Global Journal on Innovation, Opportunities and Challenges in AAI and Machine Learning
http://eurekajournals.com/IJIOCAAIML.html
ISSN: 2581-5156

Design and Implementation of Optimized Feature Extraction method in Deep Learning Models for Enhanced COVID-19 Detection

Gurjot Kaur[1], Ankita[1]

[1]Department of Computer Science & Engineering, CT University, Ludhiana.

Abstract

Nowadays, COVID-19 is a global pandemic, which was developed in 2019, and has posed enormous limitations to healthcare systems worldwide, emphasizing the need for rapid and accurate detection techniques. Early diagnosis plays an important role in controlling its spread and providing timely treatment. However, existing detection systems often face challenges in terms of accuracy, efficiency, and the capability to handle large datasets. This study offers a novel deep learning (DL) based approach to improve the detection of COVID-19 by focusing on optimized feature extraction and comparing its performance with existing systems. The research begins with an analysis of current systems for COVID-19 detection, identifying their strengths, limitations, and areas where improvements can be made. Building on this analysis, a new optimized feature extraction algorithm is proposed to extract global feature matrices from relevant datasets, aiming to enhance the efficiency of the detection procedure. A DL model is then developed to detect COVID-19, leveraging advanced neural network architectures to provide accurate results. Finally, the recital of the implemented system is associated with existing techniques using several evaluation parameters, like accuracy, precision, etc. The outcome of this study prove that the proposed system significantly outperforms current detection systems in terms of both accuracy and processing time. This research contributes to the field of AI-driven medical diagnostics and provides valuable insights for improving COVID-19 detection systems, offering a more well-organized and precise result for combating the ongoing pandemic. The proposed system also lays the foundation for future advancements in the application of DL in healthcare.

Keywords: Covid-19, Artificial Intelligence (AI), Deep Learning (DL).

Introduction

The novel coronavirus pandemic is one of the most dangerous viral infections currently affecting the world. The illness is attributed to the severe acute respiratory syndrome coronavirus, normally called SARS-CoV-2. The economies and healthcare systems of various countries have been severely impacted by this drastic viral outbreak. According to data from the WHO, about 225,024,782 cases of coronavirus infection have been recorded, including 4,636,153 documented fatalities as of September 2021. The disease spreads from person to person via small respiratory droplets, commonly referred to as aerosols [1].

To fight this dangerous virus, the WHO developed the Covid-Shield vaccine during the pandemic's peak outbreak. The anti-Covid vaccination can help control the virus's further spread. However, detecting the disease within the human body can be challenging due to limited testing resources. Additionally, while vaccinations like Immunoglobulin M (IgM) and Immunoglobulin G (IgG) are crucial for fighting the viral infection, it is often impossible to detect the antibodies produced by the body until the 14-day quarantine period is completed. Misdiagnoses can lead to false negative results (FNR), which is why scientists, researchers, and medical professionals emphasize the need for advanced technologies to effectively combat this viral infection known as COVID-19 in a faster, more efficient, and more accessible manner [2].

The background of the disease can be drawn back to Wuhan, widely recognized as the initial outbreak location in China, in December 2019. The initial spread of this viral infection presented symptoms resembling queasiness, throat clearing, elevated temperature, weariness, lung infiltrates, dyspnea, and breathlessness. The WHO reported that the second wave of the coronavirus exhibited symptoms such as pyrexia, continuous non-productive cough, dermal discomfort, ageusia and anosmia, head pain, gastrointestinal distress, changes in the color of digits, throat discomfort, and dermatological lesions [3]. The novel coronavirus is primarily an infectious illness activated by the SARS-CoV-2. Recognized and initially verified in 2019, it spread rapidly, resulting in a global pandemic. While most cases present with mild symptoms, however, some cases can advance to severe pneumonia and multiple organ failure, often referred to as serious complications. The virus is primarily transmitted through close contact via respiratory droplets released by an infected individual during sneezing or coughing. It can also be transmitted through fomite transmission, where touching dirty surfaces and then touching the nose, or eyes introduces the illness into the body. The pandemic has a gestation time of two to fourteen 24-hour periods, with an average of five days. Diagnosis primarily relies on reverse transcription polymerase chain reaction testing, sometimes supplemented by symptoms, risk factors, and chest CT scans that indicate pneumonia [4].

In response to the pandemic, various models have been created to enhance the diagnosis and control of coronavirus infections, including image processing techniques like CT scans and chest X-rays(CXR). The integration of AI, particularly deep learning (DL) and ML, has significantly enhanced the accuracy of diagnoses using these images. AI applications in computer vision, combined with technologies like the (IoT), big data analytics, and smartphones, have further advanced the fields of diagnosis, prognosis, and outbreak forecasting [5].

