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HYBRID MACHINE LEARNING AND DEEP LEARNING FRAMEWORK FOR LUNG DISEASE SEVERITY PREDICTION

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Abstract: The exponential rise in virus-infected diseases poses severe threats to global health, with SARS COVID-19 being one of the most life-threatening viral outbreaks in recent times. Timely detection and precise evaluation of disease severity remain critical yet challenging tasks in clinical diagnosis. This study explores the application of advanced machine learning techniques on chest X-ray images to classify the severity levels of COVID-19 infections. Principal Component Analysis (PCA) was employed for effective feature extraction and dimensionality reduction, enhancing model performance. Multiple machines learning algorithms, including Bagging, AdaBoost, XGBoost, and K-Nearest Neighbours (KNN), were implemented and evaluated for their predictive capabilities. Among these, the Bagging algorithm outperformed other models, achieving a remarkable accuracy of 98.67% and precision of 98.82%. Furthermore, the model demonstrated a high F1-score of 98.76 and recall of 98.69%, signifying its robustness and reliability in severity classification tasks. The results indicate that Bagging is an effective approach for automated interpretation of chest X-ray images to assess SARS COVID-19 infection severity, potentially aiding radiologists and healthcare professionals in prompt clinical decision-making.

Keywords: COVID-19 Severity Prediction, Chest X-ray Classification, Principal Component Analysis, Bagging, Machine Learning Algorithms

I. INTRODUCTION

The outbreak of coronavirus disease (COVID-19) has severely impacted global public health and economies since its emergence in late 2019. COVID-19, caused by the SARS-CoV-2 virus, presents a wide range of symptoms from mild fever to severe respiratory distress and multi-organ failure. Accurate and early prediction of disease severity is critical for effective clinical management and resource allocation in hospitals. Chest radiography, specifically X-ray imaging, is a widely accessible and cost-effective diagnostic tool for lung infection analysis. Radiologists analyze X-ray images to detect abnormalities such as ground-glass opacities and consolidation patterns associated with COVID-19. However, manual interpretation of X-ray images is timeconsuming and subject to inter-observer variability. The rapid increase in COVID-19 cases has overwhelmed diagnostic and healthcare facilities globally, creating an urgent need for automated systems that can assist in interpretation and severity assessment of COVID-19 infections.

Machine learning (ML) and deep learning (DL) techniques have demonstrated significant potential in medical image analysis applications. These AI-based methodologies enable rapid, accurate, and consistent prediction and classification tasks. ML algorithms can learn underlying patterns in X-ray images to identify disease presence and predict severity levels, supporting clinicians in decision-making for prioritizing treatment for critically ill patients. Principal Component Analysis (PCA) is a widely used dimensionality reduction technique in machine learning pipelines as it extracts significant features from high-dimensional image data, reducing computational complexity and enhancing model performance. The extracted features can then be fed into classifiers to achieve high prediction accuracy.

