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Classification of Pneumonia Disease Using Machine Learning Techniques: A Systematic Reviews

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ABSTRACT: According to the World Health Organization, pneumonia sickness claimed over two million lives in 2019. Children between the ages of one and five as well as elderly individuals frequently die. The healthcare system faces numerous obstacles, including a decline in radiologists as a result of widespread migration overseas, an increase in medical image volume, challenges in interpreting criteria, rising workloads, and an abundance of complex images that could overwhelm radiologists. This calls for deliberate actions to lessen the impact of pneumonia. Clinical decision-making technology has advanced due to increased research in medical image processing, which has been made possible by the geometric growth in diverse machine learning applications. Clinical decision-making technology has evolved as a result of increased research in medical image processing, which has been enabled by the exponential rise of various machine learning applications. Combining machine learning and deep learning in hybrid and ensemble forms provides a speedy solution to challenges that have profoundly altered society, either by saving lives or easing those afflicted. This comprehensive overview of the literature addresses various methods for classifying pneumonia utilizing machine, deep, hybrid, and ensemble learning techniques.In addition to providing a summary of the reviews in a table and deep insight into the results of the classifications, the review highlights various research gaps in the current models and potential solutions, enabling a better understanding of the model's accuracy performance and suitability for pneumonia classification. It also offers recent trends, illustrations, and an evaluation of these models' efficacy in the classification of pneumonia disease.

KEYWORDS: pneumonia; machine learning; deep learning; hybrid; ensemble learning; reviews; classification.

I. INTRODUCTION

The rapid advancement of technology over the past few decades has greatly contributed to the transformation of the health care system in a variety of ways. The system is improving over time, and this has led to numerous breakthroughs that drive the healthcare system for improved patient care. As these technologies continue to evolve, an effective method along with their processes must be developed in order to provide high-quality resources at a cost that is affordable for the majority of the population. The outcome of these factors would enable informed diagnoses and the delivery of effective results across the board [1].

Artificial intelligence finds application in many spheres of human activity. Investigating the big data world through diverse applications of artificial intelligence, machine learning, neural networks, and deep learning technologies has tremendously benefited from technological advances in clinical diagnosis [2]. The process of artificial intelligence (AI) integrates data understanding, learning, planning, and reasoning to provide a discovery output. Machines that resemble human intelligence in terms of prediction, optimization, and task automation can be categorized using artificial intelligence [3]. Machine learning (ML), a branch of artificial intelligence, aims to develop computer systems that can learn based on experience [4].

Machine learning is a broad branch of computer science concerned with developing intelligent machines capable of doing tasks that need human decision-making. The broad branch of computer science known as "machine learning" focuses on creating intelligent machines that can do tasks that call on human judgment [2]. Even though machine learning (ML) systems are computers that can perform tasks with little programming and can think and act like machines by completing difficult tasks like gathering data, which can include images, videos, and other types of media, they are still unable to perform tasks that humans can [4]. It is an interdisciplinary science that has led to a paradigm shift in technology by enabling machines to adapt to new inputs and perform a variety of tasks. Notably, many applications of machine learning can assist in training a system to execute a given task by processing large amounts of data and identifying patterns in the data. Machine learning is a collection of techniques that can be used to solve real-world problems using a computer system that learns and adapts rather than explicit programs [2]). The most widely used algorithms for machine learning include Almost any data issue may be solved with these algorithms: Algorithms for Dimensionality Reduction, Gradient Boosting, Naive Bayes, K-Nearest Neighbor (KNN), Random Forest (RF), Decision Tree, Support Vector Machine (SVM), Linear Regression, Logistic Regression, Naive Bayes LightGBM, and XGBoost.

II. MACHINE LEARNING TECHNIQUES

Supervised, unsupervised, and reinforcement learning are the three categories of machine learning. The level of human engagement and data availability have a significant impact on how different types of machine learning are deployed. According to [5] the supervised learning algorithm builds a mathematical model that combines data from the input to the desired output. However, because labelled data are fed into the system, the designed model teaches the system how to best predict the remaining data, and programmers can confirm the result or make adjustments if necessary [6]. Unlabelled data is used by an unsupervised learning algorithm to categorize and forecast event outcomes. The system works by collecting a collection of data that just comprises the input, discovering the structures in the form of clustering, and then identifying those features. It then looks for patterns that have similar characteristics to predict the outcomes [7].

Another subset of machine learning is called reinforcement learning, and it deals with how software agents behave in a given environment to get the best possible results. It is used to assist the computer in mastering huge, unpredictable, and extremely flexible difficult jobs [8]. Furthermore, a subfield of machine learning known as neural networks use an artificial neural network—a network of neurons—to address artificial intelligence challenges [6]. It is modelled using artificial neural networks that distribute weight across the nodes, much like a biological neuron. The activation function determines the amplitude of the output, whilst the inputs are weighted and summed to form the linear combination. The term "deep learning system" refers to a neural network that uses several hidden layers and nodes within each of the hidden layers.

