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Enhancing Automated Lung Disease Detection: An Approached Using Multi Network Features and ECOC-SVM Ensemble

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COVID-19 is a viral pneumonia that causes symptoms in the lungs of infected individuals. The presence of the symptoms must be diagnosed as soon as possible.Other than RT-PCR test, One of the most common diagnosis for any lung related infection is by having an X-ray. In most cases, the goal is to differentiate between healthy individuals, viral Pneumonia and Covid-19 cases. Lung infection diagnosis can be performed with computer-aided diagnosis of a patient's chest X-ray scan for a quick and accurate diagnosis. In view of having a more accurate automated system, a hybrid transfer learning method with Error-Correction Output Codes (ECOC) was proposed to enhance the automated diagnosis.The proposal first considers the frozen features existing network without any training. This serves to preserve generalization. Subsequently, the features were concatenated from a feature vector. However, instead of implementing the features in a single multi-class single-machine learning model, an ensemble of machine learning methods was proposed. In particular, the ensemble Error Correction Output Code (ECOC) was considered. By combining network features including GoogLeNet, ResNet-18, and ShuffleNet for feature extraction, the results were tested against the conventional fine-tuning approach of Transfer Learning (TL). X-ray input data were collected from the open-source repositories. In this implementations, Support Vector Machine (SVM) as the base classifier. The proposed network attempts to categorize the input data into one of three categories: COVID-19, healthy, or non-COVID-19 pneumonia. The mean accuracy of our method was 96.21% compared to the existing fine-tuning pre-trained model, which yielded 89.1% for GoogLeNet, 88.95% for ResNet-18, and 89.31% for ShuffleNet. This strongly suggests that an improvement is achieved owing to the inclusion of features from various networks and a more complex final classification layer, which is the ensemble configuration.

Keywords: transfer learning, deep learning, ECOC ensemble, COVID-19 lung infection, chest X-ray

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1. INTRODUCTION

COVID-19 is a viral pneumonia that caused a global outbreak in 2019 and is still spreading in certain parts of the world. The most prevalent symptom of COVID-19 and other similar coronavirus families is viral pneumonia, which manifests in the lungs. Owing to the ubiquitous availability of X-ray machines in hospitals and the speed at which X-rays can be obtained, Chest X-ray (CXR) scans are one of the quickest and most cost-effective means of diagnosing COVID-19. At this point, the formal approach to diagnosis is by performing an RT-PCR test. However, automated diagnosis using CXR may be useful in differentiating between viral pneumonia and Covid-19 cases. This may act as a preliminary evaluation in such cases.

With the motivation established, the question remains as to how this endeavor can be automated. More specifically, what approaches can be employed to continuously enhance recognition? With these questions in place, many have turned to Deep learning approaches employing various Convolutional Neural Network (CNN) methods.Along this direction, a motivation arises on implementation of transfer learning approach in deep learning. Transfer learning refers to the method of deploying existing deep learning networks either by fine-tuning training or by extracting features as trainable features. In the former case, the convolutional weights were adjusted. This approach has been shown to be effective in various applications. Thus, it is logical to explore this approach. Another element deployed to further enhance the recognition is the implementation of concatenated features from different networks. This is akin to observing X-ray images from various network viewpoints. Furthermore, an ensemble of learners was deployed to enhance recognition.

The remainder of this paper is structured as follows. In Section 2, the relevant research works are discussed. In Section 3, the methodology of this study, including deep learning architectures and ECOC, is discussed in detail. The results and analysis are presented in Section 4. Finally, Section 5 concludes the paper and discusses future work.

2. LITERATURE REVIEW

In this section, some of the relevant studies related to the proposed research are discussed. In general, the use of computer-aided diagnosis (CAD) in radioimaging for diagnosis has been growing in popularity for decades [1]. In particular, deep learning using convolutional neural networks (CNN) has been mostly used for image-based diagnosis [2], such as the detection of lung nodules [3] and the diagnosis of breast cancer [1]. Furthermore, CAD is an excellent method of diagnosis if COVID-19 test kits are in short availability or unavailable. Machines can perform rapid triage, allowing patients to receive the most suitable therapy, depending on their triage [4]. In particular, CXR scans of COVID-19 patients show bilateral ground-glass opacity (GGO) and consolidation with a peripheral and posterior lung distribution [5]. Deep learning in the form of a convolutional neural network (CNN) has been used to detect COVID-19 using CXR. In [6], various networks were employed to classify lung conditions, including COVID-19, normal, tuberculosis (TB), and viral pneumonia, with AlexNet and ResNet-18 achieving an accuracy greater than 95%.

