Journal of Telecommunication, Electronic and Computer Engineering
ISSN: 2180 – 1843 e-ISSN: 2289-8131 Vol. 17 No. 2 (2025) 23-30
jtec.utem.edu.my
DOI: https://doi.org/10.54554/jtec.2025.17.02.003

Comparative Analysis of Machine Learning Models on the Classification of Pneumonia Disease Using Chest X-ray Images

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Article Info

Article history:
Received Aug 4th, 2024
Revised Jan 10th, 2025
Accepted Jun 16th, 2025
Published Jun 30th, 2025

Index Terms:
Pneumonia classification
Support vector Machine (SVM)
K-Nearest Neighbor (KNN)
Random Forest (RF)

Abstract

Pneumonia is one of the leading causes of illness and death globally. If not treated promptly, it can be fatal. Early detection of pneumonia significantly reduces mortality rates and improves the chances of recovery. Among the key diagnostic tools for pneumonia is the chest X-ray, which is widely used due to its affordability. However, diagnosing pneumonia based on chest X-ray images can be challenging, as the visual symptoms may resemble those of other respiratory conditions. These diagnostic challenges are often subjective and dependent on the practitioner's experience. To address this, computer-aided diagnostic (CAD) technologies can assist healthcare professionals in improving diagnostic accuracy. This research proposes a machine learning-based method to classify pneumonia using chest X-ray images. Specifically, it presents a framework that employs Random Forest (RF), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) models for automated pneumonia detection. This study involves developing and evaluating these models on chest X-ray images resized to 224 × 224 pixels. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. The results demonstrate high classification accuracy: SVM achieved 97%, KNN 98% and RF 94%. These outcomes outperform some previously reviewed models and show potential for accelerating early diagnosis and treatment of pneumonia disease.

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I. INTRODUCTION

Pneumonia is a disease that affects both children and adults worldwide, with the highest mortality rates in Southern Asia and Sub-Saharan Africa [1]. In 2019, pneumonia was responsible for 14% of fatalities among children under the age of five [1]. Without intensified efforts to combat the disease, an estimated two million Nigerian children could die from pneumonia over the next decade [2]. According to the International Vaccine Access Center [3], despite notable advancements, the burden of pneumonia and diarrhea remains disproportionately high, with more than 70% of deaths in children under five occurring in just 15 countries, including Nigeria.

Acute respiratory infection rates tend to rise seasonally in many Northern Hemisphere countries. These seasonal increases are typically due to epidemics of respiratory pathogens such as seasonal influenza, respiratory syncytial virus (RSV), and other common respiratory viruses, including human metapn eumovirus (hMPV), as well as mycoplasma pneumoniae [4]. Many countries routinely monitor these infections as part of public health surveillance systems

Pneumonia can be caused by viruses, fungi, or bacteria. The symptoms of bacterial and viral pneumonia are often similar and may include cough, fever, dyspnoea, chest pain, and fatigue [5]. Diagnosis typically involves imaging techniques such as computed tomography (CT) scans and chest X-rays, as well as laboratory test [6].

Viral pneumonia may present with more severe symptoms than bacterial pneumonia. In children under five, pneumonia may be suspected when they present with a cough and/or breathing difficulties, with or without fever, along with signs such as chest indrawing. Pneumonia can range from mild to severe and may be acquired in the community or within a hospital setting [7].

This condition poses a particular risk to children under five and elderly individuals with weakened immune systems. In 2018, pneumonia killed over a million children worldwide and remains a life-threatening illness if not detected and treated early [8]. Diagnosis often involves radiography, CT scan, or MRI scans, with chest x-rays being the most commonly used method to detect pneumonia and other respiratory conditions.

Historically, diagnosing pneumonia involved a combination of clinical examination, patient medical history, and chest X-rays. With technological advancements in biomedical imaging, chest X-rays have become more affordable and accessible, making them a widespread diagnostic tool for respiratory diseases like pneumonia.

On the World Pneumonia Day, November 12, 2024, the Global Initiative for Asthma (GINA), a founding member of the Forum of International Respiratory Societies (FIRS), called for immediate action to prevent pneumonia deaths among high-risk groups, especially children under five and the elderly. Despite the availability of effective preventative therapies, many low- and middle-income countries (LMICs) continue to lack adequate access to them [9].

