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DETECTION OF LUNG DISEASES FROM COLORIZED CHEST X-RAY IMAGES USING DEEP LEARNING

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Abstract

In recent years, there have been significant advancements in the utilization of machine learning, incorporating data mining and deep learning techniques, for the analysis of chest X-ray images. These methods play a vital role as decision support tools, aiding radiologists in expediting the diagnostic process. Chest X-ray (CXR) images have proven their value in diagnosing and monitoring various pulmonary diseases, such as COVID-19 and Pneumonia and Tuberculosis. This study aims to detect these lung diseases by applying a deep learning method. To achieve this, we applied Convolutional Neural Network (CNN) and Transfer (VGG16) models in the publicly available dataset comprising 7135 CXR images. The obtained results show the effectiveness of deep learning in detecting lung diseases, as well as the importance of coloring CXR images to increase the accuracy of disease detection.

Keywords: *Deep Learning, Lung Diseases, Convolutional Neural Networks*

I. INTRODUCTION

In recent years, the importance of data mining and artificial intelligence (AI) techniques has been increasing in the diagnosis of several diseases. Data mining approaches enable the analysis of large and diverse datasets, including clinical records, medical imaging, laboratory results, and patient demographics. By extracting meaningful patterns, associations, and features from these datasets, data mining techniques facilitate the identification of relevant biomarkers, risk factors, and disease subtypes that contribute to accurate disease detection. AI approaches, such as machine learning and deep

learning, leverage data mining outputs to create powerful disease detection systems. These systems are developed using labeled datasets and can accurately differentiate between different types of pulmonary diseases, including COVID-19, Pneumonia, and Tuberculosis (TB).

COVID-19 is a disease first seen in Wuhan, China, and spread over the world in late 2019. The disease affected the whole world, and caused major problems in health services, in a short period. The World Health Organization (WHO) has defined it as a serious pandemic disease due to its rate of spread. WHO reported that the number of patients worldwide exceeded 657 million and the number of deaths reached more than 6.6 million and was increasing day after day in January 2023 [1], [2]. The COVID-19 disease has a wide range of symptoms that appear after an average incubation period of 2-5 days [3]. The most common signs and symptoms of infection are known as high fever, dry cough, sore throat, fatigue, headache, weakness, muscle pain, shortness of breath, and in some scenarios there are no symptoms (asymptomatic) [4]. It is difficult to diagnose this disease quickly because its symptoms are similar to those of other lung diseases, such as Pneumonia and Tuberculosis.

Differentiating these lung diseases using chest imaging technology is essential for managing infection control decisions and early diagnosis and treatment plans. Despite the availability of antibiotics, pneumonia remains the most common cause of death from lung diseases, especially in children. In addition, death rates have increased due to drug-resistant pulmonary tuberculosis, caused by Mycobacterium tuberculosis [5]. Therefore, there is a clear need for a robust artificial intelligence (AI) system that can detect and categorize various respiratory diseases that overlap with clinic presentations, so that the correct treatment regimen can be directed.

Chest X-rays (CRX), computed tomography scans, and magnetic resonance imaging (MRI) are the common imaging techniques used to diagnose lung diseases. The gold standard for diagnosing lung diseases is the MRI or CT scan, however, they are more expensive, expose the patient to radiation, and are not widely available worldwide. In contrast, CXR is one of the most widely used diagnostic imaging methods for cardiothoracic and pulmonary problems. It is rapid, simple, inexpensive, and exposes the patient to less radiation [6].

There are difficulties in differentiating CXR patterns of lung disease, which often results in significant variability among readers across radiologists [7]. The workload of radiologists will rise due to expected pandemic waves, and new automated image analysis techniques that may improve the qualitative assessment of radiologists are

urgently needed. To help make the diagnosis, these meets will label or segment parts of your CXR. Decision support systems, which aim to aid clinical decision-making, have emerged as a new research direction in healthcare [8]. The automated identification of lung diseases, especially their early detection and classification, has aroused great interest from clinical and AI researchers in the last months of the pandemic.

The most common COVID-19 detection technology is real-time polymerase chain reaction (RT-PCR). However, it has drawbacks such as false negative results and it may take a long period in some countries to receive results. Furthermore, many countries lack adequate resources and testing facilities to implement COVID-19 testing on a large scale. To overcome these problems, CRX analysis is used to be an alternative method for PCR testing.

