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RESEARCH ARTICLE

Pneumonia Detection Using Chest Radiographs With Novel EfficientNetV2L Model

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ABSTRACT Pneumonia is a potentially life-threatening infectious disease that is typically diagnosed through physical examinations and diagnostic imaging techniques such as chest X-rays, ultrasounds or lung biopsies. Accurate diagnosis is crucial as wrong diagnosis, inadequate treatment or lack of treatment can cause serious consequences for patients and may become fatal. The advancements in deep learning have significantly contributed to aiding medical experts in diagnosing pneumonia by assisting in their decision-making process. By leveraging deep learning models, healthcare professionals can enhance diagnostic accuracy and make informed treatment decisions for patients suspected of having pneumonia. In this study, six deep learning models including CNN, InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L are implemented and evaluated. The study also incorporates the Adam optimizer, which effectively adjusts the epoch for all the models. The models are trained on a dataset of 5856 chest X-ray images and show 87.78%, 88.94%, 90.7%, 91.66%, 87.98% and 94.02% accuracy for CNN, InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L, respectively. Notably, EfficientNetV2L demonstrates the highest accuracy and proves its robustness for pneumonia detection. These findings highlight the potential of deep learning models in accurately detecting and predicting pneumonia based on chest X-ray images, providing valuable support in clinical decision-making and improving patient treatment.

INDEX TERMS Pneumonia detection, transfer learning, efficientnetv2l, data augmentation, chest X-rays.

I. INTRODUCTION

Pneumonia is an infectious disease that causes inflammation of the tissues in one or both lungs. Over one million people are hospitalized in the United States each year due to pneumonia [1]. Fortunately, pneumonia can be treated with medications such as antibiotics and antivirals. Early diagnosis and treatment are essential to prevent complications that might result in mortality from pneumonia. Pneumonia is an infectious disease caused by fungus, bacteria and viruses that inflame the air sacs in one or both lungs. Lungs infection harms the pulmonary alveoli which are little balloon-shaped bags at the bottom of the bronchioles. Pneumonia is classified into numerous forms, including mycoplasma pneumonia, viral pneumonia, bacterial pneumonia and others. Bacterial pneumonia is caused by bacteria or fungus. Bacterial pneumonia causes a variety of symptoms including physical weakness, old age, disease, inadequate nutrition and a

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weakened immune system [2]. It is risky for people of all ages but especially dangerous for smokers, alcoholics, recent surgical patients, asthmatics, virus infections and those with weakened immune systems. Viruses that cause viral pneumonia such as the flu, account for nearly one-third of all pneumonia cases. When a person is attacked by viral pneumonia, the risk of developing bacterial pneumonia increases, and more likely to develop bacterial pneumonia as well [3].

Pneumonia is a common and potentially life-threatening respiratory infection that poses a significant global health burden [4]. The timely and accurate detection of pneumonia is critical for effective treatment and patient care. Deep learning models use multiple layers of artificial neural networks to provide cutting-edge solutions in a variety of fields including speech recognition, language translation, image processing and others. Over the past few years, the utilization of deep learning methods has surfaced as highly encouraging methods for the automation of pneumonia diagnosis. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have showcased their potential for efficiently scrutinizing medical imaging data such as chest X-rays and computed tomography (CT) scans for detecting instances of pneumonia. These models possess the ability to learn intricate patterns and features from vast datasets to identify abnormal lung conditions infected with pneumonia with remarkable precision [5]. Further research and advancements in deep learning are continually refining pneumonia detection methods, paving the way for more advanced and reliable diagnostic tools in the field of respiratory medicine. A significant proportion of pneumonia cases are prevalent in economically disadvantaged and developing countries, characterized by a dearth of medical facilities, a dense population, pollution, and unsanitary surroundings. As a result, averting the potential fatality of this disease hinges on the timely identification and provision of care. The assessment of respiratory ailments typically encompasses radiographic assessment of the lungs, which entails methods such as CT, magnetic resonance imaging (MRI) and radiography (X-rays).

Employing X-ray images presents an affordable and non-intrusive approach to scrutinizing lung conditions [6]. The interpretation of chest X-rays to detect pneumonia can often be ambiguous, leading to potential confusion with other medical conditions. The congestive heart failure and lung scarring can imitate pneumonia symptoms. A focused assessment of chest X-rays for pneumonia cases might yield misleading results. This inherent challenge contributes significantly to the misclassification of X-ray images within datasets. Consequently, developing an algorithm capable of accurately identifying thoracic disorders, including pneumonia holds substantial value in enhancing healthcare accessibility, especially in remote and underserved regions. The complexity is addressed by evaluating the performance of diverse pre-trained CNN model versions for the accurate diagnosis of both pathological and normal chest X-rays, subsequently employing a range of classifiers to refine the results [7].

Detecting pneumonia accurately from chest X-ray images is a complex problem in medical diagnostics. The challenge lies in identifying the intricate and subtle patterns associated with pneumonia. Traditional methods rely on manual interpretation by radiologists which can be subjective and time-consuming [8]. Deep learning-based approaches offer promise in automating the detection process. One major challenge is the scarcity of annotated data for training deep learning models. Annotated datasets of chest X-ray images with pneumonia cases are often limited and imbalanced, making it difficult for models to generalize effectively [9]. Additionally, variations in imaging conditions including equipment positioning and image quality further complicate the task. Overcoming these challenges and developing a robust deep learning model to precisely identify pneumonia from chest X-rays is crucial for enhancing diagnostic efficiency and improving patient outcomes in clinical settings. Deep learning methodologies effectively tackle the challenges outlined above, often achieving disease prediction accuracy comparable to occasionally surpassing, that of conventional radiologists. Among these approaches, CNNs have garnered significant attention due to their remarkable capabilities in image segmentation and classification tasks. Leveraging deep learning and computer vision techniques for the detection of biomedical issues, particularly in images, has proven immensely advantageous. These techniques facilitate swift and accurate disease diagnoses, rivaling the expertise of dependable radiologists [10]. In Figure 1, a graphical abstract diagram of pneumonia detection is given, showing various modules of the pneumonia detection system. In this regard, this study proposes a CNN model for pneumonia detection and makes the following contributions:

- Proposed a deep learning model EfficientNetV2L for pneumonia detection involving the chest X-ray images from patients. In addition, several state-of-the-art CNN architectures such as InceptionResNetV2, Xception, VGG16 and ResNet50 are utilized for pneumonia detection using chest X-ray images.
- Experiments involve using a large dataset of 5856 chest X-ray images with pneumonia and normal classes from a rich variety of patients from different age groups. Train-test split involves dividing the dataset into training and testing sets, with a further 15% split for validation within the training set.
- The study's focus is on training and evaluating deep learning models on chest X-ray images, aiming to improve diagnostic efficiency and enhance patient outcomes in clinical settings. The overall goal is to achieve accurate pneumonia detection through the proposed deep learning models.
- To increase generalizability and robustness of the EfficientNetV2L model, k-fold cross-validation is also carried out. Moreover, performance of the EfficientNetV2L model is judged in comparison