DL and ML are crucial methods utilized for COVID-19 detection. DL is particularly effective in medical image analysis, automating the recognition of infections and achieving superior outcomes with minimal human intervention. This approach has proven vital in analyzing radiological images, such as those used in tumor and nodule classification. In contrast, ML focuses on predicting outcomes based on historical data, demographics, and outbreak severity, effectively managing large, complex datasets to support decision-making in COVID-19 prognosis. Together, DL and ML improve the efficiency of pandemic detection [6].

The datasets working for pandemic detection include the Johns Hopkins University dashboard for visualizing the 2019 Novel Coronavirus, which aggregates data from sources such as WHO and CDC; a novel coronavirus image database with 345 X-ray images; a CT image database containing 349 confirmed and 398 non-coronavirus cases; and several segmentation datasets featuring labeled CT images. Additionally, ongoing Twitter datasets track millions of tweets, alongside global news and climate data, and various demographic datasets from WorldPop. Other data sources encompass Apple and Google mobility reports, testing data from Our World in Data, government response data from ACAPS, security incident data from ACLED, and a comprehensive C3 pandemic Information Repository filled with analysis-available datasets [7].

The novel CNN model for pandemic diagnosis has achieved robust classification performance, validated through a tenfold cross-validation procedure that utilized metrics such as accuracy, specificity, sensitivity, and precision [8]. Confusion matrices effectively summarize classification decisions, highlighting the model's performance through accurately recognized positives, inaccurately recognized positives, correctly recognized negatives, and incorrectly recognized negatives [9]. Notably, the EfficientNetB0 model attained the highest detection accuracy of 96.8% on the test set, outperforming VGG16 and ResNet50, which recorded accuracies of 90.0% and 94.3%, respectively [10]. Furthermore, the analysis done in another paper reached a classification accuracy of 94.7% using features deeply extracted using the ResNet50 model in conjunction with an SVM classifier with a linear kernel, while the fine-tuned ResNet50 algorithm obtained 92.6% correctness, and the end-to-end trained CNN technique generated 91.6% correctness [11].

The contributions of this research are centered on the growth of a novel and optimized system for the recognition of COVID-19 using DL techniques. First, the study aims to critically analyze existing diagnostic models and identify limitations such as dataset size, model accuracy, and generalizability. Building upon this analysis, the research proposes the implementation of an optimized feature extraction algorithm to enhance the identification of global feature matrices, which are essential for accurate detection and resolving the over fitting and under fitting problems.

The second key contribution is the design of a novel system to further improve COVID-19 detection performance. The research seeks to identify and retain the most relevant features for classification, enhancing model efficiency and accuracy.

Lastly, the study provides a comparative analysis between the proposed system and existing models, demonstrating its effectiveness and superiority in terms of diagnostic accuracy, sensitivity, and specificity. Through these contributions, the research aims to address key challenges in COVID-19 detection, offering a more efficient and reliable solution for healthcare systems worldwide.

The remaining paper is represented: Section 2 contains a literature review: that defines the related work and research gap. Section 3 contains methodology: defines the methods and processes, and Section 4 provides result analysis. Finally, Section 6 providesa conclusion and future scope of the study.

Literature Review

This survey section's main objective is to provide a complete indication of previous research studies that explored various ML and DL techniques in predicting and diagnosing COVID-19 outcomes. It highlights the methodologies used, datasets, simulation tools, and the corresponding outcomes and challenges identified in each study as illustrated in Table I.

Table I: comparative analysis of several studies

Author Name	Methods	Gaps	Dataset	Simulation Tools | Parameters	Outcomes
Ali BouNassif et al.(2022) [12]	VGG16 VGG19 Inception-ResNetV2	The key gap is the limited dataset size, which hinders the models' performance despite using data augmentation.	Speech Corpus Dataset and Image Dataset.	• Python tool • Vgg16 accuracy - 85.25% • Inception-RestNetV2 = 82.22%	The most important key factor of the research analysis is the fine-tuning accuracy of the VGG16 model was 89.64%, which was previously 85.25% only.
Marwah Ahmed Halwani et al.(2024) [13]	DT RF SVM	The key gap identified was the challenge of ensuring that AI models can be effectively	Dataset: 50 RT-PCR-positive COVID-19	• Python tool • DT with accuracy-76 % • RF with accuracy = 80%	The main important findings revolved around AI for its significant analytical

