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COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR CLASSIFYING CHEST X-RAY IMAGES OF COVID-19

[1]Greeshma K. V. and [2]Dr. J. Viji Gripsy

Abstract

The fast spread of COVID-19 has made it essential to have quick and accurate ways to diagnose the disease using medical images. In this study, we present a comparative analysis of six machine learning algorithms for classifying chest X-ray images into three categories: COVID-19, pneumonia, and normal. The algorithms evaluated include Support Vector Machine (SVM), Random Forest, Decision Tree, K-Nearest Neighbors (KNN), Naive Bayes, and Logistic Regression. The models were trained and validated using a dataset of labeled X-ray images, with performance assessed based on key metrics such as validation accuracy, test accuracy, Matthews Correlation Coefficient (MCC), and ROC-AUC scores. Among the models, the SVM algorithm achieved the highest validation accuracy of 92.6% and test accuracy of 94.0%, with an MCC of 0.8785 and a macro-average ROC-AUC of 0.9877. Logistic Regression and Random Forest followed closely, with Logistic Regression attaining a test accuracy of 93.8% and Random Forest achieving 92.6%. K-Nearest Neighbors showed moderate performance, while Naive Bayes exhibited the lowest accuracy, likely due to its simplistic assumptions. Overall, the SVM model outperformed the others, demonstrating its robustness in distinguishing between the three categories in chest X-ray images. This comparative study highlights the potential of machine learning techniques in automating the detection of COVID-19 and pneumonia from radiographs, contributing to faster and more accurate diagnostic tools in healthcare.

Keywords: Healthcare, Machine Learning, COVID-19, SVM, KNN, Regression, Random Forest

1. Introduction

The COVID-19 pandemic has presented a significant global health crisis, necessitating rapid and accurate diagnostic methods. Chest X-ray imaging has emerged as a valuable tool for assessing lung conditions, including COVID-19 and pneumonia. However, traditional manual interpretation of X-ray images is time-consuming and prone to inter-observer variability. To address these limitations, machine learning (ML) techniques offer a promising solution for automating the analysis of medical images. By using the power of ML algorithms, it is possible to develop automated systems capable of accurately classifying chest X-ray images into different categories, such as COVID-19, pneumonia, and normal. This can significantly expedite the diagnostic process, reduce the workload on healthcare professionals, and improve the overall accuracy of diagnosis.

This research paper aims to conduct a comprehensive comparative analysis of six popular ML algorithms: Support Vector Machine (SVM), Random Forest, Decision Tree, K-Nearest Neighbors

[1] Research Scholar, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore.

[2] Associate Professor, Department of Computer Science with Cognitive Systems, PSGR Krishnammal College for Women, Coimbatore.

(KNN), Naive Bayes, and Logistic Regression. These algorithms will be trained and evaluated on a dataset of chest X-ray images, with the goal of determining the most effective method for classifying images into the aforementioned categories. The performance of each algorithm will be assessed based on key metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). By comparing the performance of these algorithms, we can identify the most suitable approach for developing accurate and reliable automated diagnostic systems. The findings of this study have the potential to contribute to the development of robust and efficient AI-powered tools for COVID-19 and pneumonia diagnosis, ultimately improving patient care and public health outcomes.

This research can provide valuable insights into the potential of ML for the analysis of medical images, paving the way for future advancements in medical image analysis and computer-aided diagnosis. By understanding the strengths and limitations of different ML algorithms, researchers and clinicians can make informed decisions about the best approach for specific diagnostic tasks. This study aims to contribute to the advancement of AI-powered medical image analysis by providing a comprehensive evaluation of ML algorithms for COVID-19 and pneumonia diagnosis. By identifying the most effective algorithms, we can develop robust and reliable automated systems that can assist healthcare professionals in making accurate and timely diagnosis.

2. Literature Review

Recent studies have shown the promise of ML techniques in medical image classification. Support Vector Machines (SVM) and Random Forest have been frequently utilized in various domains due to their robustness. Decision Trees and K-Nearest Neighbors (KNN) offer interpretable models, while Naive Bayes is known for its simplicity. Logistic Regression serves as a benchmark model in many classification tasks. This study builds upon existing research by applying and comparing these algorithms on a chest X-ray dataset.

