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Deep Learning-Based Pneumonia Detection Using CNN and ANN Pretrained VGG16 Model

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ABSTRACT

The recent significant growth in the volume of available data has led to the widespread adoption of artificial intelligence across various disciplines. The use of artificial intelligence and machine learning in medicine is increasing, particularly in fields that utilize numerous types of biological images and where diagnostic processes rely on collecting and analysing large numbers of digital images. Machine learning enhances the accuracy and consistency of medical image interpretation. To improve decision-making in establishing accurate diagnoses, this research explores the application of machine learning algorithms to interpret chest X-ray images. The paper focuses on employing a deep learning approach based on a convolutional neural network to develop a processing model. This model aims to assist in a classification task that determines whether a chest X-ray shows changes associated with pneumonia, categorizing the images into two groups based on the detection results.

Keywords: Pneumonia Detection, Deep Learning, CNN, VGG16, Transfer Learning, Medical Imaging.

1. INTRODUCTION

Deep learning is a subset of machine learning, which is itself a branch of artificial intelligence. It involves neural networks with multiple layers, enabling them to learn from large volumes of data. Unlike traditional machine learning, where feature extraction is performed manually, deep learning models can automatically discover the representations required for tasks directly from raw data. This capability makes deep learning especially powerful for applications such as image and speech recognition, natural language processing, and autonomous driving.

Pneumonia is a serious respiratory infection that primarily affects the lungs by causing inflammation of the air sacs. Early and accurate detection of pneumonia is essential for effective treatment and improved patient outcomes. However, diagnosing pneumonia can be challenging, especially in regions with limited access to experienced radiologists. This paper aims to develop a deep learning model to automatically detect pneumonia from chest X-ray images. The model will assist healthcare professionals by identifying pneumonia cases with high accuracy, enabling timely and reliable diagnoses. By leveraging convolutional neural networks (CNNs) and a large dataset of labelled chest X-rays, the paper seeks to create a robust and efficient tool for pneumonia detection that can be deployed in clinical settings to enhance diagnostic capabilities and alleviate the workload of medical professionals.

The objective of this paper is to develop a deep learning model to accurately detect pneumonia from chest X-ray images. Collect and preprocess a large, labelled dataset of chest X-ray images. Design and implement a convolutional neural network (CNN) optimized specifically for pneumonia detection. Train the CNN to achieve high accuracy, precision, recall, and F1-score. Evaluate the model on a separate test dataset to validate its effectiveness. Create a user-friendly interface that allows healthcare professionals to upload X-ray images and receive diagnostic results. Ensure the model is scalable and deployable in clinical settings, including resource-limited environments. Continuously monitor and update the model with new data to maintain and improve diagnostic accuracy. Implement techniques to make the model's predictions interpretable for healthcare professionals.

The scope of the pneumonia detection paper includes several key areas. The paper will involve collecting and preprocessing a large dataset of chest X-ray images, incorporating augmentation techniques to enhance model training. It will also encompass the design, implementation, and optimization of a convolutional neural network (CNN) specifically tailored for pneumonia detection. Model training will focus on achieving high performance metrics such as accuracy, precision, recall, and F1-score. Evaluation will be conducted using a separate test dataset to ensure the model's reliability and generalizability.

Additionally, the paper will develop a user-friendly interface to facilitate the easy upload of Xray images and provide instant diagnostic results for healthcare professionals. The model will be designed to be scalable and deployable in various clinical settings, including those with limited resources. Continuous monitoring and updating of the model with new data will be implemented to maintain and enhance its diagnostic capabilities over time. Finally, the paper will explore methods to make the model's predictions interpretable, thereby increasing trust and adoption among healthcare providers.

