COVID-19 Identification in CLAHE Enhanced CT Scans with Class Imbalance using Ensembled ResNets

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***Abstract*—The occurrence of imbalanced datasets in medical imaging has proven to be a challenge for the development of models to analyze and evaluate the underlying condition. In this paper, the bias of the chest CT scan dataset is handled by taking discrete splits and employing ResNets to detect COVID-19 in each split. The scraped images were pre-processed using CLAHE histogram for comparison with low contrast images. Multiple ResNets were extended to form an ensemble neural network model using ANNs which handles the class imbalance. The system has an overall accuracy of 87.23% and the performance is assessed for each class. The image features identified are visualized using the GradCAM algorithm and some of the commonly found clinical features in the CT scan images of the patients suffering from this disease are summarized for better understanding the working of the model.**

Keywords—Imbalanced Data, COVID-19 detection, Ensemble ResNets, Chest CT-scans

I. Introduction

Deep neural network architectures have been widely used in the classification of medical images for the detection of the underlying condition [1]. These systems have the ability to identify and learn extensive features from the image datasets for discerning the clinical features detected in them.

COVID-19 [2] is a disease caused by the Severe Acute Respiratory Syndrome Coronavirus 2 or (SARS-CoV-2). It is a highly communicable disease with people experiencing respiratory illness and recovery expected with effective and appropriate treatment methods. The most commonly used test for the disease is the RT-PCR (Reverse Transcription Polymerase Chain Reaction) [3]. The identification of this disease can also be done by analyzing the chest CT scans of the patients for some of the widely observed clinical features given below [4]:

1) Ground Glass Opacities (or GGOs)

One of the most common findings in chest CT scans of people diagnosed with COVID-19 infections is GGOs [5]. Usually multifocal, bilateral and peripheral but in the early phase of this disease. They initially start developing from the inferior lobe of the right lung as a unifocal lesion.

2) Air space consolidation or opacification

This refers to the condition in which there is replacement of the usually present gas by fluids or solids in the lung parenchyma (small airways present in the lungs) [6].

3) Crazy paving appearance

This occurs in the more later stages of the infection. Here, thickened interlobular and intralobular lines in combination with a ground glass pattern are visible in the CT scans of the patients [7].

4) Bronchovascular thickening in the lesion

This refers to the widened vessels observed through the chest CT scans. The bronchial walls become thicker due to inflammation owing to the accumulation of liquid or mucus [8].

5) Traction bronchiectasis

This is a common condition observed in patients that arises when the airways to lungs may get damaged around GGOs [9]. Due to this, there will be accumulation of the mucus in the lungs, leading to a variety of complications including buildup of bacteria causing other infections.

6) Formation of subpleural bands

This is a comparatively rare condition found in patients where there is a formation of thin curvilinear opacities between the surface of the lungs and the chest walls [10].

The need for a model to handle highly imbalanced dataset would help in the identification of the disease with its estimated severity for timely treatment. With the spread of the disease to over 214 countries [11] of the world with widely varying severity and the low detection rates of the disease due to its asymptomatic nature, the identification of the disease is proving to be a challenge.

Residual deep neural networks or ResNets [12] follow the architecture of Convolutional Neural Networks (or CNNs) [13]. They exhibit high control over the information that flows from one cell to the next in the cell using a parameterized forget gate. These networks have a more refined residual block, a pre-activation variant of residual block for simplifying the flow of learned gradients in the network.

In the field of auxiliary medical diagnosis technology, ensembled deep neural networks [14] have performed extremely capably for the detection of clinical features in the medial images. Ensemble network architectures [15] use the activations and the feature weights learned from the individual deep neural models and their learnings are enhanced for increasing the efficiency of their performance.

Images available for training may not be of uniform contrast or brightness for the neural network to identify features within them [16]. To improve the contrast improvement index, entropy and measure of enhancement [17], Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for their normalization. The images are split into regions and histograms are calculated for each region which are then interpolated in between.

Gradient-weighted Class Activation Mapping (or GradCAM) [18] algorithms are a generalization of the Class Activation Mapping [19] algorithms used for producing visual explanations for trained deep neural models. The better localization and clear class discriminative saliency maps allow the understanding of the gradient weights built up at the final layer in the deep neural architecture [20]. They are combined with existing pixel-shaped visualizations to create high-resolution class-discriminative visualization.

In this paper, class imbalance is handled by creating splits of equal ratios of images across both COVID-19 and non-COVID-19 images. Each split is trained using a ResNet model and the outputs of the individual models are ensembled using a feed forward neural network. The effect of increasing contrast within the image by using CLAHE enhancement is analyzed. The features identified by the trained network are visualized using the GradCAM algorithm.