R. S. Saeed and B. K.Oleiwi [10] reviewed recent deep learning (DL)-based systems that make use of various medical imaging modalities, including CT and chest X-rays (CXR), with particular focus on COVID-19 diagnosis. They analyzed 58 studies and discussed the commonly used datasets for training these models. The study aimed to guide both technical and medical professionals in understanding how DL methods are applied to medical imaging and how these approaches can be generalized to tackle other diseases, including COVID-19 [10].

Artificial intelligence (AI) has made significant advancements in image processing tasks. With the expansion of big data processing capabilities and parallel computing, AI has grown increasingly prominent in areas such as natural language processing, computer vision and speech recognition. Machine learning, a subset of AI, enables systems to learn from data and generate results. Recent studies highlight the promising role of this technology in medical and healthcare applications, specifically in medical image processing.

Medical imaging is a critical component of modern healthcare, providing visual representations of the human anatomy for clinical studies [11]. Chest radiography is one of the most common diagnostic tools for pneumonia. However, the heterogeneity of chest images and variability in interpretation can lead to diagnostic errors and delays. Early detection is essential for effective treatment signs of pneumonia is crucial to the diagnosis [12, 13]. Early identification of pneumonia is critical for establishing the most appropriate treatment [14].

Image processing is the process of extracting usable information from an image, improving image quality, or transforming images to make them more interpretable for future research [15]. Applications for image processing in computer vision range from surveillance systems to medical imaging, making it a crucial field of study. The methods and procedures used to create images of the human body—or specific areas of it—for therapeutic applications including diagnosis and treatment are referred to as medical imaging. A wide range of modalities are used in medical imaging, such as computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, positron emission tomography, and X-rays. A common diagnostic imaging technology is radiography, also referred to as X-ray imaging.

A. There are various types of machine learning, but some of the most commonly used are:

1. Supervised learning: This is the process of training a model using a labelled dataset in which each example is assigned a specific label or outcome. The model learns to link input data to the appropriate output labels, enabling it to make accurate predictions on previously unknown data.

2. Unsupervised learning: In this approach, the model is trained on an unlabeled dataset to discover patterns and relationships in the data. Unsupervised learning is frequently employed in tasks like dimensionality reduction, anomaly detection, and grouping.

3.Reinforcement learning: This method involves teaching an agent to make decisions in a situation where it receives feedback for its actions in the form of rewards or penalties. Overtime, the agent learns which actions produce favorable outcomes and which ones do not, ultimately optimizing its decisions to maximize rewards.

B. Applications of Machine Learning

There are numerous uses for machine learning in numerous industries, including:

1. Computer vision: Machine learning techniques are used to analyze and interpret visual data, including images and videos. Applications include facial recognition, and autonomous driving and medical imaging.

2. Natural language processing (NLP): Machine learning is applied to understand, interpret, and generate human language.

3. Predictive analytics: By analyzing big datasets using machine learning algorithms, future or events can be forecasted. This is useful in industries including marketing, finance, and healthcare.

4. Robotics: Machine learning allows robots to sense their surroundings, make choices, and perform tasks autonomously.

5. Healthcare: Machine learning algorithms assist in disease diagnosis, therapy planning, and drug development by analyzing complex medical data.

6. Fraud detection: Machine learning can identify patterns in data that may include fraudulent activities, such as credit card or insurance fraud.

C. Models and Techniques for Machine Learning

This section focuses primarily on neural networks, which have advantages and disadvantages like other machine learning techniques. Some of the machine learning techniques that are most frequently used are as follows:

1. Logistic regression: This technique is used to predict one or more predictor variables. It models the probability of a binary outcome using logistic regression.

3. Decision trees: This method is applied to tasks involving classification or regression, where the objective is to forecast an outcome variable (either continuous or categorical) given a set of input factors. Recursively dividing the data according to the input variables, decision trees provide a predictive model that resembles a tree.

4. Random forests: An extension of decision trees, this technique builds multiple decision trees and aggregates their predictions to reduce overfitting and increase accuracy.

6. Neural networks: This method entails creating models that draw inspiration from the composition and capabilities of the human brain. The "neurons" that make up neural networks are interconnected nodes with the ability to identify patterns in data.

7. Clustering: The purpose of this approach is to group comparable data points according to their attributes. It is applied to unsupervised learning tasks. In this context,

clustering methods like hierarchical clustering and K-means clustering are frequently employed.

