EGBE 601 Medical Signal Processing and Instrumentation
Term Project Report

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Topic:

Low-pass Filter Effect on COVID-19 Detection Convolutional Neural Network Model

Abstract:

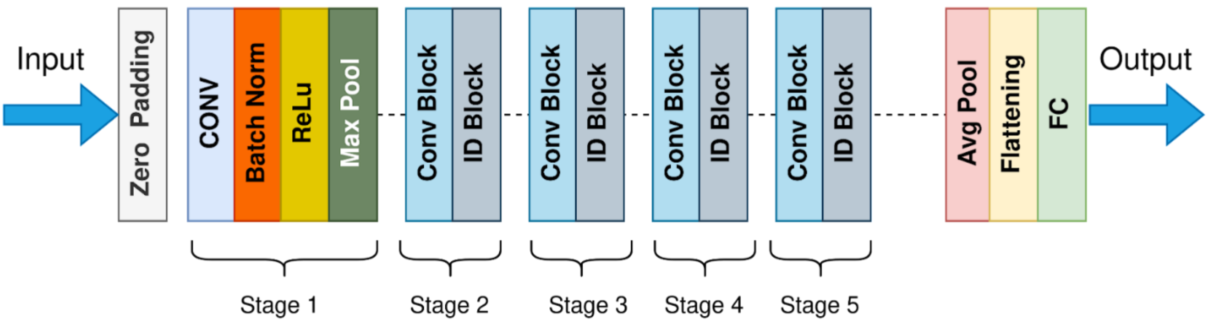
The COVID-19 pandemic has become a global crisis, causing millions of deaths. To diagnose COVID-19 and initiate treatment, a chest X-ray interpreted by a radiologist is required. The shortage of radiologists, a problem already exacerbated by an aging society, has been further strained by the high demand for imaging diagnosis due to the COVID-19 pandemic. This shortage impacts the time to confirm diagnoses, administer drugs, and hospitalize patients, leading to increased disease burden, poorer prognoses, and higher mortality rates. Shorter times to receive treatment and hospitalization lead to better outcomes. Machine learning assistance with diagnoses could help reduce the workload of radiologists and improve patient prognoses. Processing numerous images requires significant storage space and fast processing times. A low-pass filter is applied to reduce processing time and memory requirements. In this study, we explore the performance of Convolutional neural networks (CNNs) after applying a low-pass filter by varying cutoff percentages and measuring model accuracy. Chest X-ray images acquired from Kaggle featuring three distinct conditions—normal, viral pneumonia, and COVID-positive chest X-rays—are used. The ResNet50 CNN model will be used for pretraining the dataset. After assessing the results at various cutoff percentages, PCA will be used to gain intuitive insights into the data structure. Using a low-pass filter with a lower cutoff percentage resulted in increased blurriness and loss of high-frequency details. Non-linear relationships are observed between the low pass filter cutoff and the CNN model's accuracy. A higher cutoff percentage demonstrates higher accuracy. PCA analysis reveals that the highest accuracies in distinguishing features occur at a 90% cutoff.

Introduction:

The COVID-19 pandemic has spread widely across the world. According to the WHO, over 7 million deaths and 774 million cases have been reported between January 2020 and March 2024[1]. The disease is a respiratory tract infection with a range of symptoms from upper respiratory tract infections to mild-to-severe pneumonia requiring ventilatory support and intensive care[2]. The mortality rate of COVID-19 pneumonia could be up to 55% in elderly patients, and late diagnosis contributes to high rates of intensive-care hospitalization and mortality[3]. The shortage of radiologists, an already persistent problem exacerbated by an aging society and an insufficient number of radiologists, contributes to the high demand for imaging diagnosis from the COVID-19 pandemic[4]. This shortage impacts the time to confirmed diagnosis, administration of drugs, and hospitalization, leading to an increased disease burden, poor prognosis, and higher mortality rates[5]. Faster diagnosis through chest X-rays could reduce the mortality rate and disease burden. The typical CXR findings of COVID-19 include bilateral peripheral and basal multifocal airspace opacities, such as ground-glass opacity (GGO) and consolidation in the bilateral lower lobe[6]. These findings can distinguish COVID-19 from other viral pneumonia and normal lungs. Using deep learning to assist with imaging diagnosis would help with patient hospitalization and reduce the workload of radiologists.

