Research article

Dynamic learning for imbalanced data in learning chest X-ray and CT images

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ARTICLE INFO

ABSTRACT

Massive annotated datasets are necessary for networks of deep learning. When a topic is being researched for the first time, as in the situation of the viral epidemic, handling it with limited annotated datasets might be difficult. Additionally, the datasets are quite unbalanced in this situation, with limited findings coming from significant instances of the novel illness. We offer a technique that allows a class balancing algorithm to understand and detect lung disease signs from chest X-ray and CT images. Deep learning techniques are used to train and evaluate images, enabling the extraction of basic visual attributes. The training objects' characteristics, instances, categories, and relative data modeling are all represented probabilistically. It is possible to identify a minority category in the classification process by using an imbalance-based sample analyzer. In order to address the imbalance problem, learning samples from the minority class are examined. The Support Vector Machine (SVM) is used to categorize images in clustering. Physicians and medical professionals can use the CNN model to validate their initial assessments of malignant and benign categorization. The proposed technique for class imbalance (3-Phase Dynamic Learning (3PDL)) and parallel CNN model (Hybrid Feature Fusion (HFF)) for multiple modalities achieve a high F1 score of 96.83 and precision is 96.87, its outstanding accuracy and generalization suggest that it may be utilized to create a pathologist's help tool.

1. Introduction

Lung diseases are a significant public health problem, heartbreaking millions of individuals worldwide. The World Health Organization estimates that Chronic Obstructive Pulmonary Disease (COPD), a category of lung disease that comprises chronic bronchitis and emphysema, is the third leading cause of mortality globally. In the US, lung cancer is the leading cause of cancer-related mortality in both men and women [1]. Asthma, another common lung disease, affects approximately 9.7% of the US population, with

the highest prevalence among children under 18 years of age. The economic burden of lung diseases is also significant, with direct and indirect costs totaling billions of dollars annually. Despite the prevalence and impact of lung diseases, many can be prevented through measures such as avoiding tobacco smoke and air pollution and getting vaccinated against respiratory infections [2,3].

Asthma, Chronic Obstructive Pulmonary Disease (COPD), and lung cancer are examples of lung disorders that pose a serious public health risk. The World Health Organisation (WHO) claims, around 235 million people currently suffer from asthma, while COPD affects around 384 million people worldwide. In terms of mortality, lung cancer is the leading germ of cancer-related deaths, accounting for approximately 1.8 million deaths annually [4,5]. The prevalence of lung diseases varies widely by region, with the highest rates generally occurring in low- and middle-income countries. Risk factors for lung diseases include tobacco smoking, air pollution, and occupational exposure to hazardous substances. Prevention and early detection are important for reducing the burden of lung diseases [6,7].

The worldwide pandemic COVID-19, which developed from the new coronavirus SARS-CoV-2, has spread to all continents. As of January 2021, there have been over 88 million confirmed causalities and over 1.9 million deaths globally [8,9]. The highest number of causalities has been reported in the United States, Brazil, and India. The impact of COVID-19 has been felt not only in terms of the number of people affected but also in terms of the economic and social disruptions caused by the pandemic. In an effort to stop the virus from spreading, some nations have enacted measures including lockdowns and travel restrictions [10]. Despite the widespread distribution of vaccines, the pandemic continues to evolve and pose a significant threat to global health [11,12].

Artificial neural networks are used in deep learning, a kind of machine learning that may aid in the early identification, diagnosis, and treatment of lung disorders [13,14]. In the field of medical imaging, deep learning algorithms can be used to analyze chest X-rays and other imaging modalities to identify abnormalities can facilitate the identification of lung disorders such as pneumonia, lung cancer, and COPD. These algorithms can be trained on large datasets of images, allowing them to learn to recognize patterns and features that may be uncontrollable for a human observer to discern [15,16]. Deep learning techniques have also been applied to the analysis of electronic health records, with the goal of identifying risk factors for lung diseases and predicting the likelihood of patients developing these conditions [17,18]. Additionally, deep learning algorithms are being explored as a tool for predicting the severity of lung diseases and the response of patients to different treatment options. This could potentially allow doctors to tailor treatment plans to individual patients and improve outcomes [19]. The approaches of deep learning in the context of lung diseases is an active domain of research, and it is likely that these techniques will continue to be developed and refined in the coming years [20].

Data imbalance is a known issue in medical datasets, where the number of instances belonging to a single class (e.g. a particular disease) is significantly larger or smaller than the number of instances belonging to the other class (e.g. healthy). This can occur due to a number of factors, such as the prevalence of the disease in the population being studied, or the fact that certain diseases are more severe and require more intense medical intervention, leading to more data being collected on these cases [21,22]. The imbalanced distribution of data can pose problems for deep learning algorithms, as they may be biased towards the majority class. This can lead to poor performance on the minority class, such as low accuracy or low sensitivity (the ability to correctly identify the minority class) [23].

Biases can arise in medical image datasets due to various factors, including differences in patient populations, imaging protocols, and annotator variability. Bias can also be introduced during the data collection and annotation process, such as by selecting only specific demographics or disease types. The class imbalance was present in the dataset that we used in this study, and several techniques were applied to address this issue [24]. One of the techniques mentioned is applying a weight or cost schema to modify the learner, which helps reduce bias and increase the variance of the majority group. However, assigning an effective cost value to the minority group can be challenging, and it requires experience and domain expertise to determine the appropriate value.

There are several approaches that can be taken to address data imbalances in medical datasets. One approach is to over-sample the minority class, by synthesizing artificial examples of the minority class or by duplicating existing examples [25]. Another approach is to under-sample the majority class, by removing some of the examples from the majority class. Utilizing algorithms that are especially made to manage unbalanced data, such as those that alter the cost of misclassification or employ sampling methods to balance the data, is another possibility. [26,22]. It is important to carefully consider the issue of data imbalance and take steps to address it in order to ensure that deep learning models are able to accurately and reliably make predictions on medical data.

To address the problem of imbalanced data, where one class of interest may have much fewer occurrences than other categories, class-balancing techniques are frequently utilized in medical image analysis. This is especially important when analyzing lung X-ray or CT images since aberrant results may be less common than benign findings in these images [27,28].

In order to prevent the model from being biased towards the dominant class throughout learning, the class-balancing method modifies the weights of the various classes. Using weighted loss functions, where the loss function is altered to give the minority class greater weight during training, is one popular way to do this. For instance, the cross-entropy loss is modulated by the focal loss function, which decreases the contribution of correctly classified cases and raises the contribution of incorrectly classified instances. To raise the total amount of training instances, an alternative strategy is to oversample the minority class. This may be accomplished by simply copying already-existing instances or by creating new synthetic instances using data augmentation techniques like rotation, scaling, or the addition of noise [29].

The possibility for overfitting to the minority category and the chance of generating bias if the oversampling or weighting is done incorrectly are two drawbacks of class-balancing methods. If there is a lack of data, oversampling the minority class may not be practical and might raise the computational cost of training. However, some techniques, such as augmentation, need to be used carefully to prevent the introduction of additional artifacts that impair the performance of the model [30,31].

A combination of Convolutional Neural Networks (CNNs) and boosting techniques to develop a deep learning method for identifying chest diseases in medical images. Boosting is a deep machine learning technique that involves training weak models and then

combining their predictions to produce a more accurate overall model. It can be used to improve the performance of many types of models, including CNNs. By customizing the CNNs to exploit chest-specific disease patterns and using boosting and ensemble learning techniques, we improve the accuracy of our model for diagnosing diseases/tumors in medical images.

1. Different tactics and approaches are utilized to control class imbalance in deep learning; we have presented a unique solution for solving the class imbalance problem 3-Phase Dynamic Learning (3PDL) using Random Oversampling and Under-sampling.
2. For the investigation of chest disorders utilizing CT and X-ray images, a two-phase autonomous deep hybrid learning-based classification and detection system is proposed.
3. By lowering overfitting, raising robustness, and enhancing generalization, ensemble learning can boost a model's performance. It's vital to note that several ensemble approaches should be tested and their effectiveness evaluated in order to determine the optimum strategy. The performance of ensemble learning is greatly reliant on the variety of the models employed and how they are integrated.

The most recent state-of-the-art works for the classification of Chest X-rays and CT-Scans are reviewed in section 2. In section 3, our proposed and innovative solution for Class imbalance is 3-Phase Dynamic Learning (3PDL), and the parallel deep learning model for feature extraction is Hybrid Feature Fusion (HFF) model. We discuss the fundamental preprocessing techniques and present thorough thought and implementation. Section 4 comprises the training and testing results of various pretrained CNN models of two various imaging techniques and datasets used in healthcare. The final section 5 concludes this study.

2. Related work

The performance of Computer-Aided Detection (CAD) systems for lung disease detection has significantly increased with the advent of computing resources such as the Graphics Processing Unit (GPU) and the Convolutional Neural Network (CNN). The first CAD system for identifying lung nodules or damaged lung cells was created in the late 1980s, but at that time, the limited computing power precluded the use of sophisticated image processing techniques. With the advent of GPU and CNN, the performance of CAD applications has significantly improved, allowing for faster and more accurate detection of lung diseases [32,33].

In addition to the technical advances, the use of CAD systems has also been aided by the availability of large datasets of medical images and the development of deep learning algorithms that can be trained on these datasets. This has allowed for the creation of more sophisticated CAD systems that can analyze complex medical images and provide decision support for diagnosis and treatment planning [34,35]. The combination of technological advances and the availability of large datasets has greatly improved the achievement of CAD systems for lung disease diagnosis, and it is likely that these systems will continue to evolve and improve in the coming years [36,37].

Several studies have proposed the use of deep learning models for the detection of lung cancer and other lung diseases. These models often focus on the detection of thorax diseases using approaches such as 3D Convolutional Neural Networks (CNNs) and multi-scale prediction strategies [38–43].

The study proposed the use of a 3D deep CNN with multi-scale prediction approaches to observe lung nodules from segmented images. However, as you mentioned, this work was not able to classify the types of diseases and the multi-scale prediction approaches were only applied to small nodules [44,45].

The utilization of effective deep learning architectures for the detection and diagnosis of lung diseases is an active area of research and there is still much work to be done. In particular, there is a need for models that can accurately classify different types of diseases and handle a wide range of nodule sizes. Additionally, there is a need for models that can be implemented in clinical settings and provide practical decision support for doctors and other medical professionals [40,46,47].

