Evaluation of filtering and contrast in X-ray and computerized tomography scan lung classification

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ABSTRACT

Deep learning provides many convenient methods to help medical practitioners take informed decisions about diverse ailments. The goal of this project is to measure the effectiveness of filters and contrast enhancement techniques qualitatively and quantitatively in classifying lung scan images. Transfer deep learning was used to obtain the necessary results, with DenseNet 121 being the base model. Salt and pepper filter was used to introduce noise, and 3×3 mean and 5×5 mean with contrast limited adaptive histogram equalization (CLAHE) was used to minimize the effect of noise. All layers excluding the rearmost were frozen, and new dense and dropout layers were added to identify features of computerized tomography (CT) scan images of lungs. The resultant models were of comparable accuracy, where the model with no filter gave the accurate results for the given data, and the one using the 5×5 mean filter gave better adaptability in classification of unseen data. The misclassification between normal and pneumonia affected lungs is relatively higher, because of the lack of distinct features between them.

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1. INTRODUCTION

Lung diseases such as pneumonia, tuberculosis, and more recently, coronaviruse disease 2019 (COVID-19), have presented a significant risk to the overall public health on a global scale. The onset of the COVID-19 outbreaks, originating from the SARS-CoV-2 virus, has underscored the critical importance of maintaining good lung health and the need to effectively detect, diagnose and treat respiratory diseases [1]. In addition to infectious diseases, smoking, air pollution [2] and occupational hazards [3] have contributed to the deterioration of lung health, increasing the risk of serious diseases such as asthma and lung cancer. To meet these challenges and improve the overall health of populations worldwide, innovative strategies to detect, prevent, diagnose and treat respiratory diseases are essential [4].

Machine learning has become a powerful tool for early and accurate detection of lung diseases, which has significantly reduced lung disease-related deaths. Before the introduction of machine learning models, the diagnosis of lung diseases was based on the subjective interpretation of radiologists or doctors, which often led to inconsistencies and inaccuracies. In addition, analyzing medical images such as computerized tomography (CT) scans took time, causing delays in both diagnosis and treatment.

Over the past few years, machine learning algorithms have sparked a revolution, completely transforming the interpretation of large amounts of medical image data, enabling rapid and accurate detection of lung nodules that may indicate diseases such as lung cancer [5]. These algorithms can distinguish between benign and malignant nodes with high accuracy, facilitating earlier diagnosis. In addition, machine learning models can use information related to environmental exposure, smoking history and age to predict the likelihood of developing lung disease, enabling early intervention and preventative measures for those at risk. As a result, this approach promotes better treatment outcomes and higher survival rates [6].

The purpose of this article is to contribute to the field by evaluating the effectiveness of filtering and contrast techniques in the classification of lung scan images. In doing so, we respond to the challenges of the complexity of lung disease and the need for more accurate and efficient diagnostic methods. The following sections detail the methodology and results of our study, which demonstrate the impact of these methods on lung CT scan image classification and their potential to improve the accuracy of early diagnosis.

2. METHOD

Our methodology represents a comprehensive approach adapted to evaluate filtering and contrast enhancement techniques in the classification of lung radiographs. It aims to improve the accuracy and robustness of lung scan classification by handling the complexity of the dataset and optimizing the efficacy of the convolutional neural network (CNN) model's performance. The journey begins with the careful collection of data from various sources, culminating in the compilation of a rich and challenging dataset spanning four distinct categories, each representing a different respiratory disease. This dataset forms the foundation upon which a series of critical steps evolve, from data addition to denoising, to prepare the data for effective model training. Using a pre-trained architecture, the CNN model plays a key role in achieving accurate classification. Our methodology is evolving as a carefully designed framework that aims to advance the field of medical image analysis is shown in Figure 1.

