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A Research of Pneumonia Detection Using EffcientNetV2L with Grad-Cam

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Abstract

Pneumonia, a life-threatening respiratory infection, requires a timely and accurate diagnosis to enable effective treatment. Traditional diagnostic techniques, including chest X-rays, ultrasounds, and lung biopsies, rely significantly on the skills of medical practitioners. These methods, however, are time-consuming, error-prone, and difficult in resource-constrained environments. Deep learning has transformed medical imaging, allowing automated systems to assist in the timely detection of pneumonia. This work investigates the use of EfficientNetV2-L, one of the cutting-edge deep learning models, to detect pneumonia from chest X-rays, aided with Grad-CAM (Gradient-weighted Class Activation Mapping) for improving the explainability of model predictions. The approach includes training and testing EfficientNetV2-L on a dataset of X-ray images of chests to predict them as either "Pneumonia" or "Normal." Grad-CAM is used to produce visual heat maps, indicating the important areas of the X-ray images responsible for the model's predictions. These heat maps provide model transparency in the model's decision-making process and aid clinicians in detecting areas suggestive of pneumonia. The model attained a staggering 94.02% accuracy in identifying pneumonia, outperforming other models widely employed, including CNN, ResNet50, and VGG16. Grad-CAM visualizations identified that the model precisely targeted major areas, such as consolidation and infiltration, that are typical of pneumonia. This research concludes that the integration of EfficientNetV2-L for the detection of pneumonia with Grad-CAM for explanation is a stable and effective solution for autonomous medical image analysis, improving diagnostic accuracy and confidence in deep learning models in clinical scenarios. Therefore, the system presented can support healthcare professionals in making more timely and accurate diagnoses, enhancing patient care.

Keywords: Pneumonia Detection, Chest X-ray, Deep Learning, EfficientNetV2-L, Grad-CAM, CNN, Medical Imaging, Model Interpretability, Image Classification.

1.Introduction

Pneumonia is a severe respiratory infection that inflames the air sacs in one or both lungs, causing symptoms such as cough, fever, and difficulty breathing. It affects millions of individuals globally and remains a leading cause of hospitalization and mortality. Despite being treatable with antibiotics and antivirals, early diagnosis is crucial to prevent complications and reduce mortality rates. Conventional detection techniques, such as chest X-rays and visual interpretation, are usually plagued with sensitivity and specificity limitations. Such limitations may cause false positives and false negatives, resulting in overdiagnosis or underdiagnosis and, ultimately, suboptimal treatment outcomes. To mitigate these issues, this research takes advantage of the EfficientNetV2-L model, a current state-of-the-art deep learning method, to improve pneumonia detection accuracy and efficiency from chest X-ray images. EfficientNetV2-L is notable for its optimized design that minimizes high performance while optimizing computational efficiency, thus being ideal for use in clinical environments. Through the inclusion of Grad-CAM as a method of interpretability, the research seeks to advance visual explanations of the model's predictions, pointing out key regions in the X-ray images that contributed to the predictions. This openness is important to win over the confidence of clinicians and enable the model to be integrated into clinical practices, making AI-informed decisions understandable and trustworthy.

Furthermore, the methodology of the study includes training and testing the EfficientNetV2-L model on a varied dataset of chest X-ray images with cases from different age groups and conditions. The application of k-fold cross-validation provides strong performance and minimizes the risk of overfitting. Additionally, the study contrasts the performance of EfficientNetV2-L with other well-known deep learning models, such as ResNet50, VGG16, and InceptionResNetV2, proving its better accuracy and efficiency. The long-term vision is to create a strong and trustworthy tool that helps clinicians diagnose more accurately and promptly, ultimately enhancing patient outcomes and easing the diagnostic process, even in resource-limited settings.