The pneumonia detection paper has several practical applications. It can be integrated into hospital radiology departments to assist radiologists in quickly and accurately diagnose pneumonia from chest X-rays. It can be used in remote and resource-limited healthcare settings to provide reliable diagnostic support where access to experienced radiologists is scarce. The model can be incorporated into telemedicine platforms to enable remote diagnosis and consultation. It can be used in public health initiatives to screen large populations for pneumonia, especially during outbreaks. The tool can assist in clinical research by providing a consistent and automated method for analyzing chest X-ray images in studies related to pneumonia and respiratory diseases. Finally, it can be used in medical education to train healthcare professionals and students in recognizing pneumonia in chest X-rays, improving their diagnostic skills.

2. LITERATURE SURVEY

Pixel-based methods refer to machine learning techniques where each pixel in medical images, such as chest x-rays, corresponds to specific anatomical structures like lungs, heart, mediastinum, and diaphragm. Various features such as pixel intensity, spatial location, and texture statistics are used by classifiers like neural networks (NN), support vector machines (SVM), Markov random field (MRF) models, or k-nearest neighbor (KNN) classifiers. These methods are categorized into shallow machine learning and deep learning approaches. For many years, research has focused on detecting and diagnosing diseases, including pneumonia. Abeyratne proposed an automated method using cough sounds, developing a database from bedside microphones placed 40 cm to 70 cm from 91 patients. Cough sounds were used to train a logistic regression classifier, and methods were compared against WHO guidelines, achieving high sensitivity and specificity. Similar approaches by Pingale and Patil analyzed cough sounds of newborns to adolescents for pneumonia diagnosis.

The cough samples underwent analysis using Continuous Wavelet Transform (CWT). Pneumonia classification was achieved by comparing CWT coefficients with Power Spectral Density (PSD) and applying threshold values for skew ness and kurtosis. Since 2017, several studies have utilized chest X-rays (CXR) for pneumonia identification and diagnosis, benefiting from advancements in Deep Learning and Computer Vision for image recognition tasks. Traditionally, pneumonia detection relies on clinical examination, patient history, and imaging techniques such as chest X-rays and CT scans. Radiologists play a crucial role in interpreting these images for pneumonia diagnosis. However, this manual process is time-consuming and prone to human error, underscoring the need for automated approaches.

EL. Khalid , Asnaoui, [12] Different types of single and ensemble learning models were utilized to classify pneumonia. Ensemble learning involves combining multiple models into a single model to tackle a specific task, with the choice of models being determined by the requirements and characteristics of the problem at hand. Currently, ensemble models are commonly employed for making predictions, including classification and regression tasks. By training a single model independently within an ensemble, improved accuracy can be achieved. In particular, an ensemble of three models demonstrated higher accuracy in this study.

T. Rahman, E.H. Muhammad , [13] used digital x-ray images to detect the bacterial and viral pneumonia. Four different pre-trained deep Convolutional Neural Networks (CNN): AlexNet, ResNet18, DenseNet201, and SqueezeNet were used for transfer learning. This proposed study can be useful in quickly diagnosing pneumonia by the radiologist .

P. Pratik, Hemprasad Patil, [14] Early detection and prompt treatment can significantly reduce the mortality rate associated with this disease. Chest x-rays are commonly employed to identify the symptoms of the disease. In this study, a CNN-based model was utilized to automatically detect crucial features, as opposed to using hand-engineered feature selection techniques.

Wasif Khan, Nazar Zaki , [15] This helps practitioners to select the most effective and efficient methods from a real-time perspective, review the available datasets, and understand the results obtained in this domain. The usability, goodness aspects, and computational complexity of the algorithms used for intelligent pneumonia identification are examined in this research.

S. Hossain, Rafeed Rahman, [16] The study presented a pneumonia detection approach utilizing MobileNet and ResNet architectures along with Long Term Short Memory (LSTM). This research aims to simplify image analysis for both experts and non-professionals by proposing a deep learning-based method for pneumonia detection from X-ray images. A dataset containing 5856 X-ray images was utilized, and the maximum accuracy achieved by the proposed LSTM model was noted as 90.2%.