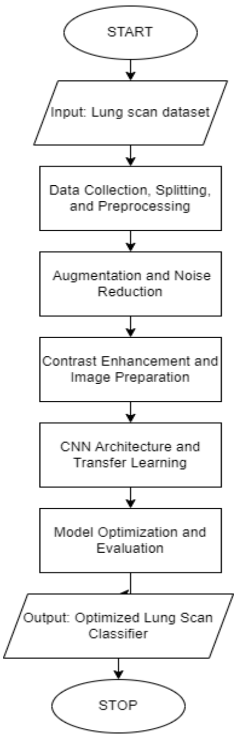

Figure 1. Workflow diagram

2.1. Data collection and preprocessing

The foundation of our methodology lies in the meticulous collection and preparation of the dataset. We sourced a diverse range of CT scan and X-ray images from both Kaggle, a well-known data repository, and local scanning centers. This dataset consists of 7,135 images distributed across four primary classes: “Normal,” “COVID-19,” “Pneumonia,” and “Tuberculosis.” The diversity in these classes not only mirrors the complexity of real-world lung scan data but also presents a formidable challenge for our study. Each image is in JPEG format, with a resolution of 1,024×1,024 pixels, ensuring a rich and high-resolution dataset [7].

2.2. Data splitting

To effectively train, validate, and test our model, the dataset was partitioned into three distinct subsets: training, testing, and validation. This division was made with careful consideration, resulting in ratios of 88%, 10%, and 2%, respectively. Moreover, each subset was meticulously categorized into “COVID-19”, “Normal”, “Pneumonia” [8], and “Tuberculosis” [9] classes, maintaining the integrity and diversity of the dataset across all sets.

2.3. Data augmentation

Recognizing the importance of a diverse and balanced training dataset, we harnessed the power of data augmentation. We implemented the image data generator method from the Keras library, an invaluable tool for introducing diversity and robustness into our training data. This method enabled a range of augmentation techniques, including horizontal and vertical flips, random zoom, and random rotation. These augmentations were thoughtfully applied to the images, serving a twofold purpose. First, they mitigated the potential introduction of bias, ensuring a balanced training dataset. Second, they empowered the CNN model to adapt to variations in the input data, a crucial attribute in real-world application scenarios.

2.4. Noise reduction

The presence of noise in medical images, often referred to as "salt and pepper noise" [10] can significantly impact the performance of machine learning models. To mitigate this, we incorporated noise reduction techniques into our methodology. Initially, we employed the salt and pepper filter, which introduced random dark and light pixels based on a user-defined threshold. This filter plays a crucial role in eliminating the disruptive salt and pepper noise, typified by sporadically placed white and black dots.

Mean and median filters: in addition to the salt and pepper filter, we applied mean and median filters. These filters function to enhance image smoothness by substituting each pixel's value with the average (mean) or central (median) value of adjacent pixels. This process significantly diminishes the influence of noise, thereby augmenting the overall image quality.

2.5. Data normalization

Normalization is a key step in preparing the data for training, ensuring that the input data is within a consistent range of values. In our methodology, we initiated this process by resizing the input images to a uniform 200×200-pixel resolution, enabling the neural network to efficiently process the data. Subsequently, we normalized the pixel values by adjusting them to have a mean of 0 and a variance of 1. This standardization is pivotal in guaranteeing that all pixels are on a similar scale, enabling the network to extract relevant features from the entire image.

2.6. Data augmentation

Building on the foundation of data augmentation, we also incorporated random flipping and rotation techniques. These augmentations are not only crucial for introducing diversity into the training data but also serve as a preventative measure against overfitting. By randomly modifying the input images while preserving their labels, we effectively expanded the variety of the training data. This augmentation approach fortifies the network's capacity to generalize and make accurate predictions when faced with unseen data [11].

2.7. Contrast enhancement CLAHE

Enhancing the contrast of input images is instrumental in ensuring the network can identify and classify features accurately. To this end, the contrast limited adaptive histogram equalization (CLAHE) technique was employed. CLAHE operates by adjusting pixel intensities based on local contrast, thereby improving the visibility of image details. The outcome is a set of images that the network can learn from effectively, ultimately improving its capability to recognize significant features [12].

2.8. Convolutional neural network architecture (DenseNet 121)

Our study leverages the power of a pre-trained DenseNet121 CNN model for image classification. DenseNet 121 is a deep CNN architecture renowned for its effectiveness in extracting features and mastering representations [13]. It is built on the concept of dense connections between layers, enabling the network to capture intricate features in the images effectively [14].

