Classification of Chest Disease Detection Using X-Ray Images through the Implantation of Efficientnetv2

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Abstract—**Chest diseases encompass a broad spectrum of conditions that can severely affect both respiratory and cardiovascular health. These diseases may arise from various factors, including infections, environmental influences, genetic predispositions, and lifestyle choices. To address these challenges, this project proposes a system for chest disease detection using X-ray images, employing the EfficientNet V2 model.The methodology begins with preprocessing steps, where an Adaptive Median Filter is used to enhance the quality of X-ray images by reducing noise while preserving important features for analysis. After preprocessing, Fuzzy C-Means (FCM) Image Segmentation is applied to precisely identify key regions within the images, improving the robustness of the classification model. EfficientNet V2 is then employed to extract features and classify the images, offering improved accuracy compared to traditional methods.Additionally, Local Binary Patterns (LBP) are incorporated for feature extraction, further enriching the input data for the model.This proposed framework aims to automate the diagnostic process, reducing the reliance on manual interpretation by radiologists. Experimental results demonstrate the effectiveness of this approach in accurately identifying and classifying chest diseases, thereby contributing to faster and more efficient patient care. The entire project is implemented using Python.**

Keywords—Fuzzy C-Means (FCM),Local Binary Patterns (LBP), Convolutional Neural Network, Lung Disease.

I. INTRODUCTION

The increasing accessibility to multimodal content, such as digital samples and audiovisual data, has significantly driven the growth of the computer vision (CV) field. Prominent areas within CV include object detection and tracking [1], as well as the computer-aided analysis of various medical imaging techniques [2]. Computer vision techniques are playing a crucial role in aiding professionals to analyze medical images, enabling faster and more accurate completion of tasks. One of the most impactful applications of CV is in the analysis of chest X-rays (CXR) [3]. Chest X-ray imaging is the most commonly used diagnostic tool worldwide for detecting a range of respiratory conditions, including pneumonia, COVID-19, bronchiectasis, and lung lesions [4]. This diagnostic modality is especially valued for its simplicity and practicality in clinical settings, facilitating the daily performance of important clinical examinations [5]. However, the effectiveness of this method heavily relies on the expertise and accessibility of specialists who can manually interpret the X-ray images. Manual inspection of chest X-ray images, while crucial, is often time-consuming and prone to human error, leading to an increased likelihood of inaccurate diagnoses. On the other hand, the use of computerized recognition models can expedite the diagnostic process and improve the overall effectiveness of the system.

Chest diseases affect approximately 65 million people globally, and every year, around 3 million individuals lose their lives due to these diseases. Early detection and intervention can save lives and help avoid invasive surgical procedures [6]. As a result, researchers have directed their efforts toward developing reliable computerized alternatives to address the challenges posed by manual CXR analysis. Initially, chest X-ray anomalies were categorized using traditional handcrafted pattern recognition techniques. While these methods were effective with smaller datasets, they required substantial domain expertise and were time-consuming. Furthermore, there was a trade-off between classification accuracy and computational efficiency, with larger feature sets improving object recognition but also increasing processing time. Conversely, smaller feature sets led to more efficient methods but often overlooked important visual details, resulting in less accurate classifications. These limitations hindered the applicability of handcrafted approaches in the evaluation of chest X-rays [7].

In recent years, the development of AI-based solutions for the automated detection of medical conditions has been ground breaking. In the medical field, AI technologies are proving invaluable by assisting with patient management, diagnosis, and treatment. These AI-driven systems relieve physicians of some of their workload and enhance their decision-making process, ultimately improving patient outcomes. Additionally, AI frameworks contribute to the operational efficiency of healthcare units by automating management tasks and streamlining workflow [8]. As the scientific community has increasingly embraced deep learning (DL) methods for digital image processing, their application to chest X-ray examinations has become widespread. Numerous well-established deep learning models, such as Convolutional Neural Networks (CNN) [9] and Recurrent Neural Networks (RNNs) [10], are used for tasks like segmentation and classification in medical imaging. Deep learning is rapidly emerging as a powerful tool in the healthcare sector, as it can handle complex tasks involving the classification and segmentation of medical conditions. The ability of deep learning systems to extract detailed image features without requiring specialized subject matter expertise makes them especially well-suited for medical image analysis.

Deep learning models are inspired by the human brain's ability to process and recall different objects, which is reflected in the architecture of Convolutional Neural Networks. Popular architectures such as VGG [11], GoogleNet [12], ResNet [13], XceptionNet [14], DenseNet [15], and EfficientNet [16] have been extensively explored in the field of medical image analysis. These models provide reliable results with relatively low computational requirements. The primary reason for utilizing deep learning algorithms in the computer-aided diagnosis of medical images is their capacity to automatically extract key features from input images and their robustness to various distortions such as changes in luminance, chrominance, clutter, blurring, and size variations. These capabilities enable deep learning-based systems to outperform traditional methods in terms of accuracy and efficiency.