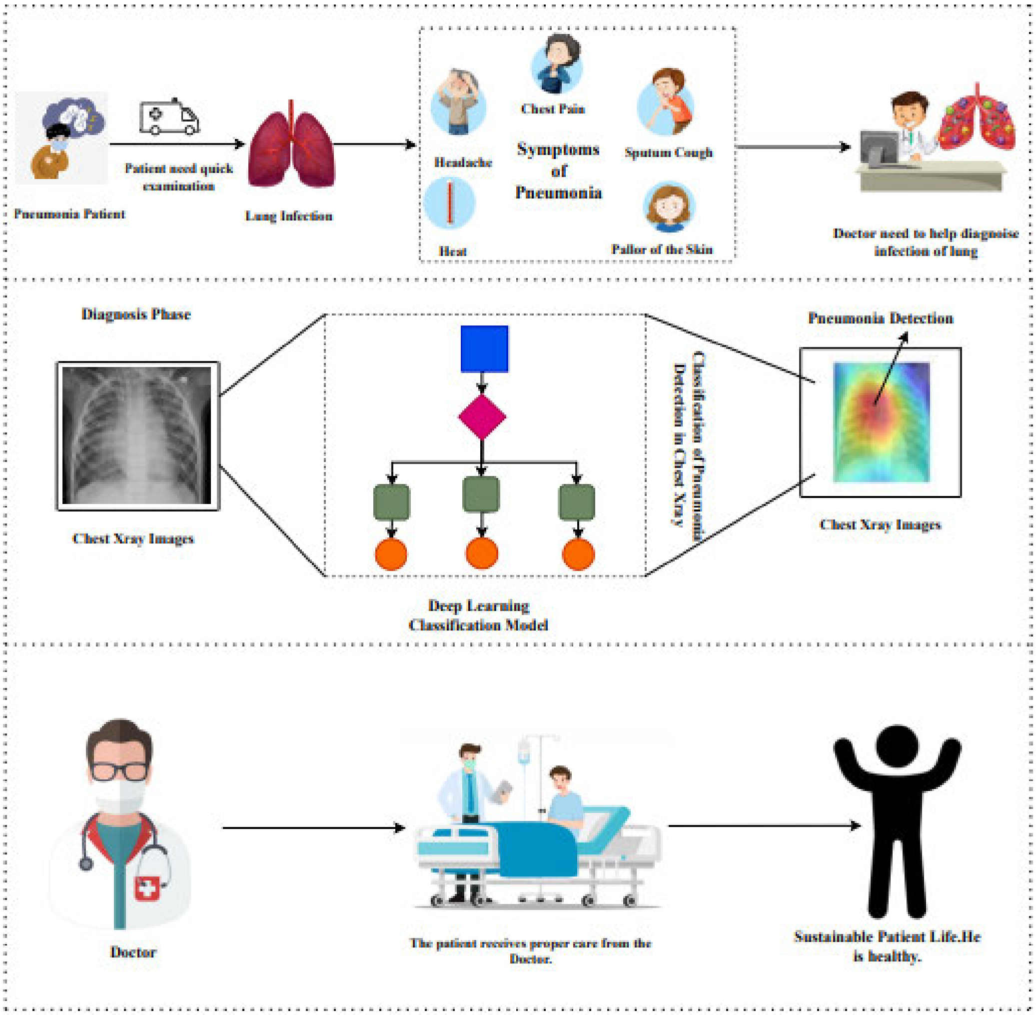

FIGURE 1. **Graphical abstract of pneumonia detection system.**

to existing state-of-the-art models for pneumonia detection.

Pneumonia detection methods, including traditional radiography and even some deep learning models, struggle with achieving high sensitivity and specificity simultaneously. False positives and false negatives are common, leading to both overdiagnosis and underdiagnosis. To proposed EfficientNetV2L model aims to address these issues by leveraging its efficient architecture to enhance sensitivity and specificity, thereby minimizing diagnostic errors. The effectiveness of many existing pneumonia detection methods is heavily reliant on the quality of the input images. Poor resolution, artifacts, or improper positioning during image acquisition can significantly impact the accuracy of diagnosis. The model, while not completely immune to image quality issues, incorporates robust features from EfficientNetV2L that contribute to improved performance even in the presence of suboptimal image conditions. This limitation by utilizing a well-curated dataset and leveraging the efficiency of EfficientNetV2L to enhance the model's ability to generalize across diverse cases, ultimately improving its diagnostic capability. Conventional deep learning models often lack interpretability, making it challenging for clinicians to trust and understand the decision-making process. The EfficientNetV2L model integrates features designed to enhance interpretability, facilitating better communication between the model and healthcare professionals. Despite this improvement, there remains a broader need for research into interpretable deep learning models for pneumonia detection. Some existing deep learning models, especially those with large architectures, may require substantial computational resources and time for training. This limitation hinders the practicality of deploying these models in real-time clinical settings. EfficientNetV2L model is designed to balance computational efficiency with performance, making it more feasible for integration into clinical workflows without compromising accuracy. EfficientNetV2L model for pneumonia detection but also underscores the limitations of current pneumonia detection methods. By acknowledging these challenges, this research aims to contribute to the ongoing efforts to advance the field of medical imaging and improve the accuracy and efficiency of pneumonia diagnosis.

The rest of the paper is distributed into the following sections: Section II discusses the related work that presents the literature of the current research works and technologies. Section III presents the methodology that involves the overall research approach, describing the data collection methods and discussing the data analysis techniques utilized. Section IV shows the results and discussion of the proposed approach. Section V presents the supporting points and establishes a connection to the broader context.

II. RELATED WORK

Pneumonia is a common respiratory illness characterized by lung inflammation and infection, often a condition brought on by pathogens like bacteria, viruses or fungus. For the disease to be effectively treated and managed, pneumonia must be detected as early and accurately as possible. Deep learning techniques have recently emerged as a promising approach for automating pneumonia detection using chest X-ray images. By leveraging CNNs and training them on diverse datasets, deep learning algorithms can learn complex patterns and features indicative of pneumonia. This enables them to identify specific visual markers and abnormalities associated with the disease [11]. Deep learning integration in pneumonia detection can improve diagnostic accuracy, minimize human error and improve healthcare efficiency. Research and annotated datasets will refine deep learning models, enabling more reliable and effective detection from chest X-ray images. This approach considers symptoms severity and potential complications, allowing radiologists to identify infiltrates, white patches in lung tissue and potential pneumonia-related complications like abscesses or pleural effusions [12].

A. X-RAY IMAGES USED IN PNEUMONIA DISEASES

Deep learning models are essential for detecting and diagnosing pneumonia using chest X-ray images. These images provide visual insights into the lung's condition, allowing algorithms to recognize patterns associated with pneumonia. Training deep learning models on diverse datasets helps distinguish between normal lung conditions and those indicative of pneumonia [13]. The information-rich nature of X-ray images, combined with the power of deep learning techniques, empowers healthcare practitioners with an automated and efficient tool for accurate pneumonia detection. This technology facilitates early intervention, enabling timely treatment and improved patient outcomes [14]. Pneumonia diagnosis involves various techniques, including CT scans, sputum tests, pulse oximetry, thoracentesis, blood gas analysis, bronchoscopy, pleural fluid cultures and complete blood counts. Treatment strategies are tailored to the underlying cause, with antibiotics for bacterial pneumonia, antiviral medications for viral pneumonia and antifungal medications for fungal pneumonia. This approach ensures appropriate treatment for the specific organism causing the infection [15].

B. ROLE OF MACHINE LEARNING IN PNEUMONIA CLASSIFICATION

Using chest X-ray images for pneumonia classification, machine learning in particular deep learning proves to be very promising. Deep learning models such as CNN-based models have demonstrated a superior ability to learn intricate patterns and features from large datasets. In the context of pneumonia detection, these models are trained on diverse chest X-ray images, enabling them to identify specific visual cues and abnormalities associated with pneumonia. By analyzing the unique characteristics of pneumonia cases, deep learning algorithms can accurately classify chest X-ray images as pneumonia or non-pneumonia cases. This automated classification process facilitates prompt identification of potential pneumonia cases, aiding in early intervention and timely treatment [31]. Machine learning improves pneumonia detection efficiency, accuracy and patient outcomes through advancements in deep learning algorithms and annotated datasets, leading to more effective diagnoses and improved healthcare practices [32]. Pneumonia is a deadly infection affecting young and elderly individuals. Researchers identified it using X-ray scans, algorithms and traditional machine learning classifiers. A mask-RCNN-based model demonstrated reliability and potency [33]. Through the use of machine learning such as support vector machine (SVM), K nearest neighbor (KNN), decision tree (DT) and deep learning such as multilayer perceptron (MLP) and RNN models, the authors studied the prediction of pneumonia disease and obtained promising accuracy.

C. ROLE OF DEEP LEARNING IN PNEUMONIA DISEASES CLASSIFICATION

The categorization of pneumonia infections using chest X-ray pictures depends heavily on deep learning. Its utilization, particularly through CNN, has revolutionized pneumonia detection. Deep learning algorithms excel at learning intricate patterns and features from extensive datasets, enabling them to extract meaningful information from chest X-ray images [34]. The integration of deep learning in pneumonia disease classification empowers healthcare professionals with an automated and efficient tool for early diagnosis [35].

In the present context, the classification of medical images has emerged as a particularly captivating and inspiring endeavor. Leveraging deep learning methodologies, a range of six distinct diseases, including one non-tissue infection-related ailment, are detected and classified. Notably, neural networks are specifically employed for the identification and categorization of interstitial lung diseases (ILDs) [36]. Another article describes the Boltzmann machine, a device that uses lung-generated tomography (CT) to analyze illnesses. Texture classification and airway detection are

TABLE 1. Performance comparison with existing stateoftheart models.

