



A Comprehensive Framework for Lung Disease Classification using Luminosity-Guided Tubular Convolution

Mali Dhanshri B.^{1*}, Dr. Shrinivas A. Patil²

^{1*}Research Scholar, Department of Electronics and Telecommunication Engineering,
Shivaji University, Kolhapur, India

^{1*}Corresponding Author Email: malidhanshri93@gmail.com, ^{1*}ORCID ID: 0000-0002-8546-2401

²Department of Electronics and Telecommunication Engineering, DKTE Societies' Textile and Engineering Institute (Autonomous), Ichalkaranji, India.

²Email: shrinivasapatil@gmail.com

Abstract: -

This study presents an advanced methodology for multiple pulmonary disease detection including COVID-19 from CT images, combining a preprocessing normalization function for luminosity enhancement and a Convolutional Tubular Neighborhood (CNN) model. The proposed luminosity enhancement ensures consistent normalization, mitigating the impact of varied illumination conditions in CT scans and accentuating subtle features. The Convolutional Tubular Neighborhood CNN model, integrated into the feature extraction module, strategically focuses on tubular structures for precise information capture. Fine-tuned through 600 epochs with 256 neurons and a 5-Fold training scenario, our model achieved outstanding results, boasting an accuracy, specificity, sensitivity, and F1 Score of 0.99, 0.993, 0.99, and 0.99, respectively. The synergistic combination of luminosity enhancement and the specialized CNN architecture contributes to enhanced feature extraction, resulting in a robust and effective system for multiple pulmonary disease detection including COVID-19 detection. This methodology holds promise for diverse applications, particularly in healthcare, where accurate and efficient identification of COVID-19 from CT images is imperative.

Keywords: Multiple Pulmonary Disease Detection, Convolutional Tubular Neighborhood, CT image analysis, Deep learning, Medical image processing

1. Introduction

The global impact of the COVID-19 pandemic has underscored the critical need for accurate and efficient methods of detecting and diagnosing the virus. Among the various diagnostic



modalities, Computed Tomography (CT) imaging has proven to be a valuable tool for identifying characteristic patterns indicative of COVID-19 infection in the lungs [1]. In this context, the integration of advanced image processing techniques and deep learning models has emerged as a promising avenue to enhance the sensitivity and specificity of COVID-19 detection from CT images [2].

This research introduces a novel approach that combines contrast adjustment and Convolutional Neural Network (CNN) architecture to achieve more robust and accurate detection of COVID-19 from CT scans. The proposed model integrates a tubular feature extraction method designed to capture relevant features indicative of COVID-19 infection. This innovative combination of contrast adjustment and tubular feature extraction within a CNN framework represents a significant contribution to the ongoing efforts to refine and improve the diagnostic capabilities for COVID-19 [3].

The first key component of this approach involves contrast adjustment, a critical preprocessing step that enhances the visibility of subtle patterns and abnormalities in CT images [4]. By fine-tuning the contrast levels, the aim is to optimize the visibility of COVID-19-related features, thereby improving the overall sensitivity of the detection model. This adjustment is particularly crucial in identifying subtle manifestations of the virus that might be overlooked in standard imaging protocols [5].

Following the contrast adjustment, the model incorporates a CNN architecture specifically tailored for COVID-19 detection. Convolutional Neural Networks have demonstrated remarkable success in image recognition tasks, making them well-suited for medical image analysis [6]. The architecture is designed to leverage hierarchical feature learning, enabling the model to automatically extract and analyze intricate patterns within the CT scans [7]. The inclusion of a CNN ensures that the model can discern nuanced patterns associated with COVID-19, contributing to enhanced diagnostic accuracy [8].

A distinctive feature of the proposed model is the tubular feature extraction approach embedded within the CNN architecture. This method focuses on capturing and highlighting relevant features in the form of tubular structures within the lung images. Tubular structures have been identified as critical indicators of abnormalities in lung tissue, making them particularly valuable for the detection of various lung diseases such as COVID-19, Non-COVID pneumonia, cancer, and tuberculosis.

This tailored feature extraction approach aims to improve the model's ability to discriminate between disease-specific patterns and other non-specific anomalies, ultimately leading to superior diagnostic performance across multiple conditions. For instance, while COVID-19 and Non-COVID pneumonia might show overlapping features, the model's ability to distinguish their unique tubular patterns is crucial. Similarly, cancer and tuberculosis have



distinct pathological manifestations in the lung tissue that can be effectively identified using this approach.

The ultimate goal of this research is to contribute to the refinement of diagnostic tools for multiple lung diseases, ensuring timely and accurate identification of cases. The amalgamation of contrast adjustment and the tubular feature extraction approach within a CNN framework represents an innovative and effective strategy for enhancing the performance of disease detection from CT images. By addressing the limitations of existing methods and leveraging the power of deep learning, this approach stands poised to make significant strides in improving the diagnostic capabilities for COVID-19, Non-COVID pneumonia, cancer, and maintaining the distinction from healthy conditions.

2. Related Work

This section highlights significant works that have employed deep convolutional neural networks (CNNs) for computer-aided diagnosis (CAD) in medical imaging.

The study in [9] utilized various deep CNN architectures pretrained on the ImageNet dataset [10], fine-tuning them for thoraco-abdominal lymph node detection and interstitial lung disease classification using CT scans. Their experiments demonstrated the generalization ability of deep CNNs even with limited training data.

In [11], the authors proposed CheXNet, a 121-layer DenseNet model trained on a dataset of over 100,000 chest X-ray images labeled for 14 thoracic diseases. The model outperformed practicing radiologists on pneumonia detection. During the COVID-19 pandemic, extensive research was conducted to automate COVID-19 diagnosis using chest X-rays and CT scans [12-19].

