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A Robust and Efficient Hybrid Classification Model for Early Diagnosis of Chest X-Ray Images of COVID-19

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Abstract

There has been a COVID-19 pandemic since December 2019, and successful medical treatment for COVID-19 patients requires rapid and accurate diagnosis. Fighting the COVID-19 pandemic requires an automated system that uses deep transfer learning to diagnose the virus on chest X-ray (CXR). CXR are frequently utilized in healthcare because they offer the potential for rapid and accurate disease diagnosis. Automated computer-aided diagnosis (CAD) systems incorporate ML or deep learning to enhance efficiency and accuracy, hence reducing future problems. Numerous AI systems based on deep learning can be employed for diagnosis; among the most widely used is the CNN, which was first developed and has demonstrated encouraging accuracy in identifying COVID-19 confirmed patients using CXR pictures. Through using X-ray images, this work will design ML and deep learning to provide faster diagnostics for Covid-19 infection. As a result, the deep transfer learning technique uses an existing model first, then applies the needed data to it again. Where a Densenet201transfer learning model was utilized, which is one of a DL techniques, as feature extraction and its combination with multilayer perceptron algorithm; these technique were applied to a data set of a National Institute Health (NIH), where several performance measures were utilized, such as precision, precision, specificity and sensitivity, as an experiment proved the efficiency of the algorithm used in terms of accuracy by 98.82%. These outcomes are encouraging when compared to other DL models that were trained on the identical dataset.

Keywords: Chest X-Ray, Deep Learning, Machine Learning, Densenet201, Multilayer Perceptron Algorithm.

Introduction

More than 670 million illnesses and no less than 6.8 million fatalities have been attributed to COVID-19 (coronavirus disease 2019) all over the world [1]. The present gold standard to detect and diagnose SARS-CoV-2 (SARS-CoV-2) is polymerase chain reaction (PCR)[2]. But the PCR test could produce false negative results[3]. Moreover, obtaining correct clinical results with high efficiency has become very important. The number of patients infected with the Coronavirus requires the correct use of resources and the provision of quality services to maintain the safety of infected patients as well as health workers. Lung tomography, one of the most frequently utilized medical instruments, has indisputable diagnostic significance in identifying a number of illnesses[4]. The benefits regarding an AI-based method include its lower cost; availability and ease of use in a variety of therapeutic settings, including both community and hospital settings. The implementation regarding such approach in high-volume diagnostic environment could be self-limiting because, despite the fact that any doctor can get a clinical impression from a lung X-ray, X-ray results should be validated through a radiologist. Specifically, the speed of results validation is based on the radiologist's availability and the size of the images need to be studied [5-7]. Because of this, the automatic identification of lung disorders through AI is now an extremely significant concept and is regularly assessed in the study disciplines of medical informatics and radiology. Therefore, the coronavirus epidemic can be better managed with prompt and accurate COVID-19 diagnosis using chest X-rays and symptoms. In addition, it will help healthcare systems, which include medical professionals, nurses, and doctors, safeguard vulnerable people[8-10]. With the help of AI, there has been a gradual expansion of AI's use in healthcare from research facilities to hospitals and public health agencies[11].

With the use of AI, there are many different ways to analyse complicated data in order to learn more about COVID-19. AI utilises ML and DL to develop algorithms that may be applied in the biomedical and clinical domains to classify and stratify patients using a variety of data sources that have been paired and processed. Using AI to identify high-risk patients early on, treat them, and control the spread of disease is the most important contribution. In addition, by alerting authorities of COVID-19 outbreaks in a timely manner, AI can aid in pandemic management [12-15]. The majority of the time, CXR are used for classifying patients with COVID-19, and the results reveal that machine learning and deep learning (DL) algorithms do very well with regard to accuracy.

Research Motivation

The availability of large, well-annotated datasets, particularly in image classification, supports better feature selection and results that have clear boundaries between different classes and sufficient data to train on. Hence the model training on such diverse data is general enough to learn and class boundaries are also present when it comes to medical data there is a high probability of generalization error due to the unbalanced and limited availability of datasets. Thus, in order to make use of pre-trained models' characteristics and classification skills, ML and DL are applied to big datasets like ImageNet, which effectively capture class boundaries.

Research Contribution

This study's primary contribution is an application of new hybrid ML and DL called DenseNet and MLP for solving the task of COVID-19 detection from CXR data; the major contributions are summarized in the following way: -

- The DL-based diagnosis of MERS-CoV (COVID-19) is the updated version of previous work[14] and consists of two phases: detection and classification in relation to chest diseases such as normal, pneumonia and Coronavirus.
- The best feature extraction techniques such as dense convolutional network was used.
- A hybrid ML and DL model was utilized by combining the pre-training DenseNet201 CNN (convolutional neural network) model for feature extraction and MLP (multi-layer perceptron) model in terms of classification.
- The proposed hybrid method provides the best accuracy for the National Institute of Health (NIH) dataset.
- To evaluate a performance of proposed models according to accuracy, f1-score, loss, specificity, sensitivity, and precision.

Here is an outline of a paper: In Section II, they survey the literature on Covid-19 classification utilizing DL architecture and CXR. In Section II, they lay out the database requirements and methodology for our proposed model. In Section IV, they present the research's detailed results and compare them to those of other algorithms. Section V concludes the paper and discusses its future endeavours.

Literature Review

For the past seven years, substantial study was done in this field on diagnosing thoracic anomalies. In order to diagnose coronavirus, radiologists employ X-ray imaging. Having said that, it does take a long time to complete this process. Health care systems can thus benefit from artificial intelligence technologies that aid in decreasing pressure. Lafraxo and El Ansari [16], introduced CoviNet, a deep learning network capable of independently detecting the existence of COVID-19 in results obtained from chest X-rays. The suggested architecture is based on a CNN, histogram

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equalisation, and an adaptive median filter. It is trained from the ground up using data that is accessible to the public. In terms of binary classification, our model was 98.62% accurate, while in terms of multi-class classification, it was 95.77% accurate.

Rezaee K et al. [17], aimed to create a system that can automatically diagnose COVID-19 from CXRs by combining traditional ML models with pre-trained DTL architectures. The next step is to choose and classify the retrieved features in a manner that enhances the decision-making level for infectious illnesses such as bacterial and viral pneumonia. Iranian researchers at the Vasei Hospital in Sabzevar built a fresh CXR database to prove our method worked. With a success rate of over 99%, our hybrid model surpassed competitors' CXR of COVID-19 and comparable pneumonia classification model.

In Anwar T and Zakir S [18], there was an adoption of DL technology allows for a diagnosis of COVID-19 in individuals through chest CT-scan. For rapid and reliable coronavirus detection, the EfficientNet architecture is utilised, boasting an accuracy of 0.897, F1 score of 0.896, and AUC of 0.895. There are three approaches to learning rate optimisation: cyclic learning rate, constant learning rate, and reduce on plateau, which involves slowing down learning when model performance stops improving. With the reduce-on-plateau method, the F1-score was 0.9, whereas with the cyclic learning rate, it was 0.86 and with the constant learning rate, it was 0.82.

