Survey on Chest X-Ray Based Classification Model Using Deep Transfer Learning for Covid-19 Detection

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Abstract. The urgent requirement for fast and accurate diagnostic tools has been emphasized by the COVID-19 pandemic, in particular for the role of CXR in the detection of lung diseases such as COVID guise pneumonia and the COVID. It has led to advances in more powerful machine learning (ML) and deep learning (DL) methods as traditional systems continued to grapple with complexity and inefficiency. To improve feature extraction quality from CXRs, here the VGG19 neural network is applied. Finally SVM and RF classification methods are applied. Ensemble models like stacking, XGBoost and CatBoost are used to improve prediction performance by pooling collective strength. A new sum fusion method is introduced where decision probabilities of the classifiers are combined, resulting in both enhanced accuracy, sensitivity, and robustness and reduced bias. The model is evaluated on large datasets and outperforms the conventional approaches with better precision for diagnosis of lung diseases. Crucially, the model is not specific to COVID-19; it can identify other life-threatening lung diseases, such as pneumonia that needs to be treated promptly. By increasing the speed and the accuracy of the diagnostic workflows, this method has a strong potential for wider clinical and healthcare system's applications, both in pandemic and in routine conditions, leading finally to a benefit also for the patient in terms of a faster and more accurate analysis.

Keywords: Identification of COVID-19, Classifier ensembles, Chest X-ray, VGG19, Ensemble methods, Deep transfer learning, Deep CNN.

1 Introduction

One common use of artificial intelligence and machine learning systems is the automation of disease diagnosis. One of the most popular and economical medical imaging procedures is a chest X-ray (CXR). However, diagnosing from chest X-rays is more complex and challenging than using CT images [1].

Usually, COVID-19 is screened with chest X-rays or CT scans, which determine characteristic patterns of COVID- 19 lung disease. Since March 2020, when the data from the chest images of COVID-19 patients became accessible, the AI community has continued intense research on methods for detecting the virus by using Chest XR or CT pictures. Deep learning has been used in a large majority of these studies, and classification accuracies have exceeded 90%. Convolutional Neural Networks (CNNs) are typically applied first in extracting the images' initial features; next, SFSS is used to reduce the dimensions of data

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from CXR images; then image classification is done with a Bayes Net Classifier.

Thus, transfer learning models can easily overfit the original task they have been trained on, and the results obtained are often suboptimal when applied to a new task. Moreover, the quality and size of the datum used during the initial training phases limit the performance of such models. To overcome this, pre-trained networks for feature extraction, as well as attention mechanism techniques, are proposed to emphasize significant features in the images. Image texture is generally a concept consisting of spatial structure (patterns) and contrast. The established effective feature extraction methods capture changes caused by COVID-19 contaminations in chest X-ray pictures. X-ray images are processed into variable features using these methods. For enhanced image quality, CXR images are subjected to Homomorphic Transformation Filtering to improve contrast and highlight critical features.

2 Literature Study

Data collection primarily encompasses large datasets of chest X-ray (CXR) images grouped under different classes such as COVID-19, Pneumonia, and No Findings. Datasets are thus the core for training machine learning models to detect diseases and classify them. Besides, due to the increasing availability and cost effectiveness of X-ray machines, CXR imaging has become one of the crucial tools for detection of COVID-19. Quality and consistency in such images play a crucial role in making accurate machine learning models. Thus, the application of pre-processing techniques is vital for the data pipeline. In general, pre-processing is used to enhance image quality and to prepare data for feature extraction such that models pay more attention to details that are most important for classification tasks [2].

Applied to the CXR image are pre-processing techniques, such as CLAHE and Homomorphic Transformation Filters for enhancing the quality. CLAHE adjusts the histogram locally in improving the contrast of the image in regions that may not be otherwise detectable by revealing patterns. The Homomorphic Transformation Filter is applied to enhance brightness and contrast, mainly in low-lighted areas. These filters emphasize key features, like lung anomalies, and entail a favorable nature for machine learning-based analysis. The images are also resized to 64 by 64 pixels resolution to avoid any inconsistency in the dataset and reduce computational complexity so that all images can be processed uniformly [2].