D. Meldon, Nimesh Naik, [17] The primary objective of this study is to analyze the patients X-ray images using OpenCV and Deep learning and decide whether the patient has pneumonia or not. We created a deep learning model to aid and address this inconvenient situation for radiologists to achieve the patient's results which can be analyzed and reported to the patient directly. They have used Keras libraries and OpenCV for achieving a high-test data accuracy rate.

This review study explores machine learning techniques aimed at accurately detecting pneumonia in images. One of the primary challenges in employing ML approaches is the availability and quality of datasets. Real-time data is crucial for effective training, as lab-based data is often limited. GDPR regulations restrict the sharing of data among hospitals and medical facilities, complicating data access.

Concerns about cyber security are also significant, with reports indicating that cyber-attacks compromised 24.3 million medical image records. This review article examines various ML strategies utilized by researchers to identify medical images and ensure the security of image data.

3. METHODOLOGY

The demand for a substantial dataset of pneumonia images is addressed in the proposed approach through data augmentation techniques. A pre-trained model is utilized to incorporate multi-scale discriminative features for class labelling, extracting characteristics from augmented images of pneumonia and normal cases. The three-step process for pneumonia detection is outlined, utilizing hierarchical architecture based on lung X-ray slices. Data pre-processing, also referred to as data cleaning, is a crucial step for machine learning engineers, occupying a significant portion of their workflow before model development. It involves tasks such as outlier detection, handling missing values, and filtering out undesired or noisy data. Similarly, image pre-processing involves actions performed at the most fundamental level of abstraction on images.

Enhancing the quality of data used for training artificial neural networks is a common technique in deep learning. Data augmentation artificially increases the size of the training dataset by introducing variations to existing data samples. This can be done manually or with algorithms that generate new data samples as needed. By employing data augmentation, you can improve the accuracy of your models and reduce the occurrence of false positives.

CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks (CNNs), also referred to as ConvNets, are a prominent type of neural network extensively employed for image recognition and classification tasks. They are widely used in applications such as face recognition and object identification. Once CNNs process an input image, their image classifiers categorize it into predefined groups, such as Dog, Cat, Tiger, or Lion. In computer vision, an input image is interpreted as a grid of pixels, where the resolution determines the amount of visual detail captured and analyzed by the network. This pixel-based interpretation forms the foundation for CNNs' ability to learn and distinguish complex patterns and features within images, making them highly effective for tasks requiring precise image analysis and classification.

VGG NET

A common deep Convolutional Neural Network (CNN) design is known as VGG, which stands for Visual Geometry Group. The term "deep" refers to the number of layers, with VGG-16 or VGG-19 having 16 or 19 convolutional layers, respectively. VGG architecture is utilized to construct advanced object identification models. The VGG Net, designed as a deep neural network, surpasses benchmarks on various tasks and datasets beyond ImageNet. It remains one of the most frequently used image recognition architectures today. VGG Nets are based on the core principles of convolutional neural networks (CNN).

