covid). Fig.1. depicts the sequence of steps to be involved in building the proposed model.

The following sections provide details on each step of the proposed model. The performance of the proposed model and pre-trained /existing models have been evaluated, based on different metrics such as accuracy, precision, sensitivity, specificity, and F1-score, in 2 class classification and 3 class classification problems. These metrics are computed by different parameters of the Confusion Matrix such as True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) [29].

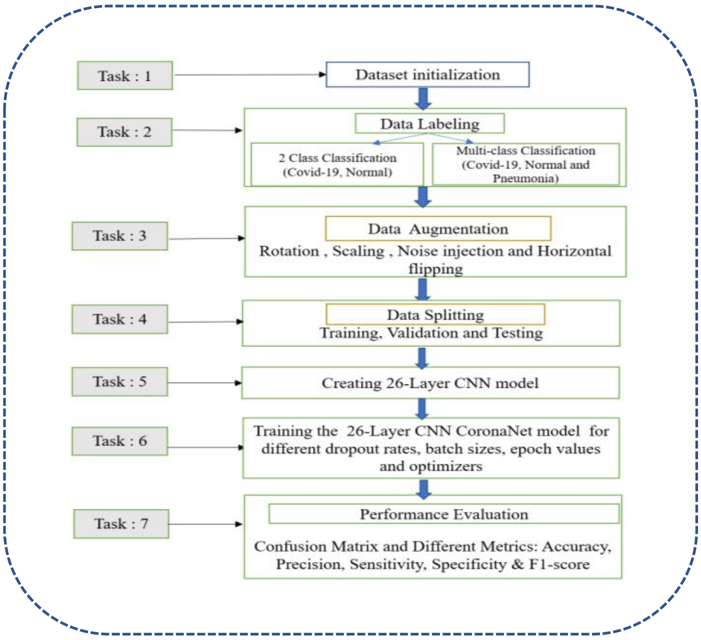

Fig.1. Flowchart of proposed model

2.1. Dataset

The public dataset of chest X-ray images has been obtained from GitHub (Covid-19-chest X-ray dataset), prepared by Joseph Paul Cohen and is used in our study. Chest X-ray and CT scan images make up the original (fundamental) dataset. In our study, only chest X-ray images are chosen for Covid-19 detection. Dataset is summarized in Table.1.

Table.1. Summary of dataset with and without augmentation

Disease	No. of samples before augmentation	No. of samples after augmentation	No. of training samples	No. of validation samples	No. of testing samples
Covid-19	1441	1860	1249	561	50
Normal	1435	1890	1282	558	50

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

Pneumonia	1459	1871	1254	567	50
Total	4335	5621	3785	1686	150

Augmented data is deployed to train the model. These images have been separated into a partition of 70% and 30% for training and validation, respectively. Sample chest X-ray images of Covid-19, Normal and Pneumonia are shown in Fig.2.

a) Covid-19 b) Normal c) Pneumonia

Fig .2. Sample chest X-ray images

2.2 Dataset Augmentation

The process of performing a set of operations on the fundamental data to increase the amount of data samples is known as data augmentation. CNN architectures often tend to overfit a small number of samples. However, accessing a massive amount of data is not perpetually feasible. Hence the data can be augmented in a computer system, by applying various transformations such as rotation, scaling, adding noise and horizontal axis flipping to the original data [7], [30].

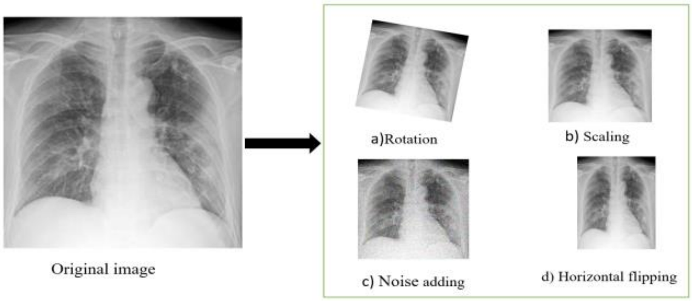

Fig .3. Illustration of data augmentation of a sample image

Fig.3. illustrates of data augmentation of a sample image of the dataset. The training set images are all rotated by 45°, 90° and 180°. Scaling is used to alter or change the size of images. CNNs can learn more powerful features by introducing noise to the images. A matrix of random numbers, frequently derived from a Gaussian distribution, are injected during the "noise addition" process. The horizontal axis flipping frequently is quite common than the vertical axis flipping. This augmentation is one of the easiest to implement and has proven useful on the datasets such as CIFAR-10 and ImageNet [30]. In this study, the augmented datasets are given as input to CNN.

2.3. Convolutional Neural Network (CNN)

CNN automatically detects the features without any human supervision. Its architecture is designed with inspiration from the organization of the visual cortex, similar to the connection model of neurons in the human brain. CNN is an organization of Input layer, Hidden layers (Convolutional, Pooling & Fully Connected layers) and Output layer as shown in the Fig.4.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

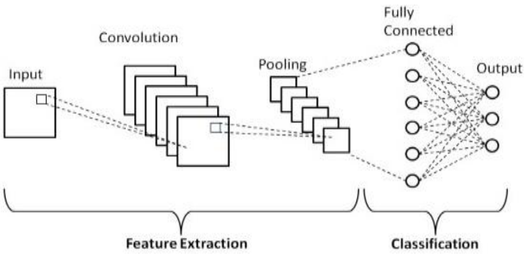

Fig .4. Architecture of CNN model

CNN models have been successfully implemented in many applications such as image classification [31], object detection [32], medical image analysis [33] etc. These models have been proved to obtain superior results in a wide range of medical image processing applications [29].

