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A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks

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Abstract

Pneumonia is a viral infection which affects a significant proportion of individuals, especially in developing and penurious countries where contamination, overcrowded, and unsanitary living conditions are widespread, along with the lack of healthcare infrastructures. Pneumonia produces pericardial effusion, a disease wherein fluids fill the chest and create inhaling problems. It is a difficult step to recognize the presence of pneumonia quickly in order to receive treatment services and improve survival chances. Deep learning, is a field of artificial intelligence which is used in the successful development of prediction models. There are various ways of detecting pneumonia such as CT-scan, pulse oximetry, and many more among which the most common way is X-ray tomography. On the other hand, examining chest X-rays (CXR) is a tough process susceptible to subjective variability. In this work, a deep learning(DL) model using VGG16 is utilized for detecting and classifying pneumonia using two CXR image datasets. The VGG16 with Neural Networks (NN) provides an accuracy value of 92.15%, recall as 0.9308, precision as 0.9428, and F1-Score0.937 for the first dataset. Furthermore, the experiment using NN with VGG16 has been performed on another CXR dataset containing 6,436 images of pneumonia, normal and covid-19. The results for the second dataset provide accuracy, recall, precision, and F1-score as 95.4%, 0.954, 0.954, and 0.954, respectively. The research outcome exhibits that VGG16 with NN provides better performance than VGG16 with Support Vector Machine (SVM), VGG16 with K-Nearest Neighbor (KNN), VGG16 with Random Forest (RF), and VGG16 with Naïve Bayes (NB) for both datasets. Further, the proposed work results exhibit improved performance results for both datasets 1 and 2 in comparison to existing models.

Keywords: Deep Learning; VGG16; CNN; Pneumonia; Neural Networks; X-ray;

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1. Introduction

Epidemics and chronic diseases have claimed the lives of countless individuals throughout historical time, causing huge crises that took many years to resolve [1][2]. Pandemics and eruptions are two different ways to define infectious diseases within communities over the years. Similarly, a pandemic is the emergence of more occurrences of injury, illness, or other medical problems than anticipated in a specific location between many or a particular group of people over a given period. The majority of the cases are ostensibly connected. The outbreak differs from a pandemic in that it is more confined and less liable to create public concern. One of the pandemics in the past includes pneumonia, which is a dangerous disease causing a large number of health issues.

In the United States alone, over 1 million individuals are hospitalized due to pneumonia each year, with nearly half a million deaths [3]. Apart from this, it was also reported by WHO in 2019 that, pneumonia killed 14% of children under the age of 5 worldwide. This motivates the expansion of a DL-based model for early pneumonia prediction so that precious human lives can be saved by providing timely medication and reducing the increased mortality rate caused due pneumonia. Chest X-ray (CXR) images is a highly effectual and accessible technique for detecting pneumonia, and serve an essential application in epidemiological studies and healthcare. Pneumonia identification in CXR images is a difficult and challenging task requiring professional radiologists' presence. It is a respiratory disease related to the chest due to the spreading of bacteria, infection, and fungus via breathing air [4]. This disease spreads to the chest, causing more breathing issues. Pneumonia is a leading cause of increased mortality in children as young as five. The most effective way of pneumonia detection is an X-ray image, which is more cost-effective and broad rather than other standard diagnostics procedures. Radiologists meticulously identify and analyze the X-ray images for detecting pneumonia which is a time-consuming process, and might lead to conflict among radiologists regarding disease prediction. Hence, this issue leads to the development of pneumonia detection methods that are safe to use in the healthcare department for real-time pneumonia diagnosis without any errors.

In disease diagnostic systems, machine learning (ML), DL and statistical methods are extremely efficient tools [5][6]. They may be used to solve highly sophisticated vision tasks in the healthcare imaging sector, such as lung disease classification, lung segmentation, and many more. Recent DL advancements have helped achieve and perhaps even significantly exceed human performance in many activities. DL can also be utilized to determine the outcome of treatments, such as chevalier studies and cancer treatment. Labeled data and DL-based algorithms are linked to encouraging results in thoracic illness categorization utilizing an X-ray image modality. Deep neural network (DNN) models have traditionally been built and tested by human professionals in a continuous trial-and-error technique that takes time, resources, and expertise [7].

To address this issue, an innovative model is presented which utilizes DNN architecture to efficiently execute ideal classification. The proposed model is designed exclusively for the classification and prediction of pneumonia by utilizing CXR radiographs. The technique works on the basis of neural network (NN) architecture, which uses several neurons to concatenate, identify and extract significant features from a set of images. Despite the state-of-the-art models, NN offers similarly focused network architectures of the train and test system, which has also been their developing premise. NN model has motivated DL-based algorithm to bring a standard choice for prediction and classifications of healthcare-based image dataset [7].

