

A HYBRID CNN AND XGBOOST APPROACH FOR ACCURATE COVID-19 PNEUMONIA DETECTION USING CHEST X-RAYS

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Abstract: The worldwide spread of COVID-19 has made things very hard for doctors, especially when it comes to quickly and accurately diagnosing COVID-19 pneumonia from chest X-rays. Traditional ways of diagnosing are often time-consuming and need a lot of medical knowledge, which can cause delays in treating patients. The main issue this study tries to solve is the need for a fast and accurate automatic method that can make finding COVID-19 pneumonia easier and more reliable. To make diagnostics work better, this study suggests a mixed classification system that combines Convolutional Neural Networks (CNN) with the XGBoost method. The main goal of this study is to create and test a strong model that does a better job of classifying COVID-19 pneumonia than existing machine learning and deep learning methods. The standard dataset used for research work as "Chest X-ray COVID-19 Pneumonia." It has 6432 chest X-ray images spread out across three classes. The suggested way combines CNN models for feature extraction, such as EfficientNetB0 and DenseNet121, with fine-tuned XGBoost algorithms to help make better decisions. The suggested hybrid model was shown to be more accurate and stable through extensive testing and comparisons with other models, such as SVM and Random Forest. There is a lot of evidence that this method works really well for helping doctors make decisions about COVID-19 tests..

Keywords: COVID-19 Pneumonia Detection, Chest X-ray Classification, Convolutional Neural Network, XGBoost Algorithm, Hybrid Deep Learning Model, Medical Image Analysis...

1. INTRODUCTION

The COVID-19 pandemic has had an effect on global health that has never been seen before. It has pushed healthcare systems around the world to quickly come up with effective ways to handle and control diseases. Early and correct identification is very important for stopping the virus from spreading and making sure that medical help is given on time. One of the worst problems that can happen after getting COVID-19 is pneumonia, which can quickly make breathing difficult and cause serious sickness if not found quickly. It has become clear that chest X-rays are an easy, quick, and inexpensive way to find pneumonia in COVID-19 patients. However, chest X-ray analysis by hand requires a lot of radiographic knowledge, which isn't always available, especially in places with limited resources [1]. So, we need to make automatic, reliable, and quick testing tools right away to help doctors find COVID-19 pneumonia more accurately and quickly.

Several machine learning and deep learning models have been tested to see how well they can classify chest X-rays to find COVID-19 pneumonia. Support Vector Machines (SVM) and Random Forest models are two traditional machine learning methods that have shown promise. However, they often fail to achieve high accuracy because they can't learn complex features from image data [2]. Deep learning techniques, especially Convolutional Neural Networks (CNN), have shown a lot of promise in medical image analysis by automatically finding complex patterns and



representations. Still, CNN models that work on their own can have problems like overfitting and choosing the wrong features, which can make them less useful when used on datasets they haven't seen before [3]. Also, many of the current methods only use deep learning models or standard machine learning algorithms, not combining their skills that work well together. As of now, there aren't any mixed methods that combine the strong feature extraction abilities of deep learning with the decision-making speed of advanced machine learning algorithms. Existing models don't always fully optimise how feature selection and classification work together, which hurts both accuracy and the speed of computation [4]. A lot of previous research also doesn't talk enough about the balance between sensitivity and specificity, which is very important in clinical tests where both false blanks and false positives can be very bad.

This study directly addresses these problems by suggesting a new hybrid method that combines CNN with the XGBoost algorithm to accurately find COVID-19 pneumonia on chest X-rays. The main goal of this study is to create and test a model that improves classification performance by using CNN-based feature extraction along with XGBoost's fine-tuned boosting features. The suggested method uses pre-trained deep learning models like EfficientNetB0 and DenseNet121 to do multi-level feature extraction. This is followed by advanced classification through XGBoost to make the method more stable and reliable for diagnostics.

The key contributions of this paper are:

The deployment of a CNN-XGBoost framework that is specifically designed for finding COVID-19 pneumonia

Putting together a feature extraction pipeline that uses EfficientNetB0 and DenseNet121 to make image representation more stable

The comparative analysis of the proposed method against existing models including SVM and Random Forest to validate its superior performance

2. RELATED WORK

As the number of COVID-19 cases has grown quickly, scientists are looking into different artificial intelligence (AI) methods that can help with diagnosis more quickly and more accurately. Traditional detection methods, like RT-PCR tests, work well, but they often take longer to process and aren't available in places where the disease is common [5] [6]. As a result, chest X-ray imaging has become an additional screening method because it is easy to get and doesn't cost much [7]. Several studies have looked at how to use machine learning and deep learning to automatically find COVID-19 pneumonia from chest X-rays. The goal is to cut down on the need for human analysis and shorten the time it takes to get a diagnosis. Early research focused on how simple machine learning models like Support Vector Machines (SVM) and Decision Trees could be used to divide chest X-rays into two groups: COVID-19 and non-COVID-19 [8]. However, these models had a hard time extracting high-level spatial traits that were needed for accurate pneumonia diagnosis [9]. Deep learning-based models, especially Convolutional Neural Networks (CNNs), have been used a lot to get around these problems because they are better at automatically learning complex feature representations from medical images [10]. CNN designs like VGG16, ResNet, and DenseNet have been used a lot to make classification more accurate [11]. However, these models can have problems, like overfitting, when they are trained on small datasets [12].

In [1], an in-depth look at COVID-19 showed how important it was to have scalable diagnosis tools in the early stages of the pandemic, laying the groundwork for AI-based methods. In line with this, the work in [2] suggested improved deep learning methods for finding pneumonia in COVID-19 patients, highlighting how important it is to use model tuning and pre-processing techniques. Similarly, the study in [3] used a deep learning model along with transfer learning to find COVID-19 pneumonia levels. This showed that using models that have already been trained could greatly improve the accuracy of diagnosis. The study in [4] also used different deep learning methods to look at chest X-ray images and found that deep feature extraction was a good way to tell the difference between healthy and pneumonia-affected lungs. New developments in transfer learning have made it possible to use CNN models that have already been trained, like EfficientNet and DenseNet, to speed up convergence and improve feature learning on smaller medical datasets [13]. Even with these changes, there are still problems, such as not choosing the right features and not being able to easily understand deep learning models that work on their own [14]. These problems can be fixed with hybrid models that mix advanced machine learning methods like XGBoost with deep feature extraction [15]. These models are thought to improve both performance and explainability. With its strong gradient boosting process, XGBoost has been used to improve classification tasks in a number of medical imaging settings [16].