Table.2. Detailed description of the pre-trained and proposed CNN(CoronaNet) models

Model	Hidden Layers	Input layer size	Output layer size
AlexNet	8	(224,224,3)	(2,1)
VGG-16	16	(224,224,3)	(2,1)
SqueezeNet	18	(227,227,3)	(2,1)
GoogleNet	22	(224,224,3)	(2,1)
Inception-V3	42	(299,299,3)	(2,1)
RestNet-50	50	(224,224,3)	(2,1)
Proposed CoronaNet	**26**	**(256,256,3)**	**(2,1)**

The base layer of CNN is called Convolutional layer [34]. In this layer, the CNN uses various kernels to convolve the input image as well as central feature maps [6]. This layer is also called as the feature extraction layer. The convolutional layer extracts one or more features from the input images, then it creates a dot product and produces one or more matrices, using the image matrices. Further, applying various filters, the convolutional layer performs various operations such as edge detection, blur and sharpening.

The pooling layer is used to reduce the resolution of activation map and the number of parameters. This layer improves computing, avoids overfitting and uses less memory. There are different varieties of pooling layers, namely sum pooling, average pooling and maximum pooling layers. Five maxpooling layers have been used in this study. The fully connected (FC) layers have full connections to all the activations in the previous layer. The last FC layer predicts the output and forwards to the output layer.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

In this study, in addition to the proposed CNN (CoronaNet) model, six more successful pre-trained models such as AlexNet [35], GoogleNet [36], VGG-16, ResNet-50, SqueezeNet [37] and Inception-V3 [38] are together described in detail, in Table.2. These models have been used for binary class and multi-class classifications.

2.4. Proposed Coronanet Model

It is a CNN consisting of five Convolutional 2D layers, five maxpooling layers and six batch normalization layers. Fig.5. shows the architecture of the proposed CoronaNet model. Table.4. presents the summary of the proposed CoronaNet model. Adam optimizer has been used for weight updation.

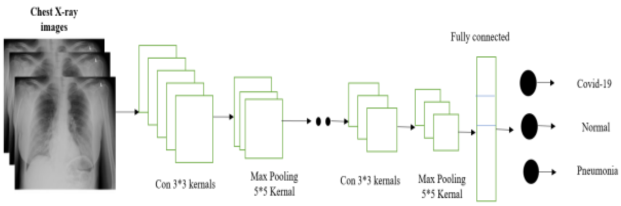

Fig .5. Architecture of CoronaNet model

The most challenging aspect is integrating all the layers (convolutional layers, activation functions and values of optimizer) to get an exquisite result from the suggested model in terms of accuracy and other assessment criteria. Initially, our CoronaNet model has been started with 21 layers, ReLU as an activation function with max pooling layers and group normalization, instead of batch normalization. This trial model has achieved an accuracy of 72.2% for multi-class classification. After switching over to batch normalization from group normalization, the classification accuracy has improved and the model has achieved a training accuracy of 89% for multiclass classification. Hence this study suggests that batch normalization performs better than group normalization as stated in Ref. [33]. The batch normalization technique is utilized to standardize the inputs and this technique has distinct advantages such as reducing training time and improving model stability [8]. First, ReLU has been used as an activation function along with max pooling layer and batch normalization. Again, switching over to Elu and Leaky ReLU instead of using ReLU as activation functions, the classification accuracy has improved in both cases. In our computer experiment (simulation), the results show that Leaky ReLU performs better than the other two activation functions, whereas Elu performs better than ReLU.

Incorporating one more convolutional layer and one maxpooling layer with our initial 21-layers architecture will be increasing the classification performance of the CoronaNet model. Hence, the initial 21-layers model has been further extended with two additional Convolutional layers, a Leaky ReLU layer, a Batch Normalization layer and Maxpooling layer, which leads to boosting of classification accuracy both in binary class and multi-class classifications, as presented in Table 3.

The same parameters, such as activation function and optimizer values, have been applied to every model. Table.3. demonstrates accuracy for 21-layer, 23-layer, and 26-layer for two and three classes classifications. It can be observed that the 26-layer model's accuracy is superior to others.

The proposed model has been developed by trying with combination of layers, different activation functions, different optimizers and other assessment criteria such as confusion matrix and various metrics.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

Layers	Accuracy of binary class classification	Accuracy of multi-class classification
21-layer	90%	72%
23-layer	93%	89%
26-layer	96%	94%

Table.3. Comparison of classification accuracy for different layers, used in CoronaNet model

2. 5. Implementation Process

Two different classification approaches viz. binary class (Covid-19, Non-Covid) classification and multi-class (Normal, Covid-19, Pneumonia) classification approaches have been adopted for estimating the performance of the CoronaNet in detecting the Covid-19 from chest X-ray images. During implementation, all the runs (simulations) of CoronaNet for different hyper-parameters have been carried out on MatlabR2021b. Hyper-parameters are the explicitly specified parameters viz. learning rate, dropout, batch size, epoch and optimizer that control the training process. They are essential for optimizing the model.