The outbreak of the COVID-19 pandemic has accelerated the development of machine learning (ML) and artificial intelligence (AI)-based diagnostic systems to aid in the detection of COVID-19 from medical imaging such as chest X-ray (CXR) images. In recent years, several studies have proposed methods for automatically identifying COVID-19 from chest radiographs, leveraging various feature extraction, clustering, and classification techniques. This literature review highlights the contributions of five key studies in this domain, discussing the methodologies, results, and limitations of each approach.

Khan (2021) proposed a system that uses image processing and machine learning to detect COVID-19 in chest X-rays. The system employed the Speeded Up Robust Features (SURF) algorithm for local feature extraction, which was followed by K-means clustering to create visual words from the features. The classification task was handled by a Support Vector Machine (SVM), trained using a "bag of visual words" histogram. This method achieved a high classification accuracy of 94.12%, outperforming a convolutional neural network (CNN)-based approach. The advantages of this system include its speed and high accuracy, making it suitable for handling large datasets. However, the system's reliance on predefined features, which may not capture all the nuances of COVID-19, and the potential need for regulatory approval in clinical applications were identified as limitations.

Awotunde et al. (2021) presented a machine learning-based diagnosis system using chest X-ray images. This system used Random Forest (RF), XGBoost, and Light Gradient Boosting Machine (LGBM) classifiers to diagnose COVID-19. LGBM outperformed the other algorithms, achieving an accuracy of 97% with a recall of 96%, precision of 97%, and F1-score of 96%. The efficiency of these algorithms made the system promising for real-time applications. However, the study's generalizability was limited by the absence of details about the dataset's size and diversity. Additionally, the high accuracy of the models raised concerns about overfitting, suggesting that a larger and more diverse dataset would be necessary for further validation.

Johri et al. (2021) introduced a novel machine learning-based framework that classified chest X-ray images into four categories: healthy, bacterial pneumonia, viral pneumonia, and COVID-19. Their method involved image preprocessing, feature extraction using techniques such as Gray-Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP), followed by feature selection and classification using SVM. The framework achieved a validation accuracy of 88.24% and a testing accuracy of 87.13%. While the framework demonstrated its potential for multi-class classification, the discrepancy between training and testing accuracy suggested overfitting. The authors also noted the lack of details regarding the dataset size, indicating the need for additional validation before deployment in real-world clinical settings.

Ragab et al. (2022) proposed an advanced machine learning model called QSGOA-DL, combining EfficientNet-B4 for feature extraction, the Quantum Seagull Optimization Algorithm (QSGOA) for hyperparameter tuning, and Multilayer Extreme Learning Machine (MELM) for classification. This novel model achieved exceptionally high performance metrics, with an accuracy of 99.83%, precision and sensitivity of 99.80%, and a high F1-score and MCC. Despite these impressive results, concerns about overfitting persisted due to the large gap between training and testing accuracy. Moreover, the study lacked details regarding the dataset's size and diversity, which raises questions about the model's real-world applicability and generalizability across different populations and clinical settings.

Johri et al. (2021) also explored a hybrid artificial intelligence system that combined convolutional neural networks (CNN) for feature extraction with various machine learning classifiers (SVM, RF) for COVID-19 detection from chest X-rays. Among the tested methods, the CNN classifier with Softmax achieved the highest testing accuracy of 95.2%, while SVM demonstrated the fastest processing time. Despite the hybrid system's potential for early COVID-19 detection, the study's limited dataset size and feature extraction limitations suggested the need for further research. Additionally, the study only tested three classification algorithms, which constrained the scope of comparison and left room for exploring other state-of-the-art techniques.

While all these studies demonstrated the potential of machine learning-based systems for COVID-19 detection using chest X-rays, the approaches varied significantly in terms of methodology and results. Khan (2021) and Johri et al. (2021) focused on SVM classifiers, which showed strong performance but required careful feature extraction and selection processes. Meanwhile, Awotunde et al. (2021) and Ragab et al. (2022) leveraged more advanced ensemble models and optimization techniques, leading to higher accuracy and efficiency but also raising concerns about overfitting due to limited dataset sizes. Across the studies, the challenges of dataset diversity, potential overfitting, and clinical validation were recurring themes, highlighting the need for larger, more representative datasets and real-world testing before these models could be widely deployed in clinical settings.