This study aims to provide an early detection and classification system for lung diseases, including COVID-19, Pneumonia, and Tuberculosis, from X-ray images. For this purpose, we first colorized the grey-scale X-ray images. Then, we utilized the Convolutional neural network models and pre-trained models to generate a lung disease diagnosis system. The study also involves comparison results of the before and after the colorization process, which has not been previously utilized. In this context, the key distinction of this study from previous studies lies in the design of the neural network model and the incorporation of colorization to enhance classification accuracy. Previous studies have often used datasets limited to two conditions, such as positive and negative COVID-19 or COVID-19 and pneumonia, or they have utilized computed tomography (CT) images instead of X-ray images, which are less commonly used for diagnosing lung diseases. Additionally, most studies have limited their evaluation metrics to accuracy alone, which is a limitation in the methodology used. However, this study aims to provide a well-balanced result by giving accuracy, increased specificity, and sensitivity values in terms of performance evaluation metrics.

II. RELATED WORKS

Many recent studies in the field of medical image analysis have introduced computer-aided diagnosis for CXR images and CT image-based disease detection, especially for conditions such as COVID-19, Pneumonia, and Tuberculosis. In this section, we specifically highlight the recent advances in medical image analysis for the diagnosis of COVID-19, Pneumonia, and TB using CXR images.

Sitaula et al. developed a strategy to improve the analysis of chest X-ray images for detecting lung infections. Their method involved using multi-scale bags of deep visual words-based features generated by using three distinct kernels and conducting convolution with max pooling operation. Their proposed approach achieved a classification accuracy of 84.37%, 88.88%, 90.29%, and 83.65% for four public CXR datasets, using the Support Vector Machine (SVM) algorithm [9].

Mahbub et al. proposed a deep-learning model with nine hidden layers for classifying CXR images into three disease categories: COVID-19, TB, and Pneumonia. The model achieved accuracy levels of 99.87% for COVID-19, 99.55% for Pneumonia, 99.76% for TB, 98.89% for COVID-19 vs. Pneumonia, 98.99% for COVID-19 vs. TB, and 100% for Pneumonia vs. TB [10].

Qaqos et al. employed stochastic gradient descent to train a deep-learning model using 6587 CXR images. With 128x128 images and 100 epochs, the model achieved 94.53% accuracy in classifying CXR images into four categories: COVID-19, Pneumonia, TB, and healthy [11]. Mostofa et al. used transfer learning with VGG16 to identify TB on CXR images, achieving 80.0% accuracy in classifying CXR images into TB and healthy categories [12].

Al-Timemy et al. used pre-trained CNN models for feature extraction and achieved a detection accuracy of 91.6% on a dataset of 2186 CXR images [13]. Similarly, in [14], a deep learning method using transfer learning with EfficientNet v2-M achieved an accuracy of 82.15% in classifying normal, pneumonia, and pneumothorax CXR images. A capsule neural network was used in [15] to categorize CXR images with COVID-19, achieving an accuracy of more than 95%.

Sitaula et al. used transfer learning and an attention mechanism with VGG16 to classify CXR images into five classes: COVID-19, Normal, no_findings, Pneumonia bacteria, and Pneumonia Viral. They evaluated their method on three CXR image datasets and reported the highest accuracy of 87.49%. They also used Grad-CAM to visualize the extracted regions on the CXR images [16].

Ashan et al. conducted a study to detect COVID-19 patients from CXR and CT images using six deep CNN learning models. They achieved an average accuracy of 82.94% on a dataset with CT images and 93.94% on a dataset with CXR images. The MobileNetV2 model outperformed NasNetMobile, and LIME was used to analyze the feature extraction [17]. Similarly, Manjurul et al. achieved high performance on the VGG16 model (98.5 ± 1.19%) among six different deep CNN models using a mixed

dataset of CT and X-ray images to classify COVID-19 patients, and the results were also explained with LIME [18].

Li et al. utilized the ResNet50 pre-trained model to classify COVID-19 and Pneumonia in CT images, achieving 95% accuracy. They used Grad-CAM to visualize significant regions in the CT images but lacked unique feature identification for model prediction [19].

Our study presents an evaluation of different deep-learning models and datasets for the classification of pulmonary diseases using chest X-ray images, ensuring the impact of colorization techniques and transfer learning on classification accuracy.