The best learning rate of a model is chosen, based on the minimum loss [29]. Hence the learning rate is chosen to be *0.0001*, since this value is used especially for ADAM optimizer in most of the CNN model studies [16], [33]. Each layer learns at the same learning rate of *0.0001* [35]. SGDM, ADAM, and RMS-prop are the optimizers which are employed for the training. Each model is trained with dropout rates such as 0.1, 0.2, 0.3, 0.4, 0.5 and 0.6, batch sizes of 16, 32, 64 and 128 and epoch values such as 10, 20, 30, 40, 50, 60 and 70. The efficiency of the proposed CoronaNet model is compared with six existing models (AlexNet, GoogleNet, VGG-16, SqueezeNet, Inception-V3 and ResNet-50) for detecting Covid-19 from chest X-ray images. The performance of the CoronaNet model and existing models has been assessed using confusion matrix and various metrics such as accuracy, precision, sensitivity, specificity and F1-score.

Table.4. Summary of proposed CoronaNet Architecture

No of Layers	Name	Layer Type	Activation Layers	Learnable Properties	Number of Learnable
1	imageinput	Image Input	256(S)*256(S)*3(C)*1(B)	-	0
2	conv	2-D Convolution	254(S)*254(S)*8(C)*1(B)	Weights 3*3*3*8 Bias 1*1*8	224
3	leakyrelu	Leaky Relu	254(S)*254(S)*8(C)*1(B)	-	0
4	batchnorm_1	Batch Normalization	254(S)*254(S)*8(C)*1(B)	Offset 1*1*8 Scale 1*1*8	16
5	maxpool	2-D Max Pooling	252(S)*252(S)*8(C)*1(B)	-	0
6	conv_1	2-D Convolution	252(S)*252(S)*16(C)*1(B)	Weights 3*3*3*16 Bias 1*1*16	1168

7	batchnorm_2	Batch Normalization	252(S)*252(S)*16(C)*1(B)	Offset 1*1*16 Scale 1*1*16	32
8	leakyrelu	Leaky Relu	256(S)*256(S)*16(C)*1(B)	-	0
9	batchnorm_3	Batch Normalization	252(S)*252(S)*16(C)*1(B	Offset 1*1*16 Scale 1*1*16	32
10	maxpool_1	2-D Max Pooling	250(S)*250(S)*16(C)*1(B)	-	0
11	conv_2	2-D Convolution	250(S)*250(S)*16(C)*1(B)	Weights 3*3*16*32 Bias 1*1*32	4640
12	batchnorm_4	Batch Normalization	250(S)*250(S)*16(C)*1(B)	Offset 1*1*32 Scale 1*1*32	64
13	maxpool_2	2-D Max Pooling	125(S)*125(S)*32(C)*1(B)	-	0
14	leakyrelu_4	Leaky Relu	125(S)*125(S)*64(C)*1(B)	-	0
15	conv_3	2-D Convolution	125(S)*125(S)*64(C)*1(B)	Weights 3*3*32*64 Bias 1*1*64	18496
16	batchnorm_5	Batch Normalization	125(S)*125(S)*64(C)*1(B)	Offset 1*1*64 Scale 1*1*64	128
17	leakyrelu_2	Leaky Relu	125(S)*125(S)*64(C)*1(B)	-	0
18	maxpool_3	2-D Max Pooling	125(S)*125(S)*64(C)*1(B)	-	0
19	conv_4	2-D Convolution	63(S)*63(S)*128(C)*1(B)	Weights 3*3*64*128 Bias 1*1*128	18464
20	leakyrelu_3	Leaky Relu	63(S)*63(S)*128(C)*1(B)	-	0
21	batchnorm_6	Batch Normalization	63(S)*63(S)*128(C)*1(B)	Offset 1*1*128 Scale 1*1*128	64
22	maxpool_4	2-D Max Pooling	63(S)*63(S)*128(C)*1(B)	-	0
23	dropout	Dropout	128(S)*128(S)*32(C)*1(B)	-	0
24	fc	Fully Connected	1(S)*1(S)*3(C)*1(B)	Weights 3*508032 Bias 3*1	1572867
25	softmax	Softmax	1(S)*1(S)*3(C)*1(B)	-	0
26	classoutput	Classification Output	1(S)*1(S)*3(C)*1(B)	-	0

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

Table.4. represents the end-to-end proposed CoronaNet architecture, including description of the 26 layers, activation functions, learnable weights and total number of parameters (1.6 million). The proposed CoronaNet model, starts with one input layer and progresses through five convolution layers (conv 1, conv 2, conv 3, conv 4, and conv 5), five Leaky ReLU layers, six
batch normalization layers and five maxpooling layers, which altogether (22 layers) forms **feature extraction unit** and the other 4 layers viz. one dropout layer, one fully connected layer, one softmax classifier and one classification output layer, which altogether forms **classification unit,** has been used in our study. In each block, Convolution, Leaky ReLU, Batch Normalization and Maxpooling layers are collectively used for designing CoronaNet model. The "ADAM" optimizer [39] has been used to train the end-to-end CoronaNet model with an initial learning rate 0.0001.