The rest of the paper is organized as follows. Section II gives the summary of some of the best deep neural networks used for medical image classification. The system design of the developed deep neural network is given in Section III, followed by the implementation details in Section IV. Results obtained from the model along with their analysis is presented in Section V. Section VI presents the conclusion of the paper with Section VII summarizing the proposed future works with improvements for the paper.

II. Related Works

The summary of some of the state-of-the-art work done in the field of classification of medical images, ensemble networks and imbalanced datasets is given below with a detailed discussion on its advantages and comparison with our developed model.

Ensemble deep neural network architectures are generally applied for the optimization of the performance of a single constructed network. Mporas and Naronglerdrit [21] evaluated the existing well-known pretrained models identification of COVID-19 in X-Ray images with publicly available datasets. Rafi [22] implemented an ensemble system for the detection of COVID-19 in X-Ray images. This network aimed to combine two state-of-the-art models, ResNet and Deep CNN, that used transfer learning techniques to achieve more accurate results. A SoftMax optimization function was used to further optimize over the trained models with pre-trained weights for faster concurrence.

In our model, the dataset contained highly imbalanced chest CT scans which were normalized using CLAHE algorithms for enhancing their features. These images were resampled and fed to a cluster of ResNet models for creating an ensemble architecture for improving the efficiency of the system and to balance the dataset by eliminating the high bias between the classes.

Liu et al [23] developed an ensemble architecture for highly imbalanced data using under sampling methods giving high performance with highly overlapped and skewed distributions. The use of classification hardness distribution concept helped to overcome the difficulties even with the presence of noise and missing values in the chosen dataset. Cahyana et al [24] expanded their minority class by oversampling to fix the size of the majority class for increasing the number of its instances for training the model for classification.

In our model, the dataset contained imbalance distribution of images in the binary classes and this was studied to improve the performance of our model by combining the attribute weights of each model trained with proportional images distributed in the classes and combined using an ensemble method. This has helped to avoid the oversampling of the minor class and ensure the high performance of the model for classification.

Deep neural architectures that implement supervised learning algorithms suffer from high prediction bias due to an imbalanced dataset resulting in poor performance and low computation efficiency. Aggarwal et al [25] used Active Learning (AL) algorithm to increase the effectiveness of labelling using an acquisition function. This function trains on the labelled dataset before picking more from the unlabeled dataset until the entire budget is spent.

Our model handles the imbalanced dataset by splitting the class with the higher images into multiple sets and training each set of the images with the images from the minor class. The performance of each deep neural model with a set of the images paired with the minor class is then saved with its learnt feature weights after training. The activations from each of the models is then used to build an ensemble network with high performance over the individual models.

Wang et al [26] performed the detection of COVID-19 in X-ray images dataset with data enhancement to 17 times the size for classification into COVID-19 positive, normal and viral pneumonia labels. They used transfer learning to fusion multiple trained models for dynamically improving their weight ratio during the training process.

In our paper, the enhancement of the dataset images were performed using CLAHE histogram for the ensemble ResNet-ANN model to extract the features for the classification of COVID-19 chest X-Ray images into COVID-19 positive and negative. This method would be applicable to study the imbalanced dataset with no oversampling to improve the quality of the training classification model. The learning of the model was visualized by using the Grad-CAM algorithm for observation.

In summary, an imbalanced COVID-19 dataset with chest CT-scans was chosen for binary classification. To improve the performance of the model, an ensemble architecture with multiple ResNets was developed with the major label split into sub-datasets for training with the minor dataset individually and the trained weights were fed into various meta classifiers for categorization. The visualizations of the trained attributes was done using the Grad-CAM algorithm and the analysis presented.

III. System Design

This section gives the details of the ensemble ResNet system for the binary classification of the COVID19 dataset with imbalanced classes.

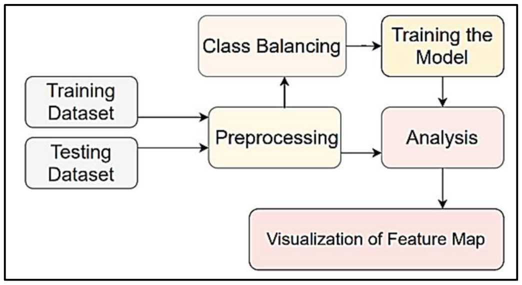

Fig. 1. Overall Architecture Diagram

Figure 1 describes the overall design which is adopted to handle class imbalance in the number of scans and to detect COVID-19 without bias towards any one class. The training and testing sets are preprocessed by using Contrast Limited Adaptive Histogram Equalization (CLAHE) to equalize the images. The training set is then balanced by splitting the set into equal parts and an ensemble of classifiers is trained. The testing set is analyzed against the trained model and the features identified by the model are visualized using GradCAM algorithm.

