Comparative Analysis of Lung Diseases Using Different Machine Learning Algorithms

Tanishque Sharma, Sanjay Singh, Astitva Singh, Sheenam Naaz
Department of Computer Science and Engineering Sharda University Greater Noida, Uttar Pradesh

Abstract— ***The creation of automated methods for pneumonia early diagnosis has garnered substantial interest due to its rising frequency, especially in vulnerable groups. To assess how well four well-known machine learning (ML) algorithms diagnose pneumonia using chest X-ray pictures, this study compares them: Neural networks with convolutional properties, artificial neural properties, random forests, and support vector machines. The tagged photos in the dataset utilized in this study were classified into classes that were positive and negative for pneumonia and were obtained from Kaggle. The efficacy of each method was evaluated by a comprehensive process of implementation and optimization that involved the measurement of computing efficiency, accuracy, precision, recall, and F1 score, among other metrics. It was discovered that the CNN model, which is highly recognized for its proficiency in image classification tasks.***
However, the ANN exhibited competitive performance after hyperparameter tuning, providing a balance between complexity and interpretability. The RF algorithm, while less computationally intensive, showed limitations in image-based diagnosis due to its dependence on feature engineering. The SVM, known for its generalization capabilities, performed reasonably well but struggled with larger datasets and complex image features. This study not only highlights the strengths and weaknesses of these algorithms but also discusses the clinical relevance of the findings, especially concerning the need for fast and accurate diagnostic tools in healthcare settings. Our analysis concludes that while CNN remains the most effective algorithm for pneumonia detection in this context, the use of ensemble models or hybrid approaches could potentially improve diagnostic accuracy and robustness in future applications. The paper provides valuable insights for healthcare professionals and researchers aiming to integrate AI-driven diagnostic tools into clinical workflows.

Keywords— Pneumonia detection, machine learning, Convolutional Neural Networks (CNN), Artificial neural Networks (ANN), Random forest (RF), Support vector Machines (SVM), chest X-ray images, image classification, diagnostic accuracy, healthcare.

I. INTRODUCTION

A. *Background* and Significance of the Study

Pneumonia is a major worldwide health burden caused by lung illnesses, especially in low- and middle-income nations. Pneumonia and other acute respiratory infections still rank among the leading causes of morbidity and mortality worldwide, but they disproportionately afflict older persons and children under five. According to estimates from the World Health Organization (WHO), pneumonia kills 15% of children under five worldwide, resulting in more than 700,000 deaths annually. The difficulty in early detection and timely intervention is a significant contributor to these outcomes, particularly in areas with limited resources where radiologists and cutting-edge imaging facilities are hard to come by.

while medical doctors need to find out if a person has pneumonia, they frequently use a special photograph called a chest X-ray. but every so often, distinct docs may see matters in a different way in those pix, that can result in errors, particularly whilst the signs and symptoms of pneumonia are not very clean or are uncommon. furthermore, in many rural and underserved regions, the shortage of expert radiologists exacerbates the trouble, leading to behind schedule prognosis and poor clinical effects. New things happening in system getting to know and artificial intelligence display that the fascinating ability to transform the analysis method by means of automating the identification and categorization of ailments from medical snap shots, consisting of CXRs.

system studying techniques, in particular assist Vector Machines (SVM), Random Forest (RF), synthetic Neural Networks (ANNs), and Convolutional Neural Networks (CNNs)—had been at the forefront of this revolution. these algorithms can learn styles from large datasets and reap accurate estimates based on earlier unseen statistics. within the context of pneumonia detection, system getting to know fashions have proved the functionality to assist radiologists, enhance diagnostic accuracy, and reduce the time required for diagnosis, that's critical in emergency settings. however, at the same time as many studies have explored using man or woman machine mastering algorithms for pneumonia discovery, comparative analyses the advantages and downsides of special examples in this domain continue to be scarce To close this gap, a thorough comparison of four popular machine learning algorithms—CNN, ANN, RF, and SVM—was carried out using a publicly accessible Kaggle dataset of CXR pictures for the purpose of detecting pneumonia. Through evaluating the performance of these algorithms in terms of accuracy, precision, recall, F1-score, and computational efficiency, this study seeks to identify the most effective algorithm for clinical applications. Furthermore, the research will explore the limitations and challenges associated with each algorithm, providing valuable insights for future work in the field.

