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Covid-19 classification using thermal images.

Thermal images capability for identifying Covid-19 using traditional machine learning classifiers.

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ABSTRACT

Medical images have been proposed as a diagnostic tool for SARS-COV-2. The image modality more investigated on this subject is computed tomography (CT), however it has some disadvantages: it uses ionizing radiation, requires unique installations along with a complicated process limiting the number of possible tests per equipment, and the economic costs can be prohibitively high for screening a large population. For these reasons, the aim of this study is to investigate thermal images as an alternative modality for diagnosis of COVID-19. The methodology used in this study consisted of using radiomics and moment features extracted from six images obtained from thermal video clips in which optical flow and super resolution were used, these features were classified using traditional machine learning methods. Accuracies were in the range of 0.433 - 0.524. These

first results conducted on thermal images suggest that the use of this type of image modality is unlikely to be favorable for COVID-19 detection.

CCS CONCEPTS

•Applied computing~Life and medical sciences~Computational biology~Imaging•Computing methodologies~Machine learning~Machine learning approaches~Classification and regression trees

KEYWORDS

Covid-19 classification, thermal videos, thermal images, machine learning

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1 Introduction

COVID-19 is a respiratory disease caused by the coronavirus SARS-CoV-2[1] that was declared a pandemic by the World Health Organization (WHO) in March 2020. According to WHO and as of June 2021, the number of global cases reached 174 million, and the confirmed deaths reached three million.[2] The respiratory illness may cause acute respiratory distress syndrome (ARDS) characterized by pulmonary infiltrates and hypoxemia.[3, 4]

The principal diagnostic tool for SARS-CoV-2 is a DNA test based on a PCR assay,[3, 5] which requires respiratory specimens extracted by nasal or pharyngeal swabs.[5] The results are delivered between 2 and 5 days. Other approaches have been proposed, as medical images, particularly computer tomography (CT)[6, 7] with reported prediction accuracy of 89% and area under the curve of 0.92. These results suggest that imaging may be an alternative diagnostic tool for COVID-19. Nevertheless, CT uses ionizing radiation, requires unique installations with a complicated process limiting the number of possible tests per equipment, and the economic costs can be high for screening a large population.

Thermography is useful to investigate pathological conditions found to alter body temperature distribution.[8] Abnormal thermal patterns are easily recognizable by infrared thermography (IRT), it can be used to find correlations with diseases, and despite it is imprecise and depends on the surrounding, IRT has advantages: it is non-contact, non-invasive, able to monitor large areas simultaneously, has harmfulness radiation effects, and can be done in real time.[9]

Artificial intelligence has been shown to improve thermography-based diagnosis in three main ways: by reducing the workload of experts; by reducing inter-observer variability; by improving diagnosis quality, as diagnosis is not subjected to human errors.[10] To our knowledge, thermal imaging and specifically thermal videos have not been comprehensively investigated as an alternative diagnostic tool of COVID-19. However, they were used to support the detection of other diseases such as breast cancer,[11] joint with machine learning, and to successfully support the diagnosis of respiratory disorders[12] without machine learning. Infrared videos can be useful for COVID-19 detection because SARS-CoV-2 infection in viremia stages is characterized by body temperature changes and in breathing patterns.[13] Thus, in principle, video recording of body temperatures could be a powerful tool as an alternative, cheap, and massive screening method, and detection at an early stage of the disease. Hence this paper presents the evaluation AI tools for the identification of SARS-CoV-2 infected people by Infrared Technology.

2 Methodology

2.1 Thermal dataset

252 volunteers were enrolled in an IRB approved prospective study aimed to test the ability of thermal videos to detect SARS-CoV-2. Participant's ages were among 75 – 18 years, height and

weight were reported, 94 volunteers were female and 158 male, 59 with positive and 193 with negative PCR results. The study recorded a set of measurements from participants regarding PCR results, demographics, vital signs, participant activities, medications, respiratory symptoms, and a thermal video session where the volunteers performed simple breath-hold in four positions – front, back, left, and right –. Thermal images were recorded in video mode, mostly at five frames per second, using a Digital Thermal Imaging Camera TI-128 from Omega Engineering Inc. (800 Connecticut Ave. Suite 5N01, Norwalk, CT 06854, USA, www.omega.com). The camera was connected to a computer running Windows® operative system from Microsoft® as suggested by provider instructions. Acquisition software Omega TI Analyzer version 4.1.8.6875 was used.

2.2 Video Preprocessing

All video clips were standardized and corrected for blur and large motions. Lucas Kanade optical Flow was used to compute the skin motion for each one of the 10 second videos and thermal images co-registration.[14] After super resolution, a set of six-images were generated (Figure 1). Video preprocessing was done with MATLAB. (2010). version 7.10.0 (R2010a). (Natick, Massachusetts: The MathWorks Inc.).