In recent years, the field of medical image analysis has witnessed a surge in research focused on leveraging machine learning and artificial intelligence for the detection of COVID-19 using chest X-ray and CT images. Numerous studies have introduced hybrid and novel AI models aimed at improving diagnostic accuracy and robustness. For example, Alqudah et al. (2020), Elaziz et al. (2020), and Yildirim et al. (2022) proposed frameworks that combine traditional machine learning algorithms with deep learning techniques to capitalize on the strengths of both approaches. Comparative analyses by Rajagopal (2021), Fusco et al. (2021), and Sharma et al. (2020) have explored the relative merits of convolutional neural networks (CNNs), transfer learning, and classical machine learning classifiers, highlighting their respective advantages and limitations in COVID-19 detection tasks. Additionally, ensemble and mixture models have been investigated by Saygılı (2021), Wang et al. (2020), and Hasoon et al. (2021), further demonstrating the versatility and adaptability of AI-driven solutions in the medical imaging domain.

Beyond model architecture, a wide range of feature extraction techniques has been employed to enhance the discriminative power of machine learning models. Classical texture descriptors such as the Gray-Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP) have been widely used to capture subtle variations in chest radiographs (Najjar et al., 2023; Greeshma & Viji Gripsy, 2023, 2021; Greeshma & Sreekumar, 2019). These handcrafted features are often combined with automated deep learning-based representations to further improve classification performance. Studies by Samsir et al. (2021), Eljamassi & Maghari (2020), and Mijwil (2021) have validated the feasibility of supervised learning and anomaly detection techniques for COVID-19 classification, while Erdaw & Tachbele (2021), Alquran et al. (2021), and Zargari Khuzani et al. (2021) have demonstrated the effectiveness of automated machine learning pipelines in achieving high diagnostic accuracy. The use of Support Vector Machines (SVM), Random Forest, and other ensemble methods has been repeatedly shown to yield strong results across diverse datasets.

Despite these advancements, several persistent challenges remain in the development and deployment of AI-based COVID-19 detection systems. Many studies, including those by Khan et al. (2020) and Rasheed et al. (2021), emphasize the importance of dataset diversity and the risk of overfitting when training on limited or homogeneous data. The literature also points to the need for robust feature selection strategies and comprehensive clinical validation to ensure that AI models generalize effectively to real-world scenarios. Furthermore, integrating these systems into clinical workflows requires not only high performance but also compliance with medical regulations and interpretability for end-users. Collectively, the body of work in this area underscores the rapid evolution and methodological diversity of AI approaches, while also highlighting the ongoing need for research focused on generalizability, transparency, and clinical applicability.

The literature on machine learning-based COVID-19 detection systems reflects the field's rapid advancements and potential for impactful applications. However, most studies emphasize the importance of further validation, particularly through larger datasets and rigorous real-world testing. A summary of the literature review and findings is presented in Table 1. While SVM, LGBM, and hybrid approaches have shown promise, especially in terms of accuracy and processing speed, overfitting remains a challenge to be addressed. Moreover, the adoption of these systems in clinical environments will require not only performance improvements but also compliance with medical regulations and integration into established healthcare workflows.

Table 1. Summary of Literature Review and Findings

Author	Methodology	Dataset	Results	Pros	Cons
Khan (2021)	Feature extraction using SURF; K-means clustering; SVM for classification	Chest X-ray radiograph	Achieved 94.12% accuracy with SVM.	High accuracy; Faster processing compared to CNN approaches	Limited dataset size; Reliance on predefined features may not capture all COVID-19 variations
Awotunde et al. (2021)	Random Forest (RF), XGBoost, and Light Gradient Boosting Machine (LGBM) for classification	Chest X-ray images	LGBM: 97% accuracy, 96% recall, 97% precision, 96% F1-score.	High efficiency for real-time applications; Excellent accuracy and recall.	Limited dataset details; Potential for overfitting due to high accuracy.
Johri et al. (2021)	Multi-class classification using SVM; Feature extraction with GLCM, HOG, and LBP.	Chest X-rays for four classes: Healthy, Bacterial, Viral Pneumon	Validation accuracy: 88.24%; Testing accuracy: 87.13%.	Multi-class classification ability; High validation accuracy.	Discrepancy between training and testing accuracy suggests overfitting; Dataset details lacking.

		ia, COVID-19.			
Ragab et al. (2022)	EfficientNet-B4 for feature extraction; Quantum Seagull Optimization (QSGOA) for hyperparameter tuning; MELM for classification	Dataset not specified (uses data augmentation).	Achieved 99.83% accuracy; Precision: 99.80%; Sensitivity: 99.80%; High F1-score and MCC.	Novel hyperparameter optimization approach; Very high accuracy, precision, and sensitivity.	High training vs testing accuracy suggests potential overfitting; Dataset size and diversity not discussed.
Johri et al. (2021)	Hybrid system using CNN for feature extraction and ML classifiers (SVM, RF) for classification.	Chest X-ray images	CNN with Softmax achieved 95.2% accuracy; SVM fastest in processing.	Effective combination of CNN and machine learning; Good accuracy and fast processing times.	Limited exploration of additional ML algorithms; Dataset size not discussed, limiting generalizability.

