SwasthyaBuddy: A Comprehensive System for Assessing Chronic Obstructive Pulmonary Disorder Patients

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ABSTRACT
Chronic Obstructive Pulmonary Disease (COPD) is a multifaceted respiratory disorder that has a significant global impact on healthcare systems and patient well-being. This paper describes an innovative approach to COPD management that employs advanced technologies to detect acid-base disorders, provide real-time statistics to healthcare providers and patients, enable online consultations, predict disease severity using AI-ML models, and seamlessly integrate medical reports with the National Digital Health Mission (NDHM). This paper introduces a method for characterizing acid-base disorders in COPD patients using arterial blood gas (ABG) reports to address the critical issue of acid-base disorders. This paper can precisely identify respiratory acidosis and alkalosis by analyzing ABG data, providing clinicians with valuable insights into the patient's condition and guiding appropriate interventions. Furthermore, this system provides both healthcare providers and patients with real-time statistics, providing them with up-to-date information on COPD trends, treatment options, and outcomes. Patients can access their health data through an easy-to-use interface, fostering a collaborative approach to COPD management. The system incorporates machine learning models to predict COPD severity based on clinical data such as ABG reports, spirometry results, and patient history across the healthcare ecosystem. The system seamlessly integrates medical reports, including ABG results, with the NDHM to promote interoperability and efficient healthcare delivery. This integration ensures the secure exchange of health information while also allowing for a comprehensive view of the patient's medical history across the healthcare ecosystem. In conclusion, this proposes an integrated approach to COPD management that uses technology to detect acid-base disorders, provide real-time statistics, provide online consultations, predict disease severity, and seamlessly integrate medical reports with the NDHM. This paper hopes to revolutionize COPD care and improve outcomes in this difficult chronic disease by combining these features

Keywords: Pneumonia, Arterial blood gas (ABG) results, Acid-base disorders, Machine learning, Deep learning, Henderson-Hasselbalch Approach, Stewart Approach.

1. INTRODUCTION

Millions of people are affected with Chronic Obstructive Pulmonary Disease (COPD), which creates difficult problems for both patients and healthcare professionals [1]. This paper introduces a complete framework that uses cutting-edge technologies to revolutionize COPD care while addressing important aspects of managing COPD, [2].

The accurate identification of acid-base abnormalities, which is essential for assessing patients' general health and prognosis, is a key focus of this research. This integrated technology effectively detects and classifies acid-base imbalances by examining arterial blood gas (ABG) [3] results, giving healthcare practitioners the information they need to choose the best course of action. Data-driven insights are crucial for managing COPD. This research includes detailed statistical analysis, providing medical professionals with useful knowledge of trends, comorbidities, and treatment outcomes. Simultaneously, patients gain a deeper understanding of their condition, fostering active engagement in their healthcare journey. Enhancing accessibility to quality healthcare, this framework includes a center locator system, aiding patients in finding nearby facilities equipped to handle COPD cases.

Furthermore, online consultations enable remote access to qualified healthcare professionals, facilitating timely interventions and continuous care [4]. This research pioneers AI-ML models for predicting COPD severity. Leveraging advanced algorithms and data analytics, this system provides precise severity assessments, enabling early intervention and optimized care delivery. Interoperability is prioritized through the seamless integration of COPD-related medical reports with the National Digital Health Mission (NDHM) infrastructure, ensuring secure data sharing among healthcare providers [5].

Finally, this study contributes to the holistic and novel care of COPD. Addressing acid-base problems, using AI & Machine Learning based algorithms to forecast severity, and supporting digital health programs like the NDHM empower both patients and healthcare workers. This paper envisages improved COPD outcomes and a better future for those who are afflicted by this ailment with accurate insights, easy data integration, and greater patient engagement.

2. LITERATURE REVIEW

COPD stands for Chronic Obstructive Pulmonary Disease. This is a lung condition that gets worse over a while and makes it hard to breathe. People who have it have chronic bronchitis and emphysema, which make it hard to breathe by inflaming and narrowing the airways. Three million people die every year from COPD, making it the third most common cause of death in the world. X-rays of the chest and CT scans of the lungs can be used to find out what's wrong. Because different lung diseases can be similar and also be very different, it is hard to make a correct diagnosis of a lung disorder.[6]. Anupama H.S, Pradeep K.R, et al [7] have found that patients with Chronic Obstructive Pulmonary Disease (COPD) frequently struggle to breathe due to obstructive airway disease. Digital stethoscopes can be used to record these noises, which can subsequently be turned into audio signals and processed further. Deep learning techniques, such as convolutional neural networks, can be used in this paper to use this audio data to diagnose breathing problems like pneumonia, asthma, and bronchiolitis.

It is one of the main reasons people get sick and die, and it has a big effect on their quality of life. People who have COPD often have acid-base disorders, with respiratory acidosis being the most common. Respiratory acidosis happens when the lungs can't get rid of enough carbon dioxide, which makes the blood more acidic. This can make you feel confused, tired, and short of breath, among other things. Metabolic alkalosis and respiratory alkalo- sis are two other acid-base disorders that can happen to people with COPD. The health of people with COPD can be greatly affected by these disorders, and if they are not treated, they can get worse. Most of the time, spirometry is used to diagnose COPD. This test measures how much air a person can forcefully exhale after taking a deep breath. Spirometry is an easy test that

doesn't hurt you and can be done in a doctor's office or clinic. X-rays of the chest, CT scans, and blood tests may also be used to diagnose COPD [8]. These tests can help find out how bad the lung damage is and rule out other conditions that might be causing symptoms that look like COPD. Machine learning has been used to predict risk factors for COPD, such as the likelihood of someone having to go to the hospital because their COPD got worse.[9].

Using machine-learning techniques, models were made to predict the likelihood that a COPD patient will need to go to the hospital for an exacerbation within the next 10 days. In addition, machine learning has been used to tell the difference between COPD and asthma in medical and administrative databases. Computer programs that use machine learning can look at a lot of data and find patterns that a person might not see. This could help make it easier to diagnose and treat COPD. Two clinical ways to check the acid-base balance of COPD patients are the Henderson-Hasselbalch Approach and the Stewart Approach. The Henderson-Hasselbalch Method [10] is a method used to calculate the pH of a solution containing a weak acid and its conjugate base. The Stewart Approach is a more comprehensive method that takes into account the effects of strong ions on acid-base balance. The Stewart Approach [10] is more complex than the Henderson-Hasselbalch Approach but provides a more accurate assessment of acid-base status in COPD patients. A machine learning-based strategy has also been developed for early detection of COPD exacerbations and subsequent triage. This strategy uses machine learning algorithms to analyze data from wearable devices and electronic health records to identify patients at high risk of exacerbation [11]. This allows for early intervention and treatment, potentially reducing the severity of exacerbations and improving patient outcomes. Machine learning has the potential to revolutionize the diagnosis and treatment of COPD, providing more accurate and personalized care for patients. In conclusion, COPD is a chronic lung disease that affects millions of people worldwide. Acid-base disorders are common in COPD patients and can have a significant impact on their health. Diagnosis of COPD is typically done through spirometry [12], and machine learning methods have been used to predict risk factors for COPD and differentiate it from other conditions. The Henderson-Hasselbalch Approach and the Stewart Approach are two methods used to assess acid-base status in COPD patients clinically.

