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A hybrid deep learning model for pneumonia detection in chest x-ray images

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ABSTRACT

Pneumonia is the leading respiratory cause of illness worldwide and has a significant impact on global health, challenging health systems, especially in resource-constrained scenarios, for immediate diagnosis. Timely and accurate diagnosis is essential to improve management and reduce mortality. Chest X-ray is a frequently used diagnostic tool, valued for its availability, rapidity, cost-effectiveness, and accuracy in detecting respiratory conditions. Recent developments in deep learning (DL) and machine learning (ML) have transformed the field of medical imaging, leading to improved diagnostics. In this context, a novel deep learning approach for automatic pneumonia detection in chest X-ray images is presented. Based on the advanced CNN architecture InceptionV3, this model is more effective at capturing features from data frames and employs LSTM networks to learn sequential data efficiently. This integration enables the model to learn both the spatial information of medical images and the temporal relationships, which enhances classification accuracy. Extensive experiments on public datasets with existing CNN-based models demonstrate that the proposed hybrid architecture surpasses traditional CNN models in accuracy, F1-score, and ROC-AUC-score, achieving 91.67%, 93.47%, and 97%, respectively. These results further support the potential of hybrid deep learning approaches as innovative methodologies for improving diagnostic accuracy and assisting healthcare professionals in lung infection diagnosis.

Contribution/Originality: This study contributes to enhanced pneumonia detection using a hybrid deep learning approach for immediate diagnosis. The results demonstrate an effective method of pneumonia diagnosis in early stages, especially in low-resource conditions, which is useful for learning both spatial and temporal dependencies from medical images.

1. INTRODUCTION

A variety of conditions affecting the respiratory tract fall into the category of lung diseases, including pneumonia, COVID-19, pulmonary fibrosis, and asthma [1]. Pneumonia and the new Coronavirus (COVID-19), among these, have become significant issues in global health. As of April 2024, there have been more than 7 million deaths from COVID-19 and over 700 million recorded infections worldwide [2]. The situation is further complicated by the virus's rapid mutation, resulting in increased transmission and infection rates. While most people are focused on COVID-19 right now, pneumonia is still a serious threat that needs to be detected early to mitigate the adverse effects it poses.

Chest X-ray is one of the most widely used imaging modalities to identify lung diseases. The most common imaging technology used in respirology is the X-ray, which provides fast, inexpensive, and accessible diagnostics and is a mainstay in the evaluation of respiratory pathology [3]. Although X-rays are effective for showing structure and are useful in identifying lung disease, repeated exposure to ionizing radiation may pose health risks. Any one of them may be unnecessary; they may not differentiate between certain diseases, such as different forms of pneumonia or early-stage lung cancer. In these situations, further imaging may be necessary, such as a CT or MRI of the chest, which provides a more detailed look at the lungs, or other tests. Recently, AI and deep learning (DL) have made significant advances, especially in the field of image classification and object detection. This process is a popular form of AI known as DL, utilizing many layers of neural networks that can automatically learn the properties of a dataset. Image classification has been revolutionized by the use of DL, with convolutional neural networks (CNNs) being a key architecture. CNNs operate on a top-down approach to learning features, using convolution to extract features of different levels (e.g., edges, textures, shapes). This technique enables CNNs to make predictions without explicit feature extraction and achieves high levels of accuracy in identification [4].

In particular, a whole new class of models called deep learning (CNNs) has dynamically contributed to substantial improvements in the field of computer vision, largely due to a method called transfer learning [5]. Commonly used object detection models include architectures such as Faster R-CNN [6] or YOLO [7] enrich the tasks with practical applications in areas such as medical imaging, autonomous driving, and surveillance.

The key contributions of this paper are:

- The proposed hybrid model is designed specifically for sequential learning. It takes InceptionV3, and, after feature extraction combined with LSTM, is able to accurately detect pneumonia from chest X-ray images.
- By integrating the spatial learning capabilities of InceptionV3 and the temporal dependency modeling of LSTM, the proposed model improves overall classification accuracy and performance in detecting pneumonia, surpassing traditional CNN-based models.
- Extensive experiments with publicly available chest X-ray datasets are performed to validate the effectiveness and robustness of the proposed hybrid model, achieving significant improvement in detection accuracies compared with current methods.
- The proposed model is reliable, cost-effective, and can aid in the easy detection of pneumonia, which will help medical professionals provide fast and accurate treatment.

The rest of the paper is organized as follows: Section 2 presents an overview of related work on pneumonia diagnostic techniques and approaches based on test summaries of the state of the art in pneumonia detection from chest X-rays using deep learning (DL) and hybrid models for the analysis of medical images. Section 3 provides the hybrid model architecture of InceptionV3 and LSTM for pneumonia detection. Section 4 includes details related to the dataset, evaluation metrics, and a comparative analysis of the proposed approach. Section 5 covers the summary of the paper and discusses insights and potential future work.