		applied to a variety of populations, leading to unreliable predictions across different settings		• SVM with accuracy = 82%	ability to predict the outcomes generated from the COVID-19 datasets.
MaadM.Milwil et al.(2021) [14]	SVM	The problem was with the unsatisfactory results of the Naive Bayes algorithm after the implementation of the COVID-19 dataset.	Covid-19 Dataset	• Python tool • SVM with accuracy = 91.8% • Sensitivity - 91.7% • Specificity - 95.9% • F1-score - 91.8% • AUC score - 97.6%	The outcome of the SVM model has been effectively worked during the process of the detection of the COVID-19 pandemic, which leads to good accuracy.
MoutazAlazab et al(2020) [15]	CNN ARIMA LSTM algorithm	A key gap related to the study was the lack of exploration into more advanced forecasting methods and the need for further validation of the diagnosis model on larger and more diverse datasets, including chest CT	CXR images dataset	• Python tool • ARIMA with accuracy = 94.80% • LSTM with accuracy = 88.43%	The main important key model was the usage of VGG16 to predict pandemic disease using the CXR image dataset.

		scans.			
Muhammad Attaullah et al(2022) [16]	ML and DL models	The major problem associated with the research strategy was failure of the COVID-19 detection because of the misanalysis of patient's symptoms as well as the medical images.	Radiography,	Python Accuracy with Proposed Model = 78.88%	The important result has been identified with the help of an integrated algorithm for the identification of the novel coronavirus at the early phase of this disease.
Kishore Medhi et al.(2020) [17]	DNN model	The key issue is the limited availability of novel coronavirus CXR and CT scan image datasets, restricting the proposed system's ability to be extensively tested and potentially achieve higher accuracy.	X-ray image dataset and statistical dataset.	Python Accuracy: DNN = 93%.	The proposed Deep CNN architecture
Loveleen Gaur et al.(2023) [18]	DL CNN like: VGG16, InceptionV3, EfficientNet	The study's findings are based on a limited dataset,	Actual Med _Covid CXR image dataset as well as the	Python Accuracy with VGG16 = 87.84%,	The study demonstrated that DL models, specifically

	B0.	which may affect the generalizability and accuracy of the DL techniques for identifying the novel coronavirus in CXR images.	Coronavirus radiography datasets,	Accuracy with InceptionV3 = 91.32%, EfficientNet B0 = 92.93%.	EfficientNet B0, can accurately detect pandemics from CXR with correctness of 94.79%, potentially reducing healthcare burdens and the need for physical screenings.
Mehmet Sevi et al.(2020) [19]	DL models: VGG19,CNN etc.	The effectiveness of DL models in diagnosing COVID-19 is currently limited by the small dataset of only 657 CXR images	CXR Dataset,	Python Accuracy: VGG19 =95%, InceptionV3 = 48%, CNN = 85%.	The VGG19 model demonstrated a high accuracy rate of 95% in classifying COVID-19, healthy patients, and viral pneumonia cases, highlighting the effectiveness of DL in diagnosing pandemics from CXR images.
L.J. Muhammad et al.(2021)[20]	ML models: DT,SVM, etc.	The COVID-19 pandemic has become endemic, affecting	Epidemiology dataset	Python Accuracy, DT =94.99% LR =94.41%	The decision tree model achieved the highest accuracy of 94.99% for

		nearly 213 countries and highlighting the need for alternative diagnostic methods like ML to alleviate the burden on healthcare systems.		Naive Bayes: =94.36% SVM=92.40 % ANN: =89.20%	diagnosing COVID-19, while SVM and naive Bayes models excelled in sensitivity and specificity with 93.34% and 94.30%, respectively.
SumayyahS.Aljameel et al.(2021)[21]	ML models: LR, RF,SVM etc.	The study demonstrated that the RF model effectively predicts mortality and survival in COVID-19 patients, receiving a correctness of 95.2% and an AUC of 0.99, despite challenges with data imbalance.	Covid-19 Patients datasets,	Python Accuracy: Original and without SMOTE dataset, LR = 87.4%, FR = 90.8%, XGB = 88.5%.	The study highlighted the importance of using the SMOTE technique to address data imbalance in predicting the death rate and endurance of pandemic patients.

A recurring theme in the reviewed literature is the challenge posed by limited and unbalanced datasets, which hinder the models' ability to generalize and achieve optimal performance. Several studies emphasized the critical need for superior, more diverse databases to enhance the robustness and accuracy of prediction models. This gap has led to a growing interest in data augmentation techniques and feature extraction methods that can improve model performance even when data availability is limited. Furthermore, the studies underline the importance of fine-tuning and optimizing popular DL models such as VGG16, InceptionV3, and EfficientNetB0 for improved accuracy in detecting COVID-19, particularly from CXR images. Another important aspect discussed in the literature is the integration of advanced forecasting models like Auto-Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM), which have shown promise in predicting disease outcomes.