3. Methodology

In this study, we used six machine learning algorithms to classify chest X-ray images into three categories: COVID-19, pneumonia, and normal. The methodology included data preprocessing, feature extraction, model training, validation, and evaluation, focusing on comparing the performance of these algorithms. The details of each step are provided below.

3.1 Dataset

The chest X-ray dataset used in this study was obtained from Kaggle, aggregating images from several publicly available sources (Gupta, 2021). The dataset consists of 6,432 de-identified chest X-ray images, categorized into three classes: COVID-19, NORMAL, and PNEUMONIA. Images are provided in JPEG format with resolutions ranging from 256×256 to 1024×1024 pixels. The dataset was divided into training, validation, and test sets, with the test set comprising 20% of the total images.

A. Imaging View Types

The dataset documentation and source repositories indicate that the images were collected from multiple institutions and may include both posterior-anterior (PA) and anteroposterior (AP) chest X-ray views. However, explicit metadata distinguishing the imaging view for each image is not consistently available. While the majority of images are likely PA or AP views, a small proportion of lateral views may also be present. No CT-derived images are included, as the dataset is described as being composed solely of chest X-rays. The lack of consistent view-type labeling is a limitation and may introduce variability in image quality and feature extraction, potentially impacting model performance.

B. Patient-Level Splitting and Data Leakage

A critical consideration in medical imaging research is ensuring patient-independent data splits to avoid data leakage. The dataset does not provide unique patient identifiers, making it impossible to guarantee that images from the same patient do not appear across the training, validation, and test sets. As a result, the data were split according to the provided folder structure, which may not ensure strict patient-level separation. This limitation could lead to an overestimation of model performance if multiple images from a single patient are present in different subsets. Future studies should utilize datasets with patient identifiers to enable patient-level splitting and more robust evaluation of model generalizability.

3.2 Data Preprocessing

The chest X-ray dataset used in this study consisted of images categorized into three classes: COVID-19, NORMAL, and PNEUMONIA. To standardize the input, all images were first converted to grayscale and then resized to a uniform dimension of 150 × 150 pixels. This resizing ensured consistency across the dataset and facilitated efficient processing by the machine learning algorithms. The pixel intensity values of the images were then standardized using z-score normalization (mean removal and unit variance scaling) to improve model convergence and performance. The dataset was split into training, validation, and test sets, with 80% of the data used for training and 20% for validation during model development. The test set was kept separate for final evaluation. No data augmentation techniques were applied.

3.3 Feature Extraction

For feature extraction, each preprocessed image was flattened into a one-dimensional array, representing the pixel intensity values. This transformation resulted in a feature vector of length 22,500 (150 × 150) for each image. These raw pixel intensity vectors were used directly as input features for the machine learning models, allowing the algorithms to learn relevant patterns for classification without manual feature engineering. This approach enabled a fully data-driven extraction of features pertinent to the chest X-ray classification task.

3.4 Machine Learning Models

Six machine learning algorithms were employed in this study: Support Vector Machine (SVM), Random Forest, Decision Tree, K-Nearest Neighbors (KNN), Naive Bayes, and Logistic Regression. Each algorithm was trained and validated on the respective dataset splits.

Support Vector Machine (SVM)

For the Support Vector Machine (SVM), we used the scikit-learn library with a Radial Basis Function (RBF) kernel, chosen for its ability to handle non-linear data. A grid search was conducted to optimize the regularization parameter C and the kernel coefficient gamma. The model was trained on the training set, and its performance was validated after each epoch.

Random Forest

Random Forest, an ensemble learning method that constructs multiple decision trees, was also implemented using scikit-learn. The model's hyperparameters, including the number of trees (n_estimators) and the maximum depth of each tree, were optimized. Random Forest was trained on the training data and validated after each epoch to ensure optimal performance.