Considerable research has been dedicated to the detection of chest abnormalities, and many studies have proposed innovative methods for recognizing various lung conditions. One such method [3] involved the use of deep learning models, specifically VGG-16 and XceptionNet, to locate pneumonia-affected regions within chest X-ray images. The approach included a data augmentation phase, where techniques like zoom, rotation, and image flipping were applied to increase the diversity of the training dataset. Afterward, deep learning algorithms were utilized to extract deep features from the X-ray images. The study reported the highest performance with the XceptionNet model, although the classification accuracy still showed room for improvement. This highlights the potential of deep learning techniques in enhancing the accuracy and efficiency of chest X-ray analysis, while underscoring the need for further optimization of these models to achieve better results.As research in this area continues to evolve, there is a growing emphasis on improving model architectures, feature extraction techniques, and training methodologies to enhance the accuracy of automated CXR diagnosis. By refining these deep learning-based models, researchers aim to provide more reliable and precise diagnostic tools that can significantly aid healthcare professionals in the timely detection and treatment of chest diseases.

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II. LITERATURE SURVEY

Muljo et al. [17] explored the use of densenet-121, a robust deep learning (DL) architecture, with dual techniques to enhance chest X-ray classification for lung disease detection, including COVID-19 and pneumonia. Automating the analysis of chest X-rays can significantly reduce the burden on crowded emergency departments by streamlining diagnoses and prioritizing critical cases. However, this approach raises important concerns regarding accountability, potential biases in datasets, and the need for human oversight in making critical medical decisions. Fine-tuning models on specific datasets can lead to overfitting, reducing the model's generalization ability to new or diverse data.

Miah et al. [18] demonstrated how advanced DL architectures could improve clinical outcomes through precise medical image analysis, especially in segmenting and classifying lung infections. Their integrated segmentation-classification approach provides more accurate diagnoses and enhances clinical utility, although the models require substantial computational resources and expertise to train.

Nawaz et al. [19] proposed an efficientdet-based approach for detecting chest abnormalities, capable of classifying multiple categories of chest diseases. Their model performed well on large, standardized datasets like the NIH database, showing its potential for real-world clinical applications, but its performance depends heavily on the quality of the dataset, and poor-quality data could hinder its ability to detect rare or underrepresented diseases.

Ait Nasser et al. [20] reviewed various DL models, including VGG, ResNet, DenseNet, and others, for chest disease detection, highlighting their ability to speed up the diagnostic process, allowing radiologists to review more cases in less time. However, real-time integration into existing medical workflows remains a challenge, requiring additional infrastructure to ensure smooth collaboration between AI tools and human radiologists. Additionally, deep learning models may overfit to specific datasets, which limits their effectiveness when applied to new data from different hospitals or populations.

Glocker et al. [21] focused on the need for rigorous validation and transparency in AI models, emphasizing how AI's role in healthcare must be accompanied by frameworks for auditing and assessing performance. This ensures the models are trustworthy and safe for clinical use, especially for vulnerable patient groups. The lack of representative and unbiased test sets is a significant hurdle in this process, especially for underrepresented or vulnerable populations. Vinayakumar et al. [22] developed a multichannel deep learning approach using pretrained EfficientNet models (B0, B1, B2), achieving high accuracy in lung disease detection by combining the strengths of multiple models. However, this approach requires significant computational resources, making it less efficient in low-resource environments or real-time applications, and raising concerns about its scalability in resource-limited settings.

Eswara Rao et al. [23] introduced a hybrid framework for respiratory disease detection using quantum feature extraction and classical classifiers, achieving impressive accuracy (97.2% and 98.8% for training and testing, respectively). However, the integration of quantum machine learning (QML) may require specialized quantum computing hardware, which may not be accessible or feasible in most healthcare settings, and the model’s performance can degrade when applied to less diverse datasets or clinical settings with real-world variations. Mukesh et al. [24] proposed an automated server system using convolutional neural networks (CNNs) like DenseNet121, ResNet50, and EfficientNetB1 to detect thoracic pathology diseases from chest X-rays, showing high accuracy in detecting conditions such as hernia and emphysema. However, the effectiveness of these models is still highly dependent on the quality and diversity of the training dataset, and a limited or biased dataset can affect the model’s ability to generalize. Additionally, the need for powerful computational resources may limit the accessibility of these models in smaller hospitals or clinics with fewer technical capabilities.

Mohammed AA et al. [25] demonstrated the significant improvements in lung disease detection accuracy achieved by deep learning, particularly convolutional neural networks (CNNs), surpassing traditional diagnostic methods in detecting subtle patterns that human radiologists might miss. However, the integration of AI in healthcare is complicated by regulatory hurdles and ethical concerns regarding accountability, especially when AI systems make mistakes or provide misleading diagnoses. Despite their accuracy, deep learning models

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are often seen as "black boxes," making it difficult for clinicians to understand how a diagnosis was made, which can limit trust and adoption in clinical practice. Eswara Rao et al. [26] proposed a hybrid CNN-Quantum classifier model that reduces memory usage and enhances portability, enabling deployment across various platforms, including real-time quantum computers. However, the reliance on quantum hardware introduces challenges, as the availability and performance of quantum devices may not be consistent, limiting the model's broader applicability and adoption in clinical settings.