While these models have demonstrated high accuracy in certain settings, there remains a need for further validation and testing on more extensive and varied datasets, especially in real-world clinical environments. Additionally, the comparison of multiple ML algorithms has been a common approach to assessing the most effective models for predicting patient outcomes, such as mortality and survival rates. These studies also highlight the role of techniques like the SMOTE technique in addressing data imbalance, which is crucial for refining the reliability and performance of prediction models.

Overall, though the existing studies provide valuable insights into the use of AI, ML, and DL for COVID-19 analysis, they also highlight significant challenges that must be addressed. These challenges include dataset limitations, model generalization issues, and the need for more advanced techniques in feature selection and model optimization. The comparative analysis presented in Table I offers a detailed summary of these studies, shedding light on their methodologies, gaps, and outcomes, and laying the foundation for future research in this area.

Methodology

This section outlines the approach and techniques employed to design, develop, and evaluate the implemented model for COVID-19 detection from CXR images using DL. The main objective of this research work is to optimize feature extraction and selection processes for accurate diagnosis, utilizing a novel algorithm for global feature extraction integrated with DL models. The methodology is structured as follows in Fig 1.

A. System Analysis

The first step in the methodology involves analyzing the existing diagnostic systems for COVID-19, especially those utilizing ML and DL techniques. This includes a comprehensive review of previous research to identify gaps, limitations, and areas where performance can be improved. Special attention is given to the challenges related to dataset limitations, model accuracy, and the effectiveness of different algorithms such as VGG16, ResNet, and SVM in detecting COVID-19 from radiological images like CXR and CT scans.

B. Data Collection and Pre-processing

For this study, a database that was developed by scholars in teamwork with medical professionals was used [22]. This dataset comprises CXR images of COVID-19-positive cases, normal cases, and viral pneumonia cases, released in stages to ensure continual updates. This dataset provides a comprehensive representation of several lung situations, ensuring robust training and evaluation of the proposed model, with future updates planned as additional data becomes available. The datasets are pre-processed to ensure consistency, including the following steps.

- **Resizing and Normalization**

All CXR images are resized i.e., 224x224 pixels to match the input dimensions expected by the DL method. Image pixel values are regularized to the variety [0, 1] to improve the efficiency of the training procedure.

➢ Data Augmentation

Given the limited dataset, this technique applied, such as rotation, zoom, shift, and flipping are applied to grow the diversity of the dataset, improving the model's ability to generalize.

C. Global Feature Extraction

The next step involves extracting global features from the pre-processed medical images. Global features are the essential characteristics that provide insight into the medical condition (in this case, COVID-19) from images. Traditional feature extraction methods often rely on manually engineered features, but DL models, particularly CNNs, are capable of automatically learning these features directly from the raw images. In this study, the feature extraction is optimized using an advanced global feature extraction algorithm. The goal of this step is to maximize the efficiency of feature extraction, ensuring that the most relevant and discriminative features are captured. This allows for better differentiation between COVID-19 and other conditions in the images. By leveraging advanced optimization algorithms, we enhance the model's capability to emphasize global features, improving the overall classification performance.