A. *Dataset Description*

The dataset contains chest CT-scans scraped from the Web [27] with the distribution given in Table I. Class 0 refers to the images that are obtained from those who have not tested positive for COVID-19 and Class-1 images are collected from those tested COVID-19 positive. The dataset has a high imbalance of positive images.

TABLE I. Images Per Class Distribution

Severity	Class 0	Class 1
Training set	566	5810
Testing set	50	100

B. *Preprocessing*

The CT Scan images are preprocessed by applying the CLAHE filter [28] which is a variant of Adaptive Histogram Equalization (AHE) [29]. AHE works on the principle of contrast amplification [30] and has a disadvantage of over amplifying noise when there are near-constant regions. This is overcome by using CLAHE which clips the histogram at a clip limit thereby limiting amplification to a value between 3 and 4. CLAHE performs histogram equalization locally, pixel by pixel. Algorithm 1 is used for applying CLAHE normalization on the collected CT-scans and to improve the contrast of the images.

Algorithm 1: CLAHE Normalization for pre-processing the images

```
input  : img: chest CT-scan images for normal and positive
         COVID-19, clipLimit: threshold for contrast limiting
output: Normalised_img: images after normalisation with
         CLAHE histogram
Function CLAHEimages(img,clipLimit):
    Resized_img ← img.resize()
    Grayscale_img
      ← Resized_img.convertColour(RGB_to_GRAY)
    Normalized_img ← Grayscale_img.createCLAHE(clipLimit)
    Normalized_img.save()
end
```

C. *Class Balancing*

Imbalance in dataset [31] classes can result in the model overfitting the data of the major class and not being able to predict the minor class effectively. To resolve this, resampling [32] of the dataset using replication of minority classes is performed by calculating the ratio with which the dataset should be split as seen in Algorithm 2. This ensures the majority class is balanced with the minority class as in each split, all the samples of the minority class are present and the same number of differing samples of majority class are present. The split factor determines the balance of major and minor classes.

Algorithm 2: Determining Dataset Split Ratio

```
input  : n: size of majority class, m: size of minority class,
         factor: split factor
output: split_ratio: number of splits in dataset
Function split_dataset(n, m):
    if m > n then
        split_ratio ←factor*⌊m/n⌋
    else if n > m then
        split_ratio ←factor*⌊n/m⌋
    end
end
```

D. *Modelling Each Data Split*

Once the dataset is split into divisions with equal ratios of major and minor classes, each division is modelled using the ResNet model. ResNets [33] are a deep neural model that solve the vanishing gradient problem by using "Residual blocks" which are seen in Figure 2.

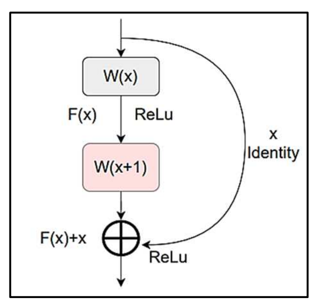

Fig. 2. Structure of ResNet Block

The core aspect of residual blocks are "skip connections" [34]. Using skip connections the output $H(x)$ can be defined as,

$$H(x) = F(x) + x \tag{1}$$

ResNets resolve the vanishing gradient problem by creating many small networks that are ensembled together to create a deeper network. The output of a previous layer is added to a deeper layer and this process is repeated throughout the network ensuring that there is a continuous propagation of values.

E. Ensemble ResNet Architecture

Once ResNets are built for each dataset split, an ensemble network is created. Ensembling [35] involves modelling the predictions of individually trained models in order to improve the performance of detection. Each individual ResNet is trained on a particular dataset split and then the entire training set is run against the trained ResNets as seen in Figure 3. The output predictions of the ResNet models are then trained using a Level-1 classifier achieving a two-step optimization in learning. The Level-1 classifier is chosen as an ANN based on the overall performance of the classification model.