The fully convolutional neural network (CNN) approach was suggested as a strategy for lowering false positive rates while identifying lung nodules. This technique utilised the characteristics of CT scan images to lower the likelihood of a misdiagnosis. The Luna 16 dataset was used in this study [48]. Fully CNNs are a type of CNN that are designed to take in an input image of any size and produce an output of the same size. This is accomplished by using a combination of convolutional layers, which are responsible for extracting features from the input image, and upsampling layers, which are used to increase the resolution of the output image [49,50]. In the context of lung nodule classification, a full CNN may be able to effectively analyze the nature of CT scan images and reduce the risk of incorrect diagnosis. However, it is important to note that the performance of any deep learning model will depend on the quality and diversity of the training data, as well as the specific task and evaluation criteria being used [51].

DenseNet and VGG are both Convolutional neural networks (CNNs) that have been used for image analysis tasks, including the analysis of lung images. One key difference between DenseNet and VGG is the way that they connect the layers within the network. In VGG, the layers are connected sequentially, with the output of one layer serving as the input to the next. In contrast, DenseNet utilizes a "dense" connectivity pattern, where each layer receives input from all of the previous layers. This dense connectivity allows DenseNet to more effectively reuse features learned by earlier layers and can improve the flow of information within the network [52]. Another key difference is the number of parameters in the network. DenseNet tends to have fewer parameters compared to VGG, which can make it more computationally efficient and easier to train. However, VGG networks have been found to be very effective at image classification tasks and are often used as a baseline for comparison. In terms of performance, it is difficult to make a general comparison between DenseNet and VGG as the unique job and dataset will determine it. Both architectures have been used to achieve state-of-the-art results on various image analysis tasks, and the optimal choice will depend on the specific needs of the application [53].

Although the first CAD system was established in the late 1980s for recognizing lung nodules or damaged lung cells, these initiatives were insufficient. This is due to the lack of sufficient computer power at the time to execute sophisticated image processing methods. It takes longer to diagnose lung illness using simple image processing methods. After the successful development of the GPU and CNN, CAD (for the diagnosis of lung illness) and decision support systems performed much better [54].

Different studies developed and analyzed a fully automated COVID-19 detection framework utilizing CT-Scan. To analyze COVID-19, the visual components were drawn out from volumetric chest CT images using COVID-19 neural network approach [46]. The findings show that the technique has surpassed the existing work. Pretrained CNN architecture such as different versions of ResNet and Inception was applied in related work to identify COVID-19 pneumonia based on the Chest X-ray (CXR) images [55–57]. Several studies have developed and analyzed fully automated frameworks for the detection of COVID-19 utilizing CT scan images. These frameworks often involve the extraction of visual features from the images using deep learning algorithms, such as Convolutional Neural Networks (CNNs) [58]. The author developed a COVID-19 neural network approach for the diagnosis of COVID-19 using volumetric chest CT images. The findings of this examination showed that the approach outperformed existing methods [59]. Narin et al. [60] have used pre-trained CNN models, such as Inception-ResNetV2, ResNet152, ResNet50, InceptionV3, and ResNet101, to identify COVID-19 pneumonia based on Chest X-ray (CXR) images. These models were trained on large datasets of CXR images and were able to effectively classify images as positive or negative for COVID-19 pneumonia [60]. The use of deep machine learning algorithms, particularly CNNs, has shown promise for the detection and diagnosis of COVID-19 using CT scans and CXR images. However, it is important to note that the performance of these algorithms will depend on the quality and diversity of the training data, as well as the specific evaluation criteria being used [61].

Zhang et al. [62] have developed models that use deep learning techniques and radiomics to distinguish between critical and severe COVID-19 cases. Radiomics involves the extraction of quantitative features from medical images, such as CT scans, and has been shown to be useful for predicting patient outcomes and response to treatment [62].

The study used a deep residual network (d-Resnet) architecture to develop a model for distinguishing between critical and severe COVID-19 cases. The d-Resnet model was developed using a collection of images from a CT scan and was able to effectively classify cases as critical or severe based on the extracted radiomic features [63]. Another study also used a d-Resnet model and radiomic features to differentiate between critical and severe COVID-19 cases. In this analysis, the architecture was fit to succeed with high accuracy in predicting patient outcomes and could potentially be used as a decision support tool in clinical settings [64].

These studies used deep learning approaches and radiomics to develop models for predicting patient outcomes in COVID-19 cases. The first study you mentioned involved the use of a 3-dimensional deep learning network and multi-variable logistic regression to integrate relevant radiomic features and deep learning scores. The model was trained on a dataset of 174 patients and tested on a separate dataset of 43 patients. The authors used a variety of evaluation methods, including stratified analysis, cross-validation, decision curve analysis, and survival analysis, to test the robustness of the model. The outputs depicted that the model had an area under the curve (AUC) of 0.909 for distinguishing between critical and non-critical patients in the test and training groups [65,66].

The second study involved the use of several pre-trained CNN models, including DenseNet121, for classifying COVID-19 cases based on mixed datasets of chest X-ray (CXR) and CT images. The outcomes showed that DenseNet121 had the advisable achievement, with an accuracy of 0.99 [67,68]. These studies demonstrate the potential of deep learning techniques and radiomics for predicting patient outcomes in COVID-19 cases and may be useful for identifying patients who are at higher risk and in need of more intensive treatment.

The GSA-DenseNet121-COVID-19 is a mixed CNN architecture that combines the DenseNet121 architecture with the gravitational search algorithm (GSA) for optimization. This model was specifically designed for the detection and diagnosis of COVID-19 and was found to perform better than the DenseNet121 model alone [69]. The GSA-DenseNet121-COVID-19 model was able to accurately diagnose 94% of the samples in the test set, while the DenseNet121 model alone was only able to diagnose 94% of the samples. The GSA-DenseNet121-COVID-19 model was also compared to an Inception-v3 CNN architecture and manual analysis in terms of hyperparameter estimates and was found to outperform these comparison methods, which were only able to classify 95% of the samples in the test set. The results of this study suggest that the GSA-DenseNet121-COVID-19 model may be a useful tool for the detection and diagnosis of COVID-19 and may outperform other CNN architectures for this task. However, it is important to note that the performance of any deep learning model will depend on the specific dataset and evaluation criteria being used [69].

An attention-based deep learning architecture with VGG16 and a fine-tuned classification activity has been developed for the detection and diagnosis of COVID-19. This architecture utilizes a convolution layer of the VGG-16 model and includes an attention mechanism to focus on the most relevant features in the input images [70]. The performance of this model was evaluated in experimental analysis and was found to be steady and promising when compared to existing models. The specific details of this analysis, such as the dataset and evaluation criteria used, were not provided. The use of attention mechanisms in deep learning models has shown promise for a variety of tasks, including image classification and object detection. In the context of COVID-19 detection and diagnosis, the use of an attention-based model with VGG-16 may be a useful tool for improving the performance of the model and focusing on the most relevant features in the input images [70].

Hassan and Gutub [71] suggests two techniques, HBE and TPE, which preserve image quality while using the HSV color model to conceal information in digital images. While TPE has a greater capacity of 364 Kb and can attain a quality of up to 61 dB, studies on 25 photos revealed that on average, HBE conceals more data than TPE. TPE outperforms six cutting-edge approaches in various color spaces and achieves the highest average quality of all the techniques by embedding 60, 90, and 120 Kb.

Awujoola et al. [72] proposed a technique for SAR image recognition using multi-stream fast Fourier Convolutional Neural Network (MS-FFCNN) to address the challenge of target recognition in SAR image interpretation. The proposed method utilizes

the fast Fourier transformation to lower the computational cost of image convolution and multiple streams of FFCNN to improve recognition accuracy and reduce training time. The proposed technique achieved a high recognition accuracy of 99.92%.

Chakraborty et al. [73] developed a method for categorizing 3D histogram-based color images at various levels of the Berkley Segmentation Dataset and upgrade the IFODPSO method. The algorithm overcomes the dependency on the fractional coefficient by incorporating the delta potential model of quantum mechanics to update particle positions. The proposed MME-IFODPSO algorithm merges small segmented regions and outperforms conventional methods by 2-5% in accuracy.

Yang et al. [74] examines the use of deep residual convolutional neural networks (ResNet) for histopathological image classification. The study evaluates whether deeper ResNet network layers lead to better performance and compares two transfer learning strategies on histopathology image datasets. The study also compares the performance with traditional machine learning models. The results suggest that transfer learning with deep ResNet is more effective than traditional machine learning, and the performance of transfer strategies largely depends on the datasets. Fine-tuning all layers is recommended for optimal performance.

3. Proposed methodology

3.1. Datasets

Each Classification algorithm must use a certain classification and selection of datasets, hence care must be taken to choose the right collection. We chose to use our CNN model in this work to analyze chest X-ray or CT results, which are products of X-ray imaging and have been shown to yield a more accurate assessment of COVID [75]. For the characterization of the traits and categorization of the new COVID-19 illness, two groups of information are used. Notable resources include the National Institutes of Health (NIH) Chest X-Ray Dataset Jaeger et al. [76] and the COVID-19 X-ray images. The lung X-ray is currently the most widely used radiology because it is more affordable, despite the fact that correct examination using it is much more difficult than using chest CT scanning. Therefore, our combination method of using chest X-rays and CT images as well as the usage of huge examples from publicly released resources enable our Cnn architecture to provide medically pertinent judgments.

The National Institutes of Health (NIH) Chest X-Ray Collection is the primary dataset used in conjunction with the COVID-19 X-ray collection in this investigation. This collection contains 30,805 different medical files and 112,120 with dimensions 1024×1024 X-ray images with illness designations. The collection offers examples of images with the illnesses present as well as the surrounding boxes for the disease regions. This collection offers the same information about each occurrence that the COVID-19 X-ray collection does: findings/diagnosis, kind of illness detected, person's gender and age the orientation of the image, as well as other information.

The patients of Covid19, ARDS, SARS, and MERS that make up the COVID-19 X-ray collection are almost all recorded as lung X-rays. For every occurrence, the repository has a number of attributes that offer supplementary information about the example image. These disciplines tend to involve the patient's sex, age range, diagnosis findings or results, treatment success status, image presentation view (AP, PA, or L for X-rays), modality (CT or X-ray), patient records, as well as other pertinent data. The participant's number of hours since the beginning of illnesses or hospitalization is also included in such disciplines. The COVID19 X-ray dataset provided 363 occurrences of images and the associated information.