CNNs are used in a wide range of applications in image classification and segmentation[7]. Various feature extraction models have been proposed, such as ResNet[8]. ResNet50 is a deep convolutional neural network that uses residual learning to facilitate training deeper models. It achieves significant improvements in image recognition tasks by introducing shortcut connections that perform identity mapping, allowing layers to learn residual functions, according to **Figure 1**. This architecture enables the training of networks that are much deeper than previously possible without degradation in performance, leading to better feature extraction for tasks like medical image classification[9]. ResNet50's advantages include enhanced accuracy and efficiency in processing complex image data. It has been demonstrated that such models effectively extract features from objects in an image[10]. The processing time could be improved by adding a Low-pass filter. This would reduce high-frequency components and decrease the computational complexity of subsequent image-processing tasks, potentially speeding up processing times and lowering memory requirements for storing and handling images[11]. Principal Component Analysis (PCA) is a commonly used efficient method for visualizing how these models extracted the features and classified the images for their COVID-19 detection[12].

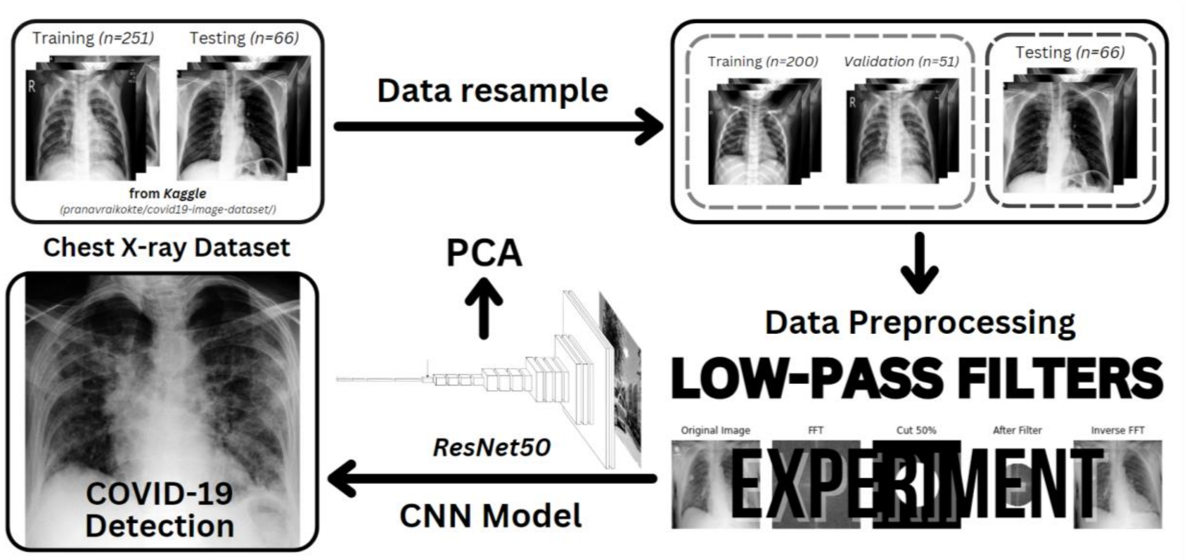
Figure 1 ResNet50 Model Architecture[13]



Methods:

In this study, we examined the efficacy of low-pass filtering on a CNN model's ability to detect COVID-19 from chest X-ray images as in the study workflow in **Figure 2**. We used a resampled Kaggle dataset and applied low-pass filters to preserve only critical image frequencies, generating 11 datasets across different cutoff percentages. The ResNet50 architecture-based CNN model was trained on these datasets. The performance was then evaluated, with the best models undergoing PCA for insights into feature separability and distribution.

