Enhanced Pneumonia Detection from Chest X-rays Using Machine Learning and Deep Neural Architectures

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Abstract*—*Pneumonia* is a major worldwide health concern, particularly for vulnerable groups such as babies and the elderly. Despite advances in medical imaging, diagnosing pneumonia using a chest X-ray remains difficult, due to the subtle presentation of symptoms and the variety in picture interpretation. This study utilizes modern machine learning can improve the accuracy and speed of diagnosing pneumonia using chest X-ray images. Utilizing a comprehensive dataset from the Kaggle online repository, consisting of over 5,000 annotated images, we evaluate the efficacy of various machine learning models including deep convolutional neural networks (CNN) and ensemble learning techniques. Our findings indicate that models like the Fuzzy opponent histogram filter combined with Logistic model trees (LMT) achieved the highest accuracy at 96.97%, while the deep learning-based Lenet (CNN) with LMT closely followed at 95.85%. The study aims to improve diagnostic precision, reduce interpretation discrepancies, and facilitate faster clinical decision-making by identifying the most effective machine learning approaches for real-world applications in healthcare settings.

***Index Terms*—Artificial intelligence, Chest X-rays, Fuzzy opponent histogram filter, Machine learning, Pneumonia.**

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I. Introduction

Pneumonia is a major health concern across the world, accounting for the majority of illnesses and deaths, particularly among young children and the elderly. Chest X-ray imaging is commonly used for diagnosis; however, it can be difficult to interpret, especially if the symptoms are mild. Recent breakthroughs demonstrated that the application of machine learning algorithms considerably enhances the capacity of chest X-ray imaging to identify pneumonia; hence, it accelerates the diagnostic process and leads to dramatically better patient outcomes (Singh, et al., 2024). Another kind of pneumonia is acinetobacter baumannii, which is notable for its resistance to strong antibiotics such as carbapenems and colistin. This resistance complicates therapy, highlighting the need for more effective therapeutic procedures. Although utilizing a mixture of antibiotics has been somewhat successful, the outcomes vary and are not always constant (Shein, et al., 2024). Pneumonia is a serious respiratory disease that can take many different forms, including bacterial pneumonia, virus-induced pneumonia, mycoplasma-caused pneumonia, and others that may be parasitic or fungal in origin. This illness can also be classified according to where it was acquired: In a hospital, in the community, or by aspiration. Every year, this condition causes over a million hospital admissions in the United States, as well as half a million fatalities.

Globally, the effect is even more striking, with the World Health Organization stating in 2019 that pneumonia is the main cause of mortality among children under five, accounting for 14% of all fatalities in this age range (Yang, et al., 2020). This highlights the crucial need for improved diagnostic and treatment options.

An X-ray picture is the most trustworthy diagnostic tool due to its low cost and comprehensive nature when compared to other traditional diagnostic procedures. X-rays are valuable because they offer good pictures of the lungs, allowing healthcare personnel to better diagnose and assess the severity of the infection (Rajpurkar, et al., 2017). In reality, radiologists devote a significant amount of time and attention to scrutinizing and interpreting X-ray pictures, which may be exhausting and can lead to dispute among physicians over the outcome. Early pneumonia identification using deep learning-based algorithms would considerably simplify the procedure and assist deliver treatment more quickly, thereby lowering mortality and saving lives (Hasan, et al., 2021). Even now, pneumonia remains the most frequent illness in areas such as Sub-Saharan Africa and South Asia, affecting both the elderly and the young. Artificial intelligence (AI), especially the use of neural networks and deep learning technologies, has transformed how medical pictures are processed (Pant, et al., 2020). In the health industry, AI and machine learning are increasingly being used for biomedical image processing to improve diagnosis accuracy and efficiency (Racic, et al., 2021). Computer vision is an excellent high-speed, objective evaluation technique for all types of pneumonia, whether viral, bacterial, or fungal, to improve diagnosis and therapy. Furthermore, the COVID-19 pandemic has expedited the development of computer-aided diagnosis techniques. These mostly use convolutional neural networks (CNN) and deep learning approaches to improve pneumonia detection and classification. It emphasizes its involvement in global health emergencies (Szepesi and Szilágyi, 2022). Machine learning techniques are increasingly being used to enhance pneumonia detection with chest X-rays. Deep learning algorithms are effective at detecting specific patterns such as alveolar or interstitial infiltration, which frequently indicate bacterial and viral pneumonia, respectively. Sufficiency in terms of data used for training aided in the development of distinctions and distinguishing between bacterial and viral causes (Rahman, et al., 2020). Transfer learning has also shown to be a valuable method for biological picture categorization. This strategy includes adapting and reusing a model developed on a big dataset, such as imagenet, to fit other but related objectives. Furthermore, ensemble approaches, which combine judgments from several classifiers, are utilized to harness discriminative information that all base classifiers may possess, hence enhancing prediction accuracy (Kundu, et al., 2021). The major goal of this research is to use machine learning and AI to improve the identification and categorization of pneumonia from chest X-ray images, ultimately improving treatment results and decreasing death rates. The study is designed to begin by introducing the literature on hassle detection and evaluation, followed by an in-depth methodological section that explains statistics pre-processing, feature extraction strategies, and model assessment methodologies. The repercussions section provides a comparative evaluation of the overall performance metrics among unique machine learning models, which leads into a full discussion of the findings' significance for medical exercise and future research possibilities.

