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A NOVEL IMAGE-INVARIANT FEATURE EXTRACTION USING SLIDING WINDOW FOR MACHINE LEARNING

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ABSTRACT

Feature extraction is an important task in building machine learning and deep learning applications. A gray-level cooccurrence matrix, a histogram of oriented gradients, a local binary pattern, principal component analysis, and linear discriminant analysis are some of the feature extraction methods that are used in a lot of research studies. However, these methods are sensitive to image quality, have trouble with non-linear relationships, are difficult to compute, and cannot capture global or contextual information. These limitations often require additional preprocessing or modifications to enhance their performance in practical applications. The goal of this study is to come up with a feature extraction method that works with all kinds of image changes and can pick up both local and global features to make machine learning classifiers work better. To achieve this, we propose in this research a new feature extraction method that is based on the concept of a sliding window to extract local and global image-invariant features. For evaluating the proposed method, we have used the chest X-Ray medical images from the publicly available Novel COVID-19 Chest X-Ray Repository dataset at Kaggle. We conducted experiments using five benchmark feature extraction methods and eight state-of-the-art machine learning classifiers to assess the significance of the proposed feature extraction. For binary classification, the tests indicated that MLP had better accuracy, recall, precision, specificity, and balanced accuracy than other methods (96.25% for accuracy, 96.05% for recall, 92.4% for precision, 96.34% for specificity, and 96.19% for balanced accuracy). The dense MLP neural network, which has two hidden layers with 1024 and 512 neurons each, was able to correctly classify with a 93.98% accuracy, 92.07% recall, 93.21% precision, and 95.32% specificity. It also had a balanced accuracy of 93.69% when it came to multiclass classification.

Keywords: S*liding window, Feature extraction, Local patterns, Global patterns, Hyperparameters.*

1. INTRODUCTION

Differential diagnosis is the process of identifying two or more diseases with similar symptoms or signs, such as COVID-19 or bacterial pneumonia, by analyzing radiological features in chest X-rays, based on similarities and differences in their imaging patterns. This medical image classification task is also called as Image-based diagnostic classification which can be achieved by applying machine learning. Image based diagnostic classification involves applying feature selection or feature extraction before applying machine learning classifiers or using deep learning techniques like convolutional neural networks for automated feature extraction to classify medical images into respective diagnostic categories.

The manual approach to effectively discriminate COVID-19 and Pneumonia chest X-ray images is a challenging task due to overlapping radiographic features. Disease diagnosis using machine learning involves learning appropriate features to distinguish between Viral Pneumonia, Bacterial Pneumonia and COVID-19 Chest X-ray images. Thus, the research challenge here is to extract appropriate and most significant image features that can be utilized by the machine learning classifier(s) to discriminate between the medical images. Below, we mention

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the challenges faced by machine learning based solutions.

1.1 Challenges for Machine Learning Based AI Solution w.r.t Disease Diagnosis

When compared to deep learning-based image diagnosis, machine learning-based image diagnosis can be more challenging due to manual feature extraction, handling large and complex data, feature engineering, and generalization and scalability issues. Although deep learning models, like convolutional neural networks (CNNs), are more flexible, scalable, and better suited for handling image data, a proper feature extraction followed by machine learning can also be effective for classification tasks such as Tuberculosis, pneumonia or COVID diagnosis. Some of the main challenges for machine learning are mentioned below.

(i) Feature Extraction vs. Automatic Feature Learning

Traditional machine learning models involve manual feature extraction from images, which can be time-consuming and reliant on human expertise. This process is particularly challenging in complex tasks like medical image diagnosis, where subtle patterns are difficult to interpret. On the other hand, automated feature extraction methods such as Convolutional Neural Networks (CNNs), can automatically learn features from raw image data without manual intervention by identifying intricate patterns at different levels of abstraction and more complex representations. Machine learning classifiers when integrated with automated feature extraction methods can identify complex image patterns. Such machine learning models could be more efficient and adaptable for complex image-based tasks like medical diagnosis, as they can discover relevant features independently through multiple layers of computation.

(ii) Need for Feature Engineering - Traditional machine learning relies on the quality of features extracted from images, which can be error-prone, insignificant, may not be better representative of images. Feature extraction which learns abstract, relevant, and discriminative features from images can aid machine learning classifiers to attain better detection rates. Such feature extraction methods can reduce the need for human intervention in feature design, allowing machine learning models to perform better with minimal manual feature extraction, especially when large datasets are available.

(iii) Generalization and Overfitting - Traditional machine learning models can overfit training data due to their hand-engineered features, which may not capture the underlying data patterns or be too simplistic. This issue is particularly significant when the features are not robust enough to represent the diversity of images in a medical dataset. Deep learning models, which use regularization techniques and are designed to automatically learn from the data, are less prone to overfitting when trained on large datasets. They also reduce the likelihood of fitting noise or irrelevant patterns, making them more resilient to overfitting in complex image classification tasks.

Despite deep learning being the preferred solution for complex tasks like image diagnosis, traditional machine learning models can still improve their performance and achieve results comparable to deep learning when we can extract the best representative features from images which forms the main motivation for the research.

1.2 Research Motivation

Despite, deep learning has significantly impacted fields like medical image analysis, yet traditional machine learning models can still be effective with proper techniques. Focusing on feature engineering, data augmentation, ensemble methods, hyperparameter optimization, and domain knowledge can improve performance and achieve competitive results, especially when computational resources or labeled data are limited. Existing machine learning relies on manual feature extraction to improve performance. In medical image classification, manually engineered features like textures, shapes, edges, or morphological features can capture important patterns that deep learning models may not immediately focus on without extensive data. Thus, there is a scope to design and propose new feature extraction methods that can extract image features that best represent the respective disease categories which forms the main motivation for this research. Feature extraction methods used in deep learning are not explainable. There is a scope to propose explainable feature extraction method. Thus, in this research, we introduce a new feature extraction technique for disease classification and prediction using medical images which is explainable and interpretable. The feature extraction method presented in this paper is designed to extract invariant image features which can aid machine learning classifiers to attain a better performance.