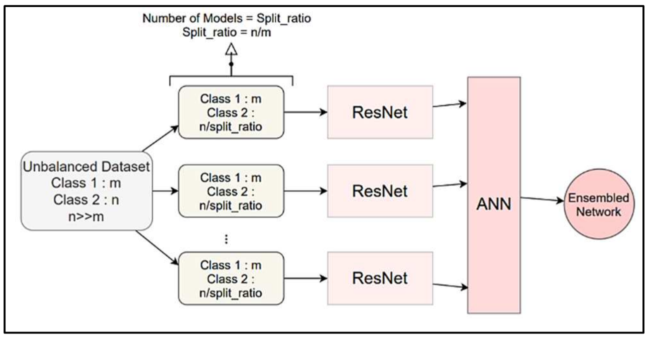

Fig. 3. Ensemble Network to Resolve Class Imbalance

IV. System Implementation

The neural models are implemented using Google Colab with Intel(R) Xeon(R) CPU @ 2.20GHz Processor, 13 GB RAM and 12GB NVIDIA Tesla K80 graphics processor.

A. Dataset Preprocessing

The images from the dataset contain chest CT-scans from both patients tested positive for COVID-19 and those who tested negative. These images undergo normalization using Contrast Limited Adaptive Histogram Equalization (CLAHE) [36] normalization for over-amplification of the contrast. This procedure is applied on the luminance channel of the images and the results are after equalizing only the luminance channel [37] of an Hue Saturation Value (HSV) image. The clip limit [38] which acts as the threshold for contrast limiting is taken as 5. Figure 4 a) and b) show how CLAHE histogram equalization increases the contrast within the image and shows how the features within the image get highlighted with better equalization. Once CLAHE histogram equalization is applied, the CT scan images are augmented using Keras's Image Data Generator [39]. Augmentation parameters used are specified in Table II.

B. Balancing the Dataset

The processed data set is then resampled to avoid class imbalance. In this dataset collected, positive COVID-19 images are the major class and negative COVID-19 images are the minor class. The split factor of the dataset is taken as 2 i.e. the number of positive COVID-19 images in each dataset split is twice the number of negative COVID-19 images in that split.

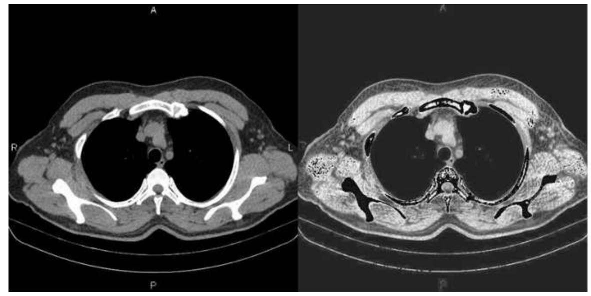

Fig. 4. CT Scan Image of COVID-19 Positive Patient a) Original Image b) with CLAHE Histogram Equalization

TABLE II. Image Data Generator Parameters

Parameter	Value
Rotation Range	40 degrees
Width_shift_range	0.2
Height_shift_range	0.2
Rescale	1/255
Shear_range	0.2
Zoom_range	0.2
Horizontal_flip	True

TABLE III. Training Parameters of Individual ResNet Models

Parameter	Value
ResNet Version	1
Number of Layers	20
Loss	Categorical Cross Entropy
Optimizer	Adam
Learning Rate	0.01
Batch Size	64
Epochs	10

The number of dataset splits is calculated to be 5 according to Algorithm 2. Each of the 5 dataset splits has 566 non COVID-19 images and 1162 positive COVID-19 images.

C. ResNet Model

The ResNet model was built using Keras and TensorFlow [40]. The model has an initial convolutional layer with 16 filters of 32 x 32 dimensions applied. The outputs of the initial convolutional layer are fed to a batch normalization layer followed by an activation layer. Next, 64 filters of 32 x 32 dimensions are applied followed by layers of batch normalization, activation and convolution. This process is repeated by reducing the dimensions of the filters by half and doubling the number of the filters until the number of filters reaches 256 and the dimensions are 8 x 8.

At each stage of the ResNet there are residual blocks that concatenate the output of the previous block with the output of the current block using a concatenation layer. The activation function used in these hidden layers is ReLu [41]. The final stage of the ResNet involves average pooling and flattening the vectors to form a 1D tensor. The output layer has 2 nodes which are activated using SoftMax activation [41]. The ResNet models are trained using the parameters described in Table III.

D. Ensemble Neural Network

Once the ResNet models are trained, each image of the training set is run through each of the 5 models and the output activations are noted and then fed into a Level-1 meta classifier. The Level-1 classifier learns the features from the already optimized activations and tries to determine if the CT scan images have COVID-19 or not.

