Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Software Impacts 13 (2022) 100337

Contents lists available at ScienceDirect

Software Impacts

journal homepage: www.journals.elsevier.com/software-impacts

Original software publication

Source Code for Optimized Parallel Inception: A Fast COVID-19 Screening Software

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ARTICLE INFO

Keywords:
COVID-19
Coronavirus
H1N1 virus
Outbreak
Screening
Deep Learning

ABSTRACT

COVID-19 and swine-origin influenza A (H1N1) are both pandemics that sparked significant concern worldwide. These two viruses have the same symptoms and occur at a collision timeline. Optimized Parallel Inception (OPI) presents a new strategy to screen the COVID-19 from H1N1 with use of only symptoms. In this paper, the process of preprocessing, screening, and specifying feature importance by OPI and particle swarm optimization is presented. Experimental results indicate 98.88 accuracy for screening COVID-19, H1N1, and Neither COVID-19 Nor H1N1.

Code metadata

Current code version	v1
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2022-72
Permanent link to Reproducible Capsule	https://codeocean.com/capsule/6231633/tree/v1
Legal Code License	MIT License
Code versioning system used	Created by Python with GPU support (3.7.3, miniconda 4.7.10)
Software code languages, tools, and services used	Python
Compilation requirements, operating environments dependencies	Linux operating system with NVIDIA CUDA version 10.1 and higher
If available Link to developer documentation/manual	N/A
Support email for questions	alireza.tavakol@ut.ac.ir

1. Introduction

In the last days of 2019, the novel coronavirus with code name COVID-19 emerged in Wuhan, China. COVID-19 spread through the world rapidly and caused 6,297,362 by 20th of May 2022 [1]. Various variants of COVID-19 caused major issues in the autumn and winter. The influenza virus is notable for its periodic occurrence, and yearly economic impact [2]. The annual seasonal influenza epidemic infects 3–5 million people with serious conditions worldwide [3]. Number of infections for both diseases rose between October and April. Due to the body immune system reaction, common symptoms of H1N1 include high fever, coryza, and myalgia. In severe cases, viral pneumonia, superimposed bacterial pneumonia, and hemorrhagic bronchitis have been reported [4]. The most common COVID-19's symptoms are cough, weakness, myalgia, fever, headache, impaired sense of smell, impaired sense of taste, sore throat, runny nose, and nasal congestion [5]. The common symptoms of both COVID-19 and H1N1 are similar, which makes their screening task challenging [6]. Optimized Parallel Inception is a new deep learning model that aims to solve this challenge by using symptoms like: 'Breathing Problem', 'Fever', 'Dry Cough', 'Headache', 'Sore Throat', 'Running Nose', 'Fatigue', 'Asthma', 'Chronic Lung Disease', 'Heart Disease', 'Diabetes', 'Hypertension', 'Gastrointestinal', 'Abroad Travel', 'Contact with COVID-19 Patients', 'Attended Large

The code (and data) in this article has been certified as Reproducible by Code Ocean: (https://codeocean.com/). More information on the Reproducibility Badge Initiative is available at https://www.elsevier.com/physical-sciences-and-engineering/computer-science/journals.

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https://doi.org/10.1016/j.simpa.2022.100337
Received 21 May 2022; Received in revised form 12 June 2022; Accepted 17 June 2022

Gathering', 'Visited Public Exposed Places', and 'Family Working in Public Exposed Places'.

In this paper, we propose a novel deep learning model with the name of Optimized Parallel Inception (OPI) [7] with combination of Particle Swarm Optimization (PSO) [8] to choose best sets of features and discriminate between COVID-19 and H1N1 patients from Neither COVID-19 Nor H1N1. Proposed model helps healthcare system to detect patient with 98.88% accuracy in total with screening accuracy of 99.2% and 99.6% for COVID-19 and H1N1, respectively only using 18 features. Proposed structure is well tuned against null values and can use 10 features and report 97% accuracy still.

2. Description of OPI with PSO

OPI is composed of a 3 heads Convolutional Neural Network (CNN) [9] that uses a combination of symptoms information to screen COVID-19 and H1N1 patients from Neither COVID-19 Nor H1N1. Proposed structure uses 1-dimension convolutional layer and uses three different paths to extract distinguishable features. Each head predicts a class individually and based on achieved accuracy by each head soft or hard voting is used at the end. Proposed structure is shown in Fig. 1.

2.1. Inception layer

Proposed structure composed of conventional 1-dimension convolutional layer at the beginning. Then a set of inception layers is used throughout the OPI with different kernel sizes. These inception layers are responsible to extract the relationship between co-occurring and comorbidities symptoms. Earliest inception layers composed of convolutional layers with 7 and 9 kernel sizes. The upper layers of OPI are composed of convolutional layers with 3 and 5 kernel sizes. The opposite hierarchy is occurring for filter sizes.