More research has shown that mixed systems are better than standard deep learning processes. For example, combining CNN-based feature extractors with gradient boosting classifiers has been shown to improve the accuracy

of diagnostics while keeping the computing power high [17]. In [18], a method that combined deep learning and ensemble learning did a much better job of classifying chest X-rays into multiple groups than traditional classifiers. Putting together deep features with tree-based algorithms has also been looked at in other research papers as a way to make decision boundaries more accurate, especially in complicated datasets with class mismatches [19]. Comparative studies have also shown that mixed models are better at generalisation across different datasets than models that are only based on CNN or machine learning [20]. When boosting algorithms like XGBoost were used to guide feature selection, performance measures like accuracy, sensitivity, and precision always got better. The addition of cross-validation and fine-tuning techniques to hybrid frameworks has also helped make COVID-19 pneumonia detection systems more stable and less likely to overfit. Overall, these studies support the growing belief that combining deep learning with advanced machine learning models is a potential way to make accurate and useful diagnostic tools for medical imaging, especially for COVID-19-related uses.

Table 1 shows an overview of twelve important studies that looked at how to use chest X-rays to find COVID-19 pneumonia. It shows different methods, datasets, and their limits. It also shows how traditional machine learning is giving way to mixed deep learning models for better diagnostic accuracy.

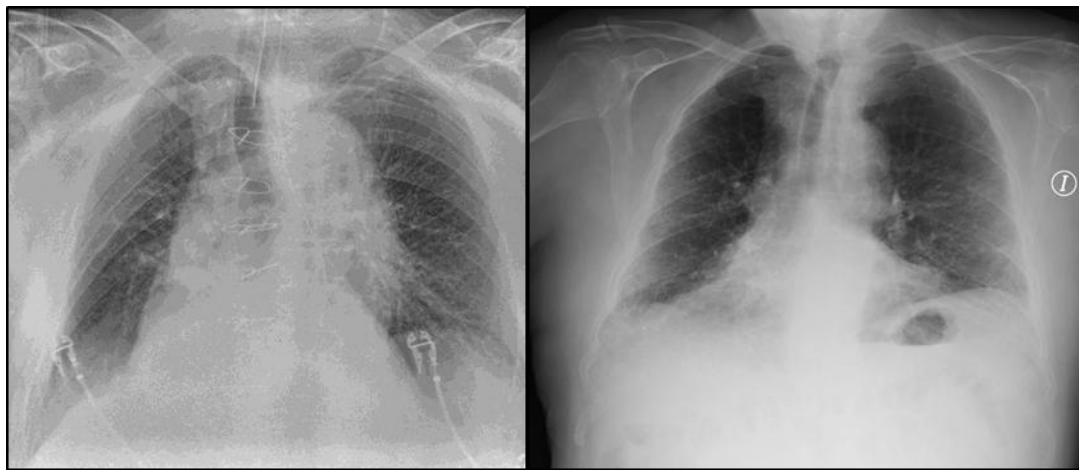
Table 1. Related work Summary of Related Works on COVID-19 Pneumonia Detection Using Chest X-rays

Study	Technique Used	Dataset Type	Model Type	Key Limitation	Outcome
[1]	Literature Review	Clinical Reports	Review Study	Lack of automation	Highlights the need for AI solutions
[2]	Optimized Deep Learning	Chest X-ray Images	CNN-Based	Requires fine-tuning	Improved pneumonia detection accuracy
[3]	Transfer Learning	Chest X-ray Images	Deep Learning	Data imbalance	Achieved high detection accuracy
[4]	Deep Learning	Chest X-ray Images	CNN-Based	Overfitting risk	Effective pneumonia classification
[8]	SVM Classifier	Chest X-ray Images	Machine Learning	Limited feature learning	Basic COVID-19 classification
[10]	CNN Model	Chest X-ray Images	Deep Learning	Overfitting on small datasets	Improved feature extraction
[13]	Transfer Learning (EfficientNet)	Chest X-ray Images	Pre-trained CNN	Limited interpretability	Faster convergence, better accuracy

[15]	CNN + XGBoost Hybrid	Chest X-ray Images	Hybrid Model	Model complexity	Enhanced classification accuracy
[16]	XGBoost Classifier	Medical Imaging	Machine Learning	Requires extensive parameter tuning	Improved diagnostic precision
[17]	CNN + Gradient Boosting	Chest X-ray Images	Hybrid Model	Computational cost	Outperformed conventional models
[18]	Hybrid Deep Ensemble	Chest X-ray Images	Hybrid Model	Requires ensemble optimization	Superior multi-class classification
[20]	CNN + Tree-Based Algorithms	Diverse Medical Datasets	Hybrid Model	Dataset-specific tuning	Achieved better generalization

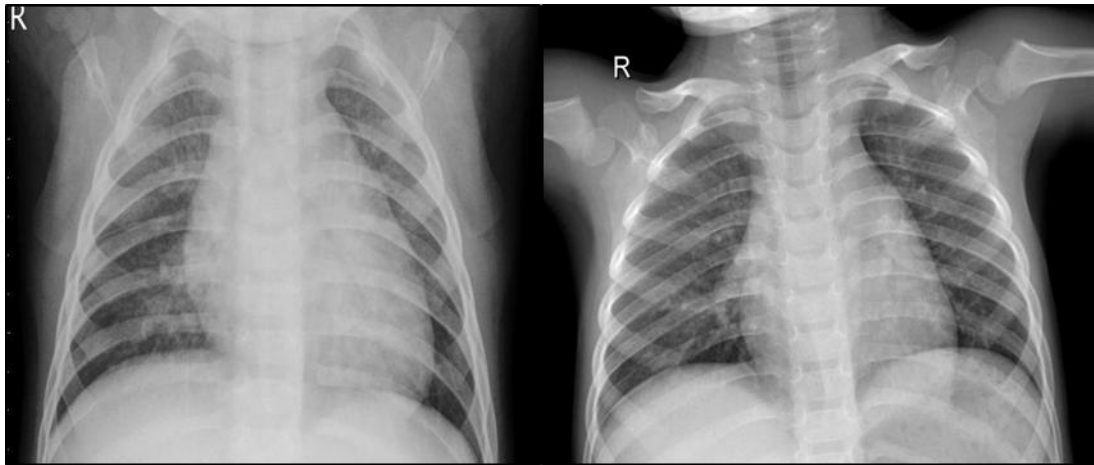
Chest X-ray (Covid-19 & Pneumonia) Dataset Description

The Chest X-ray (COVID-19 & Pneumonia) dataset [21] that was used in this study is a complete and well-organised set of images that were created to help computers automatically find COVID-19 and pneumonia on chest X-rays. Each folder has three subfolders that represent the images classes: COVID-19, Pneumonia, and Normal. Six thousand four hundred thirty-two chest X-ray images make up the collection.