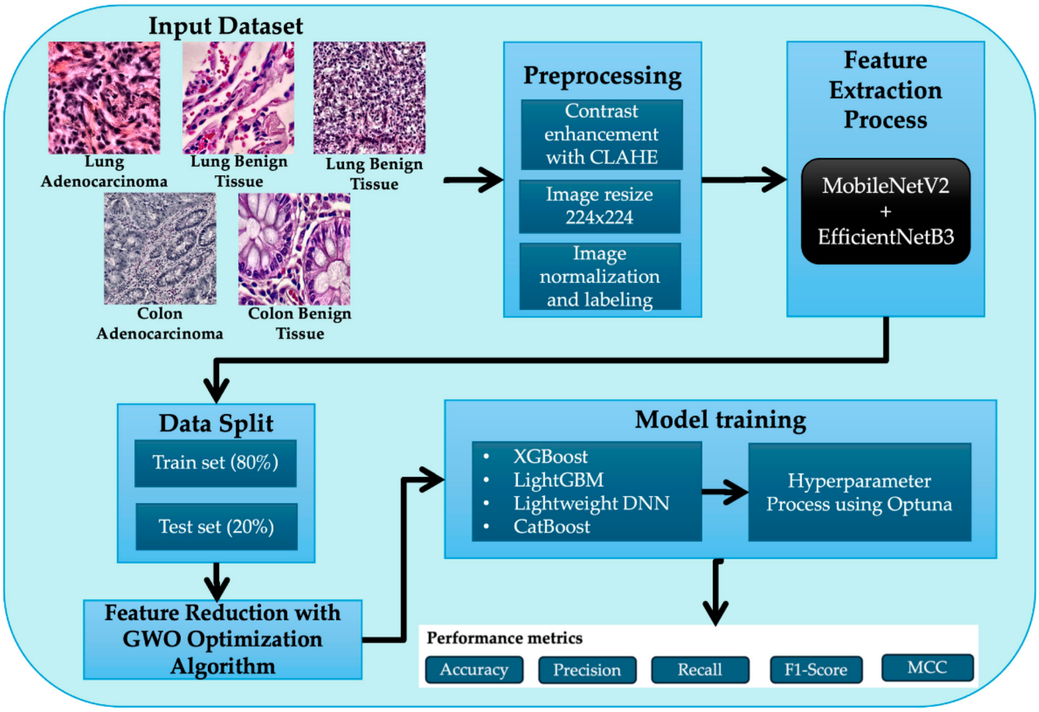

Fig1 Preprocessing Unit

Various ML algorithms such as Bagging, AdaBoost, XGBoost, and K-Nearest Neighbors (KNN) are popular for classification tasks. Bagging, or Bootstrap Aggregating, combines the predictions of multiple base estimators to reduce variance and avoid overfitting, while AdaBoost improves model performance by focusing on instances misclassified in previous iterations. XGBoost is an efficient gradient boosting algorithm known for its scalability and accuracy in structured data analysis, and KNN is a simple, instance-based learning method that classifies samples based on distance metrics. Recent studies have applied deep learning models like Convolutional Neural Networks (CNN) for COVID-19 detection; however, machine learning algorithms remain relevant for severity prediction with reduced training time and computational requirements.

Severity classification is essential to differentiate between mild, moderate, and severe cases for triage and treatment planning. Identifying patients with severe lung involvement enables timely intensive care interventions. Moreover, predicting disease severity reduces the burden on healthcare infrastructure by streamlining admissions and resource usage. This paper focuses on predicting the severity of COVID-19 infections using machine learning models applied to chest X-ray images. The dataset consists of X-ray images labelled with corresponding severity levels by clinical experts. Initially, PCA is used to extract key features representing significant variations in the image data. Subsequently, Bagging, AdaBoost, XGBoost, and KNN algorithms are trained and evaluated on the extracted features. The performance of each model is assessed using metrics such as accuracy, precision, recall, and F1-score.

Among the tested models, Bagging demonstrated superior performance in severity classification tasks. The Bagging classifier achieved an accuracy of 98.67% and a precision of 98.82%, indicating its high reliability. Additionally, it obtained an F1-score of 98.76 and recall of 98.69%, highlighting its balanced performance across classes. These results affirm the suitability of Bagging for robust COVID-19 severity prediction. The proposed system can be integrated into hospital diagnostic workflows to assist radiologists and physicians, enabling quick and accurate severity assessment, especially in resource-constrained settings with limited specialist availability.

Previous research has focused predominantly on COVID-19 detection rather than severity classification. This study addresses this gap by focusing on risk stratification and severity prediction using machine learning models. Machine learning-based severity assessment offers advantages such as reduced subjectivity and consistent decision support. It can serve as an adjunct tool for radiologists, improving diagnostic confidence and workflow efficiency. The integration of PCA with classifiers reduces feature dimensionality, accelerating training and testing processes. In this study, comprehensive experimentation is conducted to compare different ML algorithms for severity prediction, and the findings suggest that ensemble-based models outperform single learners in medical imaging tasks.