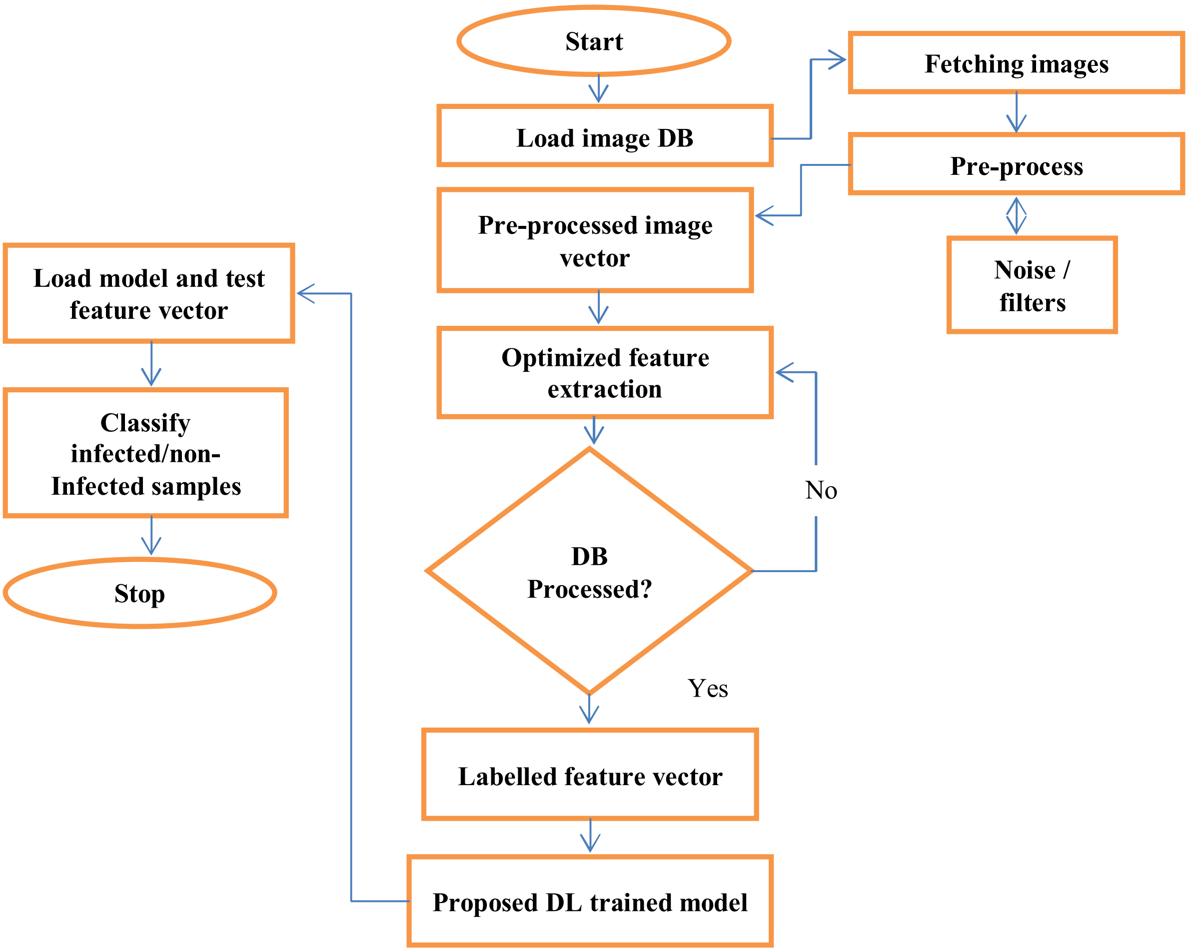

Figure 1: Flowchart of Research Methodology

The process begins by loading the image database, which contains medical images of patients, including those who are COVID-positive and those who are COVID-negative. The database serves as the primary source of input for the detection pipeline. Images are fetched individually or in batches, and they undergo a critical pre-processing stage. Pre-processing involves applying various techniques, such as noise removal and filtering, to enhance image quality, standardize the input, and eliminate unwanted artifacts. This ensures that the images are clean and consistent, making them suitable for accurate feature extraction.

A decision point checks whether the entire database has been processed. If not, the system loops back to continue feature extraction for the remaining images. Once all images have been analyzed, the extracted features are labeled according to their categories: "COVID-positive" for infected patients and "COVID-negative" for healthy individuals or those with other conditions. These labeled feature vectors are then used to train a proposed deep-learning model. DL architecture, such as a CNN, is typically employed to learn from the labeled features. During training, the model identifies patterns and relationships in the labeled data, enabling it to differentiate between COVID-positive and COVID-negative cases accurately.

After the model is trained, it is loaded for testing using new, unseen data. In this stage, test feature vectors are passed into the trained model, which classifies the input images based on the patterns it has learned. The model outputs predictions, categorizing the images as either infected or non-infected. This classification is the ultimate goal of the pipeline, as it enables automated and accurate detection of COVID-19 cases. Finally, the procedure concludes, by providing a well-organized tool for detecting COVID-19 using medical imaging.

Result analysis

The results analysis section evaluates the performance and insights derived from the COVID-19 detection system. This section also presents a comparative analysis between baseline models and the proposed approach to underline the enhancements in accuracy and error reduction. The generalizability of the model was validated on diverse test samples, and statistical significance tests were conducted to ensure the reliability of the observed results. This comprehensive analysis demonstrates the system's effectiveness and robustness in COVID-19 detection tasks.

A. Experimental setup

The proposed methodology was implemented using MATLAB, leveraging its robust DL toolboxes for model development and evaluation. The experimentations were conducted on a workstation prepared with an 11th Gen Intel® Core™ i7 processor, 24 GB of RAM, and successively on the Windows 10 64-bit platform, ensuring adequate computational resources for handling data processing and model training tasks.