2. LITERATURE REVIEW

In this section, we discussed the earlier works where deep learning or hybrid deep learning-based solutions are presented. Shao [8] in the use of CNNs for pneumonia in chest X-ray images, the research not only shows that CNN architecture can achieve better diagnostic accuracy and efficiency, but also demonstrates the power of combining advanced CNNs with medical imaging to automate disease identification. The accuracy of the model is 94.8%. In the study, the model applied medical image classification using the NIH Chest X-ray dataset, which includes 112,120 images.

Sah and Mahmud [9] reviewed the application of generative AI in medical imaging, focusing on pneumonia detection. While no specific model was implemented, the study highlighted the potential of generative models to enhance diagnostic accuracy and discussed challenges in adopting generative AI across datasets like CheXpert and

COVIDx. Singh et al. [10] employ Vision Transformers for pneumonia detection on chest X-ray images, demonstrating the effectiveness of transformer-based models in capturing complex image features. The proposed method outperforms traditional approaches in terms of accuracy and robustness. The model achieved a classification accuracy of 96.5%. The model was tested on the NIH Chest X-ray dataset, demonstrating superior performance compared to traditional CNN-based models. Ortiz-Toro et al. [11] utilize textural features extracted from chest X-ray images for automatic pneumonia detection. The method achieves competitive results and provides an alternative to traditional DL approaches, emphasizing the importance of texture-based features in medical imaging. The model achieves an accuracy of 92.3%. It was tested with the 138 chest X-rays in the Montgomery County X-ray Set, highlighting the significance of using a texture-based approach. The model has a 96.9% accuracy. It was suggested that the model might be more effective after being trained and tested on the ChestX-ray14 dataset, demonstrating the advantages of ensemble methods to improve robustness.

Kundu et al. [12] presented an ensemble of one or more deep-learning models on top for improved pneumonia detection accuracy. Compared with single-model techniques, our ensemble approach is more robust and has less model bias in benchmark datasets, and the best performing model with an accuracy of 96.9%. The ChestX-ray14 dataset, where the model was trained and tested, showed that ensemble approaches could improve robustness. Li [13] proposes a new architecture for chest X-ray images based on an attention mechanism called Attention U-Net for pneumonia detection. This negatively impacts feature localization and contributes to a reduction in diagnostic accuracy, particularly in challenging cases. The model achieves an accuracy of 97.2%. The model was validated using the CheXpert dataset, consisting of 224,316 labeled chest X-rays, demonstrating the impact of attention mechanisms. Hasan et al. [14] discussed advancements in DL techniques for pneumonia prediction from chest X-ray images, analyzing recent models and trends. It highlights the progress in accuracy, efficiency, and deployment feasibility in clinical settings. The model reports accuracy improvements up to 98% using datasets like ChestX-ray14 and RSNA Pneumonia Detection Challenge data.

Meenakshi et al. [15] employ traditional image processing techniques combined with machine learning for pneumonia detection. The approach focuses on feature extraction from X-ray images, offering a cost-effective solution for resource-constrained settings. The model achieved an accuracy of 91.5%. The study utilized a dataset of 5,856 chest X-ray images, collected from publicly available repositories. Sharma and Guleria [16] review analyzing DL methods for pneumonia detection using chest X-ray images. The paper categorizes existing approaches, identifies research gaps, and suggests future directions for improving diagnostic models. The author summarizes results from multiple models that achieved accuracies ranging from 90% to 98%. Datasets like NIH ChestX-ray and RSNA Pneumonia Detection Challenge are frequently referenced.

Another deep-learning framework based on pneumonia detection from chest X-rays is proposed by Solanki and Agrawal [17]. The study emphasizes the role of innovative architectures in achieving high diagnostic accuracy while maintaining computational efficiency. The model accuracy is 95.8%. With a dataset of 5863 chest X-ray images on which the study was conducted, the study also demonstrated how efficient this model could be in real life.

Reshan et al. [18] utilize the MobileNet model for pneumonia detection, demonstrating its suitability for lightweight and real-time applications. This tradeoff is beneficial for mobile healthcare systems where computational resources may be limited. The model achieves an accuracy of 93.4%. The NIH ChestX-ray dataset was used to train the model, highlighting its small size and actual diagnostic speed.

Sharma et al. [19] focused on the detection of pneumonia regions in chest X-rays via image processing techniques. The research describes how effective the segmentation methods are in detecting the exact regions affected by pneumonia. Model detection accuracy is 89%. This has been tested on a dataset of 560 X-ray images captured from local hospitals.

Wahid et al. [20] implement an enhanced Restricted Boltzmann Machine for pneumonia detection. This model achieved an accuracy of 94.7%. Experiments on the CheXpert dataset again demonstrate that the potential of unsupervised learning techniques can effectively mine useful information from a massive amount of known training medical data, validating the model.