The input images are resized to a fixed size of 256×256 pixels, ensuring compatibility with the model's requirements. Furthermore, we employed augmentation methods on data, such as flips and random rotations, to diversify the training dataset [15]. This augmentation strategy not only enhances the size of the training dataset but also bolsters the network's resilience against variations in the input data. A robust and adaptable model is essential for accurate lung scan classification [16].

2.9. Transfer learning

Transferred-learning technique was used to maximize the accuracy of the model [17], due to the small size of the dataset available [18]. It enables a model that has been trained for one task to be utilized for another task, usually one with less labeled data or a problem domain that is similar [19]. We used transfer learning to enhance the functionality of our CNN model for lung scan detection [20].

2.9.1. Densenet 121

Our choice of architecture for the CNN was Densenet121, a pre-trained model that initially underwent training on the extensive ImageNet dataset, comprising over 1 million annotated images categorized into 1,000 classes [21]. Leveraging the features and weights learned during this pre-training phase proved invaluable for enhancing our lung scan classification model. In our implementation, we capitalized on the power of transfer learning by using the Densenet121 model as a feature extractor. This approach enabled us to make use of the knowledge encoded in the pre-trained model. We further improved the Densenet121 architecture by introducing a custom fully connected layer as the final layer of the network. The process of training the model on our own labeled lung scan dataset, while preserving the pre-trained weights and modifying only the weights in the custom layer, is known as fine-tuning [22]. The primary advantage of fine-tuning is that it allows us to effectively train the model using a smaller amount of labeled data [23]. The features acquired by the pre-trained model are instrumental in classifying lung scans with high accuracy, even when confronted with limited training data and a relatively short training time [24].

2.9.2. Modifications

In adapting the Densenet121 architecture as shown in Figure 2 to our specific lung scan classification task, we made several strategic modifications. We introduced a flattening layer to convert the feature maps into a suitable format for subsequent processing. A densely connected layer comprising 80 neurons was introduced, alongside a dropout rate of 0.4, augmenting the model's capacity to generalize proficiently.

The final layer of our modified architecture was tailored to the requirements of our classification task, consisting of four output classes with a softmax activation function. The selection of a dropout rate of 0.4 was reached through a systematic experimentation process, where we trained multiple models with varying dropout rates ranging from 0.2 to 0.5, in steps of 0.05. This process allowed us to fine-tune the dropout rate for optimal model performance and robustness. These modifications ensured that the Densenet121 architecture [25] was aligned with the specific demands of our lung scan classification problem, resulting in a model that could effectively capture the nuances of respiratory conditions and provide accurate classifications.

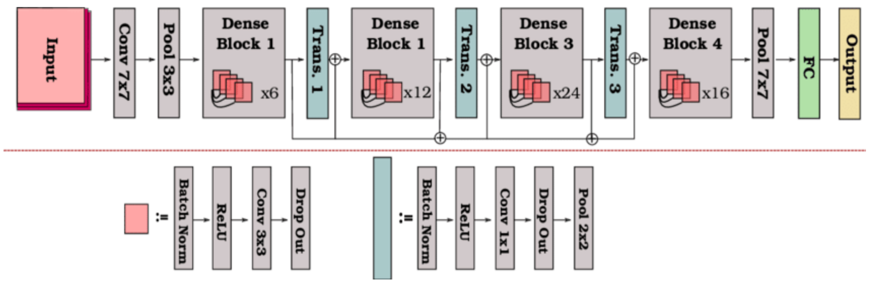

Figure 2. Densenet architecture

3. RESULTS AND DISCUSSION

3.1. Visual exploration of preprocessing techniques in lung scan classification

In this pivotal section, our rigorous evaluation and analysis of lung scan classification unfold a narrative that goes beyond numerical results, shedding light on the efficacy of various filtering and enhancement techniques in medical image analysis. Visual representations in Figures 3 to 7 provide a glimpse into the impact of preprocessing techniques. Figure 3 exhibits minimal discrepancies in processed images with no filter, highlighting areas of interest amidst random zoom, rotations, and flips. Figure 4 showcase effects of the salt and pepper filter, Figures 5 to 7 introduce mean filters for noise reduction and enhanced interpretability of pathological features. These visual insights pave the way for a comprehensive discussion of technique effectiveness in improving interpretability and classification accuracy, setting the stage for subsequent quantitative analyses and implications.