2.2. Decision layer

The last layer of the OPI is the decision layer. The aim of this layer is to choose the best strategy for predicting classes of instances. The first strategy uses the difference between accuracy of the main and two auxiliary paths in the training phase. If the difference is $>= 0.1\%$, then output of the path with the maximum accuracy will determine the model's decision in the testing phase. If the difference is < 0.1 in the training phase, then soft voting of all paths determines the OPI's decision in the testing phase.

2.3. PSO

PSO is used with a combination of OPI to choose the smallest subsets of features to achieve an acceptable level of accuracy for screening. PSO uses the OPI with a random subset of features and try predict the class of instances. Then PSO increases the search area and evaluate the OPI with various combination of features. PSO choses best sets of features based on screening accuracy and loss.

2.4. Framework

Whole process of using OPI with PSO for using optimal subsets of features and screen the COVID-19 and H1N1 patient from Neither COVID-19 Nor H1N1 is implemented in a forward path. First model is trained on 10 batches of training and validation sets then based on difference between accuracy of each path one of the strategies is used for predicting unlabeled instances. Proposed structure is trained with ADAM, batch size of 32 for training and evaluation and learning rate equals to 0.0001. To train the model properly exponential scheduling is put in place to reduce learning rate by 0.1 with 30 epochs intervals without any change to the learning process. Whole framework is trained on 10 loops with an initial population of 20 individuals. The framework repeats these loops with maximum 10 iteration for each individuals' particles (Proposed set of features) to find best sets of features. Finally based on best result and sets of features weight of the OPI is going to be updated and saved for real time testing phase.

Table 1
Results of screening using the OPI for each class.

Class name	Precision	Sensitivity	Specificity	AUROC
Neither COVID-19 Nor H1N1	100%	100%	95.46%	0.998
H1N1	100%	100%	99.71%	0.998
COVID-19	96.48%	96.82%	100%	0.991

3. Empirical result

OPI has been evaluated with use of combined COVID-19, H1N1 datasets. NVIDIA CUDA version 10.1 and higher are the requisites for optimized and fast solutions. We recommend users to set the hyperparameters into default settings. The information about required libraries, visualization format, example scripts is provided in the meta data environment of the code ocean.

3.1. Detailed result

To investigate the achieved result in detail we report precision, sensitivity, Specificity, and Area under Receiver Operating Characteristic (AUROC) in Table 1. Based on Table 1, result of achieved specificity in class "Neither COVID-19 Nor H1N1" and class "COVID-19" shows that the detection rate for true negative case in "COVID-19" class is higher than the class of "Neither COVID-19 Nor H1N1". Although, based on achieved sensitivity, the detection rate for true positive case in "Neither COVID-19 Nor H1N1" is much higher than the class of "COVID-19". Also, detection of H1N1 in patients with proposed OPI is more accurate than COVID-19. The comparison between proposed model and similar researches is shown in Table 2.

The empirical results of framework demonstrate following features:

- Higher performance: The proposed OPI detects the COVID-19 and H1N1 patients with accurate precision and high sensitivity. In case of COVID-19 detection the OPI outperforms ML and Deep Learning (DL) algorithms such as Gradient-Boosting [10], RF [11], Logistic Regression (LR) [12], Supported Vector Machine (SVM) [13], and Bayesian network [14].
- Intelligent feature selection: The OPI is compatible with newly seen data and can be used to fill null values or only use subsets of available symptoms for screening COVID-19 and H1N1 patient from Neither COVID-19 Nor H1N1.

4. Impact and future applications

OPI is an algorithm that actively works with respiratory viruses' symptoms and screens the COVID-19 from H1N1 patients. Compared to similar research that developed only for COVID19 detection in patients, OPI can detect COVID-19 and H1N1 patients but discriminate between COVID-19 and H1N1 patients. OPI performance in case of true positive and true negative detection rate outperforms other ML and DL algorithms. The proposed models help the healthcare providers in pandemics by rapid screening and decreasing human interactions. OPI screening ability helps healthcare providers to tune the model to discriminate between various strains of COVID-19 too.

The future of OPI is made up of different possibilities. Developing an online application to gather more dataset and tune the OPI based on the new dataset. OPI can be the first response application to screen precisely the new variants of COVID-19. Another potential field for OPI can be seen changing the structure of OPI itself. Making the OPI shallow and decreasing the number of layers to decrease cost for training the modified OPI and increase the convergence to optimal solution.