DL plays an important role while predicting the classification results [8]. Similarly, there are various models in DL which are used in the healthcare department for disease prediction [9]. But the usage of the DL models is dependent on the type of data. The used dataset in the paper is in the form of images, which shows the NN model is the suitable model for the type of dataset taken for the experiment. The NN is a model for analyzing information with a uniform grid, such as radiographs in the healthcare department, that is influenced by the organization of the human vision network and created to acquire spatial stratification of characteristics, spanning from the lowest to the highest level structures, autonomously and flexibly [9][10][11]. The convolution layer, pooling layer along with fully connected layers are the three levels of hierarchy that create a NN architecture where the initial two layers extract information, while the final layer is used to link the nodes completely and transfers those characteristics to the output layer and shows the classification results. There are various architectures of NN models which can be used for classification tasks. The architectures include Visual Geometry Group (VGG), ResNet (Residual Network), GoogleNet etc., for predicting accurate results in various sectors [9]. This work presents the use of the VGG16 transfer learning model for feature extraction due to its applicability with no restrictions for smaller strides and window size. It has the ability to insert 16 deep layers and hence can perform better on larger datasets. The proposed work presents a DL based model for quick and early pneumonia diagnosis by utilizing one of the NN architectures called, VGG16, in which the number of layers has been kept to 16 to decrease the higher computation time issues.

Further, section II introduces the state-of-the-art model. Section III describes the datasets and methodology used in the proposed method for pneumonia classification and prediction. Apart from this, the performance metrics along

with the results have been mentioned in Section IV. Lastly, the conclusion and future scopes have been discussed in section V.

2. Present State-of-the-art

This section describes works done using pre-trained and ensemble models for pneumonia prediction in CXR images. A hybrid ensemble model has been presented by Sirazitdinov et al. [5] for predicting pneumonia. This model was created using Adam optimizer, batch size of 8, where the learning rate, training-testing ratio, and input image size have been kept as 0.0001, 75:25 and 512*512, respectively. The results are concluded in the recall, and precision, along with F1-score values as 0.284, 0.288, and 0.286, respectively.

Ahmad et al. [12] have utilized a deep convolutional neural network(CNN) technique for feature extraction from the CXR radiographs dataset. The data were categorized into AUC, which indicated the severity of the patients' health challenges. The conclusion has been mentioned in the form of AUC as 0.98. Rajpurkar et al. [3] designed a 121-layer CheXNet model for predicting pneumonia in CXR data. The results were calculated as an F1-score and contrasted to an average real median F1-score value of 0.387, which is substantially lower than that of the CheXNet algorithm.

Zech et al. [13] have presented a CNN approach for pneumonia diagnosis and observed that the presented model might exaggerate real-world pneumonia forecasting accuracy. The experiment resulted in an AUC of 0.931. Rahimzadeh et al. [14] created a Deep CNN framework that predicts results in the form of efficiency by integrating the ResNet50V2 and XceptionNet models. The results were compared to other existing models with the highest accuracy of 91.4%. A CNN algorithm for the identification of pneumonia had been developed by Ieracitano et al. [15].

This model performs feature extraction from X-ray data of the chest and fuzzy images. Furthermore, the proposed model has been also compared to pre-existing algorithms and resulted an accuracy rate of up to 81%. Zhang et al. [16] have evaluated a variety of AI-based algorithms to detect pneumonia and concluded that Inf-Net algorithms might perform much better after doing a thorough analysis of the existing algorithms. Kundu et al. [17] have used an ensemble of three CNN frameworks, namely ResNet, DenseNet, and GoogleNet to diagnose pneumonia, with good results when compared to previous design techniques. Two datasets were used to perform the research in which results were shown in the form of accuracy as 87.02%, and 98.8% for Radiological Society of North America (RSNA) and Kermany's datasets, respectively.

Yaseliani et al. [18] have presented an ensemble hybrid DL system, consisting of an SVM, radial basis function, and logistic regression, in which three different classification processes are used, namely a fully connected layer for the categorization of images. In the second step, the weights have been set through which the features from the images are extracted. Lastly, the computer-aided model has been utilized for classifying CXR images. Mabrouk et al. [19] have expanded a DL model by combining DenseNet169, MobileNetV2, and Vision Transformer models for the prediction of pneumonia using CXR images. The three models were employed to extract the features from images, and finally, the extracted features have been used for the experimental process.