In order to extract the most valuable characteristics from the high-dimensional data, Vikas Jindal [13], et al have presented a hybrid feature selection model. To determine how well the features perform across different categorization models, these features are then passed on to the classification models. The experimental data showed that the proposed hybrid feature selection model could accurately diagnose COPD with a 95.18\% Kappa Statistic.[13] A machine learning-based strategy has also been developed for early detection of COPD exacerbations and subsequent triage. Machine learning could change the way COPD is diagnosed and treated by making care more accurate and tailored to each patient. Millions of people around the world have Chronic Obstructive Pulmonary Disease (COPD), which is a long-term lung disease. Machine learning has been used to predict COPD risk factors, such as the likelihood of someone being hospitalized because their COPD got worse. [1][14].

Additionally, machine learning has been used to differentiate asthma from COPD in medico-administrative databases [15][16]. The accuracy of machine learning algorithms for COPD diagnosis and classification has been found to be higher than traditional methods [15][16]. There are, however, some research gaps in how machine learning can be used to help people with COPD. One of these gaps is the need for more research on how machine learning can be used to predict how COPD will get worse [1]. Another hole is that there should be more

research on how machine learning can be used to guess how COPD patients will respond to treatment. [14]. Additionally, there is a need for more studies that focus on the use of machine learning in identifying subtypes of COPD and developing personalized treatment plans for patients [1][15].

The questionnaire covered demographic information, disease awareness, knowledge, and respiratory symptoms related to Chronic Obstructive Pulmonary Disorder (COPD). The third group of patients talked about how to manage their disease, risk factors like smoking, being close to polluting fuels inside, or being exposed to dust or chemicals at work, and when pulmonary function tests shouldn't be done. The measurements used were blood pressure, weight, height, waist circumference, and hip circumference.[1] In terms of acid-base disorders, the Henderson-Hasselbalch Approach and the Stewart Approach are two methods used to assess acid-base status in COPD patients clinically. A machine learning-based strategy has also been developed for early detection of COPD exacerbations and subsequent triage [1]. However, there is a need for more research on the use of machine learning in identifying biomarkers for COPD and developing personalized treatment plans based on these biomarkers [17]
Nagendra Kumar V V et al. pointed out three important areas that need more research: the need for multiple layers of diagnosis, the types of lifestyle conditions that can cause COPD, and the choice of features. What they did was take into account the patterns and dynamics of the present. [18]

There are also some problems with the way machine learning is being used now to treat COPD. To give you an example, some studies haven't included data from monitoring lung function, which means that COPD isn't always found.[1] Additionally, the model parameters in some studies were chosen as the software default parameters, which may not be optimal [1]. Furthermore, none of the cited research works have proposed an end-to-end system that aids in the diagnosis and treatment of the COPD patients utilising the advances in artificial intelligence and machine learning. In conclusion, artificial intelligence and machine learning have the potential to revolutionize the diagnosis and treatment of COPD, providing more accurate and personalized care for patients. But there are still research gaps that need to be filled before machine learning can fully be used to help people with COPD. Some of these gaps have already been mentioned.

3. PROPOSED MODEL

The proposed model is a platform called SwasthyaBuddy which acts as a one-stop solution for COPD patients and doctors. The platform offers features such as determining acid-base disorders of a COPD patient, providing past report statistics to doctors and patients, a model to detect pneumonia in patients from their X-ray images, an algorithm to calculate the severity of a COPD patient's condition, a COPD center locator, online consultation through video call and integration of patient's medical records [19]. The platform has a two-factor authentication for security. It aids doctors in assisting patients by enabling the doctors to conduct tests, view patient lists and reports, and see the number of COPD patients listed to them on a daily basis. Each of the components of the proposed model have been described in this section. A diagrammatic representation of the proposed model is shown in Fig 1.

An arterial blood gas (ABG) test can measure how much oxygen and carbon dioxide are in the blood. It does this by drawing blood from an artery in the body, as shown in the Fig 2. During the test, the pH balance (also called the acid-base balance) of the blood is also

checked. In the proposed model, an ABG report of the patient consisting of vital measurements is used. Through OCR, these measurements are captured and filled in automatically. Any missing values can be entered in and provided to the system. All past generated reports can be viewed through the dashboard and can even be downloaded in the form of PDF files or emailed to the doctor. An example of the output of the generated report is shown in the Fig 2 which is present in the results section.

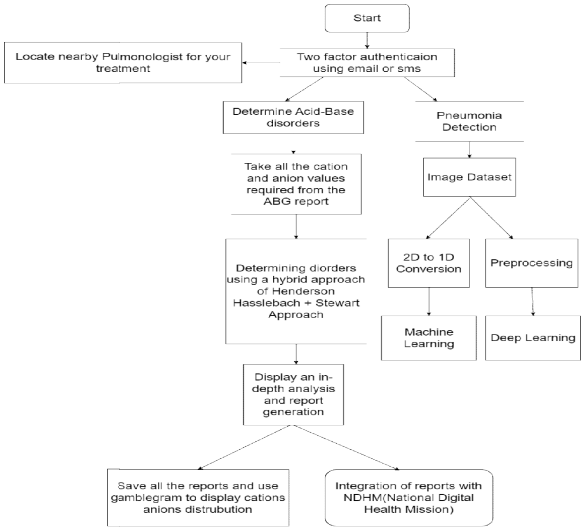

Figure 1: Proposed Model of SwasthyaBuddy

RADIOMETER ABL800 BASIC

ABL800 Basic		07:59 AM	11/25/2013
Patient Report	Syringe - S 195 uL	Sample #	77208
Identifications			
Patient ID			
Patient Last Name			
Sex	Male		
Sample type	Arterial		
$FO_2(I)$	21.0%		
T	37.0%C		
pH	7.407		[7.350 - 7.450]
$pCO2$	41.1	mmHg	[35.0 - 45.0]
pO_2	104	mmHg	[83.0 - 108]
$cHCO_3^-(P,st)c$	25.5	g/dL	
↓ ctHb	9.2	g/dL	[12.0 - 16.0]
sO_2	98.1	%	[95.0 - 99.0]
cK^+	4.1	mmol/L	[3.5 - 4.5]
↑ ctHb	139	mg/dL	[70.0 - 105.0]
↓ cLac	0.5	mmol/L	[0.5 - 1.6]
↓ cNa^+	124	mmol/L	[135 - 145]
↓ cCl^-	95	mmol/L	[98 - 106]
↓ cCa^{2+}	1.06	mmol/L	[1.15 - 1.29]
ABEc	1.2	mmol/L	
Calculated Values			
$cCa^{2+}(7.4)_c$	1.07	mmol/L	
$ctCo_2(P)c$	59.7	vol%	
Anion Gap_c	3.1	mmol/L	
Anion Gap, K^+c	7.1	mmol/L	
Hct_c	28.6	%	
pH(st)c	7.416		
p50e	26.44	mmHg	
$pO_2(A\text{-}a)e$	-----	mmHg	
$pO_2(a/A)e$	104.6	%	
RIe	-4	%	
mOsmc	255.2	mmol/kg	
Temperature Corrected Values			
pH(T)	7.407		
$pCO_2(T)$	41.1	mmHg	
$pO_2(T)$	104	mmHg	