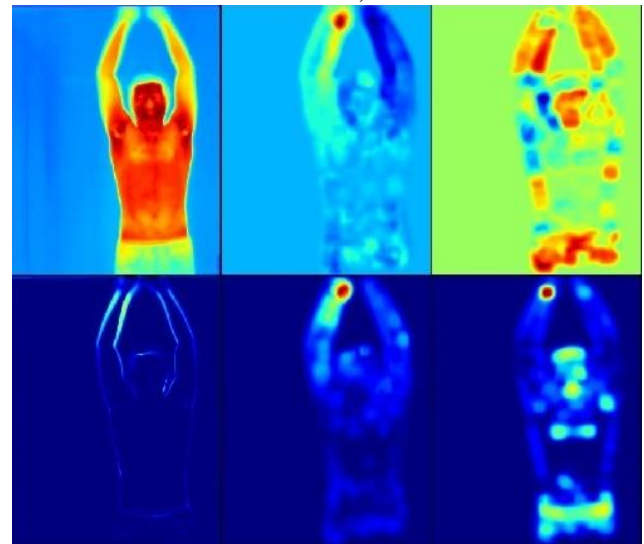


Figure 1: Mean skin temperature (top left); temperature-variance (bottom left); mean horizontal motion (top center); mean vertical motion (top right); standard deviation horizontal motion (bottom center); and standard deviation vertical motion (bottom right).

2.3 Data Preprocessing

Preprocessing consisted in segmenting the upper body to remove background data. All segmented images were reviewed and manually refined to avoid loss of information in regions where intensities were low enough – due to presence of hair, masks, and bras – to be removed along with the background.

2.4 Feature Extraction

Heat patterns were quantified by extracting 108 radiomic features – six different descriptors obtained from each of the six images at three different image resolutions (370x288, 185x144 and 93x72 pixels): contrast, dissimilarity, homogeneity, angular second moment, energy, and correlation– and 24 moment features – four different descriptors obtained from each of the six images: mean, standard deviation, skewness, and kurtosis– from the segmented images. The radiomic features quantified the heterogeneity by using the gray level cooccurrence matrix (GLCM), it is expected to reflect the overall average for degree of correlation among heat intensities in neighboring locations. Basic statistics of the distribution of heat in the image were also collected by using the moment features.

2.5 Data transformation

Power transform – Yeo-Johnson transformation – was applied to highly skewed features. Adjustment was implemented using a robust fitting model based on age, height, and weight. Negative cases were considered as reference control. Significant features were selected with a single-rank Wilcoxon test.

2.6 Classification

We split the data in 70% training and 30% testing sets. The two classes in order were negative and positive results from the PCR-test. 200 repetitions of cross-validation were applied, as well as a balanced method approach with classes reweight. Image segmentation, feature extraction and transformation processes were done using Python programming language (2019) version 3.7.6 (Python Software Foundation, <https://www.python.org/>). Adjustment and classification were executed in R Core Team (2020) version 4.0.2. (R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>.)

3 Results

3.1 Classification using image features. Four views

In this first task, classifications of image features were performed using the four views separately using AdaBoost classifiers. Classification results are summarized in Table 1. Accuracies of the four views are in the range of 0.433 – 0.524, while areas under the curve are in the range of 0.397 – 0.515.

Table 1: COVID-19 classification performance. Four views separately.

Metric	Back		Front		Left		Right	
	95% CI		95% CI		95% CI		95% CI	
Accuracy	0.524	(0.46, 0.59)	0.433	(0.37, 0.50)	0.409	(0.38, 0.47)	0.496	(0.43, 0.56)
AUC	0.515	(0.43, 0.60)	0.435	(0.35, 0.52)	0.397	(0.31, 0.49)	0.470	(0.38, 0.56)
Sensitivity	0.475	(0.34, 0.61)	0.424	(0.30, 0.56)	0.373	(0.25, 0.51)	0.492	(0.36, 0.63)
Specificity	0.539	(0.47, 0.61)	0.435	(0.36, 0.51)	0.420	(0.35, 0.49)	0.497	(0.43, 0.57)
Balanced error	0.493	(0.43, 0.57)	0.571	(0.50, 0.64)	0.604	(0.53, 0.67)	0.508	(0.44, 0.58)

3.2 Classification using image features. All views

Image features were extracted from the four views and used together for classification. Five methods – SVM, AdaBoost, KNN, Random Forest and Naïve Bayes – were used, all of them obtained classification accuracies in the range of 0.536 – 0.569.

“Data Not Found.”

3.3 Classification using image features. Female and male patients

We compared results among female and male patients using the images features extracted from individual views, using AdaBoost. Results from the Front view are reported here as outcomes from the different views did not presented relevant differences.