Different machine learning algorithms are implemented as a part of determining the best meta classifier. It is observed from Figure 5 that the Artificial Neural Network (ANN) performed as the best Level-1 classifier with the accuracy of the predicted images at 87.13%. This can be attributed to the size of the dataset being smaller along with the presence of imbalanced data classes enabling the deep neural model to execute its own feature engineering to search for features and converge faster during the training of the model.

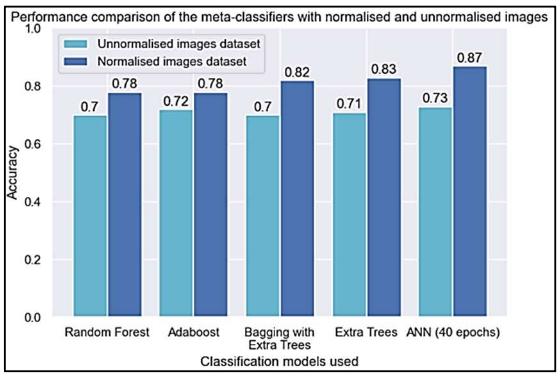

Fig. 5. Performance Comparison of Meta-Classifiers with Normalized and Unnormalized Images

The Level-1 ANN model has 10 input nodes corresponding to the output probabilities of 5 level-0 models. It is followed by 7 hidden layers with 8,16,32,64,64,32,16 and 8 nodes each activated by ReLu activation function. The output layer has 1 node activated by Sigmoid [41] activation function. The Level-1 ANN classifier is trained using the parameters given in Table IV.

TABLE IV. TRAINING PARAMETERS OF LEVEL-1 ANN CLASSIFIER

Parameter	Value
Loss	Binary Cross Entropy
Optimizer	Adam
Learning Rate	0.01
Batch Size	32
Epochs	50

V. RESULTS AND ANALYSIS

This section presented the results obtained from the classification of COVID-19 CT-scan images using the ensembled ResNet model developed.

A. Training plot of the ensemble ResNet for the classification of COVID-19 CT scans with and without CLAHE histogram

The training plot of the ensemble ResNet-ANN model using the ANN as meta-classifier is given in Figure 6 along with the variation of accuracy and loss. This helps to identify the learnings of the model to stop the training before overfitting the data but with enough time to avoid underfitting the data.

The accuracy is observed to have reached a peak at about 92.34% with the loss at 17.49%.

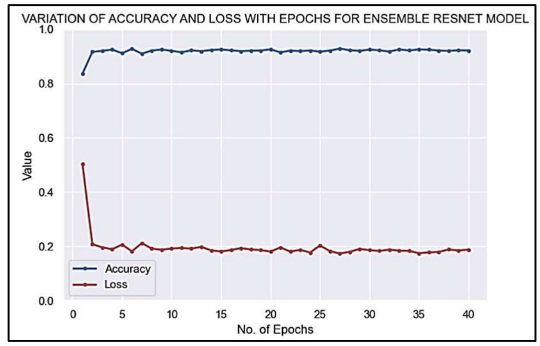

Fig. 6. Variation of Accuracy and Loss with Epochs for Ensemble ResNet Model

B. Confusion matrix of the ensemble ResNet model trained with images normalised with CLAHE histogram

The confusion matrix of the ensemble ResNet-ANN network in Figure 7 is observed to understand the performance of the network for the binary classification of images. The identification of the classes by the developed architecture proves the ability of the model to handle imbalanced datasets.

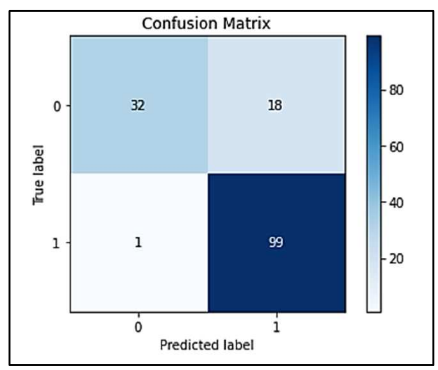

Fig. 7. Confusion Matrix for the Ensembled ResNet Performance Model

C. Performance comparison of the ensemble deep neural model for normalised and unnormalised images

The performance of the trained ensemble model for binary classification is analyzed with accuracy, precision recall and F1-score values.

Accuracy [42] gives the ratio of the correctly classified instances to the total number of instances.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \qquad (2)$$

Recall [42] value gives the proportion of actual positive instances to the total number of predicted positive instances.

$$Recall = TP/TP + FN \quad (3)$$

Precision [42] gives the proportion of predicted positive values that are actually positive and its variance with no. of dense layers.

$$Precision = TP/TP + FP \quad (4)$$

F1 score [42] combines the precision and recall value of the trained deep neural model using a harmonic mean.

$$F1\,Score = 2 * Precion * Recall/(Precision + Recall) \quad (5)$$

F1 Score is a better measure to seek a balance between Precision and Recall. This is highly useful in cases such as here where there is an uneven class distribution (large number of Actual Negatives).