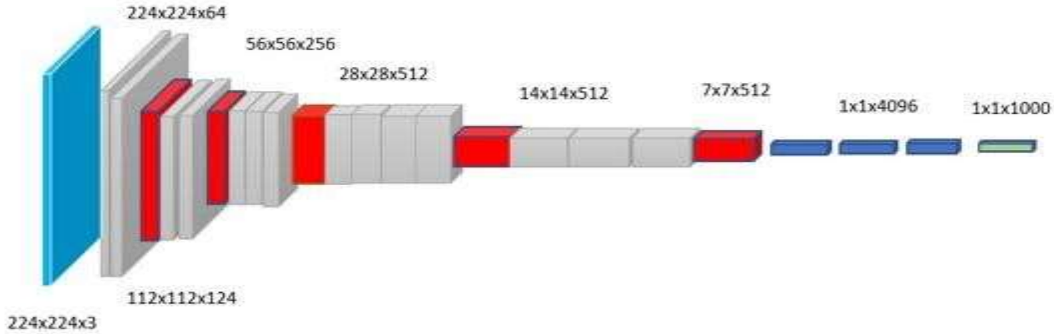

Figure 1: VGG Net

The VGG16 model processes 224x224x3 pixel images as input. It starts with two convolutional layers, each outputting 224x224x64, followed by a max-pooling layer that reduces the dimensions to 112x112x64. Then, there are two convolutional layers, each outputting 112x112x128 pixels, followed by another max-pooling layer reducing the size to 56x56x128. Next, there are three convolutional layers, each outputting 56x56x256 pixels, followed by a maxpooling layer that reduces the dimensions to 28x28x256. Afterward, there are three convolutional layers, each outputting 28x28x512 pixels, with a subsequent max-pooling layer shrinking the dimensions to 14x14x512. Finally, the model has three convolutional layers, each outputting 14x14x512 pixels, followed by a max-pooling layer that reduces the dimensions to 7x7x512, leading into two fully-connected layers with 4096 nodes each as shown in Figure 1.

VGG-16 concludes with a dense output layer comprising 1000 nodes, allowing it to classify images into one of 1000 classes. However, training VGG-16 is notoriously resource-intensive; the original model was trained on an NVIDIA Titan GPU for 2-3 weeks. The weight file for the trained VGG-16 model is substantial, weighing in at 528 MB, which poses inefficiency in terms of storage space and bandwidth usage. Moreover, with 138 million parameters, the model faces challenges related to gradient explosion during training.

DENSNET:

DenseNet, a recent advancement in neural networks for visual object detection, differs significantly from ResNet. Unlike ResNet, which adds the output of the previous layer to the output of the subsequent layer, DenseNet concatenates the outputs of all previous layers with the output of the current layer. This approach aims to address the issue of vanishing gradients that can lead to decreased accuracy in deep neural networks. DenseNet was specifically designed to mitigate this problem by ensuring that information from earlier layers is directly accessible to later layers, thus facilitating better gradient flow and potentially improving performance.

DEEP-PNEUMONIA FRAMEWORK

As demonstrated in the literature, numerous deep learning models have been developed to diagnose pneumonia from chest X-ray images, each offering different performance metrics to validate model accuracy. One of the significant challenges has been identifying an effective and efficient model that excels in all performance metrics. The goals of our study are to (i) propose a deep learning framework for pneumonia classification using four distinct models, and (ii) evaluate the proposed models by comparing them with recently introduced models. A deep learning framework for pneumonia diagnosis was created, as illustrated in Figure 2. This model has two main tiers. The first tier is dedicated to image preprocessing tasks such as resizing, augmentation, data splitting, and normalization. Data normalization rescales the pixel values of images to the range [0,1]. The second tier focuses on feature extraction and image classification using various deep learning models.