Figure 2 Our Experimental Design



1) Dataset preparation

This study utilizes a public dataset from <u>*Kaggle*</u> *(pranavraikokte/covid19-image-dataset/)*, uploaded for training COVID-19 detection models using chest X-ray images. The dataset comprises 317 chest X-ray images, with 251 images for training (including training and validation) and 66 images for testing. It is composed of three distinct classes: COVID-19 pneumonia, normal, and other viral pneumonia films. However, since there is an inherent imbalance among the classes of the training samples, a resampling strategy was conducted to reduce potential biases and ensure a more equitable representation of each class.

2) Low-pass filter application on the dataset

As our objective is to empirically determine the impact of applying a low-pass filter on the performance of a CNN model trained for COVID-19 detection from chest X-ray images, the low-pass filter is implemented as a preprocessing approach to preserve only the low-frequency components of the images according to the cutoff percentage in the images to feed to the model. First, we apply a Fast Fourier Transform (FFT) to shift the chest X-ray images into the frequency domain, enabling the application of a low-pass filter that preserves only the desired lower frequency components based on the cutoff percentage—such as a 30% cutoff allowing only the lowest 30% of frequencies to pass. Thus, lower frequencies are preserved, while higher frequencies beyond this threshold are cut out. Then, the application of an Inverse FFT (IFFT) was done to reconstruct the images back to the spatial domain.

Our experiment:

At this step, we conducted our experiment on how a low-pass filter affects the performance of the neural network model training. We systematically vary the cutoff percentage of the low-pass filter across the entire spectrum every 10% interval from 0% to 100% to investigate its effect on the CNN model's training efficacy. Then, we applied these low-pass filters with each cutoff percentage to the same resampled dataset, generating new datasets. This process generates 11 distinct datasets, each corresponding to a specific cutoff setting, thereby preparing comprehensive datasets for subsequent model training. Then, model performance metrics, the accuracy, were computed and compared across different preprocessing approaches.

3) CNN model development

In our study, we developed a CNN model utilizing the ResNet50 architecture, pre-trained on the ImageNet dataset, with a final layer adapted for classifying chest X-ray images into categories: COVID-19, normal, or other viral pneumonia cases. The model's learning rate was strategically set to linearly decay from 0.0001 to 0.00001 over 20 epochs to balance rapid convergence early in training with fine-tuning accuracy in later stages. Training was facilitated by employing callbacks for dynamic learning rate adjustment, optimal performance checkpointing, and early stopping based on validation accuracy and loss.

The experiment assessed the effect of applying a low-pass filter at various cutoff percentages on the model's training and generalization capabilities. The preprocessed datasets filtered at each cutoff percentage were used for training. The model was compiled using the Adam optimizer, targeting accuracy through the sparse categorical cross-entropy loss function. Post-training, the model weights leading to the highest validation accuracy were evaluated on a testing dataset to determine the performance of each model from different preprocessing approaches in diagnosing COVID-19 from chest X-ray images.