II. Literature Review

The biggest problem of overfitting in computer-assisted vision applications occurs, especially when working with limited labeled data. This is compensated for by applying augmentation techniques such as image data augmentation, which add new samples to the dataset, increase its size and diversity, and help the network learn generalizable features. Such techniques have been well-tested across a range of applications including image classification, object recognition, and semantic segmentation (Kumar, et al., 2024). In addition, the latest research (Li, et al., 2023) has been conducted on the potential applications of artificial general intelligence models in medical imaging and healthcare. This paper discusses the capabilities of large language models, large vision models, and large multimodal models, which are discussed in detail along with their key features, enabling technologies, and development trajectories. It also indicates a roadmap for their evolution and practical application in the medical field by discussing future research directions and possible impacts on health care.

Another study by (Sailunaz, et al., 2024) describes a statistical deformation model-based data augmentation technique for volumetric medical picture segmentation. This approach considerably enhances the automatic segmentation of organs at risk in computed tomography (CT) scans, solving the issue of restricted data availability. It utilizes varied and enhanced data manipulation on CT scans from a limited number of patients in improving the approach's precision in treatment planning, with minimized adverse impacts of radiation on non-targeted organs. The "Healthcare Federated Ensemble Internet of Learning Cloud Doctor System" is a worldwide cloud-based diagnostic machine learning system that uses Internet of Things (IoT) devices to produce precise and reliable diagnoses. It applies a federated ensemble learning strategy for creating a decentralized global prediction model from local healthcare models, which ensures biomedical security and integrity of the patient data. In performance validations, the proposed approach achieved exceptional accuracies of 99.24% with Chest X-ray data and 99.0% with magnetic resonance imaging (MRI) brain tumor data, thus proving its adequacy for precise diagnostics in IoT-enabled healthcare environments (Khan et al., 2024).

Another proposal for a hybrid deep learning model was put forth for pediatric pneumonia detection based on the architecture of EfficientNetV2. It extracts features from radiographic images and then combines them through the use of a combined classifier using SVM and RFT. Its accuracy improves 4% better than earlier approaches and has also performed well with unknown datasets (Ravi, 2024). Cardiovascular diseases are the leading cause of death worldwide, accounting for 31% of all deaths annually, so early detection is critical for proper treatment (Selvanandhini and Karthikeyan, 2024). Combining medical research with machine learning provides holistic views of treatment outcomes and important risk factors. Advanced classification techniques developed using machine learning can be used to detect diseases early on, enabling customized preventive measures.

The collaboration of data scientists, medical professionals, and regulatory bodies is important to deal with issues of data privacy and interpretability of models. Furthermore, the number of innovative research is produced to the development of the Hybrid Deep Neural Network (VGG16-PCA-PB3C), which has dramatically increased the accuracy and speed of leukemia genomes (Kaur and Singh, 2024). In this model, feature extraction is done with the help of the Visual Geometry Group and dimensionality reduction is done by the help of principal component analysis, and training it is done by parallel Big-Bang-Big-Crunch optimization technique. The algorithm has been tested on the Classification of Normal versus Malignant Cells dataset and achieved 95% accuracy and 94% precision, thereby helping clinicians to improve the accuracy of the classification of leukemia.

Further, research into transfer learning techniques aims at verifying how successful it will be for various forms of brain tumor detection; more so on early diagnosis based on the usage of pre-trained models, such as VGG-16, VGG-19, Inception-v3, ResNet-50, DenseNet, and MobileNet on classifying MRI data with good precision. Such efforts again mark an area that recognizes how new-generation ML tools and methodologies contribute toward streamlining medical diagnostic methods. The study in reference (Shamshad, et al., 2024) is aimed to improve the accuracy of treatment planning and patient outcomes by using the best possible approaches for accurate and automated analysis of brain tumors. It is noted that the model VGG-16 surpasses earlier methods, yielding the highest accuracy at 97% while it only consumes 22% of the processing time used by previous techniques.

In another study, (Venkatraman and Reddy, 2024) uses the SVM and VGG16 classifiers to improve the outcome of lung cancer detection. By using a hybrid approach on the dataset "IQ-OTH/NCCD," this model efficiently distinguishes between aggressive, benign, and normal cases, showing how combining traditional machine learning with deep learning addresses the issues of accuracy and efficiency and renders it a significant improvement on present approaches. Further medical imaging innovations are presented in (El-Ghandour and Obayya, 2024), where a new pneumonia classification approach uses three optimized pre-trained CNN models combined with the XGBoost algorithm. Bayesian optimization is used to fine-tune each CNN model so that the feature representation is optimized while general features are lost to the minimum. Excellent results of the technique were achieved with a correct classification rate of 99.15%, accuracy of 99.53%, sensitivity of 99.30%, and an area under the curve (AUC) of 0.9972%, which can aid radiologists in confirming pneumonia diagnoses more reliably.

