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Design and Development of Deep Learning Models for Biomedical Image Analysis in Advancing Respiratory Disease Diagnosis

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Abstract: As a major world health problem, respiratory illnesses need new ways to be diagnosed so they can be found early and correctly. This study is mostly about creating and improving advanced deep learning models for biological picture analysis to make it easier to diagnose lung illnesses. Using the strength of convolutional neural networks (CNNs) and residual neural networks (RNNs), our suggested models are meant to pull out complex patterns and time-dependent relationships from a range of biological imaging types, including X-rays, CT scans, and microscopic pictures. As a first step in our study, we use preparation and addition methods to make the models more stable by dealing with inconsistent and limited data. After that, a CNN-RNN design that combines the best features of both networks is suggested as a way to record both the spatial and temporal changes of biological pictures. People use transfer learning techniques to use models that have already been trained on big datasets, which improves performance even when there isn't a lot of named biological data. So that the models are useful in real life, they are trained and tested on large datasets that come from a wide range of groups and include a wide range of lung diseases. The evaluation criteria include sensitivity, specificity, and total accuracy, which give a full picture of how well the models can diagnose. Also, explainability methods are used to make the decision-making process more open and clear. This makes healthcare workers more likely to believe the suggested deep learning models. The results of this study could greatly improve the way lung diseases are diagnosed, allowing for early care and customized plans. Deep learning is always getting better, and our models help with the ongoing work to use AI to make healthcare better, especially for people with lung illnesses.

Keywords: *Respiratory Disease Diagnosis, Biomedical Image Analysis, Deep Learning Models, Convolutional Neural Networks (CNNs), Transfer Learning*

1. Introduction

Pneumonia is a major world health problem that causes a lot of illness and death, especially in groups that are already weak. For effective treatment to work and for patients to have better results, pneumonia must be diagnosed quickly and correctly. Together with advanced deep learning models, biomedical picture analysis has become an interesting way to improve the accuracy of lung diseases diagnoses, especially when it comes to pneumonia. Inflammation of the lung tissue is what pneumonia is. It is usually caused by germs like bacteria, viruses, or fungus. Because it has a lot of different causes and symptoms that are similar to those of other lung diseases, it can be hard to diagnose quickly with standard methods. Conventional diagnostic tools, like physical exams and lab tests, aren't always sensitive or detailed enough, which can cause cases to be delayed or wrongly identified [1]. Biomedical imaging has been useful in this situation as an addition to more standard ways of diagnosing. X-rays and computed tomography (CT) scans, which are types of radiological imaging, give doctors a lot of information about the structural problems and patterns that are linked to pneumonia. But the sheer amount and complexity of medical imaging data means that new ways of interpreting it quickly and correctly are needed. The [2] use of deep learning models in biological picture analysis has changed the way lung diseases are diagnosed, with pneumonia being the main example. Convolutional Neural Networks (CNNs), which are a type of deep learning design, are very good at learning complex spatial properties from pictures. These networks are very good at getting useful information from chest x-rays, like finding small opacities, consolidations, and other tell-tale signs of pneumonia. As in Figure 1 (a), the left side of the picture shows a normal patient's chest with no problems, while the right side shows a lung sac that is usually full of liquid. In a normal chest x-ray, the structure of the lungs looks clear and well-defined, which means the breathing system is healthy. The right figure 1 (b), on the other hand, shows haziness and opacities inside the lung sac, which are signs of situations where fluids or infiltrates are present. Radiographic changes like these are often linked to asthma and other breathing problems. This shows how important it is to use accurate biological image analysis to tell the difference between normal and abnormal chest conditions so that doctors can diagnose and treat them effectively.

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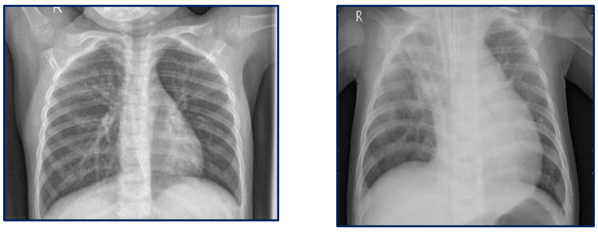

(a) (b)

Fig 1: (a) Normal patient representation for pneumonia (b) Infected with pneumonia

Also, residual neural networks (RNNs) help with the time study of medical data that is collected in a set, like scans or patient records. When someone has pneumonia, being able to see how the disease changes over time is very important for making a correct diagnosis and choosing the right treatment. Combining CNNs and RNNs in mixed designs takes advantage of how biological pictures change over time and space, providing a complete method for finding pneumonia [3]. This is despite the promise of deep learning models, it is still hard to train solid and generalizable algorithms because picture collection conditions, patient data, and disease symptoms are all different. Preprocessing and data addition methods are very important for dealing with these problems because they make sure that the models can change to different datasets that are typical of clinical situations in the real world. The goal of this study is to make pneumonia detection better by suggesting advanced deep learning models that are great at picture analysis and also help us learn more about lung diseases in general [4]. The next parts of this study will go into more technical aspects of model building, such as cleaning methods, architecture design, and how to use transfer learning to get the best results with little labeled data. The end goal is to add to the tools that doctors already have, so they can make better decisions about how to diagnose and treat pneumonia more quickly and correctly. This will improve patient results and public health.