III. MATERIALS AND METHODS

Dataset

In this study, Chest X-ray (Pneumonia, COVID-19, Tuberculosis) images, which are part of the publicly available datasets on Kaggle were used. The data that support the findings of this study are openly available at [https://www.kaggle.com/datasets/jtiptj/chest-xray-pneumoniacovid19tuberculosis]. The dataset includes the classes Normal (healthy people), Pneumonia, Covid-19, and Tuberculosis. The dataset is divided into training, testing, and validation, as shown in Table 1.

There are 7135 CXR images in the used dataset. Specifically, there are 6326 images allocated for training, 38 images for validation, and 771 images for testing purposes. To ensure uniformity of images with the same pixel ratios and to avoid distortion, images were set to 128 × 128 pixels. Data was preprocessed by making changes to the rotation range, width shift range, height shift range, shift range, zoom range, and horizontal flip.

Table 1. The data distribution of the CXR dataset.

Chest X-ray Dataset	NORMAL	COVID19	PNEUMONIA	TUBERCULOSIS
Training	1341	460	3875	650
Validation	8	10	8	12
Testing	234	106	390	41

Coloring Dataset

In this step of work and unlike previous works, the images in the dataset were colorized using the DeOldify method. DeOldify is an advanced colorization method that utilizes Convolutional Neural Networks (CNNs) to automatically add color to black-and-white images, resulting in impressive and realistic outcomes [20]. DeOldify is used in the coloring dataset with different render factors. The render factor is a parameter that adjusts the level of colorization applied to the images, providing control over the intensity of the colorization effect [20]. Figure 1. displays a sample of chest X-ray images in their original form, alongside colorized versions using render factors of 35 and 77 (from left to right).

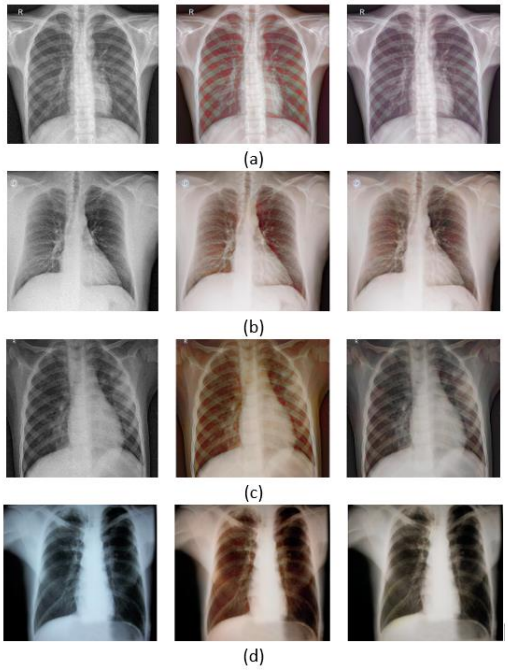

Figure 1. Original and colorized Chest X-ray images of (a) Normal, (b) COVID-19, (c) Pneumonia, and (d) Tuberculosis.

Convolutional Neural Networks and Transfer Learning

Deep learning is one of the most popular artificial intelligence methods used to solve classification problems [21]. It has shown remarkable success in a variety of applications, including major improvements in the medical field. Convolutional neural networks (CNNs) are one of the most widely used and effective architectures of deep learning, especially in areas such as computer vision, and image processing [22]. CNNs

have emerged as a powerful class of feedforward neural networks specifically suited for interpreting multidimensional data like photographs. Unlike multilayer perceptrons, CNNs optimize memory usage by parameter sharing and sparse connections. The input images are transformed into matrices, allowing different parts of the CNN to process them. The model consists of alternating convolutional and pooling layers, forming a sequence of operations within the network. The “ReLu” activation function was used in the hidden layer and the “softmax” function in the output layer.

Convolutional layer

The convolutional layer plays a crucial role in identifying distinctive patterns within the input data. It involves a series of convolutions (dot products) applied to the input matrix, resulting in the generation of a feature map. This process combines multiple filters into an image-processing kernel, representing various motifs. In this study, CNN based model with 4 convolutional layers was used for feature extraction.

Pooling layer

The Pooling layer performs down-sampling by reducing the spatial dimensions of the output volume, effectively decreasing the number of feature maps and network parameters [23]. This process not only aids in improving the model's generalization by mitigating overfitting, but it also generates a set of features that remain resilient to translational shifts and distortions [24].