Moreover, the deep learning model "PneuCoNet," which is proposed by (Dasgupta and Sen, 2024), detects pneumonia, COVID-19, or normal cases with 93% accuracy through chest X-rays. The present model has been improved to treat critical respiratory disorders. The CNNs used in (Deepak, 2024) are to aid in the earlier detection of pneumonia. It is done using the transfer learning to process datasets to develop a multi-classification model that includes SqueezeNet, ResNet-50, and EfficientNet-b0. This model classifies chest X-rays into Normal/Abnormal and specific types of pneumonia, with an astonishing 99% accuracy in the detection of Normal/Abnormal X-rays and a 97% accuracy in the identification of specific bacterial or viral pneumonia conditions, ultimately enhancing the precision of diagnosis and response time in medical environments.

Using medical imaging has revealed the challenges in diagnosis, mainly due to the variable presentation of pneumonia, which often closely mimics other respiratory conditions and easily leads to diagnostic errors. Although such studies are listed in Table I, more yet to be tapped potential from combining ensemble methods and transfer learning in machine learning models to further enhance accuracy and reliability into real settings. This research bridges this gap by systematically evaluating the efficacy of these integrated machine learning approaches on a diverse clinical dataset, thereby enhancing the precision and dependability of pneumonia diagnoses and potentially improving patient outcomes in clinical practice.

III. Methodology

This research uses an image mining technique to classify X-ray images as either showing pneumonia or normal. Image mining is the process of extracting valuable patterns and insights from image data, which can be particularly useful in medical diagnostics. The study focuses on two distinct categories of X-ray images. Fig. 1 in the study illustrates the types of images analyzed:

- Pneumonia infected Fig. 1 is an X-ray image that demonstrates typical characteristics of pneumonia, such as consolidation or infiltration patterns in the lungs. Such visual cues are vital for the diagnosis of pneumonia; thus, the healthcare provider will be able to identify the infected patients promptly.
- Normal image: They are X-rays that show no pneumonia or abnormalities. They help to establish control in the study. This will set the accuracy of the image mining technique in its ability to discriminate between healthy lung tissues and those affected.

A. Dataset

Dataset description

The study utilizes a comprehensive dataset sourced from the Kaggle online repository, consisting of 5,216 chest X-ray images. These images are categorized into four distinct classes, reflecting various diagnostic categories relevant to the study.

Class distribution

The dataset contains 3,875 images from patients diagnosed with pneumonia, which were the main target

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TABLE I
EXISTING STUDIES RELATED TO THE CONTRIBUTION OF AI AND ML IN THE HEALTHCARE ENVIRONMENT

References	Focus area	Techniques	Key features	Outcomes	Application
(Kumar, et al., 2024)	Computer vision	Data augmentation	Enhances variety, reduces overfitting	Effective in object recognition and segmentation	Image processing
(Li, et al., 2023)	Artificial general intelligence in healthcare	Large language models, large vision/multimodal models	Broad AI integration	Potential revolution in medical AI applications	Medical imaging
(Sailunaz, et al., 2024)	Medical imaging	Statistical deformation model	Realistic data augmentation	Improved organ segmentation accuracy	CT scans
(Khan et al., 2024)	IoT in healthcare	FDEIoL, federated learning	Combines IoT for global model accuracy	High accuracy in diagnostics	IoT healthcare systems
(Ravi, 2024)	Pediatric pneumonia	EfficientNetV2, SVM, RFT	Integrates features into a stacked classifier	Outperforms previous models by 4% in accuracy	Pediatric diagnostics
(Selvanandhini and Karthikeyan, 2024)	CVD early detection	Machine learning and medical research	Combines clinical and data science	Enhances early detection and interventions	Cardiovascular health
(Kaur and Singh, 2024)	Leukemia diagnosis	Hybrid deep NN (VGG16-PCA-PB3C)	Feature extraction and dimensionality reduction	Accuracy of 95%, precision of 94%	Leukemia detection
(Shamshad, et al., 2024)	Brain tumor analysis	VGG-16, transfer learning	Optimal approaches for automated analysis	Best accuracy (97%) and efficiency	Brain tumor diagnosis
(Venkatraman and Reddy, 2024)	Lung cancer detection	SVM, VGG16	Hybrid model, distinguishes case types	Improves accuracy and efficiency	Lung cancer diagnosis
(El-Ghandour and Obayya, 2024)	Pneumonia classification	Optimized CNNs, XGBoost	Bayesian optimization for feature representation	High classification rate and accuracy	Pneumonia diagnosis
(Dasgupta and Sen, 2024)	Critical condition diagnosis	PneuCoNet	Classifies X-rays with deep learning	Accuracy of 93% in identifying conditions	Diagnostic imaging
(Deepak, 2024)	Pneumonia detection	CNNs, transfer learning	Multiclassification model	Accurate detection of pneumonia phases	Pneumonia screening

FDEIoL: Federated ensemble internet of learning cloud doctor system, CVD: Cardiovascular diseases, PCA: Principal component analysis, CNNs: Convolutional neural networks, IoT: Internet of Things

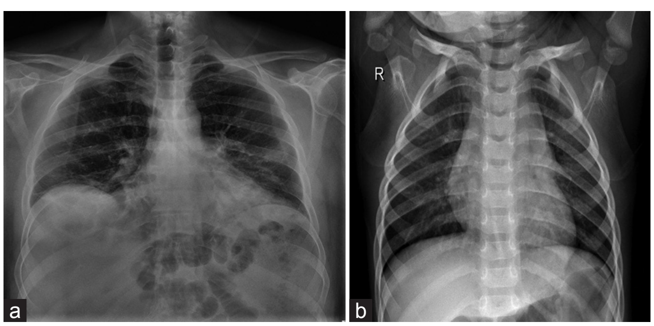

Fig. 1. (a) Pneumonia infected. (b) Normal. Examples of X-ray images used in the study, with (a) showing a pneumonia-infected image and (b) displaying a normal image.