Ref.	Year	Technique	DataSet	Number of sample	Accuracy	Precision	Recall	F1 Score
[16]	2019	CNN	chest x-ray	15 million	68%	-	-	-
[17]	2020	Xception	chest x-ray	1300	89.6%	90%	89.92%	89.8%
[18]	2019	InceptionV3	chest x-ray	5856	92.8%	-	-	-
[19]	2020	CNN	chest x-ray	5216	85.26%	-	94%	89%
[20]	2019	CNN	chest x-ray	100,000	80.90%	-	-	-
[21]	2022	CNN	chest x-ray	5233	92.8%	92.6%	96.2%	94.3%
[22]	2019	VGG16	chest x-ray	21149	79.51%	-	-	-
[23]	2022	CNN	chest x-ray	5216	93.91%	93.96%	92.99%	93.43%
[24]	2018	ResNet50	chest x-ray	112,120	84.1%	-	-	-
[25]	2022	VGG16	chest x-ray	15,153	89.34%	89%	89%	89%
[26]	2019	InceptionV3	chest x-ray	5,000	78.5%	-	-	-
[27]	2023	ResNet50	chest x-ray	5863	82.8%	80.6%	80.6%	-
[28]	2023	EfficientNet	chest x-ray	5856	90.38%	90.64%	88.72%	89.51%
[29]	2023	InceptionresnetV2	chest x-ray	5856	89%	89%	88%	94%
[30]	2023	EfficientNetB0	chest x-ray	10,000	83%	32%	33%	52%

two novel strategies that are introduced in the study using two datasets. CNN networks are employed to build on the kernel to evaluate the patient's brain tissue. They use a dual framework, for example using CNN to feature extraction first and then classifying images based on the feature data. In a different study, the scientists created several models to support the accuracy of the top model's pneumonia detection results [37]. They used a dataset of 26,684 images to train the CNN models AlexNet, LeNet, GoogleNet, ResNet and VGGNet using a 1024×1024 image resolution. Their study's findings showed that the VGGNet model had an accuracy rate of 97%, while the ResNet model had the lowest accuracy rate at 74% [38]. Similarly, the authors employed mask R-CNN and RetinaNet, two different types of CNN, and got good results [39].

D. SEGMENTATION-BASED PNEUMONIA DETECTION

Segmentation-based pneumonia detection using deep learning has emerged as a promising methodology in the field of medical imaging. This approach focuses on accurately identifying and segmenting the regions of pneumonia within chest X-ray images. By leveraging advanced deep learning architectures such as U-Net or Mask R-CNN, these models can effectively learn to segment and isolate the areas of the lungs affected by pneumonia. This segmentation process provides crucial insights into the location and extent of the infection, facilitating precise diagnosis and treatment planning [40]. Segmentation-based pneumonia detection using deep learning allows healthcare professionals to visualize and analyze specific regions, enabling more accurate and targeted interventions. This approach quantifies pneumonia severity and progression, enabling efficient monitoring and follow-up care. Research and advancements in segmentation-based pneumonia detection hold promise for improving diagnostic capabilities and patient outcomes in respiratory medicine.

Mask-RCNN is a deep neural network used for pulmonary image segmentation, image augmentation, dropout and L2 regularization detecting pneumonia using both global and local characteristics [41]. The authors used both a 3D deep CNN with dense connections and a 3D deep CNN with shortcut connections. The gradient vanishing issue is resolved by shortcuts and dense connections. Deep networks can capture both the general and specific characteristics of lung nodules because of connections [42]. A CNN-based approach combined with rib suppression and lung field segmentation is applied. For pixel patches obtained in the lung area, three CNN models are trained on images of varied resolutions, and feature fusion is used to merge all the data [43]. Image augmentation and a region-based CNN are employed to partition the pulmonary pictures and identify pneumonia in [44]. Image segmentation is the division of an image into a number of smaller sections. Typically, the properties of the pixels in these sub-regions are similar and they do not cross [45]. With the ongoing development of modern computer science and medical technology, medical images are now divided into separate image types that are different from standard images. This is an important area of application for picture segmentation [46]. These elements lead to interesting tissues appearing in some segments. The contrast lessens and the edge part becomes rather ambiguous and uneven. Therefore, accurate medical image segmentation is a very difficult scientific research task. Medical image segmentation typically calls for extremely high results regarding integrity and accuracy [47]. Following the completion of the preliminary imaging, specific technical tools are typically required to process the results appropriately in order to show distinct and recognizable tissues of interest [48]. The comparative related work is described in Table 15.

III. MATERIALS AND METHODS

The methodology for pneumonia detection using deep learning based on chest X-ray images involves several key components, as shown in Figure 2. Six deep learning models, such as CNN, InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L have been used in this study. These models are implemented and fine-tuned using the Tensor Flow library, a widely adopted deep learning framework. In order to improve the model's robustness and

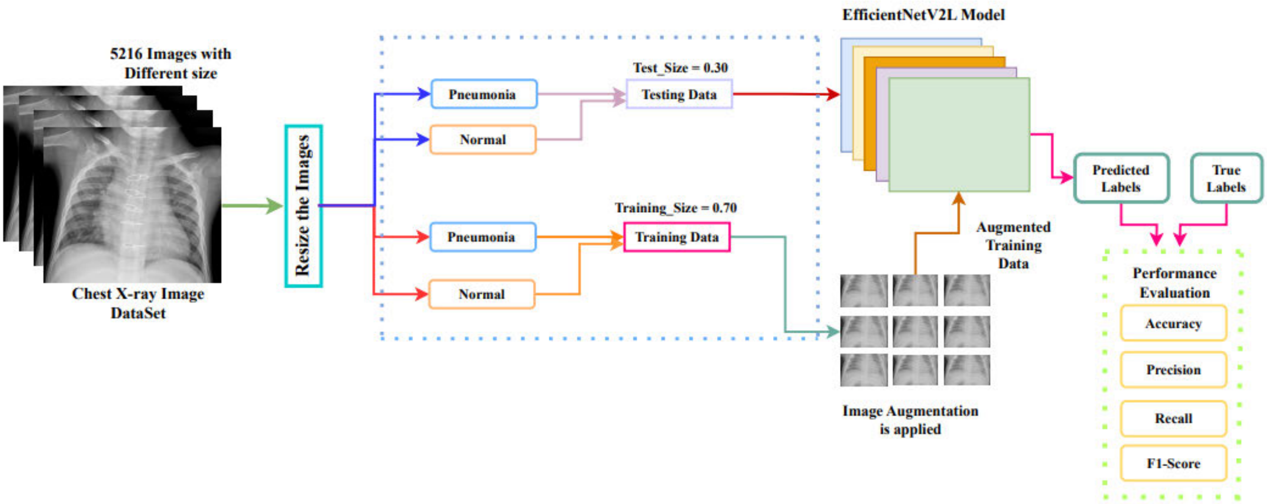

FIGURE 2. Methodology of pneumonia detection using efficient NetV2L model.

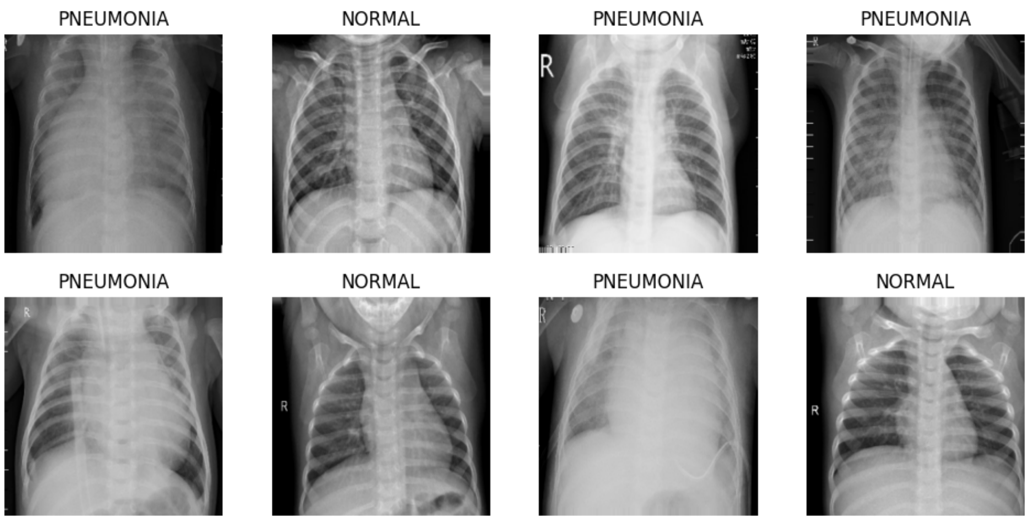

FIGURE 3. Chest x-ray images for pneumonia detection.

prevent overfitting, data augmentation techniques including random rotations, shifts, flips and zooms to the original images have been applied to generate additional training samples. Furthermore, the X-ray images underwent pre-processing steps such as normalization of pixel values and resizing to a standardized input size. This comprehensive methodology allowed us to leverage diverse deep learning models, implement effective data augmentation, preprocess the chest X-ray images, efficiently train and evaluate the pneumonia detection models.