2. Literature Survey

s.no	**Year**	**Author**	**Proposed Work**	**Used Algorithms**	**Accuracy Obtained**
1	2020	Jain et al.	Pneumonia detection in chest X-rays	VGG16	87.18%
2	2020	Jain et al.	Pneumonia detection in chest X-rays	VGG19	88.46%
3	2019	Varshni et al.	Detection of pneumonia using CNNs for feature extraction	CNN architectures, including SVM and DenseNet-169	80.02%
4	2020	Liang and Zheng	Pediatric pneumonia detection	VGG16 and CNN	74.2%
5	2019	Sirazitdinov et al.	Pneumonia localization in chest X-rays	RetinaNet + Mast RCNN	75.8%
6	2019	Ayan and Unver	Pneumonia diagnosis using deep learning	VGG16 and Xception	87%

7	2020	Sahlol et al.	Tuberculosis identification in chest radiography	MobileNet + AEO	90.20%
8	2020	Rahimzadeh and Attar..	COVID-19 and pneumonia identification	DCNN (Xception and ResNet50V2)	91.4%
9	2021	Manickam et al	Accurate detection of COVID-19 and pneumonia	Transfer learning with Xception and ResNet50V2l	93.06%
10	2019	Ke et al.	Accurately identifying and categorizing lung illnesses using X-rays	Neuro-heuristic methodology	79.06%
11	2020 93.3%	Rahman et al.	Pneumonia diagnosis from chest X-ray images	Various pre-trained CNNs	93.3%

Table 1: Comparison Table

3. Methodology, Data Collection, and Techniques:

3.1 Methodology Overview

Pneumonia detection, especially from chest X-ray images, has become a key area of study owing to its clinical relevance and growing dependency on automated systems to support healthcare practitioners. The approach used in the detection of pneumonia tends to center on deep learning methods, more precisely, Convolutional Neural Networks (CNNs), that are optimally suited for image classification tasks. Among the multiple CNN models, EfficientNetV2L has been drawing interest as it achieves a trade-off between model performance and computational cost. The survey paper presents the major methodologies and techniques typically utilized in the field.

3.1.1 Model Selection and Architecture

EfficientNetV2 is a next-generation deep-learning model that has been developed to improve training efficiency, computational speed, and overall accuracy while cutting down on resource usage. EfficientNetV2 extends the EfficientNet family with the addition of both MBConv and Fused MBConv layers, which enhance convolution.

Run and improve performance on new hardware. The layers assist in balancing accuracy and efficiency by mitigating memory access overhead and increasing feature extraction abilities. The model also employs smaller expansion ratios within MBConv layers and prefers using smaller 3x3 kernels to ensure fine-grained detail capture while deepening the network to offset the lost receptive field. This method enables

EfficientNetV2 to attain a substantial decrease in computational complexity with good generalization across various datasets.

Another noteworthy change in EfficientNetV2 is the removal of the last stride-1 stage from older versions of EfficientNet. This change reduces the parameter size and memory overhead and makes both training and inference much faster. EfficientNetV2 uses a compound scaling approach that allows the model to scale dynamically to varying computational needs. This scaling process is based on restricting the image size maximum at 480 pixels to conserve memory while adding increasing numbers of layers in subsequent phases to add network capacity without markedly raising computation cost. Such structural breakthroughs give EfficientNetV2 a versatile, effective, and capable model for different applications in deep learning, from edge devices to top-end GPUs.