3. Results And Discussion

3.1. Dropout

Convolutional neural networks with large number of parameters and hyper-parameters are powerful machine learning systems. However, overfitting is a serious issue in these deep learning networks. These large networks are slow to use, making it difficult to deal with overfitting by combining the predictions of many different large neural networks. Dropout is one of the hyper-parameters in CNN and it is a method for resolving overfitting issue [40]. The other hyper-parameters, used in this simulation, are epoch **10** for both classifications. The learning rate and batch size have a big impact on the network's performance. They have a significant correlation with each other**.** In practical terms, in order to determine the optimum batch size, it is recommended to try for smaller batch sizes first (usually 32 or 64). Keeping the learning rate low, when the batch size is decreased, the network is allowed to train better. i.e., small batch sizes require small learning rates [41]. In this performance test, ADAM is employed as optimizer along with small learning rate 0.0001 in both classifications.

Table.5. Performance test accuracy (in %) of the CoronaNet model, trained for different dropout rates

Type of classification	Batch size	Dropout rates					
		0.1	0.2	0.3	0.4	0.5	0.6
Binary class	32	92.6	90.2	92.0	89.6	89.3	82.9
	64	85.8	**93.8**	87.9	93.3	91.9	87.5
Multi-class	32	91.9	92.3	91.5	89.3	**92.7**	87.2
	64	88.3	91.6	89.7	91.0	80.0	81.6

Table.5. provides the performance of the CoronaNet for the different dropout rates such as 0.1, 0.2, 0.3, 0.4, 0.5 and 0.6. and batch sizes 32 and 64 in both classifications. For binary class classification, dropout rate 0.2 has yielded the highest accuracy of 93.8% whereas for multi-class classification, dropout rate 0.5 has yielded the highest accuracy of 92.7%.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

3.2. Batch Size

It is one of the most significant hyper-parameters for customizing the deep learning model. Hence in this performance test, the learning rate 0.0001 is used in both classifications and dropout rates 0.2 and 0.5 are used in binary and multi classifications respectively as per Table.5.

Table.6. Performance test accuracy (in %) of the CoronaNet model, trained for different batch sizes

Type of classification	Batch size			
	16	32	64	128
Binary class	89.5	91.5	**96.4**	91.3
Multi-class	92.7	**94.4**	88.1	91.4

Table.6. shows the performance test accuracy for different batch sizes, such as 16, 32, 64, and 128. For binary class classification, batch size 64 has achieved the highest accuracy of 96.4% and for multi-class classification, batch size 32 has achieved the highest accuracy of 94.4%.

3.3. EPOCH

The importance of epochs in deep learning has also been studied in numerous experimental studies. One epoch is counted when ((Number of iterations * Batch size) / (Total number of images for training)). As the epoch values increase, more number of times the weights are changed in the neural network and the curve goes from underfitting to optimal and optimal to overfitting.

Hence in this performance test, the learning rate 0.0001 is used in both classifications and dropout rates 0.2 and 0.5 are used in binary and multi classifications respectively as per Table.5. Also, the batch sizes 64 and 32 are used in binary and multi classifications respectively as per Table.6.

Type of classification	Epoch values						
	10	20	30	40	50	60	70
Binary class	92.7	94.5	94.7	92.3	**96.4**	90.3	90.3
Multi-class	91.23	92.8	**94.4**	90.6	91.5	90.9	90.0

Table.7. Performance test accuracy (in %) of the CoronaNet model, trained for various epoch values

Table.7. shows the performance of the CoronaNet for different epoch values such as 10, 20, 30, 40, 50, 60 and 70. Epoch value 50 has yielded the highest accuracy of 96.4% for binary class classification and epoch value 30 has yielded the highest accuracy of 94.4% for multi-class classification.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

Table.8. Performance of different optimizers for binary class and multi-class classifications of six pre-trained models and proposed CoronaNet model

Models	Binary class classification						Multi-class classification				
AlexNet	Optimizer	Accuracy	Precision	Sensitivity	Specificity	F1-Score	Accuracy	Precision	Sensitivity	Specificity	F1-Score
	Sgdm	94.8 %	91.19%	98.87 %	90.90 %	92.8%	93.7 %	89.63%	92.51 %	94.31 %	91.39 %
	Adam	**95.9 %**	95.85%	96.35 %	95.37 %	94.79 %	**93.9 %**	86.52	96.53	92.89 %	92.8%
	Rms-prop	91.2 %	96.89%	87.79 %	96.05 %	93.07 %	91.5 %	92.22%	85.16 %	95.45 %	93.07 %
GoogleNet	Sgdm	91.5 %	92.22%	85.16 %	95.45 %	93.07 %	82.8 %	83.41%	96.40 %	91.39 %	93.79 %
	Adam	**92.8 %**	83.41%	96.40 %	91.39 %	92.74 %	**83.89 %**	86.52	96.53	92.89 %	95.3%
	Rms-prop	80.7 %	92.47%	66.54 %	94.81 %	91.39 %	82.9 %	84.97%	94.79 %	92.07	92.8%
ResNet-50	Sgdm	92.3 %	85.49	100.00%	86.00 %	95.3%	**90.8 %**	92.74%	92.74 %	95.95 %	90.16 %
	Adam	**93.7 %**	92.22%	95.69 %	91.62 %	90.16 %	89.80	81.10	96.06	91.27	93.08
	Rms-prop	91.5 %	94.30	90.09 %	93.25 %	89.11 %	88.1 %	87.56%	81.25 %	92.74 %	91.39 %
VGG-16	Sgdm	95.1 %	91.47%	99.15 %	91.20 %	95.3%	91.9 %	93.79%	90.29 %	96.56 %	92.8%
	Adam	**96.3 %**	96.12%	96.87 %	95.68 %	90.16 %	90.4 %	93.79%	91.66 %	96.49 %	93.07 %