Triveni et al. [19], combined CNN with popular ML techniques like Bayes, RF, KNN, and MLP. The results show that for one dataset, the InceptionV3 architecture with an SVM classifier using a linear kernel achieves a 99.421 percent accuracy rate, making it the best extractor-classifier combo. A further standard, the optimal setup, is ResNet50 with MLP, which achieves an accuracy of 97.461%.

Karajah, and Awad [20], accelerated the process of diagnosing COVID-19 infections utilizing X-ray images by using a capabilities of DL and transfer learning. An updated version of a method from VGG 16 is the one that is being suggested here. It achieves better accuracy by modifying the architecture of the VGG16. After that, the model can determine if an X-ray image is normal or COVID-19-related. Modified VGG 16 achieves a 99.7 percent success rate.

Al Majid, et al.[21] utilized the Xception, InceptionV3, and MobileNetv3 models. Results show that models trained with Xception achieve 91% accuracy, InceptionV3 models 89% accuracy, and MobileNetV3 models 86% accuracy.

Kim et al.[22], provided to accomplish multiclass respiratory disease classification, a thorough training approach. Cutting and resizing procedures were employed in the initial pre-processing stage to remove any extraneous information from the samples. An efficientNetv2 network that has already been trained was utilised to generate a nominal feature set and assign the correct categories to subsequent photos. The three categories can be classified more accurately using this technique, yet the algorithm has performance and customisation limitations that worsen as the classes get bigger.

In Nawaz et al. [23], for identifying and classifying eight different types of chest deformity categories using X-rays, a method depending on DL work known as CXR-EffDet model was developed. EfficientDet-D0 depending on EfficientNet-B0 has been utilized for computing a specific set of key points samples and complete the classification task. Additionally, it is economically adaptable in identifying a range of CXR abnormalities; since it utilizes a single-stage object identifier to detect a number of different chest diseases, there is little performance degradation of images with a hazy effect.

Research Gaps

Advancements in medical imaging and artificial intelligence (AI) have exhibited potential in the automation of COVID-19 detection and diagnosis, thereby mitigating the temporal limitations inherent in conventional diagnostic procedures. By employing deep learning frameworks including EfficientNetv2 and CoviNet, as well as pre-trained models such as EfficientNetv2, scientists have successfully detected COVID-19 in chest X-ray and CT scan images with remarkable precision. A successful integration of convolutional neural networks with conventional ML techniques, such as KNN, Bayes, RF, and Neaural Networks, has highlighted the potential for enhanced classification results through the use of such combinations of classifiers. Nonetheless, there are still obstacles that must be overcome, such as the inability of algorithms to process larger classes, the requirement for real-time predictions, and the criticality of

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validating results in real-world healthcare environments. Although these developments enhance the efficacy and dependability of diagnostics, continuous research endeavours to tackle these obstacles and further optimise these methodologies.

Materials and Methods

This section provides a proposed methodology with each method that have used for this research development. Also it provides the algorithms and flowchart of each proposed algorithm.

Proposed Methodology

This research investigates a classification of CXR images, which is a crucial task in identifying cases of normality, pneumonia, and COVID-19. Based on an extensive review of the literature, they acknowledge the importance of machine learning and DL methodologies in a field of medical image analysis, specifically a DenseNet201 structure and the incorporation of Multilayer Perceptrons (MLP) to improve the precision of classification. It highlights the use of SMOTE for effective data balance and the necessity of downsizing photos to a standard 128 × 128 x 3 resolution as prerequisite preprocessing steps. The aim of this study is to provide a theoretical contribution to the rapidly evolving field of medical picture diagnostics. In particular, it uses complex NN designs, preparation methods, and data balancing strategies to improve the precision and reliability of CXR classification. Model architecture & preprocessing concerns are equally important as project outcome assessment indicators in our research technique. A number of measures, such as classified crossentropy loss, accuracy in training and validation, among others, will be used to assess the model. This method ensures that the model's learning dynamics are well understood. In addition, the implementation of testing datasets will play a important role in assessing a model's capacity for generalisation. An efficacy of the model in medical diagnostics will be evaluated using f1-score, sensitivity, specificity, loss, accuracy, and precision. This metric is particularly significant in this context. Through the integration of a comprehensive performance evaluation, our research endeavors to provide a holistic comprehension of the efficacy of the suggested methodology in precisely categorising CXR images, specifically with regard to cases involving COVID-19, pneumonia, and norm. The whole proposed model process described in below subsections and Fig 1 which provides each steps of proposed framework.

Data collection

The NIH CXR dataset includes 112,120 radiographs from 30,805 distinct patients that have been given pathologic diagnoses for experimental purposes. To generate these designations, the authors used natural language processing in the texts of disease classifications from relevant radiological reports, it is available on internet Kaggle website.

Table 1. Count images CXR image dataset

Category	Count
COVID	5634
Normal	6000
Pneumonia	5000

Table 1 shows the count images screenshots for dataset according the given categories displayed the total count of each category of CXR image dataset where total 5634 images are in COVID, 6000 images are in normal category and 5000 images are in pneumonia category of multiple diseases.

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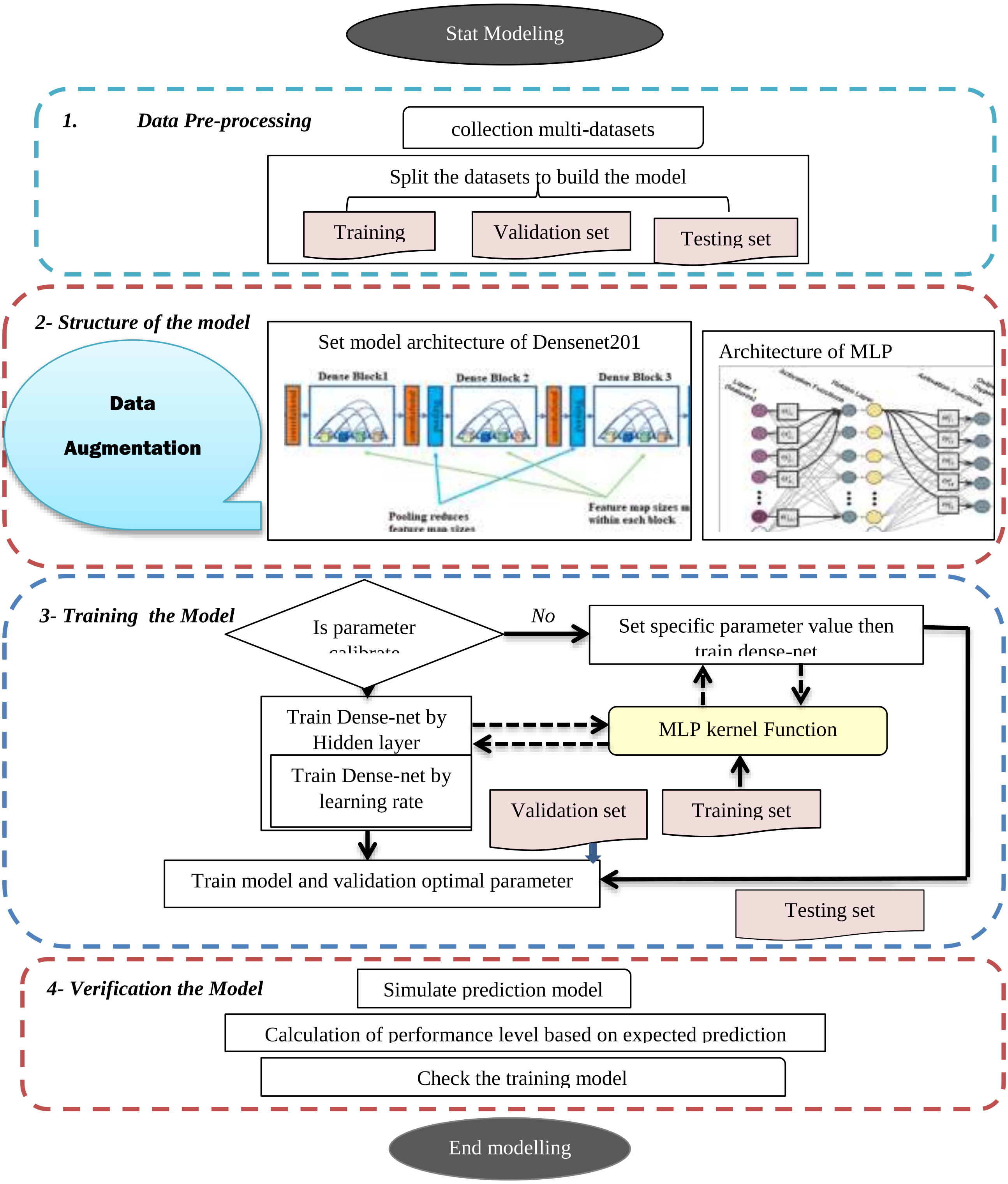