Notes

↑ Value(s) above reference range
↓ Value(s) below reference range
c Calculated value(s)
e Estimated value(s)

Figure 2: Traditional ABG Reports

There are four severity levels: Low, Moderate, High and Very High. The process is initiated by obtaining the pH, HCO3 and CO2 levels of the patient. These values are used to categorise

into four disease states: metabolic alkalosis, metabolic acidosis, respiratory alkalosis and respiratory acidosis. The high level overview of the steps are mentioned in algorithm.

Algorithm for Predicting COPD Severity Level

Requirements: Patient data, including pH level, HCO3, and CO2
Ensure: Predicted COPD severity level

a) Check for acid-base disorder.
b) If acid-base disorder is present, evaluate acid-base disorder.
c) Check for respiratory disorder.
d) If respiratory disorder is present, evaluate respiratory disorder.
e) Check for metabolic disorder.
f) If metabolic disorder is present, evaluate metabolic disorder.
g) Look for mixed disorders.
h) If mixed disorders are present, evaluate mixed disorders.
i) Use Hybrid Henderson-Hasselbach and Stewart
j) Approach to do a quantitative check.
k) Predict COPD severity level based on the results of the quantitative check.

Return: Predicted COPD severity level

Further categorization and calculations are performed once these categorizations are made. The approach for that has been succinctly represented in Figure 3. These are then used to determine the severity level of the patient. Once the severity level is calculated and displayed, the next action steps to take are also mentioned. For example, in case of a mild severity an online consultation with a doctor can be booked. While in case of a High or Very High severity an offline appointment with a doctor can be scheduled.

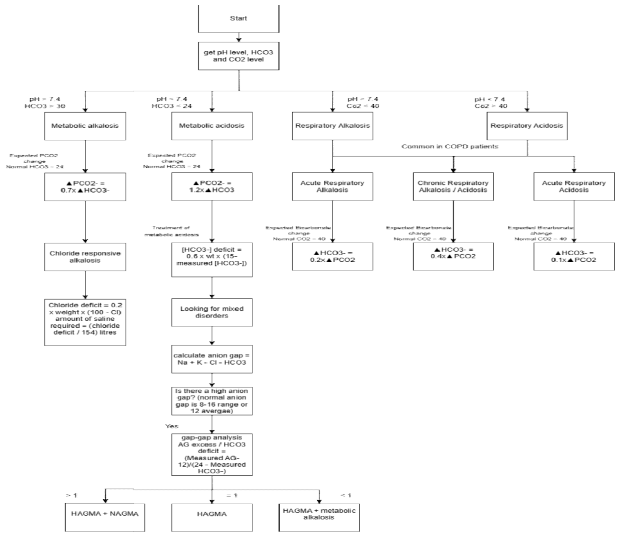

Figure 3: Approach for Disorder Categorization to Predict COPD Severity Level

3.3 Other Components

The body works to maintain electroneutrality at all times, meaning that the sum of positively charged cations and negatively charged anions should be equal. A gamblegram chart is a visual representation that displays the most prevalent anions and cations in plasma. For each

report, gamblegram charts are used as visualizations to inspect the gap between the anions and the cations. An illustration of a gamblegram chart is shown by Figure 4 in the results section.

Another critical feature is the COPD Centre Locator, which uses GPS data to indicate nearby COPD centres and ABG test centres on a map. This feature ensures that patients can easily find and access the necessary medical facilities.

The platform also offers an Online Consultation system. Within the platform, there is a seamless system to book online consultations, with patient statistics being directly shared during the call with the doctor. This integration enhances the convenience and efficiency of medical consultations.

The platform connects with the National Digital Health Mission (NDHM), promoting data standards, privacy, and interoperability throughout the entire national healthcare ecosystem. Together, these characteristics offer a patient-centric approach, vastly enhancing COPD care and patient accessibility.

The overall system workflow is designed to ensure that healthcare providers and patients can communicate easily. While doctors have full access to patient information for better decision-making, patients may conveniently access their data, schedule consultations, and find local COPD facilities, as shown in Figure 4.

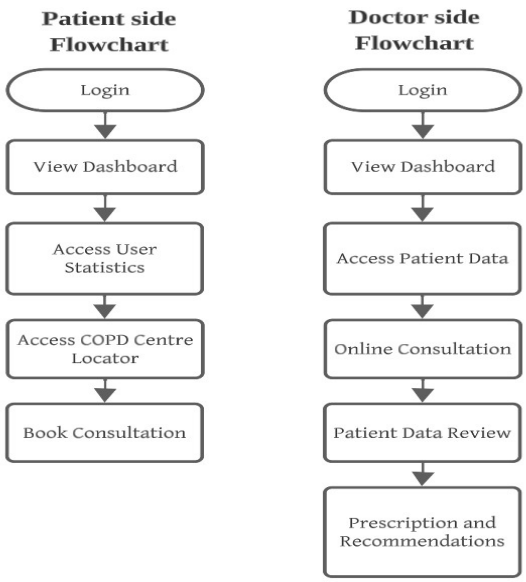

Figure 4: Patient side and Doctor side Flowchart

3.4. Pneumonia Detection Methodology

The proposed pneumonia detection techniques are explained in two different sections. Detection by the machine learning models is presented in the first section which is followed

by the description of deep learning identification methods. An overview of the methodology is shown in Figure 5.

For Machine Learning Algorithms, the initial step is to convert the data from 2 dimensions to 1-dimension, for efficient working. Post conversion of the dimensions of image dataset, labelling will be required for the categorical data as numerical classification will be taken into account. Hence, label encoding is employed to convert the Normal, Bacteria and Virus labels into numerical categories. The following machine learning algorithms were used in the study's analysis. Random Forest is an ensemble learning method that uses more than one decision tree to make the model more accurate and less likely to overfit. CART stands for "Classification and Regression Trees." It is a decision tree algorithm that can be used for both regression and classification tasks. Logistic regression is a type of statistical modeling that is most often used for classifying things into two groups.