B. Evaluation parameters

The proposed model performance was analyzed using different parameters, comprising accuracy, precision, recall, and mean squared error (MSE), providing a complete view of the proposed model's classification and regression performance. To assess the performance of the

COVID-19 detection system, several calculation metrics were employed to ensure analysis of the model's classification capabilities:

- ***Accuracy:*** It measures the amount of accurately categorized samples out of the total no. of samples. While accuracy provides a good overview, it can be misleading for imbalanced databases and is therefore complemented by other metrics. It is a key metric for understanding overall model performance and is calculated as described in Equation 1:

$$Accuracy = \frac{(\mathrm{tp} + \mathrm{tn})}{(\mathrm{tp} + \mathrm{tn} + \mathrm{fp} + \mathrm{fn})} \quad (1)$$

Where tp is true_positive, tn is true_negative, fp is false positive, and fn is false negative.

- ***Precision:*** It quantifies the amount of tp predictions out of all positive forecasts made by the proposed model. It is particularly useful in evaluating the proposed model's ability to minimize fp, ensuring reliability in diagnosing COVID-19 cases. It is calculated as described in Equation 2:

$$Precision = \frac{\mathrm{tp}}{(\mathrm{tp} + \mathrm{fp})} \quad (2)$$

- ***Recall:*** It measures the model's ability to properly identify all actual positive cases. It is critical in healthcare applications like COVID-19 detection, where false negatives can have severe consequences. It is described in Equation 3:

$$Recall = \frac{\mathrm{tp}}{(\mathrm{tp} + \mathrm{fn})} \quad (3)$$

- ***Mean Squared Error:*** It is used to evaluate the regression capabilities of the model when predicting continuous values such as probabilities. It computes the average of the squared differences between predicted and actual values if insight into the model's prediction error. Its calculation is described in Equation 4:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2 \quad (4)$$

Where: yi= true values, y`i= predicted values, and n= total number of values.

These metrics collectively ensure a composed evaluation of the system. Precision and recall are particularly crucial in domains like healthcare, where the costs of fp and fn differ significantly. The use of MSE further strengthens the analysis by providing an understanding of continuous prediction errors, making the evaluation both robust and multi-faceted.

C. Results

Table II showcases the performance of various ML and DL modelscalculated on COVID-19 detection tasks, with their respective accuracy percentages, while Fig 2 illustrates the visual representation of the various methods based on accuracy.

TABLE III: comparative analysis of various methods based on accuracy

Ref no.	Methods	Accuracy (%)
[1]	VGG16	85.25
	Inception-ResNetV2	82.22
[2]	DT	76.00
	RF	80.00
[4]	ARIM	94.80
	LSTM	88.43
[6]	DNN model	93.00
[7]	VGG16	87.84
	InceptionV3	91.32
	EfficientNetB0	92.93
[8]	VGG19	95.00
	InceptionV3	48.00
	CNN	85.00
[9]	DT	94.99
	LR	94.41
	Naïve Bayes	94.36
	SVM	92.40
	ANN	89.20
[10]	LR	87.40
	RF	90.40