The researchers in [7] implemented five pretrained CNN, that is, ResNet-50, ResNet-101, ResNet-152, InceptionV3, and Inception-ResNetV2, to detect four classes of lung conditions (COVID-19, normal, viral pneumonia, and bacterial pneumonia) through CXR. The ResNet50 model resulted in the highest accuracy. Moreover, five transfer learning models (AlexNet, MobileNetv2, ShuffleNet, SqueezeNet, and Xception) with three optimizers (Adam, SGDM, and RMSProp) were thoroughly investigated in [8]. Similarly in [9], a deep learning-based network called confidence-aware anomaly detection (CAAD) was proposed. The proposed model achieved an AUC of 83.61% and sensitivity of 71.70%. The issue with the CAAD method is that its mean accuracy was relatively low, despite the fact that it did not use any fine-tuning.

The authors in [10] proposed MH-COVIDNet which used an image contrast enhancement algorithm as the preprocessing stage. Four deep learning models (AlexNet, VGG19, GoogLeNet, and ResNet) were employed to classify three lung conditions (COVID-19, normal, and pneumonia). Furthermore, two feature selection algorithms, that is, metaheuristic algorithms of binary particle swarm optimization and binary grey wolf optimization, were used. AlexNet achieved accuracy of 97.55%, VGG19 had accuracy of 98.16%, 95.1%, and 95.71%, respectively. It should be noted that image-contrast enhancement algorithms are computationally expensive.

In [11], five transfer learning networks were employed to classify normal and COVID-19 patients using CXR. Two preprocessing steps were performed: resizing the channel size and augmenting the images (rotation, flipping, and pixel swaps) owing to insufficient input data. In addition, three optimizers (Adam, SGDM, and RMSProp) were used at four different training rates to reduce overfitting. The best result, with a validation accuracy of 97%, was obtained on MobileNetv2 using the Adam optimizer and a learning rate of 3×10^{-4}.

Based on the literature review, it can be concluded that in general, many deep learning approaches have been applied for the purpose of flagging the categories of lung-related diseases, specifically Covid-19 Cases. Transfer learning was also investigated for this purpose. The opportunity for improvement lies in the classification layer and further optimization of the transfer learning approaches. One of the challenges in fine-tuning is over fitting and lack of generalization. In countering this, many approaches have considered employing more dropout layers to enhance generalization. Another alternative is to extract the features as it is for the machine learning model. Hybrid transfer learning with Error-Correcting Output Codes (ECOC) has been proposed as a feature extractor technique for SVM classifiers used to detect malware classes [12]. By "hybrid," the term refers to to combination of features from various network. When compared to the existing state-of-the-art, the proposed approach provided excellent accuracy. Given the potential of hybrid transfer learning, we propose using CXRs to classify lung diseases into three classes: COVID-19, healthy, and non-COVID-19 pneumonia. Based on the existing literature review on the subject matter, there is an obvious trend that existing researchers are currently exploring various methods to enhance the current technology particularly deep learning technologies. There seems to be a limited image dataset pertaining to subject matter. This research intends to add to the existing work by contributing to and exploring mixed pre-trained model feature extraction with an ECOC ensemble of support vector machines. The final classification layer which is commonly a logistic function is replaced with a classification layer that better deals with non-linearity.

3. METHODOLOGY

In this section, details of the proposed approach are discussed. The literature review in the previous section showed that the transfer learning approach in deep learning has been implemented in various studies, yielding good results. There exists an opportunity for further improvement by considering further optimization at the classification layer. Often, the final layer of deep learning consists of some form of logistic function to determine label of classes. The objective of this study was to implement an ensemble classification layer to enhance transfer learning. The strategy deployed was to implement a more complex ensemble of binary classifiers instead of a single multi-class classifier.

This broad concept involves utilising features from various pretrained deep learning network and implementing and ensemble machine learning model for classification. The extracted features are fed to the ensemble for classification and further evaluated using independent test dataset. As discussed earlier, transfer learning in deep learning consists of two types: frozen feature transfer and fine-tuning. The latter involves fine-tuning of the features. This has the risk of over fitting but may facilitate better network performance. On the contrary, "frozen" features are extracted as it is without performing and training. This may be beneficial for preserving the generalization of the network, because an ensemble of machine learners was considered, the frozen feature approach was considered.