The feature extraction phase is taken after pre-processing and implemented by the use of a deep CNN, particularly VGG-inspired architecture. Since CNNs are very efficient for image data as they can automatically identify and detect features such as edges, textures, and patterns useful in recognizing diseases in X-ray images, the convolutional layers do the job of filtering an input image by learning filters that catch such features. These extracted features undergo activation functions like ReLu where non-linearity is introduced into the model and the network could learn more complex patterns. The max pooling layer abstracts crucial information while reducing the dimensionality of feature maps, thereby lowering the complexity burden of the computations. This is a hierarchical extraction process that captures low-level and high-level features; as such, the model automatically focuses on the simple textures of the images as well as marks complex disease markers [2].

Algorithms such as edge detection have been increasing their usage in COVID-19 diagnosis through transfer learning-based feature extraction [3,5]. Self-supervised learning is a method whereby pre-trained models trained on large datasets are sought after to be repurposed for a particular task; in this case, COVID-19 classification using the CXR. The more desirable route is to use such an approach since the models can draw very meaningful features much more effectively than having to start from scratch with lesser datasets. Knowledge transfer helps models to mitigate overfitting, increase accuracy levels, and develop faster. The edge detection algorithms are, therefore, able to distinguish them from such important features; for instance, the edge of the lungs and the infection sites linked to the new coronavirus. This is a new approach with potential in improving the accuracy, efficiency, and interpretability of the COVID-19 and the information contained in CXR images [3].

EfficientNet, a deep learning architecture, has been shown to deliver strong results in COVID-19 diagnosis models [4,6,7]. In the frequentist (standard) version, EfficientNet achieves a balanced accuracy (BAcc) of 98.95%, outperforming DenseNet in some cases. However, in the Bayesian counterpart, DenseNet performs slightly better than EfficientNet. Despite these differences, both architectures deliver robust performance across various metrics, with their standard versions providing slightly better overall results. Importantly, pre-processing with a segmentation approach, which focuses on specific regions of interest in the images, yields results compared to those obtained using images with only histogram equalization. This highlights the significance of guiding CNN models, such as DenseNet-121, to analyze specific regions of the image that are physiologically relevant, tuning the model's ability to infer disease accurately [6,7].

To detect COVID-19, CXR pictures were employed and the relevant measurement range is primarily the lungs. However, CXR images are not precisely aligned, and the lobe position may vary from one picture to another. As a result, segmenting the lung region from the rest of the image becomes a crucial step in improving the accuracy of predictions. Given the size of many datasets, manual segmentation of each image is impractical. Therefore, automated segmentation techniques, such as those based on simulated neural networks, are recommended. ANN-based distribution can accurately isolate the lobe region in each picture, making some relevant area for COVID-19 detection. This method improves the precision of the diagnosis by eliminating extraneous data from the background, leading to more accurate predictions [6].

In addition to CNN-based feature extraction, FAWT is also engaged, especially in COVID-19 diagnosis through CT scans. It is a DWT—an advanced wavelet decomposition. This method is applied for image decompositions, as per their frequencies and resolutions that are better than the rest for effective extraction of the high-frequency details that might not be explicit otherwise. FAWT decomposes the CT scan images into subbands, which are helpful in getting time-frequency information from them. To improve the accuracy of the classification, we used some combination of features like PCA, LDA, RF, and SVM algorithms. Feature extraction combined with advanced machine learning presents a robust solution toward the ends of delivering correct diagnosis results for COVID-19 [4,7].