D. Pneumonia

Pneumonia is a lung infection that causes inflammation and makes breathing difficult [16]. It exists in several forms, including:

1. Community-acquired pneumonia (CAP): CAP is the most prevalent type of pneumonia and is contracted outside of a medical facility. It can be caused by bacteria, viruses, or other organisms. Typical initial symptoms include coughing, fever, and shortness of breath. According to a study published in the Journal of the American Medical Association, Haemophilus influenzae and Mycoplasma pneumoniae are the next most common bacteria that cause community-acquired pneumonia (CAP), after streptococcus pneumoniae [7].
2. Hospital-acquired pneumonia (HAP): HAP is a type of pneumonia that develops during hospitalization for another illness or treatment. The bacteria responsible for HAP are often more resistant to antibiotics than those causing CAP. A review published in the Annals of Translational Medicine identifies Pseudomonas aeruginosa, Klebsiella pneumoniae, and Acinetobacter baumannii as the most frequent bacteria causing HAP [17].
3. Ventilator-associated pneumonia (VAP): VAP is a form of HAP that affects patients who need mechanical ventilation. It is caused by bacteria entering the lungs through the ventilator tube. A comprehensive review and meta-analysis published in the Journal of Hospital Infection report Pseudomonas aeruginosa, Klebsiella pneumoniae, and Staphylococcus aureus are the most commonly identified pathogens in VAP cases.
4. Aspiration pneumonia: Aspiration pneumonia results from inhaling food, drink, or vomiting into the lungs. It commonly affects individuals with conditions such as Parkinson's disease or stroke who experience difficulty swallowing. Research published in the Journal of the American Medical Directors Association notes that anaerobic bacteria are the most common pathogens causing aspiration pneumonia, followed by Haemophilus influenzae and Streptococcus pneumoniae [18].

II. RELATED WORKS

P. Rajpurkar et al. [19] in "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning", (arXiv preprint) aimed to develop a deep learning algorithm capable of assisting radiologists in detecting pneumonia from chest X-rays. The approach utilized a Convolution Neural Network (CNN) trained on a dataset of 112,120 chest X-rays. The model achieved an AUC of 0.888, which was comparable to radiologist-level performance. However, a notable limitation of this study was the severe imbalance in the dataset, with a relatively low proportion of pneumonia cases.

M. Hussain, M. R. Hasan, J. Choi and A. Sohail [20] in "Differential Data Augmentation Techniques for Medical Imaging Classification Tasks," achieved an improved accuracy of 88% (compared to 68%) by optimizing data augmentation approaches. One approach, the mix-up technique, applied a linear combination of input images to enhance dataset diversity. Important medical imaging models such as SegNet, U-Net, and AcrettacNet were also reviewed. These models designed specifically for medical purposes require extensive fine-tuning due to the high sensitivity of medical diagnoses, where errors can have serious consequences. The field continues to see ongoing research in medical data analysis and segmentation.

L. A. Arani, F. Sadoughi and M. Langarizadeh [21] developed “An Expert System for Pneumonia Diagnosis Applying Fuzzy Logic”, which aimed to differentiate between pneumonia and other respiratory conditions. The system incorporated 17 fuzzy input variables, a user interface, fuzzy fire, defuzzifire, fuzzy fire, and inference engine. Given 17 clinical indicators as input, a fuzzy expert system was able to diagnose pneumonia or make a normal prediction. However, the system lacks self-learning capabilities, limiting its adaptability over time.

To create a lightweight, deployable, and precise model to help in the detection of pneumonia, an ensemble model for pneumonia identification using chest X-ray images was developed by H. Bhatt and M. A. Shah in 2023 [22]. The process comprises a Convolutional Neural Network architecture, which is made up of three distinct models with varying kernel sizes. The model achieved an F1score of 88.56% and a high recall value of 99.23%. Despite the strong recall, the model’s accuracy and precision were relatively lower, and the use of small datasets led to overfitting issues.

The management of pediatric pneumonia in Nigeria, the most populous nation in Africa, was examined by K. Mulholland [23]. The goal is to examine whether diagnostic problems influenced patient outcomes. Data from 12 hospitals were analyzed using WHO-defined criteria for severe malaria, alongside CFR and ARI algorithms. Despite all hospitals having access to antibiotics and oxygen, malaria was identified as the leading diagnosis among children showing severe pneumonia symptoms, suggesting potential diagnostic misclassification and contributing to Nigeria’s low child survival rates.