of the study for the detection of pneumonia and 1,341 images of healthy people, used as control samples to help develop the classification models. Despite an imbalanced distribution between pneumonia cases (3,875) and healthy individuals (1,341), the dataset still enabled model training with reasonable class separation. However, due to the class skew toward pneumonia, the model's learning is biased toward the majority class, and the detection process may favor pneumonia classification. To mitigate this, class weights and performance metrics such as precision, recall, and F1-score were used for a more holistic evaluation of robustness.

B. Data Representation

The dataset in Fig. 2 is treated as a collection of features, which are the X-ray images; every image would be considered as a transaction of the features in this approach. This simplifies the analysis since it considers repeatable and recognizable patterns in images. Every single image is represented by a code of the sort which describes classification; "A" for an infected pneumonia status, and "D" indicates the normal kind. This descriptive type of classification method helps keep organized the dataset such that it does not require unnecessary lengthy processing as well as subsequent analysis.

This study treats the images as transactional features using a method, which is equivalent to the way an item is considered in market basket analysis, as every item of the transaction would be analyzed according to its frequency and association with other features of the transaction that is the image. This approach enables the use of data mining techniques, such as classification and pattern recognition to differentiate between pneumonia-infected and normal images based on their inherent characteristics. This methodology not only improves the efficiency of the diagnostic process but also enhances the accuracy with which these conditions are identified and classified.

C. Feature Extraction

The raw X-ray images are subjected to a series of feature extraction techniques to reduce the data dimensionality and

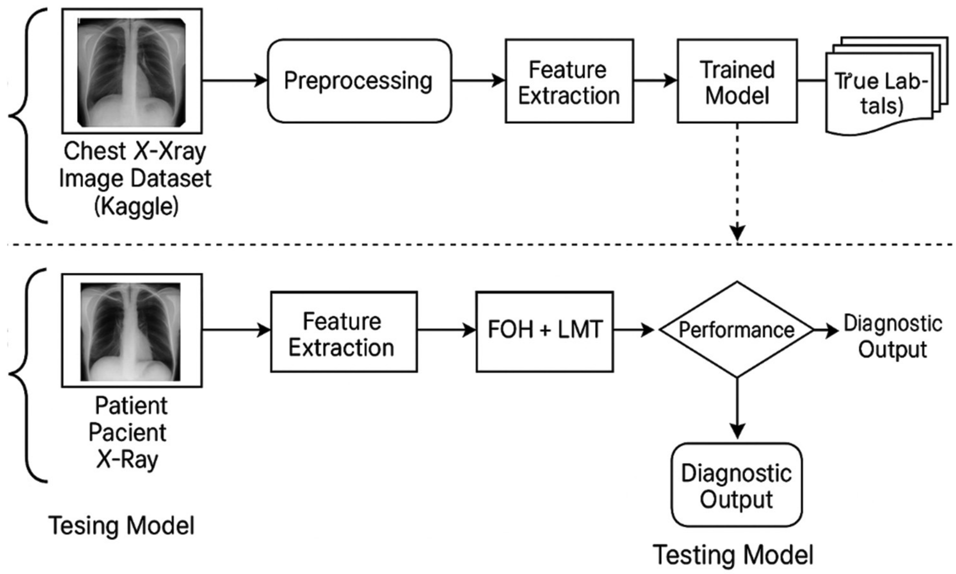

Fig. 2. Illustration of the proposed methodology for creating and evaluating the classification model.

enhance relevant features for classification. This process involves compressing and altering the visual information into a compact feature vector that captures essential diagnostic information.

D. Dataset Preparation

The dataset accommodates an identical distribution of pneumonia-infected and normal chest X-ray pictures. These images undergo pre-processing to ensure they may be as it should be formatted for the following device learning steps. During pre-processing, all images were carefully reviewed for artifacts or annotations (e.g., text labels, and markers such as “R”) that could introduce class-specific biases. We verified that the presence of such markers was not unique to any single class (normal or pneumonia) and ensured that models learned from medically relevant features rather than superficial visual cues. If such markers were found consistently in only one class, they were either cropped out or excluded from training to prevent unintentional model bias.

E. Model Training and Validation

The feature vectors were used to train the classification model using the Weka machine learning platform. It involves the training process as described below:

In addition, to ensure fair evaluation, the model performance was assessed on unseen test data. A 10-fold stratified cross-validation technique was employed, wherein each fold, the model was trained on 90% of the data and validated on the remaining 10%, ensuring that no sample used for training appeared in the corresponding test set. This approach ensures generalization performance is not inflated by data leakage.

F. Classification Model

This model classifies every image as either pneumonia-infected or normal using the processed feature vectors. Results from the training set form the basis of the model, which then applies to the test set.

G. Diagnostic Evaluation

The final stage includes the diagnostic testing of the model on unseen data from the test set. Here, the actual image labels are compared with the output of the model to test its accuracy and effectiveness. The performance of various models is statistically analyzed to conclude which one produces the most accurate classification.