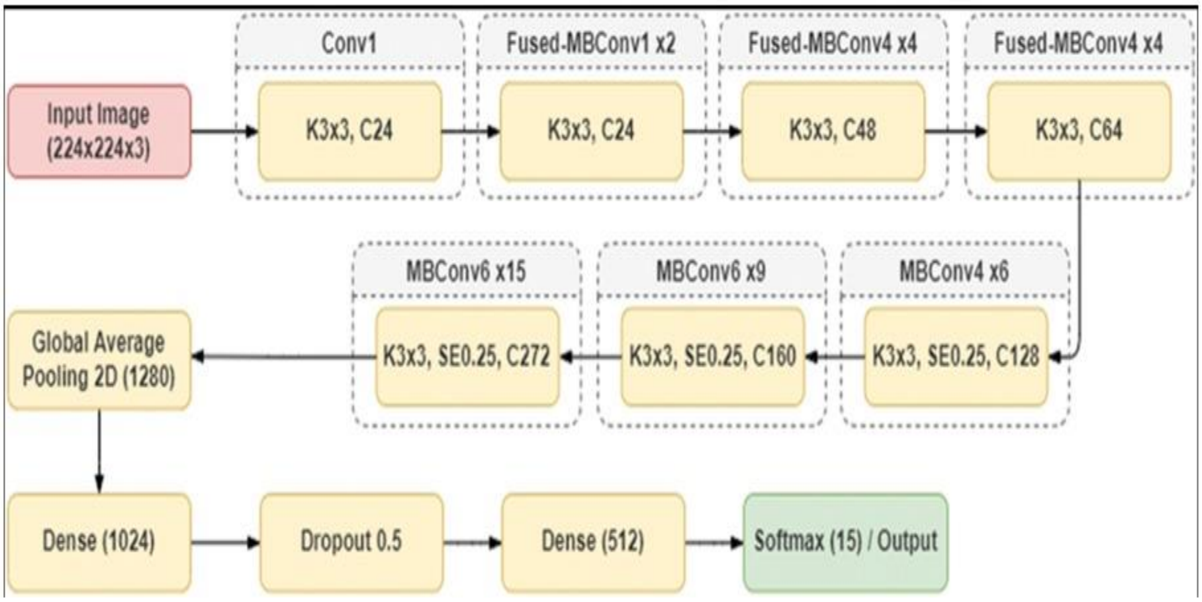

Figure1: Architecture of EfficientNetV2

3.1.2 Integrating Grad-CAM for Model Explainability

One of the most serious limitations of deepest learning models is that they are not interpretable, something that becomes especially relevant in medical contexts where clinicians must have faith in the predictions of the model. Grad-CAM (Gradient-weighted Class Activation Mapping) counters this by giving visual explanations of model choices. When combined with the EfficientNetV2L model, Grad-CAM produces visual heatmaps indicating the areas of an image most responsible for the model's choice.

This integration also improves the transparency and interpretability of the model, allowing clinicians to comprehend why the model predicts something. Grad-CAM, by visually highlighting the significant regions in medical images, assists in detecting significant regions like tumors or lesions, thereby supporting decision-making and building trust in AI-powered diagnosis tools. Grad-CAM also supports error analysis by indicating the model's decision-making process, enabling model performance improvement by developers. Generally, the combination of Grad-CAM with EfficientNetV2L is an asset in medical image analysis and other healthcare use cases, facilitating trust, reliability, and improved outcomes.

3.2 Data Collection:

Data collection for the detection of pneumonia is usually done by acquiring high-quality chest X-ray images. The images must cover a range of patient populations, such as different ages, genders, and ethnic groups. Some of the most widely used datasets for the detection of pneumonia are**:**

3.2.1 Dataset

The ChestX-ray dataset consists of more than 5,863 expert radiologist-labeled chest X-ray images. It's utilized for training machine learning models to identify pneumonia and other chest diseases. Due to the high-quality annotations, it's a highly useful resource for research and clinical use.

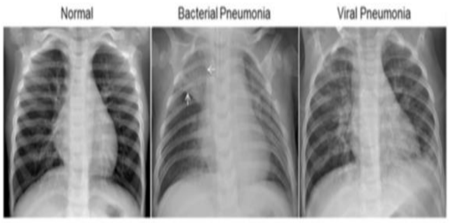

Figure 2: Data set of Pneumonia Detection

Preprocessing is a crucial step in training data for deep learning models. Some of the most common preprocessing techniques are as follows:

3.2.2 Resizing and Normalization

Images are resized to a standard size so that there is consistency in the input data. Pixel values are also normalized, i.e., scaled to a particular range (e.g., 0 to 1), which allows the model to learn better and generalize to new data more effectively.