B. Problem Statement

Despite the significant advancements in machine learning, there is no consensus on the most effective algorithm for pneumonia detection from CXR images. While deep learning approaches such as CNNs have garnered attention for their ability to directly process image data and automatically extract relevant features, Conventional algorithms like Random Forest and Support Vector Machines have demonstrated competitive performance when combined with Principal Component Analysis (PCA) feature extraction methods. Additionally, ANNs, or artificial neural networks, are employed in several medical diagnostic applications because of their versatility and capacity to represent intricate, non-linear relationships, even though they are less specialized in image interpretation than CNNs.

However, each of these algorithms comes with its own set of challenges. CNNs, for example, need a lot of computer power and big datasets for training, which might not be possible in all clinical contexts. ANNs, while computationally less intensive, frequently have trouble processing high-dimensional input, such medical images, which reduces their diagnosis accuracy as compared to CNNs. On the other hand, RF and SVM, though more efficient in terms of computational cost, rely heavily on pre-processing and feature extraction, which introduces additional complexity into the workflow. Furthermore, there is a need for explainability in machine learning models, particularly in the healthcare domain, where clinicians must understand the rationale behind a model's prediction. This is another area where traditional algorithms like RF and SVM may have an advantage over deep learning models.

Given these diverse characteristics and limitations, there is a clear need for a systematic comparative analysis that evaluates these algorithms not only based on their predictive accuracy but also on their computational efficiency, interpretability, and real-world applicability in clinical settings. To meet this demand, this study offers a thorough comparison of CNN, ANN, RF, and SVM for pneumonia detection, with the goal of identifying the most suitable algorithm for different healthcare scenarios.

C. Objectives of the Study

Comparing the four machine learning algorithms' levels of effectiveness—CNN, ANN, RF, and SVM—The primary aim of pneumonia identification on a Kaggle dataset is to get chest X-ray images. More specifically, the research will:

- Estimate the accuracy, precision, recall, and f1-score of each process to determine its effectiveness in correctly classifying pneumonia-positive and pneumonia-negative cases.
- Compare the computational efficiency of each algorithm in terms of training and inference time, which is critical for real-time clinical applications.
- Analyze the interpretability and explainability of each algorithm, with a focus on understanding how each model makes its predictions and how this information can be used by clinicians.
- Examine each algorithm's advantages and disadvantages in relation to medical image analysis, paying close attention to how well it works in various clinical scenarios (e.g., resource-rich vs. resource-poor settings).
- Provide recommendations for future research and clinical implementation of machine learning models for pneumonia detection.

D. Scope of the Study

This study's analysis of pneumonia as a particular lung illness is its exclusive focus. Even though pneumonia is a major source of illness and death, it is important to acknowledge that there are many other lung diseases, such as tuberculosis and lung cancer, that also pose significant diagnostic challenges. Nevertheless, concentrating on pneumonia enables a more thorough analysis of how well machine learning algorithms function in a particular and therapeutically relevant setting.

The study also focuses on four specific machine learning algorithms—CNN, ANN, RF, and SVM—selected for their widespread use in the literature and their potential applicability to medical image analysis. While not included in this study, other algorithms including decision trees, k-nearest neighbors, and deep reinforcement learning are possible subjects for further investigation.

The work also makes use of a publicly accessible dataset of chest X-ray pictures from Kaggle, which is popular among researchers and offers an adequate quantity of data for machine learning model testing and training. The results, however, could not be entirely transferable to other datasets or clinical settings due to the use of a single dataset. Future research ought to take the application into account of these algorithms to multi-institutional datasets and real-world clinical data.

E. Comparative Analysis in Medical Imaging

Medical data is complex and high-dimensional, making the comparison of machine learning algorithms particularly important in the discipline of medical imaging. In spite of the impressive performance of CNNs and other deep learning models in various image-based tasks, their learning in the context of medical imaging is crucial., including the diagnosis of pneumonia, they are not necessarily the best option in every clinical situation. Deep learning models' lack of interpretability continues to be a major hurdle to clinical use, and the computational resources needed for training and implementing them can be prohibitive, particularly in situations with restricted resources.