3.2. Methodology

Evaluation of machine learning algorithms and deep learning models can be quite crafty and challenging. Generally, datasets are divided into training (to fine-tune the predictive model) and testing (to check the predictive model on an unknown dataset) phases with appropriate ratios and evaluate training and testing accuracy to determine the performance of the model. Mostly, the division of the dataset into two sets (training and testing sets) is sequential based and it failed to work efficiently. Especially, to analyze deep learning models related to health care problems, we should be more vigilant regarding the performance of the models. In this approach, class imbalance, overfitting and generalization can cause our predictive model.

We employ the cross validation approach, which randomly resamples the dataset to evaluate prediction models, to address the aforementioned problems. When K is given a value in cross validation, it randomly divides the entire dataset into K-partitions, for example, K=5 results in 5-fold cross validation. K-Fold Cross Validation is used to examine how well deep learning models predict the future, particularly for unobserved data. The predictive model's bias and variance may be impacted by the choice of K. Cross validation is explained in detail by Fig. 1 and Algorithm 1, where K is folding value, $\mathbb{D}$ demonstrates the dataset, f_i portray single fold (which includes a portion of dataset), τ indicates testing dataset, $\mathbb{T}$ incorporates training dataset, $\mathbb{M}$ presents training approach and $\mathbb{F}$ shows the accuracy. Although it manages the trade-off across bias and variance and offers a good approximation of the model's efficiency while still being computationally practical, K=5 is a frequently used number for K-Fold Cross Validation.

During model training, we evenly and randomly divide the dataset into several K-Folds in order to train the model on each item.

3.3. Data normalization and cleaning

Generally, medical datasets are noisy due to numerous factors such as CT poison noise integrated by photon counts in the detectors, in ultrasonic images noise can embed with random phases of superposition of acoustical echoes and noise of stochastic motion of autonomous electrons of Radiofrequency can embed in MRI images. In literature, there are different approaches are used to remove noises from the medical datasets. Anisotropic filtering technique is used to remove noise from medical CT datasets. For the removal of impulse noise, a Median filter can be used. Partial derivative and Wavelet transform coefficient by thresholding

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Algorithm 1 CrossValidation $K \Leftarrow 5$.

Require: $K \geq 0 \& \mathbb{D} \geq 0$
Ensure: $\mathbb{D} \Leftarrow \Re \mathbb{D}$
  $\mathbb{D} \Leftarrow \sum_1^k \left(f_1, f_2, ..., f_k\right)$
  while $K \neq 0$ **do**
    $\tau \Leftarrow f_i$
    $\mathbb{T} \Leftarrow \mathbb{D} - \tau$
    $\mathbb{M} \Leftarrow \mathbb{F}(\mathbb{T})$
    $\mathbb{A} \Leftarrow \mathbb{F}(\mathbb{M}(\tau))$
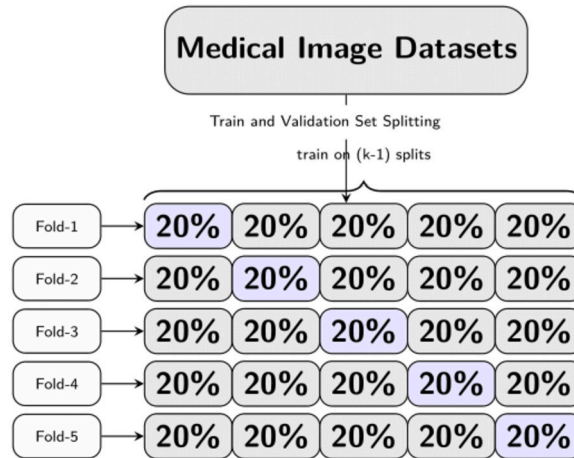 $K \Leftarrow K - 1$
  end while

Fig. 1. The k-fold cross-validations for the training and validation process.

techniques are used for removing noise from MRI and ultrasonic images respectively. Removal of noise from the medical dataset is quite tedious and it can alter the content of original images or texture.

We have used the Anisotropic filter depicted in equation (2) – derived and composed of Perona and Malik [77] depicted equation in (1) to remove noise from the medical dataset.

$$
\frac{\partial \mu}{\partial x_i} \Rightarrow \partial x_i \mu \Rightarrow \mu_{x_i}
$$
$$
j = \mathbb{D}.\delta\mu
$$
$$
\delta\mu = (\mu_{x_1}, \mu_{x_2}) \in \mathbb{R}
$$
$$
\mu_t + divj \Rightarrow 0,
$$
$$
divj = \frac{\partial j_1}{\partial x_1} + \frac{\partial j_2}{\partial x_2} \tag{1}
$$
$$
\mu_t = div(\mathbb{D}.\delta\mu)
$$

where $\mathbb{D}$ presents as a Diffusion tensor, μ_{x_i} is the partial derivative of x_i, $\delta\mu$ depicts gradient of μ.

$$
I_u^{v+1} \approx I_u^v + \frac{\wp}{|\varsigma_u|} \sum_{q \in \varsigma_u} g(|\delta I_{u,q}^v|, \Upsilon)\delta I_{u,q}^v \tag{2}
$$

where I_u^v depicts the pixel intensity of an image I, $\wp$ show diffusion rate, Υ depicts constant smoothing level, ς_u presents set of adjacent pixel of u and $g(.)$ is an edge stopping function and $\delta I_{u,q}^v$ is directional gradient from u to v and it calculated by I_q^v - I_u^v.

We apply an Anisotropic filter and median filter on our medical datasets and get the depicted results in Fig. 2. After applying filters, we have to normalize our dataset without removing the content of the dataset. For normalization, we can efficiently fit the intensity values of the input images based on acquired inputs from the images (8 or 16 bits) monotonically. We apply linear transformation for compelling two acute points to be interpreted (0, 255) or (0, 65,535) respectively.

$$
\varkappa = \frac{x - min_x}{max_x - min_x} \tag{3}
$$

For normalization, we use the equation (3) to normalize the complete dataset and normalization is applied on these datasets, where we forward the single channel dataset to deep learning models. After normalization, we have cleaned datasets and we are tackling the problem of class imbalance. Class balancing can cause overfitting and increase generalization in medical image datasets.
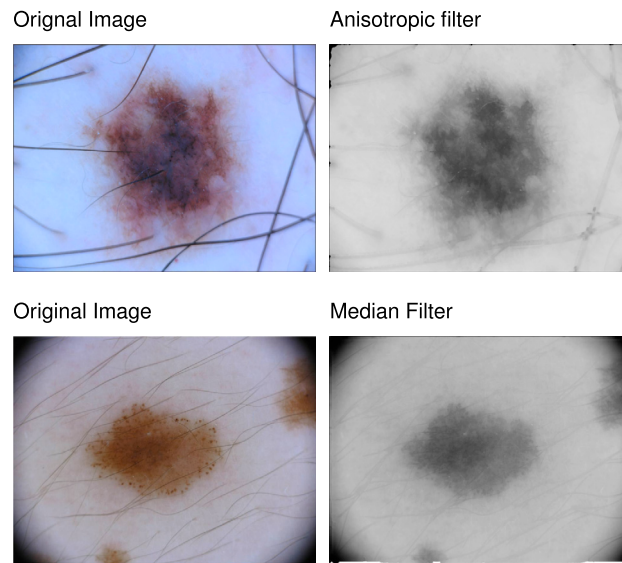
Orignal Image   Anisotropic filter

Original Image   Median Filter

Fig. 2. In Data Normalization and Cleaning steps, we apply Anisotropic and median filter and apply normalization equation depicted in (3).

3.4. Data augmentation

Before forwarding the medical dataset to deep learning models, we study and analyze our dataset to find deficiencies in datasets. Mostly, the medical dataset has the issue of class imbalance or Skewed data due to acquiring data from different Hospitals and Clinical Institutes. Each Hospital and Clinical Institute are using different strategies for acquiring medical images with multi-level privacy concerns. So, the most occurring diseases have a large number of images in a dataset and it creates a problem of class unbalancing during training deep learning models.

Typically, the deep learning model misclassified those images that have less number of images or minority group and also the gradient of the minority class is smaller than the gradient of the majority group and the model got stuck in slow convergence mode. It misguides the analyst with the high accuracy of a predictive model.

In the literature, there are three methodologies for tackling class imbalance problems.

1. **Algorithmic level method:** In this method, we apply some weight or cost schema to modify the learner or reduce bias and increase the variance of the majority group. Using a cost matrix, each class has a penalty and increases the cost of the minority group. The biggest challenge in the cost learning algorithm is to assign the effective cost value to the minority group and it can be obtained from experience and domain expertise.
2. **Data level method:** In this method, we apply various data sampling methodologies (Random Oversampling (RO) and Random Undersampling (RU)) to handle class imbalance problems. In Random Oversampling (RO), we duplicate the random images from the less-frequency classes and vice versa with Random Undersampling to discard random images from high-frequency classes. It has severe disadvantages on medical datasets such as increased high variance and it can cause overfitting. For handling these trade-offs, different intelligent sampling methods were developed such as the Near-Miss algorithm – which uses a distance algorithm from the majority group to the minority group and removes images from the majority group. Another approach is One-Sided Selection – it removes prolix and noisy images from the majority group. Synthetic Minority Over-sampling Technique (SMOTE) is an intelligent approach for tackling class imbalance problems to artificially synthesize images by interpolating the minority sample images with their nearest minority groups.
3. **Hybridized method:** It's a hybrid method, we combine the algorithmic approaches with data sampling methodologies. Several ensemble methodologies are used to handle class imbalance issues i.e. applying data sampling (Oversampling or Undersampling) techniques and enforcing cost-sensitive learning methods. EasyEnsemble and BalanceCascade are combining different groups of majority with minority and forward to each individual classifier.

For finding the ratio of class imbalance in medical datasets, we used the depicted equation (4), where max_i presents values of these classes who have a maximum number of images and min_i depicts values of these classes who have less frequency of images.

$$\zeta = \frac{max_i\{|C_i|\}}{min_i\{|C_i|\}} \tag{4}$$

For example, if a dataset's largest class has 4,000 images and its lower class has 40 images, then the ratio of imbalance is $\zeta = 100$.