Mabrouk et al. [21] combine multiple deep CNNs into an ensemble for pneumonia detection, achieving superior performance. The method highlights the advantages of combining the best of both worlds of various models. The model finished with an accuracy of 96.3%. Then, the model was evaluated using the ChestX-ray14 dataset to highlight: a) the advantages of building an ensemble of models.

For pneumonia detection, the QCSA network is introduced by Singh et al. [22] and Hashmi et al. [23]. It combines high-level feature extraction with classification methods. The model even demonstrates its effectiveness in medical imaging activities and achieves competitive outcomes. The model's accuracy reaches 95.5%. Tested on the RSNA Pneumonia Detection Challenge dataset, it is robust in feature extraction and classification.

Hashmi et al. [23] presented the detection of pneumonia using a compound-scaled deep learning architecture. This architecture scales to many scenarios with different resource constraints for optimal accuracy in diagnostics. The accuracy of the model is 97.1%. Indeed, the scalability of this architecture is demonstrated in a study that applied it to the ChestX-ray14 dataset.

Srivastava et al. [24] proposed Pneumonia Net, where a novel architecture is augmented with effective feature learning for detecting and classifying pneumonia. Empirical results on benchmark datasets show the proposed method to be accurate and robust. This technique accounts for a 96.8% accuracy on the proposed approach. The results were validated with the NIH ChestX-ray dataset and proved to be efficient in multi-class classification.

Chagas et al. [25] designed an IoT-based real-time system for pediatric pneumonia identification through chest X-ray images. The approach integrates edge computing for real-time analysis, providing a scalable solution for remote healthcare settings.

The model achieves an accuracy of 91%. The system was trained using a 585-patient dataset of X-ray images from regional health centers. Kanawade et al. [26] explore a deep learning framework for pneumonia detection, emphasizing the use of lightweight architectures suitable for resource-constrained environments. The model achieved an accuracy of 94.2%. The model was validated on the NIH ChestX-ray dataset, demonstrating its suitability for real-time applications.

Barakat et al. [27] apply machine learning techniques for pediatric pneumonia detection from chest X-rays, achieving high diagnostic accuracy and emphasizing the model's clinical applicability. The model achieved an accuracy of 93.6%. The study used the Pediatric CXR dataset, emphasizing its clinical relevance. Hasan et al. [28] investigate deep-learning techniques for pneumonia detection in COVID-19 patients. The study highlights the role of advanced architectures in distinguishing pneumonia from other respiratory conditions, especially in pandemic contexts. The model achieved an accuracy of 94.5%. The study utilized the COVIDx dataset, demonstrating the importance of tailored architectures for pandemic-specific challenges.

There are some notable gaps and challenges identified in the reviewed literature. Many studies struggle with data imbalance, leading to biased model performance, particularly for minority classes. Additionally, handling variable image sizes and resolutions often introduces inconsistencies in feature extraction. The limited availability of large, diverse, and labeled datasets also restricts the generalizability of the proposed models. Furthermore, ensemble techniques, while improving accuracy, often face issues such as high computational costs and correlated errors. Addressing these gaps requires robust data augmentation strategies, the development of standardized datasets, improved preprocessing techniques, and the refinement of ensemble methods to mitigate error correlations.

Table 1 presents a comparative analysis of existing approaches for pneumonia detection, highlighting the model types, datasets used, and the performance achieved by each method.

Table 1. Comparative analysis of the existing approaches.

Reference No.	Model Type	Dataset	Performance
12	Ensemble of DL Models (e.g., VGG)	Chest X-ray	Accuracy: 96.24%
13	Attention-enhanced CNN	Chest X-ray	Accuracy: 94.6%
15	Image processing techniques	Chest X-ray	Accuracy: 93.2%
17	Custom CNN	Chest X-ray	Accuracy: 95.4%
18	MobileNet	Chest X-ray	Accuracy: 97.62%
20	Enhanced RBM	Chest X-ray	Accuracy: 94.35%
21	Ensemble of Deep CNNs	Chest X-ray	Accuracy: 96.87%
22	QCSA Network	Chest X-ray	Accuracy: 97.18%
23	Compound Scaled DL Model	Chest X-ray	Accuracy: 94.10%
24	Pneumonia Net (Custom CNN)	Chest X-ray	Accuracy: 93.10%
25	IoT-based DL System	PediatricCXR	Accuracy: 92.80%
26	Deep Learning (CNN)	Chest X-ray	Accuracy: 91.28%
27	Machine Learning	Pediatric CXR	Accuracy: 87.23%
28	DL (CNN variants)	COVID-19 CXR	Accuracy: 94.27%