1.3 Research Objectives

The objectives of the present research contribution are outlined below.

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(i) The first objective is to propose a method to extract invariant image features from chest Xray images so as to perform feature extraction.
(ii) Feature extraction method should be explainable and interpretable.
(iii) Integrate our feature extraction method with classifiers to use the learned features by classifiers during training and show their performance is improved when compared to the same classifiers using conventional feature extraction methods such as GLCM, HOG, LBP.
(iv) To study the performance of the dense MLP neural network (DNN) which utilizes the features retrieved from medical images.

Thus, main contributions of this work are

i. A new technique is proposed to extract invariant image features which are robust to transformations.
ii. Features extracted using proposed method are fed as input to various ML classifier algorithms and their performance is evaluated.
iii. A comparison analysis is carried out to study performance of ML classifiers and dense MLP deep neural network using existing and proposed feature extraction methods.

The paper is outlined as follows. In Section 2, some of the recent related works on machine learning applications in disease diagnosis are presented. The proposed method is outlined in Section 3. Experiment results are presented in section 4. Section 5 concludes the paper.

2. RELATED WORKS

Pratik Bhowal et al. [1] curated a chest Xray image dataset through combining three CXR image repositories which are available publicly. The dataset is named as the novel COVID-19 Chest Xray Repository. This dataset has been developed for future use and reference in COVID-19 identification and diagnosis for researchers. In this work, an ensemble approach is proposed to screen covid from chest X-rays using deep learning models. For this, they used the Choquet integral for aggregation. The classifier decisions are combined by using Choquet integral, and fuzzy measures are computed using the Shapley value and Lambda fuzzy approximation. Marginal contribution is calculated using mutual information and conditional mutual information.

To evaluate three Choquet integrals, they have used three weighting schemes, each with a different set of fuzzy measures, after decisions are obtained, majority voting scheme is used to combine the decisions. For feature extraction, three standard pre-trained DCNN models are used. They are VGG-16, Inception V3, and Exception. A multi-layer perceptron is considered for classification. For experiment analysis, data is augmented with train data consisting 11443 and validation set consisting 2859 images. The test data consisted 399 medical images (10% of the original curated dataset).

The accuracies for testing dataset are 91.22%, 93.48% and 92.98% for VGG-16, Inception V3, and Exception respectively. The method [1] requires experimentation to select useful classifiers from a set of potential classifiers, which is a potential shortcoming and will be addressed in future work. We have used this dataset for experimental study of the proposed method addressed in this paper. Also, the same distribution of the testing dataset without augmenting training dataset has been considered.

A light weight CNN model is proposed by Vasilis Nikolaou et al. [2] to discriminate COVID-19 chest X-rays from viral pneumonia and healthy chest X-rays. The model overcomes low specificity issues, allowing chest imaging to diagnose COVID-19. The model attained a 91% positive predictive value and 97% specificity in discriminating normal and covid chest x-rays. A positive predictive value (86%) and a specificity (95%) is attained in discriminating normal and pneumonia images from covid chest Xray images.

Abdul Waheed et al. [3], proposed CovidGAN, a method to generate synthetic chest X-ray images using ACGAN-based model. By adding synthetic images, CNN's accuracy increased to 95%. The analysis has limitations, including potential improvements in GAN architecture and training, a small dataset due to time constraints, and the lack of cross-center validations. The synthetic samples could be enhanced by incorporating more labeled data. The study suggests the use of this method for robust radiology systems and encourages systematic large-scale collection of COVID-CXR images.

Harsh et al. [4] introduced nCOVnet, a deep learning neural network-based method for rapid COVID-19 detection using X-ray analysis of chest radiography imaging. The test dataset used for experiment consisted of 84 chest Xray images, with 42 normal and 42 non-covid class images. The accuracy of the nCOVnet was reported as 88.09% for binary class classification on the test dataset.

Wang et al.'s study introduces COVID-Net [5], an open-source deep convolutional neural

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network designed for detecting COVID-19 cases from CXR images. It uses COVIDx, an open access benchmark dataset, and an explainability method to make predictions.

Ren et al. [6] have developed a novel Deep Neural Network (DNN) called RMT-Net, which uses a ResNet-50 merged transformer for COVID-19 detection. The network uses convolutional neural networks to extract local features and transformers to capture long-distance feature information. It includes four stages for feature extraction, global self-attention method, residual blocks, and global average pooling layer. With a test accuracy of 99.12% on CT images and 97.65% on X-rays, the model [6] performs better than existing models in terms of efficiency and accuracy.

For lung segmentation from X-ray images, Rahman et al.'s study [7] suggested a unique U-Net architecture variant that performed better than the most advanced U-Net model. The findings demonstrated a dependable diagnosis with 96.11% accuracy, 94.55% precision, and 94.56% recall with segmentation. In this case, the results attained are 96.29% accuracy, 96.28% precision, and 96.28% recall without segmentation.

A machine learning-based method for identifying COVID-19 from chest X-ray radiographs is proposed in the work of Khan et al [8]. Radiographs are separated into training and testing sets by the system, which then uses the SURF method to extract feature descriptors and the K-means clustering technique to create a visual vocabulary. Its average accuracy of 94.12% has been verified on 340 X-ray radiographs. Using a large dataset of hospitals across the globe, Asmaa Abbas et al. [9] have created a deep CNN dubbed DeTraC that can correctly categorize COVID-19 chest X-ray pictures with a high accuracy of 93.1%.