3. Materials and Methods

This section introduces the method used for pneumonia prediction in CXR images along with the dataset used for the experiment. In this work, the VGG16 which is a pre-trained feature extractor is used for feature extraction. VGG16 is an NN-based architecture that gained interest after the 2014 ILSVR (Imagenet) challenge [1]. NN comes under one of the best image categorization model architectures. It is remarkable in that it contains 3x3 filter convolution and uses the same max pooling and padding layer of a 2x2 filter rather than a huge number of hyper-parameters. The convolutional and max pooling layers are structured in a similar manner across the system. Finally, for output, there are two fully connected softmax layers [20][21]. The number 16 in VGG16 is attributed to the idea that it has 16 layers of varying weights with around 138 million parameters.

3.1 Datasets Description

The first dataset is gathered from Kaggle [22], which is split into two primary directories: train folder, and test folder; both directories comprise two subdirectories, including one containing pneumonia X-ray radiographs and another containing CXR radiographs for normal lungs. A number of 5,856 anteroposterior CXR images were efficiently selected from historical pediatric patients having an age between 1 to 5 years [20]. There are two labels

being used to split all the folders: pneumonia and normal, which were applied to all the other pneumonia X-ray images. The initial data classifications were amended and merged; thereafter, the entire image dataset was reorganized into 70% for training purposes, and 30% for testing. Hence, the measure of information is assigned to the complete dataset. A number of 5,216 X-ray images were allocated to the training, and 640 radiographs to the testing data to test the system. The dataset is a publicly accessible dataset: containing JPEG images only.
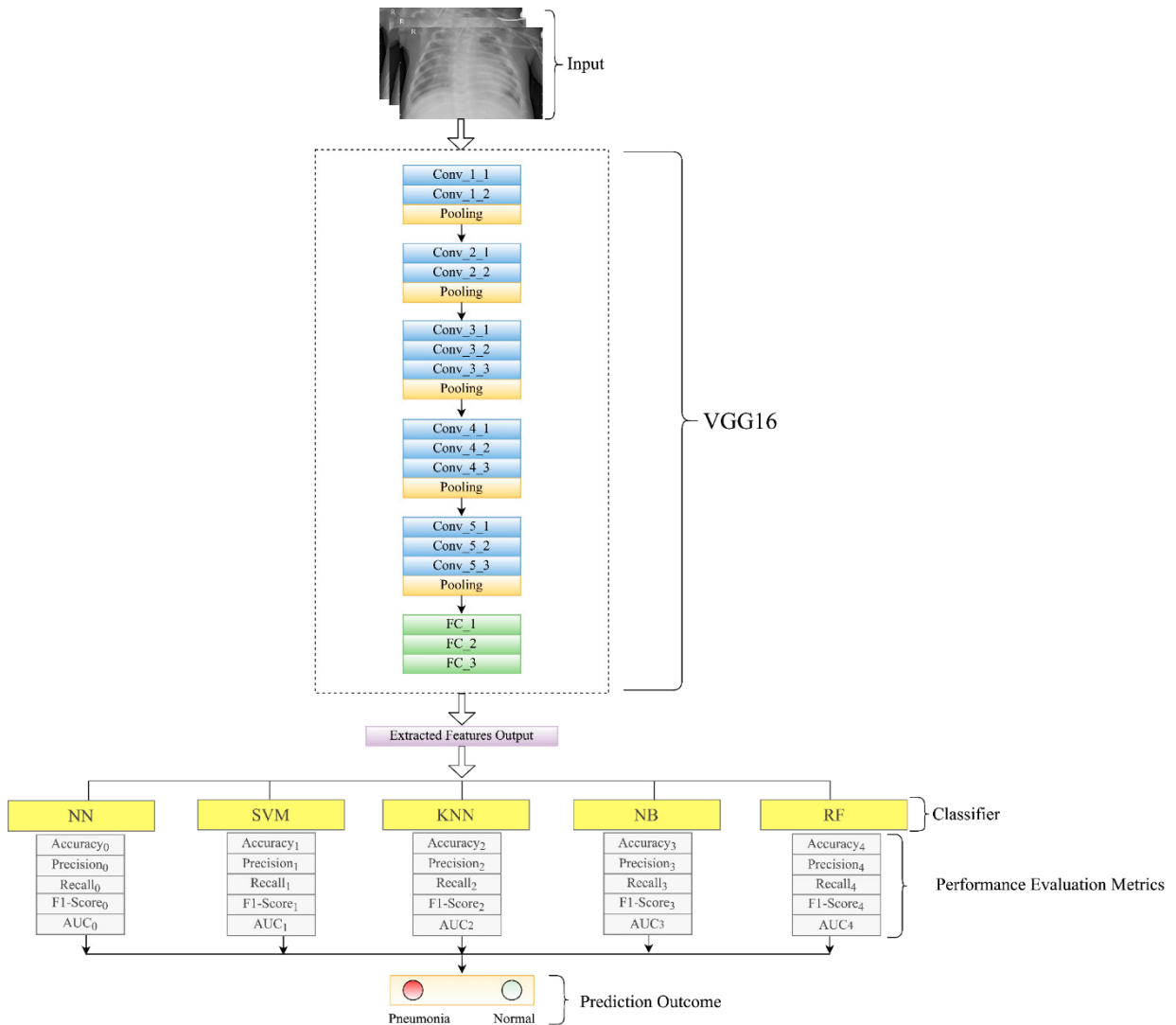