Fully connected layer

The Fully connected layer receives the feature map as input and applies an activation function to produce a non-linear transformed output. This layer plays a crucial role in aggregating features from previous stages to construct a non-linear collection of categorization features. In this particular phase, the rectified linear unit (ReLU) was utilized, which effectively addresses the vanishing gradient problem [25].

Transfer learning

Transfer learning is a well-established research area, particularly in machine learning, which involves capturing knowledge gained while solving a given problem and applying it to another, related problem. Transfer learning can be used to speed up or optimize the modeling process to improve performance. VGG16 is one of the transfer learning architectures with 16 layers based on CNN.

Proposed Work

In this study, we utilized two deep-learning architectures separately to generate a disease detection system and analyzed the performance results of these models. The

models we used are; The CNN model and the VGG16. Figure 2 shows the general structure of the proposed work.

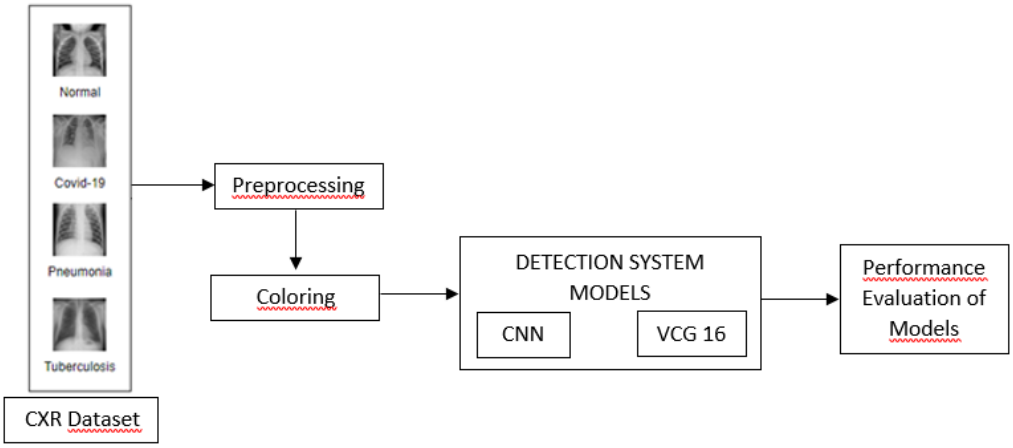

Figure 2. Flowchart of Detection System for Normal, COVID-19, Pneumonia and TB.

The CNN model generated in this study consists of four convolutional layers, a flattened layer, and the output layer with 4 units. Figure 3 shows the detailed architecture of the developed CNN model.

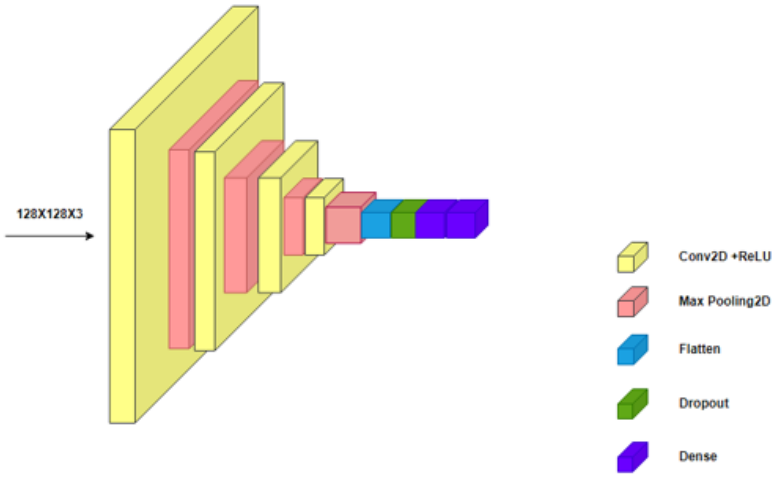

Figure 3. The proposed architecture of the CNN model for classification of chest X-ray images

The first convolution layer with 32 filters is 3x3 in size and the ReLU activation function is used, followed by max pooling with the size of 2x2. This is followed by the second convolutional layer with 64 filters of size 3x3 and ReLU activation, and another max pooling layer. The third convolutional layer is 3x3 in size and has 128 filters and is applied by ReLU activation followed by max pooling. The fourth convolutional layer also has 128 filters of size 3x3 with ReLU activation and a subsequent max pooling layer. After that, a flattened layer is used to convert the output into a one-dimensional array. A fully connected layer with 128 units is added, followed by a dropout layer to reduce overfitting. Finally, the output layer with 4 units and Softmax activation function is used for classification. The model is optimized using the ADAM optimizer and Categorical Cross-Entropy loss function. During training, the settings used were Epoch=15, Batch Size=32, and Learning Rate=7e-5.