III. Proposed Methodology

This proposed system aims to detect chest diseases from X-ray images through the implementation of EfficientNetV2. The process begins with preprocessing the images using an adaptive median filter, which enhances image quality by reducing noise and ensuring that subsequent processing steps work with high-quality input data. Following preprocessing, the images undergo a quality enhancement stage, where additional techniques are applied to further improve clarity and minimize any remaining noise. This step is essential, as it ensures the images are optimized for the following analysis.Next, the images are segmented using the Fuzzy C-Means (FCM) algorithm, which divides the image into distinct regions or segments. The relevant areas of these segments are identified, as they are the focus for further analysis. This segmentation allows the system to concentrate on the mostimportant portions of the image, improving accuracy and efficiency.

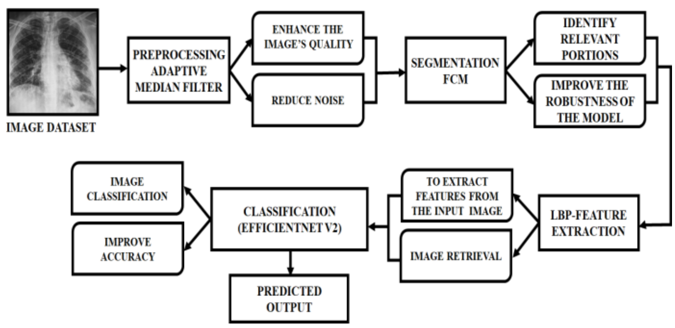

Figure 1 Block Diagram of Proposed System

To strengthen the model's robustness, the identified relevant regions are used to fine-tune the system, ensuring it can handle a wide variety of input data effectively. The following step involves feature extraction using the Local Binary Pattern (LBP) method. These features serve as inputs for the image classification task, which is performed using the EfficientNetV2 model.Finally, after classification, the system can perform image retrieval, searching for and retrieving relevant images based on the predicted classifications. The ultimate output of the system is the predicted classification result, which reflects the model's understanding and interpretation of the input chest X-ray images.

A. Preprocessing(Adaptive Median Filter)

The adaptive median filter is an advanced noise reduction technique widely used in medical image processing. Unlike traditional median filters with fixed window sizes, it adjusts based on local image characteristics, effectively removing various types of noise while preserving important details like edges and textures. This is crucial in medical imaging, where small distortions can obscure critical features such as tumors or lesions. By improving image clarity, it enhances the accuracy of subsequent stages like segmentation, feature extraction, and classification, ultimately supporting more reliable diagnostics and better patient care. This technique is particularly effective in chest X-rays, where noise can hide lung structures, leading to misdiagnosis. Additionally, its adaptability makes it suitable for various imaging modalities, ensuring consistent performance across different medical imaging types. Its ability to adapt to different noise types makes it especially effective in medical imaging, where precision is crucial for accurate diagnosis.Overall, it contributes to more precise and accurate outcomes, aiding healthcare professionals in making better-informed decisions.

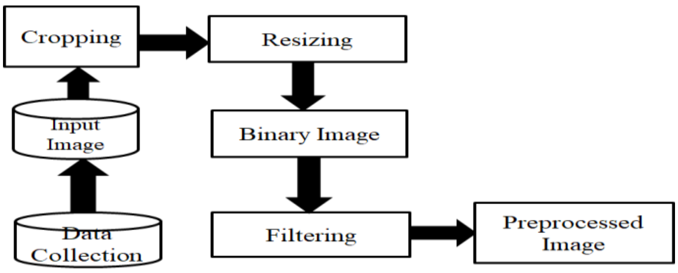

Figure 2 Data Preprocessing

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B. Enhance The Image's Quality / Reduce Noise

The preprocessing step is crucial for enhancing medical image quality by removing noise and distortions that could affect accurate analysis. Medical images, such as X-rays, MRIs, and CT scans, are often impacted by noise from sources like sensor limitations, transmission errors, or patient movement, which can obscure important details. Techniques like the adaptive median filter effectively reduce noise while preserving critical features such as edges and textures, improving image clarity and making conditions like pneumonia or cancer easier to detect. This noise reduction also supports more accurate segmentation, feature extraction, and diagnosis, leading to better patient care and treatment decisions.

C. Segmentation (FCM)

The Fuzzy C-Means (FCM) segmentation technique effectively partitions medical images into clusters based on pixel similarity, allowing each pixel to belong to multiple clusters with varying degrees of membership. This ability to handle ambiguous or overlapping boundaries makes FCM particularly useful in medical imaging, where structures like tissues, organs, and pathologies often lack distinct boundaries. FCM helps identify regions of interest, such as tumors or infections in chest X-rays and retinal diseases in eye images, improving diagnostic accuracy. It also performs well with noisy, low-resolution images, ensuring important features are not missed. By enhancing segmentation, FCM supports more efficient feature extraction and classification, leading to more reliable disease detection and better clinical decision-making.