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

	Rms-prop	94.3%	92.24%	96.74%	91.73%	92.8%	**92.6%**	79.85%	97.81	90.79	95.3%
SqueezeNet	Sgdm	88.1%	87.56%	81.25%	92.74%	91.39%	82.8%	83.41%	86.40%	91.39%	90.8%
	Adam	**94.8%**	92.74%	92.74%	95.95%	93.07%	**89.40**	94.11%	79.39%	95.95%	93.07%
	Rms-prop	91.5%	92.22%	85.16%	95.45%	93.07%	85.9%	86.52	96.53%	92.89%	92.24%
Inception-V3	Sgdm	**93.2%**	90.67%	96.15%	90.16%	95.3%	93.7%	83.41%	99.38%	91.51%	91.39%
	Adam	91.8%	84.97%	99.39%	85.50%	91.39%	**89.7%**	79.11%	97.17%	94.19%	90.16%
	Rms-prop	**93.2%**	94.30%	92.85%	93.49%	92.24%	83.5%	87.04%	94.38%	93.07%	92.24%
CoronaNet	Sgdm	95.1%	92,74%	97.81%	92.30%	92.74%	85.9%	84.97%	94.79%	72.07	96.87%
	Adam	**96.40%**	95.36%	97.44%	95.43%	92.22%	**94.40**	94.29	91.68%	97.11	93.05
	Rms-prop	88.2%	82.90%	94.11%	83.07%	88.30	80.7%	92.47%	66.54%	94.81%	89.11%

3.4. Performance Of Different Optimizers

An optimizer (learning algorithm) helps the architecture to learn more information during the training process in order to minimize the performance gap between training and validation.

Table.8. presents the results of binary class and multi-class classification problems using different optimizers, viz. SGDM (Stochastic Gradient Descent Optimization), ADAM (Adaptive Moment Estimation) and RMS-prop. According to the table, ADAM optimizer on the AlexNet, GoogleNet and SqueezeNet have produced the highest classification accuracies of 95.9%, 92.8% and 94.8% respectively for binary class classification and of 93.9%, 83.89% and 89.40% respectively for multi-class classification.

The ADAM optimizer on the ResNet-50 model has produced the highest classification accuracy of 93.7% for binary class classification while the SGDM optimizer has produced the highest accuracy of 90.8% for multi-class classification. For binary classification, the ADAM optimizer on the VGG-16 model has yielded the greatest accuracy of 96.3%, while the RMS-prop optimizer on VGG-16 has yielded the highest accuracy of 92.6% for multi-class classification. SGDM optimizer on Inception-V3 has yielded the highest classification

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

accuracy of 93.2% for binary class classification whereas ADAM optimizer on Inception-V3 has yielded the highest classification accuracy of 89.7% for multi-class classification.

In comparison to the other competitive optimization methods, the ADAM optimizer performs quite well in both classifications. The ADAM optimization technique is applied during the training phase to avoid error in each iteration. Its optimization algorithm is an adaptive learning rate algorithm is developed specifically for deep neural network training. It is simple to use and uses a little memory to implement the function. It combines the Root Mean Square Propagation (RMS-prop) and the SGDM optimization techniques [39].

The proposed CoronaNet model with ADAM optimizer has generated the highest classification accuracy of 96.4% for binary class classification and of 94.4% for multi-class classification. Hence, ADAM optimizer has been adopted in our study.

In our observation, while using the same hyper-parameter values both in the pre-trained and CoroanaNet models, their classification accuracies for binary class classification are almost closer; but that for multi-class classification are lower in pre-trained models. If different hyper-parameter values will be used in these pre-trained models, then the classification accuracies may improve.

Table.9. Hyper-parameters of proposed CoronaNet model for binary class and multi-class classifications

Hyper-parameters	Binary class classification	Multi-class classification
Learning rate	0.0001	0.0001
Batch Size	64	32
Dropout	0.2	0.5
Epoch	50	30
Optimizer	ADAM	ADAM
Activation layer	Leaky ReLU	Leaky ReLU
Hardware resource	Single CPU	Single CPU
Programming language	Matlab 2021Rb	Matlab 2021Rb

Hyper-parameters are parameters in which their values are set before starting the model training process. The various hyper parameters, used for the proposed network, are displayed in Table.9. Learning rate 0.0001(for both classes), Dropout 0.2 and 0.5, Batch size of 64 and 32, Epoch 50 and 30 values and Optimizer ADAM (for both classes) have been respectively set for training CoronaNet for binary class and multi-class classifications.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

3.5. Graphics Of Training Accuracy And Validation Loss

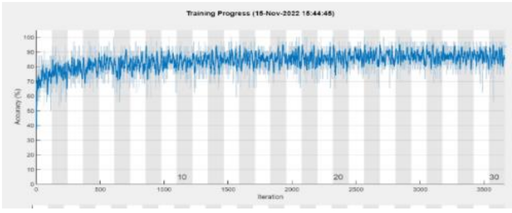

Fig.6(a). Plot of training accuracy of proposed model for multi-class classification

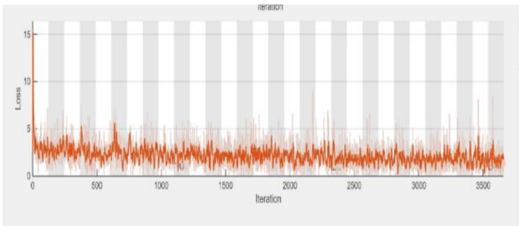

Fig.6(b). Plot of validation loss of proposed model for multi-class classification

Figs. 6(a) and 6(b) depict the performance evaluation of training and validation loss accuracy. In Fig.6(a)., the light blue color denotes training accuracy while the blue color denotes testing accuracy. The loss value for the training samples presented in Fig.6(b). The orange color indicates validation loss for training while light orange indicates that for testing. The training has been finished in 2000 iterations for binary class classification and in 3660 iterations for multi-class.