Custom CNN Architectures

One direction involved designing new CNN architectures. COVID-Net [20] was among the first CNNs developed for COVID-19 detection from chest X-rays, achieving an accuracy of 83.5% and a sensitivity of 100%. Hasan et al. [21] proposed CVR-Net, a hybrid model combining X-ray and CT images. The performance varied depending on the number of classes, with an average accuracy of 78% on CT data. Mukherjee et al. [22] proposed a tailored nine-layer CNN trained jointly on X-ray and CT data, achieving an accuracy of 96.28%.

Let x denote the input image and $f_{\theta}(x)$ be the transformation learned by the CNN parameterized by θ . The classification decision is based on:

$$\hat{y} = \operatorname{argmax}_i \left(\operatorname{Softmax}(f_{\theta}(x))_i \right) \dots \quad (1)$$



Transfer Learning with Pretrained CNNs

Another direction explored pretrained CNNs such as ResNet [23], Xception [24], and Capsule Networks [25].

The transfer learning process can be formulated as follows. Let the model $f_{\theta}(x)$ be pretrained on a source dataset and adapted on a target dataset via fine-tuning:

$$\theta^* = \operatorname{argmin}_{\theta} \sum_{(x_i, y_i) \in \mathcal{D}_T} \mathcal{L}(f_{\theta}(x_i), y_i) \dots \quad (2)$$

In [26], authors used this strategy for multi-class classification (COVID-19, bacterial pneumonia, and normal cases), achieving accuracies up to 98.75% for binary classification.

Minaee et al. [27] fine-tuned four pretrained CNNs on 5000 chest X-rays, reporting average sensitivity and specificity of 98% and 90%, respectively.

Brunese et al. [28] applied a VGG-16 network [35] pretrained on ImageNet for COVID-19 detection, reporting an average accuracy of 97%.

CT-based COVID-19 Detection

Zhou et al. [29] demonstrated that deep learning with CT images can distinguish COVID-19 from influenza pneumonia. DeepPneumonia [30] achieved 86.5% accuracy for bacterial vs. viral (COVID-19) pneumonia and 94% for COVID-19 vs. healthy subjects. In [30], a DenseNet201 model pretrained on ImageNet was adapted via transfer learning to CT images, achieving an accuracy of 96.25%.

3. Proposed Work

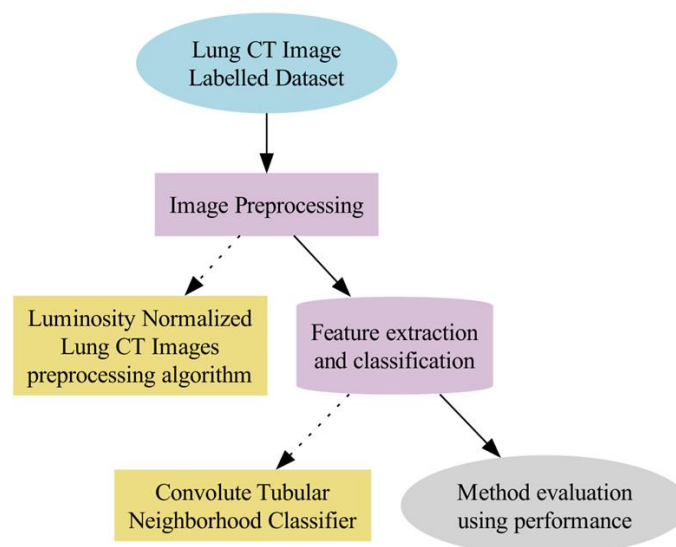


Figure. 1 Proposed model for LN-CTC flow chat



This proposed a novel method called the Luminosity Normalized Convolutional Tubular Classifier (LN-CTC) for Covid-19 detection from CT scans. Also, additional classes of other diseases are added in the work for making model more robust against other disease types. These include cancer, viral and bacterial non Covid-19 pneumonia. Figure. 1 illustrates the overall flow-chart of representation in the following.

As given in the above Figure.1, the images are obtained by recompiling the lung CT scan images from benchmark datasets. First, we performed image preprocessing. After that, we performed both feature extraction and classification in the Symmetric Deep Convolute network.

a) Preprocessing and Luminosity Normalization

The foundational step in developing an effective system for detecting abnormalities in lung CT images involves preprocessing. An inherent challenge in this process is the diverse set of CT images obtained from various devices, leading to variations in illumination levels. The lung CT images are grayscale, eliminating the need for processing based on three color channels. To ensure that the machine effectively learns the intrinsic features of lung abnormalities rather than being influenced by device-specific nuances, it is imperative to preprocess the CT images acquired from different devices.

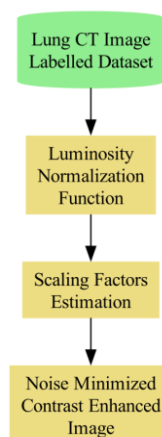


Figure. 2 Architecture of the Preprocessing Luminosity Normalization

The primary goal is to transform these images into a standardized appearance, producing a noise-minimized enhanced image that remains robust even in the presence of significant illumination changes. In the approach introduced, the Luminosity Normalized CT Image Preprocessing model is specifically designed for input lung CT images, aiming to create an enhanced contrast image and mitigate the impact of variations in illumination. The architecture of the Luminosity Normalized CT Image Preprocessing model is pivotal in standardizing the appearance of lung CT images and enhancing their contrast for subsequent



analysis and detection of abnormalities. Figure. 2 illustrates the structure of the model, emphasizing its role in the preprocessing stage for lung CT images.