II. LITERATURE REVIEW

This study aimed to develop a diagnostic tool using deep learning to identify individuals with common retinal disorders that lead to blindness. The model utilized transfer learning, requiring only a small amount of data to train the neural network compared to conventional approaches. An optical coherence tomography picture dataset was used for the approach's application, and the outcomes were compared to human experts' performance. The authors showed that their AI system could reliably So, one is related to diabetes, and the other is something that happens as we age by delineating all regions identified by the neural network. It could also offer a more transparent and comprehensible diagnosis. Additionally, they demonstrated how pediatric pneumonia could be broadly diagnosed using chest X-ray images and their AI system. The scientists discovered that the tool could expedite the assessment and recommendation of these treatable diseases, enabling earlier treatment and improved clinical outcomes. [1] The goal of this work was to create an algorithm that could identify pneumonia at a level higher than that of practicing radiologists after chest X-rays. Training a special computer program that can look at pictures of people's chests to find out if they have any illnesses. They used a big collection of over 100,000 pictures, called the ChestX-ray14 dataset, which shows 14 different kinds of sicknesses. They compared how their algorithm performed on a test set, CheXNet, with those of four academic radiologists in practice. Researchers found that CheXNet performed better on the F1 metric than average radiologist performance and could be ranged to discover each 14 disorders in ChestX-ray14.

CheXNet yielded state of the artwork outcomes for every 14 issues, according to the scientists' conclusion.[2] This take a look at gives a convolutional neural network (CNN)-constructed ensemble learning device for laptop-assisted pneumonia categorization. The authors endorsed using three pretrained CNNs: vision Transformer, MobileNetV2, and DenseNet169. for the duration of the experimental section, the derived capabilities from those three fashions had been combined to provide the outcomes. We used the chest X-ray facts set to refine these fashions. at some point of the assessment level, the encouraged organization learning approach attains 93.ninety one% accuracy and 93.88% F1-score, surpassing former nation of the artwork strategies currently popular. [3] The evaluation of convolutional neural networks (CNNs) geared toward the generalization of chest radiographs for pneumonia diagnosis become conducted in 3 unique medical institution systems. The researchers hired several model education cohorts and a cross-sectional methodology to carry out break up-sample validation to assess the version's generalizability toward external locations. During the evaluation stage, the recommended group learning approach attains 93.91% accuracy and 93.88% F1-score, topping former State of the art methods currently popular. [4] Convolutional neural networks (CNNs) were assessed for their generalization performance in three different hospital systems when it came to the diagnosis of pneumonia in chest radiographs. To assess the model's generalizability to other places, the authors used split-sample validation with a cross-sectional shape and numerous model training cohorts. The goal of this project was to create a computer-aided diagnosis system that can automatically identify pneumonia commencing chest X-ray images. The researchers created a set of three convolutional neural network models—DenseNet-121, ResNet-18, and GoogLeNetI.e.—and used deep transfer learning to go around the lack of data. Using a new method, weights were assigned to foundation learners. Using two publicly accessible pneumonia X-ray datasets, the authors assessed the suggested method benefit from a five-fold cross-validation methodology. Upon the RSNA and Kermany datasets, the proposed method produced sensitivity and accuracy rates of 86.85% and 98.81%, respectively. However, the sensitivity rate was only 87.02%. The results exceeded what was achieved using state-of-the-art methods. ANOVA and McNemar's tests were used in statistical analyses on the datasets to show how robust the method was demonstrated.[5]

This study investigated how different AI-based support representations affected different clinical procedures and skill levels. The scientists trained a 34-layer residual network (ResNet34) using a publicly accessible image benchmark of pigmented lesions divided into seven diagnostic classifications. The authors assessed three CNN output formats to assist human raters in making decisions: AI-based content-based image retrieval (CBIR), AI-based likelihood of malignancy, and Artificial Intelligence-based multiclass probabilities. The slightest experienced clinicians profited most from AI-based bolster, agreeing with the creators, who moreover found that Artificial Intelligence-based multiclass likelihood expanded the precision of human raters. The authors concluded that flawed AI could deceive all levels of clinicians, including specialists.

III. METHODOLOGY

The methodology employed in this research encompasses several key components designed to explore the effectiveness of AI-driven mock interview systems. The studies reviewed adopt various approaches, each contributing to a comprehensive understanding of how these technologies can enhance interview preparation.