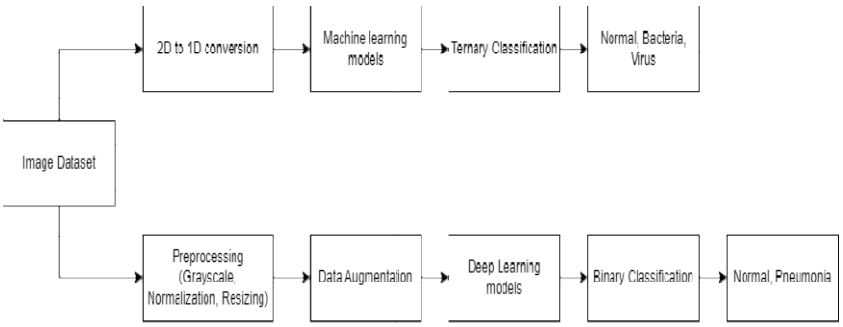

Figure 5: Pneumonia Detection Methodology

The Stochastic Gradient Descent (SGD) Classifier is a linear classifier that is made better by stochastic gradient descent. AdaBoost is a way to make a strong classifier by combining weak ones. Naive Bayes is a probabilistic classifier based on Bayes' theorem. It is based on the "naive" assumption that features don't depend on each other. These models are basic tools for machine learning. Each one has its own strengths and weaknesses for different tasks like regression and classification.

In this study, four deep learning architectures were employed for pneumonia detection: A convolutional neural network (CNN), LeNet-5, VGG16 and ResNet-50. A summary of the architectures of each of the models as well as the compilation and training parameters have been summarised in Table 1 below. The experiments done using these models have been described in the experimentation section and the comparisons of each model have been made in the results section.

4 Experimentation

This section describes in detail the experimentation done to train the models for pneumonia detection which is one of the key components of the proposed model. In subsections 4.1 and 4.2 the description of the dataset as well as the pre-processing and augmentation done on it have been described. Whereas in subsection 4.3 and subsection 4.4, the machine learning models and the deep learning models used have been described. Subsection 4.5 consists of the validation and training accuracy plots of the deep learning models.

4.1 Dataset Description

The dataset [20] consists of 17575 images of chest X-rays and is approximately 1.24 Gigabytes in size. Normal and Pneumonia are the two categories. Pneumonia is further classified as Bacteria and Virus. For Normal, Bacteria, and Virus, the image composition is 4751, 8340, and 4484, respectively. The dataset is visually described in Figure 6.

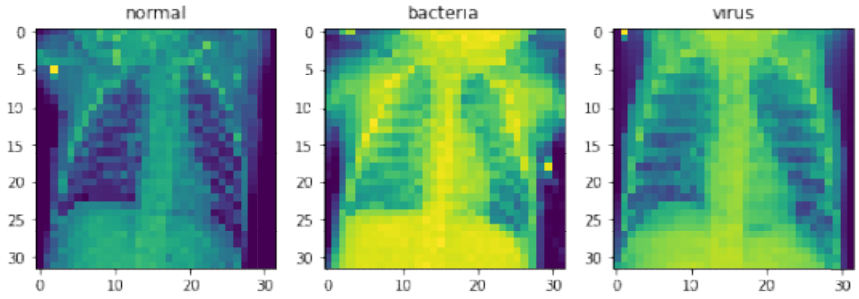

Figure 6 Dataset Images

Model Name	Layers	Compilation	Training
Convolutional Neural Network (CNN)	Input Layer, Convolutional Layer 1 (32 filters, 3x3), Max-Pooling Layer 1 (2x2), Convolutional Layer 2 (64 filters, 3x3), Max-Pooling Layer 2 (2x2), Flatten Layer, Densely Connected Layers, Output Layer	Adam optimizer, binary cross-entropy loss, 'accuracy' metric	20 epochs, validation data monitoring
LeNet-5	Input Layer, Convolutional Layer 1 (6 filters, 5x5), Max-Pooling Layer 1 (2x2), Convolutional Layer 2 (16 filters, 5x5), Max-Pooling Layer 2 (2x2), Flatten Layer, Densely Connected Layers, Output Layer	Adam optimizer, binary cross-entropy loss, 'accuracy' metric	20 epochs, validation data monitoring
VGG16	Grayscale to RGB Conversion, Base VGG16 Model, Custom Classification Layers (Dense: 512 neurons, ReLU; Dense: 1 neuron, sigmoid)	Adam optimizer, binary cross-entropy loss, 'accuracy' metric	20 epochs, validation data monitoring
ResNet50	Pre-trained ResNet50 Model, Custom Classification Layers (Global Avg Pooling, Dense: 256 neurons, ReLU; Dense: 1 neuron, sigmoid)	Adam optimizer, binary cross-entropy loss, 'accuracy' metric	20 epochs, validation data monitoring

Table 1: Summary of Deep Learning Model Architectures

4.2 Data Preprocessing and Augmentation

Preprocessing of the X-ray images included resizing to a uniform dimension of 32x32 pixels, grayscale conversion, and normalization. Although the dataset was already split into training, validation, and test folders, the dataset is first merged together, augmented and then split into training and testing parts. This is done so that more and varied data is available for better training and subsequently better accuracy of the models that are described in a later section.

Initially, the X-ray images were loaded and converted to grayscale using the OpenCV library (cv2). Grayscale conversion reduces the dimensionality of the images and simplifies processing, while retaining critical diagnostic information.

To standardize the dimensions of the images, they were resized to a common size of 32x32 pixels. This step ensures uniformity and reduces computational complexity during model training.

The pixel values of the grayscale images were normalized to the range [0, 1]. Normalization enhances convergence during model training by scaling the input values to a common range.
Data augmentation is a common technique used to artificially increase the size of the training dataset. By applying various transformations to the existing images, such as rotation, shifting,

shearing, zooming, and flipping, additional training samples were generated. This helps the model to generalize better and improves its robustness.

ImageDataGenerator from the TensorFlow Keras library has been used to perform data augmentation with the following settings:

- Rotation Range: 15 degrees
- Width Shift Range: 0.1 (fraction of total width)
- Height Shift Range: 0.1 (fraction of total height)
- Shear Range: 0.2 (shear angle in radians)
- Zoom Range: 0.2 (random zoom in [1-zoom_range, 1+zoom_range])
- Horizontal Flip: Enabled

These transformations are applied to the training images, creating variations of the original dataset. The augmented data is then used for training the various models, enhancing their ability to learn and extract meaningful features.

The augmented dataset enriches the training process and helps the model learn a wider range of patterns, ultimately leading to improved classification performance.

To evaluate the performance of the models effectively, the dataset was divided into training and test sets using the popular technique of random sampling. This step is critical to ensure an unbiased assessment of the models' generalization capabilities.