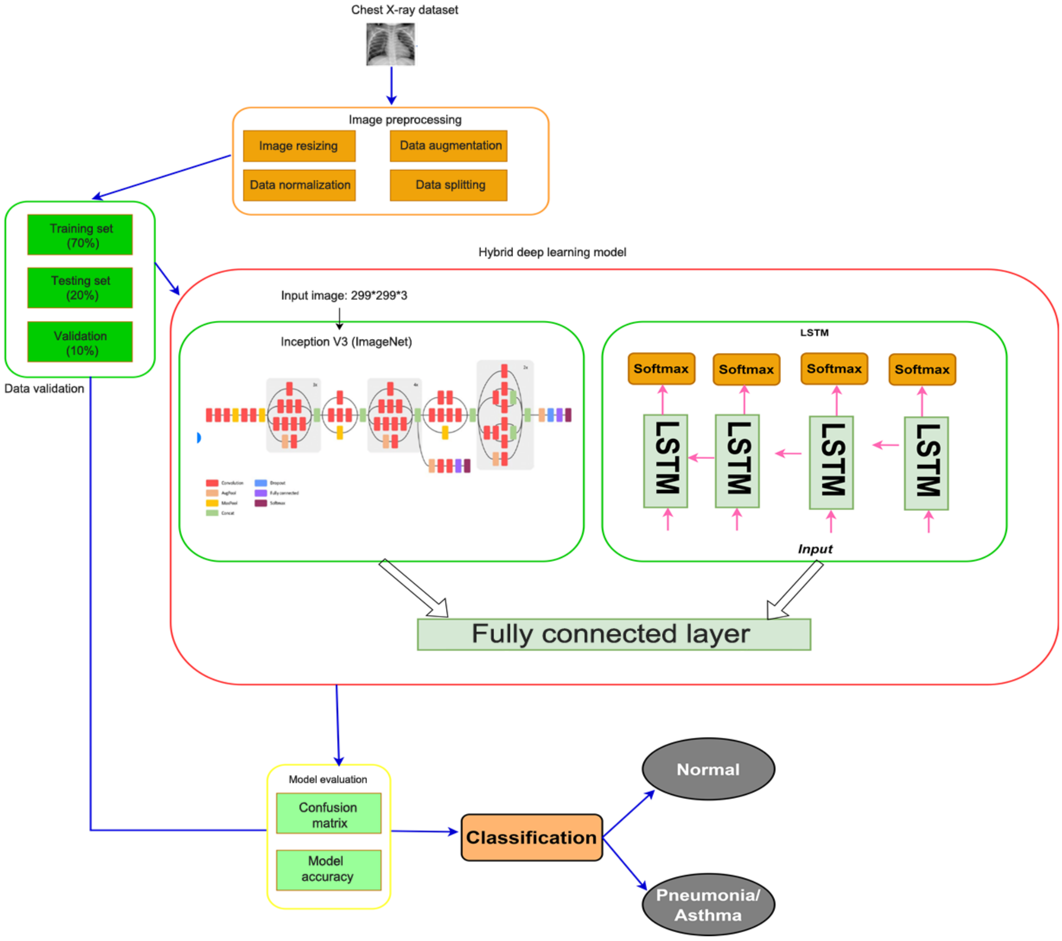

Figure 1. Proposed methodology architecture.

3. PROPOSED METHODOLOGY

A structured methodology is developed for pneumonia detection using the InceptionV3 and LSTM networks. The first step is to find a dataset that is publicly available. This dataset is preprocessed and separated into directories to combine the training, validation, and testing data for model training purposes. This is followed by chaining together preprocessing steps such as image splits, resizing, and augmentations to increase the depth of the dataset and enhance the robustness of the model. The preprocessed images are then loaded via the ImageDataGenerator class, which facilitates data augmentation and prepares data for training. Under this step, medium objects could leverage the InceptionV3 model as a powerful feature extractor that utilizes pre-trained ImageNet weights, allowing the extraction of features with the best possible descriptive potential.

3.1. Dataset

Chest X-ray images (anterior-posterior) were obtained from retrospective cohorts of pediatric patients aged 1 to 5 years at the Guangzhou Women and Children's Medical Centre in Guangzhou [29]. All chest X-rays were performed as standard clinical practice for the patients.

Since all the images have the same resolution, 299x299, a dataset was divided into training, validation, and test sets. It was trained on the training set, rerun with the validation set to check hyperparameters, then finally evaluated using the test set. The Pneumonia dataset contains Normal and Pneumonia images organized into subfolders and arranged into three folders (train, test, and validation). There are two categories (Normal/Pneumonia) and 5,863 X-ray images (JPEG). The training folder contains 5,218 X-ray images, while the testing folder contains 624 X-ray images, with an additional 18 images in the validation folder. Figure 2 and Figure 3 represent the normal images and pneumonia images from our dataset.