A study [10] analyzing eighteen CNN models for COVID-19 diagnosis on chest X-ray images found that VGG-16, ResNet-101, VGG-19, and SqueezeNet had the highest accuracy of 90.7% and F1-score of 94.3%, respectively. SqueezeNet was the closest model to two certified radiologists' diagnosis, with a competitively good accuracy of 90.7% and faster than VGG-16. The researchers recommend both models as additional tools for COVID-19 diagnosis.

By fusing extracted characteristics with the original picture pixel data, the study [11] presents a novel feature extraction technique for disease categorization. It helps differentiate between medical images such as COVID and pneumonia by converting chest x-ray images into spectrograms using information from Andrews' curve function. The logistic regression classifier achieved 97.18% accuracy, 98.34% detection rate, 97.8% precision rate, and 0.99 AUC value.

To facilitate early diagnosis, a deep learning framework [12] is suggested for tasks involving the classification of chest X-ray images. Pre-trained convolution neural network models are used in the framework's pre-processing and classification stages. Sensitivity, specificity, precision, F1 score, and accuracy of 0.95 were all attained by the top model. The next subsection presents the proposed method for feature extraction from medical images.

The COVID-19 pandemic has prompted the development of advanced diagnostic and monitoring devices, including automated detection using multi-source generated data from chest X-ray images. A new classification model [13], PDMLP-Bi-LSTM, aims to differentiate normal, COVID-19, and other pneumonia cases using multi-level abstract features and correlations. The model uses parallel deformable multi-layer perceptrons and bi-directional long-short-term memory modules to extract and analyze features on parallel channels. Extensive simulations on 4099 CXR images validate the method's performance, indicating its potential for improving public health.

The article [14] explores the use of machine learning (ML) algorithms and applications in the COVID-19 pandemic. Traditional methods have been primarily focused on simple statistical and epidemiological methodologies, but the lack of medical testing for diagnosing and identifying solutions is a significant challenge. ML has advocated for various intelligence-based approaches, frameworks, and equipment to address medical industry issues. The article investigates the application of innovative structures, such as ML, in handling COVID-19-related outbreak difficulties. The article mainly aims to look at how different types of data affect COVID-19 research, the challenges in processing that data, the role of smart methods like ML, the creation of better ML algorithms for predicting COVID-19, the success of different strategies during the pandemic, and to identify potential problems in diagnosing COVID-19 to encourage researchers to innovate and broaden their studies in other areas affected by the virus. The review aims to help data scientists form cross-disciplinary collaborations and educate strategists and policymakers on the advantages and drawbacks of utilizing data science to combat the pandemic.

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In [15], a deep uncertainty-aware transfer learning framework for COVID-19 detection using medical images is proposed. Four convolutional neural networks (CNNs) are applied to extract deep features from chest X-ray and CT images. Machine learning and statistical modeling techniques are used to identify COVID-19 cases. Results show linear support vector machine and neural network models achieve the best results, with higher predictive uncertainty estimates for CT images. The COVID-19 pandemic has heightened awareness of long COVID, persistent symptoms experienced after acute infection.

The study [16] explores machine learning techniques to estimate long-term COVID development based on a serological study with 53 healthcare professionals. Four cases were analyzed using specific symptoms, comorbidity, and antibody information. Five ML models were used, along with dimensionality reduction techniques. The feature selection procedure was found to be the most suitable, with KNN achieving the best-balanced accuracy. The finding highlights the potential of ML as a decision-support tool in inferring long COVID symptoms.

The research [17] uses machine learning to diagnose COVID-19 from routine biomarkers, achieving a 95% accuracy rate using multiple classifiers. The study uses twelve feature selection techniques and five explainable artificial intelligence methods. Biomarkers like albumin, protein, eosinophils, and total white blood cells are crucial for accurate and timely detection. This advancement in automated diagnostic systems could significantly improve patient care.

The contribution [18] presents a robust methodology for early and cost-effective COVID-19 diagnosis using vocal features and machine learning techniques. It addresses challenges like feature extraction, imbalance, and predictor training. The methodology incorporates biomechanical aspects of vocal production and demonstrates high efficacy in predicting cases, making it a non-invasive and cost-effective alternative.

The research [19] a feature engineering method for machine learning. The work mainly focused on retrieval of important invariant properties from medical images. These invariant properties could aid classifiers for better classification. Although, the method performed well, but this work is limited to extraction of a small set of invariant features from images for classification.

Research contribution [20] explores the use of deep learning (DL) techniques for lung ultrasonography (LUS) images, focusing on the COVID-19 pandemic. It presents a fully annotated dataset of LUS images from Italian hospitals and introduces several deep models for automatic analysis. The study presents a novel deep network, a new method for effective frame score aggregation, and benchmarks state-of-the-art models for estimating COVID-19 imaging biomarkers. The results show promising findings for future research.

The next subsection describes the proposed method for feature extraction.

3. PROPOSED METHOD FOR FEATURE EXTRACTION FROM IMAGES

In this section, a new technique to extract invariant image features from chest x-ray images is proposed. Our method for feature extraction is based on the sliding window. The idea behind the proposed feature extraction is to use a sliding window to extract local features in the image with respect to each sliding window whose size is wxw.

So, for a given image of size nxn, we will have (n-w+1)*(n-w+1) computations. For each sliding window of size wxw, we extract (w+3) invariant features local to each sliding window. All these locally extracted features with respect to each sliding window can capture variations in the image as a whole globally.

Thus, the proposed method aims at extraction of matrix invariant features from each chest x-ray images local to the sliding window and such invariant features which are extracted shall be then used to perform image classification and prediction for disease diagnosis using machine learning classifiers or a dense MLP, a deep neural network.