4) PCA-based visualization of CNN features

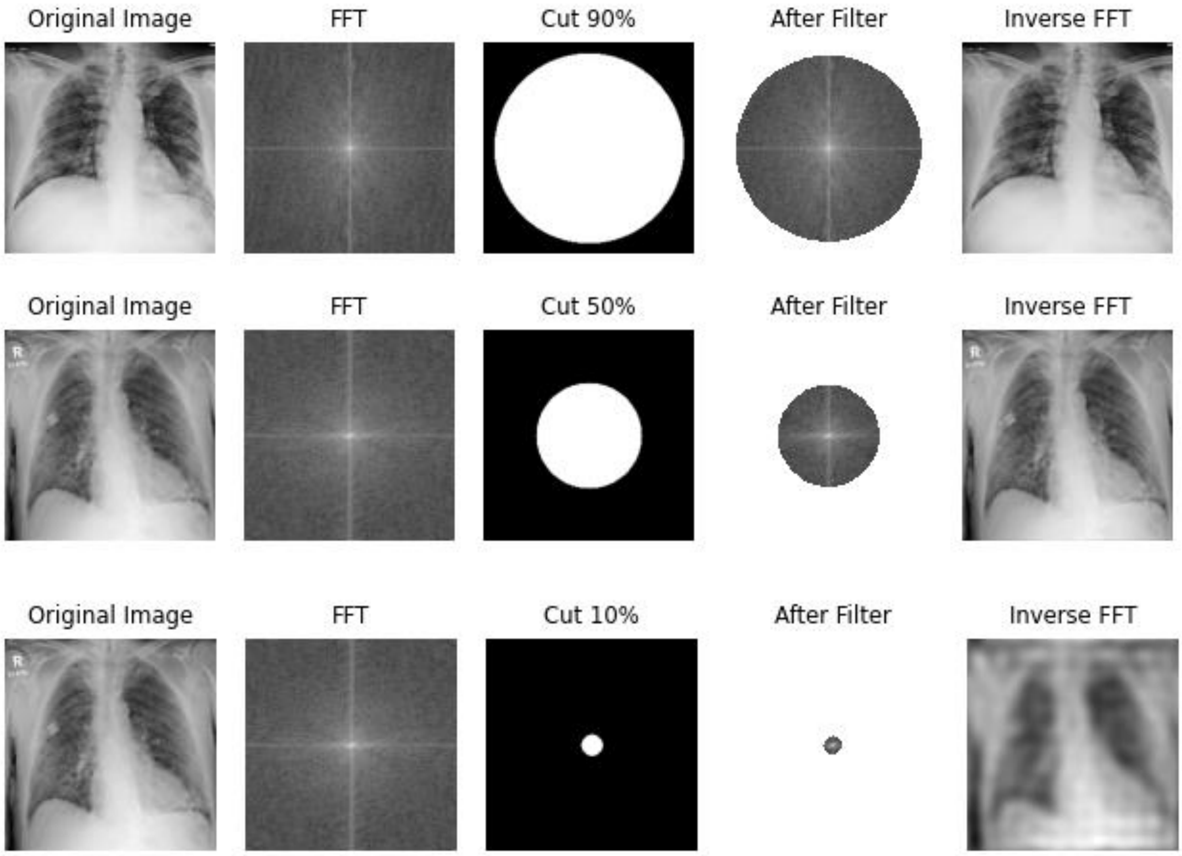
After we acknowledged the best CNN model performance from a certain cutoff percentage low-pass filter, we used principal component analysis (PCA) to understand the best model's feature extractions for detecting COVID-19 films compared to the other lower-performance models. By utilizing PCA, we aimed to unveil underlying patterns and relationships within the high-dimensional feature representations extracted by the model. Through this analysis, we visualized distinct clusters and distributions of features corresponding to different classes within the dataset. By visualizing the features in a reduced-dimensional space, we gained intuitive insights into the separability and structure of the data, facilitating informed decisions regarding model optimization and generalization.

Results:

1) Dataset preparation and Low-pass filter preprocessing

The original dataset, sourced from Kaggle and comprising 317 chest X-ray images divided into 251 training (inclusive of validation) and 66 testing images, was found to be imbalanced across its three classes: COVID-19 pneumonia, normal, and other viral pneumonia. To mitigate potential biases, a resampling strategy was implemented, resizing all images to 224x224 pixels, batching them in sizes of 32, and splitting them into training and validation subsets in an 80:20 ratio. Then, the low-pass filter was applied to the dataset, aimed at preserving only the lower frequency components of the images according to various cutoff percentages. As illustrated in **Figure 3**, applying a low-pass filter with lower cutoff percentages resulted in images becoming increasingly blurry, indicating a loss of high-frequency details such as edges and fine textures. This blurriness became more pronounced as the cutoff percentage decreased, visually confirming the filter's impact on image resolution and detail preservation.