A. DATASET DESCRIPTION

The dataset contains 5,863 X-ray images (JPEG) and 2 categories (pneumonia and normal). Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of the patients' routine clinical care. For the analysis of chest X-ray images, all chest radiographs were initially screened for quality control by removing all low-quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training in the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert [49]. This study leverages several models to perform accurate pneumonia detection, improving diagnostic efficiency and potentially enhancing patient outcomes. A total of 5,856 samples, including 1,583 normal and 4,273 pneumonia images, were used in this study. The chest X-ray scans of the volunteer patients are used to create the dataset. The rationale for using the dataset is its usage in several existing state-of-the-art approaches. For a fair comparison with these methods, the dataset can be used as a benchmark. In addition, the dataset contains a rich variety of X-ray images from patients and is well-suited to analyze the performance of the proposed model. Table 2 shows the number of images used for training, testing and validation.

TABLE 2. Dataset details for pneumonia and normal images.

Set	Pneumonia Images	Normal Images	Total Images
Training Set	3875	1341	5216
Validation Set	8	8	16
Testing Set	390	234	624

Figure 3 shows X-ray images of the patients. Each panel corresponds to an individual patient and displays their respective X-ray images of normal or pneumonia radiographs.

1) IMAGE PREPROCESSING

Image preprocessing plays a critical role in detecting pneumonia using deep learning with chest X-ray images. It involves a series of essential operations applied to the images prior to inputting them into the deep learning models. The goal is to improve the quality of images and the consistency of the data. Typical techniques include resizing the images to a standardized resolution, normalizing pixel values to a specific range, and applying contrast adjustments to improve image clarity. Additionally, noise reduction methods like Gaussian or median filtering can be employed to eliminate unwanted artifacts. Other methods of increasing the dataset and enhancing model generalization include rotation, scaling and flipping of the images. By preprocessing the images, the input data becomes more suitable for deep learning algorithms, enabling better feature extraction and improving the model's ability to identify pneumonia-related patterns. Effective image preprocessing is crucial in optimizing the performance and accuracy of pneumonia detection models, ultimately leading to more reliable diagnoses and enhanced patient care.

2) IMAGE AUGMENTATION

Image augmentation plays an important role in pneumonia detection using deep learning with chest X-ray images. It involves applying various transformations to the original images to expand the training dataset and enhance the model's performance. By introducing variations in the data, image augmentation helps improve the model's ability to generalize to unseen images. Leveraging tools such as ImageDataGenerator, a versatile module in deep learning frameworks like TensorFlow and Keras, allows for the generation of augmented image data on the fly during model training. Common augmentation techniques include rotation, translation, scaling, flipping and adding random noise. These transformations simulate real-world variations in chest X-ray images, accounting for different orientations, positions and noise levels. Additionally, image augmentation helps address the issue of imbalanced datasets where the number of pneumonia cases may be limited compared to normal cases. By generating additional samples through augmentation, the model can learn from a more balanced dataset, improving its ability to detect pneumonia accurately. By applying transformations such as rescale, rotation_range, horizontal_flip, vertical_flip, height_shift_range and width_shift_range. The dataset's diversity is enriched, aiding the model in learning a more comprehensive set of features. Additionally, resizing images is a crucial preprocessing step, ensuring uniformity in input dimensions for the neural network. Image augmentation serves as a valuable tool in pneumonia detection, enhancing the model's capability to capture essential features and ultimately improving the accuracy and reliability of the deep learning-based system.

B. DEEP LEARNING MODELS

In deep learning models, the landscape of pneumonia detection has undergone a revolutionary transformation by learning intricate patterns and features inherent in chest X-ray images. CNNs have emerged as frontrunners, largely owing to their remarkable proficiency in image classification endeavors. The realm of pneumonia detection has witnessed the successful deployment of advanced architectures, such as InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L. These models incorporate ingenious techniques like residual connections, depth-wise separable convolutions, and efficient scaling to elevate the accuracy of feature extraction. The amalgamation of these deep learning models into pneumonia detection holds the promise of substantially expediting diagnoses, improving treatment outcomes and enhancing healthcare practices in the domain of respiratory medicine. The selection of CNN models is motivated by the results reported in existing studies concerning the use of these models on image datasets. For example, [50] reports better results using a custom CNN model for X-ray-based pneumonia detection. The authors advocate the use of GoogleNet, ResNet-18 and DenseNet-121 for pneumonia detection in [6]. Similarly, AlexNet, ResNet18, DenseNet201 and SqueezeNet are used for the same task in [40] showing better performance than other deep learning models. The study [51] presents the performance analysis of deep learning models in the context of pneumonia detection and suggests using CNN variants for better performance. The current dataset is selected to make a fair comparison with existing state-of-the-art methods for pneumonia detection. The dataset serves as the benchmark, as it has been utilized by existing studies.

Pneumonia detection using CNN models plays an indispensable role, particularly in the analysis of chest X-ray images. These models excel at extracting pertinent features from input images, subsequently pooling these features to facilitate classification tasks. The inherent depth of their architecture empowers them to acquire hierarchical representations of chest X-ray images, thereby capturing intricate pneumonia-related patterns. By training on extensive datasets containing annotated images, diagnostic precision and efficiency are significantly elevated, enabling healthcare practitioners to make well-timed and informed decisions. The continuous evolution of CNN architectures, along with the

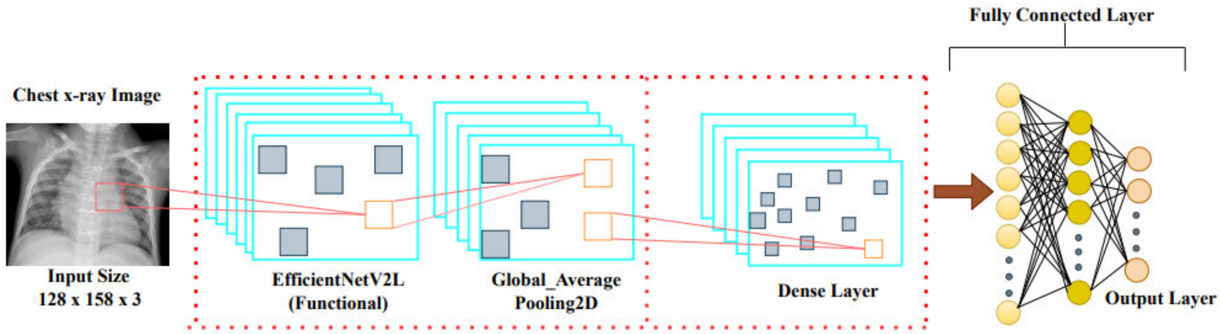

FIGURE 4. EfficientNetV2L architectural diagram.

availability of annotated datasets, continues to augment the effectiveness of pneumonia detection through deep learning. This progress not only contributes to enhanced patient outcomes but also fosters more streamlined and effective healthcare practices.

Leveraging InceptionResNetV2 models proves to be a formidable approach to pneumonia detection through deep learning, especially concerning chest X-ray images. The amalgamation of Inception and ResNet attributes empowers these models to meticulously extract intricate information from X-ray images by employing convolutional layers and residual connections. The outcome is a precise classification of X-ray images into pneumonia or non-pneumonia categories, thus elevating the accuracy of diagnoses and offering indispensable support to healthcare experts. As the capabilities of InceptionResNetV2 models continue to evolve, they harbor significant potential for further refining pneumonia detection within the realm of deep learning. This trajectory holds the promise of delivering superior patient outcomes and fostering more streamlined and effective healthcare practices, particularly in the domain of respiratory medicine.

Xception models for pneumonia detection through deep learning with chest X-ray images are a potent strategy. These models boast an architecture that employs depth-wise separable convolutions, facilitating the nuanced capture of intricate patterns and distinctive features. Through harnessing substantial datasets, Xception models adeptly discern visual attributes closely tied to pneumonia. This proficiency is reflected in their remarkable precision in precisely categorizing chest X-ray images into pneumonia or non-pneumonia cases, thereby elevating the accuracy of diagnoses. As Xception models continue to evolve and advance, their potential for refining diagnostic capabilities and ultimately enhancing patient outcomes in the realm of respiratory medicine holds great promise.