Using textural features, [9] created an autonomous pneumonia diagnosis system. Particularly in the age of Covid-19, a major source of infection, the pathologic aspects of pneumonia were a serious concern. The study's goal is to offer the instruments needed to evaluate the potential of the three textual image characterization techniques—radiomics, fractal dimension, and super pixel—as biomarkers for artificial intelligence models that will be trained to detect pneumonia illnesses. The artificial intelligence algorithms utilized in the process include Support Vector Machine, Random Forest, and K-Nearest Neighbor. In the two free access paediatric chest X-ray image datasets utilized the outputs the top performing produced models achieved 83.3% accuracy for radiomics, 91.3% accuracy for the fractal dimension and 90.5% for sensitivity for super pixel-based histones. Although there is potential for development, the results validated the approaches' applicability as trustworthy and user-friendly.

[10] uses a convolutional neural network to identify pneumonia from noisy labelled chest radiographs. Convolutional neural network (CNN) for pneumonia identification from noisy labelled chest radiographs should be developed. Using a dataset of 82,760 chest radiographs—which had noisy labels because of labelling process inconsistencies—the scientists trained a CNN model. They increased the amount of the dataset by applying data augmentation techniques and employed a data cleaning algorithm to eliminate photographs with poor quality labels. Compared to other deep learning models that were tested on the same dataset, the CNN model outperformed it with an accuracy of 91.6% on the test set. The CNN model's performance on other datasets and its comparison to non-deep learning techniques were

not assessed in the study. The accuracy of the model may have been impacted by the noisy tagging procedure, as the authors recognized.

Classification types are classified as binary or multiclass, and their strategies rely on various machine learning techniques, such as machine, deep, ensemble, and hybrid learning, which vary based on the architecture's strength, the quantity of datasets available, and the algorithms selected.

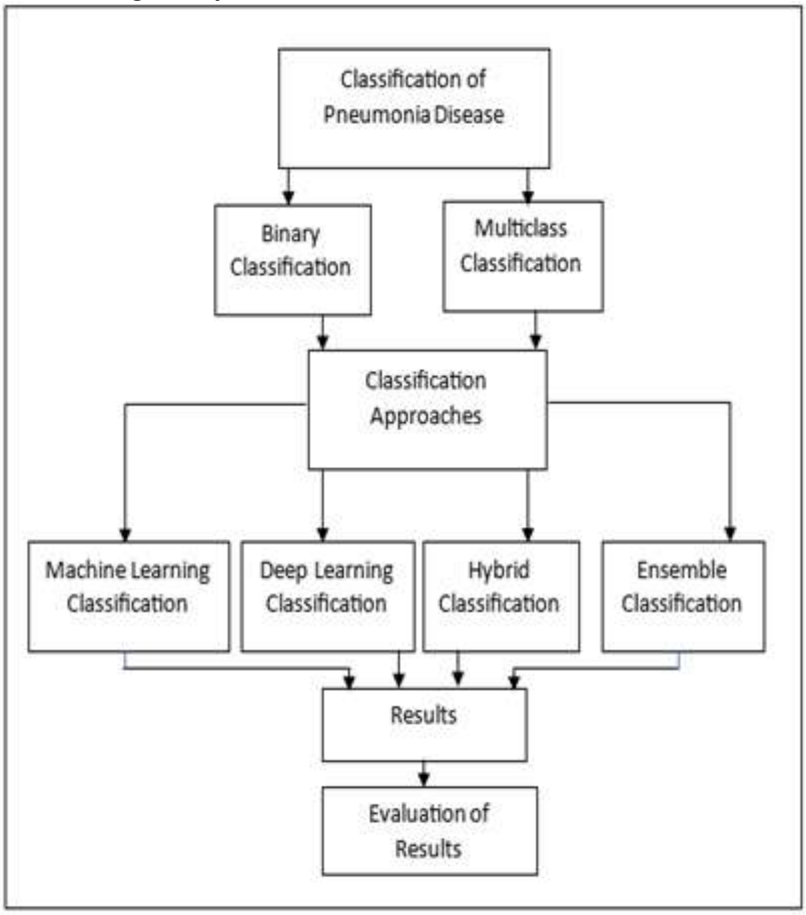

Figure 1: Classification Approaches.

[11] used machine learning to develop models for identifying pneumonia using chest x-ray images. The images' intricate anatomical structure made the radiologist's imaging projection difficult, which motivated the authors. Machine learning algorithms have been employed in a variety of domains, including the classification of different types of pneumonia. Each training image is extracted and fed into the pipeline of machine learning models, which include the Random Forest, Artificial Neural Network, and Decision Tree, using a mix of the invariant Fourier Transform and local binary pattern characteristics. The Random Forest algorithm correctly identified the data with an accuracy of 91.29%.