H. Algorithm

This study effectively makes use of both feature extraction and classification algorithms, which classify and detect pneumonia using chest X-rays. It assimilates different algorithms with these advanced features to enable an amalgamation of textural, and color properties from images with deep machine learning concepts for enhanced diagnostics.

Feature extraction methods

The feature extraction techniques utilized include:

Fuzzy opponent histogram (FOH) filter: The color histograms are processed using fuzzy logic in opponent color spaces, hence enhancing the capacity to detect even minute differences between image intensities and colors. It is very advantageous in medical imaging operations, such as the detection of pneumonia.

FCTH filter (Texture Histogram and Fuzzy Color): Combines texture and color information using fuzzy logic to create a comprehensive feature set that captures critical characteristics of the images essential for accurate classification.

Classification methods

The classification of images is performed using several robust methods:

The ensemble learning approach in the case of random forest (RF), it generates as many decision trees as the number

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of trees on training to increase the accuracy and control the overfitting of the model (Mittal and Kumar, 2023)

Logistic model tree (LMT): Combines decision tree learning with logistic regression, allowing the handling of both linear and non-linear data relationships, with logistic regression functions at the tree's leaves (Pacal, et al., 2020).

Lenet CNN: A deep learning architecture specifically designed for image recognition tasks, which uses layers of convolution, pooling, and full connection to automatically extract and learn hierarchical features necessary for classification (Ahishakiye, et al., 2021).

Algorithm implementation

The study evaluates various combinations of feature extraction and classification methods:

FOH Filter + RF
FOH Filter + LMT
FCTH Filter + RF
FCTH Filter + LMT
Lenet (CNN) + RF
Lenet (CNN) + LMT

Each combination is meticulously applied to extract features from the X-ray images, which are then classified as either normal or pneumonia-affected. These methods are tested for their effectiveness in accurately categorizing chest X-ray images into the respective classes.

Ensemble framework and workflow

An ensemble framework that incorporates deep features from CNN is created to enhance the classification process (Thibault, et al., 2007). The workflow, illustrated in Fig. 3, outlines how deep features extracted from various layers of the pre-trained LeNet model, trained on our datasets, are concatenated to form a robust feature set. The model is evaluated using standard pneumonia datasets, including the Kaggle online dataset, employing classification methods such as RF and LMTs to ensure robust validation.

This ensemble approach allows the integration of diverse classification techniques and deep learning features, resulting in a highly accurate diagnostic tool for pneumonia detection based on chest X-ray images.

Evaluation metrics

To assess the performance of the proposed classification models, we used standard evaluation metrics including Accuracy, Precision, Recall, F1-score, and receiver operating characteristic (ROC)-AUC. These are defined as follows:

- Accuracy measures the overall correctness of the model:

$$\text{Accuracy} = TP + TN/TP + TN + FP + FN$$

- Precision evaluates how many of the predicted positive cases were actually positive:

$$\text{Precision} = TP/TP + FP$$

- Recall (Sensitivity) indicates how many actual positive cases were correctly predicted:

$$\text{Recall} = TP/TP + FN$$

- F1-score is the harmonic mean of precision and recall:

$$\text{F1-score} = 2\times\frac{\text{precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$$

ROC-AUC measures the trade-off between true positive rate and false positive rate across different thresholds, providing an aggregate measure of classification performance.

Where:

- *TP* = True positives
- *TN* = True negatives
- *FP* = False positives
- *FN* = False negatives.

IV. Results and Discussion

The goal of Table II is to identify pneumonia using a chest X-ray. A comprehensive evaluation of the performance of different combinations of feature extraction and classification methods on pneumonia detection is depicted in Fig. 4, which is presented in terms of five important metrics, namely, Pneumonia Accuracy (%), Precision, Recall, F-measure, and ROC. The shaded region around each line corresponds to the standard deviation or error margin within the shaded region which reflects the model's stability for multiple runs or folds for that particular combination of feature extractor and classifier.

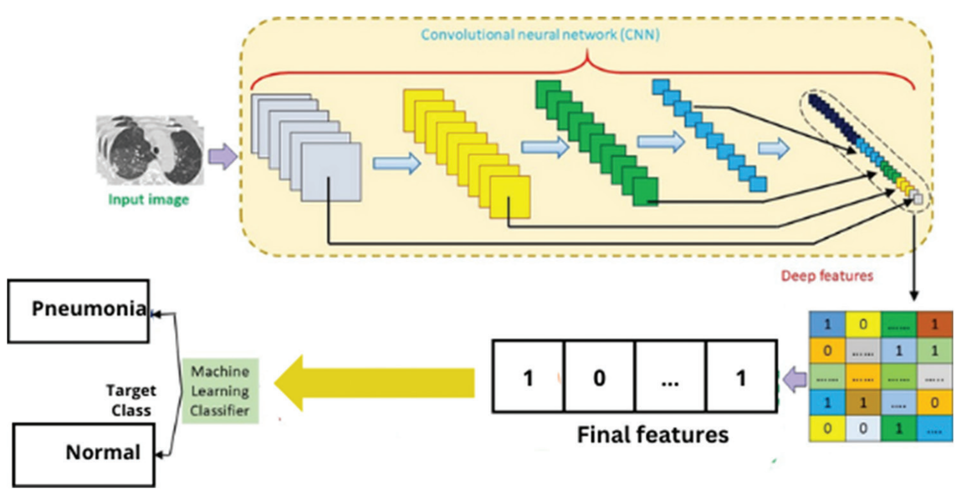

Fig. 3. Workflow of the proposed convolutional neural networks-based feature extraction approach for pneumonia detection.