Fig. 1 Proposed deep learning model for pneumonia prediction

Originally, the anterior-posterior CXR dataset was collected from retroactive groups of children patients under the age of 1-5 at Guangzhou Medical Center for Women and Children [23].

The second dataset has also been collected from Kaggle [24], which is split into two directories, namely training and testing. Each of these directories has three subfolders: pneumonia, covid-19, and normal. The dataset contains 6,432 radiographs in JPEG format, out of which training is 80% data and testing is 20% data. This dataset is originally collected from several sources such as GitHub and kaggle. The train and test folders have subfolders containing 3418 pneumonia, 1266 normal, and 460 covid-19 images and the train folder contains 855 pneumonia, 317 normal, and 116 covid-19 images. The first dataset and second dataset are used for binary and multi-class classification, respectively.

3.2 Methodology

The proposed DL model is categorized into several parts: data collection, preprocessing, feature extraction [25], training, testing, classification, and pneumonia prediction, as shown in Fig. 1. The data preprocessing is done for balancing and normalizing the data, this technique is used to set the data in a normalized form between a range of [0-255]. Thereafter, the input data is fed to the VGG16 model for feature extraction. This step is capable of extracting features from the images and feeding them to the classification for further prediction process. The VGG16 has 16 layers, including input, convolution, pooling, dense, and output, which are responsible for an in-depth and better feature extraction process. The proposed model has been implemented in the Orange 3.31.1 simulator. It uses the Adam optimizer, 0.0001(learning rate), and the ReLu activation function is utilized. Afterward, the extracted features have been fed to various classifiers, namely NN, SVM, KNN, random forest (RF), and naïve Bayes (NB), for analyzing the prediction results, whether the data sample has pneumonia or not. The training of whole model is carried out on the training dataset having 70% out of the whole data and 30 % for the test data set 1. Whereas the training and test ratio of dataset 2 has been taken as 80:20. Finally, the results of both the datasets are compared to validate the model.

4. Performance Evaluation

The results of the proposed model are estimated using various metrics, including accuracy, precision, F1-score, and recall, as shown in Table 1. These metrics require a brief definition of four terms, namely, "false positive", "true positive", "false negative", and "true negative". "false positive (FP)" refers to the samples which belong to negative classes but are predicted to belong to positive classes. "true positive (TP)" refers to samples that are classified as positive and also belong to the positive class. "false negative (FN)" samples are those that belong to the positive classes but are anticipated to belong to the negative classes. "true negative (TN)" refers to the samples which belong to the negative classes, and are predicted correctly. The metrics used for the proposed models' prediction are defined below:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$
$$Recall = TP/(TP + FN) \tag{2}$$
$$Precision = TP/(TP + FP) \tag{3}$$
$$F1 - score = 2/((1/Precision) + (1/Recall)) \tag{4}$$

The accuracy rate is a metric that indicates how many right predictions the algorithm has made. Nevertheless, if the data is unbalanced, the higher accuracy of the technique does not guarantee its capability to discriminate distinct categories effectively and efficiently. In healthcare, image categorization is a technique that can be applied to every class in the dataset. The "recall" and "precision" values provide information about the model's efficacy in such instances. The term "precision" refers to the rate of positive label accuracy. It provides the percentage of accurately predicted values to the total number of predictions classified using the model. In contrast, "recall" refers to the value %age of true positives anticipated accurately by the model. The "F1-score" balances "precision" with "recall," taking into account both FNs and FPs. Extreme values of "recall" and "precision," each of which is at the loss of the other, are assessed. To acquire an accurate determination of a normal patient along with diseased patients, it is worthwhile to examine evaluation measurement metrics instead of only the accuracy metric in diagnostic image identification.