We also utilized the VGG16 architecture, with trained weights on the dataset. Then VGG16 layers were set as non-trainable. It enhances image depth up to 512 while employing 3x3 filters, which effectively reduces the number of parameters and computational requirements. For our custom model, we constructed a fully connected layer with two layers which comprise 128 and 64 units followed by an output layer that incorporates 4 units and utilizes the Softmax activation function. The VGG16 model was chosen due to its ability to learn rich and discriminative features from images. By leveraging the pre-trained VGG16 model, we were able to take advantage of the learned features and adapt them to the task of classifying X-ray chest images into four categories: Normal, COVID-19, Pneumonia, and Tuberculosis.

IV. RESULTS AND DISCUSSION

Performance Evaluation Metrics

Log Loss

Log loss, also referred to as cross-entropy, quantifies the discrepancy between the predicted labels and the correct labels. The precise formula for calculating log loss is as follows:

$$Log\ loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log(\rho_{ij})$$

Where, N represents the total number of samples and M represents the number of classes. The variable y denotes the true label of the class, while ρ represents the

probability associated with the given sample. It's important to note that the logarithm mentioned in the formula refers specifically to the natural logarithm.

Confusion Matrix

The confusion matrix represents the False Negative (FN), False Positive (FP), True Negative (TN), and True Positive (TP) values of the classifier performs. TP refers to samples that define an actually positive state and are predicted positively by the model. FP refers to samples that define a negative condition and are predicted as positive by the model. FN refers to samples that define a negative condition and are predicted positively by the model. TN denotes samples that represent an actually negative condition and are predicted negatively by the model.

Accuracy is the ratio of the number of true and false data that the classifier correctly predicts to the total number of data. Accuracy indicates the number of examples correctly classified. Specificity represents the rate of correctly identifying negative samples, while Recall represents the rate of correctly identifying positive samples. Precision measures how accurately the model performs by analyzing the true positives predicted by the model. The F1 score is a harmonic mean of Precision and Recall, aiming to strike a balance between the two.

Mathematically, these Metrics can be defined as follows:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{FN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$F1\ Score = \frac{2 * (\mathrm{Precision} * \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})}$$

Performance Analysis Results

Table 2 provides a comparison of the performance metrics for the models and datasets used in the study.

Table 2. Results of the performance evaluation metrics

DATA	Model	Accuracy	F1-Score	Precision Score	Recall Score
Original	CNN Model	79.83%	67.48%	72.83%	68.49%
	VGG16 Model	84.29%	85.21%	89.81%	84.59%
Colorized With 35 Render Factor	CNN Model	83.19%	85.99%	89.17%	85.85%
	VGG16 Model	89.95%	92,58%	92,70%	92,58%
Colorized With 77 Render Factor	CNN Model	79,55%	78,20%	79,17%	78.85%
	VGG16 Model	87,53%	89,59%	90,87%	89,08%

For the "Original" dataset, the CNN Model and Transfer Learning Model achieved an accuracy of 79.83% and 84.29%, respectively. The F1-Score, Precision Score, and Recall Score varied for each model. The CNN model achieved an accuracy of 83.19% with improved F1-Score, Precision Score, and Recall Score on the "Colorized with 35 Render Factor" dataset compared to the "Original" dataset. Similarly, the VGG16 Model showed enhanced performance with an accuracy of 89.95% and higher values for all other metrics. In the case of the "Colorized with 77 Render Factor" dataset, the CNN Model had an accuracy of 79.55% and exhibited slight variations in the other metrics compared to the "Original" dataset. On the other hand, the Transfer Model demonstrated notable improvement with an accuracy of 87.53% and high values for F1-Score, Precision Score, and Recall Score.

The graphical results for loss and accuracy metrics of the CNN model compared with the VGG16 transfer learning model are shown in Figures 5-7. In the figures, the horizontal axis represents the epoch number, and the vertical axis represents the accuracy value.

Figure 4 represents the performance measurements of the models on the original dataset. Both the CNN and VGG16 models exhibit a consistent decrease in training and validation losses, indicating effective learning. Furthermore, the training and validation accuracies steadily increase and converge to high values, with the VGG16 model demonstrating better accuracy than the CNN model.