S. Sharma and K. Guleria [24] applied a deep learning method that recognizes pneumonia from chest X-ray images. Their study employed neural networks (NN) and VGG-16, comparing performance with Support Vector Machines (SVM). Results showed that VGG-16 combined with NN outperformed its combination with Support Vector Machine (SVM). However, limitations included a small data sets and limited use of hidden layers, which may have impacted model performance.

R. S. Saeed and B. K. O. C. Alwawi [25] developed a CNN-based deep learning technology for automatic COVID-19 diagnosis from chest X-ray images. Their two-stage method involved preprocessing and binary classification. The CNN model has been developed and trained in the second stage to diagnose COVID-19 data as either (positive) infections or (negative) normal cases. The proposed model achieved 96.57% training accuracy and 92.29% validation accuracy. With a low learning rate, the CNN showed promising results for COVID-19 classification.

A. H. Chehade, N Abdalla, J. M. Marion, M. Hatt, M. Oueidat and P. Chauvet [26] presented “Encoding of Lung Conditions from Chest X-ray Pictures Applying Deep Learning Techniques”, a comprehensive review of 110 studies from 2016 to 2023 on the classification of lung diseases using deep learning. According to the summary, deep learning is crucial for classifying lung diseases and holds a lot of promise for further study. This is a thorough analysis that integrates deep learning architecture, technique, and application; however, no real-world implementation was carried out.

Although pneumonia affects both children and adults, mortality remains highest in Southern Asia and Sub-Saharan Africa [1]. According to WHO predictions, if proactive measures are not taken, pneumonia could claim the lives of two million Nigerian young children over the next decade [2]. Studies such as those by H. Bhatt and M. A. Shah [22], K. Mulholland [23], and Abubeker et al. [27] highlight several challenges, including misdiagnosis, overfitting, low accuracy, poor prediction and sensitivity in existing models.

III. TECHNIQUES/METHOD(S)

A. *Methodology*

The proposed methodology for image classification is outlined as follows*:*

Step 1: Acquisition of the Chest X-ray dataset from the Hopskin Diagnostic Center

Step 2: Feature extraction using Principal component analysis (PCA)

Step 3: Development of models for SVM, KNN, and RF

Step 4: Classification using the three machine learning models.

Step 5: Evaluation of methods using standard performance metrics

Step 6: Comparative analysis of the three Models,

B. *Data Acquisition*

Collections of data: A total of 1,113 chest X-ray images were obtained from the Hopskin Diagnostic Center.

Pre-processing: The dataset in JPEG format is categorized into two classes: Pneumonia and Normal.

Label Assignment: Binary class labels are assigned in the range of 0 for Normal and 1for Pneumonia.

SVM: For a given training dataset:

T= $\{(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)\}, xi \in Rn, yi \in \{-1, +1\}$, (1)

The objective of SVM is to find an optimal hyperplane that separates the feature space into two classes. In this study, a linearly separable SVM is employed. The decision function for classification is defined as:

$$f(x) = sign(w * x + b) \quad (1)$$

where: x = Input feature
w = Model weight
b = Bias

Regression and classification using K-Nearest Neighbors (KNN) is a fundamental technique. Given a training dataset, KNN identifies the K samples that are most similar to a new input sample. The new sample is then assigned to the class that is most common among these K neighbors. Given a training dataset:

$$T = \{(x1, y1), (x2, y2) \dots (xn, yn)\} \quad (2)$$

where xi is the feature vector of the sample and $yi \in \{c1, c2, \cdots ck\}$ is a sample category. The category, i = 1, 2, ..., N; the sample feature vector is x; output y is the category to which the sample belongs:

$$y = argmax_{cj} \sum_{xi \in Nk(x)} I(y_i = c_j),\ i, j = 1,2,..k; \quad (3)$$

where: I = Indicator function, i.e I is 1 when $yi = cj$, otherwise, I is 0.

A large number of decision trees representing different subjects make up the RF classifier. To increase prediction accuracy, it is necessary to utilize the average of each tree's subgroup. Instead of depending on a single decision tree, RF predicts the outcome using a majority vote across all trees.