Recent work in the area also managed to achieve very high accuracy in COVID-19 diagnosis by applying different CNN models to extract features, followed by supervised learning algorithms such as SVM for classification. One such work attained a classification accuracy of 96.29% by having a structure of DenseNet-SVM. The same model, when tested on another dataset, provided an accuracy of 98.60%. This underscores the strength and scalability of CNN-based extraction along conventional learning classifiers, such as SVM. The approach not only enhances general accuracy for COVID-19 detection but also establishes high adaptability across datasets, further supporting the potential of hybrid models in disease diagnosis [6].

Transfer learning is also being widely employed to manage big datasets for COVID-19 diagnosis [5]. Contrary to advanced deep learning models, which are expensive both in computational resources and amount of data, this approach both scales down training time and minimises the risk of overfitting when performing experiments on multimedia-based big data, which are frequently big or/and complex data. Transfer learning resolves many data-related issues: both the cost and the error rate of perception becomes earlier, by using pretrained models that are able to cope with the heterogeneity of CXR datasets, the diagnostic process is accelerated, while maintaining high levels of accuracy [5].

The preprocessing CXR images can benefit from being processed by edge detection methods that are capable of enhancing the discernible structural features (i.e., the lung, infected area) that are necessary for correct classification. By utilizing this information for feature extraction, the transfer learning models generally augment their classification performance quite to an extent. These could be very valuable where traditional machine learning models can have trouble differentiating just slight differences between lung conditions. In general, the combination of edge detection and transfer learning is a potentially good trend for the development of COVID-19 diagnosis [3,5].

Automated segmentation of the lung region in CXR images plays an important role in establishing high accuracy for COVID-19 diagnosis. Lung positions may vary between images; therefore, the segmentation of lung area is critical because models must focus on a selected region for proper diagnosis. Considering the number of images, usually very large in most datasets, manual segmentation is not practicable; hence, ANN-based automated segmentation is recommended. The model will automatically segment the lung region so as to eliminate some features that are important in detection, thereby removing background information and thus improving the accuracy of prediction. This process is crucial for enhancement of precision and reliability of AI-based COVID-19 models [6].

An advanced version of DWT is the Flexible Analytic Wavelet Transform that supports time-frequency properties superior to DWT [8,9]. The discrete-time signal undergoes Hilbert transform to create a thin chirplet frame that supports analysis of time frequency through a pair of atoms. In the case of a combination of one LPF and two HPFs, that decomposes the ith level can be achieved as one is for the positive frequency and the other for the negative frequency. The redundancy is defined utilizing the sample parameters such as p, q, r, and s., which corresponds to time localization in wavelets while the Q-factor determines the number of oscillations. The values p and q are used in low-pass filters to control the process of reducing data, where r and s are used in increasing and decreasing of data (high-pass filter).

The terms "pattern" and "contrast" describe the two-dimensional properties which characterize texture in images. They work so well because common patterns correspond to simple micro features such as corners, edges and spots. We investigate feature extraction and filtering techniques that would be suitable for the identification of changes in CXR images resulting from infections with COVID-19. An X-ray image is transformed into column features by a feature extraction algorithm such as Gabor or Speeded-Up Robust Features (SURF) [10]. Using these methods, healthcare providers can monitor the trends and connect them with COVID-19 infections timely to assist in diagnostic and treatment processes.

3 Proposed System

The pre-processing enhancing methods that we use on our CXR pictures would be part of the suggested strategy. This entails using CLAHE and rescaling our photos to a set size. The CLAHE approach initially generates non- overlapping contextual regions also known as sub-images, tiles, or blocks for a certain input image. Each contextual region is then subjected to histogram equalization. After clipping the original histogram up to a preset value, it then redistributes the clipped pixels on each gray level.