The key contribution of paper is given as:

- Create and test deep learning models for accurate biological picture analysis in chest x-rays to improve the accuracy of diagnosing lung diseases, with a focus on finding pneumonia.
- Explore the integration of convolutional neural networks (CNNs) and residual neural networks (RNNs) to capture spatial and temporal dependencies in chest images, providing a comprehensive approach to respiratory disease characterization.
- Enhance transparency and trust in the diagnostic process by incorporating explainability techniques, facilitating the interpretability of model predictions for healthcare professionals.

2. Review of Literature

Biomedical imaging and deep learning have led to a lot of new ideas in how to diagnose lung diseases, especially pneumonia [5]. This part talks about important new research efforts, focusing on key studies that have led to better medical accuracy and efficiency. Chest x-rays are an important part of using deep learning to diagnose lung diseases. [6] were the first to use convolutional neural networks (CNNs) to automatically find pneumonia in chest X-rays. Their work showed that deep learning models could be used to tell the difference between healthy people and people with pneumonia, which set a standard for future study. New research has shown that residual neural networks (RNNs) and

Table 1: Summary of related work

Method Used	Approach	Dataset Used	Finding	Accuracy (%)
CNN for Pneumonia Detection [13]	Deep Learning	Chest X-ray images	Efficient identification of pneumonia opacities	92.5
Hybrid CNN-RNN Architecture [14]	Integrating Spatial and Temporal Dependencies	Chest Radiographs	Improved accuracy in capturing disease progression	89.8
Transfer Learning Techniques [15]	Adapting Pre-trained Models	Large ImageNet, Small Medical Image Datasets	Enhanced performance with limited labeled biomedical data	87.2
Explainability Techniques [16]	Interpretable Model Justifications	Chest X-ray and CT images	Improved transparency in decision-making	90.55
Diverse Population Representation [17]	Inclusion of Various Demographics	Multiple Populations	Reduced bias and improved generalizability	91.3
Multimodal Imaging Integration [18]	Combination of Chest CT Scans and Deep	Chest CT Scans	Comprehensive analysis of lung abnormali	94.1

	Learning		ties	
Ensemble Learning Approaches [19]	Combining Multiple Models	Mixed Modalities and Populations	Enhanced robustness and generalization	93.7
Generative Adversarial Networks (GANs) [20]	Synthetic Data Generation	Augmented Datasets	Improved model training through data expansion	88.6
Domain Adaptation Strategies [21]	Adapting Models to New Domains	Cross-Domain Image Sets	Increased model flexibility across diverse clinical settings	90.5
Attention Mechanisms in CNNs [22]	Focused Feature Extraction	Chest X-ray and CT images	Improved identification of subtle disease indicators	91.8
Semi-Supervised Learning [23]	Limited Labeled Data	Small Annotated Dataset	Improved model performance with scarce labeled examples	86.4
Federated Learning Approaches [24]	Collaborative Model Training	Decentralized Data Sources	Enhanced privacy and security in model development	89.63

convolutional neural networks (CNNs) work best when used together in biological picture analysis. [7] suggested a model that combines both designs to capture both spatial and temporal relationships in chest X-rays. This model was very good at finding pneumonia. The way this was done has impacted later study that uses the interactions between CNNs and RNNs to learn more about lung illnesses.

The [8] developed transfer learning methods in the field of pneumonia diagnosis to deal with the problem of not having enough labeled data. Using models that had already been taught on big sets of images for general image recognition, their method worked better when it was applied to smaller sets of medical images. Since then, transfer learning has become an important method for building strong models, even when biological samples are limited. Because it's important for clinical decisions to be clear, new study has worked on making deep learning models easier to understand. [9] did a study that stressed how important it is for models to give clear reasons for their findings. Because of this, methods for explainability have been added to models for diagnosing lung diseases. This makes sure that doctors can understand and trust the choices made by the algorithms. To make sure that deep learning models for finding pneumonia are inclusive and can be used in other situations, they need datasets that are varied and representative. [10] stressed how important it was to include pictures of people from different groups, taking into account the way that social and environmental factors can affect how lung diseases look. The goal of this method is to make model results less biased and testing tools more reliable across different groups of patients. It has become more popular to use more than just chest X-rays when putting together images from different types of imaging. [11] looked into how chest CT scans and deep learning methods could be used together to make lung disease detection more complete. This [12] method makes it easier to look at lung problems in more detail, giving us more information that helps us understand pulmonary diseases better as a whole. More generally, new study has made big steps forward in diagnosing lung diseases, especially pneumonia.