The train_test_split function from the scikit-learn library was used, setting the test size to 20% of the entire dataset. Additionally, a random seed (random_state) was specified for reproducibility, which ensures that the same split is obtained across different runs.

4.3 Machine Learning Description

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction (regression) or mode of the classes (classification) of the individual trees. By combining predictions from multiple models, it improves accuracy and reduces overfitting.

CART is a decision tree learning algorithm that can be used for classification and regression. It recursively divides the dataset into subsets based on the most significant attribute, resulting in a decision tree-like model. Because of its simplicity and interpretability, it is widely used.
Logistic Regression is a statistical method for analysing datasets with binary outcomes. By fitting data to a logistic curve, it predicts the likelihood of a binary outcome. Despite its name, it is used to solve classification problems rather than regression problems.

SGD Classifier is a linear classifier that optimises using stochastic gradient descent. Its efficiency and ability to handle sparse data make it particularly useful for large-scale machine learning tasks. It iteratively updates the model's weights based on a small subset of the training data.

AdaBoost (Adaptive Boosting) is a method of ensemble learning that combines multiple weak learners to produce a strong learner. It gives more weight to misclassified data points and focuses on difficult-to-classify samples iteratively, improving overall accuracy.

Based on Bayes' theorem, Naive Bayes is a probabilistic classification algorithm. Given the class label, it assumes that features are independent. Despite its simplicity and "naive" assumption, it frequently performs surprisingly well for text classification and spam filtering tasks, particularly when dealing with large datasets.

4.4 Deep Learning Models Parameter Tuning

The hyperparameters that were tuned during experimentation were learning rate, batch size, number of epochs and dropout rate. Additonally, in case of pre-trained models that were finetuned, the architecture of the head was also experimented with different layers stacked on top of the base model.

All the models were initially trained with the original dataset without any augmentations and used the original training and testing splits. However, better performance was achieved when the dataset was augmented and then split into training and testing sets.

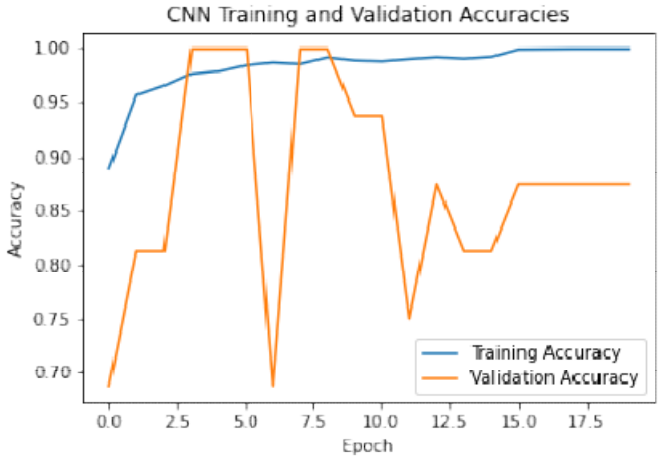

Figure 7 Training and Validation Accuracy for the CNN Model

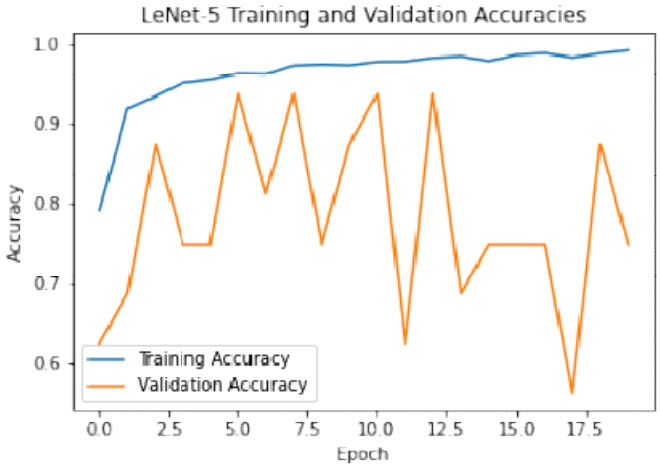

Figure 8 Training and Validation Accuracy for the LeNet-5 Model

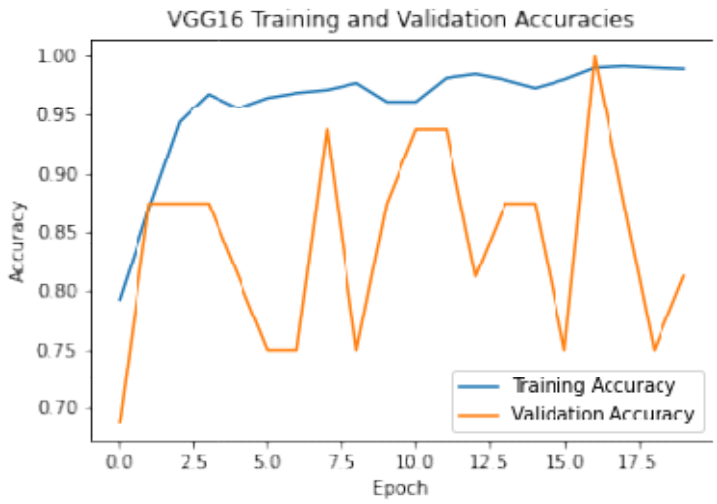

Figure 9 Training and Validation Accuracy for the VGG16 Model

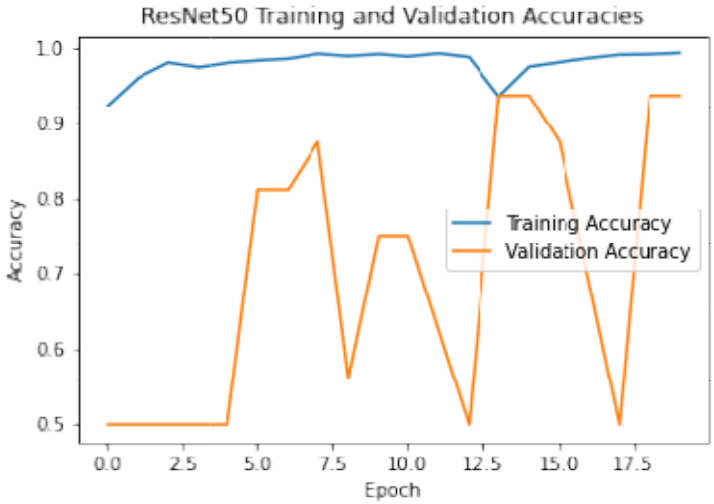

Figure 10 Training and Validation Accuracy for the Resnet50 Model

- Learning Rate:
  - Range of values: [0.001, 0.01, 0.1]
  - The learning rate tells the optimizer how many steps to take to change the model weights while it is being trained. It was tried with different values to find the best learning rate for quick convergence.
- Batch Size:
  - Range of values: [16, 32, 64]
  - Batch size is the amount of items that undergo processing in a single round of training. Different batch sizes were tried to find the best equilibrium between quicker convergence and memory use.
- Number of Epochs:
  - Range of values: [10, 20, 30]
  - How many times the model sees the whole training dataset is based on the number of epochs. Several epoch values were tried to make sure the model stays stable and doesn't fit too well.
- Dropout Rate:
  - Range of values: [0.2, 0.5]

- By randomly removing some neurons during training, dropout is a regularization method that helps keep things from getting too good. Researchers looked at a range of dropout rates to find the best one for stopping overfitting.