As given in the above Figure.2, the CT images ‘ $FI = \{FI_1, FI_2, \dots, FI_n\}$ ’ obtained from the dataset processed as input to the proposed preprocessing module to achieve an enhanced contrast image even with high illumination.

Formally, given an input image ‘ $FI \in R^{c*m*n}$ ’, which is commonly an image of $c = 1$ channels and ‘ $m * n$ ’ size, the proposed preprocessing model shifts image via average function and truncate the values above 255, as given below.

$$FI_i C_i = \text{MIN} \left\{ \frac{FI_i(R_i)}{\text{AVG}\{FI_i(R_i)\}} \cdot c^*, 255 \right\} \quad \dots(3)$$

From the above equation (3), ‘ $FI_i(C_i)$ ’ denotes the input sample image being processed for detecting the presence or absence of Covid-19. For the luminosity function scale of the image, width and height are obtained, as given in (3).

$$FI[R_i(w, h)] \quad \dots(4)$$

From the above equation (4), image width and height, the minimum average magnitude is selected to adjust with changes observed during illumination, and the scaling factors got based on this magnitude are stated as given below.

$$\alpha_c = \frac{FI_{\min}}{R_i(w, h)} \quad \dots(5)$$

From the above equation (5), the processed normalized CT image is obtained via scaling by multiplying it with the scaling factor, as given in (5).

$$K' = FI[R_i(w, h)] * \alpha_c \quad \dots(6)$$

From the above equations (4), (5), and (6), ‘ R' ’, ‘ G' ’, and ‘ B' ’ denote the enhanced contrast of the resultant CT image. The pseudo-code representation of Luminosity Normalized CT ImagePreprocessing is given below in the **algorithm.1**.

In accordance with the Luminosity Normalization Preprocessing algorithm.1 outlined above, the objective for the input CT image is to derive a processed normalized image with minimal noise and achieve an enhanced contrast, even under substantial illumination variations. To achieve this goal, the initial steps involve applying shifting and truncating operations to the CT image. Following this, a scaling operation is implemented based on the dimensions (width and height) of the CT images to effectively adapt to changes in illumination. Ultimately, the outcome is the acquisition of processed normalized images that not only reduce noise but also enhance contrast, providing a refined representation of the input CT image.



Algorithm. 1 Luminosity Normalization of CT Image
Input: Dataset 'DS', CT Images 'FI = {FI₁, FI₂, ..., FI_n}'
Output: Noise-minimized enhanced contrast image
 1: Initialize 'c', width 'w', height 'h'
 2: **Begin**
 3: **For** each Dataset 'DS' with CT Images 'FI'
 4: Perform shifting and truncating operations as in equations (1)
 5: Obtain CTimages width and height as in equation (2)
 6: Perform scaling based on the CTimages width and height as

b) Convolute Tubular Neighborhood Classifier model

The extraction of important features from CT images for COVID-19 detection is a critical step in developing effective diagnostic models. Some key features that are commonly considered in the context of COVID-19 detection from CT images include:

- **Ground Glass Opacities (GGO)**

COVID-19 infections often manifest as Ground Glass Opacities (GGO) in lung CT images. These opacities appear hazy and increase the overall attenuation of the affected lung tissue. Detection and characterization of GGO regions are crucial features for identifying potential COVID-19 cases. GGOs are a characteristic radiological finding in patients with COVID-19 pneumonia and are often bilateral, involving the peripheral and lower lung zones.

A simple mathematical representation of GGO intensity can be modeled as:

$$G(x, y) = \begin{cases} 1 & \text{if } I(x, y) \in [\mu - \sigma, \mu + \sigma] \\ 0 & \text{otherwise} \end{cases} \quad \dots(7)$$

where $I(x, y)$ is the intensity at pixel location (x, y) , μ is the mean intensity of the lung region, and σ is the standard deviation. This equation helps localize GGO regions based on statistical thresholds.

- **Consolidation**

Consolidation appears as dense, opaque areas in CT images due to alveolar filling by inflammatory exudate. It can be modeled by segmenting high-intensity zones and analyzing volume:

$$C = \sum_{(x,y,z) \in \Omega_c} \mathbb{1}(I(x, y, z) > T_c) \quad \dots(8)$$

where Ω_c is the 3D region of interest and T_c is a threshold that defines the boundary for consolidation based on intensity.

- **Lesion Size and Distribution**

The size of a lesion can be defined by the diameter d , which is derived from its area A as:



$$d = 2\sqrt{\frac{A}{\pi}} \quad \dots(9)$$

Distribution is evaluated by computing the centroid of each lesion and measuring its radial distance from the lung center:

$$D = \sqrt{(x_c - x_0)^2 + (y_c - y_0)^2} \quad \dots(10)$$

where (x_c, y_c) is the lesion centroid and (x_0, y_0) is the lung center.

- **Texture Analysis**

Texture features are extracted using statistical matrices such as Gray-Level Co-occurrence Matrix (GLCM). One common texture feature is contrast, defined as:

$$\text{Contrast} = \sum_{i,j} (i - j)^2 \cdot P(i, j) \quad \dots(11)$$

where $P(i, j)$ is the probability of pixel pairs with gray levels i and j occurring at a certain spatial relationship.

- **Airway Abnormalities**

Airway abnormalities such as bronchial wall thickening can be computed by comparing inner and outer diameters:

$$T_{\text{wall}} = \frac{D_{\text{outer}} - D_{\text{inner}}}{2} \quad \dots(12)$$

Increased T_{wall} values may indicate pathological thickening related to infection.