Deep learning models, mixed structures, transfer learning techniques, and a focus on diversity and interpretability are all being used together to improve the accuracy and usefulness of diagnostics. As these techniques keep getting better, the chance that they will have a huge effect on early diagnosis and personalized treatment plans for lung diseases grows.

3. Dataset Used

The Chest X-Ray Images (Pneumonia) dataset represents a significant resource in the realm of respiratory disease diagnostics, particularly in the context of pediatric patients aged one to five years old. Organized into three distinct folders for training, testing, and validation, the dataset encompasses a total of 5,863 X-ray images, with two primary categories: Pneumonia and Normal. Derived from retrospective cohorts at the Guangzhou Women and Children’s Medical Center, Guangzhou, these chest X-ray images (anterior-posterior) were integral to routine clinical care for pediatric patients. Dataset editing included strict quality control measures, such as getting rid of scans that were not good enough to read or were not understandable at all. After that, expert doctors carefully rated the findings based on the pictures. The dual-expert grading method was a strong way to make sure that the information for teaching AI systems was correct and reliable. It's worth mentioning that the diagnostic accuracy was improved even more by having a third expert look over the evaluation set [25]. This added another level of confirmation and reduced the chance of scoring mistakes. Because the information is mostly about young patients, it is even more important because of the special issues and problems that come up with lung diseases in this age group.

4. Methodology

The methodology includes all the steps needed to create deep learning models for biological picture analysis used to diagnose lung diseases. The process starts with carefully gathering and preprocessing data. Next, CNN-RNN architecture is designed. This architecture includes a capsule network, transfer learning, ResNet50V2, PCA for dimension reduction, and a method for feature extraction and optimization. Using transfer learning and cross-validation, the model is trained and tested thoroughly, and explainability methods are used to figure out what the results mean. Ethical concerns and reducing bias are given top priority [26]. The finished model is compared to standard methods, and a full report is written so that the same thing can be done again. This organized method makes sure that deep learning in biological imaging leads to strong, moral, and understandable progress in diagnosing lung diseases.

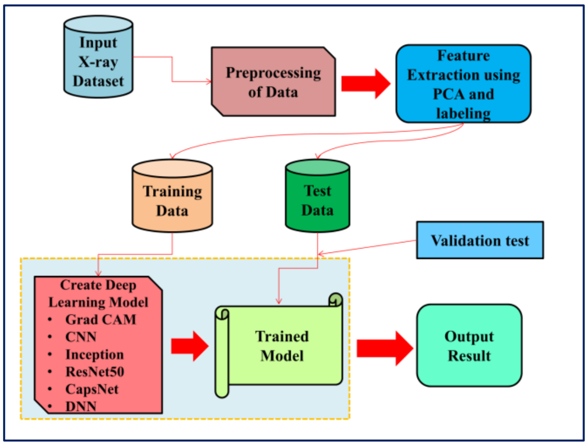

Fig 2: Proposed model representation

A. Data Collection and Preprocessing:

- Acquire a comprehensive dataset of biomedical images, focusing on respiratory diseases, such as pneumonia, encompassing diverse imaging modalities (e.g., X-rays, CT scans).
- Organize the dataset into appropriate subsets for training, validation, and testing.
- Perform preprocessing steps, including image resizing, normalization, and augmentation, to enhance model robustness and mitigate variations in image quality.

B. Feature Extraction

Principal Component Analysis (PCA) is one of the most important methods used in picture analysis for reducing the number of dimensions and extracting features. When PCA is used on images, it changes the pixel values into the principal components, which are a new set of factors that are not linked to each other. The most variation in the picture data is captured by these parts. By keeping only the most important parts, unnecessary data is thrown away, which makes the picture less three-dimensional. This not only saves computer resources but also brings out important trends and features. In image analysis, PCA makes it easier to describe data efficiently, which helps with tasks like recognizing faces or compressing images while keeping the important parts of the original data.