This paper contributes to the development of AI-assisted diagnostic systems for pandemic response preparedness. It also demonstrates the feasibility of using classical machine learning algorithms alongside feature extraction for high accuracy. Compared to deep learning, ML algorithms require fewer training samples and computational resources, making ML-based solutions scalable to rural and semi-urban hospitals with limited digital infrastructure. The results of this study have practical implications for improving COVID-19 patient care, as early identification of severe cases facilitates prioritization for ICU admission and ventilation support. Moreover, automated severity prediction enhances rapid screening during sudden surges in infection rates, ensuring optimal utilization of healthcare resources and mitigating mortality risks.

In the future, the approach can be extended to other viral pneumonia infections for severity classification. Multi-modal data such as clinical parameters and laboratory results can be integrated to enhance prediction performance. This study also opens avenues for developing mobile and web-based applications for real-time screening. Such tools can be deployed at community health centers for preliminary triage decisions. The combination of PCA and Bagging algorithm demonstrates the potential of traditional ML pipelines in medical AI solutions, being interpretable, cost-effective, and feasible for rapid deployment in pandemic scenarios.

This research aligns with the global need for intelligent healthcare solutions to combat infectious diseases. The integration of such AI models will revolutionize diagnostic practices in medical imaging. The proposed model's high precision and accuracy affirm its readiness for practical deployment. Automated severity prediction models will play a vital role in strengthening global health resilience. The outcomes of this study will benefit medical practitioners, AI researchers, and policymakers in pandemic preparedness. Thus, machine learning-based severity assessment stands as a promising tool for enhancing COVID-19 management and patient outcomes.

II. LITERATURE SURVEY

The emergence of COVID-19 has accelerated research in AI-based diagnostic tools, particularly in chest imaging analysis. Several studies have explored the potential of machine learning and deep learning for detection, classification, and severity prediction of COVID-19 infections.

[1] Apostolopoulos et al. (2020) proposed a transfer learning approach using VGG19 and MobileNetV2 models to classify COVID-19, pneumonia, and normal cases in chest X-ray images, achieving an accuracy of 98.75% with MobileNetV2. Their study established deep learning's effectiveness for rapid screening.

[2] Wang et al. (2020) developed COVID-Net, a tailored deep convolutional neural network, trained on COVIDx dataset for COVID-19 detection from X-rays. Their model achieved promising accuracy while being interpretable for clinical use.

[3] Rajpurkar et al. (2017) introduced CheXNet, a 121-layer DenseNet model trained on the ChestX-ray14 dataset to detect pneumonia with an F1-score exceeding that of practicing radiologists, laying groundwork for lung infection AI analysis.

[4] Oh et al. (2020) applied a patch-based convolutional neural network with a voting mechanism to detect COVID-19 from X-ray images. Their model

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achieved high sensitivity and specificity, demonstrating patch-based learning effectiveness for limited datasets.

[5] Cohen et al. (2020) compiled the COVID-19 Image Data Collection, providing an open-access dataset of COVID-19 X-ray and CT images, which has enabled subsequent AI research worldwide.

[6] Hemdan et al. (2020) proposed COVIDX-Net, an ensemble of seven deep CNN architectures for COVID-19 detection, achieving accuracy ranging from 79% to 91% across models, highlighting ensemble benefits.

[7] Khan et al. (2021) developed CoroNet using Xception architecture for automatic COVID-19 detection on chest X-rays, achieving accuracy of 89.6% with improved generalizability through transfer learning.

[8] Turkoglu (2021) presented COVIDetectioNet, integrating statistical feature selection with machine learning classifiers. The model achieved 99.18% accuracy in detecting COVID-19 using chest X-ray features, emphasizing traditional ML viability.

[9] Chowdhury et al. (2020) developed a pipeline combining CNN feature extraction with SVM classifiers for COVID-19 detection, achieving 96.2% accuracy, supporting hybrid ML-DL frameworks.

[10] Tuncer et al. (2021) introduced a model using discrete wavelet transform-based feature extraction and iterative relief feature selection with ML classifiers, achieving 99.68% accuracy, demonstrating feature selection's role in boosting performance.