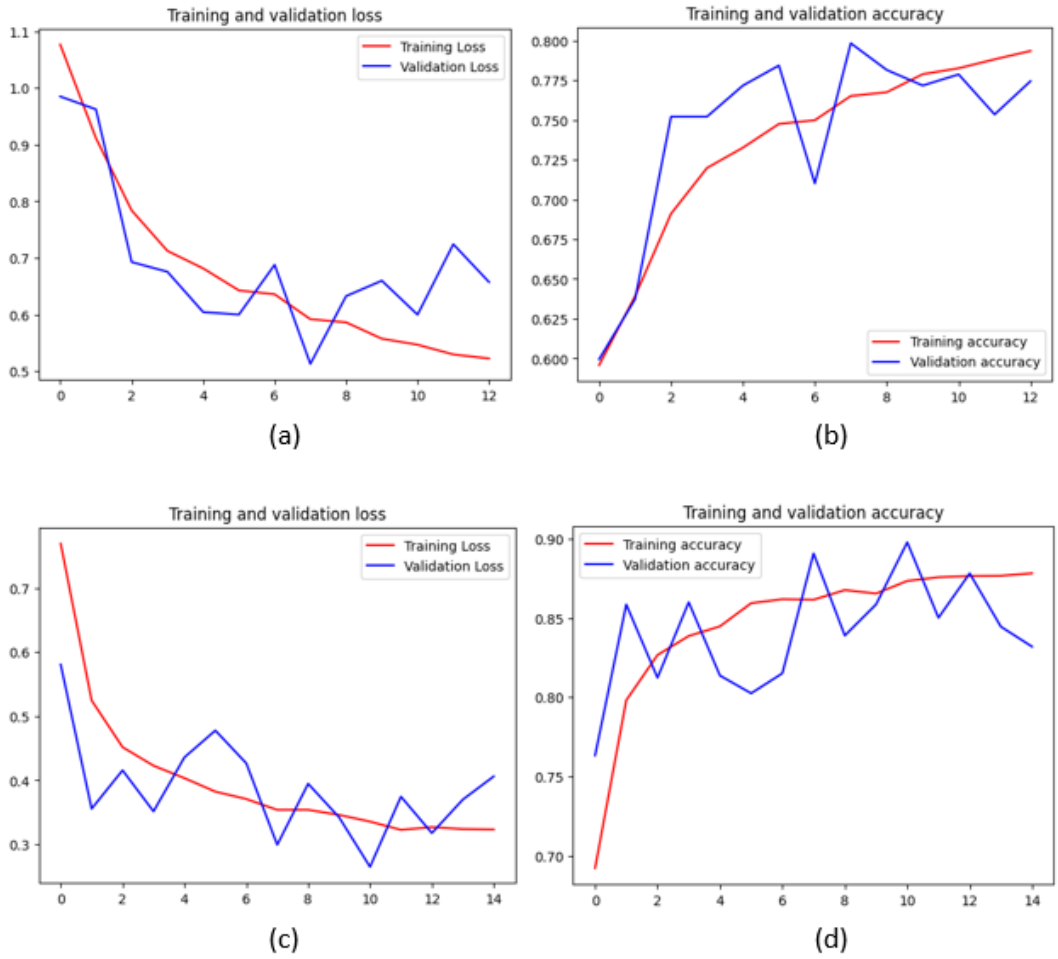

Figure 4. Results for an original dataset (a) Logarithmic loss of CNN model (b) Accuracy of CNN model, (c) Logarithmic loss of VGG16 (d) Accuracy of VGG16.

Figure 5 represents the performance measurements of the models on the colorized dataset with a render factor of 35. The CNN model experiences significant fluctuations in validation loss and higher values compared to the training loss, indicating overfitting. On the other hand, the VGG16 model effectively overcomes overfitting, as evidenced by less volatility and convergence between the training and validation losses. These results align with the accuracy curves, where the CNN model shows a higher training accuracy than the validation accuracy, indicating overfitting. In contrast, the VGG16 model exhibits similar accuracy curves for both training and validation sets, indicating effective training and better generalization to unseen data.