In order to reduce morbidity and mortality from pediatric pneumonia, [12] proposed a machine learning method for detecting the sickness. The chest X-ray is one of the instruments used to establish whether pneumonia sickness is present and whether healthcare practitioners' interpretations of chest radiography are inconsistent. This process has a great impact and results in an inaccurate diagnosis. As a result, automation of the outcome process is essential to reduce errors and allow the affected person to begin treatment as quickly as possible. The Quadratic Support Vector Machine (SVM) model, which the author utilized to balance the dataset classes using data augmentation methodologies, achieved an accuracy of 97.58%, which is greater than the current ML literature. This result shows that the method for detecting pneumonia disease is reliable.

[13] used chest x-ray clustering to develop a K-Nearest Neighbor (KNN) machine learning architecture for pneumonia. The health and medical industries have profited substantially from technical advances in machine learning, a subset of artificial

intelligence. The KNN algorithms are the most widely used machine learning algorithms. This effective classification approach is based on the premise that comparable items in a feature space can be classified together. The authors want to improve the KNN's accuracy at predicting COVID-19 and pneumonia from chest x-ray images. Although additional steps can be taken to improve accuracy using ensemble or hybrid approaches, the implementation's output shows an accuracy value of 0.95 [13].

III. DEEP LEARNING TECHNIQUES

Deep learning is another type of machine learning that has been used in a variety of applications. Deep learning, also known as hierarchical learning, is a sort of machine learning that simulates how the human brain processes information and develops patterns similar to those used in decision-making. Deep Learning systems, in contrast to task-based algorithms, acquire knowledge from data representations, which refers to unstructured or unlabeled data [14].

Deep learning models offer a more advanced approach to machine learning techniques and applications, thanks to their complicated, multi-layered neural networks. Since there is typically little to no requirement for human intervention, a large volume of data is used to feed and create the system, resulting in a non-linear transformation of the data as the output [6].

Deep learning is one of many machine learning approaches based on artificial neural networks. Convolutional neural networks (CNN), recurrent neural networks (RNN), deep neural networks (DNN), deep belief networks (DBN), and deep stacking networks (DSN) make up the deep learning architecture [15]. Medical image analysis, audio recognition, bioinformatics, machine translation, speech recognition, machine vision, and natural language processing are among the fields where deep learning applications are being used. The results in these areas have all shown significant improvements over human expertise [16, 17, 18].

The deep learning system is the creation of deep algorithms used to train and predict an output from complicated data. Above all, a deep neural network, or a deep learning system is any neural network that has more than three layers, including the input and output layers. Algorithms modelled after the human brain make up neural networks. These algorithms are capable of labelling or clustering raw data and using machine perception to understand sensory input. For the purpose of translation, neural networks are made to identify numerical patterns in the vectors of real-world data, such as text, images, sound, time series, etc. Clustering and classifying the raw data are essentially a neural network's main function [14]. Deep learning is being used in big businesses including advertising, stock market prediction, healthcare, and e-commerce. Artificial neural networks are used by the Deep Learning system to do sophisticated computations on a large volume of data. It was designed with the structure and functionality of the human brain in mind [19].

[20] developed a deep learning-based technique for automatically identifying and categorizing pneumonia from chest X-ray data. Chest X-rays were employed in this work to detect COVID-19-induced pneumonia using CNN and deep learning techniques. The suggested study successfully distinguishes between COVID-19-induced pneumonia, common pneumonia, and normal circumstances utilizing transfer learning with fine-tuning. Transfer learning is carried out utilizing Xception, Visual Geometry Group 16, and Visual Geometry Group 19. With a 98% detection rate for COVID-19-induced pneumonia, the experimental results demonstrated promise in terms of precision, recall, F1 score, specificity, false omission rate, false negative rate, false positive rate, and false discovery rate. According to experimental data, the proposed work successfully detected and distinguished COVID-19 exposure from COVID-19-induced pneumonia.

[21] used deep transfer learning to demonstrate a successful method for diagnosing pneumonia in chest X-ray pictures. The author's inspiration comes from the statistic that pneumonia kills approximately 700,000 children each year, or about 7% of the world's population. A trained radiologist typically struggles to examine chest x-rays effectively, highlighting the need for a weighted classifier approach that combines predictions from deep learning models such as MobileNetV3, DenseNet-121, InceptionV3, Xception, and ResNet-18 to improve diagnosis accuracy. The dataset is used by the network to predict the outcome via supervised learning, and transfer learning is used to increase the accuracy of deep learning models. With an accuracy of 98.43%, the weighted classifier outperformed the individual models.

[22] used X-ray images to develop a pneumonia classification system that incorporates both a convolutional neural network and the Inception-V3 architecture. This study employs X-ray images to detect pneumonia in a manner similar to prior research. The dataset is preprocessed before being used in transfer learning tasks. Several pre-trained convolutional neural network (CNN)

versions are used, including VGG16, Inception-v3, and ResNet50. CNN is integrated with Inception-V3, VGG-16, and ResNet50 to form ensembles. In addition to typical assessment measures, Cohen's kappa and area under the curve (AUC) are employed to evaluate the performance of pre-trained and ensemble deep learning models. According to the experimental data, inception-V3 with CNN had the highest accuracy and recall scores, 99.29% and 99.73%, respectively.