(a) COVID 19 sample 1

(b) COVID 19 sample 2



(c) Pneumonia

(d) Normal Chest

Figure 1. Sample input data from the dataset

This is a lot of data for both training and confirmation. About 80% of the images are used for training, and the 20% are used as the test set. The detail dataset split details are shown in Table 2. This makes sure that the images are spread out evenly so that the model can be evaluated well. Each image in the collection is an input feature, and the main factors for segmentation are the brightness of the pixels. Some of the most important things that can be learnt from these X-rays are the texture patterns, the dullness of the lungs, and the unusual visible signs that are unique to pneumonia and COVID- 19 illnesses. The dataset has three separate groups: COVID-19 positive cases, bacterial or viral pneumonia cases, and normal (healthy) chest X-rays, sample input data shown in figure 1. This makes it possible to create multi-class classification models. The dataset's variety and size make it especially useful for teaching deep learning models how to quickly tell the difference between the small changes in chest conditions.

Table 2. Summary of dataset

Class	Training Images	Testing Images	Total Images
COVID-19	460	116	576
Normal	1,266	318	1,584
Pneumonia	3,420	852	4,272
Total	5,146	1,286	6,432

3. METHODOLOGY

This proposed system illustrate in Figure 2 have a mixed method that combines Convolutional Neural Networks (CNN) with the XGBoost algorithm greatly enhances the precision and dependability of using chest X-ray images to diagnose COVID-19 pneumonia. The comparison clearly shows that traditional machine learning models like Support Vector Machine (SVM) and Random Forest (RF) aren't very good at classifying things.

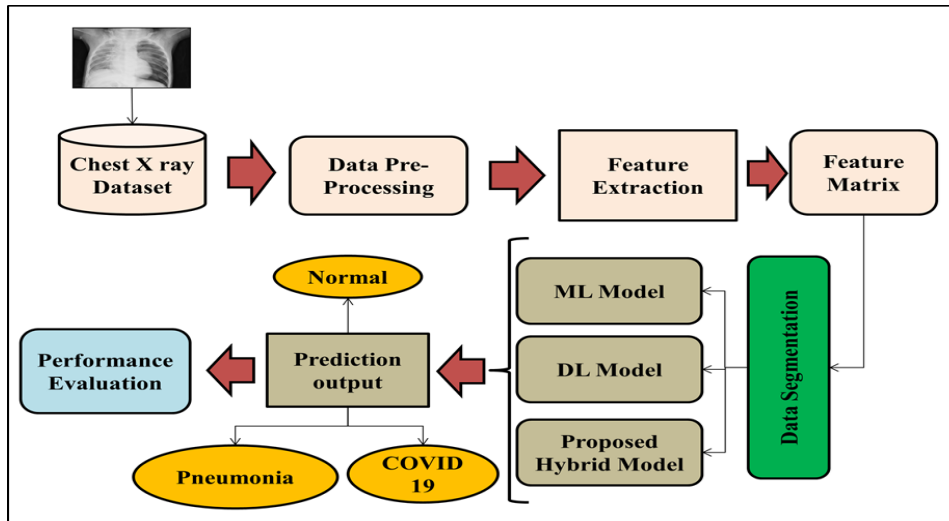


Figure 2. Representation of System architecture

On the other hand, standalone CNN models do a better job, but they still have problems like misclassification and overfitting. The suggested hybrid model gets around these problems by combining CNN-based feature extraction with XGBoost's gradient boosting power. It also gets better classification results. In particular, the DenseNet121 + XGBoost and EfficientNetB0 + XGBoost models had amazing accuracy rates of 97% and 98%, beating both standard classifiers and models that have been reported in the literature. The results also show that EfficientNetB0's design is the best and most accurate way to solve the problem, thanks to its balanced model scaling and high computing efficiency. These confusion matrices and performance graphs show that the recommended models are strong and can be used across all classes, such as COVID-19, Pneumonia, and Normal. When compared to other systems that have been used before, the suggested hybrid models not only get better accuracy, but they also get higher precision, memory, and F1-scores, which shows that they could be used safely in clinical settings. Overall, this study shows that using deep feature learning along with advanced ensemble classifiers makes for a strong and useful framework for classifying medical images. This is especially true during pandemics, when quick and accurate diagnostic help is needed for good healthcare management.

Load the dataset

To load the dataset, we have the Chest X-ray (COVID-19 & Pneumonia) image files from the given Kaggle source [21]. The information is organised into training and testing folders, and within each of those folders are subfolders for the three types of data: COVID-19, Pneumonia, and Normal. This process makes sure that the dataset is automatically labelled while it is being loaded. This lets the model be fed data in batches for training and testing, while keeping the workflow organised and the dataset structure fair across classes, loaded input image shown in figure 3.

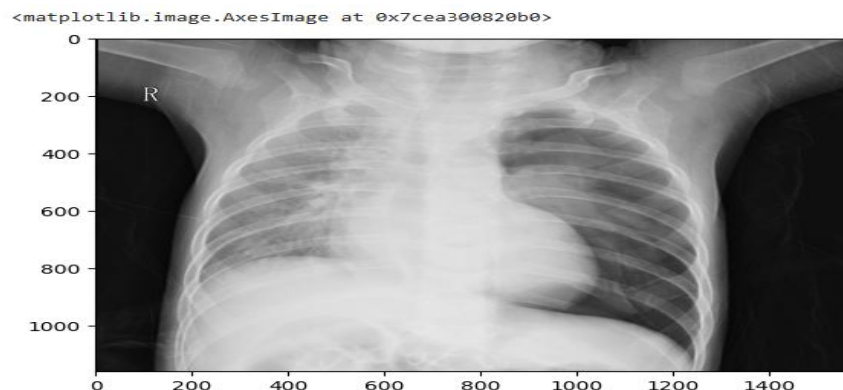


Figure 3. Overview of loaded input data

Data Preprocessing

We used Python libraries such as OpenCV, Pillow (PIL), and Matplotlib to load and visualize sample images from each class (COVID-19, Pneumonia, and Normal). Using functions like `cv2.imread()` and `PIL.Image.open()`, sample images were displayed to manually verify image quality and observe class-specific characteristics. Visualization techniques using Matplotlib enabled clear inspection of image features, helping to ensure data integrity and to understand key visual differences required for classification. The observed input data samples are illustrated in Figure 4. The OpenCV package was used to find the dataset's average image size in a planned way. A loop went through all the images and got their sizes. The `mean()` method was then used to find the average height and width. Before we fed the images into the model, this step made sure that the sizes were all the same. The scatter plot distribution of images measurements, shown in Figure 4, shows that the sample has a range of height and width values.