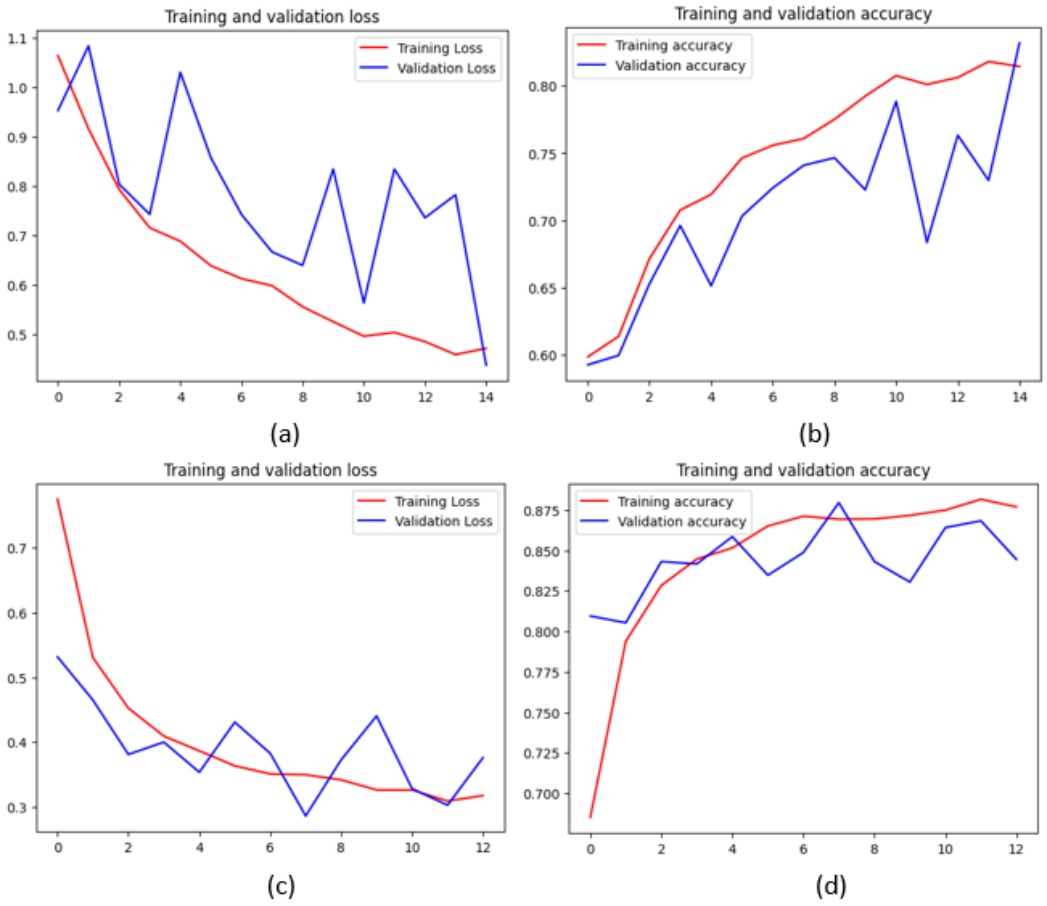

Figure 5. Results for a colorized dataset with 35 render factor (a) Logarithmic loss of CNN model, (b) Accuracy of CNN model, (c) Logarithmic loss of VGG16, (d) Accuracy of VGG16.

Figure 6 represents the performance measurements of the models on the colorized dataset with a render factor of 77. Both the CNN and VGG16 models demonstrate a gradual decrease in training and validation losses, converging to low values. The accuracy curves show consistent improvements in both training and validation accuracies, suggesting effective learning and generalization of the models to unseen data.

