An Investigation of Deep-Learned Features for Classifying Radiographic Images of COVID-19

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Keywords: Radiographic Images, COVID-19, Convolutional Neural Networks, Deep-Learned Features, RelieF.

Abstract: In this proposal, a study based on deep-learned features via transfer learning was developed to obtain a set of features and techniques for pattern recognition in the context of COVID-19 images. The proposal was based on the ResNet-50, DenseNet-201 and EfficientNet-b0 deep-learning models. In this work, the chosen layer for analysis was the avg_pool layer from each model, with 2048 features from the ResNet-50, 1920 features from the DenseNet0201 and 1280 obtained features from the EfficientNet-b0. The most relevant descriptors were defined for the classification process, applying the ReliefF algorithm and two classification strategies: individually applied classifiers and employed an ensemble of classifiers using the score-level fusion approach. Thus, the two best combinations were identified, both using the DenseNet-201 model with the same subset of features. The first combination was defined via the SMO classifier (accuracy of 98.38%) and the second via the ensemble strategy (accuracy of 97.89%). The feature subset was composed of only 210 descriptors, representing only 10% of the original set. The strategies and information presented here are relevant contributions for the specialists interested in the study and development of computer-aided diagnosis in COVID-19 images.

1 INTRODUCTION

The analysis of radiographic images is one of the stages widely used in medicine to define diagnostics and prognostics for different diseases. For instance, when the investigation of COVID-19 is considered, radiographic images were commonly used to identify the possible patterns of this disease. Thus, computational systems can be developed and applied to support specialists in this process (Organization, 2023), with the definition and classification of the main descriptors. This type of application has been widely investigated to define a computer-aided diagnosis, with multiple methodologies (Su et al., 2022; Song et al., 2022; Deb et al., 2022; Tuncer et al., 2020).

The process of analyzing radiographic images using convolutional neural networks (CNN) is a widely explored issue in the field of image processing, with important applications in the study of COVID-19 images. In this context, (Kedia et al., 2021) presented a CNN named CoVNet-19. This model was obtained using various techniques, such as transfer learning and an ensemble strategy, providing an accuracy of 99.71% in the context of radiographic images. Furthermore, another strategy presented by (Ashour et al., 2021) involved an ensemble method, with models based on bag-of-features. The choice of this type of model considered the variations and spatial orientations of the images. This proposal was able to provide an accuracy of 98.60% in the classification of radiographic images of lung regions. Finally, the authors in (Deb et al., 2022) used an ensemble with multiple pre-trained models, such as VGGNet, GoogleNet, DenseNet and NASNet and provided an accuracy of 98.58%.

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Miguel, P., Cansian, A., Rozendo, G., Medalha, G., Zanchetta do Nascimento, M. and Neves, L.
An Investigation of Deep-Learned Features for Classifying Radiographic Images of COVID-19.
DOI: 10.5220/0012038500003467
In *Proceedings of the 25th International Conference on Enterprise Information Systems (ICEIS 2023) - Volume 1*, pages 675-682
ISBN: 978-989-758-648-4; ISSN: 2184-4992

Despite the existence of several studies that proposed specific networks to solve the problem of classification in focus, other studies also address the use of already consolidated networks. In (Walvekar et al., 2020), the authors proposed an approach that employed a ResNet-50 model which was pre-trained on the ImageNet dataset with transfer learning. The experiments were defined via a public dataset (Cohen et al., 2020), with 359 radiographic images from the lung region that indicated the presence of pneumonia caused or not by COVID-19. This proposal was able to indicate an accuracy of 96.23%. The study presented by (Shamila Ebenezer et al., 2022) involved the EfficientNet-b0 model with enhanced images via Laplace algorithms and wavelet transform. The main goal was to verify the impact of these adjustments on the complete training of the CNN models. This approach provided an accuracy of 94.56%, considering radiographic images of two classes infected by COVID-19 and not infected with this disease.