- Dense Layer Neurons:
  - For the VGG16 architecture and the ResNet50 architecture, the dense layer neurons were also experimented with.
  - Range of values: [128, 256, 512].

These hyperparameters were systematically varied and tested to achieve the best performance and accuracy for each model architecture in the pneumonia detection task. To compare the models effectively, the final number of epochs used for training was 20 for each of the models as described in 1.

4.5 Validation vs Training Accuracy of Deep Learning Models

Figures 7, 8, 9, and 10 illustrate the training and validation accuracy trends during the training process for the CNN, LeNet-5, VGG16, and ResNet50 models respectively.

5 Results and Discussion

The results observed after the implementation of the two above-mentioned techniques are discussed in this section. It has two subsections where the results for machine learning models are mentioned in subsection 5.1 and the visualizations for the deep learning models are presented in section 5.2.

5.1 Machine Learning Models

Following are the results obtained, described in Figure 11

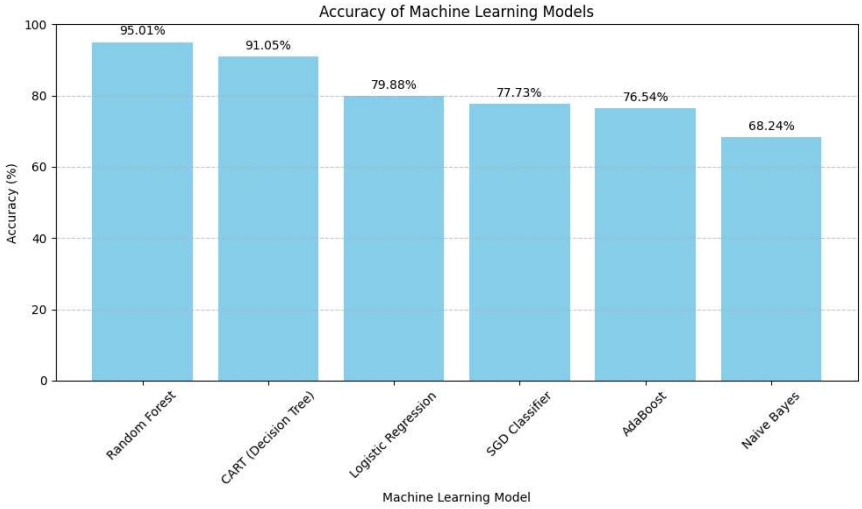

Figure 11 Machine Learning Comparison

In the analysis, Random Forest has the highest accuracy of the machine learning models, with a 95.01% accuracy. CART (Decision Tree) comes next, with an accuracy of 91.05%, representing a 4% decrease over Random Forest. Logistic Regression also performs well, with a 79.88% accuracy. The SGD Classifier and AdaBoost, on the other hand, have slightly lower accuracies of 77.73% and 76.54%, respectively. In comparison, Naive Bayes has the lowest accuracy of 68.24%. These results provide insight into the relative performance of these models, with Random Forest outperforming the others by a wide margin.

Machine Learning Model	Accuracy
Random Forest	95.01
CART (Decision Tree)	79.88
Logistic Regression	76.54
SGD Classifier	77.73
AdaBoost	76.54
Naive Bayes	68.24

Table 2 Accuracy of Machine Learning Models

5.2 Deep Learning Models

This section deals with the description of the results of the experiments conducted, providing a detailed analysis of the performance of each deep learning model architecture in the task of pneumonia detection. For each model, a description of the achieved accuracy, F1 score, confusion matrices, precision-recall curves, and training/validation accuracy trends is presented.

Convolutional Neural Network (CNN)

When it came to finding pneumonia, the CNN architecture showed promise. With an F1 score of 0.96, this model was right 94.54% of the time. These metrics show how well the model can tell the difference between "Normal" and "Pneumonia" cases.

The confusion matrix for the CNN model is shown in Figure~12. It shows how well the model works by showing the number of true positives, true negatives, false positives, and false negatives.

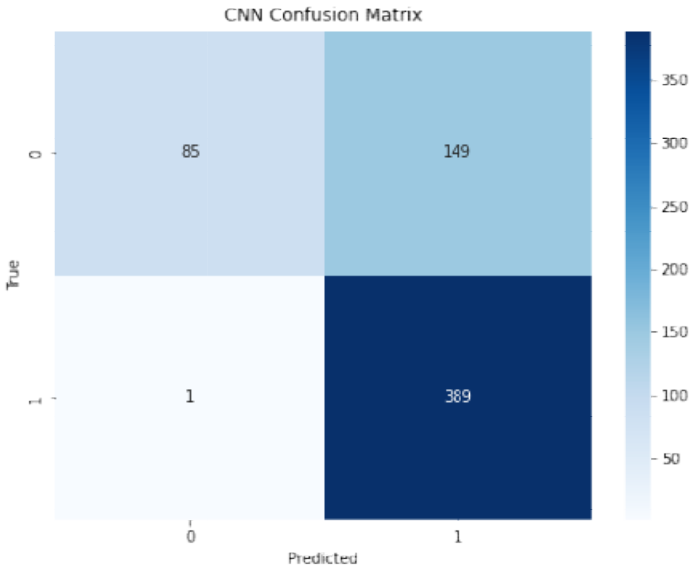

Figure 12 Confusion Matrix for the CNN Model

The precision-recall curve for the CNN model is depicted in Figure 13. It provides insights into the trade-off between precision and recall for different classification thresholds.

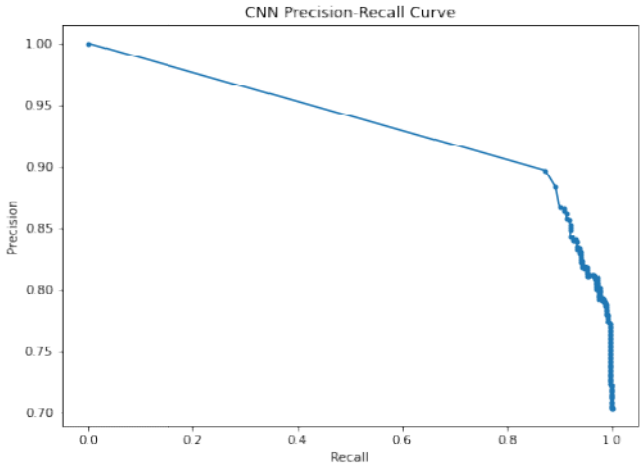

Figure 13 Precision-Recall Curve for the CNN Model

LeNet-5

The LeNet-5 architecture, known for its simplicity and effectiveness, also demonstrated competitive performance in pneumonia detection. It achieved an accuracy of **93.09%** and an F1 score of **0.95.**

The confusion matrix, precision-recall curve, and training/validation accuracy trends for the LeNet-5 model are presented like the CNN model.