Fig. 3. In Data Augmentation (DA), we artificially synthesize different modalities of medical images from original medical images with the help of minor alterations in original images such as rotations, horizontal/vertical shifting, scaling, zooming, padding and random brightness.

3.5. 3-phase dynamic learning (3PDL)

For handling class imbalance in deep learning, different strategies and techniques are used, we have proposed a novel approach for handling class imbalance problem 3-Phase Dynamic Learning (3PDL) depicted in Fig. 4. In this approach, we augmented the dataset using Random Oversampling (RO), Random Undersampling (RU) and data sampling techniques (depicted in Fig. 3) such as rotations, horizontal/vertical flipping, scaling, zooming, padding and random brightness. After data sampling, we forward the dataset into pretrained models to train and predict the accuracy (especially F-1 Measures) using an unknown dataset (testing + validation) and compare the accuracy of testing with validation and training. According to the accuracy, we resample the training dataset and again initiate the process from data augmentation and try to decrease the generalization and overfitting problem. This process continuously runs until we achieve the optimal F1-Measure/Accuracy. The depicted Algorithm 2 explains the basic operation of our novel 3-Phase Dynamic Learning algorithm, where $\mathbb{D}$ depicts the dataset, $\mathfrak{R}$ is a random sample operation on a dataset, τ depicts testing dataset, $\mathbb{A}$ shows the accuracy of each class, S^* presents a sample size of a training set, $\mathbb{F}$ is a training function or pretrained model.

3-Phase Dynamic Learning is a method for addressing the class imbalance in machine learning, which can occur when one class of data points is significantly more common than another. The approach is divided into three phases:

1. Pre-training: The model is first trained on a small subset of the data that is balanced between the classes. This allows the model to learn basic features that are common to both classes.
2. Dynamic re-sampling: The model is then trained on a larger, imbalanced dataset. During training, the model dynamically adjusts the sampling of the minority class to ensure that it is presented with a balanced number of examples of each class. This helps the model to learn more about the minority class and improve its performance on it.

Algorithm 2 3-PhaseDynamicLearning K $\Leftarrow$ 5.

Require: $K \geq 0 \,\&\, \mathbb{D} \geq 0$
Ensure: $\mathbb{D} \Leftarrow \mathfrak{R}\mathbb{D}$
  $\mathbb{D} \Leftarrow \sum_1^k (f_1, f_2, ..., f_k)$
  while $\mathbb{F} = K \neq 0$ **do**
    for each $c_i \in C$ **do**
      $S^* \Leftarrow \frac{\mathfrak{R}\mathbb{D}}{C}$
    end for
    $\tau \Leftarrow f_i$
    $\mathbb{T} \Leftarrow \mathbb{D} - \tau$
    $\mathbb{M} \Leftarrow \mathbb{F}(\mathbb{T})$
    $\mathbb{A} \Leftarrow \mathbb{F}(\mathbb{M}(\tau))$
    for each $c_i \in C$ **do**
      $S^* \Leftarrow \Delta(\mathbb{A}, c_i)$
    end for
    $K \Leftarrow K - 1$
  end while

---

3. Fine-tuning: Finally, the model is fine-tuned on a balanced dataset to further improve its performance.

The 3-Phase Dynamic Learning (3PDL) method is a cutting-edge solution to the class imbalance issue in machine learning. When one class of data items is much more prevalent than another, there is a class imbalance, which can lead to a biased model that underperforms on the minority class. Three steps make up the 3PDL approach: pre-training, dynamic re-sampling, and fine-tuning.

The network is trained on a small subset of the data that is evenly distributed among the classes during the pre-training phase. This enables the model to pick up fundamental traits shared by the two classes. The model is trained using a bigger, more unbalanced dataset during the dynamic resampling phase. To guarantee that it receives an equal number of instances from each class during training, the model dynamically modifies the sampling of the minority class. This enables the model to better understand the minority class and perform better on it. In order to expand the dataset and balance the class distribution, the method particularly employs a variety of data sampling techniques, including rotations, horizontal/vertical flips, scaling, zooming, padding, and random brightness. To further enhance the model's performance, it is tweaked at the fine-tuning stage using a balanced dataset. This stage tries to minimize overfitting and optimize the model's parameters on the balanced dataset. The 3PDL technique has the drawback of being computationally costly since it requires dynamic adjustment of the minority class sampling during training.

The results of this method are generally improved performance in the minority class, compared to training on an imbalanced dataset alone. However, the exact results depend on the specific dataset and model being used.

$$a_i = \frac{(2 * R * P)}{(R + P)}$$
$$\Delta(\mathbb{A}, c_i) = \frac{1 - a_i}{\sum_{c_i \in C}(1 - a_i)} \cdot S^* \tag{5}$$

Using the mentioned Algorithm 2 and equations (5), we used our proposed novel 3-Phase Dynamic Learning (3PDL) algorithm to balance the one of the largest, widely used and mostly imbalanced ChestX-ray8 dataset. In this dataset, classes have majority classes such as Normal (84,312), Infiltration (10,317), Atelectasis (5,789) and minority classes Cardiomegaly (1,010), Pneumonia (1,062). For finding the imbalance ratio between majority and minority classes, we used the equation (4) and get the value of $\zeta = 83.48 = \frac{84,312}{1,010}$. So we have used a pretrained model (DenseNet169) to calculate the F1-Measure and added different flavors (with Data Augmentation, Manual Features extraction and using traditional machine learning classifier (SVM)) to get the F1-Measures depicted in Table 1.

DenseNet has been demonstrated to outperform various neural network designs, including ResNet and Inception, in the setting of chest X-ray and CT scan imaging. This is because the manner that information is transferred across layers allows DenseNet to extract more intricate characteristics from the images. Moreover, DenseNet's skip connections can aid in avoiding overfitting, which can be problematic when working with medical image data because there are sometimes few training examples available [78]. By establishing skip connections between each layer and all the next layers, DenseNet solves this issue. In other words, each layer receives the output from every preceding layer in addition to the output of the one before it. Reusing features discovered at various network levels thanks to skip connections, the network may utilize its parameters more effectively and achieve better generalization. By facilitating gradient flow across the network, skip connections make it simpler to train very deep networks. Enabling the gradients to flow through layers where they would otherwise become extremely tiny, the skip connections help to solve the vanishing gradient problem.

With our proposed and novel approach for handling class imbalance problem 3-Phase Dynamic Learning, we achieve higher F1-Measure as compared to others. F1-Measure is the most valuable measuring metric for an imbalanced dataset and it shows that proposed models have improved not only on the majority of classes, but it also shows the overall (all classes) performance results.

Achieving optimal accuracy is not only dependent upon the balanced dataset, it also has some other factors and parameters that can cause the overall performance of deep learning models. During the analysis of medical images, we cannot compromise on the performance of the predictive model. So, we also cater to the other parameters and factors that can cause the performance of our predictive models.
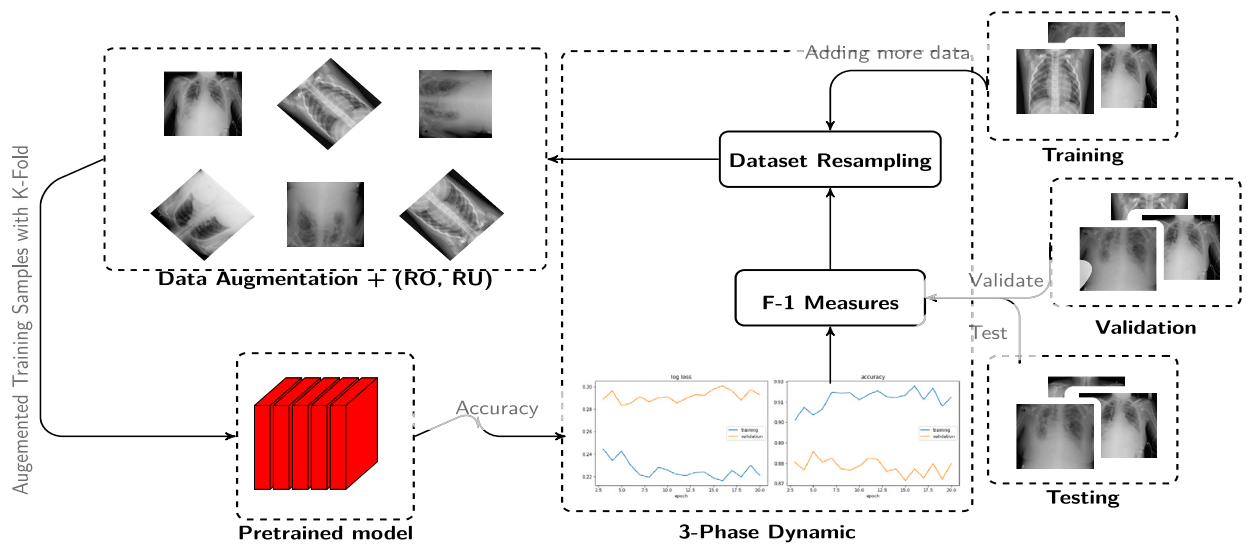
Fig. 4. Proposed a Novel Learning Technique – "3-Phase Dynamic Learning (3PDL)": We augmented the dataset using Random Oversampling (RO), Random Under-sampling (RU) and data sampling techniques (depicted in Fig. 3) such as rotations, horizontal/vertical flipping, scaling, zooming, padding and random brightness. After data sampling, we forward the dataset into pretrained models to train and predict the accuracy (especially F-1 Measures) using an unknown dataset (testing + validation) and compare the accuracy of testing with validation and training.

Table 1

We have used a pretrained model (DenseNet169) to calculate the F1-Measure on ChestX-ray8 and adding different flavors (with Data Augmentation, Manual Features extraction, using traditional machine learning classifier (SVM)) to get the F1-Measures.