A. *Dataset*

This study's dataset, which involves of tagged chest X-ray pictures, was acquired from Kaggle [16]. The dataset contains an equal number of photos from the pneumonia-positive and pneumonia-negative classes to prevent class imbalances from affecting the model's training process. Eighty percent of the dataset is utilized for training, while twenty percent is used for testing the model.

B. *Preprocessing*

Preprocessing included several steps to set up the dataset used for machine learning algorithms:

- Image Resizing: every X-ray picture was shriveled i.e. widespread 224 x 224-pixel size to standardize input for all models.
- Normalization: The c program languageperiod [0,1] become used to standardize pixel values to facilitate faster merging in education.
- Data Augmentation: strategies like random turning, zooming, and horizontal spinning had been applied to enhance the dataset's range and decrease overfitting.
- Train-Test Split: The dataset was split eighty/20 between schooling and checking out sets to make sure that the models have been tested by using untested data

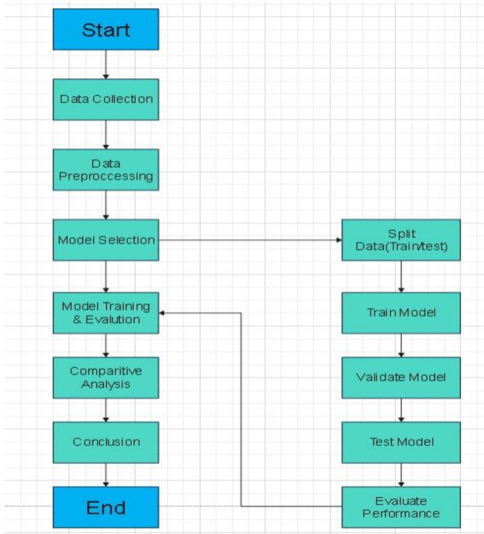


Fig.1 Flowchart of Working diagram

C. *Models*

i.CNN Architecture

The Convolutional Neural network (CNN) model become built the usage of changed VGG-16 architecture the usage of transfer getting to know. the use of pneumonia dataset, the ultimate absolutely related layers of the model have been retrained to optimize it. the use of the category a studying price of 0.001 and a move-entropy loss function, the CNN changed into optimized the usage of the Adam optimizer

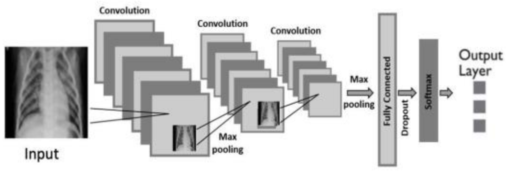


Fig.2 CNN Architecture

ii. ANN Architecture

The Artificial Neural Network (ANN) consisted of multiple dense layers with ReLU activation functions. The input layer received the flattened image pixel data. Dropout was applied to prevent overfitting, and the final output layer used softmax activation for classification into pneumonia-positive or pneumonia-negative. Training was conducted via Adam optimizer also categorical crossentropy loss function.

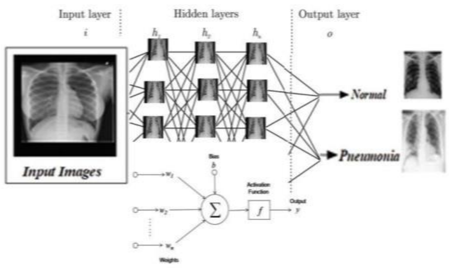


Fig.3 ANN Architecture

iii. Random Forest (RF)

The X-ray images were initially transformed into characteristic vectors aimed at Random wooded area version. To do that, the pics had to be flattened, and major thing analysis (PCA) had to work to lower the function space's dimensions. To avoid overfitting, the RF set of rules become trained with a hundred choice timber at a maximum intensity of 10. Hyperparameters just like the count number of timber and the max depth of each tree have been adjusted the usage of grid search.