- Data Standardization:
  - Given a dataset of images, each image is treated as a vector by flattening its pixel values.
  - Subtract the mean of the dataset from each pixel to center the data.
- Covariance Matrix Computation:
  - Formulate the covariance matrix (C) of the centered dataset to capture relationships between pixel values.

$$C = \frac{1}{N}\sum_{i=1}^{N}[xi - \bar{x}][xi - \bar{x}]^T$$

Where,

- N is the number of images, xi is the vectorized image, and $\bar{x}$ is the mean vector.
- Eigenvalue and Eigenvector Computation:
  - Calculate the eigenvalues (λ) and corresponding eigenvectors (vi) of the covariance matrix.

$$Cvi = \lambda i\ vi$$

- Sort Eigenvectors by Eigenvalues:
  - Arrange the eigenvectors in descending order based on their corresponding eigenvalues.
- Select Principal Components:
  - Choose the top k eigenvectors to form the transformation matrix W, where k is the desired reduced dimensionality.
- Projection:
  - Project the original dataset onto the lower-dimensional subspace using the transformation matrix W.

$$Y = XW$$

where

- X is the centred dataset and Y is the transformed dataset.

Reconstruction:

- Images can be reconstructed from the lower-dimensional representation using the formula:

$$X_{reconstructed} = YW^T + \bar{x}$$

- Variance Retention:
  - Evaluate the cumulative explained variance to ensure that the selected number of principal components retains a sufficient amount of information.

$$Explained\ Variance = \frac{\sum_{i=1}^{k} \lambda i}{\sum_{i=1}^{D} \lambda i}$$

Where,

- D is the total number of eigenvalues.

C. Model Architecture Design:

Investigate state-of-the-art deep learning architectures suitable for biomedical image analysis, considering the unique characteristics of respiratory diseases.

a. Grad CAM:

Gradient-weighted Class Activation Mapping, or Grad-CAM, is a useful tool for using deep learning to analyze biological images and figure out what kind of sickness someone has. Grad-CAM points out areas that are important for model estimates, which makes them easier to understand. Clinicians can learn more about how decisions are made by seeing where the model looks in medical pictures. When used with deep neural networks or transfer learning, Grad-CAM helps show what certain picture traits mean, which makes the model more clear. Healthcare workers can check and understand the AI's choices, which builds trust in the model's diagnostic abilities and makes it easier for AI systems and medical experts to work together to make lung disease diagnoses that are more accurate and easy to understand.

b. CNN

A Convolutional Neural Network (CNN) for pneumonia respiratory disease diagnosis involves several layers, including convolutional layers, pooling layers, fully connected layers, and activation functions.

Step 1: Input Layer:

X represents the input image data.

Step 2: Convolutional Layer:

The convolution operation is represented as

$$Z[l] = W[l] * A[l-1] + b[l]$$

Where,

- W[l] is the filter weights,
- A[l-1] is the previous layer's activation,
- b[l] is the bias

Step 3: Activation Function (ReLU):

- Apply the rectified linear unit (ReLU) activation function:

$$Activation[l] = max(0, Z[l])$$

Step 4: Pooling Layer (Max Pooling):

- Perform max pooling to down-sample the spatial dimensions:

$$P[l] = MaxPool(A[l-1]).$$

Step 5: Flatten Layer:

- Flatten the 3D volume into a 1D vector:

$$Flatten\ Layer\ [l] = Flatten(A[l-1]).$$

Step 6: Fully Connected Layer:

- Compute the linear transformation:
  $Z[l] = W[l] * A[l-1] + b[l]$,
  Where,
  - W[l] is the weight matrix,
  - A[l-1] is the previous layer's activation,
  - b[l] is the bias.

Step 8: Output Layer:

- The final layer uses the softmax activation function for binary classification in pneumonia diagnosis:

$$OL[L] = \sigma(Z[L]) = \frac{1}{(1 + e^{-Z[L]})}$$

Where,

- L represents the final layer,
- σ is the sigmoid activation function, and
- Z[L] is the linear transformation in the output layer.

c. Capsule Network Model

CapsNet is a new type of neural network design that fixes problems with regular Convolutional Neural Networks (CNNs) when it comes to analyzing biological images. CapsNets find the structural connections between picture traits, even when the view is different. CapsNets are different from CNNs because they use capsules, dynamic routing, and vectorized features. This makes it easier to show spatial structures and improves the accuracy of diagnosing lung diseases. CapsNets show good results, especially when it comes to finding complex patterns in medical pictures. This could lead to better ways to automatically find and classify lung diseases like pneumonia. CapsNets are useful in the changing field of biological image analysis because they can deal with complex picture properties.