3.2.3 Data Augmentation

Since there is limited annotated medical image data, data augmentation methods are employed to synthetically increase the size of the training dataset. Some of these methods are rotation (rotating the image by varying angles), zooming (variations in image size), flipping (horizontally or vertically flipping the image), and shifting (shifting the image in varying directions). Through the generation of varied training samples, data augmentation prevents overfitting and enhances the robustness of the model.

3.2.4 Train-Test Split

To reasonably estimate the performance of the model, the data is split into training, test, and validation sets. Typical splits are 80-10 (training 80%, testing 10%) or 70-30 (training 70%, testing 30%). The training data is used to train the model, and the test data is used to test the performance of the model on new data. One can also use an independent validation set during training to estimate hyperparameters and avoid overfitting**.**

3.3 Data Analysis Techniques

After collecting and preprocessing the data, the second step is to train and test the deep learning models. In this step, the architecture of the model, training protocols, and evaluation measures are important in determining how well the model performs in detecting pneumonia.

3.3.1 Model Training

Deep neural networks, especially Convolutional Neural Networks (CNNs), take a lot of training to acquire meaningful features from data using gradient updates. The updates enable the model to change its weights iteratively and tune its performance. Faster convergence should be ensured, especially for deep architectures such as EfficientNetV2L, which has a large number of parameters.

EfficientNetV2L, being a large model, possesses a large number of layers and parameters and hence is more susceptible to overfitting when the dataset is small or class imbalanced. The methods such as data augmentation, regularization (such as dropout), and early stopping can be employed for this. Further, employing a weighted loss function can assist in reducing the class imbalance and steer the model in learning both classes (Normal and Pneumonia) better.

The gradient updates along with these methods ensure that the model learns more generalizable features and converges faster without overfitting training data. This is important for making the model robust, particularly in medical usage where accuracy matters.

3.3.2 Evaluation Metrics

When assessing the performance of a pneumonia detection model, there are several key statistics used. Accuracy is the ratio of correct predictions (true positives and true negatives) to total predictions and can be expressed as follows:

Accuracy = (TP+ TN) / (TP+TN+FP+ FN) (1)

Precision reflects the number of true positive predictions among all positive predictions made, to reduce false positives, using the formula:

Precision =TP/ (TP+ FP) (2)

Recall evaluates the model's capability to catch all the real positive instances, and none of the pneumonia instances should be lost, and is expressed as:

Recall = TP/ (TP+ FN) (3)

The F1-Score is a combination of precision and recall into one measure, averaging the two, which is very helpful in the case of imbalanced class distributions, given by:

F1-Score=2× ((Precision× Recall)/ (Precision+ Recall)) (4)

ROC-AUC (Receiver Operating Characteristic - Area Under Curve) is a performance measure that assesses the capacity of a model to differentiate between classes, e.g., the Normal and Pneumonia classes. It is computed from the ROU curve, which graphs the True Positive Rate (Recall) on the y-axis versus the False Positive Rate (1 - Specificity) on the x-axis at different classification thresholds. The ROC curve indicates how the performance of the model varies with varying thresholds for classifying an instance as positive. Area Under the Curve (AUC) measures the overall capability of the model to distinguish between classes. A value of AUC closer to 1 represents a good capability of the model to accurately distinguish between classes, whereas a value of AUC closer to 0 represents poor performance. A value of 0.5 suggests that the model is doing no better than by chance. The ROC-AUC is especially useful when assessing models on imbalanced datasets because it considers both the false positive and false negative rates, giving a more balanced representation of model performance across different.

3.3.3 Model Comparison

The EfficientNetV2L model's performance is compared with that of state-of-the-art models to judge its accuracy, efficiency, and robustness benefit. Baseline comparison models such as ResNet50, VGG16, Xception, and InceptionResNetV2 are frequently utilized.