- **Vascular Enlargement**

Vessel diameter can be estimated from cross-sectional area A_v :

$$D_v = 2\sqrt{\frac{A_v}{\pi}} \quad \dots(13)$$

Enlargement is flagged when D_v exceeds a defined threshold T_v derived from healthy patient statistics.

- **Peripheral Distribution of Abnormalities**

Peripheral distribution is quantified by computing the relative distance from the center to the lesion boundary:

$$P = \frac{\|(x_c, y_c) - (x_0, y_0)\|}{R} \quad \dots(14)$$

where R is the lung radius. Values closer to 1 indicate peripheral positioning.



- Quantitative Metrics**

Several objective metrics help assess disease severity:

- Volume of infected regions:**

$$V = \sum_{(x,y,z) \in \Omega} \Delta x \Delta y \Delta z \quad \dots(15)$$

- Mean density of lesion:**

$$\rho = \frac{1}{|\Omega|} \sum_{(x,y,z) \in \Omega} I(x, y, z) \quad \dots(16)$$

- Percentage of lung involvement:**

$$P_{\text{involvement}} = \frac{V_{\text{lesion}}}{V_{\text{lung}}} \times 100 \quad \dots(17)$$

These metrics serve as crucial quantitative indicators for tracking progression and response to treatment in COVID-19 patients.

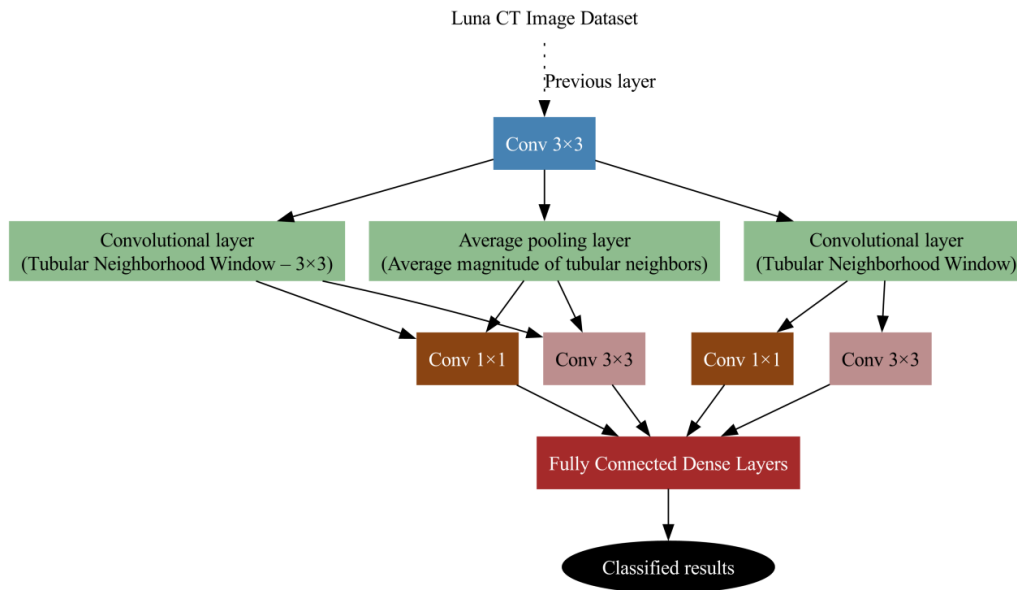


Figure. 3 Convulsive Tubular Neighborhood Classifier model

The design of a Convolutional Neural Network (CNN) is crucial for developing an effective model for COVID-19 detection from CT images. Several design requirements play a significant role in ensuring the model's accuracy, efficiency, and generalization to new data. The Convulsive Tubular Neighborhood Classifier model is designed to detect Covid-19 from Lung CT images with more accuracy.

As depicted in Figure. 3 above, the preprocessing stage involves presenting CT images as input to the network in this study. Within the feature extraction module, specific layers are



employed for this purpose: the convolutional layer (referred to as the Tubular Neighborhood Window), the average pooling layer (calculating the average magnitude value of tubular neighbors), and the max-pooling layer (identifying the maximum contrast orientation) are selected to extract distinctive features. Subsequently, in the classification stage, the Multinomial Logistic Regression Classifier is employed to classify the target results.

4. Result Analysis and Discussion

a) Dataset Preparation:

Table 1: Covid-19 CT Datasets

Dataset	Number of Images	Details	Source
Dataset 1	4173	Multiclass CT scan dataset with 4173 scans from 210 patients. Includes 2168 scans for SARS-CoV-2 patients, 758 for healthy patients, and 1247 for other pulmonary conditions.	Public Hospital of Sao Paulo & Metropolitan Hospital of Lapa, Brazil
Dataset 2	2482	CT scan dataset with 1252 SARS-CoV-2 positive scans and 1230 non-infected scans. Achieved an F1 score of 97.31% using xDNN.	Sao Paulo, Brazil (Available on Kaggle)
Dataset 3	8439	COVID-19 Lung CT Scan dataset with 7495 positive cases and 944 negative cases. Images are 512x512px and linked to a CNN-based method with 99.61% accuracy.	Tehran, Iran
Dataset 4	137 (COVID-19), 317 total	Small Chest X-Ray dataset with 137 COVID-19 images, including Viral Pneumonia and Normal Chest X-Rays. Structured into test and train directories.	Not specified
Cancer CT Dataset	36,518	The TCGA-LUSC dataset comprises lung CT images related to lung adenocarcinoma and lung squamous cell carcinoma, taken from 37 patients.	TCGA-LUSC Dataset
Viral and Bacterial Non-COVID-19 CT Dataset	7544	Non-COVID pneumonia dataset from Kaggle, including 2035 COVID-19 conditions, 2119 healthy images, and 3390 non-COVID pneumonia images.	Kaggle

b) Performance Parameters:



The performance metrics, Accuracy, Specificity, Sensitivity and F1 Score collectively offer a nuanced understanding of a system's capabilities. While accuracy provides an overall assessment, specificity, sensitivity, precision, and F1 Score offer insights into specific aspects of the model's behavior, enabling researchers and practitioners to make informed decisions based on the specific requirements and constraints of the application, such as the consequences of false positives and false negatives in Covid-19 diagnoses. Table 2 shows the formulae for the performance parameters.