In this context, there were few studies based on a detailed analysis of deep features, a fact that motivated the development of this proposal. For instance, the model presented by (Tuncer et al., 2020) considered a strategy responsible for defining features called residual exemplar local binary pattern. The features were ranked via the ReliefF algorithm and classified with multiple methods. This proposal achieved an accuracy of 100% through the SVM classifier, exploring representative radiographic images of Covid-19 and healthy. The study proposed by (Rajpal et al., 2021) used the ResNet-50 model to extract a subset of the most relevant features, considering the 2048 attributes present in the avg_pool layer. The authors manually evaluated a group of 252 features. This subset was studied via principal component analysis (PCA). A new subset was defined with the 64 most important attributes. Finally, these features were reduced again after being used as input to a feed-forward network, which selected only 16 features. The model provided an accuracy of 94.40%, considering a total of four classes: viral pneumonia; bacterial pneumonia; COVID-19 and not infected.

In this study, a proposal based on deep-learned features via transfer learning is defined to indicate the main combinations of attributes and techniques for the classification and pattern recognition in radiographic images of COVID-19. The presented approach explores three different CNN models for COVID-19 images. The corresponding deep-learned features were obtained, and a ranking method was applied to maximize the classification performance. The analysis was defined via an ensemble classification, considering the score-level fusion approach. This proposal allows for identifying the main associations with competitive results concerning the specialized literature. The main contributions presented here are:

- A strategy capable of identifying the main deep-learned features, with competitive results concerning consolidated and widely explored methods in the context of COVID-19;
- A model capable of identifying the main combinations via a reduced number of features;
- Indications of associations and conditions for the improvement of computer-aided diagnosis with a focus on the analysis of radiographic images of COVID-19.

2 METHODOLOGY

The proposed method was divided into three steps. The first step was defined to extract the deep-learned features, exploring specific layers of relevant CNN models. The second stage was proposed to compose and select the most relevant features. Finally, the third step (analysis and knowledge extraction) was indicated to guarantee the analysis of the selected features through two experiments: predictions through classifiers applied individually to each set of features; results via an ensemble classification process. An overview of the proposal is shown in Figure 1.

2.1 Dataset

This investigation explored representative radiographic images of COVID-19 that were obtained through a public dataset (Cohen et al., 2020). This dataset consists of images from different public sources. It is important to highlight that this dataset is considered dynamic, therefore, the number of samples that represent each class, as well as the type of those, are updated frequently. The used version for this study explored a total of 2.040 images divided into two classes: Healthy with 1602 samples and COVID-19 with 438 samples. It is important to note that the samples belonging to the healthy class are people who have been properly tested as non-carriers of COVID-19. Also, the images are representative of segmented regions, where it is possible to observe only the patient's lungs. In addition, the images have multiple sizes, therefore, in the training phase of the fully connected layers of each model, the images were resized to 224 pixels of height and 224 pixels of width. Figure 2 illustrates available images in the dataset explored here.

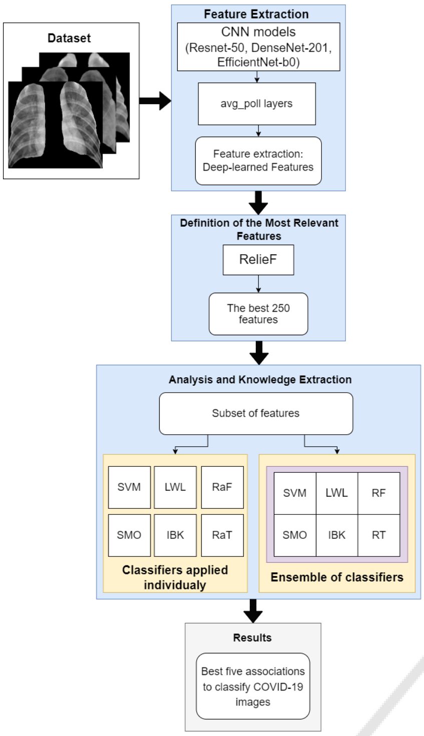

Figure 1: An overview of the proposed method for analyzing COVID-19 images.

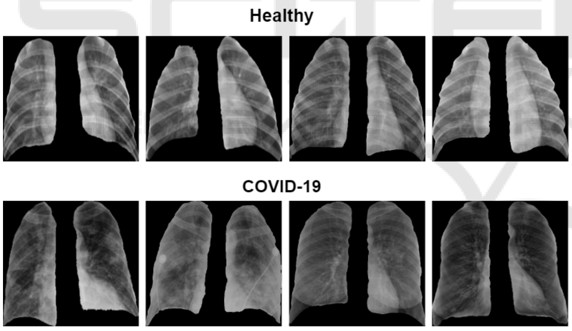

Figure 2: Illustration of images explored in our study from the dataset presented by (Cohen et al., 2020).