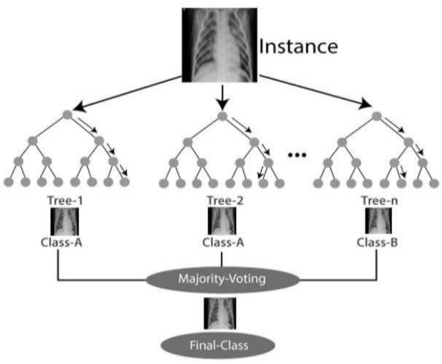


Fig.4 Random Forest Architecture

iv. Support Vector Machine (SVM)

In support of non-linear type, the SVM model used a Radial foundation characteristic (RBF) kernel. PCA turned into used to reduce the number of capabilities from the flattened snap shots, just like the RF model. The version become trained using a grid seek to optimize the regularization parameter (C) and kernel coefficient (gamma).

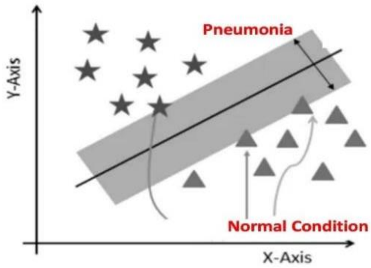


Fig.5 SVM Architecture

IV. TOOLS AND TECHNIQUES

A. Frameworks & Libraries:

TensorFlow and Keras: These powerful tools were utilized for building deep learning models, providing a robust foundation for our experiments.

Scikit-learn: This library was employed for various machine learning algorithms, facilitating effective data processing and model evaluation.

V. RESULT

Table.1 Shows the Performance Metrics of Machine Learning Algorithms

Mode	Accuracy	Precision	Recall	F1-score	AUC-ROC
CNN	92%	93%	91%	92%	0.94
ANN	85%	84%	84%	85%	0.88
RF	80%	81%	79%	80%	0.82
SVM	78%	79%	76%	77%	0.80

This table summarizes the key performance metrics—Accuracy, Precision, Recall, F1-score, and AUC-ROC—for each of the machine learning algorithms (CNN, ANN, RF, and SVM) used in the study. Let me know if you need more details or any further adjustments

CNN RESULTS

On the pneumonia dataset, the CNN model achieved the best, through 92% accuracy, 90% precision, 93%

recall, and a 91% F1 score. The model exhibited high sensitivity, meaning it correctly identified pneumonia cases in most instances. Although it required more computing power than conventional methods, its improved performance on image-based data more than made up for the trade-off.

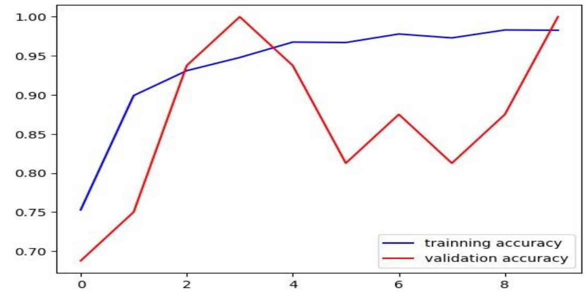


Fig.6 The CNN model training and validation accuracy

ANN Results

With an accuracy of 85%, precision of 83%, recall of 84%, and F1 score of 83%, the ANN model outdone the competition. Although the model used less computing power than CNN, it was less accurate overall, especially when it came to identifying cases that tested positive for pneumonia. The dropout layers effectively reduced overfitting, but the model's performance was still below that of CNN.