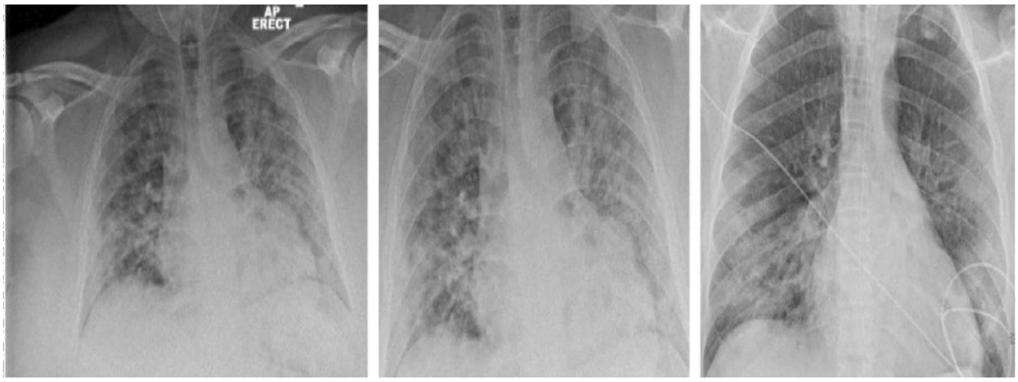

Fig. 1. Cropped Images.

Finally, these processed photos are passed through a transformation filter (fig. 1). The deep Convolutional model feeds in photos randomly. Deep convolutional neural networks have become well-known among researchers because of their proven superiority in handling huge data sets [11]. Multiple blocks of three different layers—convolution, pooling, and fully connected layers—make up a conventional CNN design [13]. Our deep CNN system architecture takes inspiration from VGG's design [13]. The dataset used for this framework is sourced from open-access repositories such as Kaggle, which provides diverse and well-labeled chest X-ray images for model development and evaluation [12]. The framework is put through two testing procedures.

The following is the initial scheme: Two classifications, COVID-19 and No-Findings, make up this binary categorization. The second technique categorizes the CXR scans according to the three classifications: COVID-19, Null, and Pneumonia. Each class considered 2250 images; the sum of images for scheme 1 was 4500 and for scheme 2, 6750 images.

3.1 Data Collection

The dataset is classified into both Covid and non-Covid categories. In the proposed approach, 30% of the dataset is reserved for validation, while the remaining 70% is used for training. The dataset includes 10,100 chest X-ray images from non-Covid-19 cases and 3,600 from Covid-19 cases, sourced from an open-access kaggle dataset referenced in research [12]. The images, provided in PNG format, vary in size from 228 × 228 × 3 to 1024 × 1024 × 3 pixels. To ensure consistency and suitability for the pre-trained model, all images were resized to 229 × 229 × 3 pixels for feature extraction. This was done to standardize the dataset processing. This will ensure all images are being resized so that input size gets standardized, hence making smoother executions with less computational time.

3.2 Data Preprocessing

The main goal of Deep models is to adapt to and use them for the majority of picture classification tasks is to reduce the computational complexity. To improve processing speed and simplify the procedure, the standard photos were reduced to 230 × 230 x 3 pixels. As regards the image processing, pre- processing will help in removing any undesirable noise in the given image. Some examples of augmentation techniques include the transformation, scaling, rotation, and translation of images. The resizing of the X-rays does not have any influence on the algorithm as the tainted areas that are part of the lesion in the lungs will not be washed away. Areas of the X-ray image that do not include the lung section which is infected had been masked during the augmentation step.

3.3 Model Training

VGG models serve as the inspiration for the CNN used in the proposed study. The term VGG, describes a standard deep CNN architecture with multiple layers. The number of layers a model uses is referred to as its "depth" with19 convolutional layers in VGG-19. Within the field of research, VGG models are extensively tested with, primarily being utilized for transfer even for Covid-19 identification, as a learning application. In information VGG-16 is regarded as one of the most efficient in science.

The VGG19 architecture as shown in fig. 2, a renowned deep learning model for image classification, comprises multiple convolutional blocks. Block3 Conv3, one of these blocks, plays a vital role in extracting features from input images. This block consists of convolutional layers and activation functions, operating in a sequential manner.