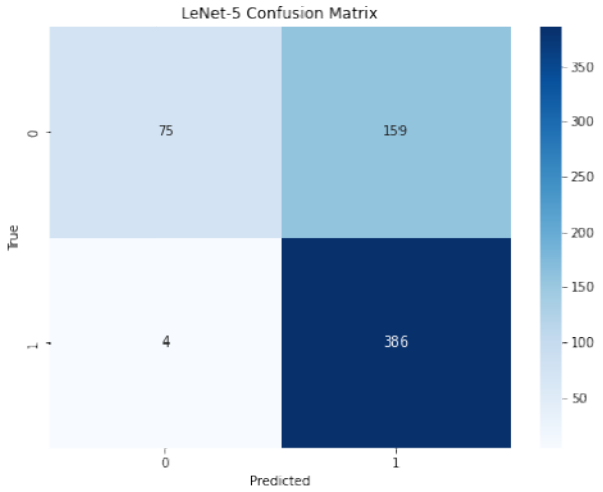

Figure 14 Confusion Matrix for the LeNet-5 Model

VGG16

The VGG16 architecture, with its deep stack of convolutional layers, exhibited notable performance in pneumonia detection. It achieved an accuracy of **95.90%** and an F1 score of **0.97.**

The confusion matrix, precision-recall curve, and training/validation accuracy trends for the VGG16 model are presented like the previous models.

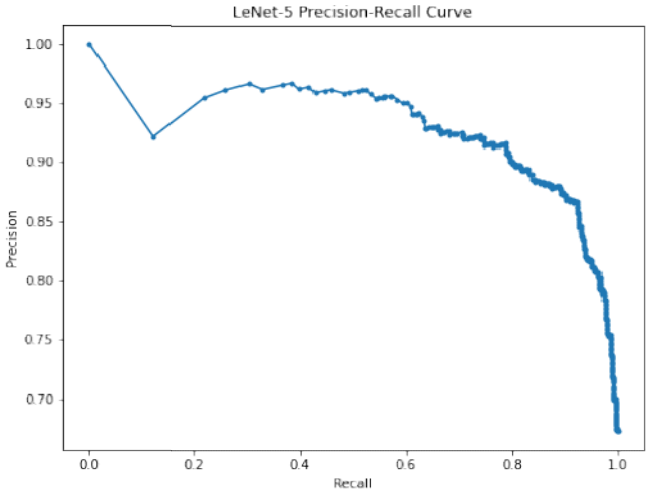

Figure 15 Precision-Recall Curve for the LeNet-5 Model

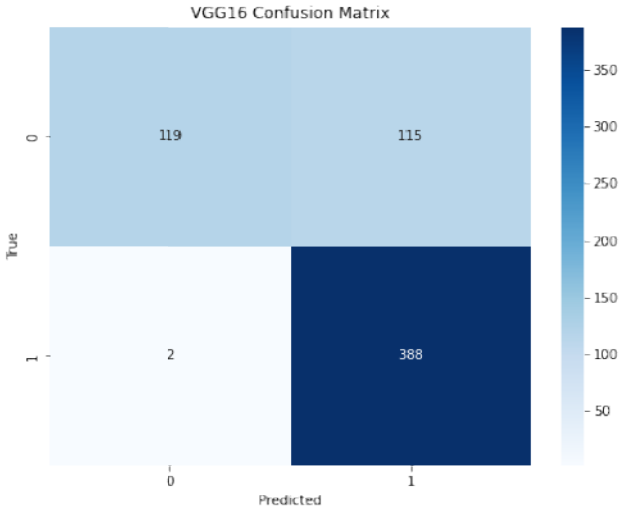

Figure 16 Confusion Matrix for the VGG16 Model

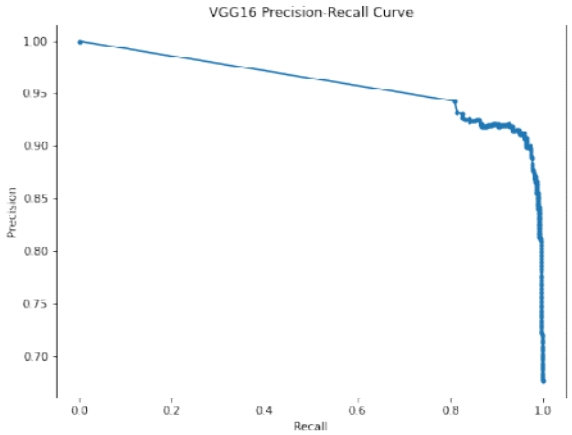

Figure 17 Precision-Recall Curve for the VGG16 Model

ResNet50

The ResNet50 architecture, known for its residual connections, demonstrated superior performance in pneumonia detection. It achieved an accuracy of **94.97%** and an F1 score of **0.96**.The confusion matrix, precision-recall curve, and training/validation accuracy trends for the ResNet50 model are presented similarly to the previous models.

The discussion analyzed the results obtained from the experiments with a focus on the implications of model performance, the clinical relevance of pneumonia detection, and any limitations or challenges encountered during the study.