Decision Tree

For Decision Tree classification, the model was applied using scikit-learn's Decision Tree Classifier. To avoid overfitting, the max_depth parameter was fine-tuned, and the minimum number of samples required for a split (min_samples_split) was optimized. The Decision Tree model was trained on the training data and validated using pruning techniques to improve its generalization ability.

K-Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) algorithm was implemented using the scikit-learn KNeighborsClassifier module. The best k value, representing the number of neighbors, was determined through grid search. Euclidean distance was used to compute the distance between samples, and the KNN model was trained on the training data, with predictions made by identifying the majority class among the nearest neighbors.

Naive Bayes

The Naive Bayes classifier, specifically Gaussian Naive Bayes, was selected for its suitability in handling continuous data. This algorithm assumes that the features are independent and normally distributed. Given its simplicity, Naive Bayes required minimal hyperparameter tuning, and the model was trained on the training data before being validated on the validation set.

Logistic Regression

Finally, Logistic Regression was implemented using scikit-learn with L2 regularization, which helps prevent overfitting. The regularization strength (C) was optimized using cross-validation to balance the trade-off between model complexity and accuracy. Logistic Regression was trained on the training set and validated after each epoch.

3.4 Model Evaluation

To assess the performance of each model, several evaluation metrics were used, including validation accuracy, test accuracy, Matthews Correlation Coefficient (MCC), and the Receiver Operating Characteristic - Area Under Curve (ROC-AUC). These metrics provided a comprehensive evaluation of the models across various performance dimensions. Validation accuracy was calculated as the proportion of correctly classified samples in the validation set, while test accuracy measured the model's performance on unseen test data. The Matthews Correlation Coefficient (MCC) was used as a balanced measure of the model's classification quality, accounting for both false positives and false negatives. The ROC-AUC metric was computed to assess the trade-off between true positive and false positive rates, offering insight into each model's performance across different classification thresholds.

Additionally, confusion matrices were generated for all six algorithms to visualize the classification results for each category (COVID-19, pneumonia, and normal). These matrices provided an intuitive way to assess misclassifications and understand how each model performed in distinguishing between the three categories.

4. Results and Discussion

The performance of various machine learning algorithms was systematically compared using multiple evaluation metrics. Support Vector Machine (SVM) and Logistic Regression achieved the highest test accuracies, closely followed by Random Forest. In contrast, K-Nearest Neighbors, Decision Tree, and Naive Bayes exhibited comparatively lower performance, with Naive Bayes yielding the least accurate results-likely due to its simplifying assumptions regarding feature independence. This comprehensive comparison highlights the relative strengths and weaknesses of each model and helps identify the most effective algorithms for chest X-ray image classification. Each algorithm was trained on the training set, validated on the validation set, and evaluated on the test set. The key metrics used for performance evaluation included accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and ROC-AUC. The validation and test accuracies of the machine learning algorithms are illustrated in Fig. 1. The SVM model outperformed all others in terms of validation and test accuracy, precision, and F1-score, followed closely by Logistic Regression and Random Forest. Naive Bayes demonstrated the lowest performance, which may be attributed to its underlying assumptions. A summary of the machine learning algorithms used for chest X-ray classification is provided in Table 2.