The publicly available data from Kaggle repository with a total of 2,892 images[1] was implemented for this research work. The dataset was labeled by competent personnel. This dataset also includes sideways images. In this implementation, only the frontal X-ray images were considered. Figs. 1-3 show some of the sample images for frontal X-ray images. The samples of the removed images are shown in Figs. 4-6. Most images were not scaled. Less than 5% of the images were removed because of non-frontal elimination.

Various features were extracted from a combination of three transfer learning networks: GoogLeNet, ResNet-18, and ShuffleNf The three networks had input dimensions of 224×224×3.The pre-trained network was selected based on input size similarity and performance in various applications. As deep learning is essentially a "black box" approach, there is no definitive approach for evaluating other than statistical approaches. We implemented the ECOC SVM as a multi-class classifier model. The training-testing ratio was 80%-20%.

3.1 Error Correction Output Code Ensemble SVM

Various configuration exist in machine learning to enhance recognition. Generally machine learning ensembles are developed to reduce the risk of single model failure. ECOC is an ensemble methodology of learning where binary classifiers are embedded as means of classifying multiple classes with two subsets of binary entry {−1, +1} and code word length of n [13]. The ECOC matrix, M, has dimension of k, where k is the number of classes. The training data is given by

$$\mathscr{X} = \{(x_1, c_1), (x_2, c_2), \cdots, (x_j, c_i), \cdots, (x_{N_{train}}, c_{N_{train}})\}^T, \tag{1}$$

[1] https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

Fig. 1. X-ray images of healthy individuals.

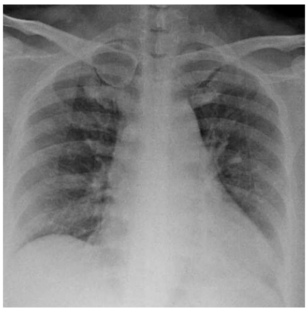

Fig. 2. X-ray images of Covid-19 patients.

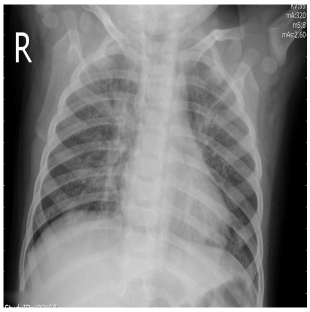

Fig. 3. X-ray images of viral pneumonia images.

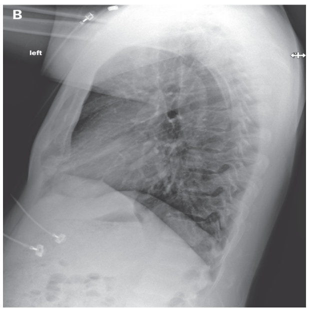

Fig. 4. Side images (Covid positive).

Fig. 5. Side images (Covid positive).

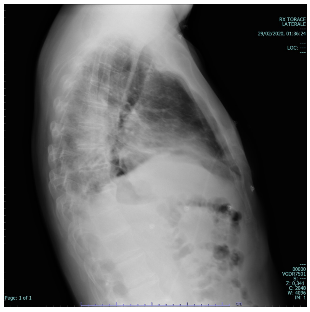

Fig. 6. Side images (Viral pneumonia).

where N_{train} is the training sample size, $x_i \in \mathscr{R}^{\mathscr{D}}$ with $\mathscr{D}$ being the input vector dimensions and c_i is the label of class i, for $i \in \{1,...,k\}$. Furthermore, the test data matrix is given by

$$\mathscr{Y} = \{(y_1,c_1),(y_2,c_2),\cdots,(y_j,c_i),\cdots,(y_{N_{test}},c_{N_{test}})\}^T, \tag{2}$$

where N_{test} is the number of test samples.

Support vector machine (SVM) is used as a base classifier. To solve quadratic programming issue we have

$$\min_{w,b,\xi_i} J(w) = 0.5||w||^2 \quad \text{s.t.} \quad cf(x_i) \geq 1 - \xi_i, \tag{3}$$

where w is the weight vector, $\xi_i \geq 0$ for $i = 1,...,N_{train}$ is the slack variable, $c \in \{1,-1\}$, and $f(x) = w^T x_i + b$.

As with ECOC configurations, each SVM acts as dichotimizers. Each SVM functions as binary classifiers. In this configuration, the “One vs One” configuration was applied. In essence, each SVM (h_i) are trained to recognise One class (C_i) from another. The matrix configuration as indicated functions as coding in order to classify a particular sample feature set into one of the classes C_i.

Table 1 shows the features extracted from the pre-trained networks. The feature layers denote the layer of nodes. As shown, these consist of global average pooling and the final output layer of the nodes. As mentioned, the pre-trained networks classifies 1000

Table 1. Feature layers and feature vectors of each network.