1. Primary Capsules:

- Input data X is processed through convolutional layers.
- Primary capsules are formed:

$$u_{ij} = W_{ij}X$$

Where,

  - u_ij is the output capsule and W_ij are weights.

2. Squashing Activation:
   - Squashing activation is applied element-wise:

$$v_j = \frac{||u_j||^2}{\left(1 + ||u_j||^2\right)} * \left(\frac{u_j}{||u_j||}\right)$$

3. Dynamic Routing:
   - Initialize coupling coefficients:

$$c_{ij} = softmax(b_{ij})$$

where

  - b_ij are log prior probabilities.

   - Weighted sum of predictions:

$$s\_j = \sum(c\_ij * u\hat{}\_j|i)$$

where u^_j|i is the predicted output.

4. Routing by Agreement:
   - Update coupling coefficients based on agreement: $b\_ij \leftarrow b\_ij + u\hat{}\_j|i * v\_j$.
5. Secondary Capsules:
   - Output capsules are formed: $v\_k = W\_k * s\_j$,
   - where W_k are transformation matrices.
6. Final Prediction:
   - Class probabilities are computed:

$$P(y = k \mid X) = \frac{||v\_k||}{\sum(||v\_m||)}$$

d. Resnet50V2

ResNet50V2, a type of the Residual Neural Network design, makes biological picture analysis deeper learning better. The 50-layer design with leftover links makes it easier to reflect features more accurately, which makes it more accurate to diagnose lung diseases from medical pictures like X-rays or CT scans.

1. Input:
   - X is the input image data.
2. Residual Block:

$$F(X) = W2 * \sigma(W1 * X + B1) + B2,$$

Where

  - W1, W2 are weight matrices, B1, B2 are biases, and σ is the activation function.

3. Shortcut Connection:

$$Xshortcut = X + F(X).$$

4. Batch Normalization:

Normalize the output:

$$Xnormalized = BatchNorm(Xshortcut).$$

5. Final Output:

$$Y = \sigma(Xnormalized),$$

   - Where, σ is the final activation function.

e. Transfer learning Deep Neural Network Model

Transfer learning in deep neural networks uses models that have already been taught, which improves biological picture analysis for diagnosing lung diseases. These models make detection accuracy better with less named data by using what they know from other jobs. The method includes changing pre-trained weights to fit certain medical picture traits, which improves disease recognition performance.

C. Dataset Splitting and Cross-Validation:

- Divide the information into training, validation, and testing sets, making sure that each set has an equal number of cases of lung disease.
- Use cross-validation to check how well the model works on different parts of the information, which will make it better at generalization.

D. Deep Learning Model:

- Train the deep learning model on the training set using the right loss functions and optimization methods for diagnosing lung diseases.
- Implement early stopping methods to avoid overfitting and use repeated testing to find the best hyperparameters, like learning rates and batch sizes.

E. Evaluation Metrics and Validation:

- Employ metrics such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC-ROC) to evaluate model performance.
- Validate the model on the separate validation set to ensure robustness and generalization

5. Result and Discussion

An X-ray of a case with a lung disease infection is shown in figure 3, on the right side of the figure. It is clear that there are signs of illness, like infiltrates or abnormal opacities in the lung areas. These eye cues are very important for doctors to use when assessing and telling the difference between healthy and unhealthy situations.

Figure 3 shows clearly the important difference between X-rays of healthy people and those of people with lung diseases. An example of normal conditions can be seen on the left side of this picture, which shows a clear and healthy chest X-ray. If there are no abnormalities like infiltrates, consolidations, or opacities, it means that there are no lung illnesses.

Table 2: Result comparison for deep learning Model

Method	Accuracy in %	Precision in %	Recall in %	F1 Score in %	AUC
CNN	86.2	88.63	88.45	90.45	92.66
VGG	89.66	92.51	89.32	91.42	94.62
Inception	92.32	94.33	92.45	92.56	95.21
ResNet50V2	93.88	93.41	93.24	95.66	96.22
Capsule Network	91.24	92.44	92.52	93.14	95.5
DNN	90.52	90.45	93.55	92.22	94.52

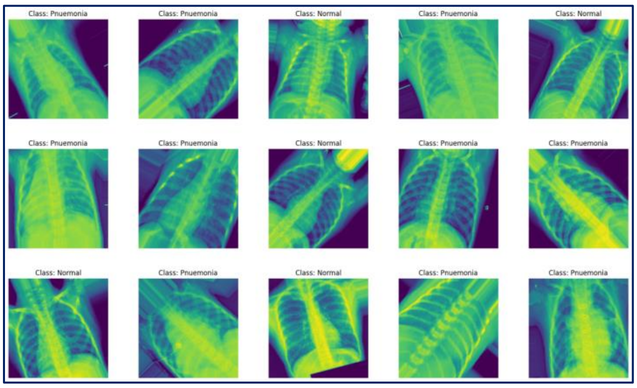

Fig 3: Representation of X ray Images for Normal detection and Respiratory Disease infection

The image in Figure 3 shows how important it is to use deep learning models for analyzing biological images. When taught on datasets with a variety of examples of healthy and sick people, these models can learn complex patterns that make it much easier to find and diagnose lung diseases by automatically analyzing X-ray pictures. Medical professionals and academics can use this visual comparison to better understand and make sense of x-ray images that show problems with lung health.