4.1 Results and Discussion

This subsection introduces and illustrates a detailed discussion of the obtained outcomes using the proposed model for pneumonia prediction.

- NN classifier with VGG16: The performance of the proposed model has been found better for the prediction of pneumonia, in which various performance metrics have been calculated with the least value of error. The model has predicted a quite better performance with an overall accuracy of 92.15%, precision as 0.9428, and recall as 0.9308, whereas F1-score is 0.937 for dataset 1 as tabulated in Table 1. The model exhibits overall accuracy of 94.5%, precision as 0.954, recall as 0.954, and F1-score as 0.954 for dataset 2.

Table 1. Performance outcome of proposed work using two different datasets

Models	Dataset 1					Dataset 2				
	Accuracy	Precision	Recall	F1-score	AUC	Accuracy	Precision	Recall	F1-score	AUC
NN with VGG16	92.15%	0.9428	0.9308	0.937	0.974	95.4%	0.954	0.954	0.954	0.988
SVM with VGG16	91.5%	0.916	0.916	0.914	0.968	94%	0.942	0.940	0.940	0.988
KNN with VGG16	91%	0.91	0.91	0.91	0.959	91.9%	0.922	0.919	0.919	0.969
RF with VGG16	87.2%	0.871	0.872	0.871	0.951	91.1%	0.912	0.911	0.911	0.971
NB with VGG16	84.8%	0.856	0.848	0.849	0.908	83.4%	0.872	0.834	0.839	0.834

The results are also shown in ROC graph as shown in Fig. 2 for first dataset and in Fig.3 for second dataset applicable to representing the degree of separatability. ROC illustrates the depiction of the relationship between recall and precision. It is used to show the evaluation of binary classification graphically. Whereas other methods result in a single value for representing the performance. ROC is a well-known curve to identify a good classifier the closer the ROC is to the top left of the graph better the model is.
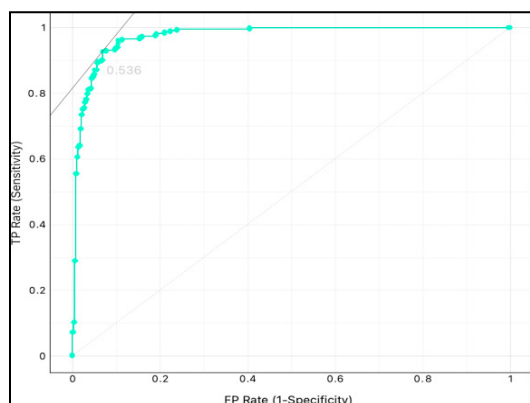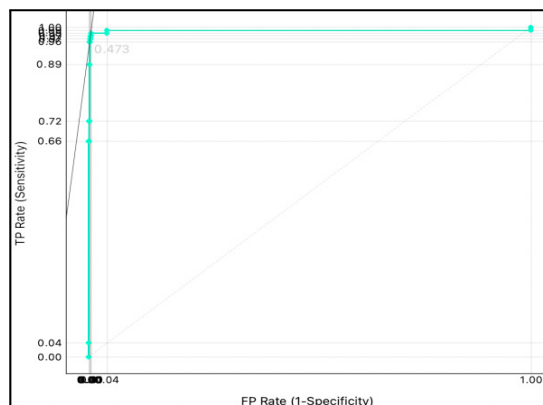