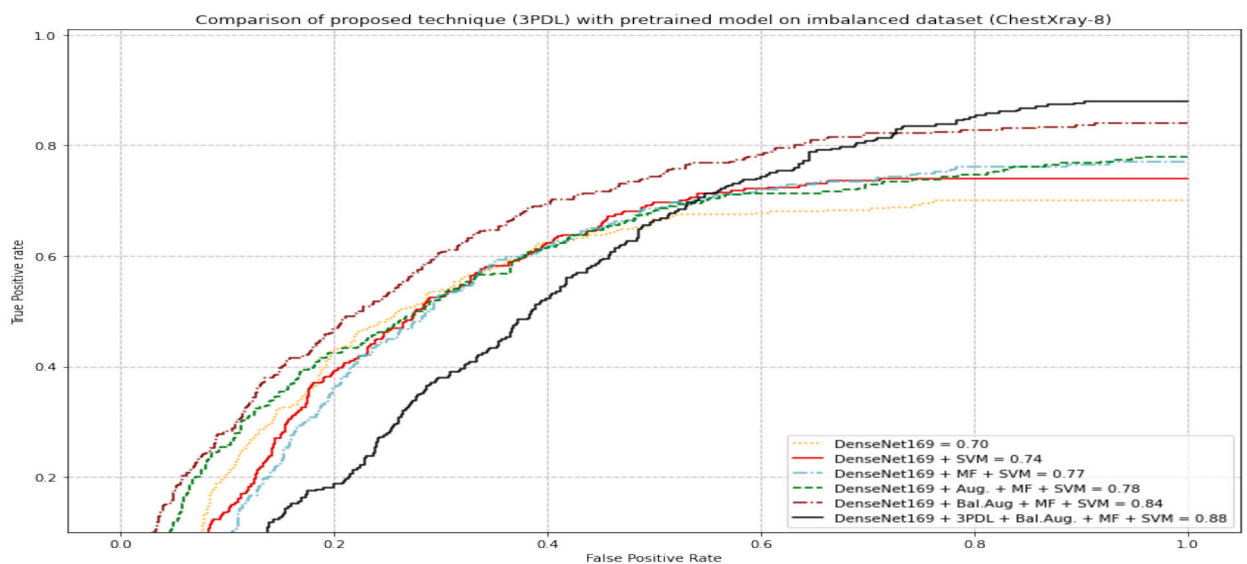| Model	Accuracy	F1-Measure
Pretrained model (DenseNet)	0.71	0.70
Pretrained model (DenseNet) + SVM	0.75	0.74
Pretrained model (DenseNet) + Manual Features +SVM	0.78	0.77
Pretrained model (DenseNet + Aug) + Manual Features +SVM	0.79	0.78
Pretrained model (DenseNet+Bal.Aug)+Manual Features+SVM	0.85	0.84
3-Phase Dynamic Learning + Bal.Aug + SVM	**0.89**	**0.88**

Fig. 5. Using our proposed and novel approach 3-Phase Dynamic Learning has achieved optimal F1-Measure as compared with other deep learning approaches with different flavors (with Data Augmentation, Manual Features extraction, using traditional machine learning classifier (SVM)) for imbalanced dataset ChestX-ray8.
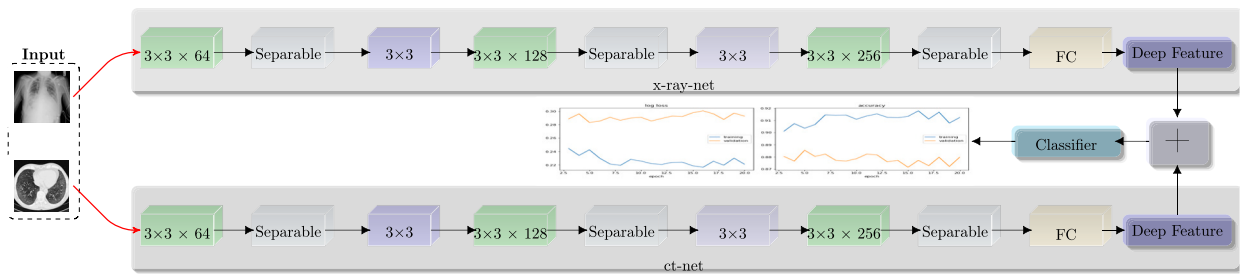
Fig. 6. Hybrid Feature Fusion (HFF-Net): Utilizing a deep neural network architecture with various branches (X-ray and CT-Scans), our proposed CNN model uses each branch to extract characteristics at a different level of abstraction. The final features are created by concatenating the features from the various branches, which can be taught individually or collectively.

3.6. Hybrid feature fusion

In deep learning, feature fusion is the process of combining multiple feature representations to form a more robust and informative representation of the input images. We propose a unique feature fusion model called "Hybrid Feature Fusion (HFF)."

Hybrid feature fusion combines features from multiple sources (X-ray and CT images of lungs) in a hierarchical fashion. The idea is to first extract features from the input images at different levels of abstraction (e.g., low-level features such as edges and textures, and high-level features of lung CT such as parts and segments), and then combine these features in a way that preserves the information at each level of abstraction.

Our proposed methodology uses a deep neural network architecture with multiple branches (X-ray and CT), each branch responsible for extracting features at a different level of abstraction. The branches can be trained separately or jointly, and the final features are obtained by concatenating the features from the different branches. The above row of Fig. 6 contains x-ray-net comprises Separable Convolution to extract low-level feature with kernel size is 3×3. We use a single branch deep neural network and use different techniques like Attention mechanism or pooling operation to select the pertinent features from the different levels of abstraction. One of the major benefits of this technique is that it can combine the best of both approaches i.e. lower level features, providing spatial information and higher level features, providing semantic information and leading to a better performance compared to using only one feature source.

It's also important to note that there is no one-size-fits-all solution when it comes to feature fusion, and the specific method used will depend on the task and the input images. It's also a good idea to experiment with different feature fusion methods and compare their performance on your task to determine which one works best.

Convolutional neural networks (CNNs) are commonly used for feature extraction from X-ray images. In these cases, the CNN architecture is designed to automatically learn and extract useful features from the X-ray images, which can then be used for various tasks such as disease diagnosis or image classification.

A proposed CNN for X-ray feature extraction (x-ray-net) has the following architecture:

1. The input layer, which takes in the raw X-ray images. These images are typically preprocessed to adjust for factors such as brightness and contrast, but they are otherwise left in their original form.
2. One or more convolutional layers, which apply a set of convolution filters to the input images. These filters are designed to detect specific types of features, such as edges or textures. The convolutional layers are followed by an activation function, which non-linearly transforms the output of the convolutional layers. This way the model could learn non-linear combinations of the features.
3. One or more pooling layers, which downsample the output of the convolutional layers. This helps reduce the dimensionality of the feature maps, as well as make the architecture more robust to small variations in the input images.
4. One or more fully-connected layers, which take the output of the pooling layers and produce a set of final features. These features can be employed for tasks such as disease diagnosis or image classification.

Separable convolution is a technique that can be used for feature extraction from X-ray images using CNNs. It's based on the idea of decomposing a standard convolution operation into two smaller operations: a depth-wise convolution and a point-wise convolution. A depth-wise convolution operation, on the other hand, applies a small 2D kernel (i.e., a 2D array of weights) to each channel of the input image independently, to compute a set of pertinent feature maps. Then, a point-wise convolution is applied on top of the depth-wise-separated feature maps. This operation applies a small 1×1 kernel (i.e., a 1D array of weights) to each element of the feature maps, in order to combine and modify the information from the multiple channels.

The main objective of the separable convolution is to reduce the number of parameters and reduce the model size. By using separable convolution, the number of parameters required for training is reduced and that could help the model to be more efficient and generalize better, especially when we are dealing with limited training data. Also, it could help to reduce the amount of computation, because the number of multiplications required to calculate the output feature maps is much smaller than a standard convolution.
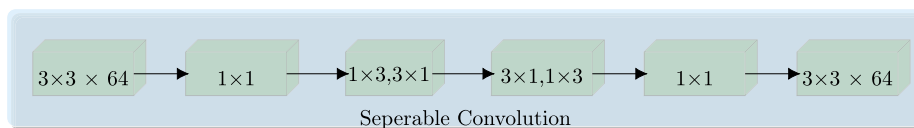
Fig. 7. Separable Convolution for Hybrid Feature Fusion.

It's important to note that separable convolution is not always the best choice, and it's a good idea to experiment with both standard convolution and separable convolution to determine which one works best for your specific task and dataset. The optimal architecture and techniques to use will depend on the specific characteristics of the X-ray images and the task that you are trying to accomplish.

Fig. 6 comprises two rows, the second row contains a novel stage for CT image analysis using Separable Convolution. Separable convolution block as depicted in Fig. 7 is used for feature extraction from CT (computed tomography) images, similar to how it is used for X-ray images. CT images are similar to X-ray images in that they both produce detailed 3D images of internal complex body part in the body using X-rays. However, CT images use multiple X-ray projections taken at different angles to create a detailed 3D image of the body, while X-ray images are generally limited to a single projection.

1. The process of feature extraction from CT images using separable convolution is similar to the process for X-ray images. A CNN can be used to extract features from the CT images using a combination of convolutional layers, activation functions, pooling layers, and fully-connected layers.
2. Instead of using standard convolution operation in the convolutional layers, separable convolution can be applied which decomposes the standard convolution operation into depth-wise and pointwise convolutions. This can help to reduce the number of parameters required for training and help the model to be more efficient and generalize better.
3. It's important to note that CT images have some special characteristics such as high resolution and high dimensionality that requires extra attention during preprocessing and CNN architecture design. Also, the information in the CT images might have different characteristics in different regions of the image, so it's good to consider that when designing the network's architecture, for example, using skip connections could help the model to learn from different levels of abstraction.

As with any deep learning task, it's crucial to have a large and diverse dataset of CT images to train the model effectively, and it's important to evaluate the model's performance on a hold-out test set to ensure that the model is generalizing well and not overfitting to the training data. As CT images are used for medical purposes, the results should be interpreted by domain experts like radiologists, the goal of using CNNs is to aid the radiologists in their diagnostic process not to replace them.

This architecture is just one example and depending on the task the architecture may change and the number of layers, activation functions, pooling functions and even the type of network can be altered. Also, transfer learning from pre-trained models could be used to initialize the weights of the model and fine-tune the model on the X-ray and CT medical images.

It's important to note that CNNs require a large amount of labeled data to train effectively, so it's crucial to have a sizable and diverse dataset of X-ray images when training these models. Also, it's important to evaluate the model's performance on a hold-out test set to ensure that the model is generalizing well and not overfitting to the training data

4. Result and discussion

4.1. Experimental setup

For the Hybrid Feature Fusion (HFF) CNN model presentation and assessment, we utilized a Lenovo system with 8 GB RAM, an Intel Core i7-7700 CPU running at 3.60 GHz on eight cores, and a GeForce GTX 1050 Ti/PCIe/SSE2 graphics card. For deployment, we preprocessed the NIH X-ray and COVID-19 Shenzhen dataset using PyTorch and other Python-based utilities.