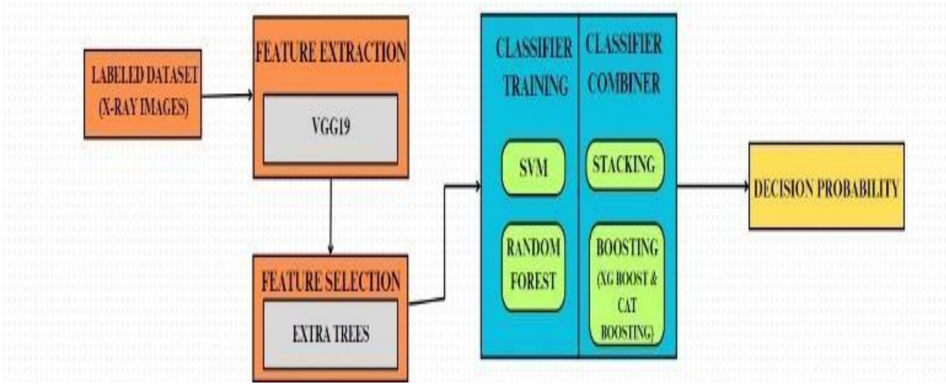

Fig. 2. Proposed Architecture.

In Block3 Conv3, the feature map input is the output of the previous layer in the VGG19 network. This feature map contains the filtered features of the previous layers. Block3 Conv3 has the convolution/kernel to this input feature map. They take a small (3x3) sliding filter that runs over the input and performs element-wise multiplications and addition. This operation essentially captures local patterns of input image.

Following is the Activation function (ReLu) applied to the output. This is the nonlinearity into the system, which gives it the possibility to learn complex patterns, not expressible on the linear functions. The convolutional and activation output makes up a new feature map that carries all the features to the next layer as an abstracted version of the previous layer.

The number of filters and the size of filter and feature map are the significant factors that affected the feature extraction in Block3 Conv3. The dimension of the filter (usually 3x3) is the extent to which the feature that is being detected by the filter is present in the input. 1: (a) A maximum filter size can be able to combine the l information, whereas a minimum filter size can concentrate on the less details. The number of filters in Block3 Conv3 is 256 so that the model can learn abundant features.

3.4 Feature Selection

Nevertheless, not all the features that are extracted can be considered equally important for the classification. That where Extra Trees come in, it helps in deciding the importance of each features by constructing multiple decision trees on randomly sampled data and features. The random thresholds are used at every split in the trees, and the feature is computed by calculating the overall impurity decrease that a feature provides across all trees. Features contributing to significant impurity reductions are retained, while less important ones are filtered out, reducing the model's complexity. By concentrating on the most important features, this combination of VGG19 for feature extraction and Extra Trees for feature selection not only elevates computational efficiency as well as strengthens the system capacity for generalization, eventually improving performance in tasks like as Covid-19 detection.

3.5 Classifier Training

Classifier training using SVM and Random Forest involves two different machine learning approaches that leverage extracted features from the dataset to build robust models. However, it is also capable of handling regression. SVM locates the support vectors, or the data points closest to the hyperplane, in the case of linearly separable data in order to maximize the margin, or the distance between the hyperplane and the support vectors. When the data is not linearly separable, SVM can project it into a higher-dimensional space where a linear hyperplane can separate the classes using kernel functions like radial basis function (RBF), polynomial, or sigmoid kernels. SVM resolves an optimization problem by maximizing the margin and minimizing classification error during the training phase. Making it effective for high-dimensional datasets like those where features are extracted from deep learning models like VGG19. SVM is particularly powerful when the data has a clear margin of separation and when the goal is to achieve a balance between generalization and classification accuracy.