2.2 Step 1: Feature Extraction

The COVID-19 images were analyzed through three deep-learning models. The chosen architectures were a residual neural network with 50 layers (ResNet-50), dense convolutional neural network with 201 layers (DenseNet-201) and the EfficientNet baseline (EfficientNet-b0) (He et al., 2016; Huang et al., 2016; Tan and Le, 2020).

2.2.1 Selected Layers

In this investigation, the features were obtained from the ResNet-50, DenseNet-201, and EfficientNet-b0 neural networks pre-trained on the ImageNet dataset (Deng et al., 2009). The adopted strategy in this proposal considered the indications presented by (Pereira dos Santos and Antonelli Ponti, 2019). In this case, the convolutional features from the initial layers were capable to bring local information about the analyzed images, like low levels of forms, borders, and colors. While features from the last layers tend to provide global descriptors. Thus, the convolutional attributes obtained from the networks were isolated through a strategy that allows the storing of the output from the layers into auxiliary structures. These structures were used as input to the feature selection method, capable of identifying the most relevant and generalizable feature sets. In this study, the avg_pool layer of each network was selected for the analyses, considering that this layer can provide contributions related to the local and global information of the images. A summary of the number of features used in our proposal is illustrated in Table 1, considering each layer here explored.

Table 1: Number of features of each avg_pool layer for each network model.

Network	Number of features
ResNet-50	2048
DenseNet-201	1920
EfficientNet-b0	1280

2.3 Step 2: Definition of the Most Relevant Features

The convolutional attributes were defined through n-dimensional matrices called $N_i[...]$, where i represents one of the layers under investigation. Each column in the N_i matrix was sequentially sorted into feature vectors $K_i[...]$, where the number of elements in N_i is equal to the number of elements in K_i. From K_i, the RelieF algorithm was applied to rank the most relevant deep features. Thus, each set K_i was distributed into subsets F in relation to j best-ranked attributes. It is important to highlight that each subset was defined through different cutoff points, considering an approach successfully applied to classify colorectal histological images (Ribeiro et al., 2019). However, our proposal identified the most relevant subset in a wider attribute space (with the first 250 best-ranked attributes), mainly due to the differences present in the context investigated here, for instance, with more attributes and samples. Thus, the initial subset was defined with $j = 10$, being incremented in steps of 10 attributes. Moreover, this limited number of deep features was established to obtain optimized solutions (with a reduced number of features) in order to minimize the presence of overfitting.

2.4 Step 3: Analysis and Knowledge Extraction

This step considered two experiments: The first experiment was defined to investigate the discriminative capabilities of the deep-learned features through multiple classifiers (individually applied). The used classifiers were: function based, such as support vector machine (SVM) and sequential minimal optimization (SMO) (Vapnik, 1963; Platt, 1998); lazy learning based, such as locally weighted learning (LWL) and instance based k (IBk) (Frank et al., 2003; Atkeson et al., 1996); and decision tree based, such as random forest (RaF) and random tree (RaT) (Breiman, 2001; Frank and Kirkby, 2023). The goal of this analysis was to obtain capable models in order to obtain the best performances, with the lowest number of features, that could contribute to the comprehension of the explored context.

The second experiment was addressed to complete the analyses previously indicated, exploring an ensemble strategy with the classifiers used in the first step. The adopted approach was a score-level fusion in order to explore the strongest points of each classifier (Ross and Nandakumar, 2009). As in the first experiment, the 250 deep features were analyzed with sets arranged for every ten features.

In addition, a 10-fold cross-validation method was applied to validate our experiments. Finally, the results were verified through different metrics, such as accuracy (ACC), F-measure and the area under the receiver operating characteristic curve (AUC).

2.4.1 Development Environment

Both the algorithm responsible to obtain the deep-learned features, and the algorithm to explore the ResNet, DenseNet, and EfficientNet models were developed in the Python language. Especially, to explore the models, the Pytorch framework was used (Paszke et al., 2019). This framework provides the ResNet-50, DenseNet-201, and EfficientNet-b0 previously coded and trained on the ImageNet dataset, considering the specifications presented by the authors of each model (He et al., 2016; Huang et al., 2016; Tan and Le, 2020).