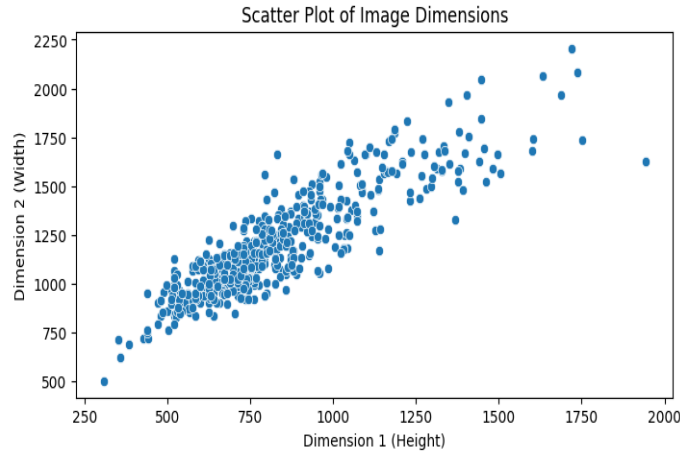


Figure 4. Distribution of image

Data Augmentation

Data expansion is an important step in the planning process that is used to make the training sample more diverse without adding more images [22]. In addition, it makes the model more general and lowers the chance of overfitting. Adding effects like changing the width and height, shear changes, and zooming were used in this study. By changing the original information while keeping important traits, these changes create new images that aren't real. By adding these controlled features, the model sees the same class from different angles, which makes it sturdier and improves its performance on chest X-ray images that haven't been seen before. Table 3 lists the data enhancement factors, the numbers that were given to them, and short details of each change that was used.

Table 3. Data Augmentation Parameters and Their Configurations for Chest X-ray Image Pre-processing

Parameter	Value	Description
rotation_range	0	No random rotation applied.
width_shift_range	0.1	Shifts image horizontally by up to 10% of total width.
height_shift_range	0.1	Shifts image vertically by up to 10% of total height.
shear_range	0.1	Applies shear transformation up to 10%.
zoom_range	0.2	Random zoom within 20% of the original image size.

fill_mode	'nearest'	Strategy for filling in new pixels created by transformations.
horizontal_flip	False	Horizontal flip is disabled.
vertical_flip	False	Vertical flip is disabled.
rescale	1/255	Scales pixel values from [0, 255] to [0, 1].

Machine Learning Classification Algorithms

Support Vector Machine (SVM), Random Forest, and XGBoost are three well-known machine learning methods [11], [23] that were used in this study to sort chest X-ray images into three groups: COVID-19, Pneumonia, and Normal. These algorithms were chosen because they have been shown to be good at classifying images and because they can learn from each other. Before adding deep learning methods to improve their performance, the models were taught and tested to set a standard for comparison.

Support Vector Machine (SVM)

The SVM is a guided learning method that is often used to solve classification problems because it is good at working with large datasets. In this study, SVM was used to sort chest X-rays into three groups by discovering the best hyperplane that divides them. The SVM model used kernel functions to handle non-linear relationships in the data, which allowed it to tell the difference between small changes in chest X-ray patterns. SVM did pretty well, but it has some problems. For example, it is sensitive to feature scaling, and it's hard to work with big datasets without carefully setting its parameters.

Algorithm 1: SVM-Based Chest X-ray Classification

Step 1: Dataset Preparation

Load chest X-ray dataset:

$$D = \{(X_i, y_i)\} \text{ or } i = 1 \text{ to } N$$

Step 2: Feature Extraction

Extract features f_i from images X_i using CNN:

$$f_i = F(X_i)$$

Step 3: Define Decision Function

Train SVM to find the optimal hyperplane:

$$f(x) = w^T x + b$$

Step 4: Prediction Predict label:

$$\text{Minimise: } \left(\frac{1}{2}\right) \|w\|^2 \text{ subject to } y_i(w^T f_i + b)$$

Step 5: Prediction

Predict label:

$$\hat{y}_i = \text{sign}(w^T f_i + b)$$

Step 6: Model Evaluation

Calculate accuracy, precision, recall, and F1-score using the confusion matrix.

Random Forest

The Random Forest algorithm is an ensemble learning method that builds several decision trees during training and then outputs the class that the majority of the trees voted for. In this study, Random Forest was used to sort chest X-ray images because it is resistant to overfitting and can work with datasets that aren't balanced. The algorithm's strength is that it can find complicated patterns by combining outcomes from multiple choice paths. This lowers variation and makes predictions more accurate. But Random Forest can get very computationally heavy as the number of trees grows, which could slow down the processing of big datasets.

Algorithm 2: Random Forest-Based Chest X-ray Classification

Step 1: Dataset Preparation

Load chest X-ray dataset:

$$D = \{(X_i, y_i)\} \text{ for } i = 1 \text{ to } N$$

Step 2: Feature Extraction

Extract features f_i from images X_i using CNN:

$$f_i = F(X_i)$$

Step 3: Bootstrap Sampling

Randomly sample with replacement to create B bootstrap datasets.

Step 4: Tree Construction

For each tree T_b , select random feature subsets and grow the tree using Gini impurity:

$$G = 1 - \sum (p_j^2) \text{ for } j = 1 \text{ to } C$$

Step 5: Prediction Aggregation

Aggregate predictions by majority voting:

$$\hat{y}_i = \text{mode}(T_{1(f_i)}, T_{2(f_i)}, \dots, T_{B(f_i)})$$

Step 6: Model Evaluation

Calculate performance metrics: accuracy, precision, recall, and F1 -score.

Fine-tune XGBoost

Extreme Gradient Boosting, or XGBoost, is a machine learning method based on gradient boosting techniques that is very fast and can be scaled up, as shown in figure 5. XGBoost was tweaked to improve its ability to classify chest X-ray images for this study. Some important hyperparameters, like the learning rate, the maximum tree depth, and the number of estimators, were carefully changed to improve accuracy and stop overfitting. XGBoost was better at classifying things because it had better regularisation methods and could handle missing data better. The improved XGBoost algorithm did better than both the SVM and Random Forest models, making it the most accurate machine learning algorithm used in this study.