Although both performances are almost similar, male patients (Figure 3) tend to be classified with slightly better accuracy than females (Figure 2), we obtained an accuracy of 0.564 for women compared to 0.595 for men.

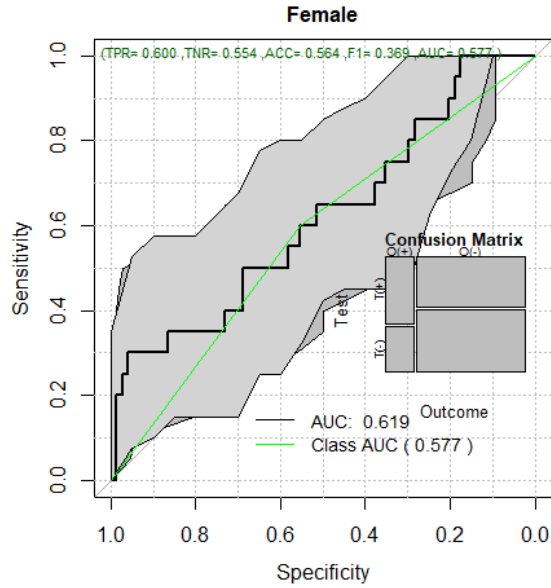


Figure 2: Areas under the receiver operating curve for COVID-19 classification. Female patients result.

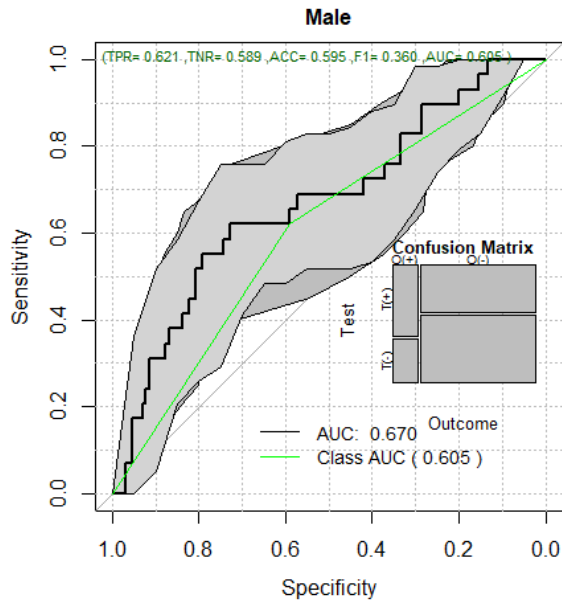


Figure 3: Areas under the receiver operating curve for COVID-19 classification. Male patients result.

3.4 Classification with vital signs and symptoms

Vital signs – temperature(C), systolic, diastolic, heart rate and oxygen saturation – and symptoms – sore throat, diarrhea, vomit, loss of smell, loss of taste, shivering, headache, myalgia, arthralgia, and the total number of symptoms – were also included for classification with AdaBoost. Similarly, to the previous experiment, these results were obtained by taking features extracted from the Front view. Figure 4 shows the areas under the curve when using image features coupled with symptoms and when using only symptoms as baseline comparison; results when combining vital signs and image features, and vital signs only, are found in Figure 5; and in Figure 6 we find results when using all information together – image features, vital signs, and symptoms – as well as results with only vital signs, and symptoms.

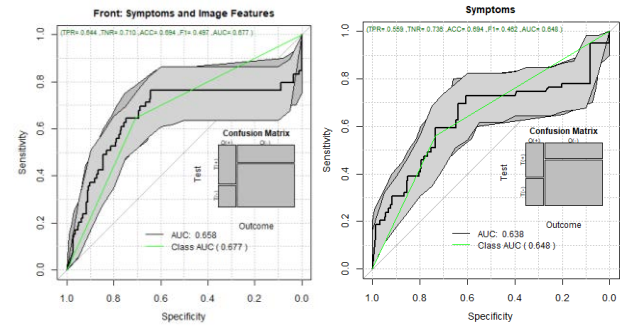


Figure 4: Areas under the receiver operating curve of COVID-19 classification using thermal features and symptoms.

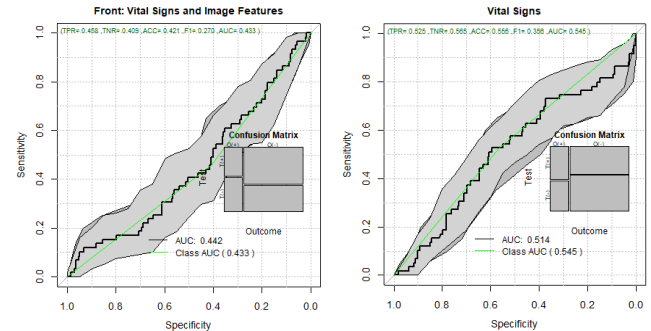


Figure 5: Areas under the receiver operating curve of COVID-19 classification using thermal features and vital signs.