In 2023, [23] developed a deep learning-based computational method for diagnosing and categorizing pneumonia. Using chest X-ray images, this study proposed a scalable and interpretable deep convolutional neural network (DCNN) for diagnosing pneumonia. The proposed revised DCNN model classifies the images into normal and pneumonia classes after extracting significant characteristics from them. A series of chest X-ray images were utilized to train and test the proposed approach. A number of performance criteria were used to evaluate the stability and effectiveness of the proposed strategy. According to the experimental data, the proposed model outperforms other cutting-edge strategies for diagnosing pneumonia. To increase the performance of the suggested model, the updated DCNN's parameters were tweaked on a regular basis to attain the best validation results. Various results were produced by running numerous experiments and applying a variety of strategies, such as data augmentation, annealing, adjusting other parameters such as learning rate, and organizing the information before feeding it into the proposed DCNN architecture. As a result, good results were achieved, with training accuracy of 98.02% and validation accuracy of 96.09%.

[24] proposed using deep learning on chest X-ray images to predict pneumonia. The possibility of bacterial and viral pneumonia infections, which can cause the patient to experience a number of chest-related problems. The fundamental goal of creating a computer-aided method for pneumonia diagnosis in children is to separate the texture by focusing on the similarities between pneumonia and all other chest diseases, which is expected to increase the accuracy of diagnoses. The approach employs Inception-V3, Xception, ResNet-50, VGG-16, and VGG-19. The models were designed to increase precision in order to improve performance and accuracy. Recall, specificity, accuracy, and AUC are provided by the Xception results, which are 97.02%, 95.06%, 94.23%, and 97.43%, respectively.

IV. ENSEMBLE LEARNING TECHNIQUES

A strategy designed to include several models in the prediction process is ensemble machine learning. Base estimators are the name given to these models. It offers a way around the technological difficulties involved in creating a single estimator [25]. For a given data set, one algorithm might not have a reliable prediction. The majority of machine learning algorithms have their limitations, therefore combining one or more would result in predictions from the models that are reliable, or in classifications, which are accomplished by combining the output from each model. An ML technique called ensemble learning combines two or more learners, such as neural networks or regression models, to provide better results. An ensemble model is more convenient to use than a single model since it integrates multiple unique models to make predictions that are more accurate. [26]. Standard ensemble techniques include bagging, boosting, stacking, and blending; other classes—maximum voting, weighted averaging, and averaging—are referred to as aggregators [25]

[27] created an ensemble pneumonia screening model that is optimized using chest x-ray pictures. Using ensemble models, the research aims to diagnose pneumonia. Preprocessing, segmentation, feature extraction, selection, and detection are all part of the methodology. The image is pre-processed using median filtering and dynamic histogram equalization (DHE). In the segmentation phase, the AHGOA (Archimedes-assisted Henry Gas Optimization Algorithm) model is used to separate the ROI from the background and create features based on the Local Gradient Increasing Pattern (LGIP), Harmonic Local Gradient Pattern (hLGP), Improved Local Ternary Pattern (ILTP), and Improved Local Gradient Pattern (ILGP) derived from the isolated ROI areas. The chosen EC + AHGOA technique had a 0.95 accuracy rate.

[28] Identification of Pneumonia on Chest X-Ray Images With a collection of deep convolutional neural networks constructed. A convolutional neural network (CNN) for detecting pneumonia from noisy labeled chest radiographs should be created. Using a dataset of 82,760 chest radiographs—which had noisy labels because of labeling process inconsistencies—the scientists trained a CNN model. They increased the amount of the dataset by applying data augmentation techniques and employed a data cleaning algorithm to eliminate photographs with poor quality labels. Compared to other deep learning models that were tested on the same dataset, the CNN model

outperformed it with an accuracy of 91.6% on the test set. The CNN model's performance on other datasets and its comparison to non-deep learning techniques were not assessed in the study.

[29] developed an ensemble of deep learning models for detecting pneumonia in chest X-ray images. This study employed chest X-ray images to detect pneumonia using a computer-aided diagnosis approach. To address the shortage of available data, deep transfer learning was developed, along with three convolutional neural network models (GoogLeNet, ResNet-18, and DenseNet-121). The approach utilized was a weighted average ensemble, and the weights assigned to the base learners were calculated using a new way. The weight vector is created by combining the scores from four conventional assessment metrics: precision, recall, f1-score, and area under the curve. The weight vector is frequently established empirically in research, which is a risky strategy.

The recommended approach was evaluated using a five-fold cross-validation scheme on two publicly available pneumonia X-ray datasets provided by the Radiological Society of North America (RSNA) and Kermany et al., respectively. The suggested technique achieved accuracy rates of 98.81% and 86.85% on the Kermany and RSNA datasets, respectively, as well as sensitivity values of 98.80% and 87.02%. Our solution outperformed commonly used ensemble techniques and produced results that were superior to those of cutting-edge technologies.