Following are the advantages of the proposed feature extraction method.

i. Matrix invariant properties-based feature extraction provides a simple, efficient, and interpretable way to extract meaningful features from image data.

ii. This method excels in scenarios where the data is limited, and the task involves capturing local patterns, or computational efficiency is a priority.

iii. By applying the applied linear algebra operations, our feature extraction method ensures robustness to transformations (like image translation, image scaling, and image rotation), i.e. extracted image features are not affected by image transformations.

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3.1 Novelty of the Proposed Method

The novelty of the feature extraction technique introduced in this paper includes

(i) No Convolution & No Filters

- Proposed feature extraction approach does not apply convolution or filters.
- Matrix invariant features are extracted using fixed-size window patches (such as 3x3, 5x5 sliding window).

(ii) Matrix Invariant Properties

- Extracted matrix invariant properties such as matrix rank, matrix determinant, matrix trace, eigen values of each window patch are not affected by image transformations.
- For every sliding window patch of size WxW, we extract (W+3) properties. These W+3 properties capture local patterns in the image which represented global pattern as a whole.

(iii) Feature Map

- The resulting feature vector (Eg: 28x28x8 or 30x30x6) represents a transformed version of the original image where each value represents features extracted from local region of the image.

3.2 Significance of the Image Invariant Features

The proposed feature extraction technique effectively captures invariant features in chest x-ray images, making it a significant tool for image analysis. The invariant features for each image include

(i) Rank Space:
Rank Space also called as dimension of column space measures number of basis vectors in the column space w.r.t image within the chosen window size. Rank space of an image represents the complexity and structure of the image. A low rank value indicates a homogeneous region while a high rank indicates a heterogeneous region with complex image patterns. For example, Healthy X-rays are low-rank with regular lung texture whereas diseased X-rays introduce high rank components because of lung opacity, fibrosis, consolidations etc. Similarly, static image structures have low rank.

(ii) Determinant: High value of a window matrix indicates more variations or complex image structure.

(iii) Trace: Represents overall Intensity in the sliding window of size wxw.

(iv) Eigenvalues:

a. Provides insight about the spread or variance of the matrix.

b. They can reveal the texture information and the structure information in the sliding window.

(v) Characteristic Polynomial: Encapsulates the matrix properties such as the sliding window matrix rank, its determinant, trace and eigen values. These features represent the characteristic structure of the image patch of size WxW.

Fig.1 depicts the pictorial representation of the proposed technique for feature extraction from chest x-ray images. For instance, consider a 32x32 chest x-ray image and a sliding window with 5x5 size.

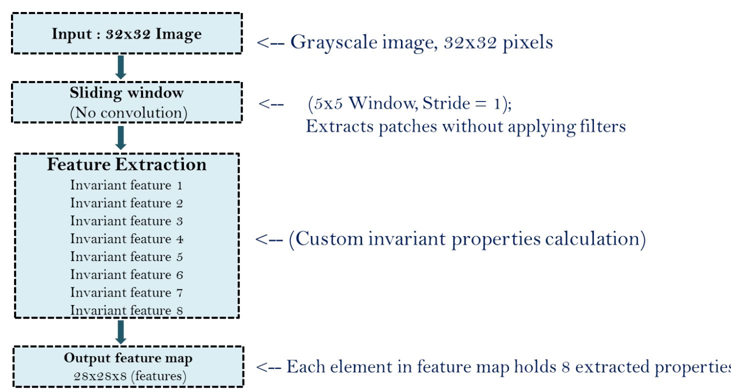

Figure 1: Utilizing the proposed technique for feature extraction

In this case, we obtain 6272 invariant features with each 5x5 sliding window shall be used for extracting 8 invariant features. Thus, the output feature map dimension is 28x28x8. In our approach, we eliminate the convolution step usually applied for feature extraction rather we consider the invariant features that are extracted.

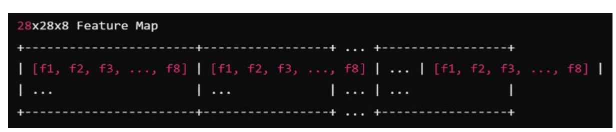

Figure 2: Demonstration of the Feature map for a 32x32 Image size and 5x5 sliding window

Fig.2 demonstrates feature map obtained w.r.t a 5x5 sliding window. The features extracted by the 5x5 sliding window are formed as a row vector. Each sliding window of size 5x5 extracts 8 image invariant features which is shown using the pictorial representation. All these features would be finally used to form a global feature vector for respective image.

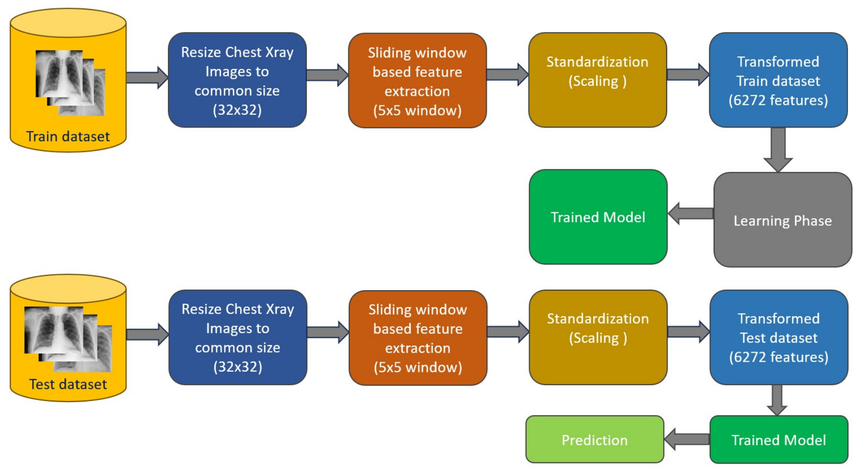

Fig.3 Proposed Architecture

4. RESULTS AND DISCUSSION

In this section, we present and discuss the experimental results which are obtained using our feature extraction technique. For classification task, along with eight benchmark machine learning classifiers, we have also considered the dense MLP model (also called as deep neural network, DNN). All experiments presented in this paper have been performed on Intel(R) Xeon(R) CPU E5-2680 v4 @ 2.40GHz (2.40 GHz) (2 processors) with a 128 GB RAM, 64-bit operating system, x64-based processor.