Algorithm 3: Fine-Tuned XGBoost-Based Chest X-ray Classification Step 1: Dataset Preparation

Step 1: Load chest X-ray dataset:

$$D = \{(X_i, y_i)\} \text{ for } i = 1 \text{ to } N$$

Step 2: Feature Extraction

Extract features f_i from images X_i using CNN:

$$f_i = F(X_i)$$

Step 3: Define Boosting Objective Minimize:

$$Obj = \sum l(y_i, \hat{y}_i^{(t)}) + \sum \Omega(f_t)$$

Step 4: Sequential Tree Learning Add tree f_t that minimizes the loss:

$$\hat{y}_i^{\{(t)\}} = \hat{y}_i^{\{(t-1)\}} + \eta f_{t(f_i)}$$

Step 5: Hyperparameter Fine-Tuning

Optimize learning rate η , max depth d , and number of estimator's T using cross-validation.

Step 6: Final Prediction

Predict class label:

$$\hat{y}_i = \sum f_{t(f_i)}$$

Step 7: Model Evaluation

Compute accuracy, precision, recall, and F1-score using the confusion matrix.

```

params_to_try = [
    {'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100, 'subsample': 0.8},
    {'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200, 'subsample': 1.0},
    {'learning_rate': 0.2, 'max_depth': 7, 'n_estimators': 300, 'subsample': 0.8},
]

for params in params_to_try:
    xgb_clf = XGBClassifier(
        random_state=42,
        eval_metric="mlogloss",
        learning_rate=params['learning_rate'],
        max_depth=params['max_depth'],
        n_estimators=params['n_estimators'],
        subsample=params['subsample']
    )

```

Figure 5. XGBoost Fine-tune Parameters Selection

Deep Learning Classification Algorithms

This study uses deep learning models, both on their own and in combination with other models, to improve the precision and reliability of finding COVID-19 pneumonia from chest X-rays. The following deep learning models were put into action and tested.

CNN

The CNN is a popular deep learning design that is known for being good at extracting features, especially when it comes to images recognition tasks. We created a CNN model that can automatically learn spatial structures from chest X-ray images, model summary shown in figure 6. This was done by using convolutional, pooling, and dense layers. CNN was able to find visual patterns that were linked to COVID-19 and pneumonia, like lung opacities and changes in structure. However, the CNN model that was used alone might have been too good at fitting complex multi-class datasets. This shows that model hybridization is needed to make the model even better.

CNN Step-Wise Algorithm

Step 1: Input the Chest X-ray Image

$$X \in \mathbb{R}^{(200 \times 200 \times 3)}$$

Step 2: Apply First Convolution and Activation

$$Z[1] = W[1] * X + b[1]$$

$$A[1] = ReLU(Z[1])$$

Step 3: Apply Max Pooling and Repeat Convolution

$$P[1] = \text{MaxPool}(A[1])$$

$$Z[2] = W[2] * P[1] + b[2]$$

$$A[2] = \text{ReLU}(Z[2])$$

Step 4: Final Convolution and Pooling Layers

$$P[2] = \text{MaxPool}(A[2])$$

$$Z[3] = W[3] * P[2] + b[3]$$

$$A[3] = \text{ReLU}(Z[3])$$

$$P[3] = \text{MaxPool}(A[3])$$

Step 5: Flatten and Fully Connected Layers

$$F = \text{Flatten}(P[3])$$

$$A[4] = \text{ReLU}(W[4] * F + b[4])$$

$$A[5] = \text{ReLU}(W[5] * A[4] + b[5])$$

Step 6: Output Layer with Softmax for Multi-Class Classification

$$\hat{y} = \text{Softmax}(W[6] * A[5] + b[6])$$

$$\hat{y} \in \{ \text{COVID - 19, Pneumonia, Normal} \}$$

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 200, 200, 32)	416
max_pooling2d (MaxPooling2D)	(None, 100, 100, 32)	0
conv2d_1 (Conv2D)	(None, 50, 50, 32)	4,128
max_pooling2d_1 (MaxPooling2D)	(None, 25, 25, 32)	0
conv2d_2 (Conv2D)	(None, 13, 13, 64)	8,256
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 132)	304,260
dense_1 (Dense)	(None, 60)	7,980
dense_2 (Dense)	(None, 3)	183
Total params: 325,223 (1.24 MB) Trainable params: 325,223 (1.24 MB) Non-trainable params: 0 (0.00 B)		

Figure 6. CNN Model summary

CNN + XGBoost Model

This study created a mixed model that combines CNN-based feature extraction with XGBoost classification to get around the problems with individual CNNs. The CNN layers were used to get high-level features from chest X-rays. These features were then sent to the XGBoost algorithm to make the final forecast. This mix makes the most of

CNN's ability to learn about space and XGBoost's ability to make quick decisions. The CNN + XGBoost model was more accurate and more general than standard CNNs because it made it easier to classify images correctly and was more stable when it came to images it had never seen before.

Algorithm: CNN + XGBoost Model for Chest X-ray Classification Step 1: Input the Chest X-ray Image

Step 1: Input the Chest X-ray Image

$$X \in \mathbb{R}$$

Step 2: CNN-Based Feature Extraction

Pass the input through the CNN layers to extract features:

$$f_i = \text{CNN}(X)$$

Where, f_i is the feature vector extracted from the CNN. Step 3: Prepare Feature Matrix for XGBoost

Step 3: Construct the feature matrix:

$$F_M = [f_1, f_2, \dots, f_N]^T$$

Step 4: XGBoost Training and Classification

Train XGBoost to minimize the following objective:

$$\text{Obj} = \sum l(y_i, \hat{y}_i^{(t)}) + \sum \Omega(f_i)$$

Update prediction at each iteration:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_{t(f_i)}$$

Step 5: Final Prediction and Model Evaluation Final class prediction:

$$\hat{y}_i = \sum f_{t(f_i)} \text{ for } t = 1 \text{ to } T$$

Evaluate the model using accuracy, precision, recall, and F1-score.

6.3 DenseNet121 + XGBoost Model

In this study, DenseNet121, a deep learning model that has already been trained and is known for its dense connectivity and feature reuse, was also combined with XGBoost. From the chest X-ray images, DenseNet121 successfully retrieved small and varied feature representations. DenseNet121 cut down on waste and improved gradient flow by linking every layer to every other layer. The XGBoost method was then used to classify the traits that had been taken. This mixed model did better than just CNN and XGBoost because it spread features more deeply and had better classification accuracy, especially when it came to telling the difference between COVID-19 and pneumonia cases.