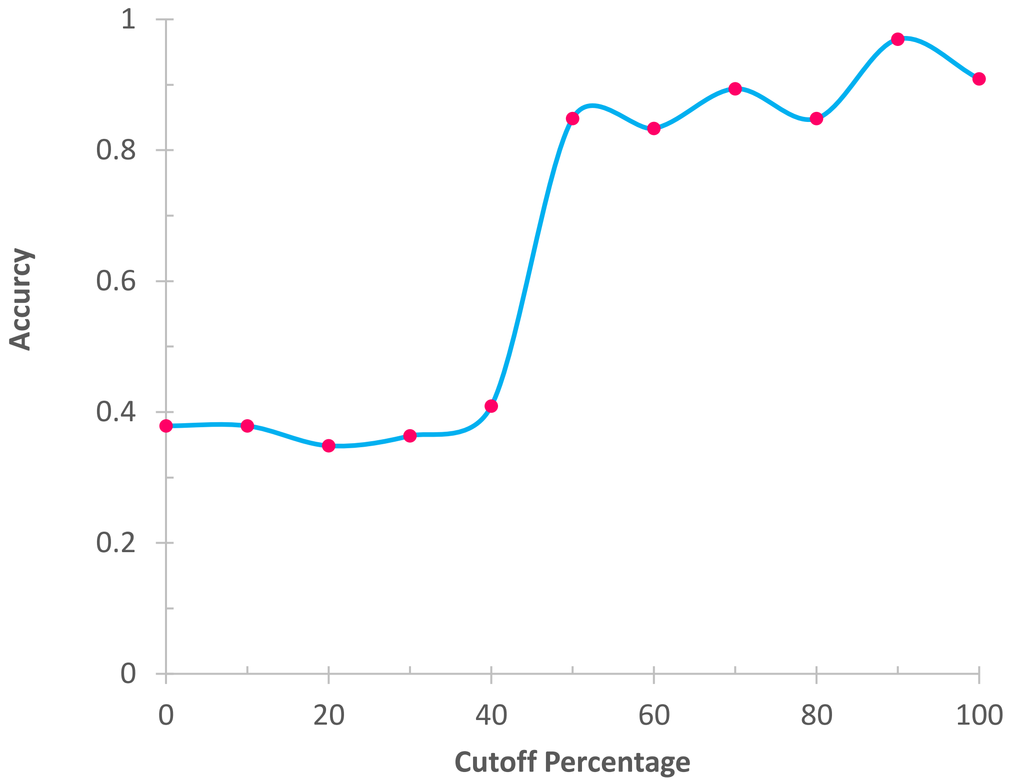
Figure 3 The example of low pass filtering with cut percentages of 90%, 50%, and 10%



2) Effects of the low-pass filters on the CNN model training

As in **Figure 4**, The results demonstrate a non-linear relationship between the low pass filter cutoff and the CNN model's accuracy, with higher cutoff percentages yielding higher accuracies. When no low-pass filter was applied, representing the 100% cutoff, the accuracy recorded was high at around 0.9090. However, the highest accuracy recorded was at a 90% cutoff with an accuracy of approximately 0.9697. As the cutoff percentage decreased, indicating stronger filtering, a general decline in accuracy was noted, reaching the lowest point at a 20% cutoff with an accuracy of approximately 0. 0.3485. Furthermore, at the lowest cutoffs at 0% and 10%, the accuracy plateaued at around 0.3788, suggesting that removing a significant portion of high-frequency components does not enhance model performance and may, in fact, impede the model's ability to accurately classify the data.