[30] developed an ensemble model based on convolutional neural networks for identifying pneumonia in chest X-ray images. The goal of this study is to develop a precise, accurate, and lightweight model to aid in the diagnosis of pneumonia. Three models with different kernel sizes were used to develop a convolutional neural network architecture. These models' outputs were combined using a novel weighted ensemble approach, which recommends a threshold value that may be adjusted to change the model's diagnostic capabilities as needed. Overfitting and a lack of data make the model perform poorly, hence gathering more varied and large-scale datasets is required. Even while the ensemble architecture works well to boost recall, it is quite expensive to compute and requires a lot of technology. Given the scenario, the variable threshold value allows you to change the weight assigned to each model's output, hence changing the classification outcome. The model was evaluated using metrics like accuracy, recall, precision, and f1-score. It achieved critically high values for the specified domain, with a recall of 99.23% and a f1-score of 88.56%, almost eliminating the risk of misclassifying a Pneumonia positive case. Because deep neural networks and transfer learning are not included in the model, it is lightweight and hence a potentially deployable diagnostic aid.

[31] created an ensemble model by combining deep learning methods. To get more accurate pneumonia imaging diagnoses, the authors integrated DenseNet-121 and EfficientNetB0 into a deep-learning neural network technique. The pre-trained model is coupled with network processing by using the feature extraction's multi-head and self-attention modules. Channel attention-based strategies were used to improve the model's integration and processing of the residual block complement. The study also examined the suggested system's operational system, architectural features, and algorithms. The empirical results on the test dataset showed a high diagnostic accuracy of 95.19%, precision of 98.38%, recall of 93.84%, F1 score of 96.06%, specificity of 97.43%, and an AUC of 0.9564. Additionally, it emphasizes the encouraging possibilities of clinical deployment in the actual world [31].

V. HYBRID TECHNIQUES

The hybrid approach improves on machine learning by combining diverse algorithms, techniques, or processes from related or unrelated fields of study or application in an easy-to-use manner with the purpose of enhancing one another. It is clear that not every problem can be solved by a single machine learning approach. While some models perform well with noisy data, they may be unable to handle input spaces with multiple dimensions. [32]. Some may do better in high-dimensional input space scaling, whilst others may struggle with sparse data. These circumstances provide a solid foundation for applying Hybrid Machine Learning (HML) techniques, which can be used to supplement candidate methods and leverage one to strengthen its shortcomings. There are countless ways to hybridize conventional machine learning techniques, and each one can be done in a different way to create new hybrid models. In order to develop a more reliable standalone algorithm, the HML smoothly blends the architecture of two or more traditional algorithms, either fully or partially, in a complimentary way [33].

[14] created machine and deep learning algorithms for identifying and categorizing lung disorders, focusing on pneumonia and Covid-19. This study proposed a novel methodology for predicting lung disorders from patient chest X-ray images, including pneumonia and Covid-19. The

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framework encompasses feature extraction, disease prediction, adaptive and reliable ROI estimation, dataset acquisition, and image quality enhancement. The dataset collection approach involved the utilization of two freely available datasets of chest X-ray pictures. X-ray image quality degraded, thus median filtering and histogram equalization were applied to improve it. They created a powerful normalization strategy to boost detection and classification results. Soft computing approaches, such as ensemble classifier, deep learning classifier, K-nearest Neighbor (KNN), support vector machine (SVM), artificial neural network (ANN), and KNN, are used for classification. It was revealed that the proposed F-RNN-LSTM model, which accounted for nearly half of the analyzed techniques, achieved higher accuracy, around 95%, with less computational expense.

[34] developed a hybrid explainable ensemble transformer encoder for detecting pneumonia in chest X-ray images. Transformer Encoder: Multi-Head Self-Attention Network and MLP Block are utilized in this study to evaluate the potential of early pneumonia detection from chest X-ray images. The properties of ensemble convolutional networks and the Transformer Encoder approach are combined to construct the proposed hybrid procedure. In two different scenarios, the ensemble learning backbone—ensemble A, which consists of DenseNet201, VGG16, and GoogleNet—and ensemble B, which consists of DenseNet201, InceptionResNetV2, and Xception—are used to extract strong features from the raw input X-ray images. In contrast, the Transformer Encoder accurately identifies diseases using a multilayer perceptron (MLP) and a self-attention method. The visual explainable saliency maps emphasize the most important anticipated places on the input X-ray images. A comprehensive training process was carried out using binary and multi-class datasets. The model's performance was assessed using ROC and PR curves, accuracy, F-1 score, sensitivity, specificity, and precision, as well as a confusion matrix. In binary classification, the proposed hybrid deep learning model achieved 99.21% classification performance in terms of overall accuracy and F1-score, while in multiclass identification, it achieved 98.19% accuracy and 97.29% F1-Score. In accordance with the evaluation criteria, the proposed model outperforms the most advanced deep learning algorithms in binary and multi-class classification results, indicating superiority and efficiency in the early diagnosis of pneumonia from chest X-ray images.