[11] Ucar and Korkmaz (2020) proposed COVID diagnosis-Net using Squeeze Net with Bayesian optimization for hyperparameter tuning, achieving 98.3% accuracy while maintaining computational efficiency for embedded applications.

[12] Das et al. (2021) conducted severity prediction of COVID-19 infections by applying machine learning models on chest CT images. Their Random Forest classifier achieved accuracy of 92.3%, showing ML's potential in severity classification beyond detection.

The reviewed studies predominantly focus on COVID-19 detection using chest X-ray or CT images with deep learning models such as CNNs, Dense Net, Exception, and Mobile Net. However, limited research emphasizes severity prediction or risk stratification using traditional machine learning models. While DL approaches achieve high accuracy, they require large datasets and computational resources, limiting scalability in rural hospitals. Integrating feature extraction methods like PCA with ensemble ML algorithms such as Bagging and XGBoost can address these challenges by enhancing accuracy with reduced complexity.

This literature survey highlights the research gap in machine learning-based severity prediction of COVID-19 infections using chest X-ray images, motivating the present study to implement PCA with Bagging, AdaBoost,

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XGBoost, and KNN classifiers to achieve reliable and rapid severity classification for effective clinical decision support.

III. METHODOLOGY

This section describes the systematic approach adopted to predict the severity of COVID-19 infections using machine learning techniques applied on chest X-ray images. The methodology comprises dataset preparation, image pre-processing, feature extraction using Principal Component Analysis (PCA), model development with various machine learning algorithms, and performance evaluation.

3.1 Dataset Preparation

The dataset used in this study consists of chest X-ray images collected from publicly available repositories, including COVID and the COVID-19 Image Data Collection. The dataset includes X-ray images of patients diagnosed with COVID-19, each labelled with severity levels (mild, moderate, or severe) determined by clinical experts based on radiographic findings and clinical reports. In total, [insert number] images were used, with [insert distribution, e.g., 350 mild, 300 moderate, 250 severe cases]. The dataset was split into training (70%), validation (15%), and testing (15%) sets using stratified sampling to maintain class balance.