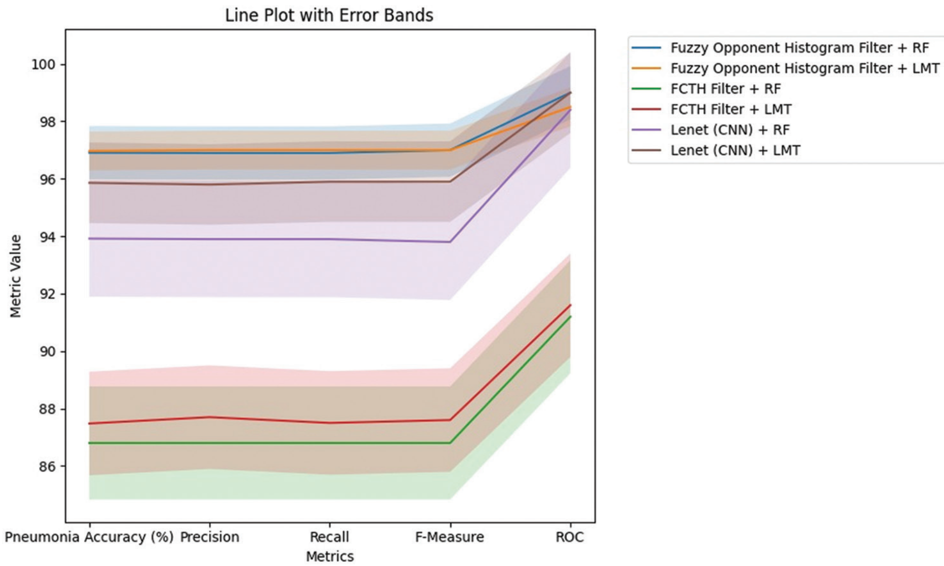

Fig. 4. Line plot with error bands for comparative evaluation of pneumonia detection models.

The combinations evaluated include:

- FOH filter with RFand LMT,
- FCTH Filter with both RF and LMT, and
- The RF and LMT are combined with LeNet (CNN).

As can be seen from the plot, the FOH Filter was combined with LMT and RF and outperformed the rest of the combinations in regard to all of the metrics, as the average values were high with very skinny error bands, meaning accurate and consistent. Like with the Lenet (CNN) combinations, the results for these too used the deep learning-based feature extractor well with a suitable classifier. Compared to these combinations, metric values of the FCTH Filter combinations with less metric values and wider error bands, representing a larger variability and less diagnostic precision.

Effectively highlighting the advantage of fuzzy logic-based feature extraction with either ensemble or hybrid classification model for enabling pneumonia detection accuracy in chest x-ray imagery, this visualization puts the focus on how fuzzy logic-based feature extraction methods will improve classifier performance for this area of study.

Fig. 5 shows the radar chart of model effectiveness in terms of five critical evaluation metrics. From the least to most expansive and balanced polygon the one that forms is the Lenet (CNN) + LMT one, this one having consistently high performance on all the metrics. The performance of both the FOH Filter + LMT method and the proposed one are strong and uniform. On the other hand, FCTH-based combinations feature also quite smaller coverage areas, indicating that they are less well-performing in metrics, such as accuracy, recall, and ROC AUC.

A comparison of six different method combinations when pneumonia is detected across the five essential performance metrics: Pneumonia accuracy (%), Precision, Recall, F-Measure, and ROC is illustrated in Fig. 6. Specific combinations are of three feature extraction technique (FOH Filter, FCTH Filter, and Lenet [CNN]), two classifiers RF

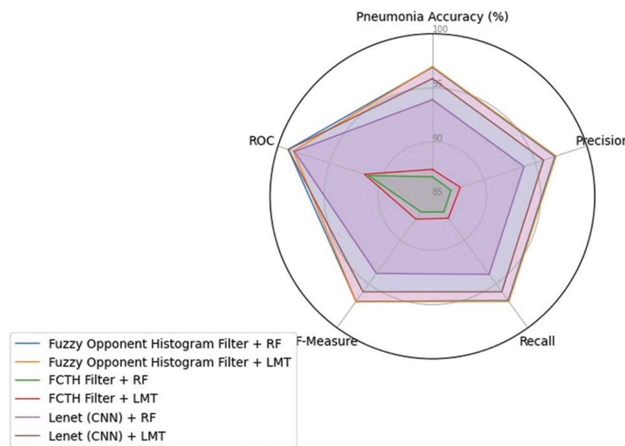

Fig. 5. Comparative radar plot of evaluation metrics for artificial intelligence-based pneumonia classification.

and LMT. As can be seen clearly in the chart, whatever combinations using the FOH Filter have performed better across all metrics when compared to other combinations. More specifically, the combination of this filter with LMT results in the highest overall values; Pneumonia Accuracy, Precision, Recall, and F-Measure go up to 98%, and ROC reaches 98.5%. Furthermore, the performance with RF is nearly the same as with its combination, ROC is a bit higher with a score of 99%.