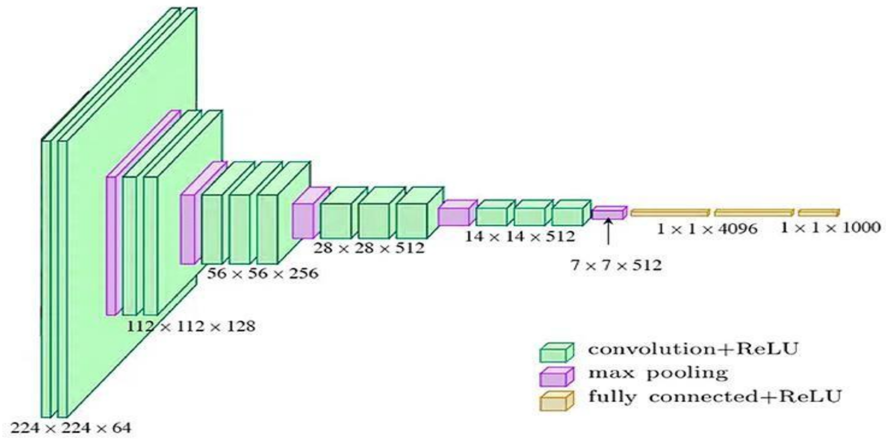

Fig. 3. Standard VGG19 Architecture.

Maximize: W^T * X + b (1)
Subject to: yi(W^T * Xi + b) >= 1, for all i
Where:
W: Weight vector
b: Bias term
X: Input feature vector
y: Class label (1 or -1)

Fig. 3 illustrates the Standard VGG19 Architecture. While Random Forest belongs to the category of ensemble the set-up predictions to make them more accurate. For fusion, predicted probabilities from both classifiers are averaged for sum fusion and the class with the maximum average is selected in decision fusion. This combination of multi-classifiers consists of SVM and Random Forest they complement each other, so the cumulative result is more strong and accurate and performs well on unseen data. Creating a mixed model, capitalizing on SVM decision boundary optimization together with Random Forest ensemble learning, and it will render a more robust and powerful machine learning model, especially against complex dataset that are obtained from some deep learning models like VGG19.

Learning method that generates a large number of generalised decision trees during the training phase, and then combines their predictions in order to mitigate overfitting and enhance accuracy. Each tree in the Random Forest is trained on a random subset of features and a random subset of the training data, with bagging or bootstrap aggregation to introduce randomness into the model and make the performance more generalizable. Every tree splits based on the feature at each node that provides the highest information gain (as determined during training, from say, entropy or Gini impurity scoring). Thanks to these splits, the tree can iteratively narrow the decision bounds of each class. It is robust, where a single decision tree can be easily overfitted, but Random Forest can reduce this risk by looking at many decision trees. Randmo Forest can also compute the importance of each feature by calculating the average minimum of impurity produced by each feature across all the trees, and it reads a popular method when the interpretability of the model is a concern.

And in combining SVM and Random Forest, the features from a very-deep neural network such as VGG19 (which provides rich and high-dimensional feature representation) are inputted to these classifiers for training. SVM is ideal for high-dimensional space that has a clear division between the different classes, whereas Random Forests are adaptive in accommodating situations with complex data structures and feature interactions. Every classifier has its own pros: if classes need to be maximally separated and where the relationship between features and target class are non-linear, then SVM would be a good model as it is flexible when we use kernels; if high generalization properties is the main concern with feature importance, Random Forest will be more robust in comparison. In training phase, the classifiers learn the mapping function transformations from extracted VGG19 features to the target classes such that SVM will search for the best decision boundary, and a forest of decision trees will be grown to describe the structure of the data. If necessary, the comprised models are fused with each other, such as the stacking, sum fusion and decision fusion to further improve the prediction results. To achieve this, they perform stacking, in which they train a meta-classifier on the predictions of SVM and Random Forest to learn how much to weigh them.