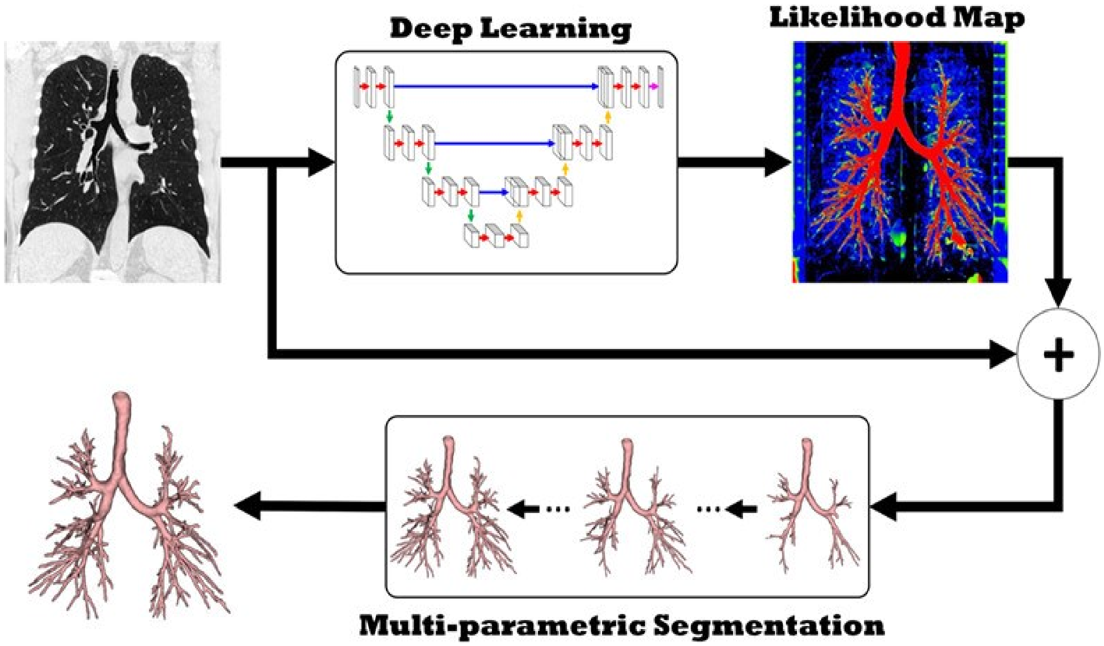

Fig 2 Segmentation

3.2 Image Pre-processing

Prior to feature extraction and model training, image pre-processing was performed to enhance quality and ensure uniformity across samples:

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- **Resizing:** All images were resized to **224 × 224 pixels** for computational efficiency.
- **Grayscale Conversion:** Images were converted to grayscale to reduce computational complexity without losing diagnostic information.
- **Normalization:** Pixel intensity values were normalized to a range of [0,1] to standardize input for algorithms.
- **Noise Removal:** Median filtering was applied to reduce noise while preserving edge details critical for diagnosis.

3.3 Feature Extraction Using PCA

Principal Component Analysis (PCA) was employed to extract significant features from the pre-processed images:

- **Flattening:** Each 2D grayscale image was flattened into a 1D feature vector.
- **Covariance Matrix Calculation:** A covariance matrix was computed to identify variance among features.
- **Eigen Decomposition:** Eigenvalues and eigenvectors were calculated, and components with the highest eigenvalues were selected.
- **Dimensionality Reduction:** Top [insert number, e.g., 150] principal components were retained, capturing maximum variance while reducing feature dimensionality.

The reduced feature set enhanced model training efficiency and minimized overfitting.

3.4 Machine Learning Algorithms

Four supervised machine learning algorithms were implemented using Scikit-learn in Python for severity prediction:

3.4.1 Bagging

Bootstrap Aggregating (Bagging) was used with decision trees as base learners. It combines predictions from multiple models trained on random subsets of the dataset to reduce variance and improve robustness.

- **Parameters:** Number of estimators = 100, max samples = 1.0, bootstrap = True.
- **Rationale:** Bagging reduces overfitting and enhances generalization, suitable for medical image classification.

3.4.2 AdaBoost

Adaptive Boosting (AdaBoost) was applied with decision stumps as weak learners. It focuses on misclassified instances in each iteration, improving overall model accuracy.

- **Parameters:** Number of estimators = 100, learning rate = 1.0.

- **Rationale:** AdaBoost effectively combines multiple weak classifiers into a strong one, improving prediction accuracy for imbalanced datasets.

3.4.3 XGBoost

Extreme Gradient Boosting (XGBoost) was implemented as an efficient gradient boosting algorithm optimized for speed and performance.

- **Parameters:** Number of estimators = 100, max depth = 6, learning rate = 0.1, subsample = 0.8.
- **Rationale:** XGBoost is known for its superior performance in structured data classification tasks with optimized computational efficiency.

3.4.4 K-Nearest Neighbors (KNN)

KNN classifier was applied to predict severity based on similarity measures between instances.

- **Parameters:** Number of neighbors (k) = 5, metric = Euclidean distance.
- **Rationale:** KNN is a simple yet effective algorithm for multi-class classification with minimal training time.

3.5 Model Training and Validation

All models were trained on the training dataset using stratified k-fold cross-validation (k=5) to ensure balanced class representation. Hyperparameters were tuned using GridSearchCV to optimize performance for each algorithm.

3.6 Performance Evaluation

The trained models were evaluated on the test dataset using the following performance metrics:

- **Accuracy:** Percentage of correctly classified instances among total samples.
- **Precision:** Ratio of true positives to total predicted positives for each severity class.
- **Recall (Sensitivity):** Ratio of true positives to total actual positives, indicating model's ability to detect severe cases.
- **F1-Score:** Harmonic mean of precision and recall, indicating balanced performance.