3.6. Confusion Matrix Of Coronanet Model

The following confusion matrices which are generated after the full iterations are over in our CoronaNet model.

	Covid-19	Non-Covid
Covid-19	535	26
Non-Covid	14	544

Fig.7(a). Confusion matrix for binaryclass classification of CoronaNet

	Covid-19	Normal	Pneumonia
Covid-19	529	28	4
Normal	29	514	15
Pneumonia	19	0	548

Fig.7(b). Confusion matrix for multi-class classification of CoronaNet

The confusion matrix of binary class classification is shown in Fig.7(a). Among the 561 Covid-19 images, 26 images are misclassified as Non-Covid, while in normal case 14 chest X-ray images are misclassified as Covid-19. Fig.7(b). depicts the confusion matrix of multi-class classification. 529 COVID-19 samples, 514 normal samples, and 548 pneumonia samples were correctly classified, totally 32 COVID-19 samples were misclassified as Normal and Pneumonia, 29 normal samples are misclassified as Covid-19. 15 normal samples are misclassified as Pneumonia1.19 Pneumonia samples are misclassified as Covid-19. Overall, the accuracy achieved by binary class classification is 96.4% and multi class classification is 94.4%.

3.7. Comparison Of the Proposed Coronanet Model With Other Existing Studies

According to the findings, the majority of other existing CNN studies have been trained on a small dataset for classification, whereas the proposed CoronaNet model has been trained on a huge dataset. Table.10. shows a comparative analysis of the existing CNN studies and the proposed CoronaNet model in terms of accuracy. The proposed model has achieved the highest accuracy of 96.4% for binary class and 94.4% for multi-class classifications.

Existing studies & CoronaNet model	Accuracy of binary class	Accuracy of multi-class
T. Ozturk et al. [18]	-	87.02%
Linda Wang et al. [19]	-	92.60%
M. Polsinelli et al. [20]	85.03%	-
M. M. Mijwil and E. A. Al-Zubaidi [21]	82.14%	-
Lourdes Duran-Lopez et al. [22]	94.24	-
Prabira Kumar Sethy et al. [23]	95.38	-
Ezz EI-Din Hemdan et al. [24]	90%	
X. Xu et al. [25]	86.7%	
M. Rahimzadeh and A. Attar [26]	-	91.40%
T. Mahmud et al. [27]	94.7%	89.6%
K. Medhi et al. [28]	93%	-
AlexNet	95.9%	93.9%
GoogleNet	92.8%	83.89%
VGG-16	96.3%	92.6%
ResNet-50	93.7%	89.8%
SqueezeNet	94.8%	89.4%
Inception-V3	92.7%	89.7%
Proposed CoronaNet	**96.4%**	**94.4%**

Table.10. Comparison of the proposed CoronaNet model with existing CNN studies

The automatic detection of Covid-19 from the test dataset of chest X-ray images using proposed CoronaNet model is illustrated in Fig.8. as an example. In this figure, the input and output images are displayed as multi-classification results of Covid-19, Normal and Pneumonia.

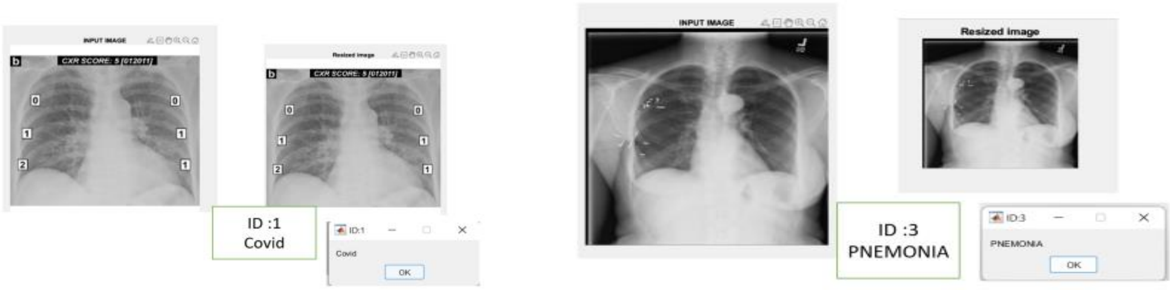

Fig .8. Illustration of classification results of the proposed CoronaNet model for randomly selected test input images