Figure 1. Proposed Methodology Flowchart for COVID-19 Detection on Chest X-Ray Images

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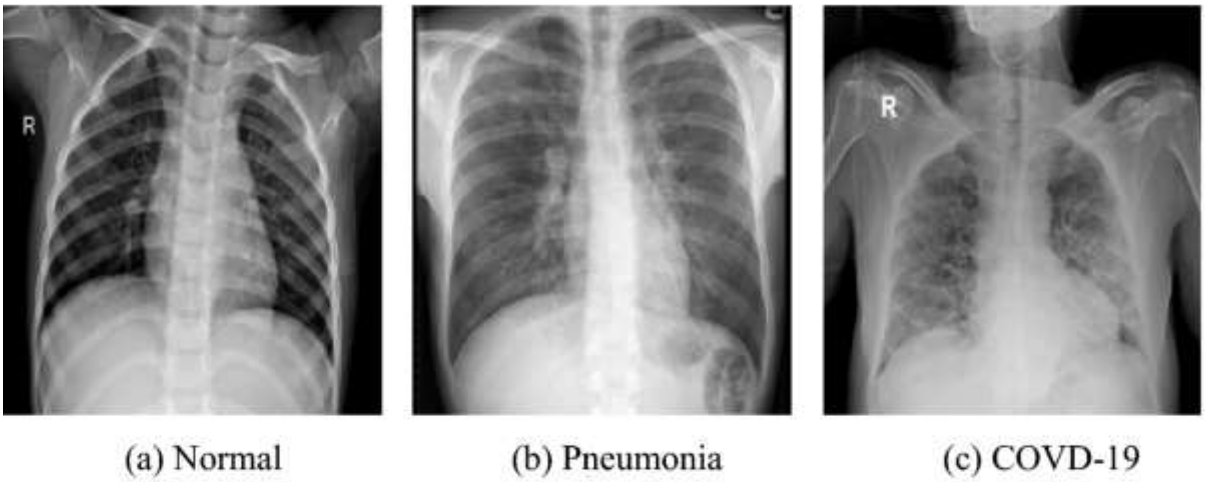

Figure 2. Sample images of collected dataset of CXR image dataset (a) Normal image, (b) Pneumonia image, (c) COVID-19 image

Fig 2 shows the sample images of collected dataset of CXR image dataset depict of CXR image dataset including three categories depicted in this way, it has achieved the first objective of this research by image data exploring and perform data analysis on CXR image dataset to detect lung cancer and COVID or pneumonia. Once data was analyzed then next step of the methodology to perform image preprocessing by applying some methods.

Data Exploration and Preprocessing

To enhance a performance of a proposed system, some pre-process was used for tuning data entry to meet deep learning requirements model: a) Images were resized; b) images were horizontal flip; c) images were vertical d) the images were rotation by 25 e) use SMOTE techniques to balance dataset f) converted images to an array to be used an input in the model's next phase. A data were divide into training and validation subsets at 60% and 20%, respectively, to make sure that the variance of images complies with the specifications needed to train the suggested model. All images have been scaled to 128 * 128 * 3 by using Pyldic library in order to match a framework's requirements. After normalising each pixel in every image to the interval, the images were all transformed to array data format [0,1].

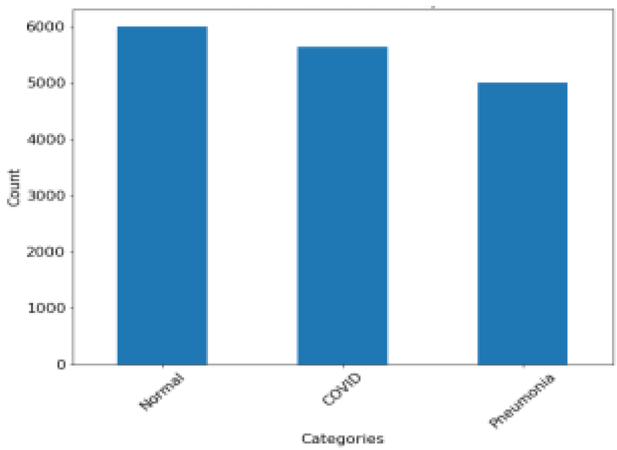

Figure 3. Data distribution before data sampling

Fig 3 display the data distribution before apply the data sampling on the collected CXR image dataset. In above figure depicts the total count plot of CXR image dataset for three classes where Normal having more than 5500 images, COVID having more than 5000 images and pneumonia having more than 4500 images.

Typically, the underrepresented class receives a low classification. Methods for reducing unbalanced data are therefore essential in classification issues. They employed SMOTE oversampling techniques in order to address the issue of class imbalance.

SMOTE (Synthetic Minority Oversampling Technique):

The initial proposal for SMOTE was made in order to generate minority-specific synthetic examples according to the feature affinity in

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minority-specific values[24]. For each minority sample, SMOTE first finds KNNs. Next, it randomly selects neighbours, and an artificial example is created between the two instances at a randomly chosen point in feature space. Assume that SMOTE chooses KXi, the k-nearest neighbours, and that Xi is a set of minority class Xi €´ Xminority. The trio of NNs associated with Xi, joined by a line. SMOTE selects an element Xˆ i from KXi and Xˆ i from Xminority at random to produce a new example (X_{new}). The value and the feature vector Xi are added to create the feature vector for X_{new}. The variance among Xi and $X\hat{}_{i}$, multiplied by the random variable theta (θ), which can take on values between 0 and 1, can be used to do this.

$$Xnew = Xi + X\hat{}i - Xi \times \theta \ldots\ldots 1$$

where Xˆi is a part of KXi: Xˆ i € Xminority. A sample that was made is a point on a line section that connects Xi to a randomly chosen Xi € KXi.