TABLE V. PERFORMANCE OF THE ENSEMBLED RESNET MODEL

Trained over CLAHE normalized images				
Class	**Precision**	**Recall**	**F1-Score**	**Accuracy**
0	0.97	0.64	0.77	0.87
1	0.85	0.99	0.91	
Avg.	0.91	0.81	0.84	
Trained over Unnormalized images				
Class	**Precision**	**Recall**	**F1-Score**	**Accuracy**
0	0.99	0.23	0.33	0.73
1	0.71	0.99	0.83	
Avg.	0.86	0.73	0.67	

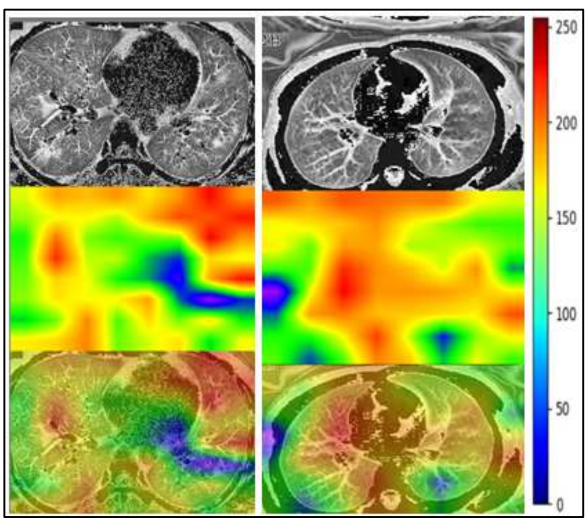

Fig. 8. GradCAM Visualization of CT Scan Images of Patient Tested Positive for COVID-19 with the Prediction Score at a) 0.51 and b) 0.79

From Table V, it is observed that the images that the model performed better when the input images were normalized with the CLAHE than the unnormalized images. The identification of the Class 0 images was performed inadequately when the model was trained with unnormalized images. An accuracy of 0.87 was obtained when the ensemble model was trained with images pre-processed with CLAHE histogram.

D. *Visualisation if the activations of the trained Ensemble ResNet model over normalised images using GradCAM*

GradCAM visualisation of the trained weights of the ensembled ResNet model on the CT scans dataset for Class-1 images is done here. This helps to provide a visual explanation for the trained deep neural model on the input dataset. From Figure 8 a) and b), the GradCAM visualization of the image is observed to possibly identify the areas of clinical features such as Ground Glass Opacities, air space opacification in the CT scan images for their classification as belonging to Class-1 or COVID-19 positive.

VI. CONCLUSION

An ensemble method is introduced to deal with class imbalance while dealing with identification of positive COVID-19 CT scans. The normalization of the images is achieved by applying CLAHE histogram over the images for enhancing their features before splitting the dataset into equally balanced parts and feeding the images to the Level-0 ResNet models for training. The output containing the activations with feature weights learned by these multiple ResNet models are used to create an ensemble network architecture for enhancing their performance and improving the existing bias in the binary classes of the images. The model performed with an accuracy of 87.23% with CLAHE enhanced images and the learning of the trained models are visually represented using GradCAM algorithm.

VII. FUTURE WORKS

The application of augmentation in the deep neural networks for the localization of the symptoms found in the visualization on CT scan images can be explored further for the diagnosis any disease. This would enhance the results presented for proper diagnosis and treatment of the patients for their recovery at the earliest.

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REFERENCES

[1] Q.-V. Pham, D. C. Nguyen, T. Huynh-The, W.-J. Hwang, and P. N. Pathirana, "Artificial Intelligence (AI) and Big Data for Coronavirus (COVID-19) Pandemic: A Survey on the State-of-the-Arts," IEEE Access, vol. 8, pp. 130820–130839, 2020.

[2] M. A. Shereen, S. Khan, A. Kazmi, N. Bashir, and R. Siddique, "COVID-19 infection: origin, transmission, and characteristics of human coronaviruses," Journal of Advanced Research, vol. 24, pp. 91–98, 2020.

[3] P. Simoni, A. Bazzocchi, G. Boitsios, A. De Leucio, M. Preziosi, and M. P. Aparisi Gómez, "Chest computed tomography (CT) features in children with reverse transcription - polymerase chain reaction (RT - PCR) - confirmed COVID - 19: A systematic review," Journal of Medical Imaging and Radiation Oncology, vol. 64, no. 5, pp. 649–659, 2020.