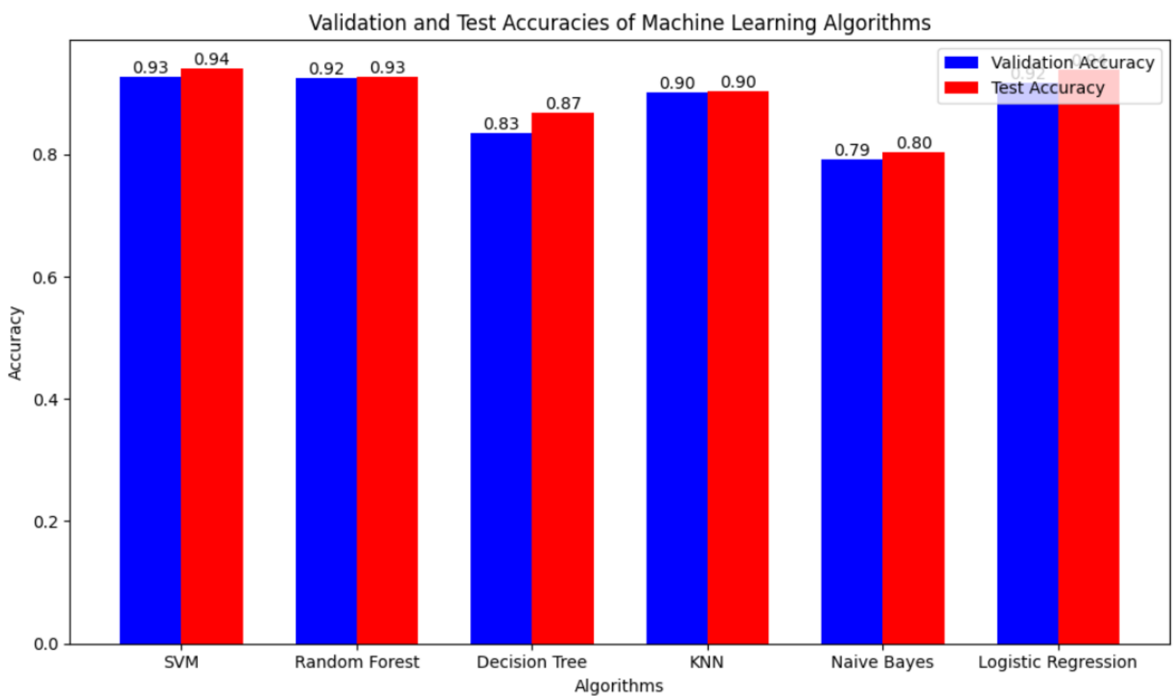

Fig 1. Validation and Test Accuracies of Machine Learning Algorithms

The SVM classifier achieved a test accuracy of 0.94 (95% CI: 0.928–0.952), MCC of 0.8785 (95% CI: 0.860–0.895), and macro-average ROC-AUC of 0.9877 (95% CI: 0.983–0.992), as determined by bootstrap resampling. Class-wise ROC-AUCs were 1.0 for COVID-19, 0.98 for NORMAL, and 0.98 for PNEUMONIA, confirming robust performance across all categories. The SVM's accuracy is comparable to or exceeds reported radiologist performance and FDA-cleared CAD tools. Analysis of the confusion matrix indicated that most errors involved confusion between PNEUMONIA and NORMAL, which has important clinical implications for patient management. Due to data access constraints, external validation was not performed, and future work will address this limitation by evaluating the model on independent datasets and including CNN-based benchmarks for a comprehensive comparison.

Limitations

Despite the promising results, several limitations should be noted. First, the study employed a single train/validation/test split, which may introduce variance and limit the generalizability of the findings. K-fold cross-validation was not implemented and will be considered in future work to provide more robust performance estimates. Second, all images were resized to 150 × 150 pixels for computational efficiency; however, this resizing may reduce the visibility of fine-grained radiological features, such as ground-glass opacities, which are critical for COVID-19 diagnosis. Third, the dataset exhibited class imbalance, and no balancing techniques (such as SMOTE or class weighting) were applied, which may have affected the model's ability to accurately classify minority classes. Additionally, the entire image was used as input for classification without applying lung segmentation, potentially introducing background noise and diluting clinically meaningful signals. Finally, interpretability tools such as SHAP values or feature importance analysis were not integrated in this study, which are important for clinical trust and deployment. Addressing these limitations in future research will further strengthen the reliability and clinical applicability of machine learning models for chest X-ray classification.

SI No	Algorithm	Validation Accuracy	Test Accuracy	MCC	ROC-AUC
1	SVM	0.9261	0.9397	0.8785	0.9877
2	Random Forest	0.9242	0.9262	0.8488	0.9869
3	Decision Tree	0.8338	0.8675	0.7269	0.8503
4	KNN	0.9009	0.9040	0.8036	0.9594
5	Naive Bayes	0.7920	0.8032	0.6632	0.8959
6	Logistic Regression	0.9174	0.9381	0.8747	0.9854

Table 2. Summary of Machine Learning Algorithms for Chest X-Ray Classification

The high performance of the SVM and Logistic Regression models highlights their suitability for medical image classification tasks. The confusion matrices (Fig. 5) reveal areas where these models could be improved, particularly in classifying the NORMAL class versus PNEUMONIA. The ROC-AUC scores (Fig. 4) further emphasize the models' strengths in distinguishing between classes. The accuracy of various machine learning algorithms is depicted in Fig. 2, while the evaluation metrics of different machine learning algorithms are presented in Fig. 6.