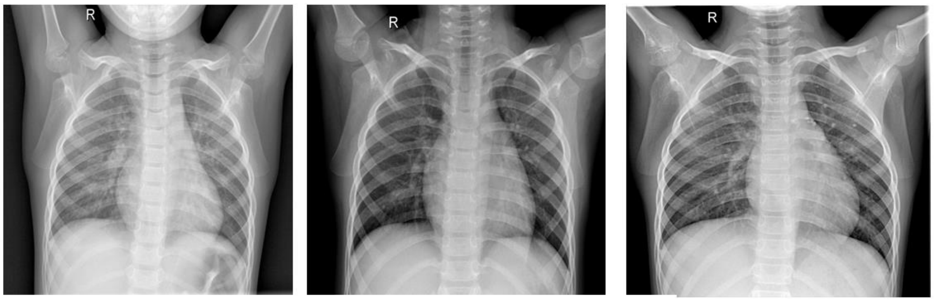

Figure 2. Normal images from the training dataset.

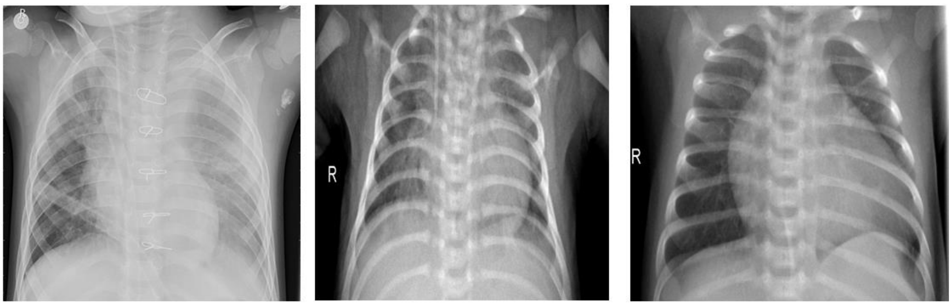

Figure 3. Pneumonia images from the training dataset.

3.2. Data Preparation

The preprocessing part involves preparing the input data to be fed into the model for training, validation, and testing. Data augmentation is used to increase the diversity of the training data by applying random transformations to the images. This helps to improve the model's generalization ability and reduce overfitting. By artificially enlarging the dataset, the model learns to recognize features from a variety of perspectives and variations, thus becoming less likely to memorize the training data. It follows the following steps: Normalizing the images ensures that the neural network receives input in a standard range, improving training stability and performance. A random rotation of the images within a specified range of 20 degrees was applied. Shifting simulates changes in the object position within the frame. This extension is beneficial to make the model more robust to changes in the position of objects.

3.3. Model (InceptionV3 and LSTM)

This development of a deep learning model for image classification uses InceptionV3 as a feature extractor and integrates an LSTM layer to handle sequential dependencies in image data, making it suitable for tasks such as image classification. First, load the pre-trained InceptionV3 model with weights from ImageNet, excluding its top layers to allow customization. The extracted feature maps are then processed by Global Average Pooling, followed by a Fully Connected Layer with 1024 neurons. An LSTM layer with 64 units is utilized, enabling the model to capture temporal relationships across frames. The final output layer contains one neuron with a sigmoid activation function, making it ideal for binary classification tasks.

During the first phase of training, all InceptionV3 layers are frozen to retain pre-trained feature representations while training only the custom layers. The model is compiled using the Adam optimizer with a learning rate of 0.0001 and binary cross-entropy loss. EarlyStopping is used to prevent overfitting by monitoring validation loss, and ModelCheckpoint saves the best-performing model. The model is trained on the dataset for 20 epochs, utilizing data generators for training and validation.

Once the initial training is complete, the InceptionV3 layers are unfrozen, allowing fine-tuning of the entire network. To prevent drastic weight updates, the learning rate is lowered to 1e-5, and the model is recompiled. A second training phase is conducted for 10 more epochs using the same dataset and callbacks. Finally, the best-performing model (saved during training) is loaded for evaluation or deployment. This approach effectively combines transfer learning and sequential modeling, making it well-suited for applications of image sequence analysis.

This model is trained on this prepared dataset and then evaluated on a test set, measuring performance using accuracy, precision, recall, and F1 score. Results visualization includes plotting of training history and confusion matrix, which helps understand the effectiveness of the model as well as areas for improvement.

4. RESULT AND DISCUSSION

The method proposed was executed with Python 3.10, utilizing additional libraries such as Pandas, TensorFlow, Matplotlib, and Keras. The system operated on Windows 11 with an Intel(R) i7 @ 3.10 GHz, NVIDIA GeForce RTX 3050 GPU, and 64 GB of RAM.

Table 2. Classwise distribution of chest x-ray samples.

Phase	Normal	Pneumonia	Total
Training	1342	3876	7895
Testing	234	390	916
Validation	9	9	24
Total	1585	4275	8835

The class-wise distribution of chest X-ray samples in the training, testing and validation phases is shown in Table 2. From these images, 8,145 are used for training the network, which further contains a majority class of 1,342 Normal and 3,876 Pneumonia cases. There are 234 Normal and 390 Pneumonia cases for the testing set (i.e., each case has 1 to N images), making a total of 916 images to evaluate the model's performance. We use a small validation set (24 images) for tuning model parameters. This dataset contains a total of 8,835 images, ensuring a well-balanced class representation and achieving better performance from the model.