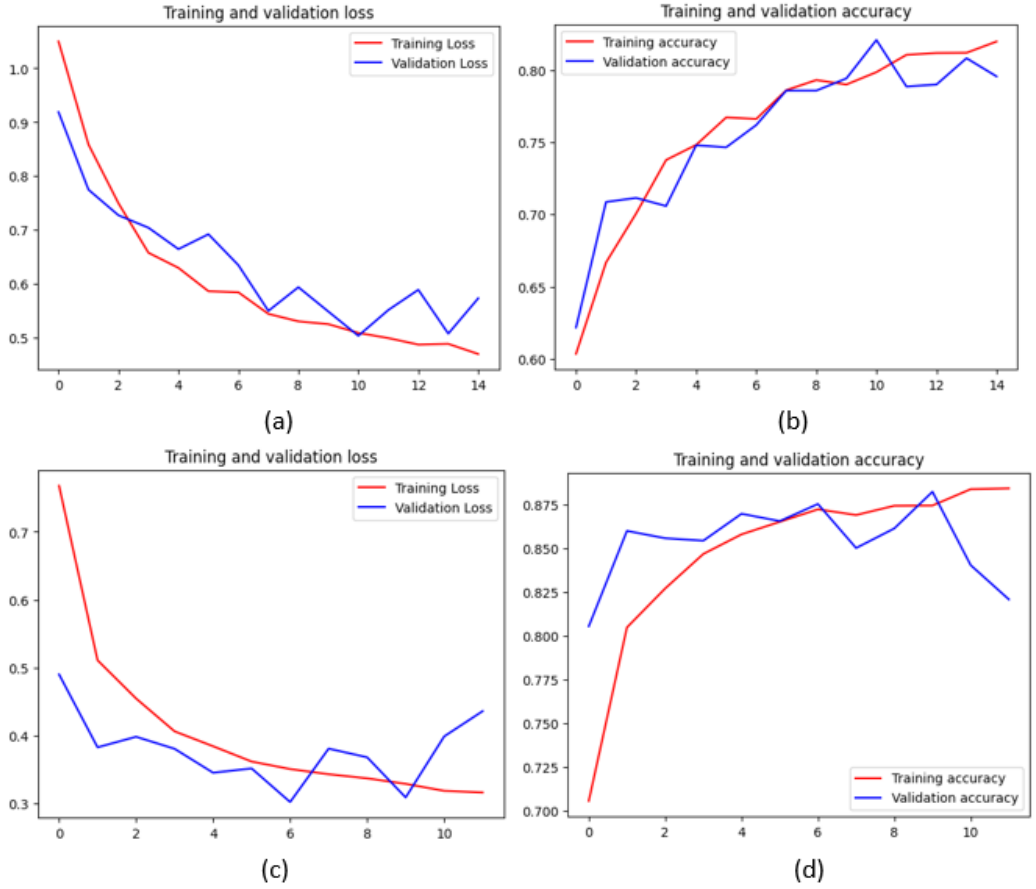

Figure 6. Results for a colorized dataset with 77 render factor (a) Logarithmic loss of CNN model, (b) Accuracy of CNN model, (c) Logarithmic loss of VGG16, (d) Accuracy of VGG16.

These results highlight the impact of colorization and the choice of render factor on the performance of the models. Colorized chest X-ray images, particularly those created with a render factor of 35, showed enhanced accuracy and better discrimination between different pulmonary diseases. The Transfer Model consistently outperformed the CNN Model across these distinct datasets, indicating the benefit of leveraging pre-existing knowledge from a pre-trained model. Overall, Table 2 provides a comprehensive evaluation of various models and datasets, shedding light on the effectiveness of colorization and transfer learning techniques in the classification of pulmonary diseases using chest X-ray images.

V. CONCLUSIONS

Chest X-rays (CXR) are widely used for diagnosing and monitoring various pulmonary diseases. This study aims to detect three different lung diseases by applying deep learning. To achieve this, we applied the Convolutional Neural Network (CNN) and Transfer learning model VGG16 on the publicly available dataset comprising 7135 CXR images. The obtained results show the effectiveness of deep learning in detecting lung diseases, as well as the importance of coloring CXR images to increase the accuracy of disease detection.

The findings demonstrate the potential of utilizing colorization techniques and transfer learning approaches to improve the accuracy of disease classification. The "Colorized with 35 Render Factor" dataset showed the most promising results, with both the CNN Model and Transfer Model achieving higher accuracy compared to the original dataset. This indicates that coloring X-ray images with an optimized rendering factor can aid in accurate disease classification. Moreover, the Transfer Model consistently outperformed the CNN Model across all datasets. By leveraging pre-existing knowledge from a pre-trained model, the Transfer Model achieved higher accuracy, F1-Score, Precision Score, and Recall Score. These findings hold significant implications for medical imaging and diagnosis, as incorporating colorized images and transfer learning can lead to earlier detection, isolation, and appropriate treatment. Further research and validation are necessary to ensure the generalizability of the proposed models, and the choice of render factor should be carefully optimized for specific datasets. Overall, this study contributes to the advancement of machine learning and data mining techniques in improving the diagnosis of pulmonary diseases, ultimately aiming to enhance healthcare outcomes and provide better decision support tools for healthcare professionals and radiologists.

Disclosure statement

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