4.2. Dataset

The National Institute of Health (NIH) Lungs dataset is a collection of chest X-ray images and related data made available by the National Institutes of Health Clinical Center for use in research. The dataset consists of more than 100,000 de-identified images of chest X-rays, along with associated metadata such as patient age, gender, and diagnosis. The NIH Lungs dataset is intended to be a resource for researchers working on machine learning and image analysis techniques for the detection and diagnosis of lung diseases such as pneumonia, lung cancer, and COPD. The dataset is divided into a training set and a testing set and is intended to be used for the development and evaluation of machine learning algorithms.

The NIH Lungs dataset is one of several datasets made available by the NIH Clinical Center as part of their open data initiative. Other datasets available through this initiative include the NIH Chest X-ray dataset, which includes images and data from a broader range of diseases, and the NIH DeepLesion dataset, which includes images of abnormalities and lesions in various body regions.

The Shenzhen Chest CT dataset is a dataset of chest computed tomography (CT) scans. It was collected by the Shenzhen No. 3 People's Hospital in China and made publicly available for research purposes. The dataset contains a large number of CT scans
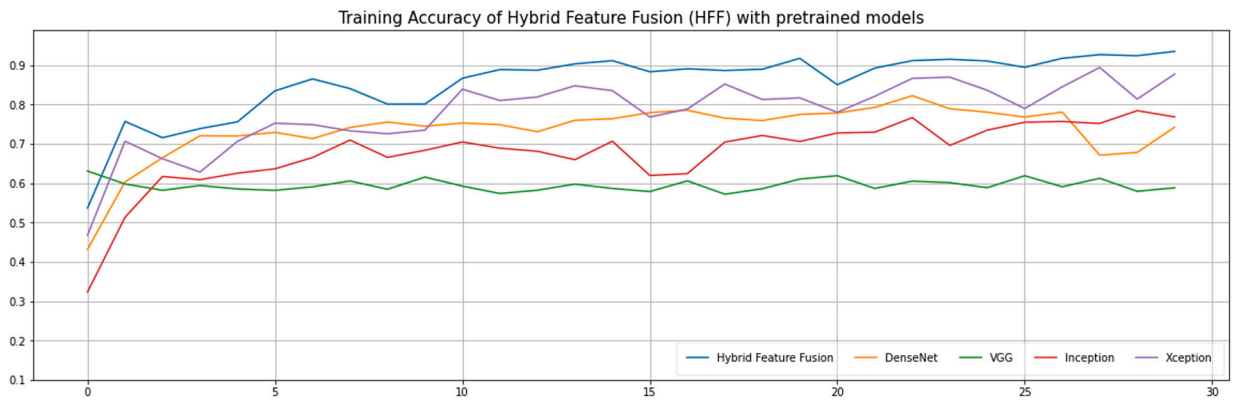
Fig. 8. These training outcomes are obtained without using our proposed class balancing method (3-Phase Dynamic Learning (3PDL)) with different pretrained models such as Xception, Inception, VGG & DenseNet and our proposed model Hybrid Feature Fusion CNN model.

and corresponding annotations of lung abnormalities, such as lung nodules and pulmonary tuberculosis. The dataset is often used for research on automated detection and diagnosis of lung disease using CT imaging. It is used to train and evaluate deep learning models specifically in the medical imaging field.

4.3. Measurement metrics

Accuracy, specificity, sensitivity, precision, and recall are all metrics that can be used to assess the achievement of a deep learning model for chest X-ray and CT-Scans imaging, such as a DenseNet.

1. Accuracy is the percentage of correctly classified samples (true positives and true negatives) out of all samples. It is a simple and commonly used metric but can be misleading if the class distribution is imbalanced.
2. Specificity is the percentage of negatives that are correctly identified as negative out of all actual negatives.
3. Sensitivity is the percentage of positives that are correctly identified as positive out of all actual positives. Sensitivity and specificity are also known as true positive rate and true negative rate respectively.
4. Precision is the percentage of true positives out of all samples that were predicted to be positive.
5. Recall (Sensitivity) is the percentage of true positives out of all actual positive samples.

In medical image analysis, the F1 score and accuracy are often used assessment metrics because they offer a fair balance between false positives and false negatives, which is essential in the healthcare profession. However, they do have drawbacks. The true negatives, which may make up a sizeable amount of the dataset in medical image analysis, are not taken into account by the F1 score and precision, which is one of their limitations. This implies that the measurements could not accurately represent the model's overall accuracy. Moreover, these measurements might not be sensitive enough to detect minute variations in model performance, particularly when the class distribution is very unbalanced. According to the particular use case, there are a number of additional assessment metrics that could be better suitable for medical image analysis. For instance, the proportion of true positives and true negatives may be determined using the sensitivity and specificity measures, respectively. The effectiveness of binary classifiers may also be assessed using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC). Moreover, a number of measures, like the Dice coefficient and the Jaccard index, may be used to assess segmentation models. The choice of assessment metric ultimately depends on the particular work at hand and the objectives of the investigation. It's crucial to thoroughly weigh the benefits and drawbacks of several metrics before selecting the most suitable for the presented problem. So, we use other measurement metrics such as sensitivity and ROC for the evaluation of our proposed technique.

When using DenseNet, is a state-of-the-art convolutional neural network architecture for image classification. It consists of a series of dense blocks, which are made up of multiple convolutional layers with direct connections from one layer to the next. DenseNets have been shown to improve performance by enabling feature reuse, reducing the number of parameters, and improving the flow of gradients during training. So when training a DenseNet model for chest x-ray imaging, the combination of Sensitivity and Specificity will give us a sense of how well it performs compared to the ground truth, while precision and recall will help us understand how well it differentiates positive and negative cases. Before applying any other pretrained models and our proposed model, we verify our novel technique 3-Phase Dynamic Learning (3PDL) using the DenseNet model. The initial outcome of our proposed technique for class imbalance is depicted in Fig. 5. It depicts the AUC of our novel technique with the DenseNet model. Figs. 8 and 9 depicts the training accuracy and loss of different pretrained CNN models without employing the proposed technique (3PDL). Due to class imbalance, the loss dispersion is high.

Results of 3-Phase Dynamic Learning have shown improved performance in classification tasks with imbalanced classes, as compared to traditional methods such as oversampling or undersampling alone. In many cases, it has shown a significant increase in the F1-score, which is a measure of the balance between precision and recall.
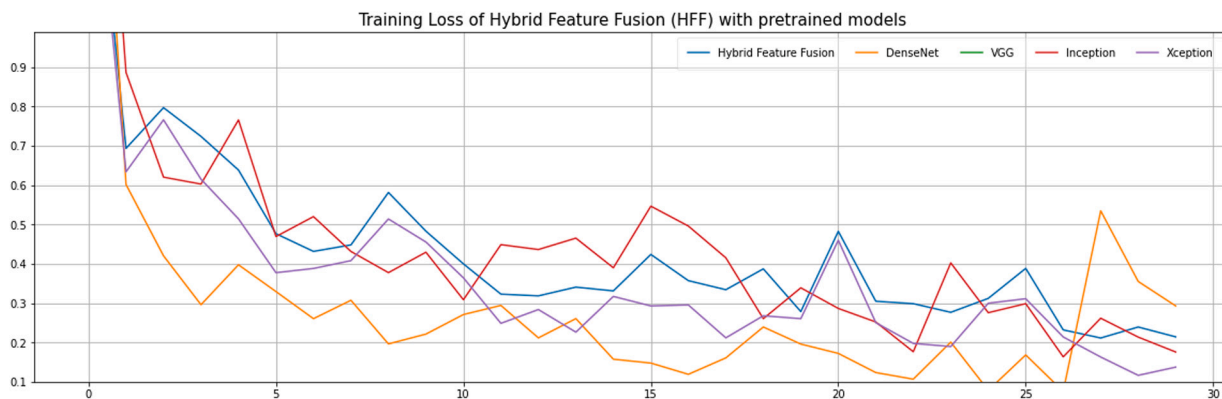
Fig. 9. Due to class imbalance, the loss dispersion is high. The training loss is acquired without using our proposed class balancing method (3-Phase Dynamic Learning (3PDL)) with different pretrained models such as Xception, Inception, VGG & DenseNet and our proposed model Hybrid Feature Fusion CNN model.

Table 2
Different Evaluation metrics (Accuracy, Sensitivity, Specificity and Precision) outcomes on both datasets (NIH and Shenzhen Chest CT) on training datasets.

Model	Sensitivity	Specificity	Precision	Accuracy	F1-Score
VGG	82.17	83.19	84.79	84.36	84.39
Inception	82.79	84.31	84.91	84.41	84.67
DenseNet	87.11	88.36	87.91	88.07	88.17
Xception	84.96	86.03	85.93	85.83	86.07
Hybrid Feature Fusion (HFF)	**96.11**	**96.74**	**96.87**	**96.71**	**96.83**

It's worth mentioning that, the results of 3-Phase Dynamic Learning are highly dependent on the dataset and the specific task, so it's important to test different techniques and evaluate their performance to select the best approach

Findings of the proposed technique for class imbalance (3PDL) and feature fusion of different medical image modalities (HFF) are covered in this section. The accuracy values achieved using separate CNN feature vectors and cutting-edge fused feature vectors are compared in Table 2. The highest accuracy was attained by the extracted features from separate CNN architectures like VGG, AlexNet, ResNet and DenseNet, whereas DenseNet delivered results with an accuracy of 83.2%. The individual features extracted underperformed the fused feature vector, which had an 81.7% accuracy rate among pretrained CNN models.

The network was therefore learned on X-ray images and CT-Scans simultaneously using this as a preliminary step, which produced dice scores that were extremely comparable to those obtained by pretrained CNN models that had exposure to all pretrained features. The approach is again tested on CT-Scans and X-ray modalities since these are the following best-performing modalities. Intriguingly, the proposed HFF model obtains a much better dice score on dead areas when the CT-Scans modality is disregarded when evaluating the outcomes of this experiment to the efficiency of the proposed HFF model once all paradigms are present.