3.6 Stacking

Stacking (Wolpert 1992) is an ensemble method that combine multiple based models and output an overall prediction. Leveraging the strengths of each, stacking boosts predictive capability when it follows the Random Forest and Support Vector Machines (SVM) model. Especially with classification tasks, SVM is known to work well in high-dimensional space, and to create good decision boundary. On the other hand, the Random Forest is a statistically strong decision tree ensemble that focuses on reducing fitting and making accurate predictions through the aggregation of multiple trees.

Each of the models makes predictions whose out-of-fold predictions are used to generate a second-level data prediction, which can either be the actual target, or a feature for training a new model. The second-level model is trained adjusting the weights for each prediction of

SVM and other classifiers (i.e., RF in our study), combining them in an optimal order for the final outcome. Such technique may serve to alleviate bias and variance, resulting in better generalization to unseen samples. By combining SVM and random forest, this hybrid model takes advantage of the complementary feature of both of them, and performs better than either one alone.

3.7 Classifier Combiner

Meta-classifier using boosting algorithm i.e, XGBoost, CatBoost that learns from prediction of classifier SVM and Random Forest. In order for each classifier to find the hidden patterns and correlations, firstly the SVM and Forest are trained independently from the same dataset. After training, these classifiers provide the predictions on a validation set for the meta-classifier. Through the incorporation of the power of XGBoost or CatBoost, the meta-classifier is able to handle complex relationships and nuances between the predictions of the base models. For instance, SVM can find good decision boundaries, but is not robust to noise or outlying data; RF can deal with noise, but is not sensitive to finer-scale relations. The meta-classifier is trained to balance the predictions from SVM and Random Forest correctly, resulting in better accuracy and generalization on new data.

Moreover, XGBoost and CatBoost also use regularization to avoid overfitting, which respectively improve the performance of the ensemble. This stacking methodology not only helps in building better, more robust predictive models but also makes it possible to understand how different algorithms can compensate for each other, finally paving the way for a more complex and stronger machine learning system. This method demonstrates the advantage of ensemble learning in complex classification challenges, by combining the strengths of boosting with the varied features of SVM and Random Forest.

4 Expected Results

The Training and Validation accuracy and loss curves of the deep transfer learning model for COVID-19 chest X-ray images using 20 epochs.

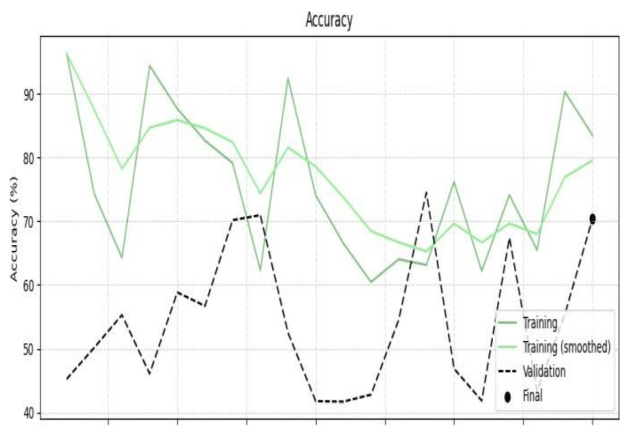

Fig. 4. Accuracy comparison.

In the above Fig. 4 the green line is the training accuracy and it varies significantly from one iteration to another with each mini-batch processed. Result As we see here, the smoothed training accuracy is continuing to increase as we train the network.

The model gets around 90% peak training accuracy in some iterations, which is an indication of good fitting to the training data. The black dashed line represents validation accuracy, which is always lower than training accuracy. It begins at about 50% and increases slowly up to about 70% in the final iteration. Black dot is the final accuracy, illustrating the ability of the model to generalize to test data.

The Training loss and validation loss is displayed below. The red line is the training loss – it goes down as the model tries to make fewer and fewer mistakes.