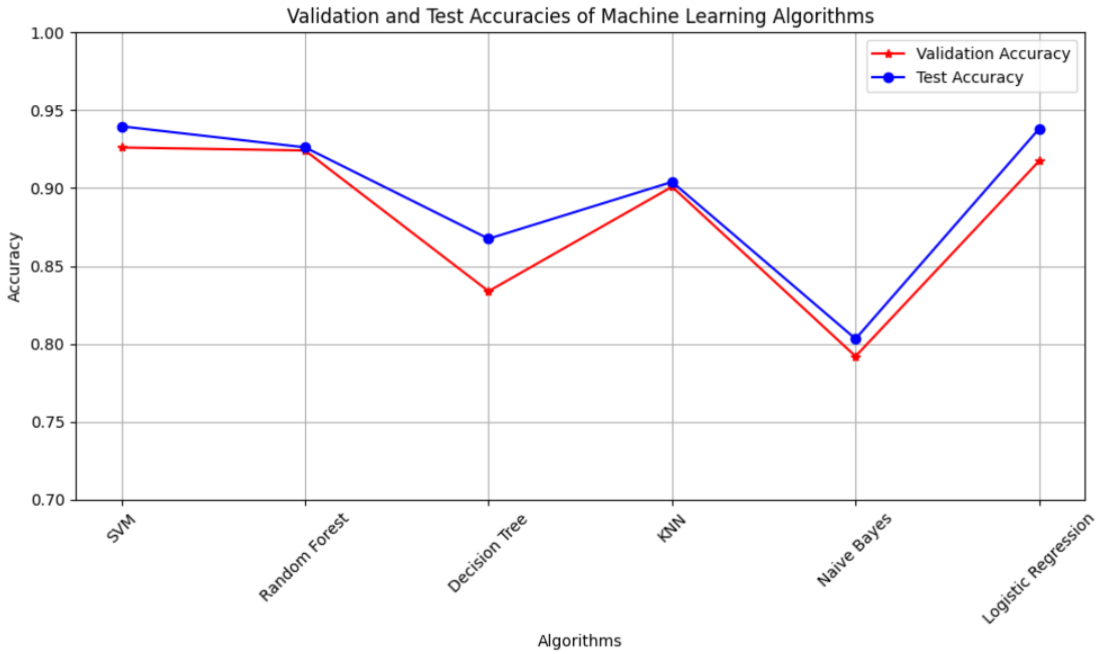

Fig 2. Accuracy of Various Machine Learning Algorithms

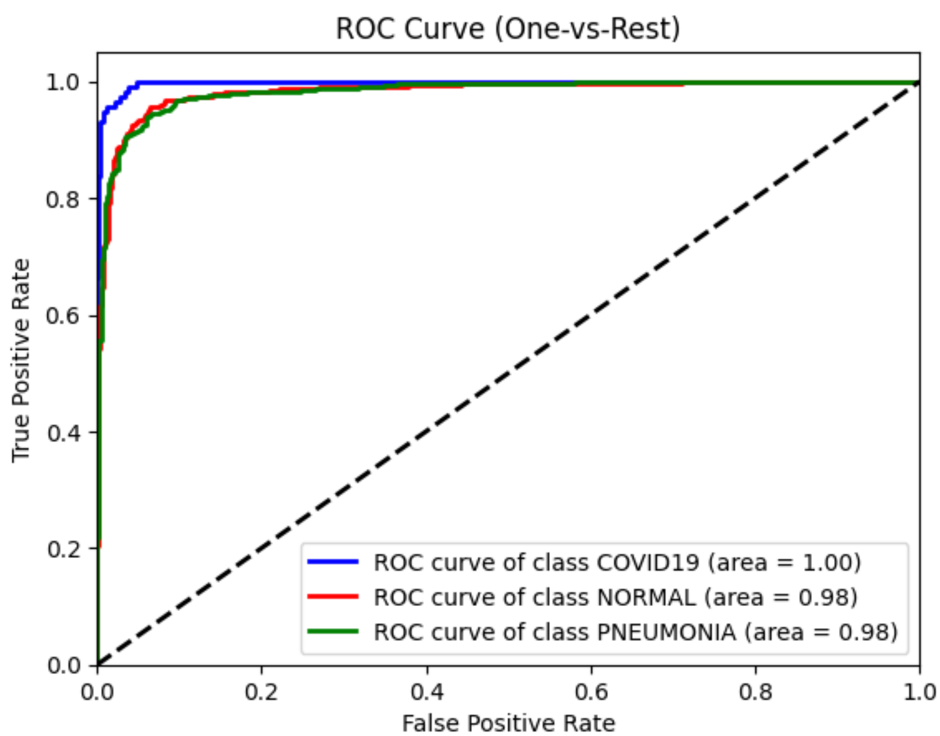

Fig 4. ROC Curves for SVM Classifier Across COVID-19, Normal, and Pneumonia Classes