VGG16 models stand as potent tools in the domain of pneumonia detection through deep learning with chest X-ray images. Their architecture, characterized by a series of convolutional layers and max-pooling layers, excels at extracting intricate hierarchical features. With the advantage of extensive dataset training, VGG16 models adeptly discern discernible patterns and irregularities associated with pneumonia. Their remarkable proficiency in accurately classifying X-ray images into either pneumonia or non-pneumonia categories has significantly bolstered the accuracy of diagnoses and instilled greater reliability. Looking ahead, the ongoing progress and evolution of VGG16 models hold the potential to further refine pneumonia detection, ultimately translating into improved patient outcomes and more streamlined healthcare practices within the realm of respiratory medicine.

ResNet50 models for pneumonia detection through deep learning using chest X-ray images prove to be a potent approach. Their architecture, characterized by the incorporation of residual connections, empowers them to grasp complex patterns and intricate features. With extensive dataset training, ResNet50 models adeptly recognize discernible visual cues that signify the presence of pneumonia. The outcome is an improvement in the accuracy and reliability of diagnoses, offering invaluable support to healthcare experts in their endeavor to identify and address pneumonia cases based on chest X-ray images. As ResNet50 models continue to advance and evolve, their potential for further enhancing pneumonia detection remains promising. This trajectory holds the potential for elevating patient outcomes and fostering more effective healthcare practices, particularly within the domain of respiratory medicine.

C. PROPOSED EFFICIENTNETV2L

EfficientNetV2L models for pneumonia detection using chest X-ray images prove to be an effective strategy. These models seamlessly integrate scaling techniques and deep neural networks, yielding a synergy that results in both efficiency and accuracy. With robust training on extensive datasets containing annotated chest X-ray images, EfficientNetV2L models adeptly capture the distinct visual characteristics associated with pneumonia. This aptitude translates into an enhancement in diagnostic efficiency and reliability, providing invaluable assistance to healthcare practitioners in identifying and addressing pneumonia cases through chest X-ray images. As the advancement of EfficientNetV2L models continues, their potential to further refine pneumonia detection holds immense promise. This trajectory not only bears the potential to elevate patient outcomes but also to foster more streamlined and effective healthcare practices within the realm of respiratory medicine. Figure 4 shows the architecture of the proposed EfficientNetV2I model for pneumonia detection.

Architectural details of the proposed model are given in Table 3 along with the details of input, functional, global, and dense layers. It also includes information on output shape, parameters for each layer and hyperparameters. The EfficientNetV2L architecture was fine-tuned for pneumonia detection from chest X-rays. Leveraging the power of deep learning, the potential of EfficientNetV2L, known for its efficiency and performance in image classification tasks, was recognized. The approach involved training the model on a diverse and extensive dataset of chest X-rays, meticulously labeled for pneumonia cases.

TABLE 3. EfficientNetV2L model configuration parameters used in the model training process along with their respective values and descriptions.

Layers	Unit	Output shape	Parameters
InputLayer	-	(None, 128, 158, 3)	0
Functional	-	(None, 4, 5, 1280)	117746848
GlobalAveragePooling2D	-	(None, 1280)	0
Dense	1	(None, 1)	1281
Optimizer	Adam		
Loss	Binary_crossentropy		
Metric	Accuracy		

The fine-tuning process aimed to optimize the network's parameters to enhance its sensitivity and specificity in identifying pneumonia-related patterns in radiographic images. Table 4 showed the EfficientNetV2L fine-tuned for pneumonia detection from chest X-rays. Table 5 show the comaprison of EfficientNetV2L with other models in terms of working and performance.

D. EVALUATION PARAMETERS

The assessment of pneumonia detection models utilizing deep learning with chest X-ray images encompasses the evaluation of various metrics, including accuracy, recall, precision and the F1 score. Accuracy gauges the model's proficiency in accurately predicting positive cases, while specificity evaluates its aptitude in correctly identifying negative cases. Precision quantifies the fraction of accurately classified positive cases out of all predicted positive cases. The F1 score presents a harmonized measure by balancing both precision and recall, thereby offering healthcare practitioners a comprehensive tool to inform their decisions and ultimately enhance patient care. The following equations are used for accuracy, precision, recall and F1 score:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

The evaluation of the model's accuracy involves the examination of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN).

$$Precision = \frac{(TP)}{(TP + FP)} \tag{2}$$

$$Recall = \frac{(TP)}{(TP + FP)} \tag{3}$$

$$F1\ score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{4}$$

IV. RESULTS AND DISCUSSION

The performance of deep learning models hinges on their ability to accurately process and interpret data to generate predictions. To gauge this performance, diverse metrics come into play, encompassing accuracy, precision, recall, and the F1 score. Accuracy serves as a barometer of overall correctness in predictions. Precision quantifies the ratio of true positive cases to all predicted positives, while recall emphasizes the reduction of false positives. These metrics collectively provide a comprehensive assessment of a model's efficacy in various aspects of data processing and prediction.

A. RESULTS OF CONVOLUTIONAL NEURAL NETWORK

CNN exhibits remarkable efficacy in tackling classification tasks, with their evaluation encompassing metrics such as accuracy, precision, recall and the F1 score. These networks learn patterns and features from chest X-ray datasets and undergo assessment using distinct test datasets. Accuracy quantifies the ratio of correctly classified instances to the overall sample size, while precision computes the fraction of accurately predicted positive instances. Through the optimization of weights and biases, CNNs achieve elevated levels of accuracy, precision, recall and F1 scores. Renowned for their proficiency, CNNs serve as invaluable tools in diverse classification tasks, particularly in scenarios involving image data.

The CNN algorithm demonstrated strong performance, achieving an accuracy of 88.78%, precision of 91.45%, recall of 90.51% and F1 score of 90.97%. These results indicate the model's ability to accurately predict outcomes and effectively capture positive instances as shown in Table 6. In addition, Figure 5 shows the confusion matrix for the CNN model. It indicates that the model has 554 correct predictions including 201 true positives and 353 true negatives while the model made 70 wrong predictions.

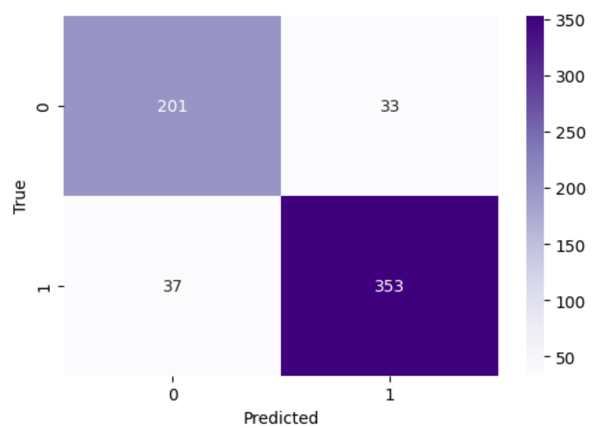

FIGURE 5. Confusion matrix for CNN model.

TABLE 4. Fine-tuning of the EfficientNetV2L for pneumonia detection from chest X-rays.

Models	Layers	Unit	Activation Function	Loss	Optimizer	Metrix	Epoch	Accuracy
EfficientNetV2L	4	1	-	Binary_Crossentropy	adam	accuracy	10	94.02%
EfficientNetV2L	4	1	sigmoid	Binary_Crossentropy	adam	accuracy	10	93.80%
EfficientNetV2L	4	1	relu	Binary_Crossentropy	RMSprop	accuracy	10	92.03%
EfficientNetV2L	4	1	softmax	categorical_crossentropy	adamax	accuracy	10	71.83%
EfficientNetV2L	4	1	tanh	Binary_crossentropy	adagrad	accuracy	10	88.73%

TABLE 5. Comparison of EfficientNetV2L model with other models.

Models	Feature
CNN	• Simple and widely used architecture for image classification. Consists of convolutional layers for feature extraction followed by fully connected layers for classification. • Simplicity and ease of implementation. • Limited capability to capture complex hierarchical features.
InceptionResNetV2	• Combines features from both Inception and ResNet50 architectures to improve overall performance. It has a complex multi-branch structure with 572 layers. • High accuracy and performance. • Increased computational complexity.
Xception	• Utilizes depth-wise separable convolutions for improved efficiency. It has 71 layers and reduces the number of parameters compared to traditional architectures. Improved efficiency and reduced parameters. • Improved efficiency and reduced parameters. • Requires substantial computational resources.
VGG16	• Simple and easy-to-understand architecture with a stack of 3x3 convolutional layers. Prone to overfitting due to a large number of parameters (16 layers). • Simple and uniform architecture with 16 weight layers, known for its ease of understanding. • Simple and straightforward architecture. • Prone to overfitting due to a large number of parameters.
ResNet50	• Introduces residual learning through skip connections, addressing the vanishing/exploding gradient problem and enabling the training of very deep networks. Addresses the vanishing gradient problem with residual connections. Consists of 50 layers and is effective for deep networks. • Effective in handling vanishing gradient problem. • Deeper models may suffer from increased training time.
EfficientNetV2L	• Achieves high accuracy with fewer parameters through compound scaling and efficient building blocks. The number of layers can vary based on the specific configuration. May require fine-tuning for specific datasets. • Efficient architecture with compound scaling (depth, width, and resolution) for improved performance and model efficiency. • Variant specifically designed for large-scale image recognition tasks. • Improved performance and efficiency compared to previous versions of EfficientNetV2L. • May lacks a comprehensive comparative analysis with other architectures, but is known for balancing performance and efficiency. • Achieves high accuracy with fewer parameters.