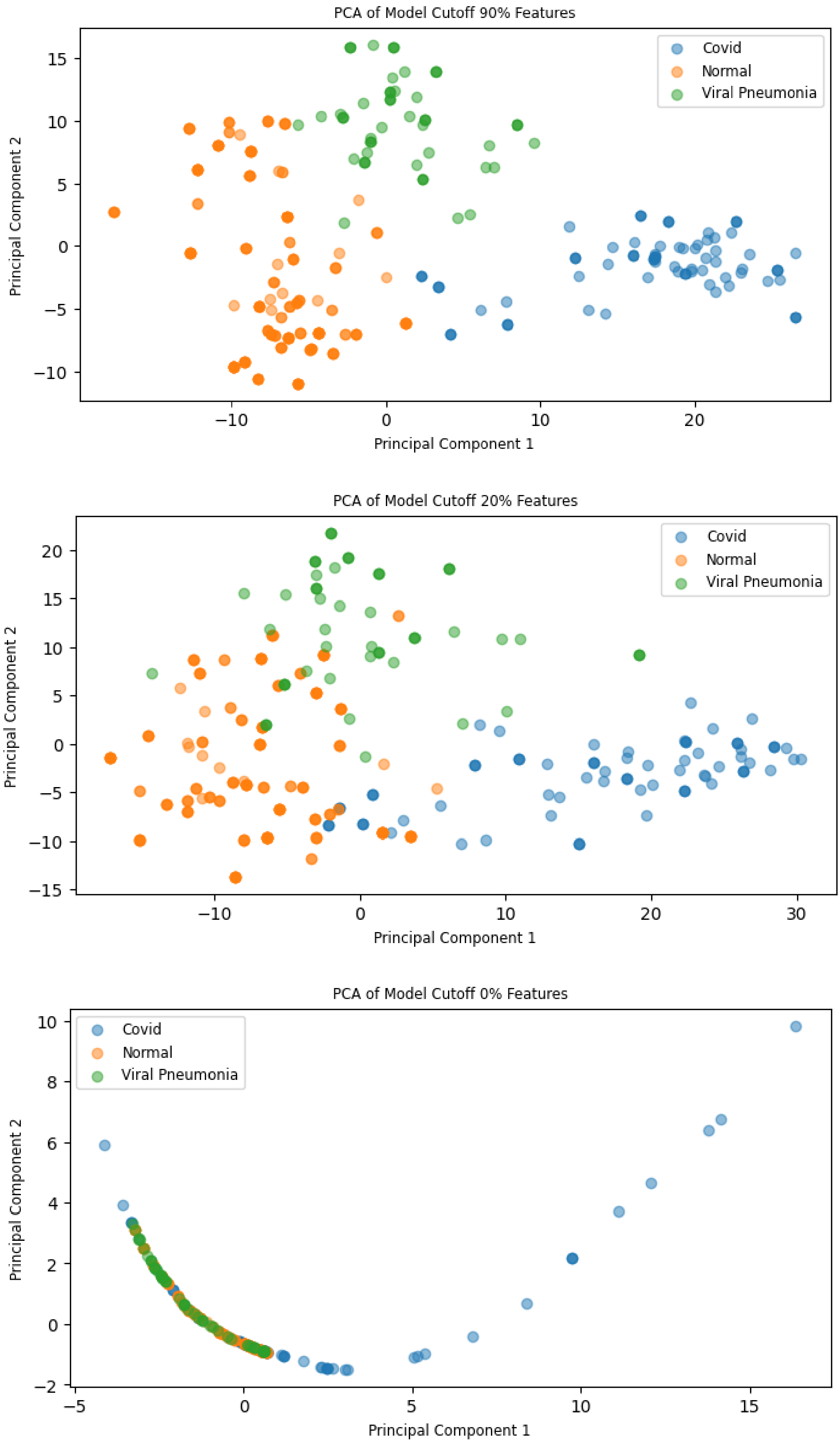
Figure 4 Cutoff percentage of the low-pass filter effect on the model accuracy



3) The visualization of the CNN model features in COVID-19 Detection

In our study of the impact of different preprocessing strategies CNNs tasked with detecting COVID-19 from chest X-ray images, we investigated how varying cutoff thresholds in a low-pass filter preprocessing step influenced the ability of PCA to discriminate between features corresponding to three classes: COVID-19, Normal, and Viral Pneumonia. These classes were visually differentiated using three distinct colors in PCA scatter plots. The PCA results for the CNN model's features at various low-pass filter cutoffs illustrate the effect of frequency component preservation on feature differentiation, as shown in **Figure 5**. At a 90% cutoff, the feature clusters for each class—COVID-19, normal, and viral pneumonia—are distinct and well-separated, which likely facilitated the highest accuracy in classification. At a 20% cutoff, clusters show greater overlap and a wider spread, indicating less distinct features due to the exclusion of many high-frequency components. The 0% cutoff PCA, where all frequency details are entirely absent, shows a convergence of class features into a tight, overlapping distribution, highlighting the inadequacy of feature separation for class discrimination in the model.