4. Conclusions

A new CNN approach (CoronaNet) is presented in this study to detect Covid-19 from chest X-ray images. The proposed approach can be used to test larger size datasets. When the results are compared to various existing binary class classification and multi-class classification models (Table 10), the proposed model has achieved the highest accuracy of 96.4% for binary class classification and 94.4% for multi-class classification. Dropout 0.5 has yielded highest accuracy 92.7% for multi-class classification and dropout 0.2 has yielded highest accuracy 93.8% for binary class classification. Batch sizes of 64 and 32 are respectively chosen for binary class classification and multi-class classification. Both the classification procedures have used the same Learning rate 0.0001. Epoch 50 and 30 are respectively chosen for binary class and multi-class classifications. In this study, ADAM optimizer has been adopted. This study /simulation suggests that batch normalization performs better than group normalization and LeakyReLU performs better than the other two activation functions viz. ReLU and Elu. Hence, LeakyReLU activation function is used in both classifications. The proposed model is less expensive to compute and has showed promising results. There is no need for manual feature extraction because proposed model is totally automated from beginning to end. The hyper-parameters dropout, batch size, epoch and optimizer, all, used for training, have a bigger impact on the classification accuracies. The proposed CoronaNet model outperforms the existing models in detecting Covid-19 from chest X-ray images. The proposed technique could be a useful tool for radiologists to diagnose and treat Covid-19 patients promptly.

Acknowledgements

The authors thank Professor K. S. Easwarakumar of Anna University CEG campus, Chennai for useful discussions, his interest and encouragement. We also thank Professor S. Sridhar of Anna University CEG campus, Chennai for useful discussions. Two of the authors (DLA & TPP) thank Professor K. P. N. Murthy (Late) for guiding and encouraging us. The first author (DLA) is very grateful to "**Baby-Perumal Research Institute**" at Chennai for research guidance and supporting us with computing facilities.

References

[1] W. Guan, et al., "Clinical Characteristics of Coronavirus Diseases 2019 in China", *The New England Journal of Medicine,* Vol.382, pp.1708-1720, 2020.

[2] Zi Yue Zu, M.Sc. et al, "Coronavirus Disease 2019 (COVID-19): *A Perspective from China"*, Radiology, Vol.296, pp. E15-E25, 2020.

[3] K. H. Shibly et all," COVID faster R–CNN: A novel framework to Diagnose Novel Coronavirus Disease (COVID-19) in X-Ray images", *Informatics in Medicine Unlocked,* Vol.20, pp .1-9, 2020.

[4] C.Jalaber et al, "Chest CT in COVID-19 pneumonia: A review of current knowledge", *Diagnostic and Interventional Imaging,* Vol.101, pp.431-437, 2020.

[5] C. Hani et al, "COVID-19 pneumonia: A review of typical CT findings and differential diagnosis", *Diagnostic and Interventional Imaging,* Vol.101, pp.263-268, 2020.

[6] S. Hassantabar, M. Ahmadi and A. Sharifi, "Diagnosis and detection of infected tissue of COVID-19 patients based on lung x-ray image using convolutional neural network approaches", Chaos, *Solitons and Fractals,* Vol.140, 110170, pp.1-11, 2020.

[7] S. H. Khan et al, "Coronavirus disease analysis using chest X-ray images and a novel deep convolutional neural network*", Photodiagnosis and Photodynamic Therapy*, Vol.35, 102473 pp. 1-11, 2021.

[8] S.H. Khan et al, "Covid-19 detection in chest X-ray images deep boosted hybrid learning", *Computers in Biology and Medicine*, Vol.137, 104816, pp .1-12, 2021.

[9] C. Long et al, "Diagnosis of the Coronavirus disease (COVID-19): rRT-PCR or CT?", *European Journal of Radiology,* Vol.126, 108961, pp. 1-5, 2020.

[10] Michael D Hope et al, "A role for CT in COVID-19? What data really tell us so far", *The Lancet,* Vol.395, 10231, pp.1189-1190, 2020.

[11] Dhablia, D., & Timande, S. (n.d.). Ensuring Data Integrity and Security in Cloud Storage.

[12] X. Ding et al, "Chest CT findings of COVID-19 pneumonia by duration of symptoms", European *Journal of Radiology*, Vol.127, 109009, pp 1-6, 2020.

[13] A.M. Ismael and A. Sengur, "Deep learning approaches for COVID-19 detection based on chest X-ray images", *Expert Systems with Applications,* Vol.164, 114054, pp. 1-77, 2021.

[14] M. F. Aslan et al, "CNN-based transfer learning–BiLSTM network: A novel approach for COVID-19 infection detection", *Applied Soft Computing Journal,* Vol.98, 106912, pp. 1-12, 2021.

[15] Vaira Suganthi Gnanasekaran et al, "Deep learning algorithm for breast masses classification in mammograms", *IET image process*, Vol.14 (12), pp. 2860-2868, 2020.

[16] L. Zou et al, "3D CNN Based Automatic Diagnosis of Attention Deficit Hyperactivity Disorder Using Functional and Structural MRI", *IEEE Access,* Vol.5, pp.23626-23636, 2017.

[17] Xinzhuo Zhao et al, "Agile convolutional neural network for pulmonary nodule classification using CT images", *International Journal of Computer Assisted Radiology and Surgery,* Vol.13, pp.585-595, 2018.

[18] J. Liu et al, "Integrate Domain Knowledge in Training CNN for Ultrasonography Breast Cancer Diagnosis", *Medical Image Computing and Computer Assisted Intervention,* Vol. 11071, pp.868-875, 2018.

[19] Dhabalia, D. (2019). A Brief Study of Windopower Renewable Energy Sources its Importance, Reviews, Benefits and Drwabacks. Journal of Innovative Research and Practice, 1(1), 01–05.