[35] used ensemble techniques and deep learning to create and deploy hybrid architectures for classifying pneumonia in medical imaging data. To generate twenty hybrid architectures, this study will combine two ensemble techniques—the Bagging Classifier with base learners (KNN, logistic Regression, SVM) and the Boosting technique (AdaBoost classifier with Decision tree as a base learner)—with five deep learning techniques (VGG16, VGG19, EfficiantVB0, MobileNetV2, DenseNet201). The four classification performance parameters that the researchers used to assess the developed designs were F1-score, accuracy, precision, and recall. Using Scott Knott's statistical test, the suggested designs were aggregated, and the best cluster of performing architectures was selected. The preliminary results show how well ensemble techniques combined with deep learning can be applied to medical picture processing. The hybrid design of the BAGSVM classifier and the MobileNetV2 feature extractor produced the greatest results, with an accuracy of 99.04 percent. We advocate using the hybrid designs BAGSVMMV2 and BAGSVMAWM, which produce the greatest results in binary categorization of pneumonia based on the investigation's findings.

In 2023, [36] developed a CNN-based hybrid model for the classification of pneumonia. The most deadly and contagious form of pneumonia served as inspiration for the writers. The use of machine learning has aided in increasing accuracy and speed. The goal is to classify pneumonia disease using a combination of deep learning models. There are three deep learning models used: Xception, EfficientNetB4, and the Convolutional Neural Network. Pre-processing and data augmentation approaches were employed to achieve a 98.00% accuracy. The result demonstrates that hybrid models are more accurate than those found in the current literature.

[37] developed a hybrid classification and identification of pneumonia using African buffalo optimization and CNN from chest x-ray images. The African Buffalo Optimization (ABO) algorithm was used in the suggested method (ABO-CNN) to improve CNN accuracy and performance. Followingthe pre-processing with the Weinmed filter to remove unwanted noises from chest X-ray images, Grey Level, Co-Occurrence Matrix (GLCM) feature extraction was conducted. After employing the ABO algorithm to extract pertinent characteristics from the dataset, a high-performance deep learning algorithm based on the CNN technique is demonstrated for pneumonia detection and classification. Experiments on various datasets demonstrated that the ABO-CNN outperforms all other classification algorithms. The suggested approach produces great results, such as 96.95%

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accuracy, 88% precision, 86% recall, and 86% F1-score. High-performance deep learning utilizing the CNN technique is finally shown for the diagnosis and classification of pneumonia. Experiments conducted on different datasets demonstrated that the ABO-CNN performs better for classification tasks than any other techniques. The suggested approach displays excellent results such as 96.95%, 88%, 86%, and 86% for accuracy, precision, recall, and F1-score, respectively.
Other assessment metrics are stated in the literature reviews. Table 1 includes the author, the year of research, and the accuracy result obtained.

VI. CONCLUSION

Pneumonia disease has been accurately demonstrated and classified by machine learning algorithms. Every classification technique has advantages and disadvantages based on how well it performs and how many datasets are available. Deploying these models or systems as of an application would be a huge benefit to the medical field because the technology would aid in automatically detecting pneumonia, saving time and ensuring early treatment to save lives. Reviews point out that combined model strength, rather than a single machine learning technique, produced superior classification accuracy in other approaches.

With remarkable precision, the paper offers a thorough analysis by several authors of the most popular machine learning techniques and their most current applications.

All things considered, using technology, and machine learning in particular, to improve healthcare results holds great promise for resolving many of the issues facing our society, particularly with regard to medical advancements.

AUTHOR(S)	**YEAR**	**TECHNIQUE (S)**	**RESULT (ACCURACY %)**
		A. Machine Learning Algorithms	
Rao et al	2022	Random Forest, Artificial Neural Network, and Decision Tree.	91.29
Kim et al	2020	Convolutional Neural Network (CNN)	91.6
Barakat et al	2023	Quadratic Support Vector Machine (QSVM)	97.58
Ortiz-Toro et al.	2022	Support Vector Machine, Random Forest and the K-Nearest Neighbour Algorithm	83.3
Firdaus	2024	K-Nearest Neighbour (KNN)	95.0
		B.Deep Learning Techniques	
Maniruzzaman, et al.	2024	Inception-V3, Xception, ResNet-50, VGG-16, and VGG-19.	95.06
Yi et al	2023	Deep convolutional neural network (DCNN)	96.09
Jain et al	2022	Xception, ResNet-50, VGG-16, and VGG-19.	98.0
Muhajd et. al.	2022	Inception-V3, VGG-16, and VGG-19.	99.29% & 99.73%,
Hashimi	2020	MobileNetV3, DenseNet-121, InceptionV3, Xception, and ResNet-18	98.43
		C.Ensemble Learning Techniques	
An et al	2024	DenseNet-121 and	95.19