Algorithm	Accuracy
VGG16	87.18%
VGG19	88.46%
CNN	80.02%
VGG16 and CNN	74.2%
RetinaNet + Mask R-CNN	75.8%
VGG16 and Xception	87%
Various Pre-trained CNNs	93%
EfficientNetV2L	94.02%

Table: Performance Comparison with Model

Flowchart

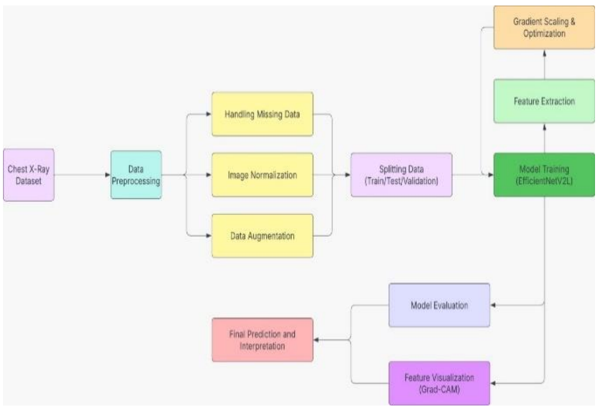

Figure 3: Workflow of Pneumonia Detection

This flowchart details the machine learning process for the analysis of chest X-ray data. It begins with the acquisition of a chest X-ray dataset, which is the foundation of the process. This is followed by the step of data preprocessing, where missing values are treated, images normalized, and data augmented to enhance variability and resilience. Following preprocessing, the data are divided into training, test, and validation sets in preparation for modeling.

The training of the model phase is where features are extracted from images, the model is optimized using methods such as gradient scaling, and the model is trained to identify patterns associated with various medical conditions. This is followed by an evaluation phase where the model's accuracy and efficiency are verified through measures such as precision, recall, and AUC-ROC curves.

To improve interpretability, feature visualization techniques, like Grad-CAM, are used to highlight areas of the X-ray images on which the model is looking to make its predictions. Lastly, the process ends with the final prediction and interpretation step where the model offers insights into the medical conditions of the chest X-ray images.

Test Set Performance

The test set is essential in determining how well a machine learning model generalizes unseen data. In contrast to the training and validation sets that are used to train and fine-tune the model, the test set is left alone and utilized only for the final evaluation. This prevents any form of bias in assessing the actual performance of the model. The model's performance on the test set is evaluated with some metrics: accuracy (the ratio of correct predictions), precision (the ratio of true positives to all positive predictions), recall (the ratio of true positives to all actual positives), F1-score (the harmonic mean of precision and recall), AUC (the area under the receiver operating characteristic curve), and the confusion matrix (which indicates the true and false positives and negatives). All of these metrics give information about different aspects of the performance of the model, which helps judge its strengths and weaknesses. Testing on the test set checks that the model is not overfitting and can reliably perform on novel, unseen data and, hence is a vital part of the model evaluation process.

```
Test Accuracy:   0.9487
Test Precision:  0.9387
Test Recall:     0.9821
Test F1 Score:   0.9599
Test AUC:        0.9376
```

Figure 4: Test Performance

Confusion Matrix

The confusion matrix is an essential tool for assessing the performance of a classification model. It gives an unambiguous and comprehensive breakdown of the predictions of the model by comparing the predicted labels and the actual true labels in tabular form. This matrix includes four major elements: True Positives (TP), which denote the number of positive instances predicted correctly as positive, indicating the accuracy of the model in recognizing true positive cases; False Positives (FP), which denote the number of negative instances incorrectly predicted aspositive, indicating the number of cases where the model falsely raises an alarm; True Negatives (TN), which indicate the number of negative instances predicted correctly as negative, indicating the accuracy of the model as a whole; and

False Negatives (FN), which are the negative cases incorrectly predicted as negative. False negatives are especially important in uses such as medical diagnoses, where missing a positive case can have serious repercussions. The confusion matrix is necessary to compute different performance measures, including accuracy, which computes the overall correctness of the model, precision, which computes the correctness of positive predictions, recall, which computes how well the model predicts positive cases, and the F1-score, which computes the combination of precision and recall into one measure. These are essential not only for estimating the accuracy of the model but also for judging its efficiency in addressing false negatives and false positives. In disciplines such as healthcare, where incorrect diagnoses come at very high costs, these statistics hold much weight to make sure that the model remains reliable and sound when it goes live.