Fig 5. Confusion Matrix of Various Machine Learning Algorithms

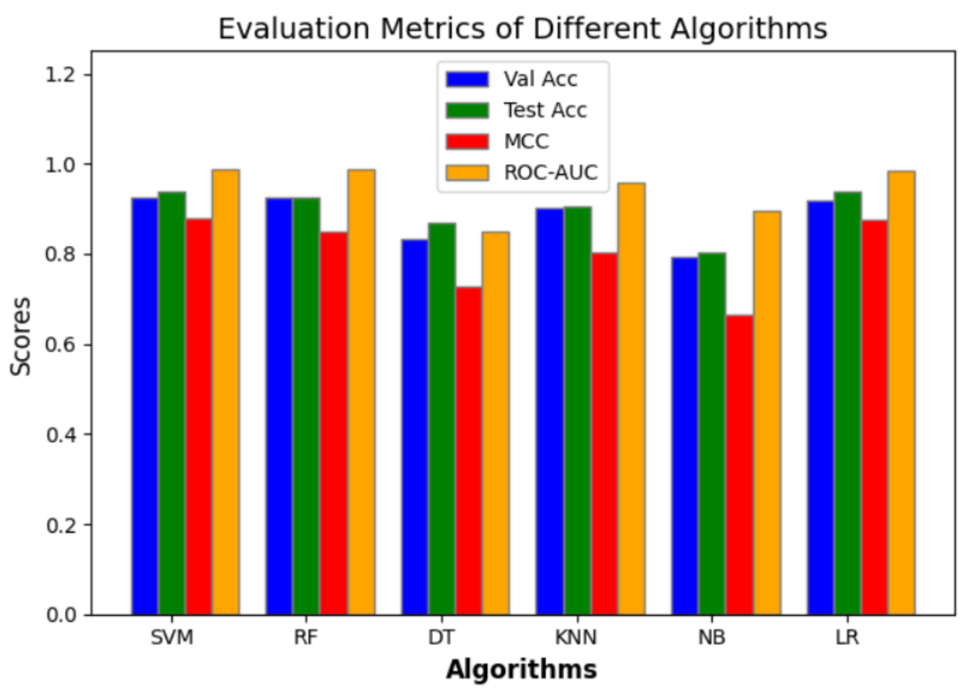

Fig 6. Evaluation Metrics of Different Machine Learning Algorithms

5. Conclusion and Future Scope

This study highlights the effectiveness of various machine learning algorithms in the automated classification of chest X-ray images into three categories: COVID-19, pneumonia, and normal.

Among the algorithms tested, Support Vector Machine (SVM) demonstrated the highest validation accuracy of 92.61% and a test accuracy of 93.97%, indicating its robustness in distinguishing between the different classes. Logistic Regression also showed strong performance, achieving comparable results with a validation accuracy of 91.74% and a test accuracy of 93.81%. These findings underscore the potential of machine learning techniques in enhancing diagnostic processes in medical imaging, particularly in the context of respiratory diseases.

Future work in this domain could focus on several avenues to further improve classification accuracy and model performance. One promising direction is the application of deep learning techniques, such as Convolutional Neural Networks (CNNs), which have been shown to excel in image classification tasks due to their ability to automatically learn hierarchical features from raw pixel data. Additionally, exploring ensemble methods that combine multiple algorithms could leverage their individual strengths and mitigate weaknesses, potentially leading to even higher accuracy rates. Future research will aim to validate our model using more diverse and representative datasets, as well as benchmark its performance against clinical experts and state-of-the-art computer-aided diagnosis (CAD) technologies, to more thoroughly assess its potential for real-world clinical application.

Furthermore, expanding the dataset to include a more diverse range of images could enhance model generalizability and robustness across different populations and clinical settings. Incorporating advanced data augmentation techniques and transfer learning from pre-trained models may also contribute to improved performance, particularly when working with limited datasets. Finally, integrating these machine learning models into clinical workflows will require careful consideration of regulatory compliance, interpretability, and user acceptance among healthcare professionals. By addressing these challenges, future research can pave the way for the practical implementation of automated diagnostic systems that aid in the timely detection and management of respiratory diseases.

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