Model	Feature Layer	Feature Vector
GoogleNet	average pooling	1024
	final layer	1000
ShuffleNet	final layer	544
	average pooling	1000
ResNet-18	final layer	1000
	average pooling	512

image objects and contains rich features sufficient to classify various domain applications. Hence, the final layer consist of 1000 outputs each denoting the probabilistic output of each class.as these layers represent the same object class, variances among the layers in the individual pre-trained networks could be limited thereby decreasing observability from different network perspective. to counter this perspective, global averaging layers were also considered. Global averaging layers contains the average values of pooling layers thereby contains more variances. Hence, in total, the feature input to ECOC-SVM is 3280. This is still a reduction as compared the number of pixels of image input 240×240 (57600).

4. RESULTS AND ANALYSIS

In this section, the results from evaluation of the proposed approach are presented. As mentioned in previous section earlier, the data was split in 80%-20% partition using a random split. The results were ran for 10 trials and the average was evaluated. As mentioned, the features from 3 pre-trained network were extracted and concatenated. In order to observe the improvement, the images were also trained using fine tuning transfer learning approach. Similarly, 10 trials approach was implemented. Table 2 shows the performance metrics for the best configuration obtained. Recall that random split training-testing was implemented thus results in each configuration may differ in each trial. The best accuracy recorded was 97%.

Table 3 shows the results (bottom section of table) and subsequently bench marking with other research work. The metrices are common machine learning classification metrices for evaluation as expressed in Table 2. Sensitivity (also known as True Positive Rate, Recall, or Hit Rate). Sensitivity measures the proportion of actual positive samples correctly identified as positive by the classifier. Specificity (also known as True Negative Rate).Specificity measures the proportion of actual negative samples correctly identified as negative by the classifier. A higher specificity indicates that the classifier is better at correctly identifying the negative samples and minimizing false positives. Precision measures the proportion of predicted positive samples that are actually positive. Precision focuses on the correctness of positive predictions and helps evaluate the classifier's ability to minimize false positives. The F1-score is a single metric that combines precision and recall into a harmonic mean, providing a balanced measure of a classifier's performance.The F1-score considers both false positives and false negatives and is useful when there is an imbalance between the positive and negative classes. Accuracy is the proportion of correct predictions out of the total number of predictions. However,

Table 2. Testing performance results for the best configuration (As highlighted * in Table 3).

Metrics	Abbreviation	Performance Results (Independent test)
Sensitivity	$Sen = \frac{TP}{TP+FN}$	95.50%
Specificity	$Spe = \frac{TN}{TN+FP}$	97.75%
Precision	$Pr = \frac{TP}{TP+FP}$	95.55%
F1-score	$F1 = \frac{2\times Pr\times Re}{Pr+Re}$	95.50%
Accuracy	$Acc = \frac{TP+TN}{TP+TN+FP+FN}$	97.00%

accuracy may not be suitable for imbalanced datasets, where a high accuracy can be achieved by simply predicting the majority class.

where TP, TN, FP, and FN are the number of true positive, true negative, false positive, and false negative samples, respectively. Acc is the accuracy, Pr is the precision, Re is the recall, F1 is the F1 score.

GoogLeNet, ResNet-18, and ShuffleNet networks have been pre-trained on ImageNet. As previously mentioned, we train these three networks using a similarly approach 80-20% train and test partition. These 3 pre-trained networks have been selected due to the fact that they use similar sized input. Applying the 3 pre-trained network network is analogues of viewing the same image from 3 different angle. Training is carried out for a total of ten times for each network. The number of epochs is 30 with 18 iteration per epoch, making the maximum number of epochs 540 per training. The optimizer is SGDM with a learning rate of 0.01. The input data are converted into $224 \times 224 \times 3$ (from grayscale to RGB) to fit into the models and cleaned to remove any irrelevant components (such as side views of CXR). The input scans are augmented by being randomly rotated from –40 degrees to 40 degrees.The mean accuracy for the performance of hybrid network features with ECOC ensemble was recorded at 96.21% with standard deviation of 0.8%. The average accuracy for GoogLeNet is 89.31% with standard deviation of 0.79%. Furthermore, ResNet-18 has an accuracy of 88.95% with standard deviation of 0.60%. Finally, ShuffleNet had an accuracy of 89.37% and standard deviation of 0.53%. In each trial, random selection of training and test evaluation. Hence, this would lower the effect of training class selection bias. The best trial yielded 97.00% on independent test evaluation. Table 2 shows the performance metric on the independent test evaluation sets. The equivalent Confusion matrix for the best configuration is shown in Fig. 7. C-19 (Covid-19), N (Healthy), P(Pneumonia). It is noteworthy that the dataset was imbalance with most data skewed towards healthy subjects without pnemonia and Covid-19.Nevertheless, the effect of the unbalanced dataset seems to be be minimal. In the case of unbalanced dataset, normally, the accuracy of the classes with highest samples would be prioritised. In other words, it will be skewed towards high sample category. However, it was observed that the recognition of the individual classes remain reasonably good.