The Lenet (CNN)-based combinations also perform very well (especially in conjunction with LMT) with all metrics over 95.9 for Pneumonia Accuracy, with the exception of: Details accuracy (95.8), Prognosis accuracy (95.3), and Healed_Pneumonia Accuracy (94.5). They indicate that CNN-derived deep features provide strength in helping with accurate medical image classification. On the other hand, the performance of the FCTH based methods is comparatively lower with respect to all metrics. The accuracy values for Pneumonia in which FCTH and RF or LMT have been used

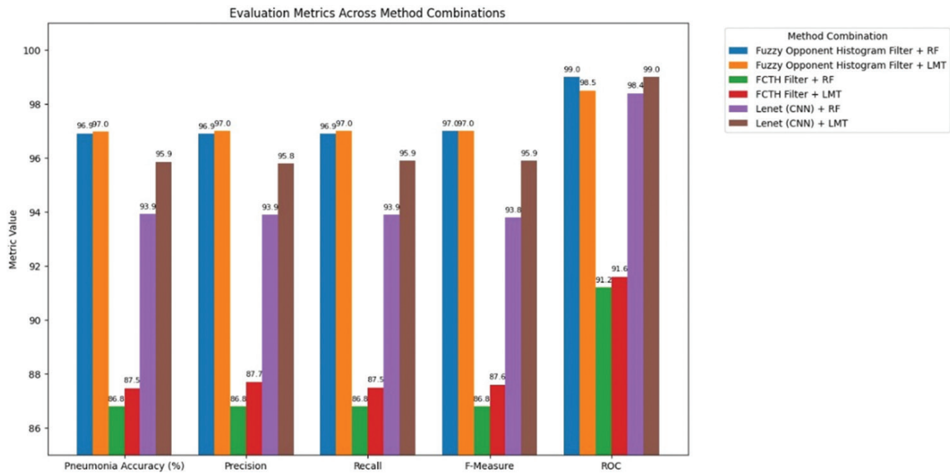

Fig. 6. Comparing evaluation metrics across feature extraction and classification techniques.

as an additive feature that is, 86.8% and 87.5% with its corresponding lower values in Precision, Recall, F-Measure and ROC.

The superior performance of the FOH Filter combined with LMT can be attributed to the complementary strengths of the two components. The FOH filter extracts color-texture information in opponent color spaces using fuzzy logic, which allows it to capture subtle gradations and variations in medical images—particularly important for detecting pneumonia patterns that may not be starkly visible. LMT, on the other hand, offers the interpretability and flexibility of decision trees with the generalization power of logistic regression, allowing it to model both linear and non-linear relationships. Together, this combination exploits both nuanced image characteristics and robust classification boundaries, leading to higher and more consistent performance compared to other methods tested.

Comparative Evaluation with VGG-16:

While numerous studies have reported high accuracy using deep learning models such as VGG-16 for pneumonia detection, we performed a comparative assessment based on literature-reported metrics. VGG-16-based models typically report accuracies in the range of 97–99% using transfer learning approaches on large datasets. In contrast, our hybrid approach combining the FOH Filter and LMT (FOH + LMT) achieved a close accuracy of 96.97% with the added advantage of reduced training time and improved interpretability. Unlike the black-box nature of VGG-16, the LMT-based approach allows for rule-based understanding of classification outcomes, which is highly valuable in clinical applications requiring transparency. This trade-off between slightly lower accuracy and higher transparency, combined with computational efficiency, makes our proposed method a practical and reliable solution in real-time diagnostic environments.

Fig. 7 shows the diagnostic accuracy and the confusion matrix, and they show that the combination of the FOH Filter with LMT and the same filter with RF have the highest classification accuracy of 96.97% and 96.91%, respectively. For both the normal and pneumonia cases, these combinations achieved the lower number of misclassifications.

As opposed to these, the FCTH Filter combinations yielded the lowest performance, that is with accuracy scores of 86.80% (FCTH + RF) and 87.48% (FCTH + LMT) for both false positives and false negatives. The Lenet (CNN) models in combination with RF and LMT form a strong middle ground, especially when Lenet + LMT reached 95.85% accuracy for the classification of normal and pneumonia-contaminated cases.

The results have proved that it was the ones including FOH Filter with the classifiers LMT and RF that yield the highest accuracy values, also proving substantial difference-making between images containing normal versus pneumonia-infected X-rays, as the application of deep learning through Lenet, which works based on a CNN, provides significant performance regarding differentiating image features.

While prior studies on brain tumor detection using VGG-16 and other pre-trained models, such as SqueezeNet, ResNet-50, and EfficientNet-b0 have achieved impressive accuracies ranging from 97% to 99%, our study focuses on pneumonia detection using chest X-ray datasets. The diagnostic nature of pneumonia and brain tumor imaging tasks differs significantly in terms of feature distribution and radiological presentation. In our study, although the absolute accuracy improvement over existing methods is marginal (peaking at 96.97%), the novelty lies in the hybrid combinations of fuzzy logic-based feature extraction with ensemble classifiers (e.g., FOH filter + LMT). Unlike deep CNNs alone, this framework demonstrates interpretability, reduced computational complexity, and comparable diagnostic power – making it more practical in resource-limited clinical environments.