D. Segmentation Process In Medical Image Analysis

The segmentation process in medical image analysis begins by loading the medical image, such as an MRI scan, followed by applying Modified Fuzzy C-Means (FCM) clustering, which groups pixels based on similarity to cluster centroids. Unlike traditional methods, FCM allows pixels to belong to multiple clusters, managing ambiguous boundaries in medical images. This results in the isolation of key structures, such as blood vessels or lesions in eye scans, aiding in the diagnosis of conditions like glaucoma or diabetic retinopathy. Enhanced feature extraction then refines the identification of these regions, improving disease detection and ensuring more accurate, reliable diagnoses.

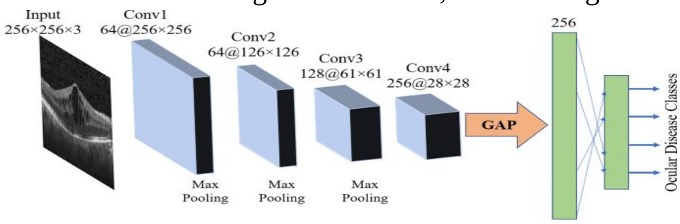

Figure 3 CNN architecture

E. Enhancing Model Robustness Through Image Segmentation

The segmentation process enhances the model's resilience to variations in image quality, patient anatomy, and artifacts, ensuring accuracy across diverse medical images. By isolating relevant areas like affected tissues or lesions, the model adapts to noise, lighting changes, and occlusions, maintaining reliability with imperfect data. This targeted segmentation facilitates more meaningful feature extraction, improving diagnostic accuracy while reducing computational burden and processing time. Additionally, it boosts the model's sensitivity and specificity, enabling early detection of diseases, even at subtle stages, and ultimately enhancing patient outcomes in real-world diagnostics. This improved accuracy and efficiency also support faster decision-making, critical for timely patient care.

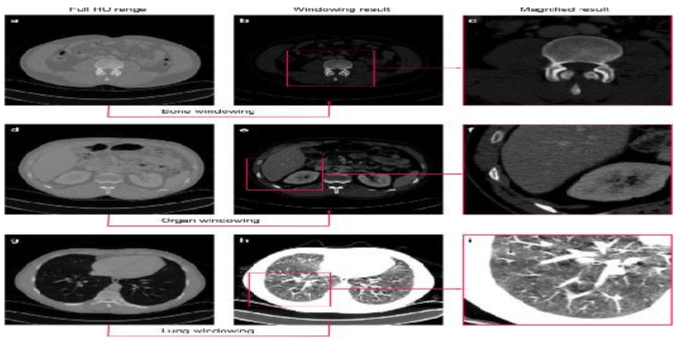

Figure 4 Enhancing Robustness Image Segmentation

F. LBP-Feature Extraction

Local Binary Pattern (LBP) feature extraction is a powerful technique in medical image analysis that identifies key patterns and textures, aiding in the detection of regions of interest, such as abnormal tissues or disease indicators. By comparing the intensity of each

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pixel to its neighbors, LBP creates binary patterns that highlight local variations, such as edges or spots, which are crucial for diagnosing conditions like tumors or tissue irregularities. When applied to segmented medical images, LBP captures subtle textural details that might be missed by general analysis methods. Its robustness to noise, illumination changes, and small-scale deformations makes it ideal for challenging medical images, ensuring reliable results even with imperfect data. LBP also enhances classification accuracy by extracting discriminative features, and when combined with machine learning models like Support Vector Machines (SVM) or deep learning, it significantly improves disease detection. In summary, LBP's efficiency, robustness, and ability to capture fine-grained textural details make it essential for automated diagnostic systems, leading to more accurate diagnoses and better patient outcomes.

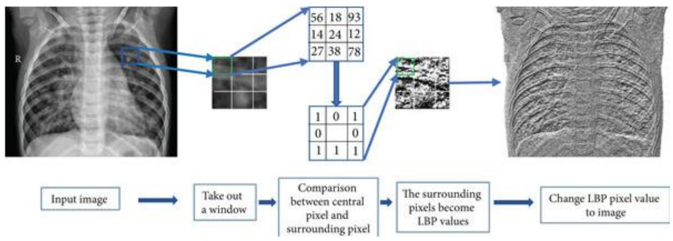

Figure 5 LBP-Feature Extraction

G. Image Retrieval For Improved Classification Accuracy

After feature extraction, image retrieval uses these features to find similar images in a dataset, improving classification accuracy. This process helps the model contextualize the extracted features by comparing them with images that share similar characteristics, providing a broader dataset for decision-making. In medical imaging, retrieving similar images allows the system to identify subtle or rare features that might be missed in a single image, improving detection of conditions, especially in early stages. It also leverages previously classified images to enhance the model's predictions, reducing misclassifications and boosting confidence in diagnosis by relying on historical data for comparison.