Fig. 2 ROC of NN with VGG16 for first dataset

Fig. 3 ROC of NN with VGG16 for second dataset

● SVM with VGG16: SVM is a model which is used for classification tasks and reduces over fitting issues in the datasets [26]. In this work, the SVM with VGG16 model is compared with the classification outcomes of the proposed NN model with VGG16 model. The outcome SVM with VGG16 has been identified in the form of recall, precision, accuracy, and F1-score as 0.915, 0.916, 91.5%, 0.914, respectively, and ROC as shown in Fig. 4 for dataset 1. However, dataset 2 achieves accuracy, recall, precision, and F1-score of 94%, 0.94, 0.942 and 0.94, respectively, using SVM with VGG16. The comparison has shown that the proposed NN with VGG16 performs better than the SVM model with VGG16, as the accuracy of NN with VGG16 is quite higher for both the datasets than SVM with VGG16 for pneumonia classification.
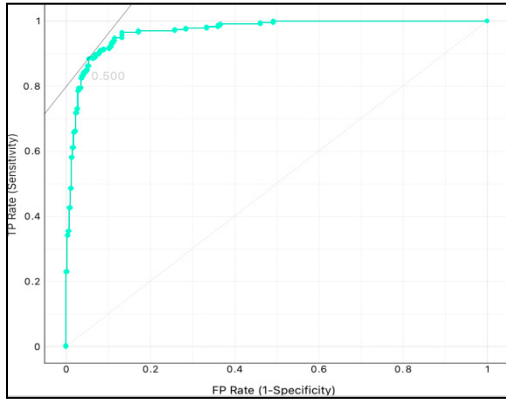
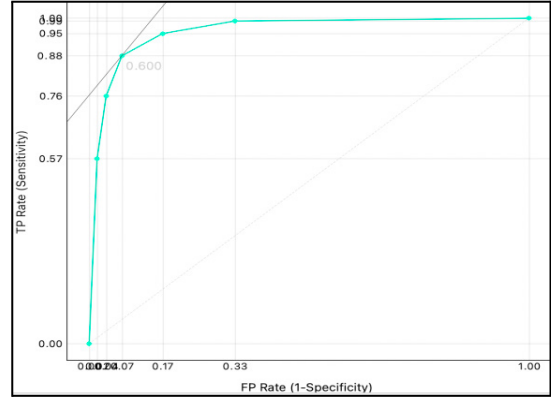Fig. 4 ROC of SVM with VGG16 for first dataset

Fig. 5 ROC of KNN with VGG16 for first dataset

● KNN with VGG16: KNN is a supervised ML model utilized for classification tasks [27]. The proposed NN model with VGG16 classification results are compared to the KNN model with VGG16 classification results. The ROC is illustrated in Fig. 5 for dataset 1. The outcome has been identified as precision, recall, accuracy, and F1-Score as 0.91, 0.91, 91%, and 0.910, respectively, for dataset 1. Dataset 2 achieves accuracy, recall, precision, and F1-Score as 91.9%, 0.919, 0.922, and 0.919, respectively. As a result of the comparison, the proposed NN model with VGG16 performs better than the KNN model with VGG16 for both the datasets.
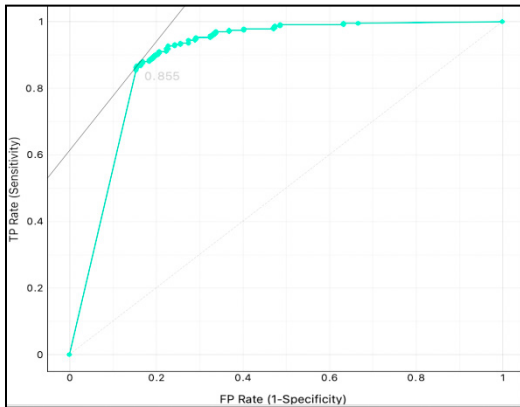

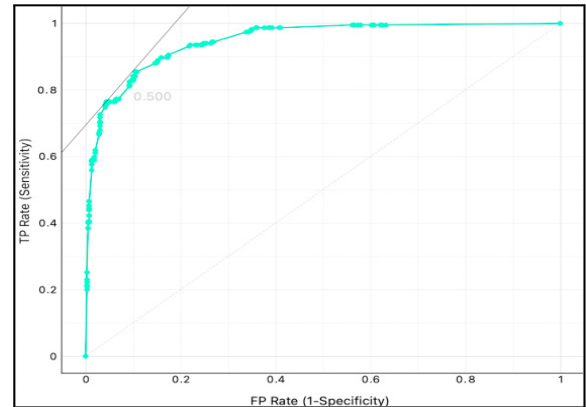Fig. 6 ROC of Naive Bayes with VGG16 for first dataset

Fig. 7 ROC of Random Forest with VGG16 for first dataset

● NB with VGG16: The classification results of NB with VGG16 model are compared with the proposed NN with VGG16 model The ROC is depicted in Fig. 6 for dataset 1. The outcomes of NB with VGG16 for dataset 1 are recorded in terms of recall, precision, accuracy, and F1-score as 0.848, 0.856, 84.8%, and 0.849, respectively ; however the dataset 2 achieves precision, recall, accuracy, and F1-score as 0.872, 0.834, 83.4%, 0.839 respectively. As a result of the comparison, the proposed NN model with VGG16 performs better than the NB model with VGG16 for both datasets, because the accuracy for pneumonia classification is substantially higher.

● Random Forest (RF) with VGG16: In comparing classification results of the proposed NN with VGG16 model and the results of RF with VGG16, it has been found that the proposed NN model with VGG16 performs better in case of a recall, precision, accuracy, and F1-score for both datasets. The results of RF with VGG16 for dataset 1 are noted as recall, precision, accuracy, and F1-score as, 0.872, 0.871, 87.2%, 0.871, respectively; however, dataset 2 achieves recall, precision, accuracy, and F1-score as 0.911, 0.912, 91.1%, 0.911 respectively. Furthermore, the ROC curve of the RF with VGG16 for dataset 1 is also shown in Fig. 7.