Table 1
Class Encoding of the Images

Class	Encoding
Normal	0
Pneumonia	1

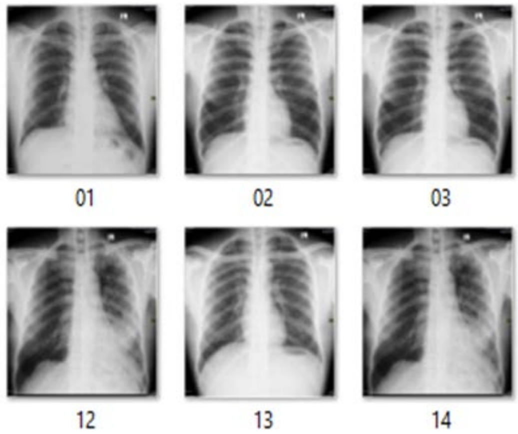

Figure 1. Pre-processed Images

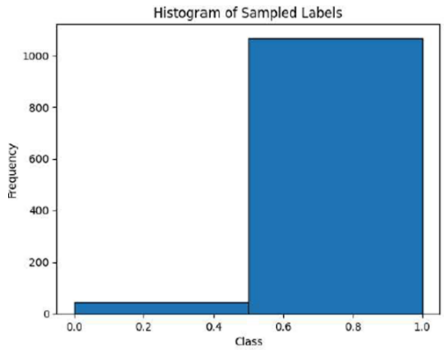

Figure 2. Imbalanced Dataset

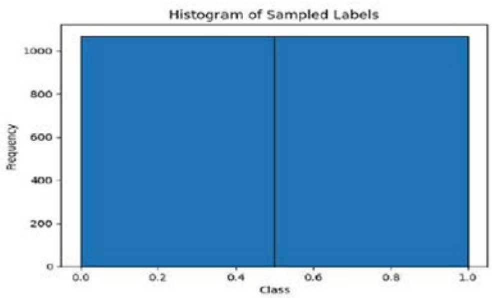

Figure 3. Balanced Dataset

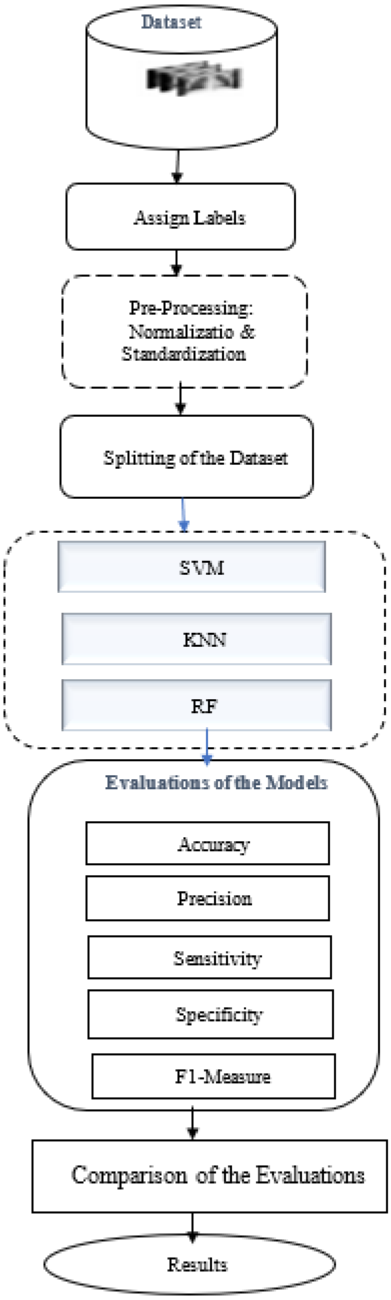

Figure 4. Conceptual Flow of Models Development

IV. RESULT

The outcomes of the models are presented in the following figures and tables.

Table 2 shows the evaluation metric results of SVM while the confusion matrix of SVM model trainer has been illustrated in Figure 5. Then the analysis of ROC curve is presented in Figure 6. The blue line indicates the ROC curve when the AUC value is equal to 0.97.

Table 3 displays the evaluation metrics obtained using the KNN technique, while the corresponding confusion matrix is illustrated in Figure 7. The ROC curve analysis is shown in Figure 8, where the blue line represents the ROC curve with an AUC value of 0.98.