Table 3. Training Parameters.

Training Parameters	Values/Types
Epochs for training	30
Batch size	32
Optimizer learning rate Adam	0.0001
Zoom and shear range Fill mode	25%
Rescale Horizontal flip	1./255
Shuffle	True
Class mode	Categorical

The training parameters are summarized in Table 3. The model was trained for 30 epochs, with a batch size of 32 (for efficient gradient updates). For stable convergence, we used the Adam optimizer with a learning rate of 0.0001. Data augmentation techniques (zoom 25%, shear 25%, rescale 1./255) and horizontal flipping were used to improve generalization. Lastly, to avoid overfitting, the dataset was shuffled (True) while training, and a categorical class mode was submitted for multi-class classification.

Table 4. Performance of the proposed models.

Parameters	InceptionV3 (ImageNet)
Accuracy	91.67
Precision	91.63
Recall	95.38
F1 Score	93.47
AUC	97.00
Training time (20 epochs)	3680 s

Performance metrics of the InceptionV3 (ImageNet) model for chest x-ray classification are shown in Table 4. The overall correctness (accuracy) of the classification is 87.12%, which shows that the model is working considerably well. Its precision (85.64%) indicates how well it avoids false positives, while recall (81.73%) indicates how well it predicts positive cases. With an F1 score of 83.64%, we achieve a balance between precision and recall, making it much easier to trust our predictions. AUC observation (94.00%) describes strong discriminative power. During training, the model took only 3,680 seconds (30 epochs) to complete computing, which is a rather good speed.

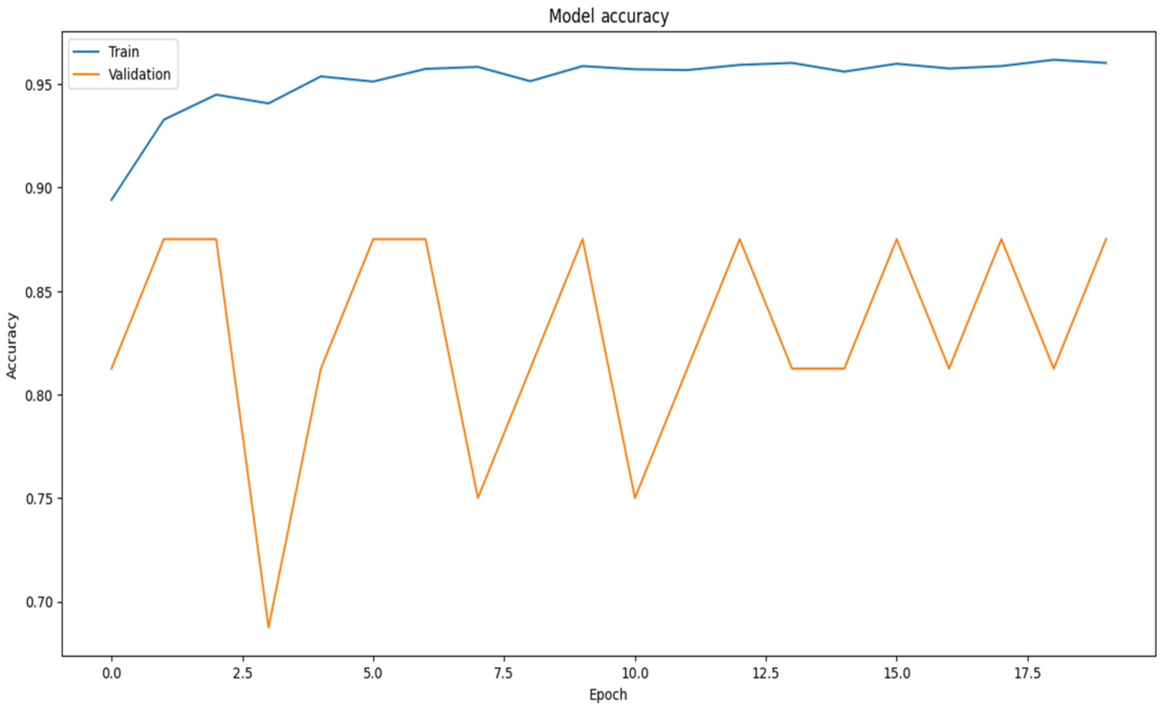

Figure 4. Accuracy of the proposed model.

Figure 4 illustrates the accuracy graph over epochs, which consists of 30 epochs, and the accuracy reaches 92%. Training accuracy typically increases as the model learns from the training data, while validation accuracy indicates how well the model generalizes to unseen data. Ideally, both lines should rise and stabilize, signaling effective learning.