[4] "The Radiology Assistant : COVID-19 Imaging findings," radiologyassistant.nl, 2020. https://radiologyassistant.nl/chest/covid-19/covid19-imaging-findings (accessed Jan. 25, 2021).

[5] R. M. M. Ali and M. B. I. Ghonimy, "Semi-quantitative CT imaging in improving visualization of faint ground glass opacities seen in early/mild

coronavirus (covid-19) cases," Egyptian Journal of Radiology and Nuclear Medicine, vol. 51, no. 1, 2020.

[6] R. Yasin and W. Gouda, "Chest X-ray findings monitoring COVID-19 disease course and severity," Egyptian Journal of Radiology and Nuclear Medicine, vol. 51, no. 1, 2020.

[7] O. M. Sultan et al., "Pulmonary ct manifestations of COVID-19: changes within 2 weeks duration from presentation," Egyptian Journal of Radiology and Nuclear Medicine, vol. 51, no. 1, 2020.

[8] G. Nino, J. Zember, R. Sanchez-Jacob, M. J. Gutierrez, K. Sharma, and M. G. Linguraru, "Pediatric Lung Imaging Features of Covid-19: A Systematic Review and Meta-Analysis," Pediatric Pulmonology, vol. 56, pp. 252–263, 2020.

[9] Y. Zheng, L. Wang, and S. Ben, "Meta‐analysis of chest CT features of patients with COVID‐19 pneumonia," Journal of Medical Virology, vol. 93, pp. 241‐249, 2020.

[10] Z. Lim et al., "Variable computed tomography appearances of COVID-19," Singapore Medical Journal, vol. 61, no. 7, pp. 387–391, 2020.

[11] Worldometer, "Coronavirus Toll Update: Cases & Deaths by Country of Wuhan, China Virus - Worldometer," Worldometers.info. https://www.worldometers.info/coronavirus/ (accessed Jan. 25, 2021).

[12] X. Cai, Y. Wang, X. Sun, W. Liu, Y. Tang, and W. Li, "Comparing the performance of ResNets on COVID-19 diagnosis using CT scans," in 2020 International Conference on Computer, Information and Telecommunication Systems (CITS), pp. 1–4, 2020.

[13] D. Haritha, N. Swaroop, and M. Mounika, "Prediction of COVID-19 Cases Using CNN with X-rays," in 2020 5th International Conference on Computing, Communication and Security (ICCCS), pp. 1–6, 2020.

[14] A. Kumar, J. Kim, D. Lyndon, M. Fulham, and D. Feng, "An Ensemble of Fine-Tuned Convolutional Neural Networks for Medical Image Classification," IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 31–40, 2017.

[15] S. Sridhar and S. Sanagavarapu, "Detection and Prognosis Evaluation of Diabetic Retinopathy using Ensemble Deep Convolutional Neural Networks," in 2020 International Electronics Symposium (IES), pp. 78–85, 2020.

[16] Y. S. Moon, B. G. Han, H. S. Yang, and H. G. Lee, "Low Contrast Image Enhancement Using Convolutional Neural Network with Simple Reflection Model," Advances in Science, Technology and Engineering Systems Journal, vol. 4, no. 1, pp. 159–164, 2019.

[17] G. Siracusano, A. La Corte, M. Gaeta, G. Cicero, M. Chiappini, and G. Finocchio, "Pipeline for Advanced Contrast Enhancement (PACE) of Chest X-ray in Evaluating COVID-19 Patients by Combining Bidimensional Empirical Mode Decomposition and Contrast Limited Adaptive Histogram Equalization (CLAHE)," Sustainability, vol. 12, no. 20, 2020.

[18] M. Lucas, M. Lerma, J. Furst, and D. Raicu, "Heatmap Template Generation for COVID-19 Biomarker Detection in Chest X-rays," in 2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE), pp. 438–445, 2020.

[19] T. Tagaris, M. Sdraka, and A. Stafylopatis, "High-Resolution Class Activation Mapping," in 2019 IEEE International Conference on Image Processing (ICIP), 4514–4518, 2019.

[20] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in 2017 IEEE International Conference on Computer Vision (ICCV), pp. 618–626, 2017.

[21] I. Mporas and P. Naronglerdrit, "COVID-19 Identification from Chest X-Rays," in 2020 International Conference on Biomedical Innovations and Applications (BIA), pp. 69–72, 2020.