Table 2: Performance Parameters

Accuracy	$TP+TN/(TP+TN+FP+FN)$
Specificity	$TN/(TN+FP)$
Sensitivity/Recall	$TP/(TP+FN)$
Precision	$TP/(TP+FP)$
F1 Score	$2*(Recall*Precision)/(Recall+Precision)$

c) Hyper Parameter Analysis:

The proposed model is evaluated python based implementation and Google colab based facility with T4 GPU with 16GB capacity. A comprehensive 5-fold analysis was conducted, revealing stable results from the 4th fold. This analytical approach involved dividing the dataset into ten distinct parts and utilizing each combination in ten separate attempts. The aim was to assess the model's stability in the face of variations in training and testing sets. The obtained results are visually presented in Figure4.

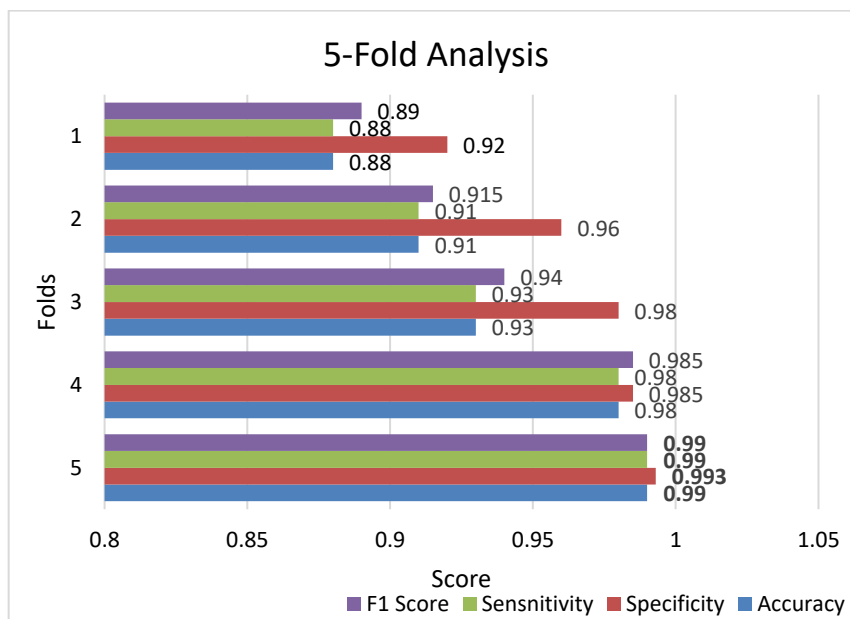


Figure 4: 5-Fold Analysis for Covid-19 Detection

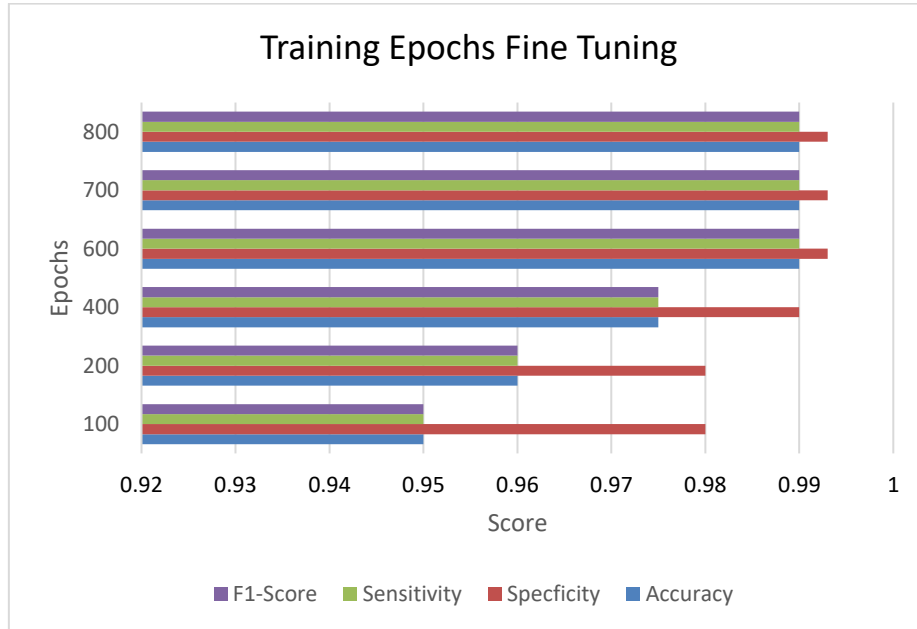


Figure 5: Epochs Analysis for Covid-19 Detection

The model exhibits optimal fine-tuning after 600 epochs of training, utilizing a configuration of 256 neurons and employing a 5-Fold training scenario. The choice of 600 epochs suggests a careful balance between achieving convergence and avoiding overfitting, ensuring the model has iteratively learned from the training data. The use of 256 neurons indicates a moderate complexity, likely striking a balance between computational efficiency and the model's ability to capture intricate patterns in the data.