Table 2

Evaluation Metric Result of SVM

SVM	Precision	Recall	F1-Score	Support
0	0.95	1.00	0.97	207
1	1.00	0.95	0.97	220
Accuracy			0.97	427
Macro avg	0.97	0.97	0.97	427
Weighted avg	0.97	0.97	0.97	427

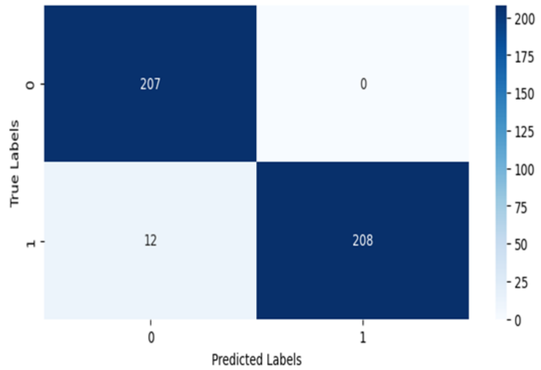

Figure 5. Confusion Matrix of SVM Model Training

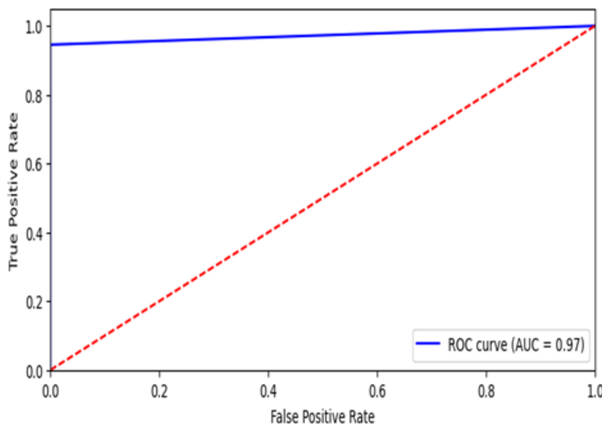

Figure 6. ROC (AUC) Graph of the SVM Mode

Table 3
Evaluation Metric Result of KNN

KNN	Precision	Recall	F1-Score	Support
0	0.96	1.00	0.98	207
1	1.00	0.96	0.98	220
accuracy			0.98	427
Macro avg	0.98	0.98	0.98	427
Weighted avg	0.98	0.98	0.98	427

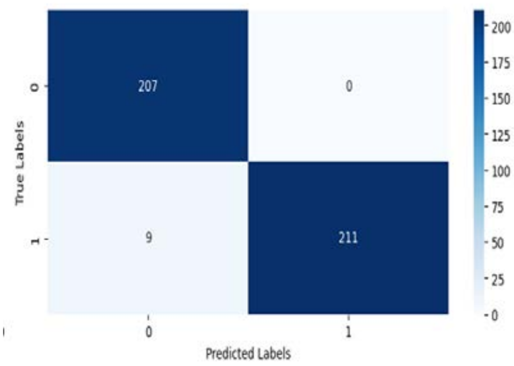

Figure 7. Confusion Matrix of the KNN Model

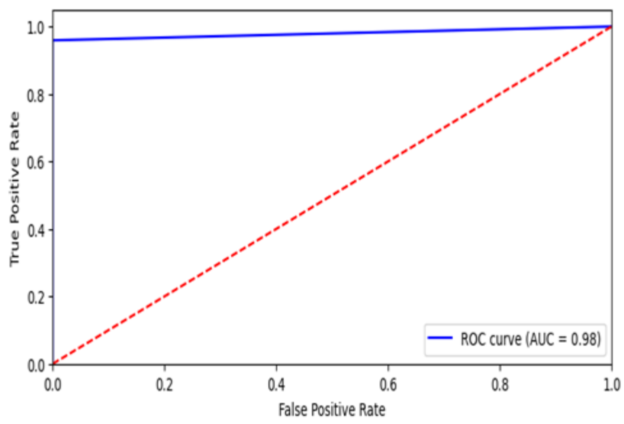

Figure 8. ROC (AUC) Graph of the KNN Model

Table 4 presents the evaluation metrics for the RF model. The confusion matrix corresponding to the training phase of the RF model is shown in Figure 9. Subsequently, the ROC curve analysis is depicted in Figure 10, where the blue line represents the ROC curve, with an AUC value of 0.95.