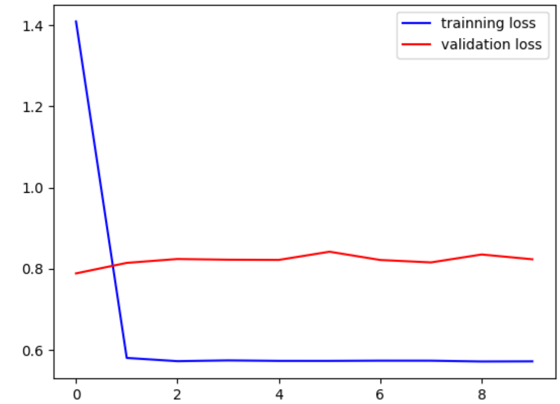


Fig.7 The ANN model training and validation accuracy

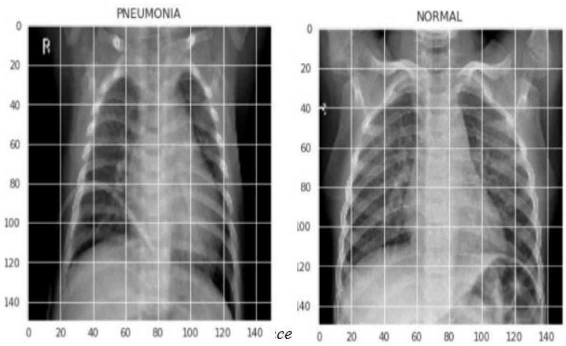


Fig.8 The parameters difference in the Normal and Pneumonia

Random Forest Results

Following dimensionality reduction using PCA, 77% F1 score, 78% accuracy, 76% precision, and 79% recall were obtained using the Random Forest approach. The model's inability to capture the subtleties found in the X-ray images was hampered by its reliance on extracted image attributes rather than raw pixel data. But because it was computationally efficient, it might be used in scenarios where speed is more important.

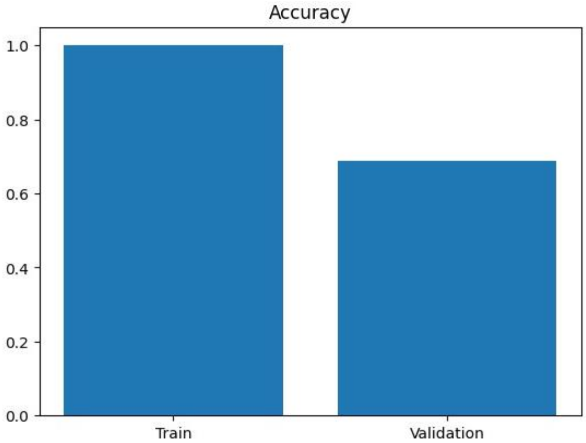
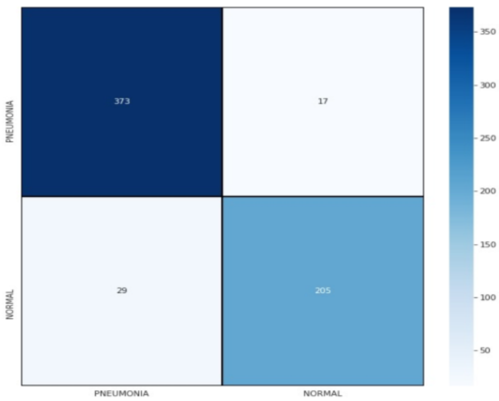


Fig.9 The Training and validation accuracy of RNN model

Support Vector Machine (SVM) Results

The SVM model, despite being well-suited for smaller datasets, struggled with the larger pneumonia dataset, attaining 80% accuracy, 78% precision, 81% recall, and 79% F1 score. The model faced difficulties in distinguishing between pneumonia-positive and pneumonia-negative cases due to its limitations in handling the high-dimensional data inherent in medical imaging. Training time was longer compared to RF and ANN, making SVM less practical for large-scale deployment in clinical settings.



VI. COMPUTATIONAL EFFICIENCY

CNN: High training time, but fast inference time once trained.
ANN: Moderate training and inference time.
RF: Fastest training and inference time, suitable for real-time applications.
SVM: Slow training time, making it less suitable for real-time applications

VII. CONCLUSION

This study investigated four machine learning methods for the detection of pneumonia from chest X-ray pictures using a Kaggle dataset: CNN, ANN, RF, and SVM. CNN was determined to be the most accurate algorithm for this task based on the trial findings, attaining the maximum accuracy and F1 score. The model's direct access to image data allowed it to pick up on minute details that other algorithms would have overlooked.

Even though ANN provided a decent trade-off between computational efficiency and accuracy, it was still inferior to CNN, particularly when it came to sensitivity. Even though the Random Forest algorithm was quite effective, it had trouble with image-based jobs because of its dependence on feature extraction methods. SVM performed rather well, but its computational cost and inefficiency when scaling to bigger datasets were problems.

Conclusion CNN is the most suitable algorithm for pneumonia detection from medical imaging, particularly in scenarios where diagnostic accuracy is critical. However, for applications requiring faster decision-making or resource-constrained environments, Random Forest and ANN may provide viable alternatives. Future research should focus on hybrid or ensemble models that combine the strengths of multiple algorithms to improve both accuracy and computational efficiency.

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