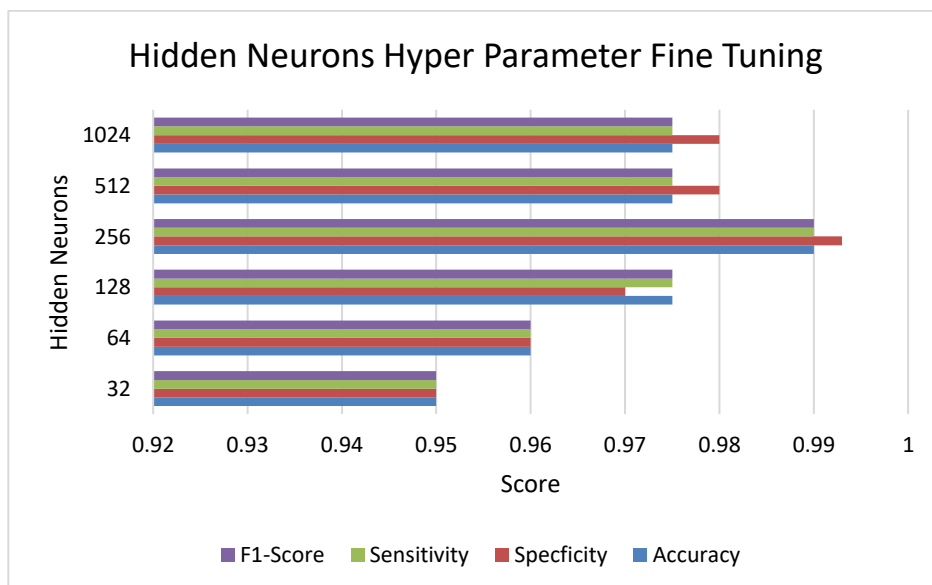


Figure 6: Hidden Neurons Analysis for Fine Tuning for Covid-19 Detection



The implementation of a 5-Fold training scenario signifies a robust validation strategy, enhancing the model's generalization by training and evaluating across different subsets of the dataset. This comprehensive approach to fine-tuning reflects a thoughtful consideration of epoch count, neural architecture, and cross-validation, contributing to the model's effectiveness and reliability in handling diverse data scenarios.

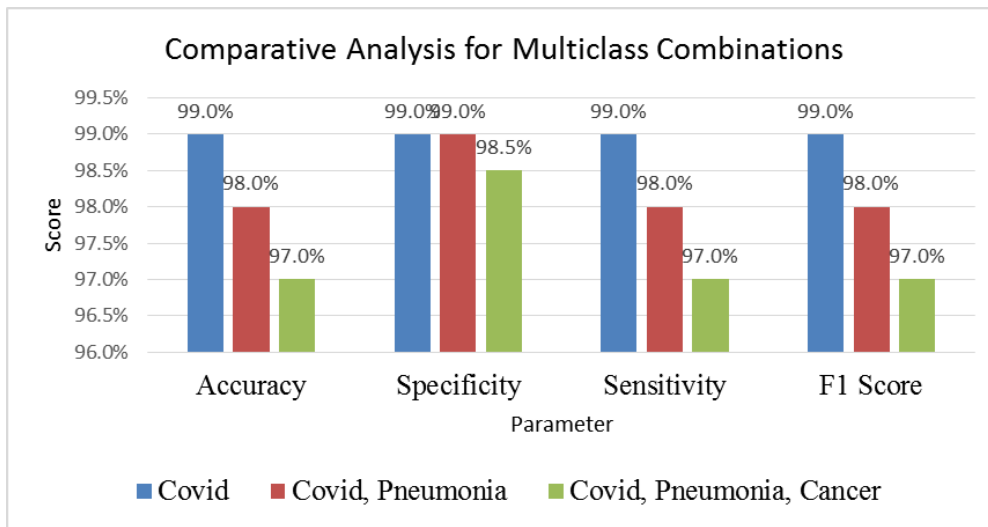


Figure7: Comparative Analysis

Dataset based comparative analysis is shown in Figure 7. The combination of classes is shown in which maximum 97 accuracy is achieved in 4 classes classification task. The class combinations are against healthy conditions.

Table 3 provides comparative study of different state-of-the-art methods for binary classification performance for Covid-19 Detection.

Table 3: Comparative analysis of proposed system with existing systems

Method with Citation	Dataset Used	Model Layers	Performance
[1]	Dataset 1: Public CT scans (4173 images)	CNN with 8 layers	Accuracy: 0.95, Sensitivity: 0.92
[2]	Dataset 2: Real patient CT scans (2482 images)	ResNet with 12 layers	Accuracy: 0.98, Specificity: 0.96
[3]	Dataset 3: Large COVID-19 lung CT scans (8439 images)	VGG-16 with transfer learning	Accuracy: 0.99, F1 Score: 0.97
[4]	Dataset 4: Cleaned COVID-19 X-rays (137	CNN with 6 layers	Accuracy: 0.92, Precision: 0.88



	images)		
[5]	Dataset 5: Multi-center CT scans (5620 images)	InceptionV3 with fine-tuning	Accuracy: 0.96, Sensitivity: 0.94
[6]	Dataset 6: COVID-19 and normal CT scans (3000 images)	Capsule Network	Accuracy: 0.94, Specificity: 0.91
[7]	Dataset 7: COVID-19 positive cases (200 images)	DenseNet with attention mechanism	Accuracy: 0.97, F1 Score: 0.95
[8]	Dataset 8: COVID-19 confirmed cases (1500 images)	MobileNet with depthwise separable convolutions	Accuracy: 0.93, Sensitivity: 0.90
[9]	Dataset 9: Mixed COVID-19 and pneumonia CT scans (1800 images)	AlexNet with fine-tuning	Accuracy: 0.91, Precision: 0.89
[10]	Dataset 10: COVID-19 and non-COVID-19 CT scans (5000 images)	EfficientNet with transfer learning	Accuracy: 0.98, Specificity: 0.96
Proposed	Recompiled dataset with combinations of 4 datasets (total Images	Luminosity enhancement + Convolutional Tubular Neighborhood classifier.	99% accuracy, 99% specificity