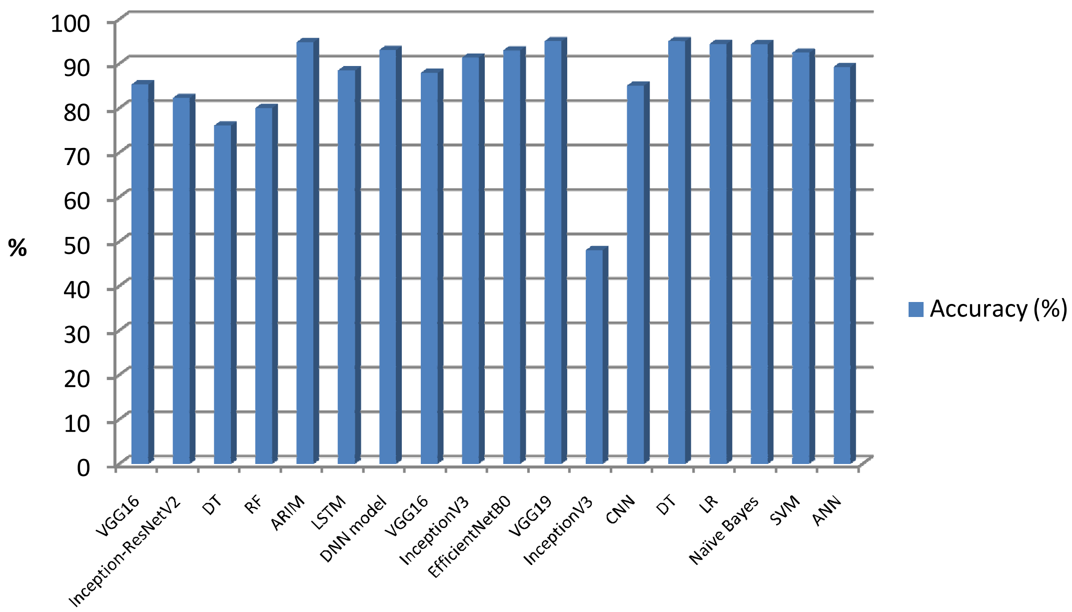

Figure 2: Visual representation of several methods

Among the DL models, VGG19 achieved the highest accuracy at 95.00%. EfficientNetB0 and InceptionV3 also performed well, with accuracies of 92.93% and 91.32%, respectively.

Traditional ML methods, such as DT, achieved 94.99% accuracy, followed closely by LR (94.41%) and RF (90.40%). Forecasting models like ARIMA reported an accuracy of 94.80%, while LSTM achieved 88.43%. These findings underscore the superior performance of DL architectures, particularly VGG19, in COVID-19 detection, emphasizing the importance of model selection for developing effective diagnostic tools. The SVM model performance for COVID-19 detection is reflected in various evaluation metrics in Table III.

Table III: Performance analysis of SVM [14]

Performance Metrics	Value (%)
Accuracy	91.80
Sensitivity	91.70
Specificity	95.90
F1-score	97.80
AUC	97.60

SVM achieved an accuracy of 91.80%, demonstrating its strong ability to classify a majority of the COVID-19 and non-COVID-19 cases correctly. With a sensitivity of 91.70%, the model effectively identified most of the true positive COVID-19 cases, indicating its effectiveness in detecting infected individuals. A specificity of 95.90% highlights the model's precision in accurately identifying non-COVID-19 cases with very few fp. The F1-score of 97.80% underlines the model's balance between precision and recall, providing an inclusive measure of its overall performance. Additionally, an AUC of 97.60% indicates a high capability for discriminating between COVID-19 positive and negative cases, showcasing SVM's strong discriminative power for this application. These results are visually represented in Figure 3, which provides a comparative analysis of SVM's performance across these key metrics, illustrating its robust classification capability for COVID-19 detection.

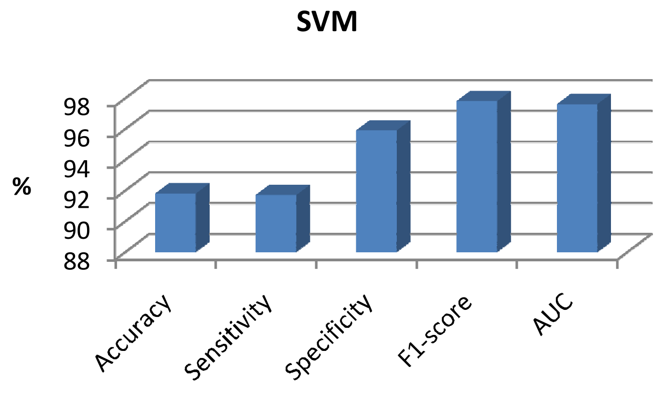

Figure 3: Visual representation of SVM performance

Conclusion and future scope

This study addresses the challenges of COVID-19 detection from CXR images using DL methodologies. The proposed system, leveraging a global feature extraction algorithm with DL models, effectively classifies CXR images into COVID-positive, Normal, and other lung infection categories. A comprehensive dataset developed by international researchers ensured a robust evaluation. Results analysis showed enhancements in accuracy and error reduction compared to baseline models. The model's generalizability was validated on diverse test samples with statistical significance tests. Implemented using MATLAB on a powerful workstation, evaluations were based on accuracy, precision, recall, and MSE. Among DL models, VGG19 achieved the highest accuracy at 95.00%. Traditional ML methods like DT, LR, and RF also performed well. SVM showed strong results with an accuracy of 91.80%, SN of 91.70%, SP of 95.90%, F1-score of 97.80%, and AUC of 97.60%. These conclusions focus on the position of model selection for effective diagnostic tools in COVID-19 detection.

Further research could explore integrating advanced DL models with multimodal data sources (e.g., radiology and clinical data) for more accurate diagnosis, leveraging transfer learning for domain adaptation, and deploying the system in real-world clinical settings for validation and refinement.

References

[1]Y. Meraihi, A. B. Gabis, S. Mirjalili, A. Ramdane-Cherif, and F. E. Alsaadi, “Machine Learning-based research for COVID-19 detection, diagnosis, and prediction: A survey,” SN Comput. Sci., vol. 3, no. 4, p. 286, 2022.