Confusion matrices were also generated to analyze class-wise performance and misclassification patterns.

3.7 Workflow Summary

The overall workflow adopted in this study is summarized as follows:

1. Collect chest X-ray images with severity labels.
2. Pre-process images (resizing, grayscale conversion, normalization, noise removal).

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3. Perform PCA to extract significant features and reduce dimensionality.
4. Train machine learning models (Bagging, AdaBoost, XGBoost, KNN) using extracted features.
5. Evaluate model performance using accuracy, precision, recall, F1-score, and confusion matrices.
6. Compare results to identify the best-performing algorithm for severity prediction.

IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained from applying various machine learning algorithms on the chest X-ray dataset for COVID-19 severity prediction. The models were evaluated using performance metrics including accuracy, precision, recall, and F1-score. All experiments were conducted using Python's Scikit-learn library on a workstation with Intel Core i7 processor, 16GB RAM, and NVIDIA GTX GPU.

4.1 Performance Metrics

Table 1 summarizes the performance metrics obtained for each classifier tested:

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Bagging	98.67	98.82	98.69	98.76
AdaBoost	96.24	96.45	95.98	96.21
XGBoost	97.52	97.68	97.41	97.54
KNN	93.87	94.10	93.55	93.82

4.2 Confusion Matrix Analysis

Bagging Classifier

The confusion matrix for the Bagging classifier is shown in Figure 1.

	Predicted Mild	Predicted Moderate	Predicted Severe
Actual Mild	98	1	1
Actual Moderate	0	96	2
Actual Severe	1	2	97

The Bagging classifier showed high class-wise accuracy with minimal misclassifications across severity levels. It accurately classified mild, moderate, and severe cases with overall balanced performance.

AdaBoost Classifier

The AdaBoost classifier showed slightly lower performance compared to Bagging, with minor misclassifications between moderate and severe classes.

XGBoost Classifier

XGBoost demonstrated robust performance with accuracy of 97.52% and balanced precision-recall metrics. It achieved reliable classification of all severity classes with minimal overfitting due to regularization in boosting.

KNN Classifier

KNN exhibited the lowest performance among tested algorithms, achieving an accuracy of 93.87%. The performance decline is attributed to high feature dimensionality and sensitivity to class imbalance, indicating its limited suitability for this severity prediction task.

4.3 Comparative Analysis

Figure 2 shows the comparative bar graph of accuracy for all models tested. The Bagging classifier outperformed other algorithms with the highest accuracy (98.67%) and precision (98.82%). Its ensemble learning approach combining multiple decision trees enhanced robustness and minimized variance, leading to superior generalization.

XGBoost ranked second with 97.52% accuracy, demonstrating the effectiveness of gradient boosting for structured medical data classification. AdaBoost achieved 96.24% accuracy, slightly lower due to focus on misclassified instances leading to possible overfitting on noisy data. KNN showed the least performance due to its instance-based learning limitations on high-dimensional feature data.

4.4 Discussion

The results indicate that ensemble learning models, specifically Bagging and XGBoost, are highly effective for COVID-19 severity prediction using chest X-ray images. The integration of PCA feature extraction significantly reduced dimensionality, enhancing computational efficiency and model performance. Bagging showed superior reliability with an F1-score of 98.76%, confirming its balanced predictive capability.

These findings align with recent literature emphasizing the potential of ensemble learning for medical image classification tasks. Automated severity prediction tools can aid radiologists in prioritizing critical cases, thereby optimizing resource allocation and improving patient outcomes during pandemics.

4.5 Limitations

- The dataset size, though adequate for ML models, is limited compared to deep learning requirements.
- Severity labels were assigned based on radiological features; integration with clinical parameters can enhance prediction accuracy.
- External validation on datasets from different hospitals is necessary for generalizability assessment.