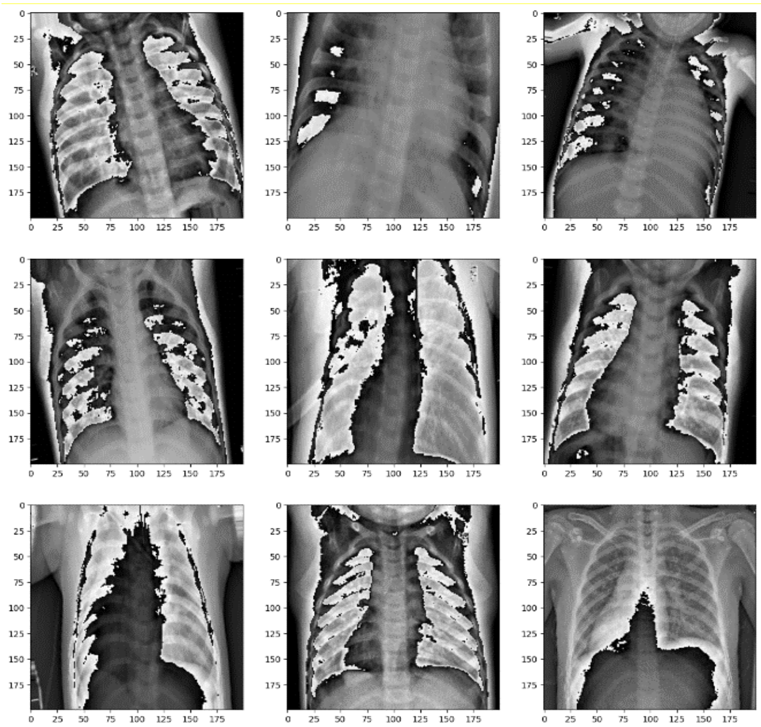

Figure 3. Preprocessed images with no filter

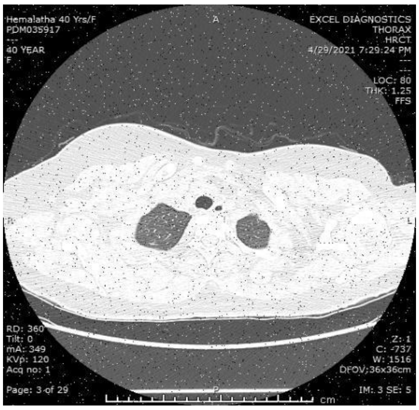

Figure 4. Salt and pepper filter applied

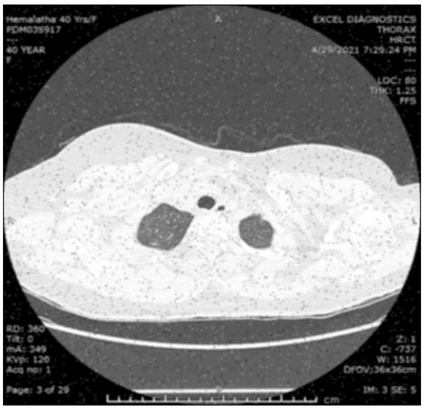

Figure 5. 3×3 mean filter for salt and pepper noise

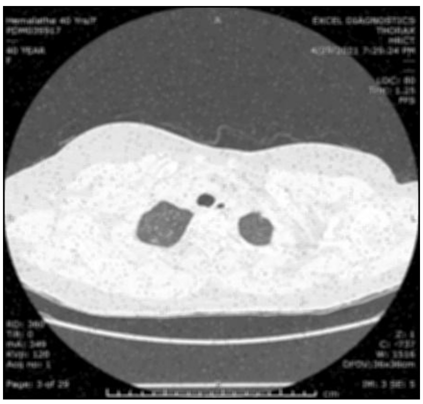

Figure 6. 5×5 mean filter for salt and pepper noise

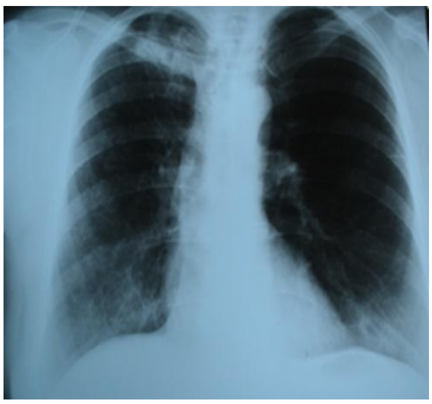

Figure 7. Tuberculosis infected lung

3.2. Filtering techniques in lung scan classification: a comparative analysis of model performance

Within machine learning, accuracy, loss, and epochs stand as crucial metrics utilized for assessing a model's performance. Accuracy represents the proportion of correct predictions made by the model, determined by dividing the number of accurate predictions by the total number of predictions made. Loss quantifies the model's adherence to the training data by assessing the disparity between the model's predicted outputs and the actual outputs of the training dataset. This measurement gauges the degree of fitting between predicted and actual outcomes. Epochs refer to the instances where the model processes and learns from the complete training dataset.

Accuracy and loss typically vary with respect to epochs in the following way: accuracy increases as the model trains for more epochs. This is because the model can learn more about the training data as it trains for longer. Loss decreases as the model trains for more epochs. This is because the model can better fit the training data as it trains for longer. However, it is important to note that accuracy and loss can also start to decrease after a certain number of epochs. This is known as overfitting. Overfitting arises when the model excessively adapts to the training data, hindering its ability to effectively generalize to unseen or new data.