TABLE 6. Results of CNN performance.

Epochs	Accuracy	Precision	Recall	F1 Score
2	0.8878	0.9145	0.9051	0.9097
4	0.8621	0.8454	0.9538	0.8964
6	0.8381	0.8121	0.9641	0.8815
8	0.8798	0.8987	0.9103	0.9045
10	0.8685	0.8830	0.9102	0.8964

B. RESULTS OF INCEPTIONRESNETV2 MODEL

InceptionResNetV2, a formidable deep learning model, seamlessly integrates the architectural strengths of Inception and ResNet paradigms to facilitate precise evaluations encompassing accuracy, precision and the F1 score. With its robust feature extraction capabilities, elevated accuracy rates and sophisticated design, this model guarantees precise predictions, impressive precision scores and outstanding F1 scores. Consequently, InceptionResNetV2 emerges as a dependable and commendable choice for classification tasks centered on image data.

The InceptionResNetV2 model demonstrated strong performance, achieving an accuracy of 88.94%, precision of 89.92%, recall of 88.94% and F1 score of 88.55%. These results indicate the model's ability to accurately predict outcomes and effectively capture positive instances as shown in Table 7. In addition, Figure 6 shows the number of correct and wrong predictions from the InceptionResNetV2 model.

TABLE 7. Results of InceptionResNetV2 model for pneumonia detection.

Epochs	Accuracy	Precision	Recall	F1 Score
2	0.8701	0.875	0.8701	0.8664
4	0.8894	0.8992	0.8894	0.8855
6	0.8814	0.8928	0.8814	0.8767
8	0.8814	0.8918	0.8814	0.8769
10	0.8669	0.8843	0.8669	0.8901

The model has comparatively 69 wrong predictions while the correct predictions are 555. The number of true negative samples is higher compared to the CNN model.

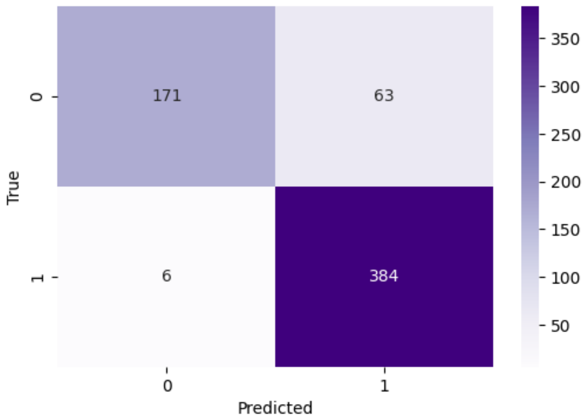

FIGURE 6. Confusion matrix for InceptionResNetV2 model.

C. RESULTS FOR XCEPTION MODEL

Xception stands as a robust and influential deep learning model tailored for image classification tasks, renowned for its remarkable prowess in accuracy, precision and F1 score evaluations. Distinguished by its novel "depth-wise separable convolution" approach, Xception adeptly captures both spatial and channel-wise dependencies, facilitating the extraction of meaningful features and ultimately attaining elevated accuracy rates. The model excels in striking a harmonious equilibrium between precision and recall, rendering it a dependable and trustworthy option for classification tasks centered on image data.

TABLE 8. Results of Xception model performance.

Epochs	Accuracy	Precision	Recall	F1 Score
2	0.8846	0.8862	0.8846	0.8825
4	0.9070	0.9072	0.9070	0.9061
6	0.8942	0.8990	0.8942	0.8915
8	0.8910	0.8995	0.8910	0.8874
10	0.8926	0.8991	0.8926	0.8895

The Xception model demonstrated strong performance on the testing set, achieving an accuracy of 90.70%, precision of 90.72%, recall of 90.70% and F1 score of 90.61%. These results indicate the model's ability to accurately predict outcomes and effectively capture positive instances as shown in Table 8. In addition, Figure 7 shows the confusion matrix of the Xception model. The confusion matrix indicates a better performance of the Xception model, compared to both CNN and InceptionResNetV2 model with 566 correct predictions while 58 predictions are wrong.

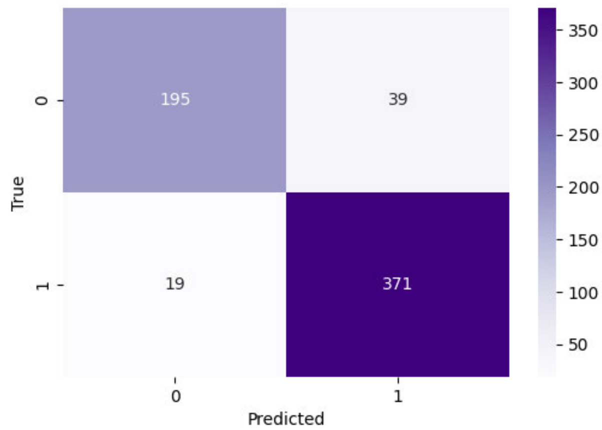

FIGURE 7. Confusion matrix for Xception model.

D. RESULTS FOR VGG16 MODEL

VGG16, a deep learning model comprising layers distinguishes itself through its exceptional aptitude in image classification tasks. The model adeptly captures complex patterns and features, leading to the attainment of elevated accuracy rates and precision scores. A defining characteristic of VGG16 is its capacity to achieve a harmonious equilibrium between precision and recall, culminating in the generation of impressive F1 scores.

TABLE 9. Performance results for VGG16 model.

Epochs	Accuracy	Precision	Recall	F1 Score
2	0.9150	0.9189	0.9150	0.9133
4	0.9006	0.9090	0.9006	0.8975
6	0.8669	0.8857	0.8669	0.8598
8	0.9102	0.9099	0.9102	0.9099
10	0.9166	0.9208	0.9166	0.9149

The VGG16 model demonstrated strong performance on the testing set, achieving an accuracy of 91.66%, precision of 92.08%, recall of 91.66% and F1 score of 91.49%. These results indicate the model's ability to accurately predict outcomes and effectively capture positive instances as shown in Table 9.

Figure 8 shows the network's confusion matrices of the VGG16 model. It shows that there is a higher difference between the performance of the VGG16 and the Xception model. VGG16 has 52 wrong predictions compared to 58 wrong predictions from the Xception model. Similarly, the number of correct predictions, i.e., 572, is also high using the VGG16 model.

E. RESULTS FOR RESNET50 MODEL

ResNet50 stands as a robust deep learning model distinguished for its remarkable prowess in accuracy, precision, recall and F1 score assessments within image classification

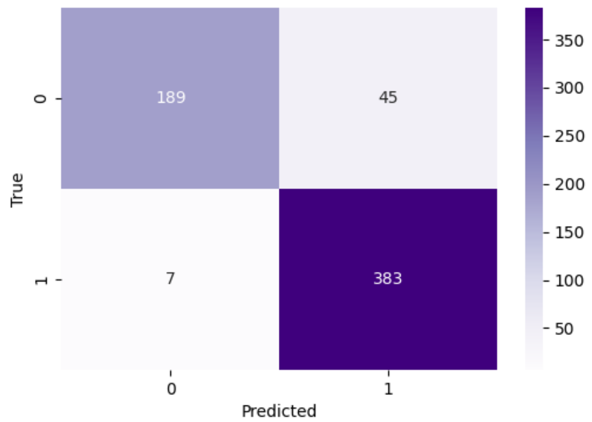

FIGURE 8. Confusion matrix for VGG16 model.

tasks. Characterized by its intricate layer architecture, the model adeptly captures complex patterns and features crucial for accurate classifications. Unique to ResNet50 are its skip connections, which effectively mitigate vanishing gradient challenges, enhancing training stability. The model effectively harmonizes precision and recall, culminating in the generation of impressive F1 scores.

TABLE 10. Performance of ResNet50 for pneumonia detection.