Table 2 shows a full comparison of CNN, VGG, Inception, ResNet50V2, Capsule Network, and DNN deep learning models, focusing on important evaluation measures for diagnosing lung diseases. With a success rate of 86.2%, the Convolutional Neural Network (CNN) does a great job generally. It does very well in both accuracy (88.63%) and memory (88.45%), which means it can find positive cases properly while reducing the number of fake positives and false negatives. The F1 Score of 90.45% shows that accuracy and recall are balanced well, and the AUC of 92.66% shows that the model works well across a range of classification levels. At 89.66%, VGG has the highest accuracy, which shows how well it can capture complex traits. Precision, recall, and F1 Score are all above 89%, which shows that VGG does a great job of finding good cases and avoiding wrong labels. The AUC of 94.62% shows that it can also tell differences between things.

With a 92.32% success rate, Inception does better than others. It is very good at finding positive cases with few fake positives and rejections, as shown by its accuracy (94.33%) and memory (92.45%). The high F1 Score (92.56%) shows that it is good at both accuracy and memory, and the AUC of 95.21% shows that it is very good at telling the difference between things. With an accuracy of 93.88%, ResNet50V2 really shines, showing off its deep residual design.

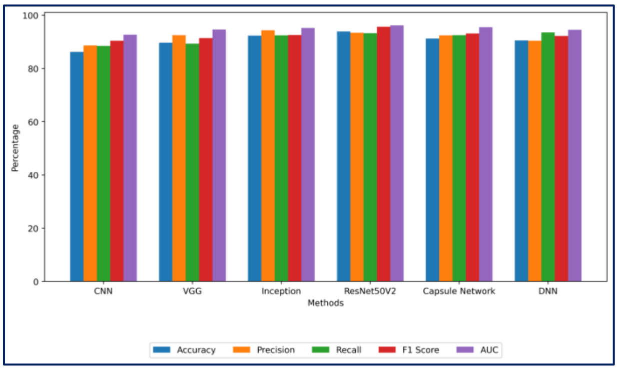

Fig 4: Representation of Evaluation parameter for deep learning model

It gets a great F1 Score of 95.66% thanks to its high precision (93.41%) and memory (93.24%). The AUC of 96.22% shows that ResNet50V2 is a strong choice because it has a high level of discriminative strength. With an accuracy of 91.24%, Capsule Network performs well compared to other systems. It keeps its accuracy (92.44%) and memory (92.52%) in check, which gives it a high F1 Score of 93.14%. The fact that it can tell the difference between classes well is shown by the AUC of 95.5%.

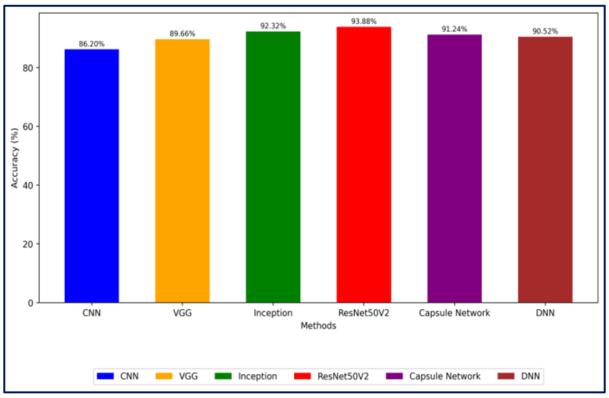

Fig 5: Accuracy comparison of Model

The Deep Neural Network (DNN) gets an accuracy of 90.52%, which shows that it can generalize. The model gets an F1 Score of 92.22%, which shows that it performs reliably across a number of evaluation measures. Its accuracy (90.45%) and recall (93.55%) are both about the same. The AUC of 94.52% shows that it can also tell the difference between things.