4.2 Performance comparison of NN, SVM, NB, RF, and KNN using VGG16 Feature Extractor

This section illustrates the comparative analysis of the various models for both datasets with respect to various performance measures:
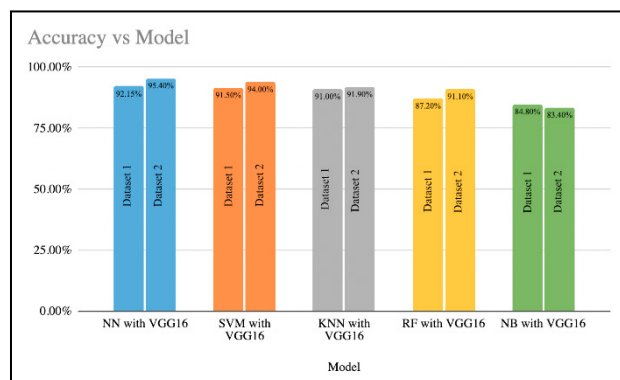

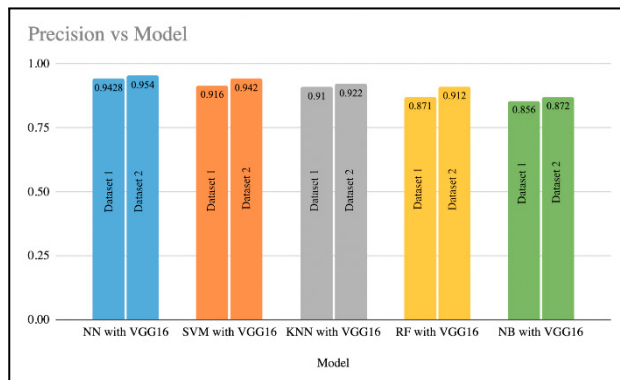Fig. 8 Accuracy comparison of several models with the proposed work (NN with VGG16)

Fig. 9 Precision comparison of several models with the proposed work (NN with VGG16)

Fig. 8 depicts the graph of accuracy comparison of several models. The proposed NN with VGG16 has been determined as the outperforming pneumonia prediction model having the highest accuracy in both datasets as compared to SVM with VGG16, KNN with VGG16, RF with VGG16, and NB with VGG16 model. As the accuracy depicts the models' performance, NN with VGG16 can be seen as the best performing model among all other models. Furthermore, for the dataset 2, the accuracy of NN with VGG16 has also been found highest among all 95.40%.

 Fig. 9 presents a graph of the precision comparison of various models, in which the proposed technique NN with VGG16 is determined to be the best model for predicting pneumonia, with the highest precision for both datasets. The precision defines the number of positive predictions made by the model, NN with VGG16 can be considered the best performing model among the others used in the study. The precision value for the second dataset has been found very high as 0.954 using NN model with VGG16 which outperforms the other models.
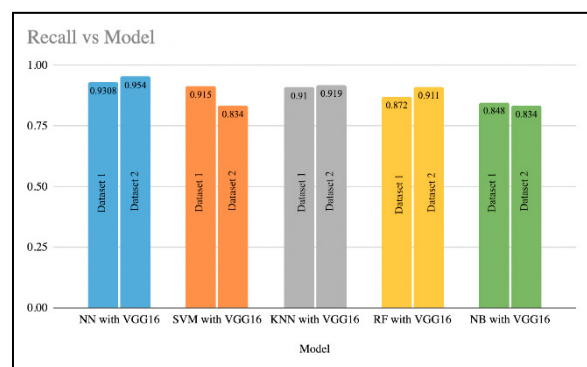

Fig. 10 Recall comparison of several models with the proposed work (NN with VGG16)
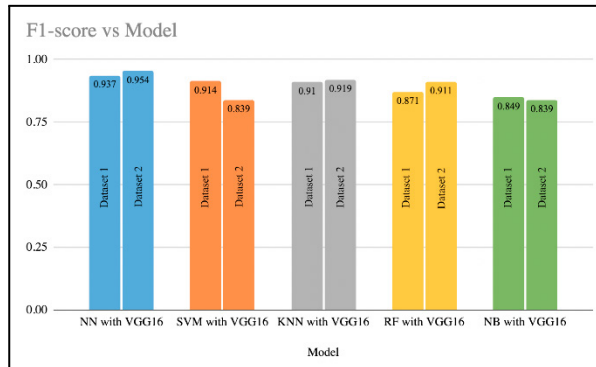

Fig. 11 F1-score comparison of several models with the proposed work (NN with VGG16)

Fig. 10 illustrates the graph of recall comparison of numerous models, in which the proposed technique NN with VGG16 has been determined as the outperforming pneumonia prediction model with the highest recall for both datasets. As recall defines how many positive predictions are truly right out of a total number of positive predictions, NN with VGG16 can be considered the highest performing model among all other models used in the study. The recall of the second dataset using NN with VGG16 is the highest among all 0.954 compared to other models.