Table 4
Evaluation Metric Result of RF Model

SVM	Precision	Recall	F1-Score	Support
0	0.93	0.95	0.94	207
1	0.95	0.93	0.94	220
Accuracy			0.94	427
Macro avg	0.94	0.94	0.94	427
Weighted avg	0.94	0.94	0.94	427

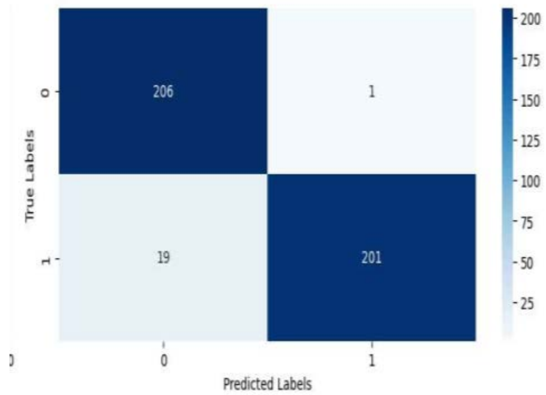

Figure 9. Confusion Matrix of RF Model Training

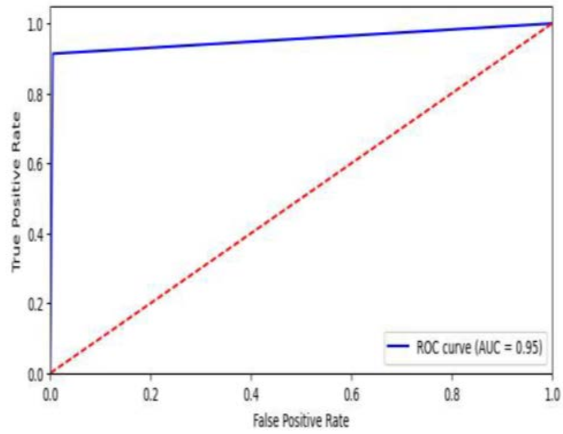

Figure 10. ROC (AUC) Graph of the SVM Model

Table 5 presents a comparative analysis of the model performance metrics, while Figure 11 illustrates a bar graph comparing the CPU wall time.

Table 5
Comparative Analysis of the Model Metric

S/N	METRICS	SVM	KNN	RF
1	Accuracy	97	98	94
2	Precision	100	100	93
3	Sensitivity	95	95	91
4	F1-Score	97	97	95
5	AUC	97	98	94

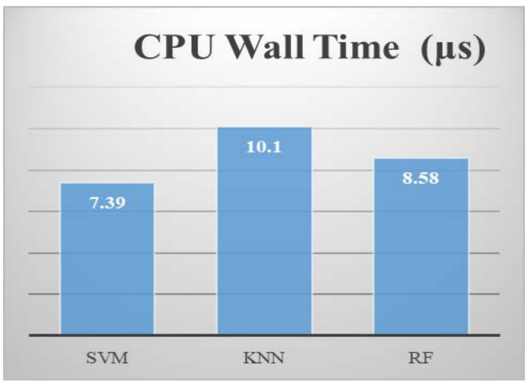

Figure 11. CPU Wall Time Comparison

Figure 12 provides a visual comparison of the evaluation metrics for all the models examined in this study. Figure 13 displays the predicted classification output images, while Figure 14 illustrates a line chart comparing the performance of all the models analyzed.