H. Model Compilation

In retinal disease detection, feature extraction is a crucial step that identifies the most relevant characteristics from preprocessed medical images. These features, such as textures and patterns, are vital for accurately classifying the images into meaningful categories. After feature extraction, Deep Convolutional Neural Networks (DCNNs) are employed for classification. DCNNs are powerful models capable of automatically learning hierarchical patterns within the data, making them exceptionally effective at analyzing complex medical images. By training on large and diverse datasets, DCNNs can detect subtle variations in the images that indicate different stages of retinal diseases.The training process ensures that the DCNN can generalize across various image conditions, including changes in image quality, lighting, and patient characteristics. This adaptability is essential for real-world diagnostic applications, where images are not always standardized. Once trained, the DCNN can be used for real-time diagnosis, allowing the system to detect retinal diseases and track their progression over time. This ability enables early detection, facilitating timely interventions and informed treatment decisions.By harnessing the power of deep learning, healthcare professionals gain access to accurate, data-driven insights that significantly improve patient outcomes and enhance the overall efficiency of disease management.

I. Model Evaluation

To ensure reliable model evaluation, the test data must be processed in the same way as the training data. The trained model then predicts the classes for each test sample. Model performance is assessed using metrics such as Accuracy, Precision, Recall, F1-Score, and Cohen's Kappa Score, which evaluate overall correctness, true positives, false positives/negatives, and the agreement between predicted and actual results. A classification report summarizes these metrics for each class, highlighting strengths and areas for improvement. Finally, predictions are visualized to provide a clearer understanding of the model's performance and readiness for deployment.

J. Classification (Efficientnet V2)

The classification process involves feeding preprocessed, segmented, and feature-extracted medical images into EfficientNet V2, an advanced and efficient Convolutional Neural Network (CNN). EfficientNet V2 is renowned for its ability to balance computational efficiency and accuracy through compound scaling,

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which optimizes the depth, width, and resolution of the network. This makes it highly suitable for large-scale medical image classification tasks, where high accuracy is critical for diagnosing diseases. Unlike traditional CNNs, EfficientNet V2 is designed to scale effectively, making it both powerful and resource-efficient, even when computational resources are limited or datasets are smaller.In medical imaging, EfficientNet V2 excels at detecting subtle variations in image features, such as the difference between healthy and abnormal tissues in X-rays, MRIs, or CT scans. Its capability to recognize complex patterns, even in low-quality or noisy images, ensures that abnormalities—whether they are early-stage or less obvious—are accurately identified. This makes it an invaluable tool in automated diagnostic systems, where early and precise disease detection is essential. Additionally, EfficientNet V2's scalability and robustness to image quality variations allow it to generalize well across diverse datasets, improving the reliability of diagnoses across different medical imaging modalities.The architecture's ability to progressively refine image representations from low-level details (such as edges and textures) to higher-level patterns that indicate disease makes it an ideal choice for complex medical image classification. In practice, its combination of speed, accuracy, and computational efficiency ensures that healthcare professionals can rely on the model for timely, accurate diagnoses, ultimately supporting better patient outcomes. By leveraging the power of EfficientNet V2, medical image analysis systems can provide consistent, high-quality results, enhancing clinical decision-making and improving overall healthcare delivery.

IV. RESULTS AND DISCUSSION

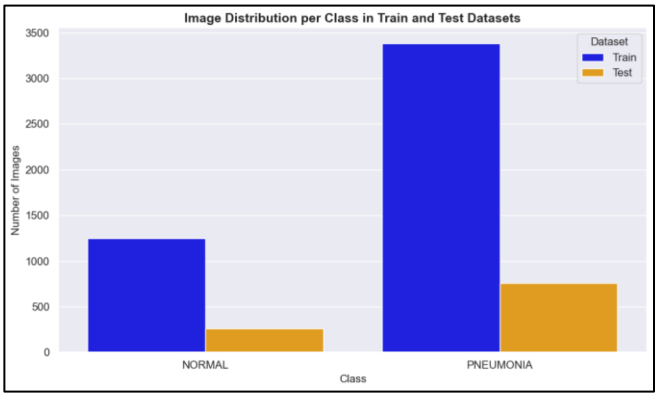

Figure 4.1 Image Distribution per class in train and datasets

Figure 4.1 illustrates the distribution of images per class in both the training and test datasets for two categories: "NORMAL" and "PNEUMONIA." The training dataset contains a substantially larger number of images for both classes compared to the test dataset. Additionally, there is a noticeable imbalance, with the "PNEUMONIA" class having a significantly higher number of images than the "NORMAL" class in both datasets.

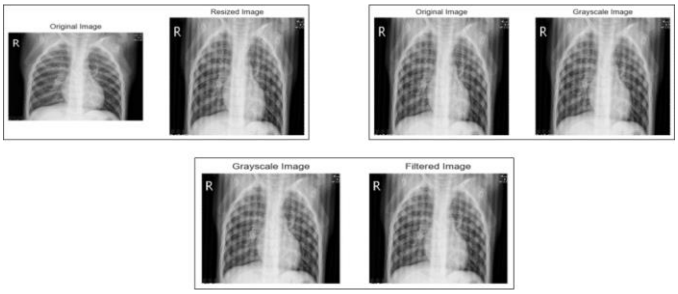

Figure 4.2 Preprocessing

Figure 4.2 displays a sequence of chest X-ray images, including the original image, a resized version, a grayscale image, and a filtered image. These different representations of the same X-ray are likely used for various image processing and analysis tasks.