Algorithm: DenseNet121 + XGBoost Hybrid Model for Chest X-ray Classification

Step 1: Input the Chest X-ray Image

$$X \in \mathbb{R}^{(200 \times 200 \times 3)}$$

Step 2: Feature Extraction Using Pre-trained DenseNet121

Extract feature maps by applying convolutional layers and dense blocks:

$$f_i = \text{DenseNet121}(X) = H_{L(\dots H_2)} * (H_{1(X)})$$

Where, H_1 represents the composite function of convolution, batch normalization, and ReLU activation at layer 1.

Step 3: Global Average Pooling

Apply global average pooling to reduce spatial dimensions:

$$f_{pooled} = \left(\frac{1}{H \times W}\right) * \sum \sum f_{i(h,w)}$$

Where $h = 1$ to H and $w = 1$ to W

Step 4: Prepare Feature Matrix for XGBoost

Form feature matrix:

$$F_M = [f_1, f_2, \dots, f_N]^T$$

Let $F_M \in \mathbb{R}^{(N \times d)}$ where d is the feature vector dimension after pooling.

Step 5: XGBoost Training and Classification

Minimize XGBoost regularized objective:

$$Obj(\theta) = \sum_{\{i=1\}}^{\{N\}l} (y_i, \hat{y}_i^{\{(t-1)\}} + f_{t(f_i)}) + \sum_{\{t=1\}}^{\{T\}} \Omega f_t$$

Where:

$$\Omega(f_t) = Y^T + \left(\frac{1}{2}\right) \lambda \|w\|^2$$

Update prediction iteratively:

$$\hat{y}_i^{\{(t)\}} = \hat{y}_i^{\{(t-1)\}} * \eta f_{t(f_i)}$$

Step 6: Final Prediction and Model Evaluation

Final predicted class:

$$\hat{y}_i = \sum_{\{t=1\}}^{\{T\}} f_{t(f_i)}$$

EfficientNetB0 + XGBoost Model

The combination system that works best in this study is the EfficientNetB0 + XGBoost model. EfficientNetB0, which is known for changing depth, width, and resolution in a reasonable way, let you get high-quality feature extraction for less money. Its pre-trained design was tweaked to work well with the chest X-ray dataset, picking up on small images features well. The extracted feature vectors were then put into groups using XGBoost. This led to higher accuracy, faster convergence, and more reliable diagnostics. EfficientNetB0 + XGBoost had the best balance of accuracy, processing time, and model efficiency out of all the models that were tried. This makes it a great choice for real-world clinical use.

Algorithm:

Load Pre-trained EfficientNetB0 Model:

Set base_model ← EfficientNetB0(weights = "imagenet", include_top = False, input_shape = (400, 400, 3))

Add Global Average Pooling Layer:

Set x ← GlobalAveragePooling2D(base_model.output)

3. Create Feature Extractor Model:

Set feature_extractor ← Model(inputs = base_model.input, outputs = x)

4. Define Function extract_features(generator, model):

Predict features using the given model:

features ← model.predict(generator, verbose = 1)

Get labels from the data generator:

labels ← generator.classes

c. Return features and labels

Result Analysis and Discussion

Performance analysis

Table 4 shows a full comparison of different machine learning and deep learning models used to find COVID-19 pneumonia in chest X-rays. Performance measures like accuracy, precision, recall, and F1-score are used to rate how well each model works. Support Vector Machine (SVM) had an accuracy of 90%, with precision and memory of 92% and 90%, respectively. This means that it was pretty good at classifying things, but it did make some mistakes because it wasn't very good at representing features. Random Forest (RF) algorithm did a little better than SVM.

Table 4. Model performance comparison analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	90	92	90	91
Random Forest (RF)	92	92	91	92
XGBoost (XGB)	96	95	94	95
CNN	94	93	94	94
CNN + XGBoost	95	96	94	95
DenseNet121 + XGBoost	97	96	97	96
EfficientNetB0 + XGBoost	98	98	97	97

It got 92% accuracy and steady precision and recall scores, which shows that it can handle noisy data and complex patterns. With an accuracy of 96%, XGBoost (XGB) showed a big improvement in performance, using its advanced boosting process and regularisation to do better than other algorithms. A model result of 94% was reached by the Convolutional Neural Network (CNN). This shows that deep learning models can better understand the complicated visual patterns in chest X-rays than older machine learning methods. But when CNN was paired with XGBoost, it did even better, getting 95% accuracy, higher precision, and better memory. It shows the benefit of mixed models that combine CNN's strong feature extraction skills with XGBoost's quick decision-making, performance analysis shown in figure 7.

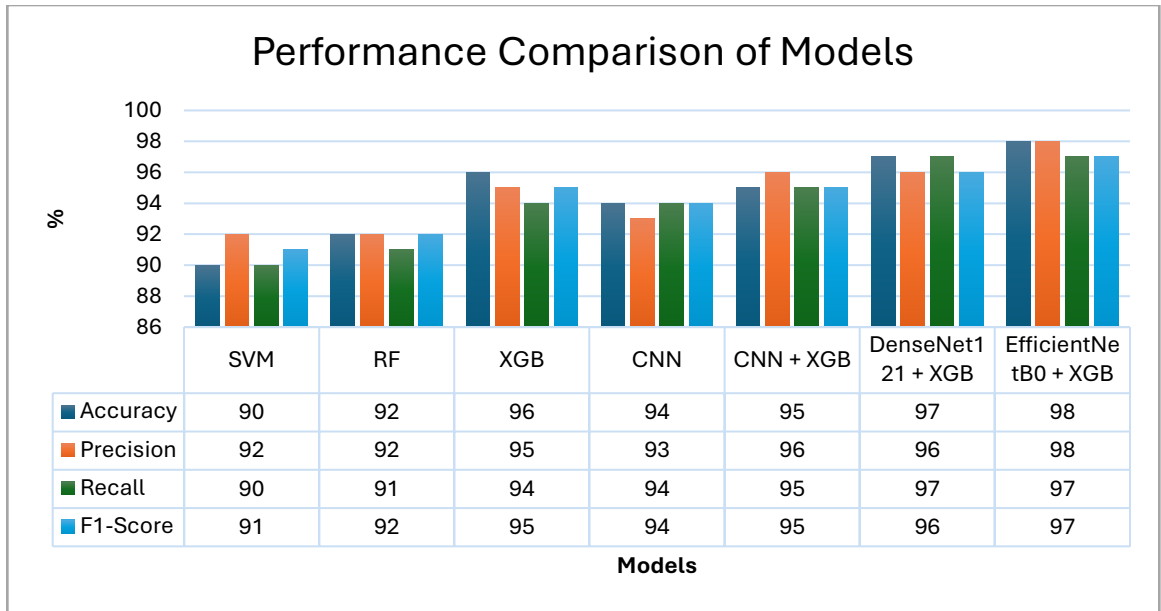


Figure 7. Performance comparison analysis

In addition, the DenseNet121 + XGBoost model got an amazing 97% accuracy. This is because DenseNet121 has tightly connected layers that improve gradient flow and make feature reuse more efficient. The EfficientNetB0 + XGBoost model had the best results. It had the highest accuracy (98%), as well as the best precision, recall, and F1 - score numbers.