		EfficientNetB0	
Nalluri & Sasikala	2024	AHGOA (Archimedes-assisted Henry Gas Optimization Algorithm)	95.0
Bhatt et al	2023	3 x 3, 5 x 5 and 7 x7 kernel layers of CNN	99.23
Mabrouket al.	2022	Convolutional neural network (CNN)	91.6
Kundu et al	2021	GoogLeNet, ResNet-18, and DenseNet-121	98.81
		D.Hybrid Learning Approach	
Goyal et al	2023	Ensemble classifier, deep learning classifier, K-nearest Neighbor (KNN), support vector machine (SVM), Artificial Neural Network (ANN)	95.0
Nkoma et al	2023	A (DenseNet201, VGG16, GoogleNet) and B (DenseNet201, InceptionResNetV2, and Xception)	98.19
Taib et al	2023	(KNN, RF, SVM) and (AdaBoost classifier with Decision tree as a base learner)with (VGG16, VGG19, EfficiantVB0, MobileNetV2, DenseNet201).	99.04
Ranparya et al	2023	Xception, EfficientNetB4, and Convolutional Neural Network.	98.0
Alalwan et al.	2024	African Buffalo Optimization and CNN	96.95

TABLE 2: AUTHORS, MODELS AND RESULT OBTAINED

REFERENCES

[1] Akinbo & Daramola (2021). Ensemble Machine Learning Algorithms for Prediction and Classification of Medical Images. DOI: 10.5772/intechopen.100602

[2] IBM (2020). What is artificial intelligence (AI)? https://www.ibm.com/topics/artificial-intelligence

[3] McCarthy, J. (1956). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence. http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf

[4] Mitchell T.M (1997). Machine Learning. McGraw-Hill Science/Engineering/Math; (March 1, 1997) 414 pages. ISBN 0070428077. https://www.cs.cmu.edu/~tom/mlbook.html

[5] Russell SJ & Norvig P. Artificial Intelligence: A Modern Approach (Third edition). Prentice Hall; 201

[6] Middleton M. (2021 February 8). Deep Learning vs. Machine Learning. https://flatironschool.com/blog/deep-learning-vs-machine-learning/

[7] Jordan M. I & T. M. Mitchell T. M (2015). Machine learning: Trends, perspectives, and prospectsScience 349, 255 (2015); DOI: 10.1126/science.aaa8415

[8] Otterlo, M. V., & Wiering, M. (2012). Reinforcement learning and markov decision processes. Reinforcement Learning. Adaptation, Learning, and Optimization, 12, 3–42. 10.1007/978-3-642-27645-3_1

[9] Ortiz-Toro C., García-Pedrero A., Lillo-Saavedra M., Gonzalo-Martín, C. (2022). Automatic detection of pneumonia in chest X-ray images using textural features,Computers in Biology and Medicine,145,105466,ISSN 0010-4825,https://doi.org/10.1016/j.compbiomed.2022.105466.

[10] Kim Y.G, S.M. Lee, K.H. Lee, R. Jang, J.B. Seo, N. Kim (2020). Optimal matrix size of chest radiographs for computer-aided detection on lung nodule or mass with deep learning. European Radiology, 30 (9) (2020), pp. 4943-4951, 10.1007/s00330-020-06892-9

[11] Rao D.S, Nair A. S. H, Rao T.V, Kumar K.P.S (2022). Classification of Pneumonia from Chest X-ray Image using Machine Learning Models. International Journal of Intelligent Systems and Applications in Engineering. IJISAE, 2022, 10(1s), 399–408

[12] Barakat N, Awad M & Abu-Nabah B.A(2023). A machine learning approach on chest X-rays for pediatric pneumonia detection. Digital Health Volume 9: 1–13 sagepub.com/journals-permissions DOI: 10.1177/20552076231180008 journals.sagepub.com/home/dhj

[13] Firdaus M (2024). KNN Machine Learning Architecture for Pneumonia Chest X-Ray Clustering (2024). Telecommunications, Computers, and Electricals Engineering Journal (TELECTRICAL) Vol. 2, No. 1, June 2024, pp. 43~51 ISSN: 3026-0744, DOI: 10.26418/telectrical. v2i1.78604

[14] Goyal, S., & Singh, R. (2023). Detection and classification of lung diseases for pneumonia and Covid-19 using machine and deep learning techniques. Journal of Ambient Intelligence and Humanized Computing, 14(4), 3239–3259. https://doi.org/10.1007/s12652-021-03464-7

[15] Sunil Ray S (2024, March 19). Top 10 Machine Learning Algorithms to Use in 2024. https://www.analyticsvidhya.com/blog/2017/09/common-machine-learning-algorithms/

[16] Hu, K., Huang, Y., Huang, W., Tan, H., Chen, Z., Zhong, & Gao, X. (2021). Deep supervised learning using self-adaptive auxiliary loss for COVID-19 diagnosis from imbalanced CT images. Neurocomputing, 458, 232-245.

[17] Ciresan, D., Meier, U., Schmidhuber, J. (2012). Multi-column deep neural networks for image classification. 2012 IEEE Conference on Computer Vision and Pattern Recognition. pp. 3642–3649. arXiv:1202.2745. doi:10.1109/cvpr.2012.6248110. ISBN 978-1-4673-1228-8.

[18] Krizhevsky A., Sutskever I., Hinton, G. (2012). ImageNet Classification with Deep Convolutional Neural Networks. (PDF). NIPS 2012: Neural Information Processing Systems, Lake Tahoe, Nevada.