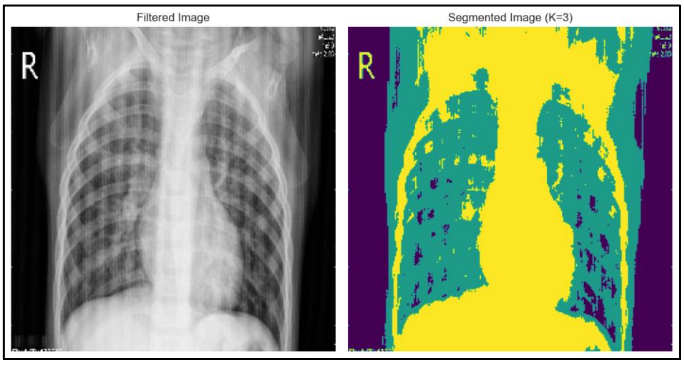

Figure 4.3 Segmentation

Figure 4.3 shows two additional versions of the chest X-ray: a Filtered Image and a Segmented Image (K=3). The Filtered Image likely underwent image processing to enhance or emphasize specific features within the X-ray, aiding medical professionals in identifying and analyzing patterns or abnormalities more effectively. The Segmented Image, with K=3, indicates the image has been divided into three distinct regions, further supporting focused analysis of key areas.

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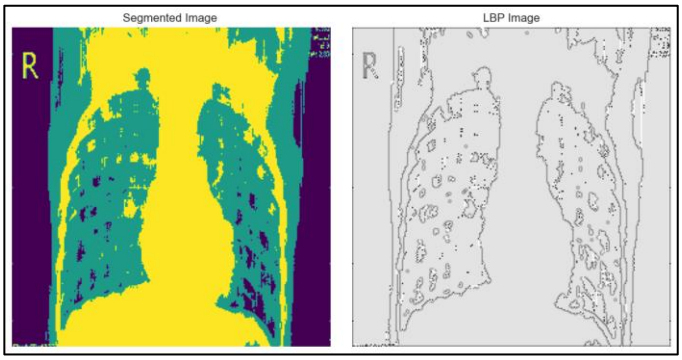

Figure 4.4 LBP Image

Figure 4.4 displays two additional representations of the chest X-ray: a Segmented Image and an LBP (Local Binary Pattern) Image. The Segmented Image uses a segmentation algorithm to divide the X-ray into distinct regions, each represented by a different color. This segmentation helps to identify and differentiate various structures or areas of interest, aiding medical professionals in their analysis and interpretation of the image.

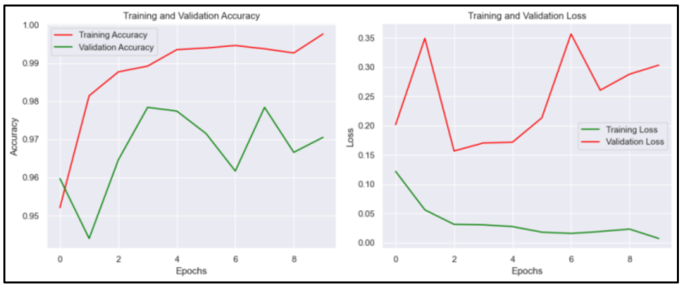

Figure 4.5 Validation Loss and Accuracy

Figure 4.5 the first plot displays the training and validation accuracy over the course of several training epochs. The training accuracy (shown in red) starts lower but gradually increases, while the validation accuracy (shown in green) fluctuates more but also shows an overall increasing trend. The second plot shows the training and validation loss over the same training epochs. The training loss (shown in red) and validation loss (shown in green) both initially decrease, indicating the model is improving its performance.

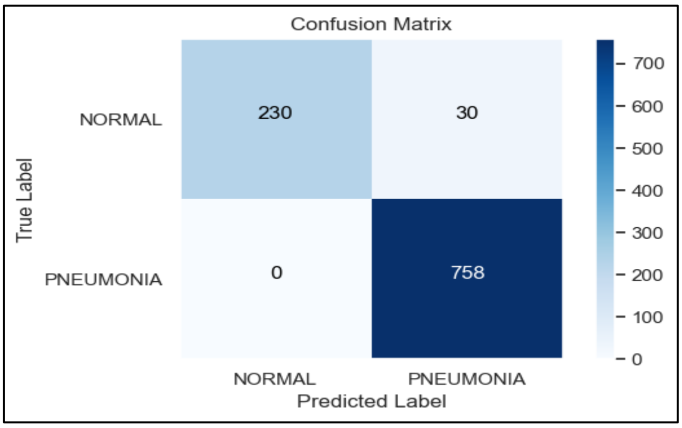

Figure 4.6 Confusion Matrix

Figure 4.6 illustrates that the image presents a confusion matrix, which is a table that summarizes the performance of a classification model by showing the number of correct and incorrect predictions made for each class.The confusion matrix shows that the model correctly classified 230 instances as "normal" and 758 instances as "pneumonia". However, the model misclassified 30 "normal" instances as "pneumonia" and did not misclassify any "pneumonia" instances as "normal".