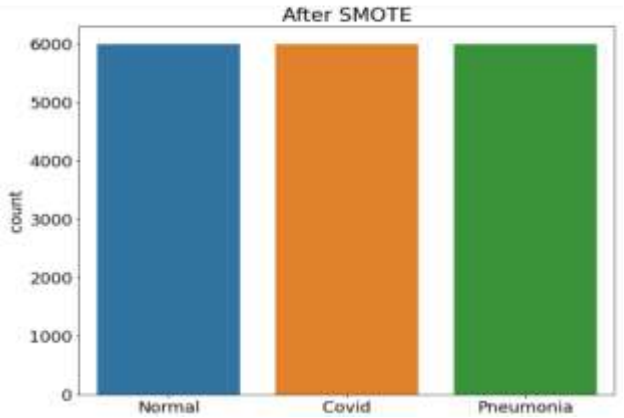

Figure 4. Data balancing after using SMOTE sampling

Fig 4 display the balanced data after apply data sampling method SMOTE on the collected CXR image dataset. The balance data count plot of the chest x-ray images information for three classes—normal, COVID, and pneumonia—shows that all 6,000 images are the same.

Data Split into Train, Test and Validation

In machine learning, it is standard procedure to split a dataset into testing, validation, and training sets in order to assess and optimise a model's performance. It makes sense to start with the percentages I indicated: 20% for validation, 20% for testing, and 60% for training.

A dataset is separated into three subgroups, to put it briefly:

- Training Set (60%): This set of data is used to teach the machine learning model by letting it pick up relationships, patterns, and features.
- Validation Set (20%): This set is utilized to test the model post-training in order to adjust hyperparameters, avoid overfitting, and gauge generalisation to new data.
- Testing Set (20%): Reserved for use only after validation and training. used once to evaluate the model's final performance on current, tested data

```
(11520, 128, 128, 3) (11520, 3)
(3600, 128, 128, 3) (3600, 3)
(2880, 128, 128, 3) (2880, 3)
```

Figure 5. Training, validation and test data

The number of images for all three training, validation and test data for CXR image dataset are considered 11520 images, 3600 images and 2880 images as illustrate in fig 5. The images were labeled into categories and then obtained the balanced dataset by creating synthetic dataset using SMOTE that are useful to training and testing the model to detect diseases. The dataset was further partitioned into a training set including 60% of the total, a validation set comprising 20%, and a testing set comprising 20%. Then also data was augmented to increase the input image size that are useful to train the more images' data to achieve good classification results.

Proposed classification Models

In this work they have used hybrid model that combine with DenseNet201 + MLP.

DenseNet201 Architecture:

Huang's proposal for a CNN architecture is DenseNet201. Fig 6 shows the dense connectivity patterns among the layers that characterise the DenseNet architectural family, of which it is one powerful member[25].

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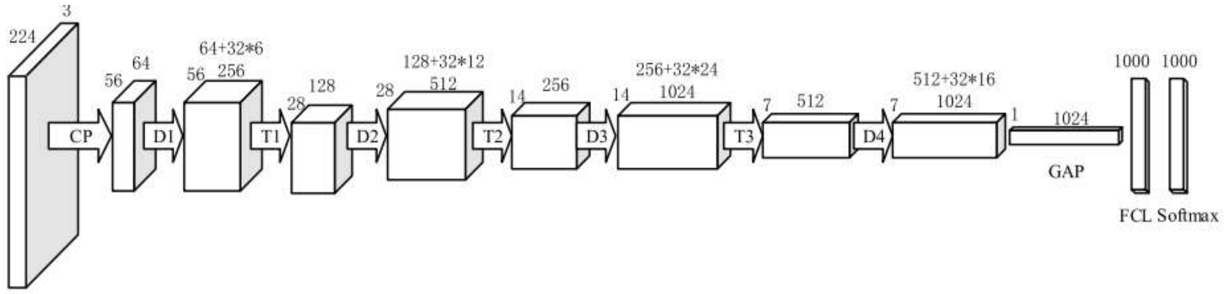

Figure 6. Densenet 201 architecture[25]

Dense connectivity is when all of the layers are connected to each other through feed-forward connections. DenseNet201 is built up of numerous dense blocks, with interconnected sets of convolutional layers inside each dense block. A transition layer takes the output from every dense block and uses a convolutional layer and a pooling operation to lower the feature maps' spatial dimensions. The last dense block is succeeded by a global average pooling layer that, after averaging the feature maps across all spatial dimensions, yields a one-dimensional vector. This vector is then inputted into a fully linked softmax layer for classification purposes[26].

Multi-Layer Perceptron (MLP)

As a kind of feedforward ANN, a MLP model is the building block of deep learning and DNN implementations. This method is a supervised learning one. The input, output, and hidden layers make up the three layers of the MLP. As a result of direct connections between each neuron in each layer, claim that this network is completely connected [27].

After receiving the input data, the input layer of a multilayer perceptron (MLP) normalises the features. Many hidden layers, the number of which can be adjusted, handle the signal processing. In the output layer, the processed data is used to produce predictions or judgements [28]. The activation function φ, as shown in Fig 8, is a nonlinear function that, in a single-neuron perceptron model, translates the summation function $(xw + b)$ to the output value y.

$$y = \varphi(xw + b)\ldots\ldots\ldots2$$

The input vector (x), weighting vector (w), bias (b), and output value (y) are all defined in Eq 2. In Fig 7, 8, one can see the MLP model's architecture in action.

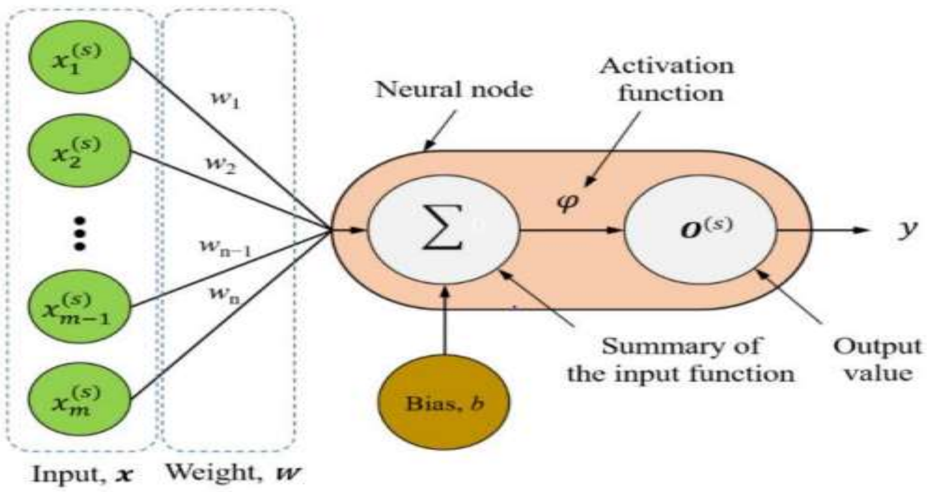

Figure 7. Single-neuron perceptron model [29].