To test the performance of each network model, the framework Pytorch Ignite was also used (Fomin et al., 2020), being so responsible for the training of the last fully connected layer of each model. The proposal was realized in a notebook with an Intel Core i5-10210U, 16 GB of RAM, NVIDIA MX 110 graphics card, and the Windows 11 operating system. Finally, the Weka 3 package was used to classify the deep-learned features, as well as to obtain all the metrics used by this project (Witten et al., 2011; Hall et al., 2009).

3 RESULTS

The approach was applied to analyze radiographic images of COVID-19 with two experiments via the deep-learned features of avg_pool layers, ResNet-50, DenseNet-201 and EfficientNet-b0 models. Thus, taking into account the accuracy metric as an initial reference, Figure 3 shows the obtained results with the ensemble of classifiers.

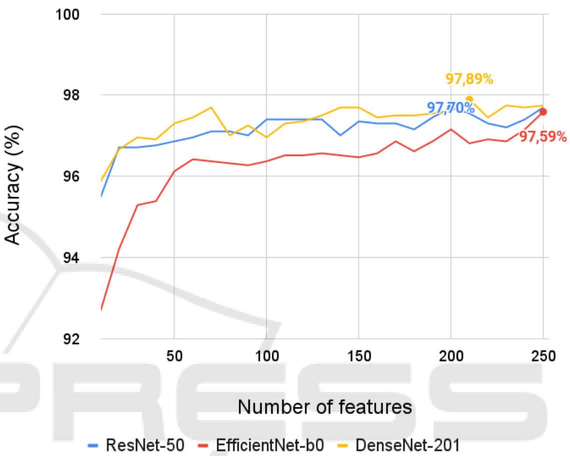

Figure 3: ACC values (%) for each subset of features, exploring the ensemble of classifiers and avg_pool layers (ReseNet-50, DenseNet-201, and EfficientNet-b0).

From the obtained results in the different compositions of deep features, it was noticed that the DenseNet-201 model indicated the best performance, with a subset of 210 attributes and an ACC value of 97.89%. In this case, the F-measure value was 0.979 and the AUC rate was 0.9941 (a performance close to that of an ideal system). These results are interesting and indicate an important contribution of the proposed methodology, since it was possible to identify a combination of techniques capable of providing an acceptable solution with only 10.94% of the original features, avoiding overfitting in this model. Also, this combination indicated a class distinction capability.

The second experiment was defined with a combination of the deep-learned features via SVM, SMO, LWL, IBK, RaF and RaT classifiers, with performances obtained individually. The results are presented in Figures 4, 5, and 6, considering the ResNet-50, DenseNet-201 and EfficientNet-b0 models, respectively.

Taking into account the results in Figure 4 (ResNet-50 model), the SMO classifier in combina-

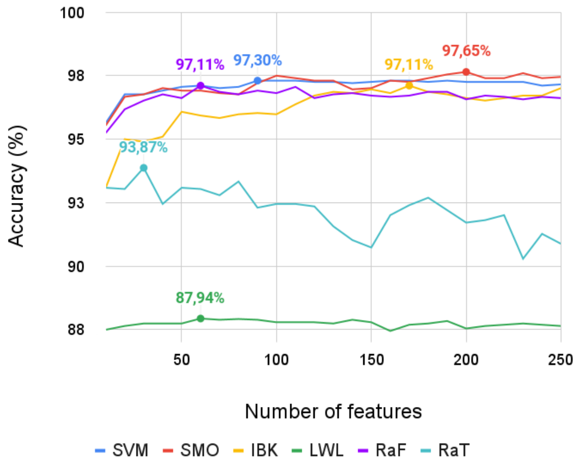

Figure 4: Accuracy values (%) obtained through the different subsets of features with each classifier: ResNet-50 and the corresponding avg_pool layer.