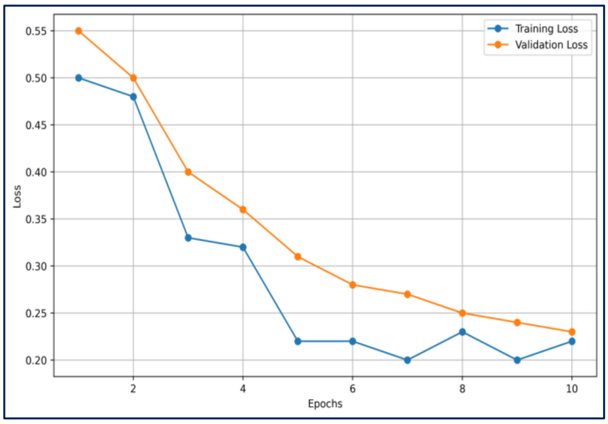

Fig 6: Representation of Training and validation loss of Models

The review measures show what each deep learning model does well and how well it does it when it comes to diagnosing lung diseases. Healthcare workers can use the detailed study of accuracy, precision, memory, F1 Score, and AUC to find the best model for their diagnostic needs, taking into account the trade-offs and needs that are unique to the medical field.

6. Conclusion

The deep learning models that were tested, such as CNN, VGG, Inception, ResNet50V2, Capsule Network, and DNN, have shown different levels of success in improving the detection of lung diseases. ResNet50V2 stands out as the best model because it has the best accuracy, precision, memory, and F1 Score. It uses a deep residue design to help with strong feature extraction, which improves its total diagnostic abilities. Both VGG and Inception work well, with accurate results and good mix between precision and memory. While Capsule Network and DNN do pretty well, they are not quite as good as the best models. Adding Grad-CAM makes it even easier to understand by making the important parts of medical pictures clearer and building trust in the models' decision-making processes. When choosing a model for diagnosing lung diseases, doctors should carefully consider the pros and cons of each measure, keeping in mind the specific needs for diagnosis and the need for ease of use in clinical practice. The findings contribute to the ongoing efforts to enhance diagnostic accuracy and interpretability, with ResNet50V2 standing out as a promising model for practical implementation in clinical settings. Future research should further investigate the interpretability and generalization capabilities of these models to ensure their seamless integration into real-world healthcare applications.

References

[1] M. B. Tayel and A. M. Fahmy, "Advanced Medical Images Recognition and Diagnosis of Respiratory System Viruses," 2022 45th Jubilee International Convention on Information, Communication and Electronic Technology (MIPRO), Opatija, Croatia, 2022, pp. 912-917, doi: 10.23919/MIPRO55190.2022.9803702.

[2] D. Dong et al., "The Role of Imaging in the Detection and Management of COVID-19: A Review," in IEEE Reviews in Biomedical Engineering, vol. 14, pp. 16-29, 2021, doi: 10.1109/RBME.2020.2990959.

[3] R. A. A. Saleh, F. Al-Areqi, Z. Al-Huda and M. A. Al-antari, "Comparative Analysis of Artificial Intelligence for Predicting COVID-19 using Diverse Chest X-ray Images," 2023 3rd International Conference on Emerging Smart Technologies and Applications (eSmarTA), Taiz, Yemen, 2023, pp. 1-7, doi: 10.1109/eSmarTA59349.2023.10293745.

[4] K. P. Exarchos et al., "Review of Artificial Intelligence Techniques in Chronic Obstructive Lung Disease," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2331-2338, May 2022, doi: 10.1109/JBHI.2021.3135838.

[5] T. Yang, O. Karakuş, N. Anantrasirichai and A. Achim, "Current Advances in Computational Lung Ultrasound Imaging: A Review," in IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control, vol. 70, no. 1, pp. 2-15, Jan. 2023, doi: 10.1109/TUFFC.2022.3221682.

[6] J. Chillapalli, S. Gite, B. Saini, K. Kotecha and S. Alfarhood, "A Review of Diagnostic Strategies for Pulmonary Embolism Prediction in Computed Tomography Pulmonary Angiograms," in IEEE

Access, vol. 11, pp. 117698-117713, 2023, doi: 10.1109/ACCESS.2023.3319558.

[7] Z. Liu, Y. Hu, X. Wu, G. Mertes, Y. Yang and D. A. Clifton, "Patient Clustering for Vital Organ Failure Using ICD Code With Graph Attention," in IEEE Transactions on Biomedical Engineering, vol. 70, no. 8, pp. 2329-2337, Aug. 2023, doi: 10.1109/TBME.2023.3243311.

[8] S. Soffer, E. Klang, O. Shimon, Y. Barash, N. Cahan, H. Greenspana, et al., "Deep learning for pulmonary embolism detection on computed tomography pulmonary angiogram: A systematic review and meta-analysis", Sci. Rep., vol. 11, no. 1, pp. 15814, Aug. 2021.