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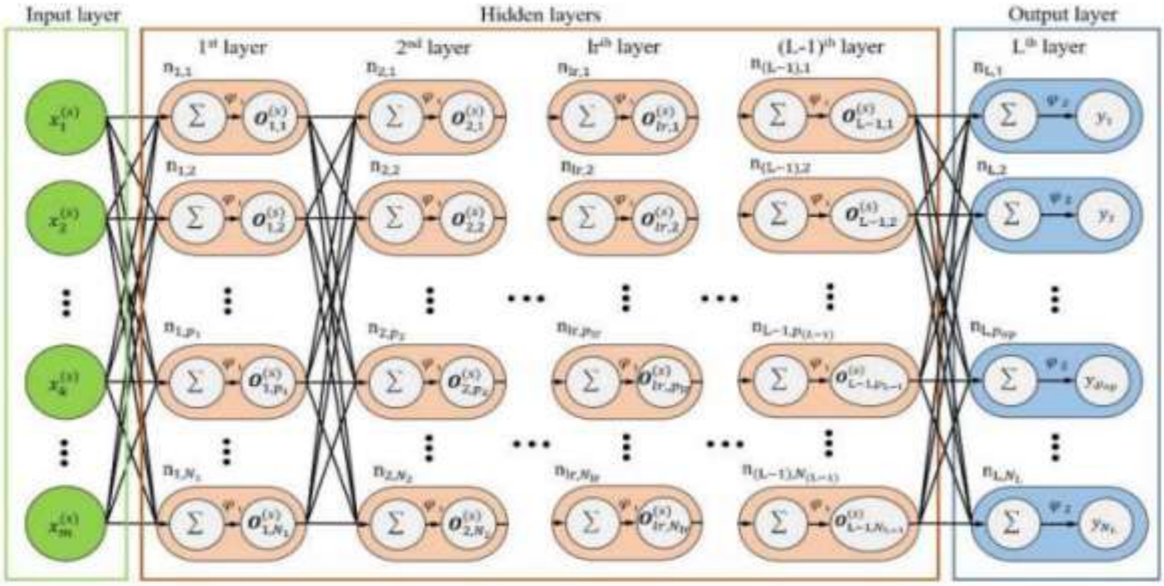

Figure 8. Structure of the multilayer perceptron (MLP)[29].

Fig 8 depicts a multilayer neural network with its input, output, and hidden layers [30].

- Input layer **-** is just responsible for distributing data over the network and does not perform any calculations. Signals are transmitted from this layer's outputs to the inputs of the hidden or output layer below it.
- Hidden layers- Transmitting signals by the input to the output, hidden layers are composed of regular neurons that analyse data collected from the preceding layer. Their input is the most recent layer's output, and their output is the most recent layer's input.
- Output layer - The output of the complete neural network's computations is typically provided by at least one neuron.

Training of Proposed Model

The models suggested for a classification of CXR images consist of a DenseNet201 structure enhanced by a Multilayer Perceptron (MLP) element, which functions as both the principal model and the reference point for evaluation. The model architecture comprises several layers: an image input layer, a DenseNet201 functional layer, and subsequent layers comprising dropout, dense, and flattening layers. In total, 50,306,627 parameters are contributed by the model. For the whole training process, used the Adam optimizer, which has a learning rate of 0.0001 and uses categorical crossentropy loss. The activation functions utilised in the MLP layers consist of Softmax for the final layer and ReLu throughout. A group size of 32 is employed, and the training process spans a total of 100 epochs. The architecture and parameterization of the model are thoroughly described, laying the groundwork for a thorough assessment of its performance and a comparison with the DenseNet201 baseline configuration with MLP augmentation.

Model: "model"

Layer (type)	Output Shape	Param #
image_input (InputLayer)	[(None, 128, 128, 3)]	0
densenet201 (Functional)	(None, None, None, 1920)	18321984
flatten (Flatten)	(None, 30720)	0
MLP_input (Dense)	(None, 1024)	31458304
dropout (Dropout)	(None, 1024)	0
MLP_Hidden_layer (Dense)	(None, 512)	524800
dropout_1 (Dropout)	(None, 512)	0
dense (Dense)	(None, 3)	1539

Total params: 50,306,627
Trainable params: 50,077,571
Non-trainable params: 229,056

Figure 9. Model summary proposed Hybrid model for CXR detection

Fig 9 above illustrates the structure of the hybrid model and contain three columns, the first for the type of layers such as (input, functional, flatten, dropout, dense), the second column shows the

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number of layers used for example input layer (128,128, 3) indicate to size of the image, the last column shows the number of parameters for each layer, and finally the total describes the number of parameters used in this model and the number of Parameters used and unused in training.

In this way, a hybrid model was designed to implement two models like- DenseNet201 CNN pre-trained model and MLP model after tuning some hyper-parameters. These models were implemented for feature extraction and disease classification by considering multiclass classification.

Evaluation Performance

Accuracy, precision, recall, and the F1-measure were some of the evaluation criteria used to analyse the models' performance. Through estimating several performance measures, the confusion matrix was utilized to evaluate the classifier's capacity to identify numerous categories. FP, TP, TN, and FN indicators are a four results of a matrix. The number of accurate forecasts is denoted by TN and TP, while the number of wrong predictions is denoted by FN and FP. The performance measures utilized in this investigation are listed in Table 2 along with brief descriptions and mathematical calculations[31].

Table 2. Performance indicators with a brief description

Measure unit	Equation	Demonstration
Accuracy (ACC)	$\frac{TP+TN}{TP+FP+TN+FN}$	Indicated as the proportion related to properly classified data to overall classified data
Precision (P)	$\frac{TP}{TP+FP}$	On a mathematical level, this may be expressed as the percentage of positive observations that were accurately anticipated divided by the total number of positive outcomes[27]
Recall or Sensitivity	$\frac{TP}{TP+FN}$	Stability, or sensitivity, is the proportion of true positives to total observations in the real class
Specificity (SP)	$\frac{TN}{TN+FP}$	TNR that determines the percentage of true negative in the rating
F-Score	$\frac{2TP}{2TP+FN+FP}$	Property might be indicated as harmonic mean related to recall or precision

Results and Discussion

Results from applying the suggested hybrid model to the Covid-19 CXR dataset are presented here. Computers running Windows 10 and powered by an Intel(R) Core (TM) i5-1035G1 CPU clocking in either 1.00 GHz or 1.19 GHz were used for the experimental testing investigation. The work has been executed utilizing a Python programming language and Jupyter notebook as the platform. The dataset has been detailed, performance metrics have been calculated, and a comparison of the existing and suggested models has been provided below.