[2]A. TchagnaKouanou et al., “An overview of supervised machine learning methods and data analysis for COVID-19 detection,” J. Healthc. Eng., vol. 2021, p. 4733167, 2021.

[3]A. Bhargava, A. Bansal, and V. Goyal, “Machine learning-based automatic detection of novel coronavirus (COVID-19) disease,” Multimed. Tools Appl., vol. 81, no. 10, pp. 13731-13750, 2022.

[4]Salman, F. M., Abu-Naser, S. S., Alajrami, E., Abu-Nasser, B. S., & Alashqar, B. A.“Covid-19 detection using artificial intelligence.” 2020.

[5]M. M. Islam, F. Karray, R. Alhajj, and J. Zeng, “A review on deep learning techniques for the diagnosis of novel Coronavirus (COVID-19),” IEEE Access, vol. 9, pp. 30551-30572, 2021.

[6]J. Nayak et al., “Intelligent system for COVID-19 prognosis: a state-of-the-art survey,” Appl. Intell., vol. 51, no. 5, pp. 2908-2938, 2021.

[7]Mohamadou, Y., Halidou, A., &Kapen, P. T. “A review of mathematical modeling, artificial intelligence and datasets used in the study, prediction and management of COVID-19”. Applied Intelligence, 50(11), 3913-3925, 2020.

[8]E. Irmak, “COVID-19 disease diagnosis from paper-based ECG trace image data using a novel convolutional neural network model,” Phys. Eng. Sci. Med., vol. 45, no. 1, pp. 167-179, 2022.

[9]Muljo, H. H., Pardamean, B., Purwandari, K., &Cenggoro, T. W.“Improving lung disease detection by joint learning with COVID-19 radiography database”. Commun. Math. Biol. Neurosci., 2022.

[10]T. Zebin and S. Rezvy, "COVID-19 detection and disease progression visualization: Deep learning on chest X-rays for classification and coarse localization," Appl. Intell., vol. 51, no. 2, pp. 1010-1021, 2021.

[11]A. M. Ismael and A. Şengür, "Deep learning approaches for COVID-19 detection based on chest X-ray images," Expert Syst. Appl., vol. 164, no. 114054, p. 114054, 2021.

[12]A. B. Nassif, I. Shahin, M. Bader, A. Hassan, and N. Werghi, "COVID-19 detection systems using deep-learning algorithms based on speech and image data," Mathematics, vol. 10, no. 4, p. 564, 2022.

[13]M. A. Halwani and M. A. Halwani, "Prediction of COVID-19 hospitalization and mortality using artificial intelligence," Healthcare (Basel), vol. 12, no. 17, p. 1694, 2024.

[14]M. M. Mijwil, "Implementation of machine learning techniques for the classification of lung X-ray images used to detect COVID-19 in humans," Iraqi J. Sci., pp. 2099-2109, 2021.

[15]M. Alazab, A. Awajan, A. Mesleh, and S. Alhyari, "COVID-19 prediction and detection using deep learning," International Journal of Computer Information Systems and Industrial Management Applications, vol. 12, pp. 14-14, 2020.

[16]M. Attaullah et al., "Initial stage COVID-19 detection system based on patients' symptoms and chest X-ray images," Appl. Artif. Intell., vol. 36, no. 1, pp. 1-20, 2022.

[17]K. Medhi, M. Jamil, and I. Hussain, "Automatic detection of COVID-19 infection from chest X-ray using deep learning," 2020.

[18]L. Gaur, U. Bhatia, N. Z. Jhanjhi, G. Muhammad, and M. Masud, "Medical image-based detection of COVID-19 using deep convolutional neural networks," Multimedia systems, vol. 29, no. 3, pp. 1729-1738, 2023.

[19]M. Sevi and I. Aydin, "COVID-19 detection using deep learning methods," in 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI), 2020.

[20]L. J. Muhammad, E. A. Algehyne, S. S. Usman, A. Ahmad, C. Chakraborty, and I. A. Mohammed, "Supervised machine learning models for prediction of COVID-19 infection using epidemiology dataset," SN Comput. Sci., vol. 2, no. 1, p. 11, 2021.

[21]S. S. Aljameel, I. U. Khan, N. Aslam, M. Aljabri, and E. S. Alsulmi, Machine Learning-Based Model to Predict the Disease Severity and Outcome in COVID-19 Patients. Scientific programming. 2021.

[22]Radiography Database COVID-19 Chest X-ray images and Lung masks Database.