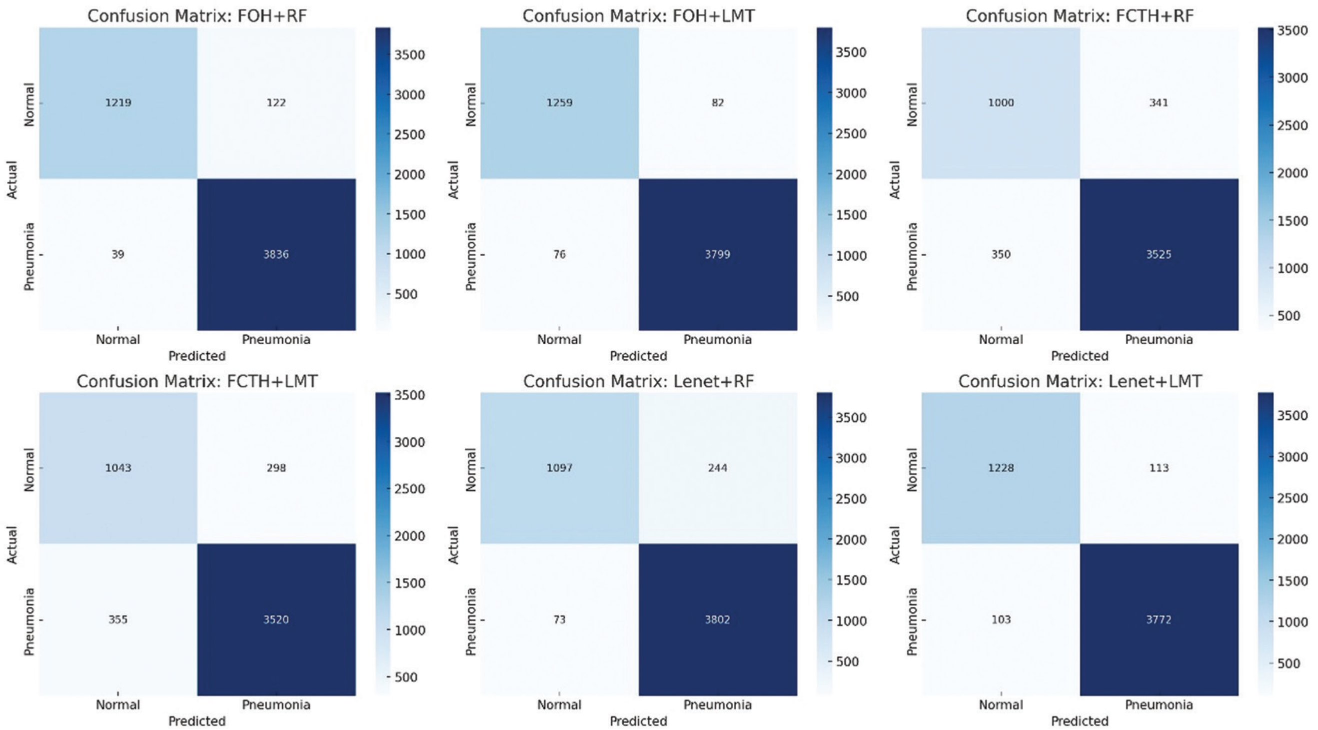

Fig. 7. Confusion matrices showing classification performance of feature extraction and classifier combinations for pneumonia detection.

TABLE II
Performance Metrics by Technique

Method combination	Pneumonia accuracy (%)	Precision %	Recall %	F-measure %	ROC%
Fuzzy opponent histogram filter + RF	96.91	0.969	0.969	0.97	0.99
Fuzzy opponent histogram filter + LMT	96.97	0.97	0.97	0.97	0.985
FCTH filter + RF	86.8	0.868	0.868	0.868	0.912
FCTH filter + LMT	87.48	0.877	0.875	0.876	0.916
Lenet (CNN) + RF	93.92	0.939	0.939	0.938	0.984
Lenet (CNN) + LMT	95.86	0.958	0.959	0.959	0.99

CNNs: Convolutional neural networks, RF: Random forest, LMT: Logistic model trees, ROC: Receiver operating characteristic

V. Conclusion

In this research, the significant capacity of adding advanced techniques of machine learning and AI over traditional methods to increase the diagnostic accuracy and precision of pneumonia which is detected in chest X-ray images has been realistically proven. Finally, our experiments demonstrate that deep learning models (especially CNNs) and ensemble methods significantly improve the precision and reliability of diagnosis and at its peak achieve 96.97% accuracy in the case of FOH Filter along with LMT. These technologies help in the better identification of pneumonia and also decrease the time it takes to identify the disease, which is vital for the proper administration of the treatment. More than that, Lenet (CNN) combined with LMT achieved great results with 95.85% accuracy, demonstrating excellent performance in medical imaging tasks. The involvement of AI in the field of medical imaging to support pneumonia diagnosis significantly reduces the subjectivity and variation inherent in the interpretation of radiographs and potentially lowers the error rate of diagnostic findings. Moving forward, these models need to be extended with larger and more diverse datasets to further test their effectiveness in different populations and clinical settings. Future research will also be important in integrating these machine learning models into real-time diagnostic platforms in the hospital setting, where their practical utility and effects on patient outcomes can be ascertained.

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