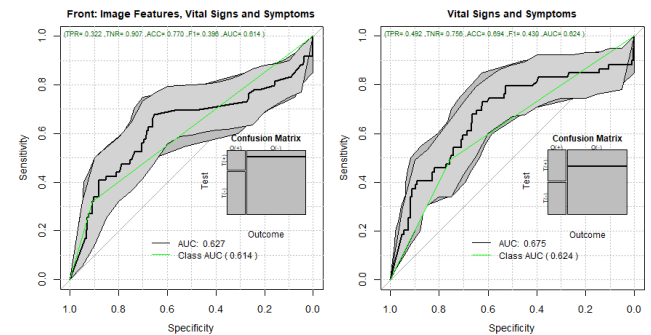


Figure 6: Areas under the receiver operating curve of

COVID-19 classification using thermal features, vital signs, and symptoms.

4 Discussion

Four views were tested to consider information from different perspectives. Considering the classification when using only the features extracted from images, accuracies obtained (around 0.5) indicate a random classification. Classification performance tends to improve slightly when using symptoms and image features, and when using all information together, however when looking at the performance when using only symptoms, and only symptoms and vital signs, we can conclude that the direct contribution of the images is not as representative as the medical information. The sex difference reported in covid-19 identification using thermal images benefit men, but they are not pronounced, however, we still need to consider some dataset limitations: small sample of females and non-standardization along the subjects, with female patients having interference caused by bras and hair.

5 Conclusion

This is a first study in which the capability of thermal images for Covid-19 identification is investigated. The methodology proposed here consisted of radiomics and moment features extracted from images obtained from thermal video clips and classified using traditional machine learning methods. The classification performance of these features indicated a random classification. In literature, we find a lack of studies on thermal images used to detect Covid-19, this work provides a first insight of the usability of this type of images. Although our study showed mostly unfavorable results, we consider more research needs to be conducted. This study presented some limitations: small sample size; data collection performed in a single center; and a stricter standardization of participants required – some of the volunteers wore masks, female's hair interferes in shoulders, neck, or face, etc. –. We expect to expand and diversify the collection centers for correct validation and generalization, furthermore we recommend conducting additional research on thermal images using different approaches and methodologies.

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REFERENCES

- [1] Wu, F., et al., A new coronavirus associated with human respiratory disease in China. *Nature*, 2020. 579(7798): p. 265-269.
- [2] Organization, W.H. WHO Coronavirus (COVID-19) Dashboard. 2021 [cited 2021; Available from: <https://covid19.who.int/>.
- [3] Guan, W.J., et al., Clinical Characteristics of Coronavirus Disease 2019 in China. *N Engl J Med*, 2020. 382(18): p. 1708-1720.
- [4] Zhou, P., et al., A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature*, 2020. 579(7798): p. 270-273.
- [5] Huang, C., et al., Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet*, 2020. 395: p. 497 - 506.
- [6] Mei, X., et al., Artificial intelligence-enabled rapid diagnosis of patients with COVID-19. *Nat Med*, 2020. 26(8): p. 1224-1228.
- [7] Wang, S., et al., A deep learning algorithm using CT images to screen for Corona virus disease (COVID-19). *Eur Radiol*, 2021.
- [8] Houdas, Y. and E.F.J. Ring, Human body temperature: its measurement and regulation. 1982, New York, New York: Springer Science+Business Media.
- [9] Lahiri, B.B., et al., Medical applications of infrared thermography: A review. *Infrared Phys Technol*, 2012. 55(4): p. 221-235.
- [10] Faust, O., et al., Application of infrared thermography in computer aided diagnosis. *Infrared Phys Technol*, 2014. 66: p. 160-175.
- [11] Yadav, S. and S. Jadhav, Thermal infrared imaging-based breast cancer diagnosis using machine learning techniques. *Multimedia Tools and Applications*, 2020.
- [12] Ferrer, L.M., et al., Use of Computed Tomography and Thermography for the Diagnosis of Respiratory Disorders in Adult Sheep, in *Sheep Farming - An Approach to Feed, Growth and Health* A. Monteiro, Editor. 2020.
- [13] Evertsen, J., et al., Diagnosis and management of pneumonia and bronchitis in outpatient primary care practices. *Prim Care Respir J*, 2010. 19(3): p. 237-41.
- [14] Kanade, T. and B.D. Lucas, An Iterative Image Registration Technique with an Application to Stereo Vision. *IJCAI'81: Proceedings of the 7th international joint conference on Artificial intelligence*, 1981. 2: p. 674 - 679.