4.1 Dataset Description

In this work, the curated dataset by Pratik Bhowal et al. [10] is utilized. The Novel COVID-19 Chestxray Repository is available publicly at Kaggle (https://www.kaggle.com/datasets/subhankarsen/novel-covid19-chestxray-repository/data) [10]. This research is mainly curated for researchers to design, validate and build their machine learning models. This dataset originally consists of 3975 images which are categorized as Normal, Covid and Bacterial Pneumonia classes. For experimental study, in this work, we have divided the original dataset into two subset datasets (i) training dataset - consisting 3576 images out of which 1475 are normal chest x-rays, 1425 chest x-rays represent bacterial pneumonia and remaining 676 are covid chest x-ray images and (ii) test dataset - consisting 399 images out of which 164 chest x-rays are normal, 159 are bacterial pneumonia and 76 are covid chest x-ray images. The training dataset and testing dataset are formed by making 90% and 10% split. This division allows for a comprehensive assessment of the trained learning models ability to accurately classify and predict chest X-rays across different categories. Table 1 shows the class distribution of training and testing datasets used for experimental study in this work.

Table 1: Class Distribution of Train and Test datasets

	Normal	Bacterial Pneumonia	COVID	Total
Training data	1475	1425	676	3576
Testing data	164	159	76	399

4.2 Experimental Results

To evaluate our feature extraction technique, in the present work, we have considered five most widely used feature extraction techniques. They are (i) GLCM – Grey-Level Co-occurrence Matrix; (ii) HOG – Histogram of Oriented Gradients; (iii) LBP – Local Binary Pattern; (iv) PCA - Principal Component Analysis; and (V) LDA - Linear Discriminant Analysis. Then, features extracted using these feature extraction methods are provided as input for machine learning classifiers. The features extracted from images are then fed to the machine learning classifiers. For classification, we have chosen (i) Logit model also called as logistic regression classifier; (ii) Decision

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tree classifier; (iii) Gaussian Naïve Bayes classifier; (iv) Support vector machine (SVM) classifier; (v) Linear discriminant analysis (LDA) classifier; (vi) Multilayer perceptron (MLP) classifier; (vii) Quadratic discriminant analysis (QDA) classifier; (vii) XGBoost classifier. For feature scaling, we have used standardization to ensure that learned model does not get biased by varied ranges of image feature values. Further, for experimental analysis, we have resized all chest x-ray images in train and test datasets to a common size, 32x32. The sliding window size chosen is 5x5. Using proposed feature extraction technique, a total of 6272 image invariant features are extracted for each chest x-ray image in train and test datasets. The train dataset with these 6272 features is input for the ML classifiers for performance evaluation and the performance of the learned model is tested on the test dataset. In another experiment, we have used dense MLP, a deep neural network model consisting two hidden layers with 1024 and 512 neurons wherein from the train dataset, a part of the dataset is separated for validation on 90%-10% basis. Below we first present results for binary classification.

4.2.1 Binary classification using novel covid-19 chestxray repository dataset using covid and normal medical images

Table.2 presents the performance of the eight ML classifiers using existing and proposed feature extraction. The performance of some of the widely used methods for feature extraction (GLCM, HOG, LBP, PCA, LDA) and the proposed method are evaluated by using these eight ML classifiers. In the first experiment, 32x32 chest x-ray images are considered and features are extracted using a 5x5 sliding window w.r.t the proposed method. The features extracted using the proposed technique are input to ML classifiers and the model is trained. After obtaining the learned model from training phase, its performance w.r.t testing dataset is evaluated. The test dataset contains unseen images during training phase. It is found that out of the eight classifiers, the Logistic regression and MLP classifiers have performed the best when the proposed feature extraction is used for disease diagnosis. It is clearly evident from the Table.2, that performance of majority classifiers using the proposed feature extraction is better compared when compared to existing methods.

Experiments are also done by scaling using min-max and quantile methods. When we evaluated for min-max and quantile scaling methods, the accuracy attained by logistic regression was 74.58% and 88.75% respectively. However, SVM performance was not consistent. In the same case, MLP has attained 95.42% and 95.41% respectively. Also, it is observed that MLP is performing consistently for all scalings w.r.t the testing and training datasets. Table.3 presents MLP classifier performance for min-max, standardization and quantile feature scaling methods w.r.t accuracy, precision, recall, specificity, f1-score and balanced accuracy performance metrics. It can be seen that the imbalanced nature of the dataset did not affect the proposed feature extraction and resulting classification performance of MLP classifier w.r.t three scaling methods.

Thus, we suggest the use MLP classifier when employing the proposed feature extraction method. Overall, the MLP performance is better when we consider average performance achieved w.r.t accuracies of the MLP model on the test dataset.