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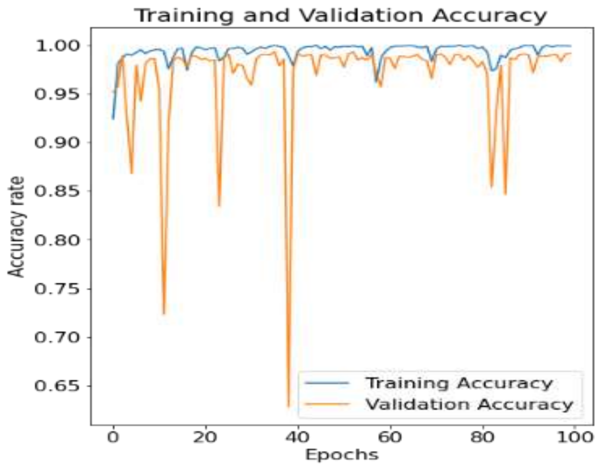
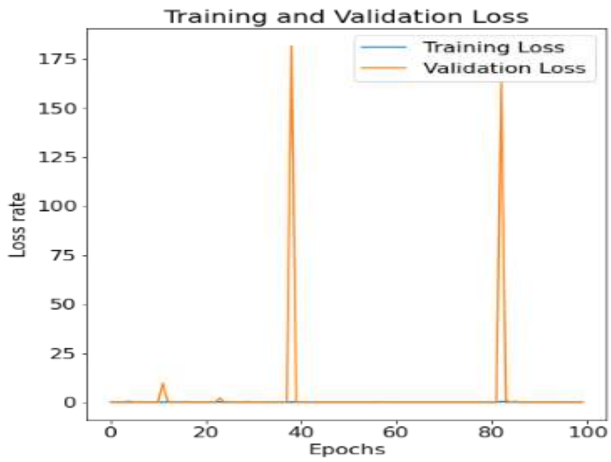


(a) Training and validation graph for accuracy on NIH dataset



(b) Training and validation graph for loss on NIH dataset

Figure 10. Training and validation graph for accuracy and loss on NIH dataset

Fig 10 shows the line graph plot to measure the training and validation results to the covid-19 classification by experimenting the proposed model with CXR images dataset and opted a training accuracy and validation accuracy as displays in Fig 10 (a) and loss as shown in Fig 10(b). In these plots, X-axis displays number of epochs from 0 to 100 with 20 interval difference and Y-axis represents accuracy in % and loss value for training and validation set. Starting from the beginning of the period, the training accuracy was 93% and the validation accuracy was 95%. The accuracy rate has number of variations with increased number of epochs and finally achieved more than 99% at 100th epoch for both training and validation set of NIH dataset. But there is no much variation in loss value of training and validation set by achieving constant loss value with ignorable differences which is very minimal from 1st epoch to the last 100th epoch. The reason for the great instability in validation for accuracy and loss are that the neural network is too large compared to the trained data.

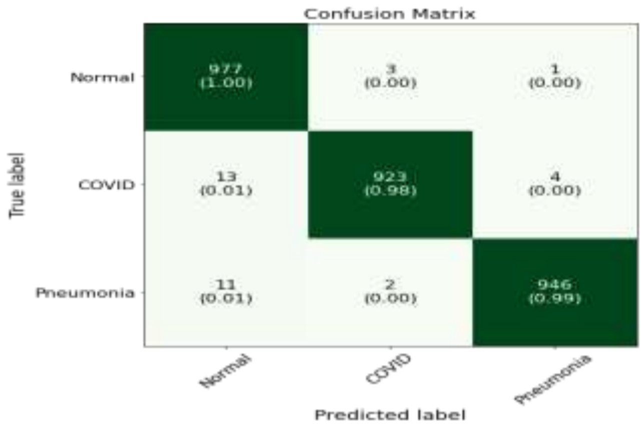


Figure 11. Confusion matrices for covid19 classification

The confusion matrix is also utilised to evaluate outcomes of a proposed hybrid DL model. In an instance of COVID detection of a three-class dataset, which includes a total of 2880 images as part of the test data, 923 of the images have been correctly classified and are displayed alongside the diagonal, while the two elements that have been incorrectly classified are distributed across the off-diagonal locations. This is illustrated in Fig 11; which can be found here. Similarly, in the case of Pneumonia detection, there are total 946 images are correctly classified as Pneumonia and 977 images are correctly classified as Normal.

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Table 3. Performance results of covid19 classification

Training loss	Training accuracy	Validation loss	Validation accuracy	Testing loss	Testing accuracy	Sensitivity	Specificity	F1-score	Precision
0.0036	99.91	0.0416	99.14	0.0590	98.82	99.69	98.61	99	99

Table 3 represents the final performance results of covid-19 classification on CXR image dataset of different sources in terms of accuracy, and loss. Some additional performance parameters are calculated for measure a proposed model performance according to specificity, sensitivity, f1-score, recall and precision. From these results analysis found that training, validation and testing accuracy are 99.91%, 99.14% and 98.82%, respectively, whereas loss values are 0.0036, 0.0416 and 0.0590, respectively. Apart from this accuracy results the sensitivity, specificity, f1-score, recall and precision are excellent which are higher than 99%, represented.