[19] Avijeet B. (2021). Top 10 Deep Learning Algorithms You Should Know in 2021. https://www.simplilearn.com/tutorials/deep-learning-tutorial/deep-learning-algorithm

[20] Jain, D. K., Singh, T., Saurabh, P., Bisen, D., Sahu, N., Mishra, J., & Rahman, H. (2022). Deep Learning-Aided Automated Pneumonia Detection and Classification Using CXR Scans. Computational Intelligence and Neuroscience, 2022, 7474304. https://doi.org/10.1155/2022/7474304

[21] Hashmi, M.F.; Katiyar, S.; Keskar, A.G.; Bokde, N.D.; Geem, Z.W. (2020). Efficient Pneumonia Detection in Chest Xray Images Using Deep Transfer Learning. Diagnostics 2020, 10, 417. https://doi.org/10.3390/diagnostics10060417

[22] Mujahid, M., Rustam, F., Álvarez, R., Luis Vidal Mazón, J., Díez, I. T., & Ashraf, I. (2022). Pneumonia Classification from X-ray Images with Inception-V3 and Convolutional Neural Network. Diagnostics (Basel, Switzerland), 12(5), 1280. https://doi.org/10.3390/diagnostics12051280

[23] Yi, R., Tang, L., Tian, Y., Liu, J., & Wu, Z. (2023). Identification and classification of pneumonia disease using a deep learning-based intelligent computational framework. Neural Computing & Applications, 35(20), 14473–14486. https://doi.org/10.1007/s00521-021-06102-7

[24] Maniruzzaman M.D, Sami A, Hoque R, & Mandal P (2024). Pneumonia prediction using deep learning in chest X-ray Images. International Journal of Science and Research Archive, 2024, 12(01), 767–773

[25] Alhamid M (2022, May 12). Ensemble Models: What Are They and When Should You Use Them? https://builtin.com/machine-learning/ensemble-model

[26] Kaylakoglu E & Murel J. (2024, March 18). What is ensemble learning? https://www.ibm.com/topics/ensemble-learning

[27] Sasikala R & Nalluri S (2024). Pneumonia screening on chest X-rays with optimized ensemble model, Expert Systems with Applications, 242 (122705), ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2023.122705

[28] Mabrouk, et al. (2022). Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks. Appl.

Sci. 2022, 12, 6448. https://doi,org/10.3390/app12136448

[29] Kundu, R., Das, R., Geem, Z. W., Han, G. T., & Sarkar, R. (2021). Pneumonia detection in chest X-ray images using an ensemble of deep learning models. PloS One, 16(9), e0256630. https://doi.org/10.1371/journal.pone.0256630

[30] Bhatt & Shah M, (2023). A Convolutional Neural Network ensemble model for Pneumonia Detection using chest X-ray images, Healthcare Analytics,3(100176). ISSN 2772-4425, https://doi.org/10.1016/j.health.2023.100176.

[31] An Q, Chen W& Wei Shao (2024). A Deep Convolutional Neural Network for Pneumonia Detection in X-ray Images with Attention Ensemble. Diagnostics 2024, 14(4), 390; https://doi.org/10.3390/diagnostics14040390

[32] Anifowose F (2020 February 6). Hybrid Machine Learning Explained in Nontechnical Terms.https//jpt.spe.org/hybrid-machine-learning-exlained-nontechnical-terms

[33] Bhattacharya A (2022, April 20). What is Hybrid Machine Learning and How to Use it? https://www.analyticsinsight.net/latest-news/what-is-hybrid-machine-learning-and-how-to-use-it

[34] Ukwuoma, C. C., Qin, Z., Heyat, M. B. B., Akhtar, F., Bamisile, O., Muaad, A. Y., Addo, D., & Al-antari, M. A. (2023). A hybrid explainable ensemble transformer encoder for pneumonia identification from chest X-ray images. Journal of Advanced Research, 48, 191-211. https://doi.org/10.1016/j.jare.2022.08.021

[35] Taib C, Haimoudi E & Abdoun O. Pneumonia Classification Using Hybrid Architectures Based on Ensemble Techniques and Deep Learning. A2IA 2023, LNNS 772, pp. 389–399, 2023.https://doi.org/10.1007/978-3-031-43520-1_33

[36] Ranpariya D, Parikh P, Manish I.P, Gajjar R. (2023). A CNN based Hybrid Model for Pneumonia Classification Using Chest X-ray Images. The 3rd International Conference on Applied Artificial Intelligence (ICAPAI) Published: 2023 DOI: 10.1109/AISP53593.2022.9760525

[37] Alalwan N, Taloba A.I, Abozeid A., Alzahrani A. I, & Al-Bayatti A.H (2024). A Hybrid Classification and Identification of Pneumonia Using African Buffalo Optimization and CNN from Chest X-Ray Images. Computer Modeling in Engineering & Sciences 2024, 138(3), 2497-2517. https://doi.org/10.32604/cmes.2023.029910