Table 2. Performance of the Existing Feature Extraction Methods vs. Proposed Feature Extraction Method for Binary Classification Using Normal and Covid Chest X-rays from Novel Covid-19 Chest Xray Repository Dataset

		Feature Extraction Methods					
S. No	**Classifier**	GLCM	HOG	LBP	PCA	LDA	Proposed
1	Logit (or Logistic Regression)	59.65	85.21	66.67	83.96	82.96	96.25(↑)
2	Decision tree (DT)	57.14	69.42	63.66	71.93	79.45	86.64(↑)
3	Gaussian Naïve Bayes (GNB)	57.39	77.94	65.66	67.92	82.96	31.25
4	Support Vector Machine (SVM)	65.41	87.72	76.19	90.48	82.46	95.83(↑)
5	Linear Discriminant Analysis (LDA)	59.90	86.22	65.66	85.71	82.96	55.00
6	Multilayer Perceptron (MLP)	66.42	89.47	73.93	88.47	82.46	96.25(↑)
7	Quadratic Discriminant Analysis (QDA)	58.40	83.71	19.05	89.22	82.96	31.67
8	XG Boost	66.42	88.47	72.18	85.71	79.95	89.17(↑)

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Table 3. Performance of MLP Classifier for Proposed Feature Extraction Method Using Normal and Covid Chest Xray Images from Novel Covid-19 Chest Xray Repository Dataset

Classifier	Accuracy	Precision	Recall	Specificity	F1 Score	Balanced Accuracy
MLP(Min-Max)	95.42	92.21	93.42	96.34	92.81	94.88
MLP (Std)	96.25	93.51	94.74	96.95	94.12	95.84
MLP (Quant)	95.00	94.44	89.47	97.56	91.89	93.52

Figure 4(a) and 4(b) shows the confusion matrix obtained for the MLP classifier for train and test datasets when features are extracted by applying the proposed method and data is scaled using standardization. The RoC plots obtained for train and test datasets are shown in Fig 4(c) and Fig 4(d) respectively for MLP classifier model.

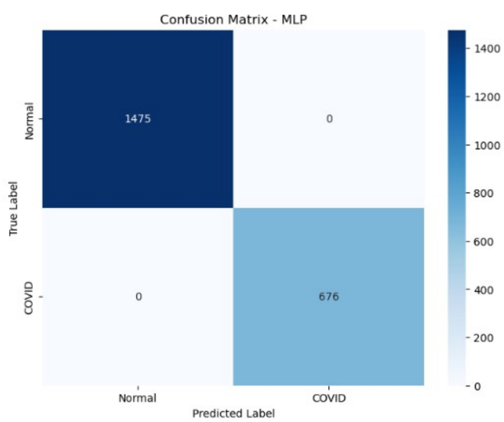

Fig 4(a) Train Confusion matrix for MLP

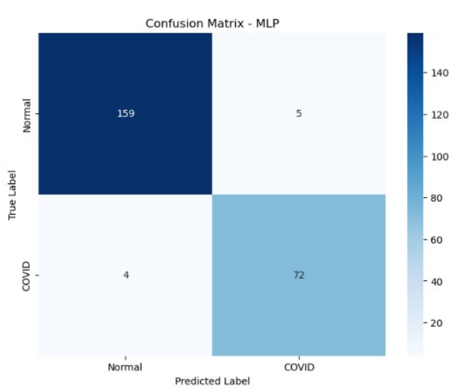

Fig 4(b) Test Confusion matrix for MLP

In another scenario, experiments are also carried by considering dense multilayer perceptron which is a deep neural network (DNN). The Dense MLP model (DNN) consisted of an input layer, two hidden layers and an output layer. The input layer consisted 6272 features that are extracted using proposed method. The two hidden layers consisted of 1024 and 512 neurons respectively. Also, each hidden layer is fully connected to previous and next layers. The output layer consisted 2 neurons for carrying binary classification. ReLU activation function is used for non-linearity. The DNN model is run for 100 epochs with a batch size of 32 and dropout rate chosen as 0.3.

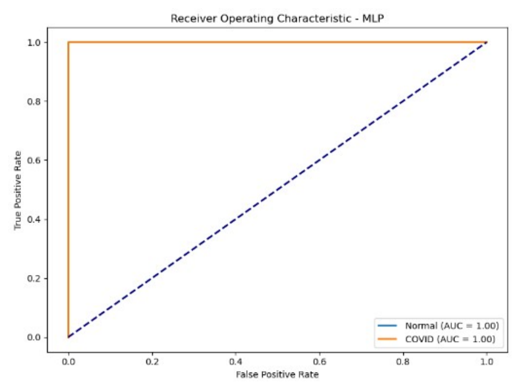

Fig 4(c) Train RoC Plot for MLP

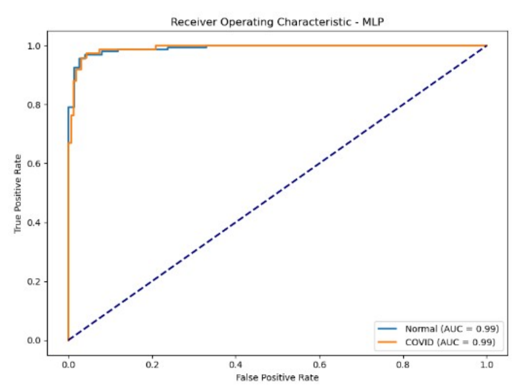

Fig 4(d) Test RoC Plot for MLP

To avoid overfitting of the DNN model, we have divided the train images originally considered into 90% train and 10% validation. Figure 5(a) and 5(b) shows the model loss and model accuracy plots for 100 epochs for train and validations cases. The train

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and test ROC plots are shown in Figure 5(c) and Figure 5(d) respectively.