[20] T. Ozturk et al, "Automated detection of COVID-19 cases using deep neural networks with chest X-ray images", *Computers in Biology and Medicine*, Vol.121, 103792, pp. 1-11, 2020.

[21] Linda Wang, Zhong Qiu Lin and Alexander Wong, "COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images", Scientific *Reports*, Nature, Vol.10:19549, pp. 1-12, 2020.
[22] M. Polsinelli, L. Cinque and G. Placidi, "A light CNN for detecting COVID-19 from CT scans of the chest", *Pattern Recognition Letters*, Vol.140, pp. 95-100, 2020.
[23] M. M. Mijwil and E. A. Al-Zubaidi, "Medical Image Classification for Coronavirus Disease (COVID-19) Using Convolutional Neural Networks", *Iraqi Journal of Science*, Vol.62, No.8, pp. 2740-2747, 2021.
[24] Lourdes Duran-Lopez et al, "COVID-XNet: A Custom Deep Learning System to Diagnose and Locate COVID-19 in Chest X-ray Images", *Appl. Sci.*, Vol.10, 5683, pp.1-12, 2020.
[25] Prabira Kumar Sethy et al., "Detection of Coronavirus Disease (COVID-19) based on Deep Features and Support Vector Machine", *Preprints (Unpublished)*, pp.1-10, 2020.
[26] Ezz EI-Din Hemdan, Marwa A.Shouman and Mohamed Esmail Karar, "COVIDX-Net : A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images", *Cornell University*, Image and Video Processing, pp.1-14, 2020. [Cite as arXiv:2003.11055 **(eess.IV)**]
[https://doi.org/10.48550/arXiv.2003.11055]
[27] X. Xu et al., "A Deep Learning System to Screen Novel Coronavirus Disease 2019 Pneumonia", *Engineering*, Vol.6, pp.1122-1129, 2020.
[28] M. Rahimzadeh and A. Attar, "A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2", Informatics *in Medicine Unlocked*, Vol.19, 100360, pp. 1-9, 2020.
[29] T. Mahmud et al, "CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization", *Computers in Biology and Medicine*, Vol.122, 103869, pp. 1-10, 2020.
[30] Mr. Dharmesh Dhabliya, M. A. P. (2019). Threats, Solution and Benefits of Secure Shell. International Journal of Control and Automation, 12(6s), 30–35.
[31] K. Medhi et al, "Automatic Detection of Covid-19 Infection from Chest X-ray using Deep Learning", medRxiv, pp. 1-6, 2020. [**doi:** https://doi.org/10.1101/2020.05.10.20097063]
[32] S. R. Nayak et al, "Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study", *Biomedical Signal Processing and Control*, Vol. 64, 102365, pp.1-12, 2021.
[33] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning", *Journal of Big Data, 6:60*, pp.1-48, 2019.
[34] S. Hira et al, "An automatic approach based on CNN architecture to detect Covid-19 disease from chest X-ray images", *Applied Intelligence*, Vol.51, pp.2864-2889, 2021.
[35] Keze Wang et al, "Dictionary Pair Classifier Driven Convolutional Neural Networks for Object Detection", *IEEE Conference on Computer Vision and Pattern Recognition*, pp.2138-2146, 2016.
[36] E. Hussain et al, "CoroDet : A deep learning based classification for COVID-19 detection using chest X-ray images", *Chaos, Solitons and Fractals*, Vol.142, 110495, pp.1-12, 2021.
[37] Ali Narin et al, "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks", *Pattern Analysis and Applications*, Vol.24, pp.1207-1220, 2021.
[38] Alex Krizhevshy, Ilya Sutskever and Geoffrey E.Hinton, "ImageNet Classification with Deep Convolutional Neural Networks", *Communications of the ACM*, Vol. 60, Issue 6, pp.84-90, 2017.

The Ciência & Engenharia - Science & Engineering Journal
ISSN: 0103-944X
Volume 11 Issue 1, 2023
pp: 1702-1720

[39] Christian Szegedy et al, "Going Deeper with Convolutions", Proceedings *of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp.1-9, 2015.

[40] Dhananjay Theckedath and R. R. Sedamkar, "Detecting Affect States Using VGG16, ResNet50 and SE-ResNet50 Networks", SN *Computer Science,* 1:79, pp.1-7, 2020.

[41] Verma, M. K., & Dhabliya, M. D. (2015). Design of Hand Motion Assist Robot for Rehabilitation Physiotherapy. International Journal of New Practices in Management and Engineering, 4(04), 07–11.

[42] Jahandad et al, "Offline Signature Verification using Deep Learning Convolutional Neural Network (CNN) Architectures GoogLeNet Inception-v1 and Inception-v3", *Procedia Computer Science,* Vol.161, pp.475-483, 2019.

[43] Diederik P. Kingma and Jimmy Lei Ba, "ADAM: A Method for Stochastic Optimization", Published as a conference paper at *ICLR 2015 (*in *San Diego, CA, USA)*.

[44] I. Kandel and M. Castelli, "The effect of batch size on the generalizability of the convolutional neural networks on a histopathology dataset", *ICT Express,* Vol.6, pp.312-315, 2020.

[45] Dhabliya, M. D. (2019). Uses and Purposes of Various Portland Cement Chemical in Construction Industry. Forest Chemicals Review, 06–10.

[46] Nitish Srivastava et al, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting", *Journal of Machine Learning Research,* Vol.15, pp. 1929-1958, 2014.