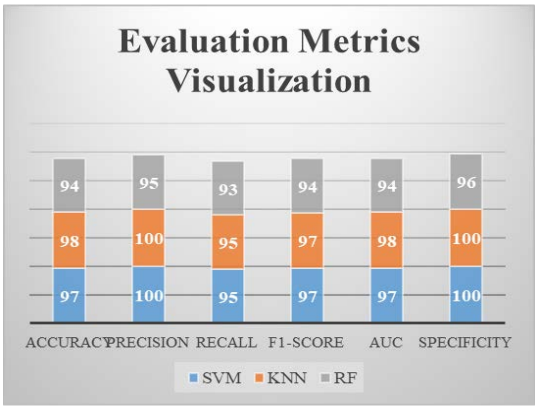

Figure 12. Comparison Chart of the Models

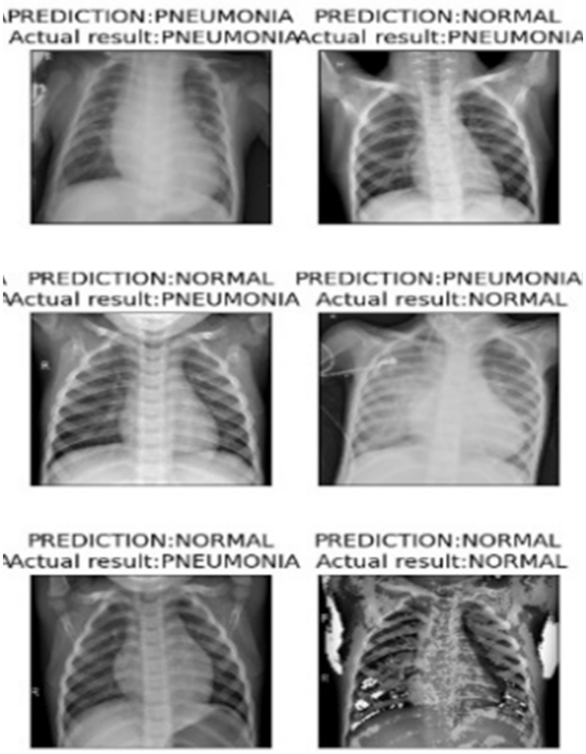

Figure 13. Classification Output (Prediction)

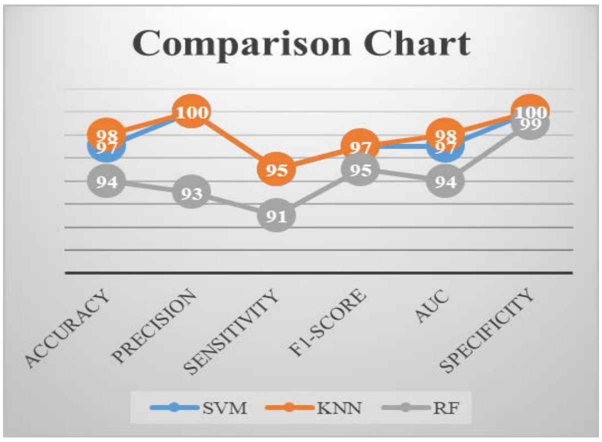

Figure 14. Comparison Chart of the Models

V. DISCUSSION

This research aimed to compare machine learning models namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF), for the classification of pneumonia disease using chest radiographs.

The experimental results demonstrated the effectiveness of these models in terms of classification accuracy. The models achieved the following accuracies: SVM at 97%, KNN at 98%, and RF at 95%. Precision and specificity were 100% for all three models. Recall was recorded at 95% for both SVM and KN, while RF achieved 91%. These models outperformed some of the previously reviewed studies. However, the dataset used was relatively small. While a larger number of images generally leads to better performance, no overfitting was observed in this case.

VI. CONCLUSION

The performance of the models was effectively evaluated using metrics such as accuracy, precision, recall, F1-score, AUC(ROC), and specificity. In terms of CPU wall time, SVM was the fastest at 7.39us, followed by RF at 8.58us. and KNN at 10.1us. In conclusion, all the three models demonstrated robust performance, highlighting their potential to assist radiologists and physicians in the automatic diagnosis of pneumonia. The results of this research are suitable for real-time deployment in pneumonia classification systems and can support medical officers who work in the radiology department for early disease detection, enabling timely treatment.

VII. FUTURE WORK

The study has shown the potential of machine learning techniques for classifying pneumonia from chest X-ray images. However, the limited dataset size posed a constraint on model performance. Future studies should incorporate a larger image dataset to further enhance accuracy. Additionally, future research should explore deep learning and transfer learning approaches, particularly ensemble and hybrid models involving transformers, to improve classification outcomes.

ACKNOWLEDGMENT

The authors would like to thank Mr. Godwin B. Akinbo for his encouragement and help in making this effort a reality.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION

The authors confirm contribution to the paper as follows: study conception and design: O.O, R.S.A; data collection: R.S.A; methodology: R.S.A, O.O, E.O.I; analysis and interpretation of findings: R.S.A, O.O, O.A.D, E.O.I; draft manuscript preparation: R.S.A, O.O. All authors had reviewed the findings and approved the final manuscript.

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