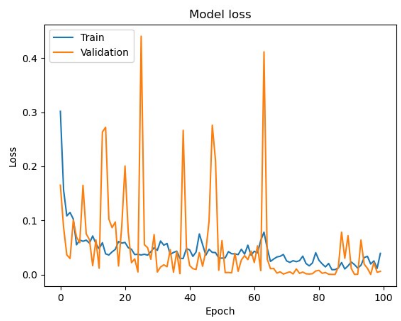

Fig 5(a) Model loss

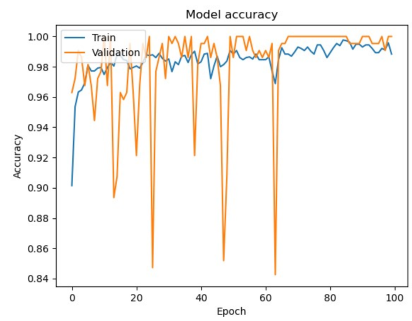

Fig 5(b) Model accuracy

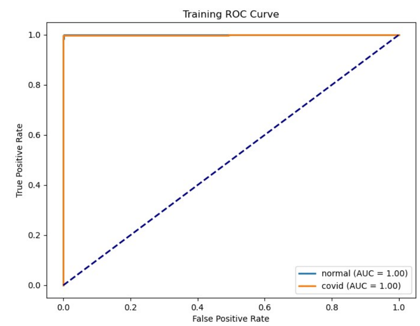

Fig 5(c) Train ROC for Dense MLP

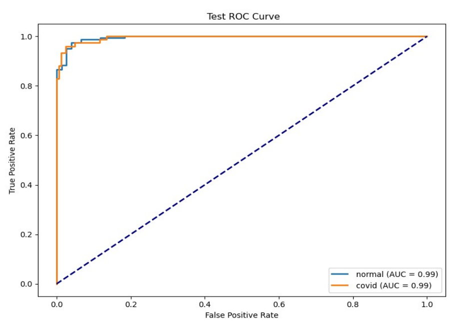

Fig 5(d) Test ROC for Dense MLP

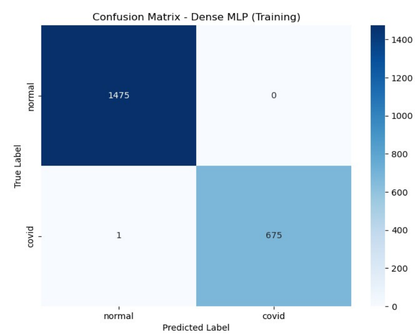

Fig 5(e) Train Confusion matrix

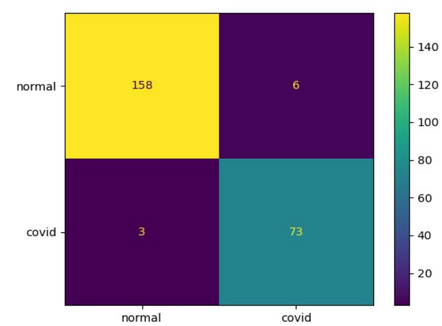

Fig 5(f) Test Confusion matrix

Table 4. Dense MLP performance metrics

Sensitivity	Specificity	Precision	Accuracy	F Score	Balanced Accuracy
96.05%	96.34%	92.4%	96.25%	0.9419	96.19%

Table 5. Performance metrics for XGBoost using proposed feature extraction

Accuracy	Recall	Precision	Specificity	Balanced Accuracy	F-score
93.98%	92.07%	93.21%	95.32%	93.69%	0.9264

Figure 5(e) and Figure 5(f) depicts the confusion matrix for train and test sets respectively obtained for the dense MLP DNN. The performance of DNN model w.r.t accuracy, precision, sensitivity, specificity, f-score and balanced accuracy metrics is depicted in the Table 4.

The balanced accuracy 96.19% implies that the model is performing well in terms of both classes, handling class imbalance effectively and F-score 0.9419 indicates that the model balances precision and recall shows the model's robustness, particularly in applications where both precision and recall are important.

4.2.1 Multiclass classification using normal, covid and pneumonia chest x-ray images using novel covid-19 chestxray repository dataset

The performance of the proposed feature extraction technique presented in this work is evaluated using eight machine learning classifiers as in the previous case and it is observed that when XGBoost is used with proposed feature extraction,

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the performance metrics are accuracy (93.98%), precision (93.21%), recall (92.07%), specificity (95.32%), balanced accuracy (93.7%) and f-score (0.9264) as depicted using Table 5.

The balanced accuracy 93.7% attained implies that the model is performing well in terms of three classes, handling class imbalance effectively and F-score 0.9264 indicates that the model balances precision and recall shows the model's robustness, particularly in applications where both precision and recall are important.

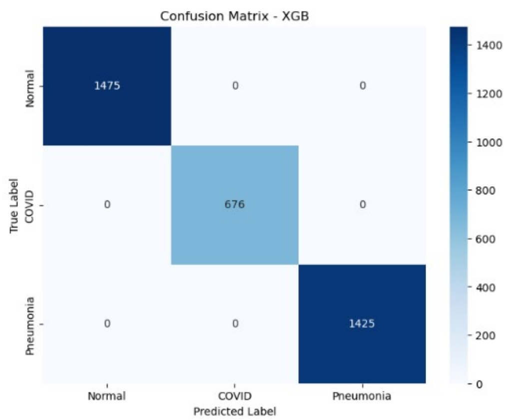

Fig 6(a) Train Confusion matrix for XGBoost

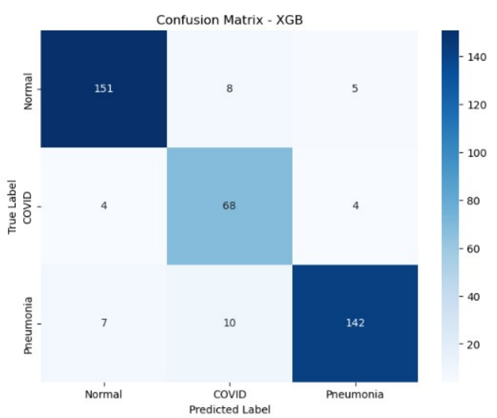

Fig 6(b) Test Confusion matrix for XGBoost

Fig 6(a) and 6(b) respectively represents the train confusion matrix, test confusion matrix for multi-class classification performed using XGBoost classifier. The RoC curve plots for train and test datasets for multiclass classification using normal, covid and pneumonia chestxrays applying the proposed feature extraction and XGBoost classifier for classification are presented using Figures 6(c) and 6(d) respectively. The performance of the proposed method is also compared to existing works in the literature and is depicted using the Table 5. The key insights from the related works are mentioned below.