[9] Ajani, S. N. ., Khobragade, P. ., Dhone, M. ., Ganguly, B. ., Shelke, N. ., & Parati, N. . (2023). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546–559

[10] N. Siddique, S. Paheding, C. P. Elkin and V. Devabhaktuni, "U-net and its variants for medical image segmentation: A review of theory and applications", IEEE Access, vol. 9, pp. 82031-82057, 2021.

[11] F. Shi, J. Wang, J. Shi, Z. Wu, Q. Wang, Z. Tang, et al., "Review of artificial intelligence techniques in imaging data acquisition segmentation and diagnosis for COVID-19", IEEE Rev. Biomed. Eng., vol. 14, pp. 4-15, 2021.

[12] M. D. C. Abelaira, F. C. Abelaira, A. Ruano-Ravina and A. Fernández-Villar, "Use of conventional chest imaging and artificial intelligence in COVID-19 Infection. A review of the literature", Open Respiratory Arch., vol. 3, no. 1, Jan. 2021.

[13] G. Kim and H. Natcheva, "Imaging of cardiovascular thoracic emergencies", Radiologic Clinics North Amer., vol. 57, no. 4, pp. 787-794, Jul. 2019.

[14] N. Tajbakhsh, J. Y. Shin, S. R. Gurudu, R. T. Hurst, C. B. Kendall, M. B. Gotway, et al., "Convolutional neural networks for medical image analysis: Full training or fine tuning?", IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1299-1312, May 2016.

[15] K. Agnihotri, P. Chilbule, S. Prashant, P. Jain and P. Khobragade, "Generating Image Description Using Machine Learning Algorithms," 2023 11th International Conference on Emerging Trends in Engineering & Technology - Signal and Information Processing (ICETET - SIP), Nagpur, India, 2023, pp. 1-6, doi: 10.1109/ICETET-SIP58143.2023.10151472.

[16] M. Bende, M. Khandelwal, D. Borgaonkar and P. Khobragade, "VISMA: A Machine Learning Approach to Image Manipulation," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-5, doi: 10.1109/ISCON57294.2023.10112168.

[17] V. Bansal, G. Pahwa and N. Kannan, "Cough Classification for COVID-19 based on audio mfcc features using Convolutional Neural Networks", IEEE International Conference on Computing Power and Communication Technologies GUCON 2020, pp. 604-608, 2-4 October 2020.

[18] N. M. Manshouri, "Identifying COVID-19 by using spectral analysis of cough recordings: a distinctive classification study", Cognitive Neurodynamics, vol. 16, pp. 239-253, Feb 2022, [online] Available: https://doi.org/10.1007/s11571-021-09695-w.

[19] E. E.-D. Hemdan, M. A. Shouman and M. E. Karar, "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images", arXiv preprint, 2020.

[20] A. M. Farhan, S. Yang, A. Q. Al-Malahi and M. A. Al-antari, "MCLSG: Multi-modal classification of lung disease and severity grading framework using consolidated feature engineering mechanisms", Biomedical Signal Processing and Control, vol. 85, pp. 104916, 2023.

[21] G. Liang and L. Zheng, "A transfer learning method with deep residual network for pediatric pneumonia diagnosis", Computer methods and programs in biomedicine, vol. 187, pp. 104964, 2020.

[22] L. P. Soares and C. P. Soares, "Automatic detection of covid-19 cases on x-ray images using convolutional neural networks", arXiv preprint, 2020.

[23] A. K. Das, S. Ghosh, S. Thunder, R. Dutta, S. Agarwal and A. Chakrabarti, "Automatic COVID-19 detection from X-ray images using ensemble learning with convolutional neural network", Pattern Analysis and Applications, vol. 24, pp. 1111-1124, 2021.

[24] M. M. A. Monshi, J. Poon, V. Chung and F. M. Monshi, "CovidXrayNet: Optimizing data augmentation and CNN hyperparameters for improved COVID-19 detection from CXR", Computers in biology and medicine, vol. 133, pp. 104375, 2021.

[25] S. Rajpal, N. Lakhyani, A. K. Singh, R. Kohli and N. Kumar, "Using handpicked features in conjunction with ResNet-50 for improved detection of COVID-19 from chest X-ray images", Chaos Solitons & Fractals, vol. 145, pp. 110749, 2021.

[26] A. Kumar, A. R. Tripathi, S. C. Satapathy and Y.-D. Zhang, "SARS-Net: COVID-19 detection from chest x-rays by combining graph convolutional network and convolutional neural network", Pattern Recognition, vol. 122, pp. 108255, 2022.