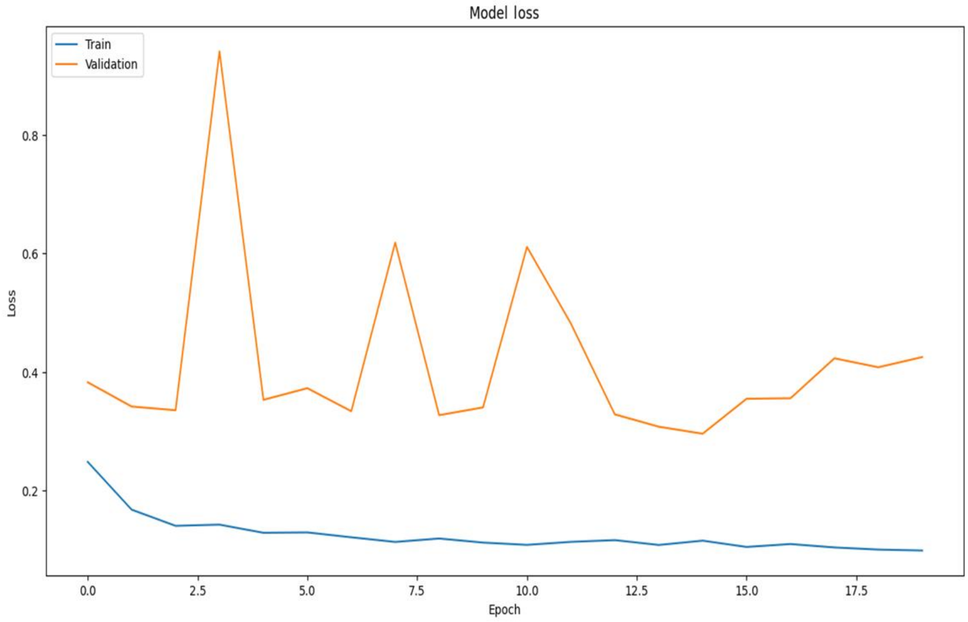

Figure 5. Loss of the proposed model.

Figure 5 illustrates a loss graph that shows a decrease in both training and validation loss, indicating that the model's predictions are improving. If training accuracy rises while validation accuracy plateaus or declines, this suggests overfitting, where the model memorizes the training data instead of generalizing.

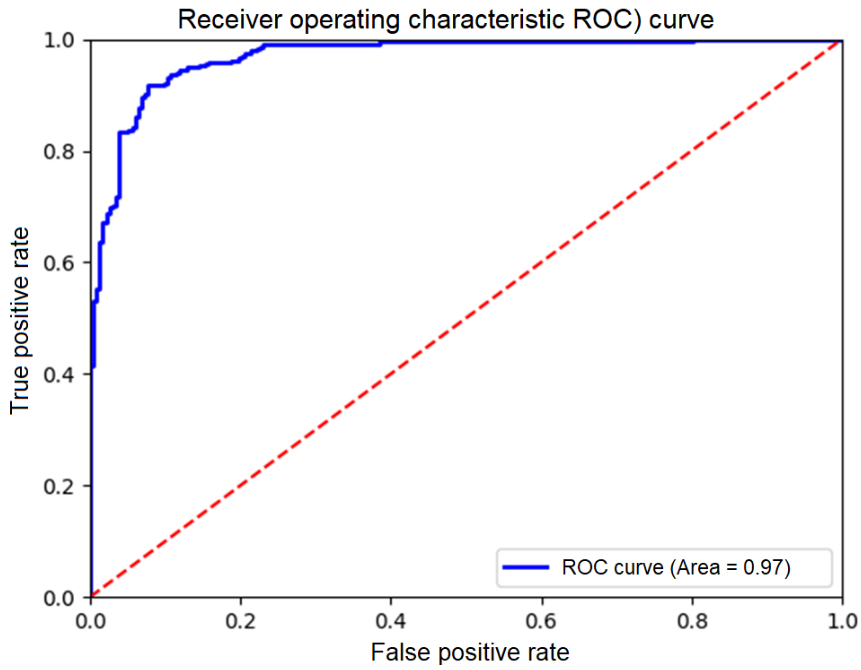

Figure 6. False positive rate of the proposed model.

Figure 6 illustrates the ROC curve for the pneumonia detection model, showing a curve that starts at the point (0,0) and ends at (1,1). As the decision threshold for classifying images as pneumonia (positive class) or normal (negative class) is adjusted, the true positive rate (sensitivity) increases, but so does the false positive rate.