Figure 5 PCA of the CNN model trainings (at cut percentages: 90%, 20% and 0%)



Discussion:

In this study, we explored the impact of low pass filtering on the performance of CNN models during training, focusing particularly on how varying the cutoff percentage of the filter affects model accuracy. Our methodology involved systematically adjusting the cutoff percentage of the low-pass filter in 10% intervals across the entire spectrum from 0% to 100%, thereby generating 11 distinct datasets.

1) Impact of Low-Pass Filtering on Image Quality and Model Performance

The application of low-pass filters led to a progressive blurring of images, as lower cutoff percentages removed higher frequency components, crucial for preserving edges and fine textures. This degradation in image quality, evidenced by increased blurriness at lower cutoff percentages, directly influenced the model's ability to learn distinctive features from the data.

Our results illustrated a non-linear relationship between the cutoff percentage of the low-pass filter and the accuracy of the CNN model. Interestingly, a 90% cutoff percentage achieved the highest model accuracy (approximately 0.9697), surpassing even the unfiltered condition (100% cutoff), which recorded an accuracy of 0.9090. This suggests that slight filtering may enhance model performance by eliminating noise or irrelevant high-frequency details that could potentially confuse the model during training.

However, as the cutoff percentage decreased beyond this optimal point, a significant decline in accuracy was observed, reaching the lowest accuracy at a 20% cutoff (approximately 0.3485). This decline underscores the importance of high-frequency components in image recognition tasks, as their removal seems to impair the model's ability to accurately classify images. The accuracy plateau observed at the lowest cutoffs (0% and 10%) further suggests that there is a threshold beyond which additional removal of high-frequency details not only fails to benefit but actively hinders model performance.

2) Further Analysis with Principal Component Analysis (PCA)

To deepen our understanding of how preprocessing influences the model's internal dynamics, we utilized PCA for a comparative analysis of feature extraction across different filtering thresholds. PCA enabled the visualization of feature distribution and separability in a lower-dimensional space, revealing the qualitative impact of low-pass filtering on the model's ability to discriminate between classes. Through PCA, we visualized how filtering at optimal thresholds improves feature separability, thereby boosting the model's discriminative capability. Notably, at a 90% cutoff, the distinct separation of feature clusters for COVID-19, Normal, and Viral Pneumonia classes highlighted the effectiveness of our preprocessing strategy in emphasizing discriminative features critical for accurate classification. This contrasted with the reduced accuracy and increased feature overlap observed at lower cutoffs, underscoring the detrimental effects of excessive filtering.

The PCA results provided visual confirmation of our accuracy findings. Our findings suggest that selective frequency component retention, facilitated by FFT and IFFT, significantly contributes to model performance by minimizing noise and enhancing relevant image features. At the 90% cutoff, feature clusters for COVID-19, Normal, and

Viral Pneumonia classes were distinctly separated, indicative of a well-performing model. This clear separability aligns with the high classification accuracy observed, illustrating that optimal filtering aids in emphasizing features that are most relevant for discrimination. Conversely, at lower cutoffs, the increasing overlap and dispersion of feature clusters mirrored the decrease in model accuracy, highlighting the detrimental effect of excessive filtering on feature distinguishability.

3) Limitations

While our study revealed the intricate balance between filtering and model performance, it also acknowledges limitations. With our small datasets, there is a high risk of overfitting the trained CNN models. The impact of low-pass filtering may vary across different datasets, model architectures, and tasks, suggesting the need for task-specific optimization of preprocessing strategies. Additionally, the combination of low pass filtering with other data augmentation or preprocessing techniques remains unexplored, presenting a potential avenue for further research to enhance model robustness and accuracy.

Conclusion:

Our analysis highlights the effects of preprocessing dataset with low-pass filters in training CNN model for medical imaging tasks. By finding the right balance between removing noise and keeping important high-frequency details, models can achieve better accuracy and distinguish features more clearly. The insights from PCA add to our understanding of how the model works, providing a useful view on how to fine-tune deep learning models for challenging diagnostic tasks.

References:

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