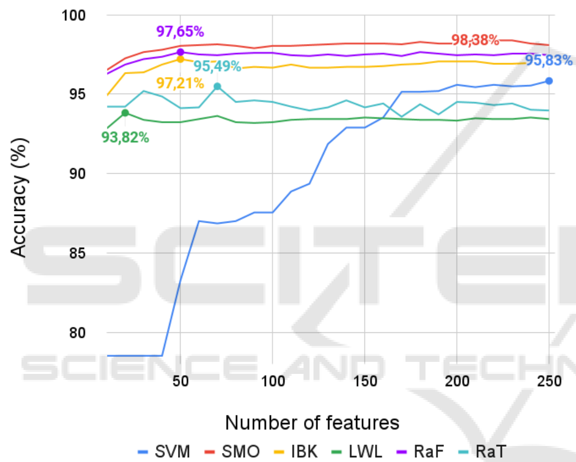

Figure 5: Results obtained of ACC values (%) provided by different subsets of features with each classifier: DenseNet-201 and the corresponding avg_pool layer.

tion with 200 deep features indicated the main strategy, with an ACC of 94.17%, F-measure of 0.9410 and an AUC of 0.9056. In relation to the DenseNet-201 model (Figure 5), the SMO classifier with 210 features indicated the best combination in this study, with an ACC of 98.38%, F-measure of 0.984 and an AUC value of 0.9814. When the EfficientNet-b0 model is considered (Figure 6), the best combination was also obtained through the SMO classifier, but with a fewer number of features (150 features). The ACC value was 97.16%, an F-measure of 0.972 and an AUC rate of 0.9603. It is important to emphasize that the SMO classifier presented the best results in each test, indicating a relevant pattern in the context investigated here.

In order to complement this analysis, Table 2 summarizes the best five results, considering all tests

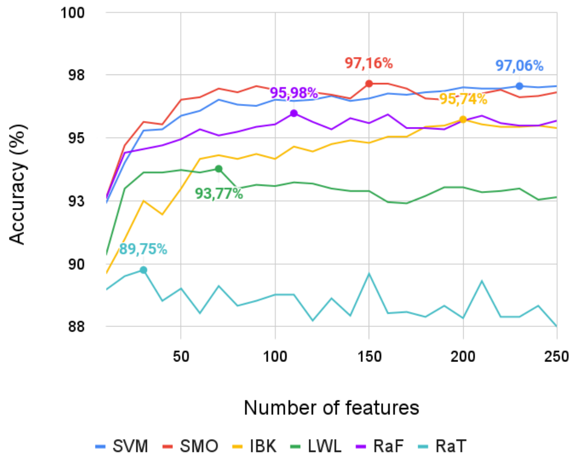

Figure 6: Accuracy values (%) achieved via different subsets of features with each classifier: EfficientNet-b0 and the corresponding avg_pool layer.

defined here.

From Table 2, it is observed that the first position is a solution involving a single classifier. However, the ensemble strategy appears in three of the five best combinations observed in this study. Moreover, in the first two positions, the solutions were obtained with the same subset: 210 deep-learned features. Also, considering the ACC metric, the difference is less than 1% among these two solutions. The second-best combination can be highlighted for its AUC (0.9941), surpassing the result obtained via the best individual combination, with the advantage of using an ensemble of classifiers.

In order to contextualize other contributions of this study, the best result according to the ACC metric (Table 2) was observed in relation to the best results obtained via ResNet-50, DenseNet-201 and EfficientNet-b0 networks (all applied directly to classify the same set of images). It is important to note that the CNN models were pre-trained into the ImageNet dataset. Thus, it was necessary to train the last fully connected layer of each network to adjust the number of classes in this analysis (Healthy and COVID-19). The training of the last fully connected layer was defined with a total of 50 epochs, considering the details presented by (He et al., 2016). Also, in order to validate the results of each epoch, the original dataset was divided into training and test sets, with an 80-20 split. The ACC, F-measure and loss metrics were considered in these experiments. Figure 7 illustrates the obtained results through the accuracy values for each epoch. The DenseNet-201 provided the best result with 33 epochs, an accuracy value of 96.57%, a loss of 0.12 and an F-measure of 0.94. On the other hand, this performance is lower in compar-

Table 2: Definitions of the five best associations to classify the COVID-19 images, with the corresponding performances (ACC, F-measure and the AUC).