Epochs	Accuracy	Precision	Recall	F1 Score
2	0.8653	0.8689	0.8653	0.8617
4	0.8657	0.8707	0.8557	0.8484
6	0.8798	0.8814	0.8798	0.8775
8	0.8701	0.8743	0.8701	0.8666
10	0.8702	0.8743	0.8701	0.8666

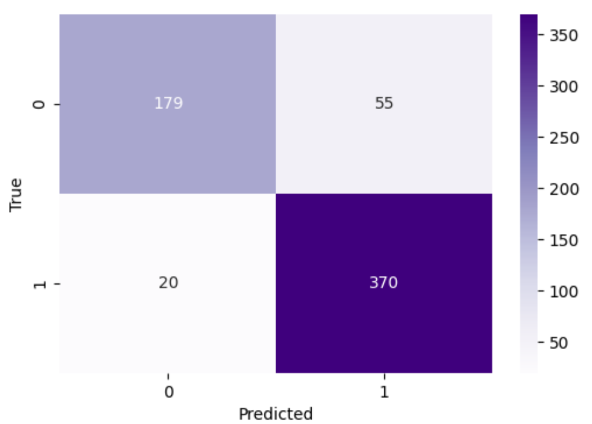

FIGURE 9. Confusion matrix for ResNet50 model.

The ResNet50 model demonstrated strong performance on the testing set, achieving an accuracy of 87.98%, precision of 88.14%, recall of 87.98% and F1 score of 87.75%. These results indicate the model's ability to accurately predict outcomes and effectively capture positive instances as shown in Table 10. Figure 9 shows the confusion matrices of the ResNet50 model. Results show that the performance of ResNet50 is poorer than those of CNN, InceptionResNetV2, Xception and VGG16 with 75 wrong predictions.

TABLE 11. Performance of EfficientNetV2L model.

Epochs	Accuracy	Precision	Recall	F1 Score
2	0.9203	0.9317	0.9572	0.9443
4	0.9373	0.9399	0.9733	0.9563
6	0.9300	0.9353	0.9666	0.9507
8	0.9380	0.9393	0.9738	0.9562
10	0.9402	0.9440	0.9724	0.9580

TABLE 12. Analysis of all employed models.

Models	Accuracy	Precision	Recall	F1 Score
CNN	0.8878	0.9145	0.9051	0.9097
InceptionResNetV2	0.8894	0.8992	0.8894	0.8855
Xception	0.9070	0.9072	0.9070	0.9061
VGG16	0.9166	0.9208	0.9166	0.9149
ResNet50	0.8798	0.8814	0.8798	0.8775
EfficientNetV2L	0.9402	0.9440	0.9724	0.9580

TABLE 13. Results of deep learning models using hyperparameter tuning.

Model	Ep.	Accuracy	Precision	Recall	F1
CNN	2	0.8878	0.9145	0.9051	0.9097
InceptionResNetV2	4	0.8894	0.8992	0.8894	0.8855
Xception	4	0.9070	0.9072	0.9070	0.9061
VGG16	10	0.9166	0.9208	0.9166	0.9149
ResNet50	6	0.8798	0.8814	0.8798	0.8775
EfficientNetV2L	10	0.9402	0.9440	0.9724	0.9580

TABLE 14. Model performance with k = 10.

Fold	Accuracy	Precision	Recall	F1-Score
1	0.9341	0.7382	0.1024	0.1762
2	0.9292	0.8072	0.0975	0.1703
3	0.9341	0.7839	0.1048	0.1807
4	0.9146	0.7118	0.1024	0.1773
5	0.9439	0.8114	0.1097	0.1916
6	0.9219	0.7009	0.0756	0.1344
7	0.9195	0.613	0.0975	0.1622
8	0.9317	0.6981	0.0902	0.1554
9	0.9195	0.6983	0.1097	0.1858
10	0.9535	0.7545	0.0929	0.1574

F. RESULTS OF PROPOSED EFFICIENTNETV2L MODEL

EfficientNetV2L is a widely esteemed deep learning model celebrated for its outstanding proficiency in accuracy, precision, recall and F1 score assessments within the domain of image classification tasks. Distinguished by its streamlined architecture, compound scaling techniques, integration of neural architecture search, and strategic utilization of building blocks, the model excels in achieving elevated accuracy rates. It not only prioritizes the generation of precise predictions but also adeptly harmonizes precision and recall, culminating in the production of impressive F1 scores.

The EfficientNetV2L model demonstrated strong performance on the testing set, achieving an accuracy of 94.02%, precision of 94.40%, recall of 97.24% and F1 score of 95.80%. These results indicate the model's ability to accurately predict outcomes and effectively capture positive instances as shown in Table 11.

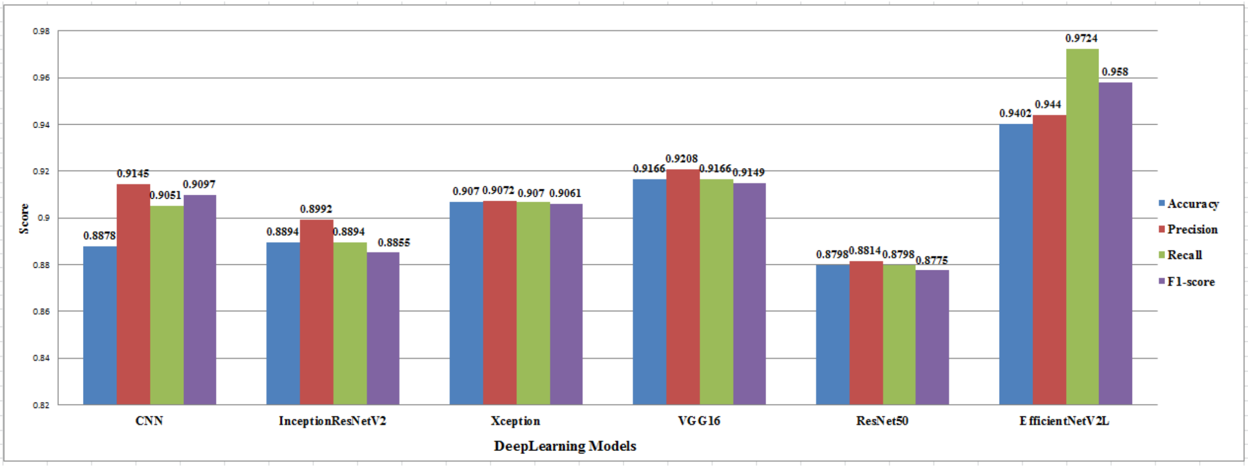

FIGURE 10. Performance analysis of deep learning models.

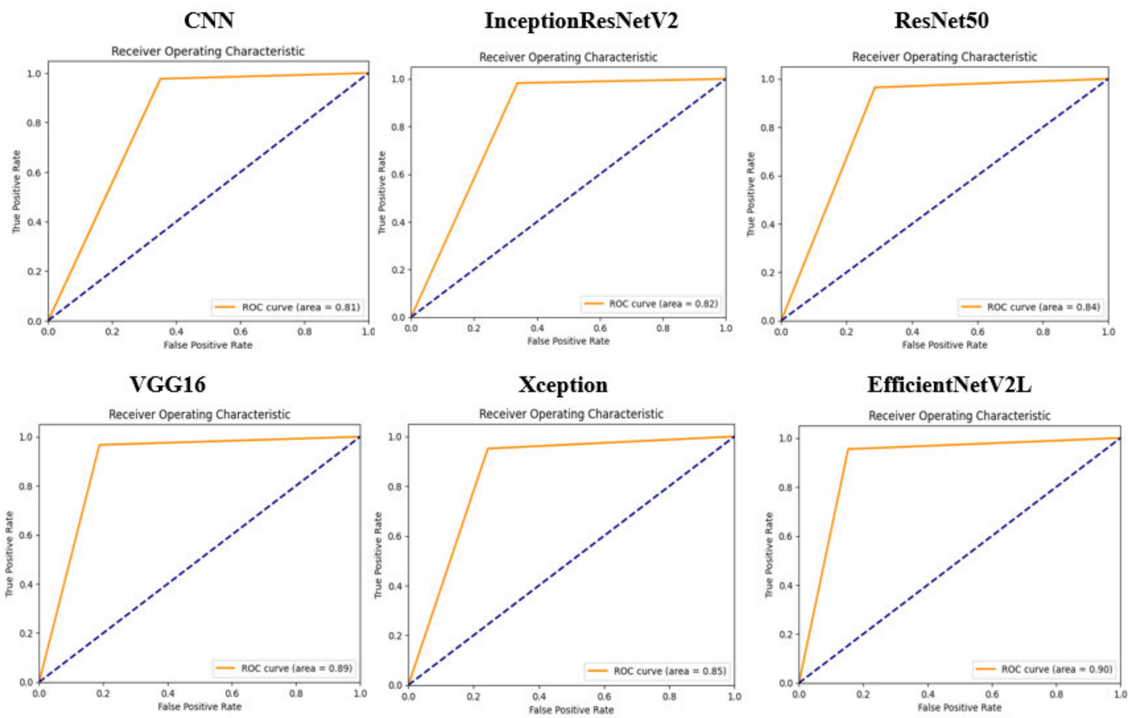

FIGURE 11. Performance regarding ROC-AUC curve.