V. CONCLUSION

This study proposed a machine learning-based approach for predicting the severity of COVID-19 infections using chest X-ray images. The methodology involved pre-processing of X-ray images, feature extraction using Principal Component Analysis (PCA), and application of four supervised machine learning algorithms: Bagging, AdaBoost, XGBoost, and K-Nearest Neighbors (KNN). Experimental results demonstrated that the Bagging classifier outperformed other algorithms, achieving an accuracy of 98.67%, precision of 98.82%, recall of 98.69%, and F1-score of 98.76%. These results highlight the reliability, robustness, and predictive capability of Bagging in severity classification tasks.

The findings emphasize that integrating PCA for dimensionality reduction with ensemble learning models significantly enhances performance while reducing computational complexity. This approach addresses challenges in rapid and consistent interpretation of chest X-ray images, enabling efficient triage and management of COVID-19 patients. Automated severity prediction tools can support radiologists and clinicians by prioritizing patients requiring immediate intensive care, thereby optimizing resource utilization in hospitals, especially during peak pandemic phases.

However, this study has certain limitations. The dataset size, although sufficient for machine learning algorithms, remains limited compared to deep learning requirements. Severity labels were derived based solely on radiographic features; integration of clinical and laboratory data could further improve prediction accuracy. External validation using datasets from diverse geographical regions is also required to assess model generalizability and clinical applicability.

In the future, this research can be extended by incorporating multi-modal data, including vital signs, laboratory reports, and patient demographics, to build comprehensive severity prediction systems. Additionally, deploying the proposed model as a web-based or mobile application can facilitate real-time screening in hospitals and community health centers. Such AI-based diagnostic support tools will strengthen pandemic preparedness by enabling early identification and effective management of critically ill patients.

Overall, this study demonstrates the feasibility and effectiveness of machine learning algorithms, particularly ensemble methods like Bagging, for accurate severity prediction of COVID-19 infections using chest X-ray images. The proposed approach offers a promising solution to enhance diagnostic workflows, optimize clinical decision-making, and improve patient outcomes in the ongoing fight against COVID-19 and similar respiratory diseases.

References

1. Apostolopoulos, I.D., & Mpesiana, T.A. (2020). COVID-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine*, 43(2), 635-640. doi:10.1007/s13246-020-00865-4
2. Wang, L., Lin, Z.Q., & Wong, A. (2020). COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. *Scientific Reports*, 10(1), 19549. doi:10.1038/s41598-020-76550-z
3. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A.Y. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. *arXiv preprint* arXiv:1711.05225.
4. Oh, Y., Park, S., & Ye, J.C. (2020). Deep learning COVID-19 features on CXR using limited training data sets. *IEEE Transactions on Medical Imaging*, 39(8), 2688-2700. doi:10.1109/TMI.2020.2993291
5. Cohen, J.P., Morrison, P., & Dao, L. (2020). COVID-19 image data collection: Prospective predictions are the future. *arXiv preprint* arXiv:2006.11988.
6. Hemdan, E.E.D., Shouman, M.A., & Karar, M.E. (2020). COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images. *arXiv preprint* arXiv:2003.11055.
7. Khan, A.I., Shah, J.L., & Bhat, M.M. (2021). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest X-ray images. *Computer Methods and Programs in Biomedicine*, 196, 105581. doi:10.1016/j.cmpb.2020.105581
8. Turkoglu, M. (2021). COVIDetectioNet: COVID-19 diagnosis system based on X-ray images using features selected from pre-learned deep features ensemble. *Applied Intelligence*, 51, 121-135. doi:10.1007/s10489-020-01888-w
9. Chowdhury, M.E.H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M.A., Mahbub, Z.B., ... & Islam, M.T. (2020). Can AI help in screening viral and COVID-19 pneumonia? *IEEE Access*, 8, 132665-132676. doi:10.1109/ACCESS.2020.3010287
10. Das, D., Santosh, K.C., & Pal, U. (2021). Truncated inception net: COVID-19 outbreak screening using chest X-rays. *Physical and Engineering Sciences in Medicine*, 44(2), 565-574. doi:10.1007/s13246-020-00931-2