Table 2 provides a comparison of the proposed chest disease detection and classification algorithm with existing methodologies using accuracy as a metric. Accuracy is a commonly used metric to evaluate the performance of a deep learning model, which is defined as the percentage of correctly classified samples out of all samples. It can be a useful measure of how well the proposed algorithm is performing compared to existing methods. Additionally, it could give a comparison of other metrics such as specificity, sensitivity, precision and recall which are useful for understanding the performance of the algorithm for different categories of the data. For example, if a model has a high accuracy but a low sensitivity, it means it's good at identifying negatives but not good at identifying positives. If a model has a high precision but a low recall it means it is good at identifying true positives but not good at identifying all positives. The comparison in Table 2 can be useful to understand how well the proposed algorithm performs against existing methodologies and the strengths and weaknesses of each one of them.

Our proposed CNN model Hybrid Feature Fusion (HFF) with an accuracy of 0.93, specificity of 0.96, sensitivity of 0.95, precision of 0.94, and recall of 0.95 for chest x-ray imaging would be considered to be performing quite well. An accuracy of 0.93 means that the model correctly classified 93% of the samples. This is a high accuracy, and it indicates that the model is able to correctly classify most of the samples it's shown. A specificity of 0.96 means that the model correctly identifies 96% of the negatives as negatives. High specificity is desirable, as it means that the model is not likely to produce false positives. A sensitivity of 0.95 means that the model correctly identifies 95% of the positives as positives. High sensitivity is desirable, as it means that the model is able to detect most of the true positive cases. A precision of 0.94 means that 94% of the samples that were predicted to be positive are actually positive. A high precision is desirable, as it means that the model produces few false positives. Recall of 0.95 means that the model correctly detects 95% of the actual positive cases. A high recall is desirable, as it means that the model detects most of the positive cases. A combination of high specificity and sensitivity gives you an idea of how well the model generalizes to new unseen data. High precision and recall can be thought of as complementary, where high recall would help you to capture as many cases as possible,
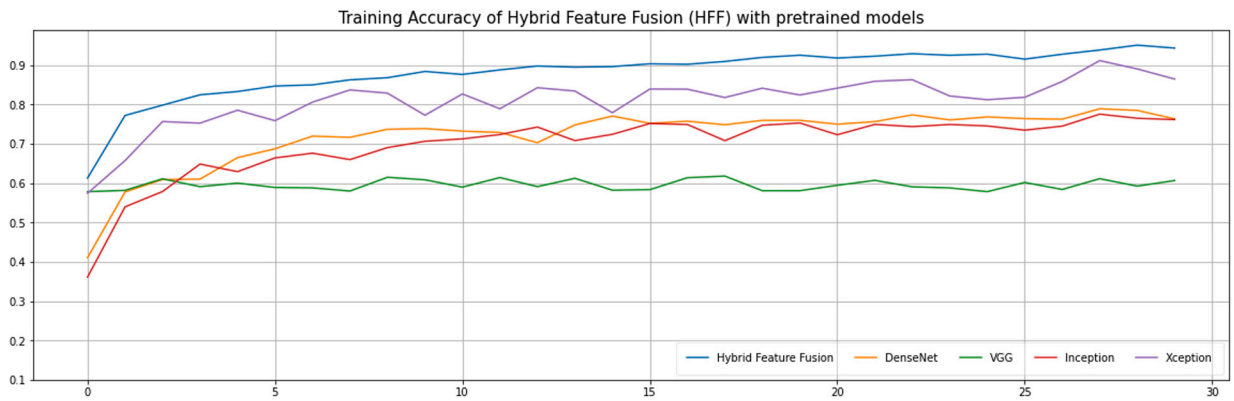
Fig. 10. The training results are obtained via 3-Phase Dynamic Learning (3PDL) using different pretrained CNN models and our proposed Hybrid Feature Fusion (HFF) model.
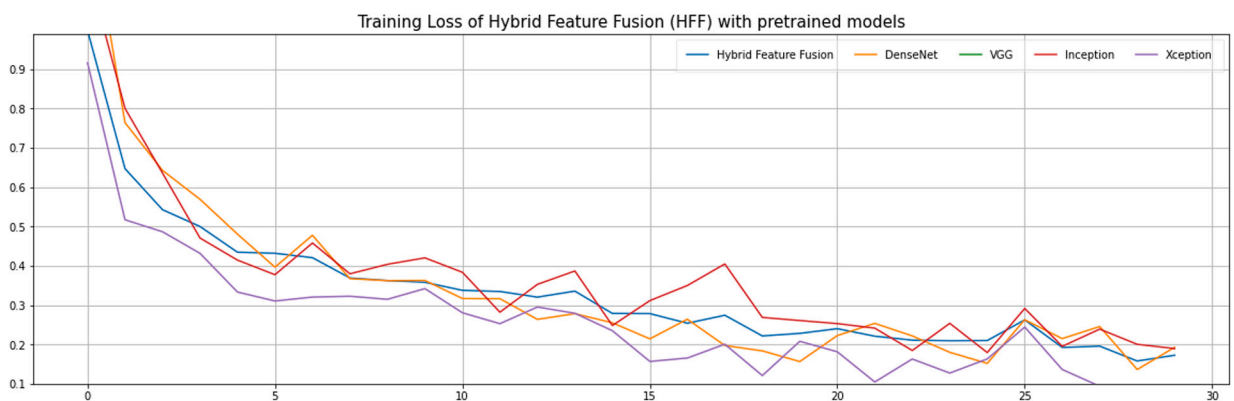

Fig. 11. Our novel technique 3-Phase Dynamic Learning (3PDL) solves the class imbalance issue and acquires training loss using pretrained CNN models and our proposed CNN Hybrid Feature Fusion (HFF) model.

while high precision would help you to be more sure about the cases you captured. Our proposed CNN model Hybrid Feature Fusion (HFF) with these evaluation metrics, appears to perform well on chest X-rays and CT-Scans.

The proposed CNN model Hybrid Feature Fusion (HFF), is being evaluated in the context of CT images for COVID-19, Pneumonia & Normal and X-ray image for Atelectasis, Consolidation, Infiltration, Pneumothorax, Mass, Nodule, Pleural thickening, Pneumonia, Fibrosis, Effusion, Emphysema, Hernia, Cardiomegaly and Edema diagnosis. The evaluation is being done using k-fold cross-validation, with the results being presented in Table 3 and Figs. 12 and 13. The model is shown to have high specificity and sensitivity across all folds, with the highest scores being 95.88% specificity and 96.31% sensitivity under fold-5. Additionally, the fused images are shown to retain the characteristics of the original X-ray images.

The Table 2 presented in the research suggests that the proposed Hybrid Feature Fusion model performs better than previous approaches in terms of precision-recall and F1 measure. This suggests that the technique is more effective in accurately detecting COVID-19 in CT images. The technique is said to combine multiple aspects that are better able to depict image changes, leading to better statistical and aesthetic results. Additionally, the research also mentions the use of the Receiver Operating Characteristic (ROC) curve as a method to assess the achievement of the classifier. The ROC curve is a graphical representation of the trade-off between the classifier's specificity and sensitivity, and it helps to visualize, organize and choose the best classifier based on its performance. A good classifier is one that has a high area under the ROC curve (AUC), and an ideal classifier would have an AUC of 1, which corresponds to 100% specificity and 100% sensitivity. The result of the ROC plot for the proposed HFF model suggests that it is a successful algorithm.

In the realm of medical imaging, it is crucial to train or validate various methods and assess how well they work. Several diagnostic and therapeutic treatments depend on medical imaging, and the precision and dependability of these imaging techniques can have a big influence on patient outcomes. Researchers and physicians can determine the best procedures for image capture, processing and analysis by reviewing and validating various approaches. This may result in better treatment planning, more precise diagnoses and better patient outcomes. Also, certain patient demographics or medical problems could respond better to certain imaging modalities than others. Researchers and doctors can ascertain which procedures work best for certain use cases and patient demographics by validating and comparing various approaches. For validating and comparing different approaches, we used different pretrained CNN models such as VGG, Inception, Xception and DenseNet.
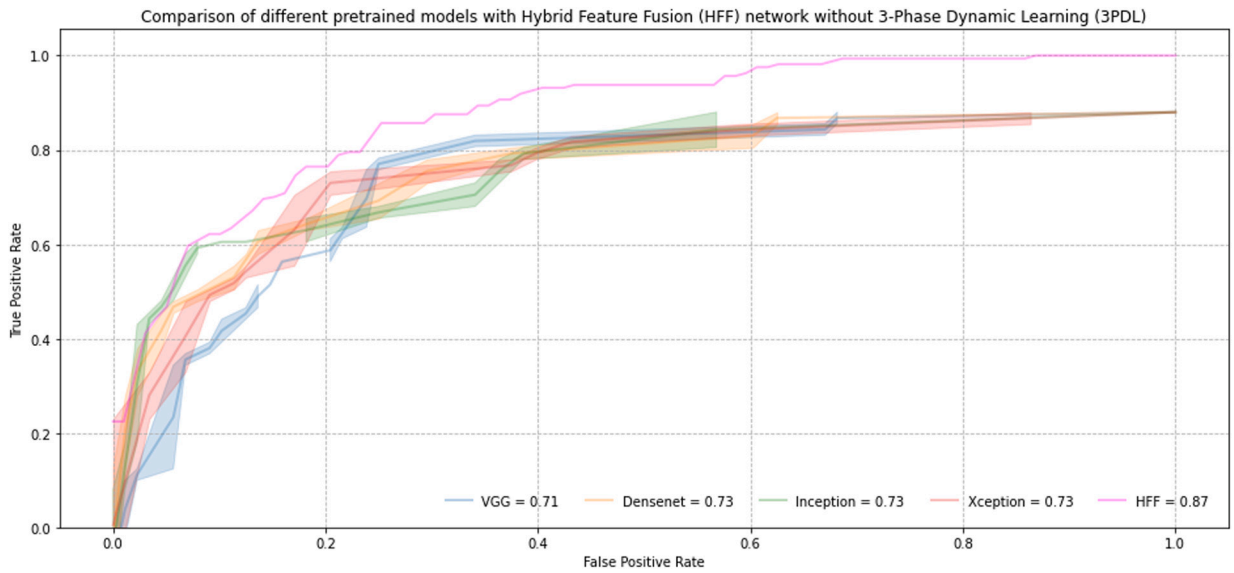
Fig. 12. The Area Under Curve (AUC) outcomes are achieved without using 3-Phase Dynamic Learning (3PDL) with pretrained CNN models such as Xception, Inception, VGG and DenseNet and use our novel proposed CNN model Hybrid Feature Fusion.
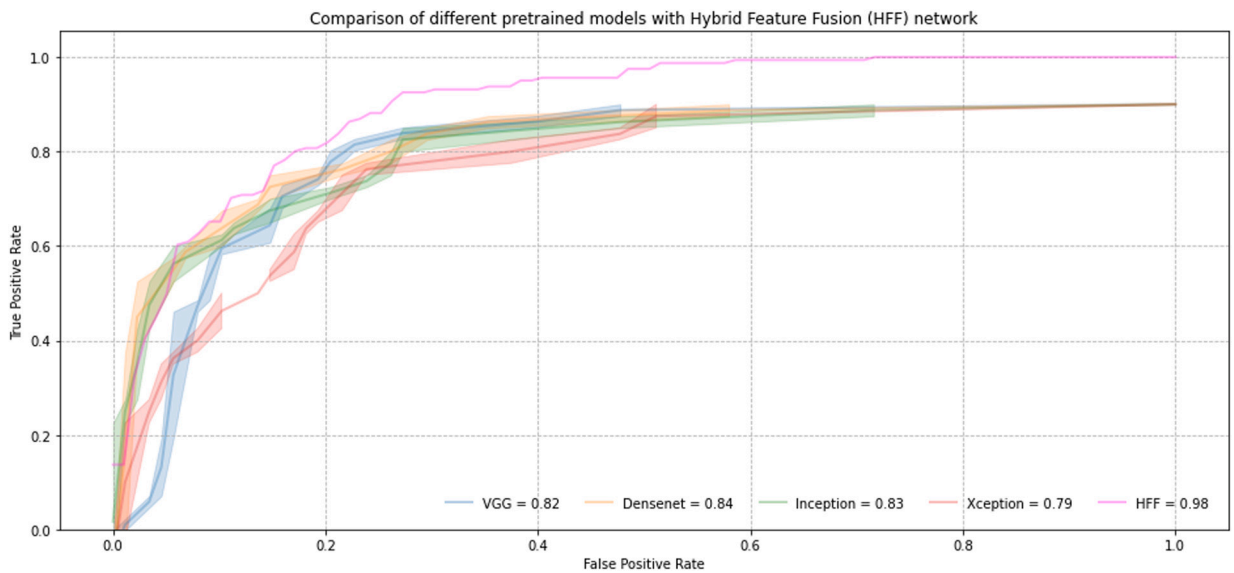