G. COMPARATIVE ANALYSIS OF ALL MODELS

Table 12 shows the outcomes of all models used in this study. Results are provided for accuracy, precision, recall and F1 scores. The suggested model outperforms every other model, including CNN, InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L, which are all fine-tuned to get the best performance with the available dataset. However, compared to all other models in use, the performance of the proposed model is superior.

Figure 10 shows a visual representation of how well each deep learning model performed for pneumonia detection. It can be observed that the proposed EfficientNetV2L model performed exceptionally well with impressive performance evaluation metrics.

H. EVALUATION USING HYPERPARAMETER TUNING

Hyperparameters in deep learning are variables that are either manually set by the user or chosen via hyperparameter optimization methods. A deep learning model's architecture and optimization are determined by these parameters. Hyperparameters have an impact on the learning process itself, as opposed to model parameters, which are learned during the training phase. Table 13 provides the best performance of each model as obtained using hyperparameter tuning.

TABLE 15. Performance comparison of EfficientNetV2L model with existing state-of-the-art models.

Ref.	Year	Technique	Dataset	No. of samples	Accuracy	Precision	Recall	F1 Score
[52]	2020	CNN	Chest x-ray	5856	83.38%	-	-	-
[53]	2021	VGG16	Chest x-ray	5856	88.78%	89.21%	93.33%	91.22%
[54]	2019	Xception	Chest x-ray	5856	82.00%	85.00%	-	-
[55]	2021	CNN	Chest x-ray	5856	84.18%	78.33%	94.05%	85.66%
[56]	2023	ResNet50	Chest x-ray	32227	78.00%	-	-	-
[57]	2020	VGG16	Chest x-ray	400	74.20%	95.10%	72.30%	82.20%
[58]	2022	Xception	Chest x-ray	5856	75.87%	-	-	-
[59]	2023	ResNet50	Chest x-ray	30227	64.00%	-	-	-
[60]	2022	Inception-ResNetV2	Chest x-ray	5857	-	-	-	82.00%
Proposed	2023	EfficientNet-V2L	Chest x-ray	5856	94.02%	94.40%	97.24%	95.80%

TABLE 16. Compare analysis of different technologies with the proposed approach.

Literature	Main Contributions
[61]	The study uses the VGG-16 convolutional neural network as a feature extractor for chest X-ray images, achieving effective feature representation and impressive accuracy and sensitivity in identifying pneumonia cases.
[62]	This study evaluates the effectiveness of deep learning techniques in identifying pneumonia from chest X-ray images, providing valuable insights into the operation of these algorithms and highlighting their potential as a reliable tool for pneumonia identification, urging further research and development.
[63]	This study presents a novel approach that integrates adaptive and altruistic Particle Swarm Optimization (PSO) with deep feature selection techniques for precise pneumonia detection from Chest X-rays, thereby enhancing the performance of deep learning models and aiding in improved pneumonia diagnosis and treatment planning.
[64]	The authors introduce a transfer learning method using channel attention deep convolutional neural network architectures for accurate pediatric pneumonia diagnosis, demonstrating its potential in improving diagnostic accuracy in pediatric healthcare settings by detecting pneumonia in chest X-ray images.
[65]	The study explores a deep learning model that uses transfer learning techniques for segmented X-ray images, demonstrating improved performance and potential for accurate pneumonia diagnosis, providing valuable insights for the advancement of diagnostic tools in the healthcare industry.
[66]	This research aims to develop a deep attention network for analyzing chest X-ray images for pneumonia diagnosis. The model effectively identifies and focuses on relevant features, improving pneumonia detection accuracy and efficiency, making it a valuable tool for healthcare professionals.
[67]	The study presents a deep learning ensemble framework model that uses large-scale CT scan and X-ray image datasets for accurate COVID-19 and pneumonia detection, demonstrating enhanced accuracy and highlighting the potential of integrating diverse imaging modalities for efficient and reliable diagnosis.
[68]	This study focuses on a deep learning-based image classification model for accurate pneumonia detection, enhancing diagnostic capabilities and facilitating timely medical interventions, thereby improving the quality of care.
Proposed	The proposed research focuses on the implementation and evaluation of six models for pneumonia detection, including Inception, Xception, VGG16, CNN, ResNet50 and EfficientNetV2L, providing insights for the development of accurate and reliable diagnostic tools in the healthcare sector.

I. ROC-AUC OF MODELS PERFORMANCE

To purify insights and render prudent judgments, proposed data-driven solutions leverage an array of neural network architectures, encompassing CNN, InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L. Evaluation of model efficacy is conducted through ROC-AUC and PR-AUC metrics, ensuring resilient classification performance and a thorough grasp of model dynamics, exemplified in Figures 11. The precision parameter delineates the accurately predicted values vis-à -vis the total predictions, elucidating the discernment of identified attacks in real-world systems, elucidated in the result section tables. EfficientNetV2L, distinguished by its exceptional scalability and efficiency, notably excels in attaining a commendable ROC-AUC, underscoring its proficiency in addressing intricate classification challenges with optimal efficacy.

J. RESULTS OF K-FOLD CROSS-VALIDATION

For performance validation, k-fold cross-validation is carried out for the proposed approach. Table 14 shows the results with the training time and for $k = 10$, respectively. Results indicate that the performance of the proposed models varies slightly across different folds, however, its average performance is better than other models.

K. COMPARATIVE ANALYSIS WITH EXISTING MODELS

Comparative analysis is carried out between various models from existing literature that performed pneumonia detection using deep learning models. These studies are selected because they use the same dataset for experiments and can be used as the benchmark to evaluate the performance of the proposed EfficientNetV2L model. Table 15 highlights the performance variations of different deep learning models and approves the superior performance of the EfficientNetV2L model.

L. COMPARE ANALYSIS OF DIFFERENT STUDIES WITH PROPOSED APPROACH

Although several approaches and technologies have been investigated in this study, as shown in Table 16. The proposed approach integrates the finest features to provide a thorough and effective solution to the issue at hand. To develop a cutting-edge strategy that has the potential to dramatically improve the area by combining insights and methods from these many sources. The contribution of the proposed method demonstrates the value of multidisciplinary cooperation and innovative problem-solving, paving the way for promising future advances.

V. CONCLUSION

In conclusion, the classification of digital chest X-ray images using deep learning techniques for pneumonia detection is proposed. The research implemented several CNN models, including CNN InceptionResNetV2, Xception, VGG16, ResNet50 and EfficientNetV2L using Python programming and using the tools Google Colab. Initial experiments showed promising results, with the models achieving accuracy rates of 88.78%, 88.94%, 90.7%, 91.66%, 87.98% and 94.02%. These accuracy values indicate the potential of these models to serve as decision support tools for pneumonia diagnosis based on X-ray images. However, the paper acknowledges some limitations and highlights the need for further research. One concern is the possibility of overfitting due to the dataset's size. To address this, the authors suggest gathering more data to enhance the model's generalization ability. The paper also emphasizes the importance of exploring various preprocessing techniques and CNN configurations to improve the models' performance. Additionally, data augmentation techniques are proposed to increase the dataset's size, which can aid in better generalization. Furthermore, the authors suggest incorporating additional X-ray datasets that include data labels for various pathologies. This expansion would enable the models to differentiate between different lung abnormalities, enhancing accuracy and reliability. By conducting a series of experiments, want to provide the best pre-trained models and classifiers for use in further research in a related field. The EfficientNetV2L model, which uses chest radiographs for pneumonia detection, offers potential for future advancement in medical imaging and artificial intelligence. It can be improved by incorporating multi-modal data, incorporating clinical information, and exploring transfer learning from related medical domains. The model's interpretability and explainability aspects can address trust and acceptance concerns in clinical settings. Its scalability across diverse populations and demographics is crucial for its effectiveness. The model's potential for early detection and prognosis prediction could significantly impact patient outcomes.

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(Mudasir Ali, Mobeen Shahroz, and Urooj Akram contributed equally to this work.)

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