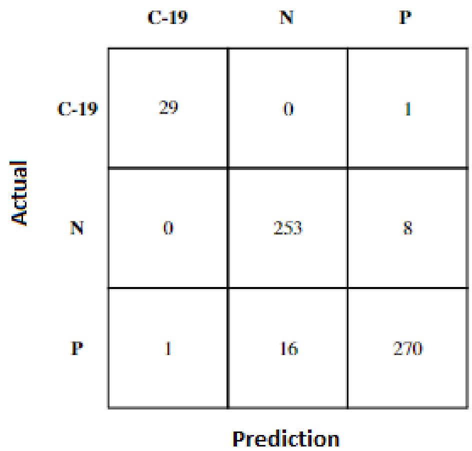

Fig. 7. Confusion matrix (Independent test evaluation).

4.1 Bench Marking with Relevant Research Work

Table 3 (**top section:Other research work)** shows the bench marking with other relevant research work. It is noteworthy that the dataset used are not of the same origin. Hence, this may not serve as an "apple to apple" comparison can be considered a best fit bench marking exercise. It is however noteworthy that most of the research work results reported test results in the range of 90%-98%. The best result from similar approaches [14] which implements extracted frozen features yielded 97.38%. This approach applied XGboost as the classifier layer. More relevant in bench marking is the comparison with the fine tuning transfer learning approaches in comparison with the ECOC-TL (Refer to **described dataset** section of Table 3. The improvement of approximately 6% on independent test evaluation was observed. This could be attributed to both ECOC ensemble and the implementation of of features from the different network allowing from more description of the image.

Table 3. Bench marking with other research work.

Reference	Description	Accuracy
	Other research work	
[14]	Extracted DL features using XGBoost (XGB)	97.87%
[15]	Capsule Net	98.3%
[16]	VGG19	89.3%
[17]	VGG19	97.00%
[18]	Stack Learning Ensemble	99.00%
[19]	Stack Learning Ensemble	97.7%
	Described dataset	
Proposed	ECOC with TL	97.00% (*best**)
		96.21% (mean)
Benchmarking	GoogLeNet	89.31% (mean)
Benchmarking	ResNet-18	89.37% (mean)
Benchmarking	ShuffleNet	88.95% (mean)

5. CONCLUSION

During the pandemic, various studies have been conducted among academic circles to enable automated diagnosis using X-ray images. Automated diagnosis of COVID-19 using X-ray images is an active area of research and development. While X-ray imaging is not the primary diagnostic tool for COVID-19 (typically performed through PCR testing or CT scans), it can provide useful information for screening and triage purposes, especially in regions with limited access to other diagnostic resources. In an effort to further explore improvements in applying deep learning to this imaging concept, transfer learning with multiple feature extractions from a pre-trained deep learning network was explored this research report, and a hybrid transfer learning method with ECOC ensemble learning to extract features from CXR scans was proposed. This approach was successful in achieving a mean independent test accuracy of 96.21% and a positive prediction of 96.7% for COVID-19 positive cases, making this network performance on par with many existing networks proposed by other researchers for the same function. As a contribution to the body of knowledge, the research have reported on the slight improvement achieved by implementing ECOC ensemble and feature extraction from multiple deep learning pre-trained network. An exhaustive evaluation using other pre-trained networks can be further explored. Using features from the selected pre-trained network have thus yielded an improved accuracy as compared to using fine-tuning approach on existing deep learning approach. For future implementations, further exploration can be conducted on feature selection. This may involve weighted features to eliminate non-discriminating features to allow for better classification. Theoretically, this would allow for improvements, as the current features were derived from training with a large image database consisting of daily objects. Despite the fact that these proved useful in encouraging generalization, the same features may not contribute to recognition.

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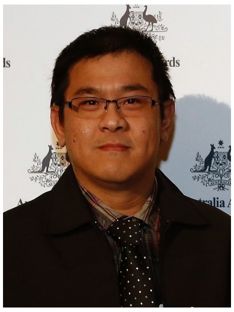

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