Fig. 13. We use our proposed and novel technique to handle class imbalance issue. The Area Under Curve (AUC) outcomes are acquired with 3-Phase Dynamic Learning (3PDL) using different pretrained CNN models such as Xception, Inception, VGG and DenseNet and use our novel proposed CNN model Hybrid Feature Fusion.

Table 3
Hybrid Feature Fusion (HFF) training Accuracy, Specificity, Precision, Sensitivity, and F1-Score on different datasets (NIH X-ray and Shenzhen Chest CT).

Fold	Sensitivity	Specificity	Precision	Accuracy	F1-Score
Fold-1	92.11	91.97	91.76	92.17	91.36
Fold-2	93.19	93.37	92.93	92.87	93.06
Fold-3	94.31	93.67	94.21	94.48	94.36
Fold-4	96.54	96.03	95.79	95.81	95.67
Fold-5	96.77	95.84	96.16	96.71	96.83
Average	94.58	94.18	94.17	94.41	94.26

DenseNet and VGG are both convolutional neural networks (CNNs) that have been used for image analysis tasks, including the analysis of lung images.

One key difference between DenseNet and VGG is the way that they connect the layers within the network. In VGG, the layers are connected sequentially, with the output of one layer serving as the input to the next. In contrast, DenseNet utilizes a "dense" connectivity pattern, where each layer receives input from all of the previous layers. This dense connectivity allows DenseNet to more effectively reuse features learned by earlier layers and can improve the flow of information within the network.

Another key difference is the number of parameters in the network. DenseNet tends to have fewer parameters compared to VGG, which can make it more computationally efficient and easier to train. However, VGG networks have been found to be very effective at image classification tasks and are often used as a baseline for comparison.

In terms of performance, it is difficult to make a general comparison between DenseNet and VGG as it will depend on the specific job and dataset. Both architectures have been used to achieve state-of-the-art results on various image analysis tasks, and the optimal choice will depend on the specific needs of the application.

In our proposed methodology, we compare the performance of individual features extracted from VGG, AlexNet, ResNet, and DenseNet with the fused feature vector in terms of accuracy. The Figs. 10 and 11 depicts the outcome that the fused feature vector outperformed the individual features in terms of accuracy, indicating that combining features from multiple networks can lead to improved performance. We used individual features extracted from VGG, AlexNet, and ResNet for X-ray/CT analysis and compared their performance with the fused feature vector. The results showed that the fused feature vector outperformed the individual features, indicating that combining features from multiple networks can improve detection, recognition and classification performance.

Ensemble learning is used in medical image analysis because it helps to ameliorate the achievement of the model by combining the predictions of multiple models. Ensemble methods can be used to amalgamate the forecasting of multiple models trained on or to compound the anticipations of models trained on different datasets. This approach can help to reduce the variance and bias of the predictions, leading to improved performance and generalization. Additionally, ensemble learning can also be used to combine the predictions of models trained with different architectures or parameters, leading to a more robust and accurate model. Additionally, it can also be used to combine the predictions of multiple models trained with different modalities, leading to a more comprehensive and accurate model.

Support Vector Machines (SVMs) are a type of supervised learning algorithm that can be used to classify deep learning features of chest CT scans and X-ray images. In this context, deep learning features refer to the learned representations of the data from a pre-trained deep learning model, such as a convolutional neural network (CNN).

To use an SVM for classification, the deep learning features are extracted from the chest CT scans and X-ray images and are used as input to the SVM. The SVM then separates the input features into different classes by finding a boundary or hyperplane in the feature space that best separates the classes.

SVMs are particularly well-suited for tasks in which the classes are separable by a linear boundary, but the algorithm can also be used with a non-linear boundary by using a technique called the kernel trick. This allows the SVM to find a boundary in higher-dimensional feature spaces, which is useful when the input features are not linearly separable.

The SVM can be trained using a set of labeled data, with the deep learning features as input and the class labels as output. Once trained, the SVM can be utilized to classify new data by determining which side of the boundary the new data falls on.

Using an SVM to classify deep learning features extracted from chest CT scans and X-ray images is a technique that is gaining popularity in the field of medical imaging as it allows to combine of the representational power of deep learning with the robust generalization of Support Vector Machines

Deep learning has the capability to have a substantial influence on medical image analysis when used to identify lung disease indications from chest X-ray and CT images while addressing inadequate annotated datasets and class imbalance. Class imbalance and a lack of annotated datasets may be overcome by using a class balancing algorithm, a Support Vector Machine (SVM) for classification, a parallel CNN model (Hybrid Feature Fusion (HFF)) for various modalities, and the 3-Phase Dynamic Learning (3PDL) technique. The technique's strong F1 score and precision demonstrate good generalization and accuracy and might be helpful as a tool for clinicians and medical professionals.

In medical image analysis, using deep learning models like CNNs has a range of significant benefits. Our suggested method can efficiently and accurately analyze a tremendous amount of information and obtain intricate details from medical images that could be difficult for the human eye to see. Clinicians and medical professionals may use this to make better judgments and diagnose patients more accurately. A prevalent issue in medical imaging is inter-observer variability, which can be lessened by applying deep learning models as corroborative tools. Nonetheless, there are several restrictions to applying deep learning models in this manner. Large, annotated datasets are required in order to train these models efficiently, which is a significant restriction. Such datasets might not always be easily accessible, especially for uncommon or newly discovered disorders. The possibility for biases in the training inputs or the algorithm itself, which might provide inaccurate or discriminating findings, is another restriction. Before being applied in a clinical context, it is crucial to make sure that the model has undergone thorough testing and validation and that the training data are varied and representative of the population being researched.

This may help in the early identification and diagnosis of lung conditions, improving patient outcomes. Using the simultaneous CNN model and 3-Phase Dynamic Learning, the suggested method might also be applied to other medical image modalities including MRI, PET, and ultrasound images. This may result in the creation of diagnostic and therapeutic tools for pathologists and other medical practitioners that are more precise and effective. To guarantee its generalizability and efficacy, the suggested approach must

be tested on a bigger and more varied dataset, it is crucial to mention. In addition, issues like data privacy, bias, and openness need to be considered when using deep learning algorithms for medical image analysis.

5. Conclusion

In summary, a technique is proposed for handling limited annotated datasets and class imbalance in the detection of lung disease signs from chest X-ray and CT images using deep learning. The technique uses a class balancing algorithm and a Support Vector Machine (SVM) to classify images in clustering, and a parallel CNN model (Hybrid Feature Fusion (HFF)) for multiple modalities to achieve a high F1 score and precision. The technique shows good generalization and accuracy and may be useful as a tool for medical practitioners and clinicians. The technique proposed in this study uses deep learning techniques to train and evaluate chest X-ray and CT images and utilizes a class-balancing algorithm to detect signs of lung disease. The 3-Phase Dynamic Learning (3PDL) method and the Hybrid Feature Fusion (HFF) parallel CNN model are used to address the problem of class imbalance and improve the accuracy of the model. The technique achieves high F1 scores and precision and has the potential to be used as a tool to aid pathologists in their assessments.

The proposed class balancing techniques 3PDL is computationally expensive. In the future, we reorganize the 3PDL algorithm to minimize the computational cost. Further, we evaluate other medical image modalities such as MRI, PET and ultrasound images with parallel CNN model and 3-Phase Dynamic Learning to acquire optimal results for the pathologist's tool.

Funding

CRediT authorship contribution statement

Saeed Iqbal and **Adnan N. Qureshi**: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper. **Jianqiang Li:** Analyzed and interpreted the data; Performed the experiments; Wrote the paper. **Imran Arshad Choudhry:** Contributed reagents, materials, analysis tools or data; Performed the experiments; Wrote the paper. **Tariq Mahmood:** Conceived and designed the experiments; Wrote the paper.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Saeed Iqbal reports financial support was provided by Beijing University of Technology. Saeed iqbal reports a relationship with University of Central Punjab that includes: funding grants.

Data availability

Data will be made available on request.

Acknowledgements

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