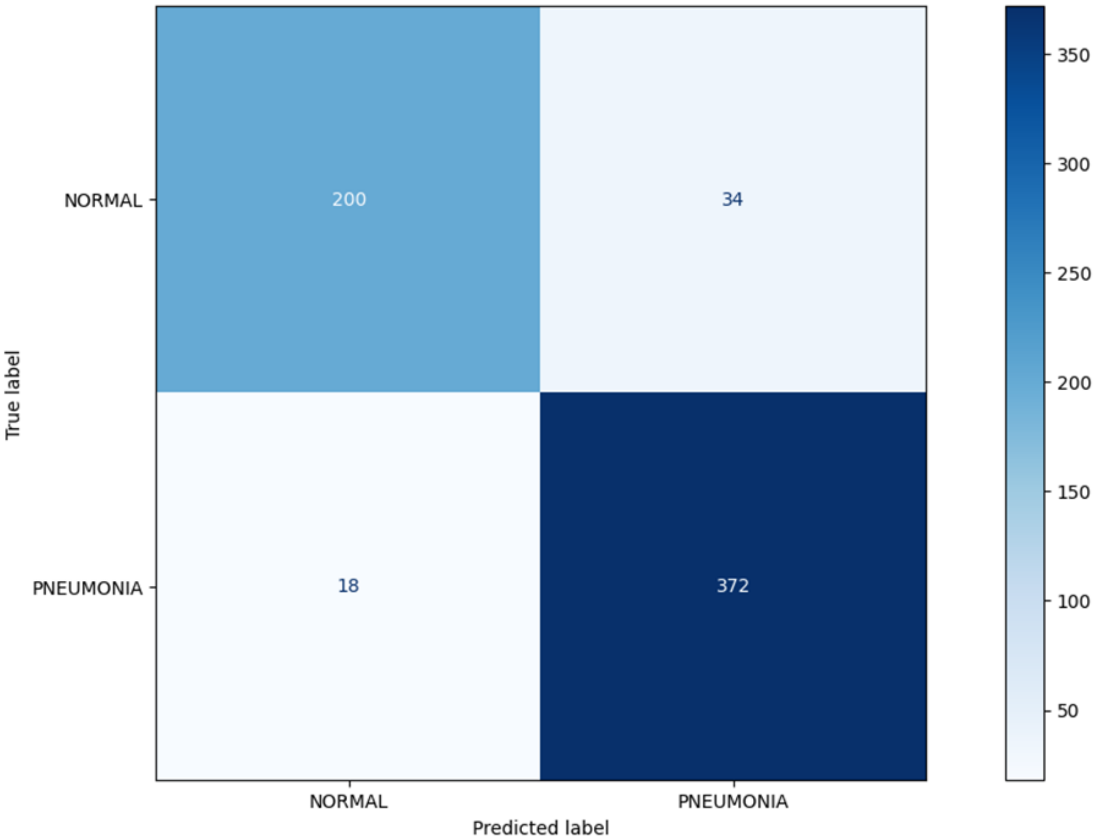

Figure 7. Confusion matrices.

Figure 7 depicts the confusion matrix that illustrates model performance on accurately classifying pneumonia and normal cases. True positives (372) and true negatives (200) refer to cases that were correctly classified, while false positives (34) and false negatives (18) refer to misclassified cases. As shown, the model analysis correctly classifies diseases with low misclassification and high accuracy in distinguishing pneumonia from other diseases. The effectiveness of the model is highlighted by the heatmap, which visually represents the calculations done by the model.

The InceptionV3 + LSTM model demonstrated strong performance on the test dataset, achieving an accuracy of 91.67%, indicating that it correctly classified the majority of the samples. The precision of 91.63% suggests that most of the positive predictions were correct, while the recall of 95.38% shows that the model successfully identified a high proportion of actual positive cases. An F1 score of 93.47% confirms a balanced trade-off between precision and recall, which corresponds to the imbalance in false positives and false negatives observed during experimentation. The AUC score is 97.00%, indicating the model's reliable discriminative capacity to differentiate between classes, demonstrating very good discrimination performance. This model appears to have an effective optimization process, with a training time of 3680 seconds across 30 epochs, making it suitable for addressing real-world problems such as pneumonia diagnosis in medical imaging classification.

5. CONCLUSION

This study contributes by demonstrating the benefits of a hybrid deep learning (DL) approach that leverages the deep feature extraction capabilities of InceptionV3 and the sequential learning advantages of LSTM networks in automating pneumonia diagnosis from chest X-ray images. The performance of the proposed model is notable, achieving 91.67% accuracy, 93.47 F1 score, and a ROC-AUC of 97, indicating it outperforms traditional CNN-based approaches. The model provides an effective method for early-stage pneumonia diagnosis, particularly in low-resource settings, and is capable of learning both spatial and temporal dependencies from medical images. The results highlight the higher efficacy of hybrid DL techniques in attaining superior diagnostic accuracy, which can assist clinicians in managing respiratory diseases more effectively. This work advances AI-powered medical imaging solutions, potentially leading to more reliable and accessible diagnostic devices. Future research could involve applying this approach to different datasets and integrating explainable AI (XAI) models for more accurate and interpretable pneumonia classification. Additionally, incorporating multi-modal data, including medical records and clinical metadata, could further enhance disease classification accuracy.

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