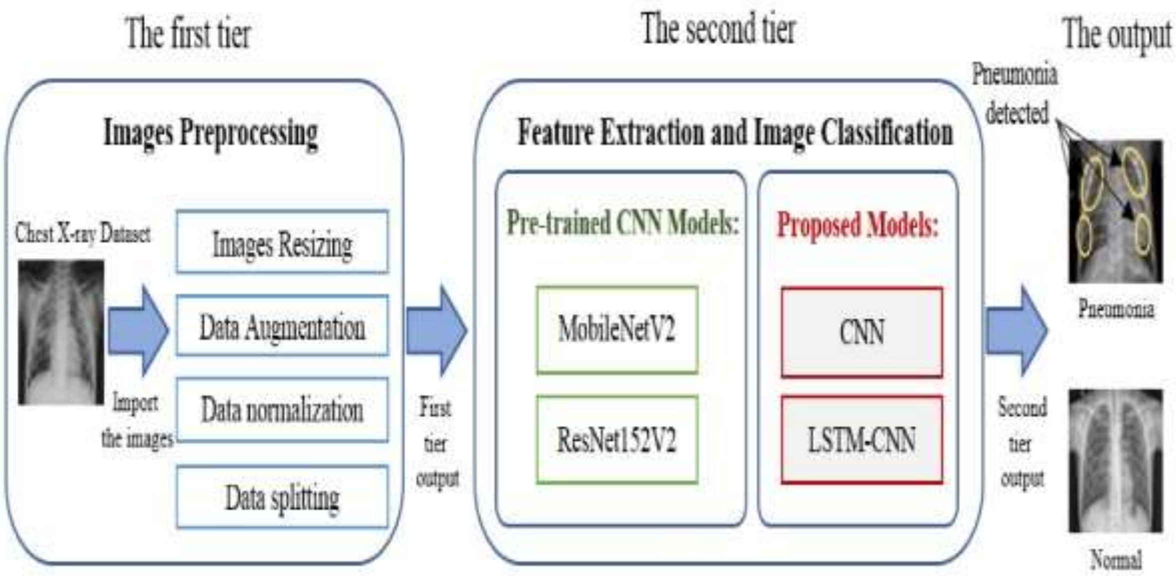

Figure 2: The proposed deep learning framework for pneumonia diagnosis.

The proposed deep learning framework is structured into two main tiers. The first tier is responsible for image preprocessing, including resizing the dimensions of the chest X-ray images to a standard size suitable for the model, applying augmentation techniques such as rotation, shifting, and flipping to increase the diversity of the training dataset, dividing the dataset into training, validation, and test sets to ensure unbiased evaluation of the model, and rescaling the pixel values of the images to the range [0,1] to standardize the input data for the models.

The second tier focuses on feature extraction and image classification. Convolutional layers are used to automatically extract relevant features from the X-ray images, and different types of deep learning models are implemented to classify the images into pneumonia and normal categories. The models are evaluated based on metrics such as precision, recall, F1-score, and support, and their results are compared with other state-of-the-art models in the field to highlight their strengths and areas for improvement. By integrating these components, the framework aims to provide a robust solution for pneumonia diagnosis, potentially leading to faster and more accurate clinical decisions. This enhanced description aims to clarify the goals and methodology of our study, providing a detailed overview of the framework and its components.

4. RESULTS AND ANALYSIS

We train the convolutional neural network to detect pneumonia by using epochs to achieve the final accuracy. However, the convolutional neural network doesn't always provide a definitive final accuracy; it predicts pneumonia without giving a conclusive result. Vanishing gradients can disrupt accuracy in the convolutional neural network, resulting in the lack of a definitive outcome.

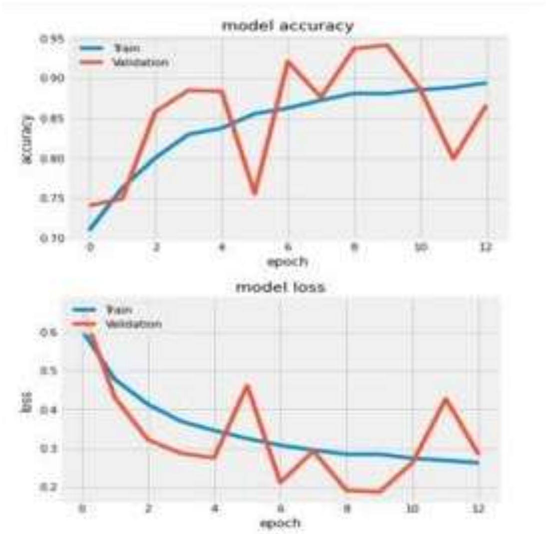

Figure 3: Results of CNN

Using a convolutional neural network (CNN) only predicts pneumonia. The CNN model for this paper, as shown in figure 3, has two subcategories: training loss and accuracy, and testing loss and accuracy. With 10 epochs to extract values for the x and y axes, the CNN model achieves an accuracy of 91.21 and a loss of 21.11.

We use VGG16 to detect pneumonia. VGG, short for Visual Geometry Group, is used for image classification problems. We build, train, and test the VGG16 model. Unlike other models, VGG16 does not suffer from the vanishing gradient problem, ensuring final accuracy and loss are preserved. In this model, the final accuracy is 37%. Figure 4 of the paper shows the VGG16 model, which has two subcategories: training loss and accuracy, and testing loss and accuracy. With 10 epochs to extract values for the x and y axes, the VGG16 model achieves an accuracy of 37.50% and a loss of 18.11.