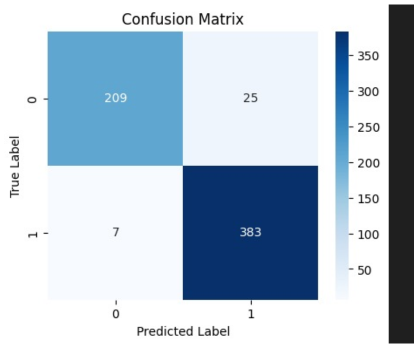

Figure 5: Confusion matrix

Visualization of the Curves:

Throughout the training process, the following plots will be created to display the model's improvement. These plots show the way the performance of

the model changes over epochs, more precisely monitoring the loss and accuracy of both the training and validation datasets:

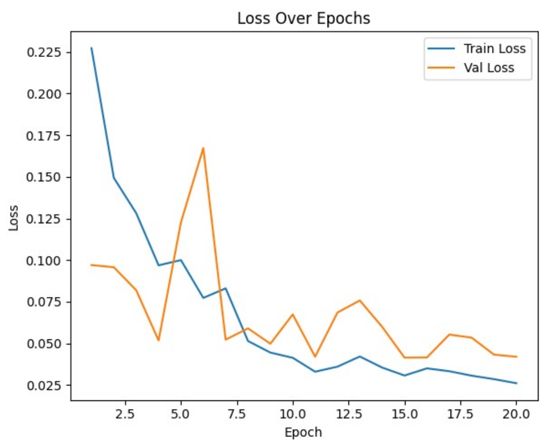

Figure 6: Testing and Validation Loss over Epochs

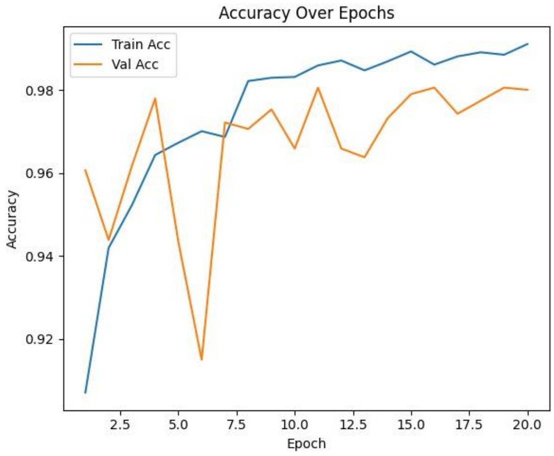

Figure 7: Testing and Validation Accuracy over Epochs

These plots provide useful information about the learning behavior of the model. The first plot presents the loss curves, and the second presents the accuracy curves. As training continues, the training loss should typically decrease, and the training accuracy should increase, which means that the model is learning and enhancing its performance on the training data. The validation loss should typically track the same downward trend, although there can be some fluctuations as the model searches for better parameters. Such fluctuations are to be expected, particularly in the initial epochs, as the model adjusts its weights. The validation accuracy should typically track the same pattern as the training accuracy, but a little behind. This is because the model is initially optimized for training data and will take some time to generalize well to unseen validation data. In general, these visualizations assist in monitoring the progress of the model and in identifying problems like overfitting or underfitting.