F1-score is a performance metric which is used to identify the performance of a classifier. The range of the F1-score is between 0-1. The value of the F1-score near 1 shows the better performance of the model. Fig.11 depicts an F1-score comparison of various models, in which the proposed NN with VGG16 has been identified as the best model for predicting pneumonia, with the highest F1-score value for both the datasets, when compared to the SVM with VGG16, KNN with VGG16, RF with VGG16, and NB with VGG16. The F1-score determines the harmonic mean of precision and recall; hence, NN with VGG16 can be considered the best-performing model among the other models used in the study. The NN with VGG16 has achieved an F1-score value of 0.954 for dataset 2, which is the highest among all.

4.3 *Performance outcome comparison of the proposed model with the existing models*

In this section of the paper, the results of NN with the VGG16 model are compared with the results of the models presented in the literature review as shown in Table. 2. In this comparison, it has been found that the proposed model outperforms the other models i.e. ResNet50V2+XceptionNet [14], CovNNet[15] and GoogleNet+ResNet18+DenseNet[17] in terms of accuracy. Whereas the precision and recall have been found quite higher than RetinaNet+Mask R-CNN presented in [5]. Finally, the F1-score is also found higher than in 121-Layer ChexNet[3] and RetinaNet+Mask R-CNN[5]. Conclusively, the proposed model exhibits better results for datasets 1 and 2 than other models presented in the literature.

Table 2. Performance comparison of NN with VGG16 feature extractor with the existing models

Reference	Model	Dataset	Accuracy	Precision	Recall	F1-score
[14]	ResNet50V2+XceptionNet	Chest X-ray (11,302 images)	91.4%	-	-	-
[15]	ConvNet	Chest X-ray (26,684 images)	81%	-	-	-
[17]	GoogleNet+ResNet+DensNet121	RSNA	86.85%	-	-	-
[5]	RetinaNet+Mask R-CNN	Chest X-ray (26,684 images)	-	0.288	0.284	0.286
[3]	121-layer ChexNet	Frontal view X-ray (1,00,000 images)	-	-	-	0.387
Proposed NN with VGG16 (Dataset 1)		Chest X-ray (5,856 images)	92.15%	0.9428	0.9308	0.937
Proposed NN with VGG16 (Dataset 2)		Chest X-ray (6,436 images)	95.4%	0.954	0.954	0.954

5. Conclusion and Future Scope

Early identification of pneumonia is essential for selecting the best alternative treatments and providing the timely medication to save precious lives. X-ray images are among the most common methods for detecting pneumonia; unfortunately, they are susceptible to cross variability, and the identification is dependent on the ability of the clinician to detect initial pneumonia symptoms. In this article, a DL-based model is presented to support health professionals, and it leverages the DL-based classification of CXR radiographs into 2 categories: normal and pneumonia. The results of the research exhibit that NN with VGG16 model provides better performance for datasets 1 and 2 than SVM with VGG16 model, KNN with VGG16 model, Random Forest with VGG16 model, and NB with VGG16 model. The NN with VGG16 model provides an accuracy value of 92.15%, precision as 0.9428, recall as 0.9308, and F1-score 0.937 for dataset 1; however the dataset 2 achieves accuracy value of 95.4%, precision 0.954, recall 0.954, and F1-score 0.954 which is highest among all. It is concluded that the proposed model NN with VGG16 exhibits better performance than other classification models mentioned in the literature review section. The highest accuracy results achieved with proposed NN with VGG16 for pneumonia prediction are 92.15% and 95.4% for dataset 1 and dataset2 respectively. The research outcome exhibits that the proposed model NN with VGG16 exhibits the highest accuracy of 95.4% for dataset 2 as compared to other existing models to diagnose normal lungs,

covid-19, and pneumonia. In the future work, to achieve higher performance outcomes of the DL model the dataset can be increased with augmentation and the number of hidden layers may be increased for the deep convolutions in the model.

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