Ranking	Network	Combination	ACC (%)	F-measure	AUC
1°	DenseNet-201	210 Features, SMO classifier	98.38%	0.984	0.9814
2°	DenseNet-201	210 Features, Ensemble	97.89%	0.979	0.9941
3°	ResNet-50	200 Features, Ensemble	97.70%	0.977	0.9932
4°	ResNet-50	200 Features, SMO classifier	97.65%	0.977	0.9684
5°	EfficientNet-b0	250 Features, Ensemble	97.59%	0.970	0.9882

ison to those via proposed associations, as shown in Table 2. This information indicates another important contribution of this study.

Figure 7: Accuracy values (%) obtained after classifying the images with the ResNet-50, DenseNet-201 and EffientNet-b0 models, exploring results with up to 50 epochs.

Finally, the relevance of the best result in relation to the specialized Literature was verified. It is noted that the explored techniques consider different strategies and datasets from those explored here. Thus, these facts do not allow a direct comparison between the approaches but provide an illustrative overview of the model through some important works in this area, Table 3.

From Table 3, it is verified that the best combination from our proposal was capable of obtaining results between the main works available in the specialized Literature. Even with the less expressive result compared to those indicated by some methods (Tuncer et al., 2020; Kedia et al., 2021; Ashour et al., 2021; Deb et al., 2022), the advantage of the proposed methodology was a solution with competitive results via a reduced number of features, making the knowledge more comprehensive for specialists interested in computer-aided diagnosis.

4 CONCLUSIONS

This work presented a detailed study of deep-learned features via transfer learning, considering avg_pool layer from the ResNet-50, DenseNet-201, and EfficientNet-b0 networks. The best combinations were identified with a full understanding of the subset of deep-learned features for the classification and pattern recognition in COVID-19 images. The reduced set of features was obtained via a strategy based on the RelieF algorithm, with the use of multiple classifiers and a robust ensemble strategy. This type of association and the obtained information through our experiments are relevant contributions presented here. For instance, the best two combinations were obtained from the DenseNet-201 model, using the same subset: 210 deep-learned features. This total of features represented only 10.94% of the original set. In the test applying individual classifiers, the SMO algorithm was capable of indicating the best results, with an ACC of 98.38%. In the test with the ensemble strategy, the result was an ACC of 97.89%, a value subtly lower than that indicated via the SMO association.

When the best results were compared to those obtained with the use of complete neural networks, it was verified that the solutions with our proposal surpassed the performances provided by the CNN models. Finally, when the results were observed in relation to some related works, our study was able to define models with performances among the available specialized literature, providing relevant information regarding the main associations via a reduced number of deep features. Therefore, we believe that this contribution is useful for specialists interested in investigating computational systems for radiographic images of COVID-19.

In future works, it is intended to explore different architectures of CNNs and perform the combined use with descriptors based on fractal techniques, in addition to the indication of techniques to highlight the best-ranked attributes in the activation maps (class activation mapping).

Table 3: Illustrative overview of the different methods available in the specialized literature to investigate the context of radiographic images of COVID-19.

Reference	Approach	ACC (%)	AUC
(Tuncer et al., 2020)	ResExLBP, RelieF, SVM	100%	-
(Kedia et al., 2021)	CoVNet-19, Ensemble Learning, Transfer learning	99.71%	0.99
(Ashour et al., 2021)	Bag of features, Ensemble	98.60%	0.98
(Deb et al., 2022)	Multi model ensemble architecture	98.58%	0.95
Proposed	Transfer learning, DenseNet-201, RelieF, SMO	98.38%	0.98
(Walvekar et al., 2020)	ResNet-50	96.23%	0.96
(Shamila Ebenezer et al., 2022)	EfficientNet-b0, Image Enchancement	94.56%	0.93
(Rajpal et al., 2021)	Handpicked Features, ResNet-50	94.40%	0.97
(Hemdan et al., 2020)	DenseNet-121, VGG19	90.00%	0.90

ACKNOWLEDGEMENTS

This study was financed in part by the: National Council for Scientific and Technological Development CNPq (Grants #313643/2021-0, #311404/2021-9 and #120993/2020-1); State of Minas Gerais Research Foundation - FAPEMIG (Grant #APQ-00578-18); WZTECH NETWORKS, São José do Rio Preto, São Paulo.

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