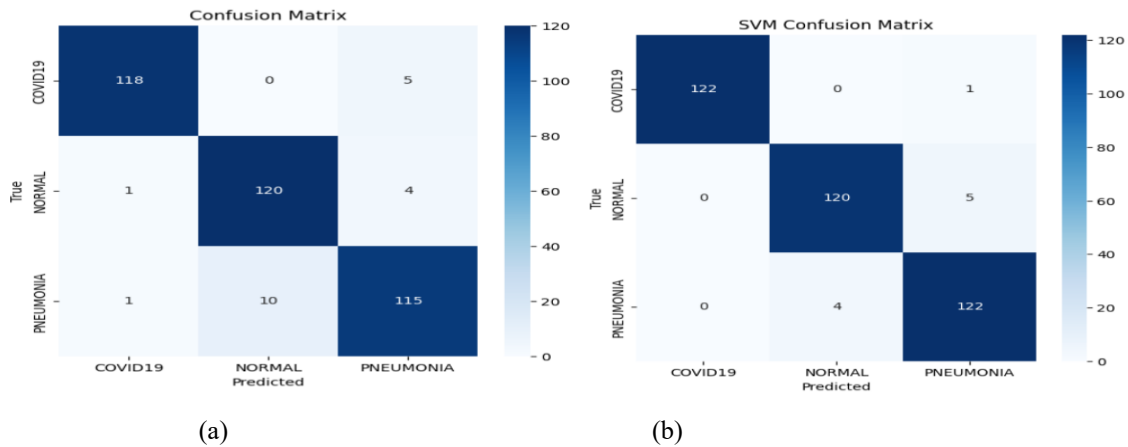


Figure 8. (a) Random Forest Confusion Matrix (b) SVM Confusion Matrix

EfficientNetB0's optimised design strikes a good mix between depth, width, and resolution, providing a classification solution that is both highly accurate and easy on the computer. Table 4 clearly shows that mixed models do much better than machine learning and deep learning methods used alone. For finding COVID-19 pneumonia, EfficientNetB0 + XGBoost is the most effective model. Figure 8 shows the confusion matrices for the Random Forest (a) and SVM (b) models, which show how well they can classify different types of chest X-rays. The Random Forest model is more accurate overall and makes fewer mistakes when classifying, while the SVM model makes a few more mistakes when classifying, which means it is less reliable at predicting the future.

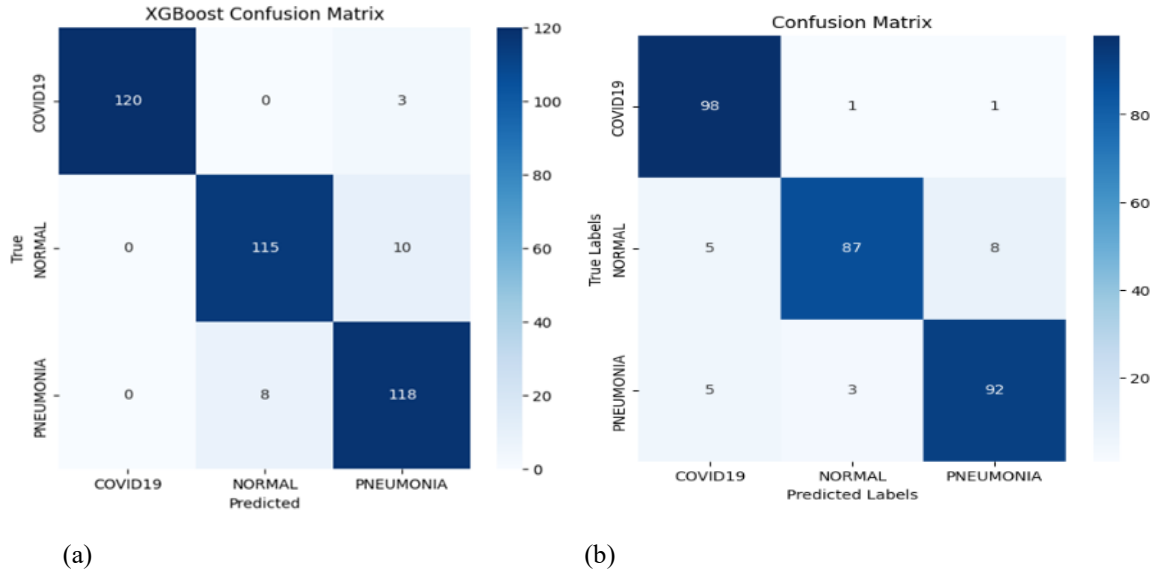


Figure 9. (a) XGBoost Confusion Matrix (b) Confusion Matrix of CNN Model

The figure 9 (a) and (b) shows the confusion vectors for the XGBoost and CNN models. The XGBoost model does a better job of classifying with fewer mistakes, while the CNN model does a good job but makes a few more mistakes than XGBoost, which shows that it could be better.