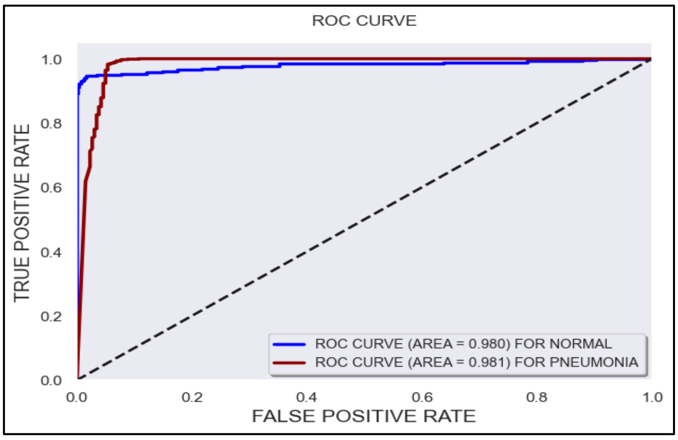

Figure 5.7 ROC Curve

Figure 4.7 displays a Receiver Operating Characteristic (ROC) curve, which visually represents the performance of a binary classification model. The ROC curve plots the true positive rate (also referred to as sensitivity or recall) on the y-axis against the false positive rate (1 - specificity) on the x-axis.

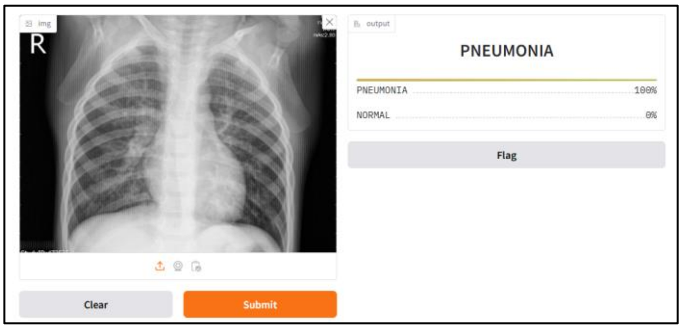

Figure 4.8 Predicted Output

Figure 4.8 shows a chest X-ray indicating the presence of pneumonia. The image is accompanied by a diagnostic tool that provides the classification results, confirming the X-ray as "PNEUMONIA" with a 100% probability, while the probability for a normal state is 0%.

V. Conclusion

The proposed framework for chest disease detection using X-ray images presents a highly effective approach by integrating advanced preprocessing, segmentation, and classification techniques. The Adaptive Median Filter plays a crucial role in preserving essential image details while reducing noise, providing a solid foundation for further analysis. The use of Fuzzy C-Means Image Segmentation enhances the accuracy of region identification, leading to improved model performance. By combining EfficientNetV2 with Local Binary Patterns (LBP), the framework employs cutting-edge deep learning methods to extract and analyze features, delivering superior classification accuracy over traditional techniques. This automated diagnostic process reduces reliance on manual interpretations, easing the workload of radiologists and enabling faster diagnoses. Experimental results confirm the framework's efficiency and reliability, demonstrating its potential for practical clinical use. Developed in Python, this project marks a significant advancement in applying AI-driven solutions to healthcare, ultimately supporting timely interventions and better patient outcomes.The proposed framework also offers scalability, allowing it to be adapted to different datasets and diverse types of chest diseases, making it a versatile tool for a wide range of medical conditions.

References

[1]. Nawaz, M.; Nazir, T.; Javed, A.; Tariq, U.; Yong, H.S.; Khan, M.A.; Cha, J. An efficient deep learning approach to automatic glaucoma detection using optic disc and optic cup localization. Sensors 2022, 22, 434.

[2]. Nawaz, M.; Nazir, T.; Masood, M.; Mehmood, A.; Mahum, R.; Khan, M.A.; Kadry, S.; Thinnukool, O. Analysis of brain MRI images using improved cornernet approach. Diagnostics 2021, 11, 1856.

[3]. Ayan, E.; Ünver, H.M. Diagnosis of pneumonia from chest X-ray images using deep learning. In Proceedings of the 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), Istanbul, Türkiye, 24–26 April 2019; pp. 1–5.

[4]. Haghanifar, A.; Majdabadi, M.M.; Choi, Y.; Deivalakshmi, S.; Ko, S. Covid-cxnet: Detecting covid-19 in frontal chest x-ray images using deep learning. Multimed. Tools Appl. 2022, 81, 30615–30645.