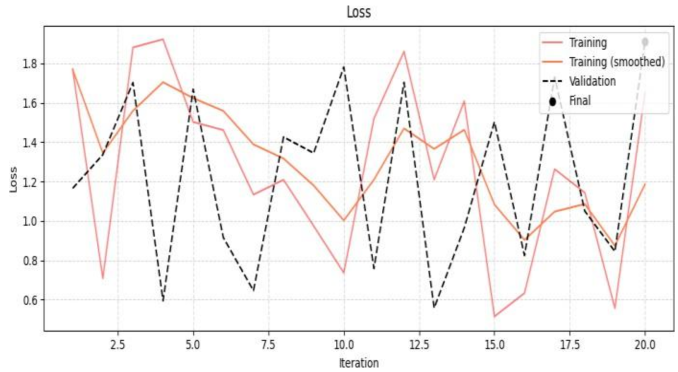

Fig. 5. Loss curve.

Training loss (lighter red line) smoothed shows its downward trend allows to see that the model is optimising during training (fig. 5). Validation loss (black dashed line) stays higher and jittery than training loss. It is shown as a black dot, and the end validation loss highlights troubles of generalisation. Variability could be due to a limited size of dataset or variations in data.

5 Conclusion

An efficient way to addressing the challenging problem of picture classification – specially in detection is shown by the combination of advanced machine learning models, deep learning architectures e.g. VGG19 and ensemble methods e.g. stacking and boosting. The Kaggle data which is used in this paper contains both Covid and non-Covid cases and the size and resolution of X-ray images differs a lot. Use of transfer learning, where pre-trained VGG models are used for feature extraction, also optimizes the classification process in the identification of COVID-19. VGG19 that is a deep CNN, is good at extracting the features in a hierarchy manner from the input data.

VGG19, which is notoriously easy to generalize to other image datasets. ‘The combination of SVM-Random Forest after feature extraction demonstrated the complementary aspects of both the models for Covid-19 identification. SVMs, which attempt to maximize the margin between the classes, are especially well-suited to such high-dimensional feature sets.

Random Forest (an ensemble learning method) reduces overfitting and improves model stability by building many decision trees and combining their predictions.

Several stack ensemble methods also improve accuracy by pooling SVM & Random Forest predictions together. In this solution, predictions are inputs into a meta-classifier (like LR in your case), who will learn to give optimal weights for predictions from each base model. This multi-layer system is able to reveal subtler structures of the

Better generalization to the test dataset than individual models could achieve individually, focusing on more accurate detection of COVID-19 features from CXR. The work investigates the metaclassifiers based on boosting techniques such as XGBoost and CatBoost. These boosting algorithms can be considered as iteratively improving weak learners by concentrating on the errors of the base classifiers. Boosting algorithms improve how well the model handles particularly noisy data, like lung X-rays with varying image quality and subtle Covid-19-related abnormalities, by correcting for these errors. The regularization methods that are implemented in XGBoost and CatBoost are also quite helpful in avoiding overfitting, thus the model is stable, even when you are working with very large and complex datasets. The proposed model is ensured to have high accuracy for the detection of Covid-19 and strong generalization ability over diverse patient cohorts provided by the integration of stacking and boosting techniques. Meticulous quality, strong, and reliable detection systems, could also assist clinicians in recognition of Covid-19 cases and that might lead to quicker diagnoses and improved patient outcomes.

In conclusion, this paper demonstrates that the fusion of learning models such as VGG19, traditional machine learning classifiers, such as SVM and Random Forest, and advanced ensemble techniques, such as stacking and boosting, offers a powerful and sophisticated model for Covid-19 detection. Each part of the model plays its own unique role in promoting the whole performance of the classification system: VGG19: extracts important features from the chest X-rays; SVM and Random Forest: have the same constant strength in classification; boosting algorithms: are used to perfect the final www.scmatters.org predictions. The multi-classifier method greatly enhances the model accuracy, generalization, robustness, hence rendering it a powerful tool for practical medical diagnosis in real world against COVID-19. The results demonstrate the effectiveness of the ensemble learning for medical image analysis and indicate its potential to be generalized for the future disease detection applications.

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