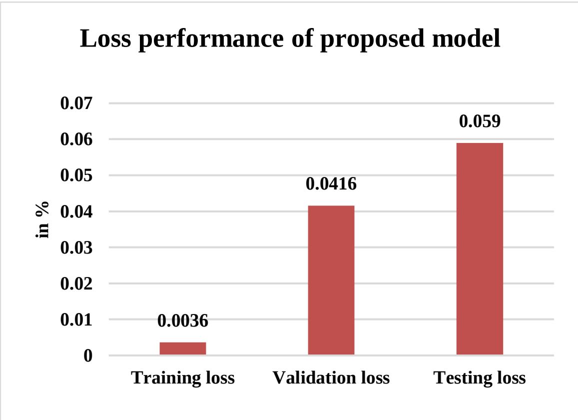

Figure 12. Bar graph loss with train/test and val. dataset of proposed model

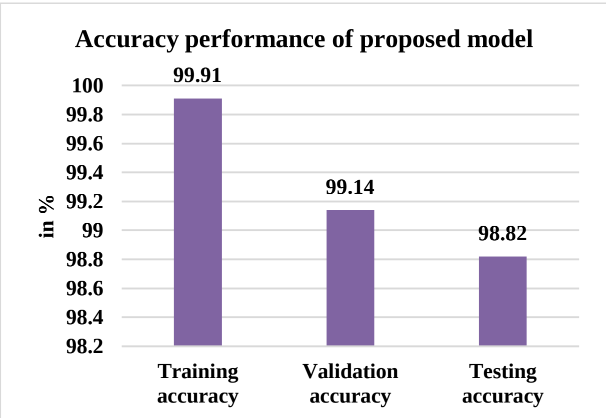

Figure 13. Bar graph accuracy with train/test and val. dataset of proposed model

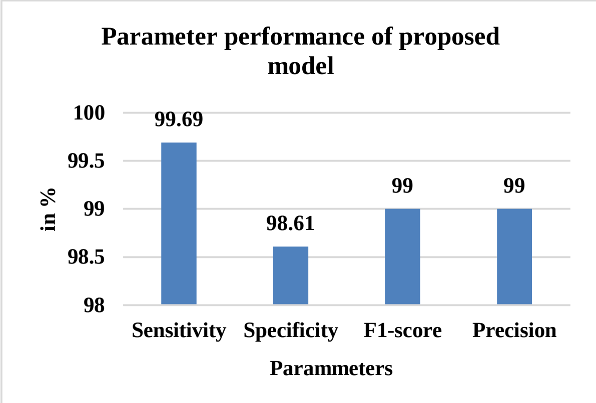

Figure 14. Bar graph of parameter performance of proposed model

The Hybrid DenseNet201 + MLP model exhibits outstanding performance when assessed on a Chest X-ray (CXR) dataset. Demonstrating robustness during validation, the model attains a 99.14% accuracy with a loss of 0.0416 Fig 12, after achieving a training accuracy of 99.91% Fig 13 with a training loss of 0.0036. The results of testing provide additional evidence of its efficacy, as it achieved a significant accuracy of 98.82% with a negligible loss of 0.0590. The model's capability to accurately classify positive and negative instances is underscored by sensitivity and specificity metrics totaling 99.69% and 98.61%, respectively. The visual representation of the model's performance trends during training, validation, and testing on the CXR dataset is depicted in Figs12 and 13. A graphical summary of critical performance parameters is provided in Fig 14, which reaffirms the balanced capabilities and precision of the Hybrid DenseNet201 + MLP model in the domain of chest X-ray analysis.

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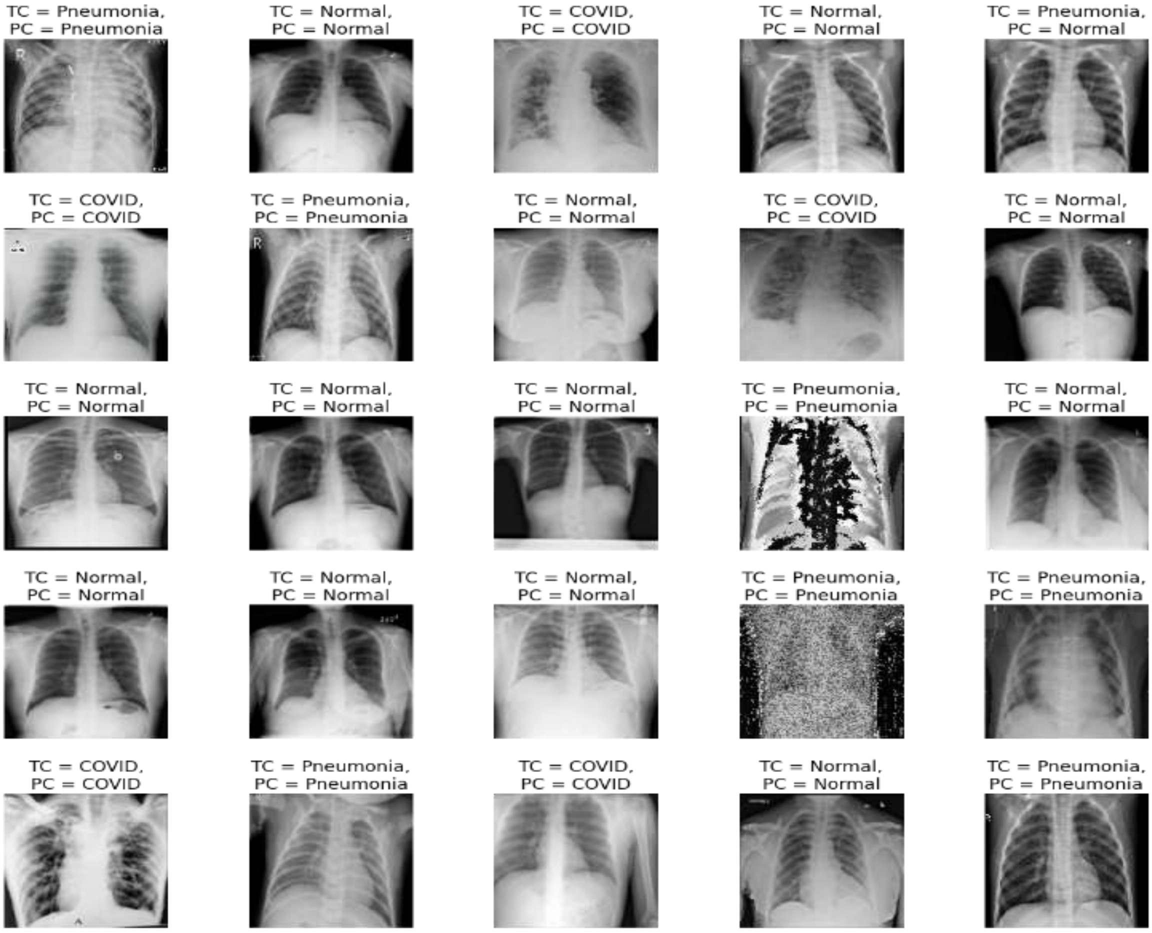

Figure. 15. Prediction results on CXR image dataset for multiple disease

The prediction results after perform testing on test data of CXR image dataset by proposed hybrid (DenseNet201+MLP) deep learning model as shown in Fig 15. It displayed the predicted class (PC) and True class (TC) as Normal, COVID and Pneumonia for the given sample images of CXR images. From the entire research found the final prediction results for multiclass classification of many diseases that are predicted more accurate that are successful to correctly detection of COVID or Pneumonia by CXR images.

Table 4.Comparison between existing and proposed models

References	Year	Models	Accuracy	Recall	Specificity	F1-score	Precision	Loss
Wu et al.[31]	2020	Multilayer machine vision classifier	83.57	98.68	/	0.8981	82.42	/
Hong et al.[15]	2021	EfficientNet	85.32	77.97	88.98	/	/	/
Kim et al.[22]	2022	EfficientNet v2-M	82.15	81.40	91.65	/	/	0.6933
Uparkar et al. [32]	2023	Visual Geometric Group Data Spatial Transformer with CNN (VDSNet)	70.24	0.63	/	0.65	0.67	/
Nawaz et al. [23]	2023	CXray-EffDet	94.53	92.36	/	91.16	90	/
Reshan et al. [33]	2023	MobileNet	93.75	94.39	/	93.18	91.36	/
Proposed work	**2024**	**Proposed model**	**98.82**	**99.69**	**98.61**	**99**	**99**	**0.0590**