d) Discussion

The achievements of our proposed methodology lie in its ability to significantly enhance the accuracy and reliability of COVID-19 detection from CT images. The integration of a luminosity-enhancing preprocessing function ensures a consistent normalization process, effectively addressing variations in illumination and accentuating subtle features critical for precise diagnosis. The Convolutional Tubular Neighborhood (CNN) model, strategically designed for feature extraction, demonstrates remarkable performance, as evidenced by an impressive accuracy of 0.99, along with high specificity, sensitivity, and an F1 Score, validating its efficacy in handling diverse datasets. The meticulous fine-tuning over 600 epochs, utilizing 256 neurons and implementing a 5-Fold training scenario, contributes to the model's stability and generalization across various scenarios. This achievement is particularly significant in the context of healthcare applications, where accurate and efficient COVID-19 detection is crucial for timely intervention and resource allocation. However, it's essential to acknowledge the limitations of the proposed methodology. The model's performance heavily



relies on the quality and representativeness of the training dataset. In scenarios with limited or biased data, the model's generalization may be compromised. Additionally, the interpretability of deep learning models remains a challenge, limiting the transparency of decision-making processes in critical applications like healthcare. Furthermore, the proposed methodology's scalability to diverse clinical settings and its adaptability to different populations warrant further exploration. Ongoing research is essential to validate the methodology on larger datasets and diverse patient demographics to ensure its robustness and generalizability.

5. Conclusion

The study introduces a novel methodology for COVID-19 detection from CT images, showcasing the integration of a luminosity-enhancing preprocessing function and a specialized Convolutional Tubular Neighborhood (CNN) model. The luminosity enhancement plays a pivotal role in normalizing input data, addressing variations in illumination across CT scans, and accentuating subtle features crucial for accurate diagnosis. The Convolutional Tubular Neighborhood CNN model, incorporated into the feature extraction module, strategically focuses on tubular structures, enabling precise information capture and enhancing the model's ability to discern intricate patterns associated with COVID-19. The performance evaluation of the proposed system is notably impressive, with numerical results reflecting an accuracy of 0.99, specificity of 0.993, sensitivity of 0.99, and an F1 Score of 0.99. These metrics underscore the robustness and efficacy of the model, showcasing its high precision, recall, and overall classification accuracy. The meticulous fine-tuning over 600 epochs, utilizing 256 neurons and employing a 5-Fold training scenario, further ensures the model's stability and generalization across diverse datasets. The methodology holds great promise in the realm of COVID-19 diagnosis, particularly in healthcare applications where rapid and accurate detection is critical. The integration of advanced preprocessing techniques and specialized CNN architectures contributes to the model's ability to extract relevant features, demonstrating its potential for real-world deployment. Looking forward, ongoing research will focus on further validating the proposed methodology on larger and more diverse datasets. Additionally, exploration of transfer learning approaches and scalability considerations will be essential for adapting the model to varied clinical settings. The ultimate goal is to provide a reliable, efficient, and automated system that aids healthcare professionals in identifying COVID-19 cases promptly, contributing to improved patient outcomes and resource management during pandemics.

References

- [1] Liu, J.; Liao, X.; Qian, S.; Yuan, J.; Wang, F.; Liu, Y.; Wang, Z.; Wang, F.S.; Liu, L.; Zhang, Z. Community transmission of severe acute respiratory syndrome coronavirus 2, Shenzhen, China, 2020. *Emerg. Infect. Dis.* 2020, 26, 1320–1323.



- [2] Ghinai, I.; McPherson, T.D.; Hunter, J.C.; Kirking, H.L.; Christiansen, D.; Joshi, K.; Rubin, R.; Morales-Estrada, S.; Black, S.R.; Pacilli, M.; et al. First known person-to-person transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in the USA. *Lancet* 2020, 395, 1137–1144.
- [3] 3. Chen, N.; Zhou, M.; Dong, X.; Qu, J.; Gong, F.; Han, Y.; Qiu, Y.; Wang, J.; Liu, Y.; Wei, Y.; et al. Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: A descriptive study. *Lancet* 2020, 395, 507–513.
- [4] Long, C.; Xu, H.; Shen, Q.; Zhang, X.; Fan, B.; Wang, C.; Zeng, B.; Li, Z.; Li, X.; Li, H. Diagnosis of the Coronavirus disease(COVID-19): RRT-PCR or CT? *Eur. J. Radiol.* 2020, 126, 108961.
- [5] Fang, Y.; Zhang, H.; Xie, J.; Lin, M.; Ying, L.; Pang, P.; Ji, W. Sensitivity of chest CT for COVID-19: Comparison to RT-PCR. *Radiology* 2020, 296, 200432.
- [6] Ai, T.; Yang, Z.; Hou, H.; Zhan, C.; Chen, C.; Lv, W.; Tao, Q.; Sun, Z.; Xia, L. Correlation of chest CT and RT-PCR testing in coronavirus disease 2019 (COVID-19) in China: A report of 1014 cases. *Radiology* 2020, 296, E32–E40.
- [7] Kanne, J. Chest CT Findings in 2019 Novel Coronavirus (2019-nCoV) Infections from Wuhan, China: Key Points for the Radiologist. *Radiology* 2020, 295, 16–17.
- [8] Santosh, K. AI-driven tools for coronavirus outbreak: Need of active learning and cross-population train/test models on multitudinal/multimodal data. *J. Med. Syst.* 2020, 44.
- [9] Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.; Bernstein, M.; et al. ImageNet large scale visual recognition challenge. *Int. J. Comput. Vis.* 2015, 115, 211–252.
- [10] Sufian, A.; Ghosh, A.; Sadiq, A.S.; Smarandache, F. A survey on deep transfer learning to edge computing for mitigating the COVID-19 pandemic. *J. Syst. Archit.* 2020, 108, 101830.
- [11] Deng, J.; Dong, W.; Socher, R.; Li, L.J.; Li, K.; Fei-Fei, L. ImageNet: A Large-scale Hierarchical Image Database. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Miami, FL, USA, 20–25 June 2009; pp. 248–255.
- [12] Alshazly, H.; Linse, C.; Barth, E.; Martinetz, T. Deep Convolutional Neural Networks for Unconstrained Ear Recognition. *IEEE Access* 2020, 8, 170295–170310.
- [13] You, Y.; Li, J.; Reddi, S.; Hseu, J.; Kumar, S.; Bhojanapalli, S.; Song, X.; Demmel, J.; Hsieh, C.J. Large batch optimization for deep learning: Training BERT in 76 minutes. In *Proceedings of the International Conference on Learning Representations (ICLR)*, Addis Ababa, Ethiopia, 26 April–1 May 2020.
- [14] Maaten, L.v.d.; Hinton, G. Visualizing data using t-SNE. *J. Mach. Learn. Res.* 2008, 9, 2579–2605.