Figure 4: Results of VGG16

We utilize DenseNet to detect pneumonia. DenseNet, a densely connected neural network, connects each layer to every other layer in a feed-forward fashion. In our model, specifically DenseNet121, we build, train, and test it. Unlike some models, DenseNet does not suffer from vanishing gradient issues, ensuring accurate final accuracy and loss. In this model, the final accuracy is 85%. The graphs above illustrate accuracy and loss plots based on training and testing data. We allocated 80% for training and 20% for testing. The model's accuracy was defined and evaluated using validation accuracy. The epochs were used to analyze the model's training and testing phases. The graphs above show the model's loss. They depict validation loss using epochs to analyze and train the model, aiming for minimal loss. The results of DenseNet is given in Figure 5.

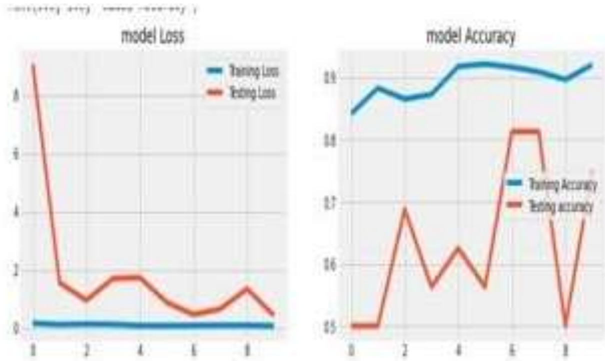

Figure 5: Results of Dense Net

To determine the highest accuracy among three models— Convolutional Neural Network (CNN), VGG16, and DenseNet. we compared their performance metrics as presented in Figure 6. The CNN achieved the highest accuracy at 91.23%, surpassing VGG16 with 37.50% and DenseNet with 85.42%. Each model was trained using 10 epochs with 165 steps per epoch. The results of noramal and Pneumonia cases are given in Figure 7.