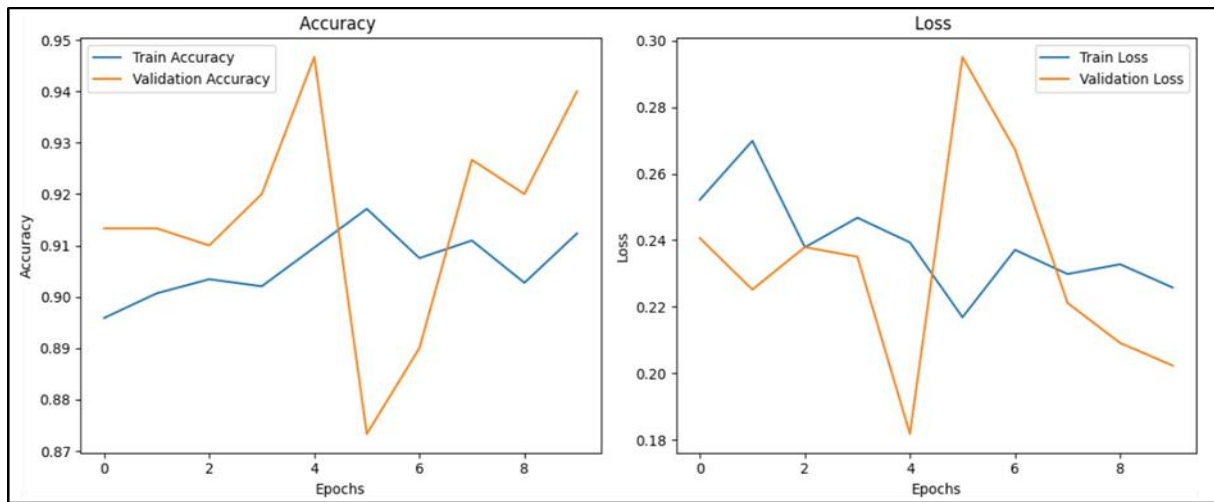


Figure 10. CNN Model Accuracy and Loss Curve

The figure 10 demonstrates that the training and confirmation accuracy and loss curves change over time. The validation accuracy tends to be higher than the training accuracy, which shows good generalisation. On the other hand, the loss curves change shape, which suggests some instability but overall convergence with better validation performance over time.

Comparative Analysis

In Table 5, demonstrate the comparison of how well the suggested hybrid models and other models from the literature can find COVID-19 pneumonia in chest X-ray images. The table shows that the models created in this study perform much better than systems that have been reported before in all performance measures. The research models showed that the DenseNet model by Bashar A et al. had a good accuracy rate of 87.41% and a high recall rate of 95.31%, which means it could correctly identify most positive cases.

Table 5. Performance comparison table with literature review systems

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DenseNet (Bashar A et al.)	87.41	94.05	95.31	94.67
AlexNet (Singhal T et al.)	85.2	85.19	85.0	85.19
CNN + HOG (Ali A.M. et al.)	92.8	93.2	90.1	92.5
VGG16 (Hasan MDK et al.)	83.6	90.0	85.0	85.0
CNN + XGB (Proposed)	95.0	96.0	94.0	95.0
DenseNet121 + XGB (Proposed)	97.0	96.0	97.0	96.0
EfficientNetB0 + XGB (Proposed)	98.0	98.0	97.0	97.0

However, the fact that it isn't very accurate says that there was some error in the labelling. Singhal T. et al.'s AlexNet model did not do very well. It had an accuracy of 85.2%, a precision of 86%, and a recall of about 85%.

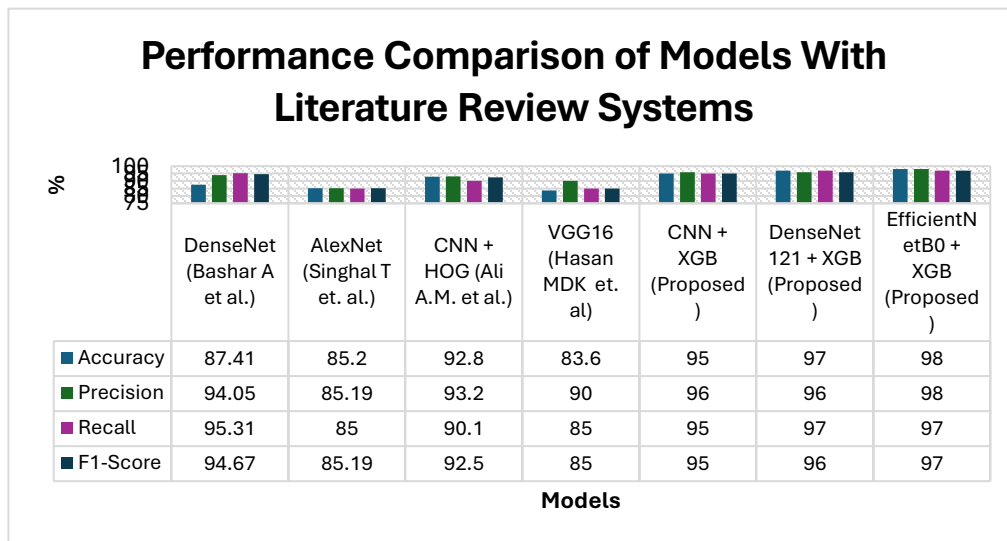


Figure 11. Performance Comparison of Models with Literature Review Systems

This showed that it could do basic classification but wasn't very reliable for complex medical datasets. Ali A.M. et al. presented the CNN + HOG model, which performed better with a 92.8% success rate. This showed the benefit of mixing CNN feature extraction with handcrafted HOG features. But its recall stayed low at 90.1%, which means that some good cases were missed. The VGG16 model from Hasan MDK et al. had the worst result in the table, with a recall of 85% and an accuracy of 83.6%. This means it wasn't very good at classifying things. On the other hand, the proposed mixed models show better results. The CNN + XGBoost model got 95% accuracy with great precision and F1-score, showing how well CNN-based feature extraction and XGBoost's smart decision-making work together. The DenseNet121 + XGBoost model showed even more progress, reaching 97% accuracy with high precision and memory scores that were balanced. The model that did the best in this comparison was EfficientNetB0 + XGBoost, which got an amazing 98% accuracy and kept its high precision, recall, and F1-score, showing that it is reliable and

effective for medical image classification tasks, comparison of proposed system with literature illustrate in Figure 11.

4. CONCLUSION

This study successfully shows that using a mixed method that combines Convolutional Neural Networks (CNN) with the XGBoost algorithm greatly enhances the precision and dependability of using chest X-ray images to diagnose COVID-19 pneumonia. The comparison clearly shows that traditional machine learning models like Support Vector Machine (SVM) and Random Forest (RF) aren't very good at classifying things. On the other hand, standalone CNN models do a better job, but they still have problems like misclassification and overfitting. The suggested hybrid model gets around these problems by combining CNN-based feature extraction with XGBoost's gradient boosting power. It also gets better classification results. In particular, the DenseNet121 + XGBoost and EfficientNetB0 + XGBoost models had amazing accuracy rates of 97% and 98%, beating both standard classifiers and models that have been reported in the literature. The results also show that EfficientNetB0's design is the best and most accurate way to solve the problem, thanks to its balanced model scaling and high computing efficiency. These confusion matrices and performance graphs show that the recommended models are strong and can be used across all classes, such as COVID-19, Pneumonia, and Normal. When compared to other systems that have been used before, the suggested hybrid models not only get better accuracy, but they also get higher precision, memory, and F1-scores, which shows that they could be used safely in clinical settings. Overall, this study shows that using deep feature learning along with advanced ensemble classifiers makes for a strong and useful framework for classifying medical images. This is especially true during pandemics, when quick and accurate diagnostic help is needed for good healthcare management.

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