Comparing different models for lung scan classification: this study involved an assessment of the effectiveness of three distinct models for classifying lung scans: i) model 1: no filter, ii) model 2: 3×3 mean filter, and iii) model 3: 5×5 mean filter. Our study findings revealed that the 5×5 mean filter model exhibited superior performance compared to the other models concerning both accuracy and validation accuracy. Table 1 shows the accuracy and validation accuracy of the different models.

Table 1. Model accuracies for test and validation dataset

Model	Accuracy (%)	Validation accuracy (%)
No filter	83.46	81.23
3×3 mean filter	83.54	79.32
5×5 mean filter	84.68	83.24

The accuracy plot as shown in Figure 8 illustrates the model's accuracy on both the training and validation sets throughout the training process. The sudden jump in accuracy in the initial epochs is due to the accumulation of features from clustering. The model is able to learn the most important features of the data quickly, which leads to a rapid increase in accuracy. However, as the model trains for more epochs, it starts to learn less important features, which leads to a stagnation in accuracy. The validation accuracy is also fluctuating, which is due to the unevenness of the data that is used for validation. Some of the data in the validation set may be more difficult for the model to classify than other data. Consequently, this can result in the model overfitting to the training data, causing a decline in performance when applied to the validation dataset.

The loss plot as shown in Figure 9 demonstrates the model's loss concerning both the training and validation sets throughout the training duration. Initially, the model rapidly learns the data, reducing the loss on both sets. Yet, beyond a certain epoch count, the loss on the validation set begins to rise, indicating potential overfitting of the model to the training data. This divergence implies a decrease in generalization ability. Overall, the results in Figures 8 and 9 suggest that the model is able to learn the data quickly and achieve a high accuracy on the training set. However, the model is also starting to overfit to the training data. This is evident from the increase in loss on the validation set and the fluctuation in validation accuracy.