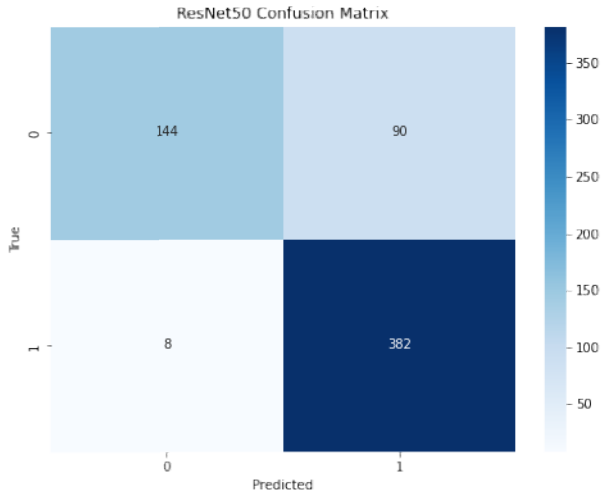

Figure 18 Confusion Matrix for the Resnet50 Model

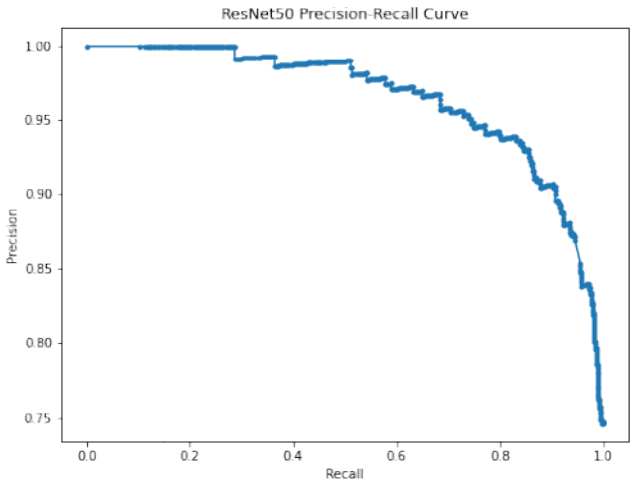

Figure 19 Precision-Recall Curve for the Resnet50 Model

5.3 **Overall System Result**

The outcomes for the patient statistics as well as the severity calculation algorithm are shown in this section, which include Gamblegram charts (Fig 20) that illustrate the progression of COPD and the response to treatment, as well as generated reports (Fig 21) that offer vital insights into acid-base disorders and guide the diagnostic methodology. Once all the data from the ABG report is available and the generate report button is pressed, the necessary computations are done. The report generated consists of the anion gap which is crucial in determining the severity level for the patient. Furthermore, the report indicates the expected or normal range of values for each metric and represents the measurements in a tabular format with outlier values being shown in red color.

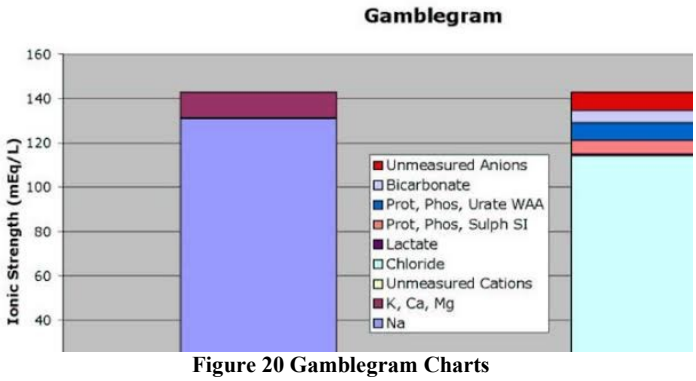

Figure 20 Gamblegram Charts

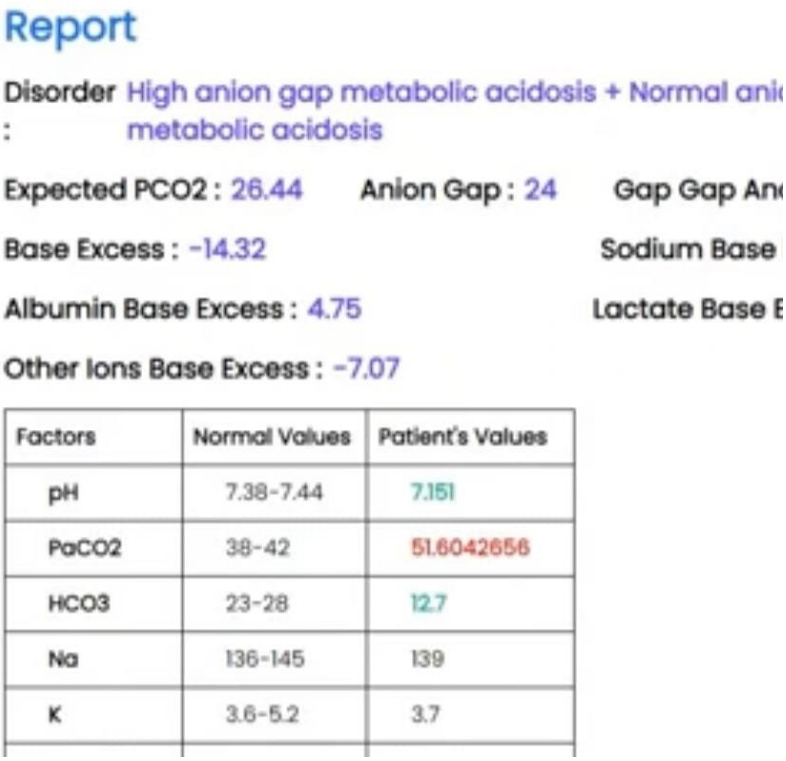

Figure 21 Generated Report

6 Conclusion

The research report concludes with a thorough assessment of machine learning and deep learning models in a classification assignment, with a focus on how well they perform in image processing. The paper's highlights included a thorough analysis of these models to ascertain their reliability in projecting the target variable, illuminating their varying levels of efficacy.

Random Forest, one of the machine learning models, has the best accuracy at 95.01 percent, closely followed by CART (Decision Tree) at 91.05 percent. With accuracy rates ranging from 68.24 percent to 79.88 percent, Logistic Regression, SGD Classifier, AdaBoost, and Naive Bayes likewise displayed their respective prowess in classification tasks.

Convolutional Neural Network (CNN) and well-known designs like LeNet-5, VGG16, and ResNet50 demonstrated outstanding accuracy rates ranging from 93.09 to 95.90% in the field of deep learning. These models not only produced excellent F1 scores but also outstanding accuracy, demonstrating an effective trade-off between precision and recall.

The results highlight how crucially important model selection and performance assessment are when performing image processing tasks. The extraordinary capacity of deep learning models, such as VGG16, to handle challenging classification tasks highlights the importance of these models for image-centric applications. With useful information about their aptitude for image processing and classification problems, this research makes a significant contribution to the rapidly developing fields of machine learning and deep learning.

This research project's future scope includes several interesting pathways for furthering this understanding of Chronic Obstructive Pulmonary Disease (COPD) and its management. For starters, combining many data sources, including clinical, genetic, environmental, and lifestyle data, can provide a more thorough picture of COPD etiology. Deep learning and natural language processing, for example, can unearth detailed patterns and relationships within COPD patient data, giving light on nuanced aspects leading to the condition. Furthermore, predictive analytics can be used to identify patients who are at high risk of developing COPD, enhancing early identification and lowering healthcare expenses. Personalized therapy regimens based on specific patient profiles can subsequently be devised, optimizing COPD care. Regional inequities can be highlighted through geospatial analysis, allowing for focused awareness campaigns and resource allocation. Incorporating patient-centric features, such as educational materials and self-assessment tools, into the analytical dashboard can empower patients to actively participate in their care. Finally, encouraging multidisciplinary collaboration among healthcare professionals, data scientists, public health specialists, and patient advocacy groups is critical for comprehensive COPD research and the development of effective prevention and management measures. These future directions seek to not just progress COPD research, but also to improve patient outcomes and raise awareness [21] on a larger scale.

7 Future Scope

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