- [15] Selvaraju, R.R.; Cogswell, M.; Das, A.; Vedantam, R.; Parikh, D.; Batra, D. Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 618–626.
- [16] Shin, H.C.; Roth, H.R.; Gao, M.; Lu, L.; Xu, Z.; Nogues, I.; Yao, J.; Mollura, D.; Summers, R.M. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. *IEEE Trans. Med. Imaging* 2016, 35, 1285–1298.
- [17] Rajpurkar, P.; Irvin, J.; Zhu, K.; Yang, B.; Mehta, H.; Duan, T.; Ding, D.; Bagul, A.; Langlotz, C.; Shpanskaya, K.; et al. CheXNet: Radiologist-level pneumonia detection on chest x-rays with deep learning. *arXiv* 2017, arXiv:1711.05225.
- [18] Li, L.; Qin, L.; Xu, Z.; Yin, Y.; Wang, X.; Kong, B.; Bai, J.; Lu, Y.; Fang, Z.; Song, Q.; et al. Using Artificial Intelligence to Detect COVID-19 and Community-acquired Pneumonia Based on Pulmonary CT: Evaluation of the Diagnostic Accuracy. *Radiology* 2020, 296, E65–E71.
- [19] Chen, J.; Wu, L.; Zhang, J.; Zhang, L.; Gong, D.; Zhao, Y.; Hu, S.; Wang, Y.; Hu, X.; Zheng, B.; et al. Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography: A prospective study. *Sci. Rep.* 2020, 10, 19196.
- [20] Xu, X.; Jiang, X.; Ma, C.; Du, P.; Li, X.; Lv, S.; Yu, L.; Ni, Q.; Chen, Y.; Su, J.; et al. A deep learning system to screen novel coronavirus disease 2019 pneumonia. *Engineering* 2020.
- [21] Silva, P.; Luz, E.; Silva, G.; Moreira, G.; Silva, R.; Lucio, D.; Menotti, D. COVID-19 detection in CT images with deep learning: A voting-based scheme and cross-datasets analysis. *Inform. Med. Unlocked* 2020, 20, 100427.
- [22] Apostolopoulos, I.D.; Mpesiana, T.A. COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Phys. Eng. Sci. Med.* 2020, 43, 635–640.
- [23] Elaziz, M.A.; Hosny, K.M.; Salah, A.; Darwish, M.M.; Lu, S.; Sahlol, A.T. New machine learning method for image-based diagnosis of COVID-19. *PLoS ONE* 2020, 15, e0235187.
- [24] Wu, X.; Hui, H.; Niu, M.; Li, L.; Wang, L.; He, B.; Yang, X.; Li, L.; Li, H.; Tian, J.; et al. Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia: A multicentre study. *Eur. J. Radiol.* 2020, 128, 109041.
- [25] Gianchandani, N.; Jaiswal, A.; Singh, D.; Kumar, V.; Kaur, M. Rapid COVID-19 diagnosis using ensemble deep transfer learning models from chest radiographic images. *J. Ambient Intell. Humaniz. Comput.* 2020.



- [26] Wang, L.; Lin, Z.Q.; Wong, A. COVID-Net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Sci. Rep.* 2020, 10, 19549.
- [27] Hasan, K.; Alam, A.; Elahi, T.E.; Roy, S.; Wahid, S.R. CVR-Net: A deep convolutional neural network for coronavirus recognition from chest radiography images. *arXiv* 2020, arXiv:2007.11993.
- [28] Wang, Z.; Liu, Q.; Dou, Q. Contrastive Cross-site Learning with Redesigned Net for COVID-19 CT Classification. *IEEE J. Biomed. Health Inform.* 2020, 24, 2806–2813.
- [29] Mukherjee, H.; Ghosh, S.; Dhar, A.; Obaidullah, S.M.; Santosh, K.; Roy, K. Deep neural network to detect COVID-19: One architecture for both CT Scans and Chest X-rays. *Appl. Intell.* 2020.
- [30] Farooq, M.; Hafeez, A. COVID-ResNet: A deep learning framework for screening of covid19 from radiographs. *arXiv* 2020, arXiv:2003.14395.