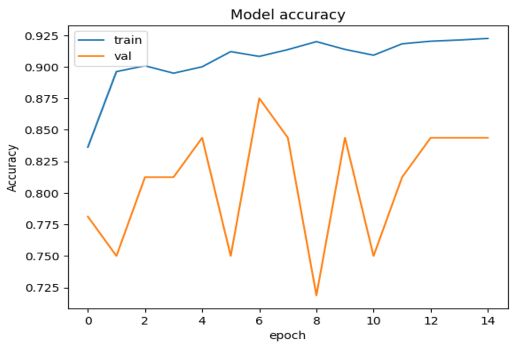

Figure 8. Accuracy plot for no filter model

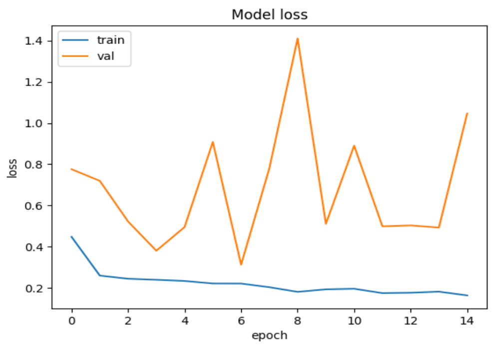

Figure 9. Loss plot for no filter model

Figures 8 and 9 show the accuracy and loss plots for the model with no filter, while Figures 10 and 11 show the accuracy and loss plots for the model with the 3×3 mean filter. The accuracy plot for the 3×3 mean filter model in Figure 10 shows a similar trend to the accuracy plot for the model with no filter as shown in Figure 8. The accuracy increases rapidly in the initial epochs and then stagnates. However, the accuracy of the 3×3 mean filter model is slightly lower than the accuracy of the model with no filter. This suggests that the 3×3 mean filter may be introducing some noise into the data, which is making it more difficult for the model to classify the data accurately. The loss plot for the 3×3 mean filter model in Figure 11 shows a similar trend to the loss plot for the model with no filter as shown in Figure 9. The loss decreases rapidly in the initial epochs and then starts to increase after a certain number of epochs. This suggests that the 3×3 mean filter is not able to completely prevent the model from overfitting to the training data. The results in Figures 10 and 11 suggest that the 3×3 mean filter does not provide any significant improvement in the accuracy or generalization of the model. However, the 3×3 mean filter may be able to reduce the overall loss of the model.

There are few possible reasons why the 3×3 mean filter may be causing a decrease in accuracy:
– The utilization of a 3×3 mean filter might blur lung edges, potentially hindering the model’s ability to recognize lung features.
– The 3×3 mean filter may be introducing some noise into the data, which can make it more difficult for the model to classify the data accurately.
– The 3×3 mean filter may be removing some important features from the data, which can make it more difficult for the model to learn the data.

There are few possible solutions to the problem of the decrease in accuracy:
– Use a different filtering technique, such as a median filter or a Gaussian filter.
– Use a smaller filter size, such as a 3×3 median filter or a 5×5 Gaussian filter.
– Use a data augmentation technique, such as random cropping or random flipping, to introduce more diversity into the training data.
– Use a more advanced regularization approach, like dropout or weight decay, to mitigate the model’s tendency to overfit on the training data.