[22] T. H. Rafi, "An ensemble deep transfer-learning approach to identify COVID-19 cases from chest X-ray images," in 2020 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), pp. 1–5, 2020.

[23] Z. Liu et al., "Self-paced Ensemble for Highly Imbalanced Massive Data Classification," in 2020 IEEE 36th International Conference on Data Engineering (ICDE), pp. 841–852, 2020.

[24] N. Cahyana, S. Khomsah, and A. S. Aribowo, "Improving Imbalanced Dataset Classification Using Oversampling and Gradient Boosting," in 2019 5th International Conference on Science in Information Technology (ICSITech), pp. 217–222, 2019.

[25] U. Aggarwal, A. Popescu, and C. Hudelot, "Active Learning for Imbalanced Datasets," in 2020 IEEE Winter Conference on Applications of Computer Vision (WACV), pp. 1417–1426, 2020.

[26] N. Wang, H. Liu, and C. Xu, "Deep Learning for The Detection of COVID-19 Using Transfer Learning and Model Integration," in 2020 IEEE 10th International Conference on Electronics Information and Emergency Communication (ICEIEC), pp. 281–284, 2020.

[27] "Radiopaedia.org, the wiki-based collaborative Radiology resource," Radiopaedia.org, 2019. https://radiopaedia.org/ (accessed Jan. 29, 2021).

[28] E. D. Carvalho, E. D. Carvalho, A. O. de Carvalho Filho, A. D. de Sousa, and R. de Andrade Lira Rabulo, "COVID-19 diagnosis in CT images using CNN to extract features and multiple classifiers," in 2020 IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE), pp. 425–431, 2020.

[29] A. Kaur and C. Singh, "Contrast enhancement for cephalometric images using wavelet-based modified adaptive histogram equalization," Applied Soft Computing, vol. 51, pp. 180–191, 2017.

[30] D. Sonker, "Comparison of Histogram Equalization Techniques for Image Enhancement of Grayscale images in Natural and Unnatural light," International Journal of Engineering Research and Development, vol. 8, no. 9, pp. 57–61, 2013.

[31] J. L. Leevy, T. M. Khoshgoftaar, R. A. Bauder, and N. Seliya, "A survey on addressing high-class imbalance in big data," Journal of Big Data, vol. 5, no. 1, 2018.

[32] A. Puri and M. K. Gupta, "Comparative Analysis of Resampling Techniques under Noisy Imbalanced Datasets," in 2019 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), pp. 1–5, 2019.

[33] D. Hernandez, R. Pereira, and P. Georgevia, "COVID-19 detection through X-Ray chest images," in 2020 International Conference Automatics and Informatics (ICAI), pp. 1–5, 2020.

[34] Y. Furusho and K. Ikeda, "Theoretical analysis of skip connections and batch normalization from generalization and optimization perspectives," APSIPA Transactions on Signal and Information Processing, vol. 9, no. e9, pp. 1–7, 2020.

[35] S. Rajaraman, J. Siegelman, P. O. Alderson, L. S. Folio, L. R. Folio, and S. K. Antani, "Iteratively Pruned Deep Learning Ensembles for COVID-19 Detection in Chest X-rays," IEEE Access, vol. 8, pp. 115041–115050, 2020.

[36] R. M. James and A. Sunyoto, "Detection Of CT - Scan Lungs COVID-19 Image Using Convolutional Neural Network And CLAHE," in 2020 3rd International Conference on Information and Communications Technology (ICOIACT), pp. 302–307, 2020.

[37] A. Ajmal, C. Hollitt, M. Frean, and H. Al-Sahaf, "A Comparison of RGB and HSV Colour Spaces for Visual Attention Models," in 2018 International Conference on Image and Vision Computing New Zealand (IVCNZ), pp. 1–6, 2018.

[38] P. Patil and H. Patil, "X-ray Imaging Based Pneumonia Classification using Deep Learning and Adaptive Clip Limit based," in 2020 IEEE 4th Conference on Information & Communication Technology (CICT), pp. 1–4, 2020.

[39] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," Journal of Big Data, vol. 6, no. 1, pp. 1–48, 2019.

[40] A. Géron, Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition,. O'Reilly Media, Inc., 2019.

[41] M. A. Mercioni and S. Holban, "The Most Used Activation Functions: Classic Versus Current," in 2020 International Conference on Development and Application Systems (DAS), pp. 141–145, 2020.

[42] T. B. Alakus and I. Turkoglu, "Comparison of deep learning approaches to predict COVID-19 infection," Chaos, Solitons & Fractals, vol. 140, 2020.