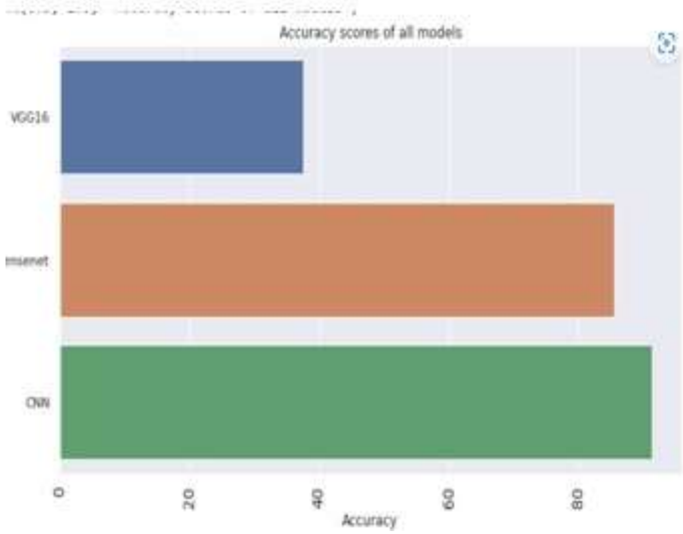

Figure 6: Accuracy Results of Models

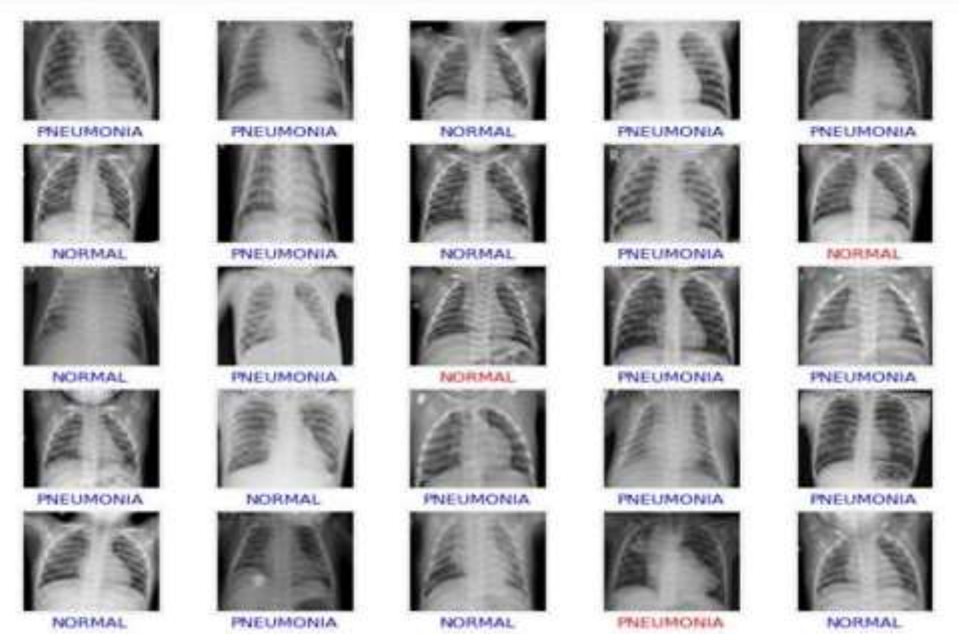

Figure 7: Results for Normal and Pneumonia Cases

In pneumonia detection using deep learning, the classification report plays a crucial role in evaluating the model's performance comprehensively. Metrics such as precision, recall, F1-score, and accuracy provide valuable insights into how effectively the model distinguishes between pneumonia and normal cases. This analysis is essential for healthcare professionals and data scientists to ensure reliable and effective diagnostic support.

In our paper, we implemented a convolutional neural network (CNN) model specifically designed for pneumonia detection. The CNN model leverages deep learning techniques to accurately classify X-ray images. We utilized 10 examples to illustrate both accurate and inaccurate predictions: accurate forecasts are represented in blue, while inaccurate ones are highlighted in red. The model was trained, validated, and tested using epochs to optimize its performance, resulting in final metrics such as loss and accuracy. Ultimately, the CNN model was evaluated on its ability to predict pneumonia from X-ray images. This summary encapsulates the key aspects of your description in a clear and concise manner.

CONCLUSION:

This research explores the application of deep learning to classify digital chest X-ray images based on the presence or absence of pneumonia-related abnormalities. Python programming and scientific methodologies were employed to develop a convolutional neural network (CNN) model. Initial findings indicate that while the model achieves high accuracy—approaching 90%—the large dataset size poses a risk of overfitting. The predictive model shows potential as a decision support tool, given its high accuracy, yet it remains complementary to the expertise and physical presence of medical professionals for accurate diagnosis. Developing a robust and reliable disease classification model is crucial, requiring comprehensive data collection and experimentation. Future research directions include exploring alternative CNN architectures, refining preprocessing techniques, implementing data augmentation strategies, and incorporating additional X-ray datasets annotated with various medical conditions. These steps aim to further enhance the model's accuracy and applicability in clinical settings.

FUTURE SCOPE:

A deep Convolutional Neural Network (CNN) method was utilized to detect pneumonia presence in chest X-ray images. The dataset comprised 12,000 frames of both affected and unaffected chest X-rays, which were used to train various Deep CNN architectures. Preprocessing and data augmentation were performed using the Chest X-ray 8 dataset, incorporating matrix factorization techniques to increase frame diversity. Modified images were generated using a combination of Deep Convolutional Generative Adversarial Networks (DCGAN) and basic image editing methods. The proposed Deep CNN model was implemented using VGG19 architecture, achieving a high accuracy of 99.34% in predicting unidentified chest X-ray images. Comparative analyses were conducted between the CNN results and those obtained from other classification methods, including VGG16Net, AlexNet, and Inception Net.

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