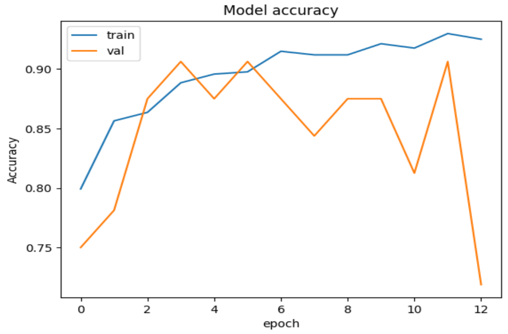

Figure 10. Accuracy plot for 3×3 mean filter model

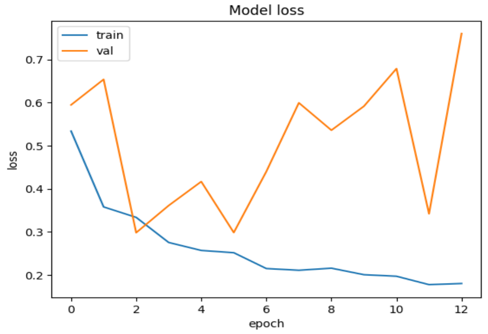

Figure 11. Loss plot for 3×3 mean filter model

Figures 12 and 13 show the accuracy and loss plots for the model with the 5×5 mean filter. The accuracy plot for the 5×5 mean filter model in Figure 12 shows a similar trend to the accuracy plot for the model with no filter as shown in Figure 8. The accuracy increases rapidly in the initial epochs and then stagnates. However, the accuracy of the 5×5 mean filter model is comparable to the accuracy of the model with no filter. This suggests that the 5×5 mean filter is able to remove noise from the data without blurring the edges of the lungs or removing important features. The loss plot for the 5×5 mean filter model in Figure 13 shows a similar trend to the loss plot for the model with no filter as shown in Figure 9. The loss decreases rapidly in the initial epochs and then starts to increase after a certain number of epochs. However, the loss of the 5×5 mean filter model is slightly lower than the loss of the model with no filter. This suggests that the 5×5 mean filter is able to help the model to learn the data more efficiently and prevent overfitting. The validation accuracy of the 5×5 mean filter model is substantially higher than the validation accuracy of the model with no filter. This suggests that the 5×5 mean filter is able to improve the generalizability of the model. The results in Figures 12 and 13 suggest that the 5×5 mean filter is a good choice for filtering lung scan images before training a deep learning model. The 5×5 mean filter is able to remove noise from the images without blurring the edges of the lungs or removing important features. It is also able to help the model to learn the data more efficiently and prevent overfitting.

Comparison of the 3×3 mean filter with the 5×5 mean filter: the 5×5 mean filter outperforms the 3×3 mean filter in terms of accuracy and validation accuracy. This is likely because the 5×5 mean filter is better at removing noise from the images without blurring the edges of the lungs or removing important features. The 5×5 mean filter is a good choice for filtering lung scan images before training a deep learning model. It is able to remove noise from the images without blurring the edges of the lungs or removing important features. It is also able to help the model to learn the data more efficiently and prevent overfitting.

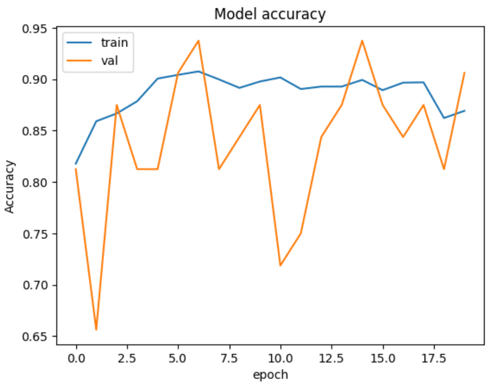

Figure 12. Accuracy plot for 5×5 mean filter model

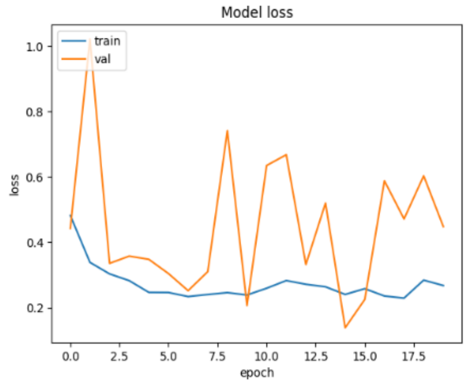

Figure 13. Loss plot for 5×5 mean filter model

3.3. Filter impact and model evaluation: a comparative analysis of lung scan classification models

The evaluation of classification models through confusion matrices [26] and F1-scores provides crucial insights into their performance. In our project focusing on lung scan images, three models were assessed: no filter [27], 3×3 mean filter, and 5×5 mean filter. In our project, the indices 0, 1, 2, and 3 represent the four classes of lung scan images: COVID-19, Normal, Pneumonia, and Tuberculosis. The no filter model demonstrated good overall performance with an F1 score of 0.74. It excelled in predicting COVID-19 and normal samples, yet exhibited lesser accuracy in predicting Pneumonia and Tuberculosis samples, with F1-scores of 0.77 and 0.67, respectively.

Comparatively, the 3×3 mean filter model showed a similar overall performance (F1-score of 0.72) to the no filter model. While proficient in predicting COVID-19 and normal samples, it displayed a slight decrease in accuracy for Pneumonia and Tuberculosis samples, with F1-scores of 0.74 and 0.60, respectively. Notably, the 5×5 mean filter model outperformed both counterparts with the highest overall F1-score of 0.73. It demonstrated robust predictions across all four classes, with F1-scores of at least 0.58 [28].

The superior performance of the 5×5 mean filter model suggests its effectiveness in enhancing the model's ability to distinguish between different lung conditions. Additionally, a potential explanation for the increase in misclassification between Normal and Pneumonia samples with the 3×3 mean filter points to issues such as blurring edges or introducing noise. In conclusion, our findings highlight the significance of filter selection in optimizing classification models for lung scan images, with the 5×5 mean filter emerging as the most effective choice for improved accuracy and overall performance. The DenseNet documentation and repository link of our project [29] is attached for reference. Figures 14 to 16 represent the confusion matrices for no filter, 3×3 mean filter, 5×5 mean filter model respectively.