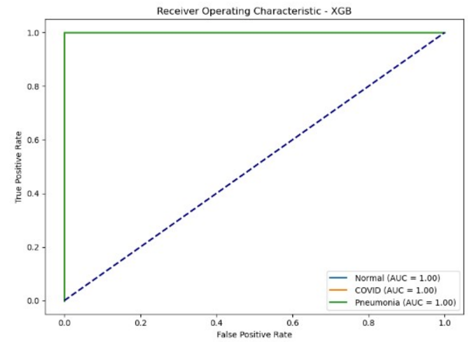

Fig 6(c) Train ROC plot for XGBoost

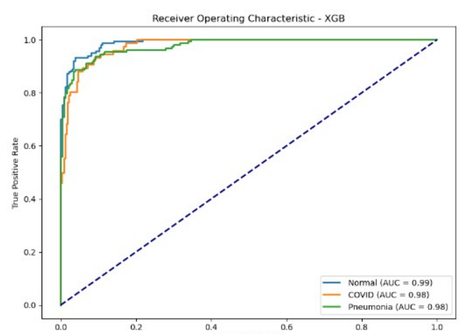

Fig 6(d) Test ROC plot for XGBoost

Overall Performance: The models with the highest accuracy are often those that balance both sensitivity and specificity, like the ones based on DenseNet201, VGG-16, and our methods.

Synthetic Data and Augmentation: Approaches like CovidGAN with synthetic data augmentation (Waheed et al.) significantly improve performance, especially for sensitivity and precision.

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Different Approaches: Models that use deep CNN architectures (like VGG-16 and VGG-19) and newer techniques, such as XGBoost (Sravan Kiran et al.), show great results in accuracy and balance across different measures.

Some models, such as Asmaa Abbas et al.'s DeTraC deep CNN, prioritize sensitivity, achieving perfect sensitivity but lacking specificity and F1 score data. Some models prioritize precision and F1 scores, especially in cases where false positives are particularly problematic. For instance, the XGBoost-based model by Sravan Kiran et al. achieves impressive F1 scores (97.84%) and precision (93.39%), which can be crucial for real-world applications where minimizing false positives is important.

Table.5 Performance of some of the related research works in the literature

S. No	Authors & Ref.No	Year	Learning Strategy	Accuracy	Recall	Precision	Specificity	Balance Accuracy
1	Pratik Bhowal et al. [1]	2021	3 class classification using DCNN for feature extraction and dense MLP for classification (VGG-16, Inception V3 and Exception)	91.22%, 93.48% and 92.98%	92%, 94% and 93%	92%, 94% and 93%	-	-
2	Vasilis Nikolaou et al. [2]	2021	hybrid CNN using a pre-trained ConvNet	91.53%	87.02%	81.82%	93.13%	90.07%
3	Abdul Waheed et al. [3]	2020	CovidGAN using CNN (Actual data + Synthetic Augmentation (CNN-SA)	85.41%	69.44%	89.28%	95%	82.22%
			Actual data + Synthetic Augmentation (CNN-SA)	94.79%	90.27%	95.58%	97.5%	93.88%
4	Harsh Panwar et al. [4]	2020	nCOVnet	88.01%	97.62%	82%	78.57%	88.09%
5	Wang et al. [5]	2020	COVID-Net	93.33%	91.0%	98.9%	-	-
6	Rahman et al. [7]	2021	DenseNet201	95.11%	94.55%	94.56%	95.59%	0.9543
7	Khan et al. [8]	2021	SVM	94.12%	-	-	-	-
8	Asmaa Abbas et al. [9]	2021	DeTraC deep CNN	93.1%	100%	-	-	-
9	Chow LS et al. [10]	2023	VGG-16	94.3%	95.2%	93.3%	-	-
10	El Houby et al. [12]	2024	VGG-19	95%	96%	-	94%	95%
11	Sravan kiran et al. [11]	2025	Proposed feature extraction and classification using XGBoost	95.37%	88.39%	93.57%	97.84%	93.39%
12	Our method	2025	Sliding window-based feature extraction and dense MLP for binary classification	96.25%	96.05%	92.4%	96.34%	96.19%
13	Our method	2025	Sliding window-based feature extraction and dense MLP for multiclass classification	93.98%	92.07%	93.21%	95.32%	93.69%

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The proposed sliding window-based feature extraction with the dense MLP method for binary classification shows strong results, with 96.25% accuracy, 96.05% sensitivity, and a 96.34% F1 score, which places it among the top-performing methods. When extended to multiclass classification, our method shows slightly lower accuracy (93.98%), but still maintains strong performance across sensitivity, specificity, and precision (93.69%). The performance can be increased by considering more train data. Our method also stands out, offering strong performance in both binary and multiclass classification tasks. However, depending on the application's needs, prioritizing certain metrics like sensitivity or specificity may influence model choice.

5. CONCLUSION

Feature selection and Feature extraction techniques directly affects the effectiveness and performance of learning models, it is critical in deep learning and machine learning applications. This study introduces a sliding window feature extraction method that enhances the effectiveness and efficiency of machine learning classifiers by being independent of image manipulations. The method improves binary and multiclass classification accuracy of chest X-ray images, particularly in differentiating between pneumonia, COVID-19, and normal images. The experiments use chest x-ray images from the Novel Covid-19 Chest X-Ray Repository collection. The suggested approach outperformed state-of-the-art research in terms of accuracy, recall, precision, specificity, and

balanced accuracy for both binary and multiclass classification. Our method shows competitive performance for both binary and multiclass classification tasks, with high accuracy, sensitivity, and a well-rounded set of metrics, particularly for binary classification. The present research study in this work suggests future research to develop new feature extraction techniques for effectively classifying and forecasting diseases from medical images.

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