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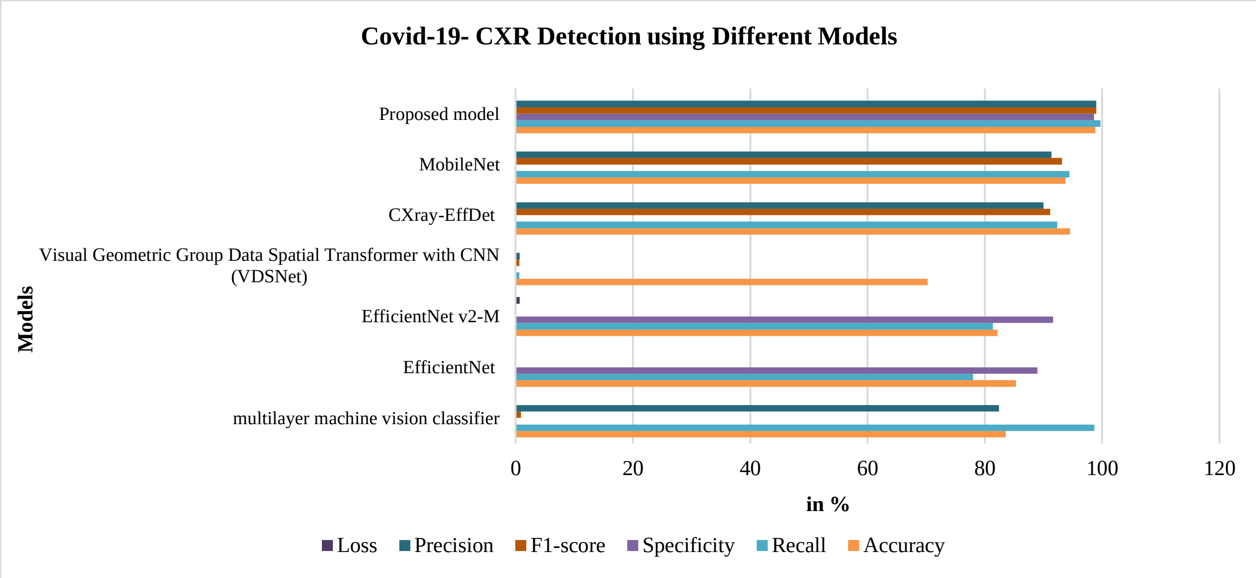

Figure 16. Comparative Bar graph of parameter performance of different models for Covid-19 CXR detection

The hybrid model in the "Proposed work" row outperforms various state-of-the-art COVID-19 Chest X-ray (CXR) detection algorithms with 98.82% accuracy. Its high recall of 99.69% and specificity of 98.61% show its ability to detect positive and negative instances, respectively. The model's accuracy and balance are shown by its 99% F1-score and precision metrics. The suggested method detects COVID-19 CXR better than several existing models, notably EfficientNet and MobileNet. Fig 16 shows that the suggested model outperforms other models in accuracy, recall, specificity, F1-score, precision, as well as loss. This implies that the Hybrid DenseNet201 + MLP model may accurately and reliably classify COVID-19 CXR.

Conclusion

The data set for the Coronavirus is small and cannot be diagnosed using CXR. Neural networks have been able to diagnose this virus. This study mainly aims to retrain pre-trained deep learning models and machine learning (ML) models as an accurate tool for coronavirus (COVID-19) diagnosis for CXRs. This work presents new, completely safe and tailored methods for classifying chest X-ray images for multiple classifications of clinical categories: Normal, Pneumonia, as well as COVID-19. To this end, two deep learning techniques depend-on the Densenet201 and MLP transfer learning convolutional network architecture are presented here. The combined response of all techniques permit for improved discrimination between patients with COVID-19, patients with other diseases with characteristics similar to COVID-19, and normal cases. The proposed methods were validated on a dataset retrieved specifically for this research. Despite the poor quality of chest X-ray images associated with the nature of portable devices, the proposed methods provided global accuracy values of 98.82% and 99%, respectively, which enabled reliable analysis of portable X-ray images to facilitate clinical decision making. - Manufacturing process.

Future study will investigate transfer learning as well as domain adaptation to enhance the "Hybrid DenseNet201 + MLP" model on varied datasets. Evaluating the model's medical decision-making requires interpretability research. Adding attention mechanisms and clever data augmentation procedures may help the model spot subtle Chest X-ray patterns. Clinical relevance will be improved by domain specialists' collaboration. To prove its practicality, the model is deployed in real-world healthcare settings and monitored continuously. These efforts seek to make the model a useful and reliable clinical tool for Chest X-ray categorization.

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Data Availability

The datasets generated analysed during the current study are available in the only repository, web link https://www.kaggle.com/datasets/nih-chest-xrays/data

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Authors sign on ethical consideration's approval.
- Ethical Clearance: The project was approved by the local ethical committee at University of Sfax.

Authors' Contribution Statement

A.M. Sh.: conceptualization, formal analysis, data analysis; investigation, data curation, methodology, research design, writing an original draft, visualization, validation, software. I.A. and M.B.: supervision, writing – review & editing. All authors have read and agreed to the published version of the manuscript.

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آلة هجينة قوية ونموذج قائم على التعلم العميق للتصنيف والتعرف في صور الأشعة السينية للصدر

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الخلاصة

لقد كانت هناك جائحة كوفيد-19 منذ ديسمبر 2019، ويتطلب العلاج الطبي الناجح لمرضى كوفيد-19 تشخيصًا سريعًا ودقيقًا. تتطلب مكافحة جائحة كوفيد-19 نظامًا آليًا يستخدم التعلم بالانتقال العميق لتشخيص الفيروس باستخدام الأشعة السينية على الصدر (CXR). يتم استخدام CXR بشكل متكرر في الرعاية الصحية لأنها توفر إمكانية التشخيص السريع والدقيق للأمراض. تتضمن أنظمة التشخيص الآلي بمساعدة الكمبيوتر (CAD) التعلم الآلي أو التعلم العميق لتعزيز الكفاءة والدقة، وبالتالي تقليل المشكلات المستقبلية. يمكن استخدام العديد من أنظمة الذكاء الاصطناعي القائمة على التعلم العميق للتشخيص؛ ومن بين أكثر هذه الشبكات استخدامًا شبكة CNN، التي تم تطويرها لأول مرة وأظهرت دقة مشجعة في تحديد المرضى المؤكد إصابتهم بفيروس كوفيد-19 باستخدام صور CXR. ومن خلال استخدام صور الأشعة السينية، سيعمل هذا العمل على تصميم التعلم الآلي والتعلم العميق لتوفير تشخيص أسرع لعدوى كوفيد-19. ونتيجة لذلك، تستخدم تقنية التعلم بالنقل العميق نموذجًا موجودًا أولاً، ثم تطبق البيانات المطلوبة عليه مرة أخرى. حيث تم استخدام نموذج التعلم Densenet201transfer، وهو أحد تقنيات التعلم عن بعد، كاستخراج الميزة ودمجها مع خوارزمية الإدراك الحسي متعدد الطبقات؛ تم تطبيق هذه التقنية على مجموعة بيانات تابعة للمعهد الوطني للصحة (NIH)، حيث تم استخدام العديد من مقاييس الأداء مثل الدقة والدقة والنوعية والحساسية، حيث أثبتت التجربة كفاءة الخوارزمية المستخدمة من حيث الدقة بنسبة 98.82 %. تعتبر هذه النتائج مشجعة عند مقارنتها بنماذج التعلم عن بعد الأخرى التي تم تدريبها على مجموعة البيانات المماثلة

الكلمات المفتاحية: الأشعة السينية للصدر، التعلم العميق، التعلم الآلي، Densenet201، خوارزمية الإدراك الحسي متعدد الطبقات.