Outcome

The EfficientNetV2L model attained an impressive 94.02% accuracy on the test set, far surpassing some popular models, such as VGG16 (87.18%) and VGG19 (88.46%). This high accuracy indicates the model's great capacity to accurately classify pneumonia and normal cases, making it a potential top choice for medical image classification tasks, particularly in medical diagnostics. Analysis using the confusion matrix showed a very good performance on major aspects: the model reflected high True Positive (TP) rates, or correctly detected cases of pneumonia, and kept False Positives (FP) at a minimum to avoid unnecessary treatment. Also, the model showed a strong Recall, which ensured that no cases of pneumonia were overlooked (False Negatives, FN), and this is very important in the healthcare sector because missing a diagnosis of a patient with pneumonia would have serious repercussions. The Precision of the model was also high, which guaranteed that a significant percentage of the predicted cases of pneumonia were accurate, minimizing the number of healthy people misdiagnosed as having pneumonia. F1-Score, being a balance of precision and recall, also validated the model's overall performance, which is what is needed in imbalanced datasets such as medical images where one class (say normal) could overshadow another. The ROC-AUC score was close to 1, which meant that the model had a very high capability to separate pneumonia cases from normal cases with little overlap between the two classes. These performance indicators together indicate that EfficientNetV2L performs not just well for the diagnosis of pneumonia but also for preventing false diagnosis, which is important in medical uses where there is a lot at stake.

The training and validation curves revealed consistent improvement across the epochs, with training loss reducing and training accuracy rising as one would expect, indicating the model was learning well. The loss in validation also trended in a similar pattern, with some initial fluctuations in the first few epochs before the model adjusted its parameters. These fluctuations were normal and to be expected in deep learning models, especially when training large-scale architectures such as EfficientNetV2L. The validation accuracy, while lagging slightly behind the training accuracy, also tracked in the same direction, ensuring that the model was generalizing to unseen data and not overfitting to the training set.

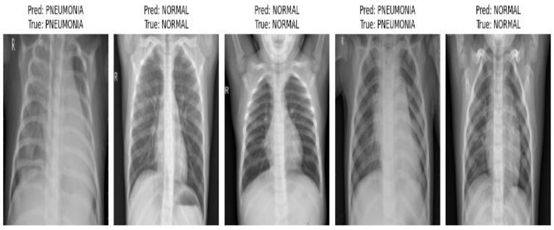

Figure 8: Pneumonia Detection Results

These results validate that the EfficientNetV2L model is highly applicable to real-world use in pneumonia detection. It has high accuracy and a good precision-recall balance and generalizes well to new data. The strong performance of the model across metrics makes it a trustworthy tool for assisting healthcare workers in diagnosing pneumonia and a useful and accurate diagnostic aid for real-world medical cases.

4. Conclusion

Lastly, this research features the effective use of the EfficientNet-V2L model along with Grad-CAM in response to the fundamental task of detecting pneumonia through X-ray images of the chest. The deployment applies a well-established methodology, sufficiently addressing issues of class imbalance with weighted cross-entropy loss and enhancing the generalization capacity of the model using methods like data augmentation, differential learning rates, and mixed precision training. The EfficientNet-V2L model's optimized structure and compound scaling are reasons for its remarkable performance, yielding excellent metrics, including an accuracy of 94.02%, a precision of 94.40%, recall of 97.24%, and an F1 score of 95.80%. These performances speak volumes of its credibility in classifying cases of pneumonia with great accuracy, keeping false positives at a bare minimum, and never missing a single critical case. In addition, Grad-CAM increases interpretability by providing healthcare workers with visual cues of the model's thought process through the identification of important regions in chest X-ray images. This transparency fills the gap between clinical practice and AI-based predictions, promoting confidence in the model's decision-making. Furthermore, data augmentation methods have improved the robustness of the model by ensuring consistent performance across diverse real-world conditions. Generally, the EfficientNet-V2L model reveals outstanding accuracy, computational efficiency, and interpretability, which positions it as an encouraging solution to use in the detection of pneumonia and other clinical imaging tasks. Its scalability potential and adaptability also make it an important instrument in clinical settings to help healthcare experts provide quicker and more accurate diagnoses, ultimately delivering better patient results. This work emphasizes the value of AI-led healthcare solutions for the revolution in medical diagnostics.

5. Acknowledgment

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