Capability of OPI helps to disseminate other disease too. Thus, extending the screening possibilities to more than COVID-19, H1N1, and Neither COVID-19 Nor H1N1 is another path for OPI. Tuning OPI to screen H5N1, seasonal flu, B-Victoria influenza, COVID-19,

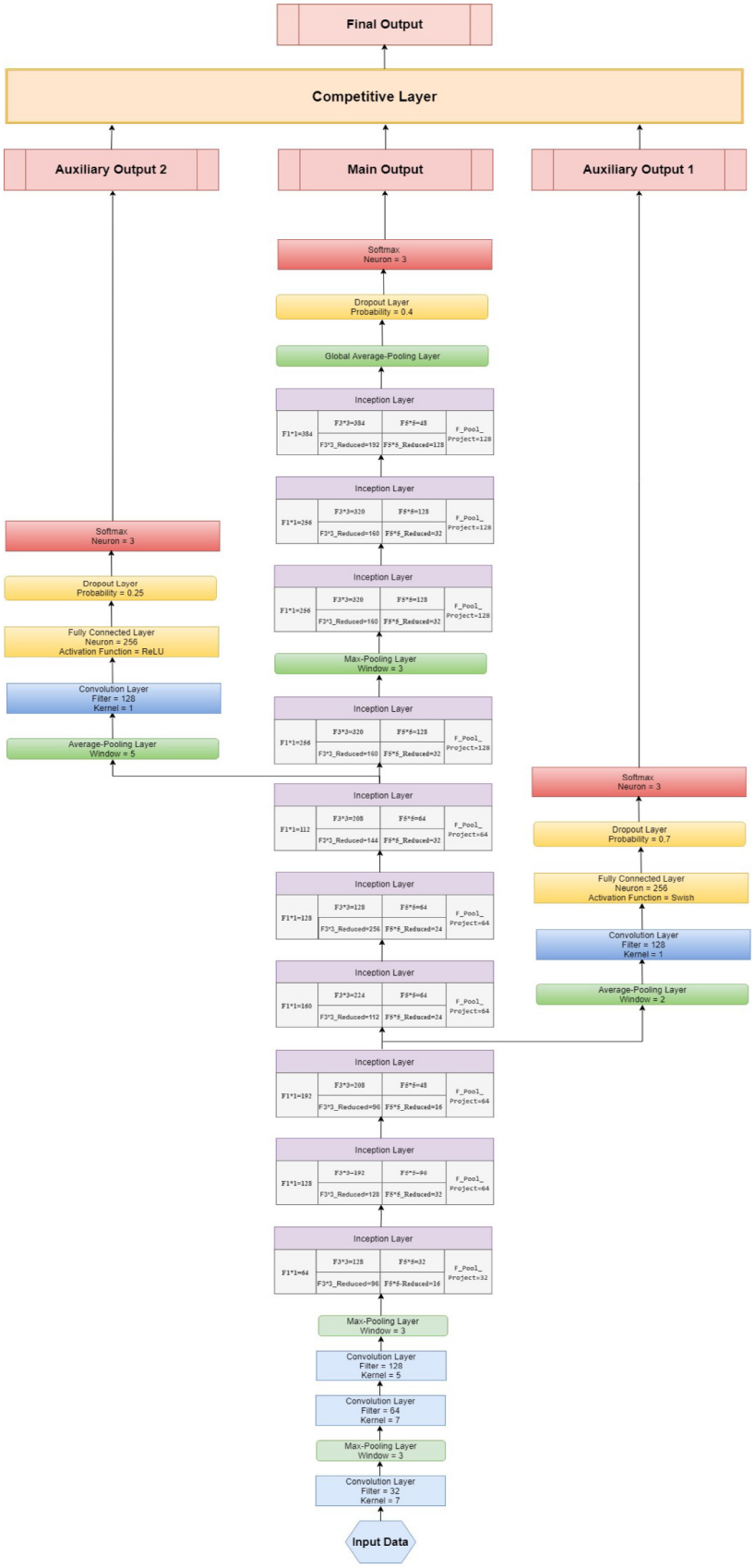

Fig. 1. Architecture of Optimized Parallel Inception (OPI).

Table 2
Comparison of proposed model with similar work for COVID-19 detection.

Author	Model's name	Accuracy	Sensitivity	Specificity	Most important features
Zoabi et al. (2021)	Gradient-Boosting	–	87.30%	71.98%	Fever and cough
Iwendi et al. (2020)	RF	94%	75%	–	Fever, cough and cold
Khanday et al. (2020)	LR	96.2%	96%	–	chest pain and lung disease
de Moraes Batista et al. (2020)	SVM	–	68%	85%	Number of lymphocytes, leukocytes and eosinophils in blood test
Shi et al. (2021)	RF	87.9%	90.7%	83.3%	Number of infected segments in lungs
Canas et al. (2021)	Bayesian Network	–	73%	72%	Loss of smell, chest pain, persistent cough, abdominal pain, blisters on the feet, eye soreness, and unusual muscle pain
Proposed Model	OPI	98.88%	98.90%	98.39%	Dry cough and breathing problem

and Ebola from each other extends the possible applications for OPI. Due to the capability of OPI to discriminate between disease with similar symptoms, application of OPI will be extended to detect various variants of the same viral diseases.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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