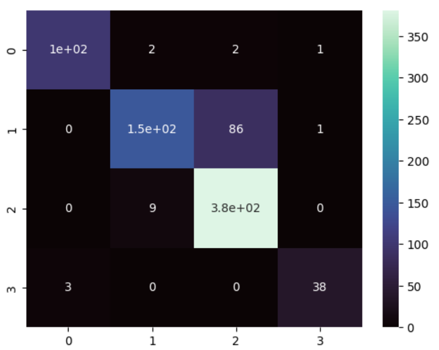

Figure 14. Confusion matrix for no filter model

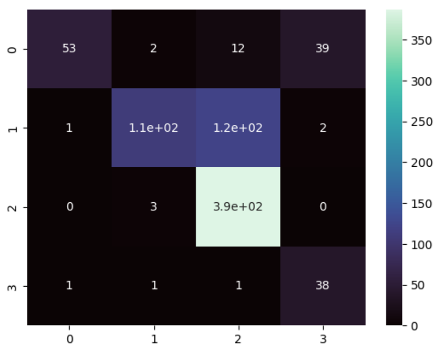

Figure 15. Confusion matrix for 3×3 mean filter model

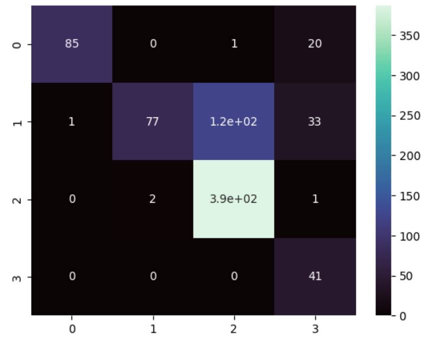

Figure 16. Confusion matrix for 5×5 mean model

4. CONCLUSION

In this comprehensive study, we meticulously evaluated various filtering and contrast enhancement techniques for lung scan image classification using deep learning. By applying transfer learning with DenseNet 121 and introducing filters such as salt and pepper, 3×3 mean, and 5×5 mean with CLAHE, we aimed to enhance image quality. Qualitative analysis through visual representations emphasized the impact of these techniques. Notably, the model with no filter exhibited minimal discrepancies, while the 5×5 mean filter effectively reduced noise without compromising lung feature clarity. Quantitative analysis revealed reasonable performance across all models, with accuracy ranging from 83.46% to 84.68%. Significantly, the 5×5 mean filter model consistently outperformed others, achieving a higher accuracy of 84.68% and an impressive validation accuracy of 83.24%. Examining accuracy and loss trends, the 5x5 mean filter model not only demonstrated higher accuracy but also maintained a more stable validation accuracy over epochs, suggesting improved generalization. In contrast, the 3×3 mean filter model exhibited a slight decrease in accuracy, indicating potential challenges in noise handling or preserving critical features.

The insight provided by confusion matrices and F1-scores highlighted the superior performance of the 5×5 mean filter model across all classes. Meanwhile, the 3×3 mean filter model showed comparable results to the no filter model, with minor variations in predicting Pneumonia and Tuberculosis samples. Exploring potential explanations for model discrepancies, especially in distinguishing between Normal and Pneumonia samples with the 3×3 mean filter, underscores the importance of careful filter selection and customization in medical image analysis. The novelty of this study lies in the systematic evaluation of filtering techniques on lung scan image classification. The success of the 5×5 mean filter in enhancing both quantitative metrics and visual interpretability suggests its potential as a valuable tool in future medical image analysis. To further advance this field, future investigations could focus on optimizing filter parameters, exploring ensemble approaches, developing adaptive filtering strategies, extending dataset exploration, and collaborating with medical professionals for thorough clinical validation, ensuring the real-world applicability of these advancements. In conclusion, our study contributes valuable insights to the nuanced impact of filtering techniques on the classification of lung scan images, paving the way for future advancements in this critical domain of medical imaging.

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