[5]. De Moura, J.; Novo, J.; Ortega, M. Fully automatic deep convolutional approaches for the analysis of COVID-19 using chest X-ray images. Appl. Soft Comput. 2022, 115, 108190. [6]. Gayathri, J.; Abraham, B.; Sujarani, M.; Nair, M.S. A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed forward neural network. Comput. Biol. Med. 2022, 141, 105134.

[7]. Tan, T.; Das, B.; Soni, R.; Fejes, M.; Yang, H.; Ranjan, S.; Szabo, D.A.; Melapudi, V.; Shriram, K.; Agrawal, U.; et al. Multimodal trained artificial intelligence solution to triage chest X-ray for COVID-19 using pristine ground-truth, versus radiologists. Neurocomputing 2022, 485, 36–46.

[8]. Ayalew, A.M.; Salau, A.O.; Abeje, B.T.; Enyew, B. Detection and Classification of COVID-19 Disease from X-ray Images Using Convolutional Neural Networks and Histogram of Oriented Gradients. Biomed. Signal Process. Control. 2022, 74, 103430.

[9]. Fukushima, K.J.B.C. Biological cybernetics neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biol. Cybern. 1980, 36, 193–202.

[10]. Schuster, M.; Paliwal, K.K. Bidirectional recurrent neural networks. IEEE Trans. Signal Process. 1997, 45, 2673–2681.

[11]. Nawaz, M.; Mehmood, Z.; Nazir, T.; Naqvi, R.A.; Rehman, A.; Iqbal, M.; Saba, T. Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering. Microsc. Res. Tech. 2022, 85, 339–351.
[12]. Ballester, P.; Araujo, R.M. On the performance of GoogLeNet and AlexNet applied to sketches. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, Phoenix, AR, USA, 12–17 February 2016.
[13]. Wu, Z.; Shen, C.; Van Den Hengel, A. Wider or deeper: Revisiting the resnet model for visual recognition. Pattern Recognit. 2019, 90, 119–133.
[14]. Singh, K.K.; Siddhartha, M.; Singh, A. Diagnosis of coronavirus disease (COVID-19) from chest X-ray images using modified XceptionNet. Rom. J. Inf. Sci. Technol. 2020, 23, 91–115. Diagnostics 2023, 13, 248 21 of 22
[15]. Hamza, A.; Khan, M.A.; Alhaisoni, M.; Al Hejaili, A.; Shaban, K.A.; Alsubai, S.; Alasiry, A.; Marzougui, M. D2BOF-COVIDNet: A Framework of Deep Bayesian Optimization and Fusion-Assisted Optimal Deep Features for COVID-19 Classification Using Chest X-ray and MRI Scans. Diagnostics 2023, 13, 101.
[16]. Marques, G.; Agarwal, D.; Díez, I.d.l.T. Automated medical diagnosis of COVID-19 through EfficientNet convolutional neural network. Appl. Soft Comput. 2020, 96, 106691.
[17]. Muljo, HeryHarjono, et al. "Improving lung disease detection by joint learning with COVID-19 radiography database." Commun. Math. Biol. Neurosci. 2022 (2022): Article-ID.
[18]. Miah, Md Asiful Islam, et al. "InfLocNet: Enhanced Lung Infection Localization and Disease Detection from Chest X-Ray Images Using Lightweight Deep Learning." arXiv preprint arXiv:2408.06459 (2024).
[19]. Nawaz, Marriam, et al. "CXray-EffDet: chest disease detection and classification from X-ray images using the EfficientDet model." Diagnostics 13.2 (2023): 248.
[20]. Ait Nasser, Adnane, and Moulay A. Akhloufi. "A review of recent advances in deep learning models for chest disease detection using radiography." Diagnostics 13.1 (2023): 159.
[21]. Glocker, Ben, et al. "Algorithmic encoding of protected characteristics in chest X-ray disease detection models." EBioMedicine 89 (2023).
[22]. Ravi, Vinayakumar, Vasundhara Acharya, and Mamoun Alazab. "A multichannel EfficientNet deep learning-based stacking ensemble approach for lung disease detection using chest X-ray images." Cluster Computing 26.2 (2023): 1181-1203.
[23]. Eswara Rao, G. V., and B. Rajitha. "HQF-CC: hybrid framework for automated respiratory disease detection based on quantum feature extractor and custom classifier model using chest X-rays." International Journal of Information Technology 16.2 (2024): 1145-1153.
[24]. Mann, Mukesh, et al. "Utilization of deep convolutional neural networks for accurate chest X-ray diagnosis and disease detection." Interdisciplinary Sciences: Computational Life Sciences 15.3 (2023): 374-392.
Al-qaness, Mohammed AA, et al. "Chest X-ray Images for [25]. Lung Disease Detection Using Deep Learning Techniques: A Comprehensive Survey." Archives of Computational Methods in Engineering (2024): 1-35.
[26]. Eswara Rao, G. V., and B. Rajitha. "HQF-CC: hybrid framework for automated respiratory disease detection based on quantum feature extractor and custom classifier model using chest X-rays." International Journal of Information Technology 16.2 (2024): 1145-1153.