

An Intelligent Approach for COVID-19 Detection Using Deep Transfer Learning Model

Mustafa Abdul Salam¹ and Mohamed A. Torad²

(Corresponding author: Mustafa Abdul Salam)

Artificial Intelligence Department, Faculty of Computers and Artificial Intelligence, Benha University¹
Qism Banha, Banha, Al Qalyubia Governorate, Egypt

Department of Communication and Electronics Engineering, Higher Technological Institute, Egypt²
(Email: mustafa.abdo@fci.bu.edu.eg)

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Abstract

Coronavirus disease (COVID-19) appeared in the last quarter of 2019. A Coronavirus wildfire around the world, where the infection and death rates uprise dramatically every day. In this paper, an enhanced convolutional neural network based on transfer learning was proposed to detect patients infected with COVID-19 using chest X-ray radiographs. The proposed model helps radiologists to diagnose COVID-19 disease automatically with high accuracy. The proposed method is introduced to afford precise identification of infected persons. Referring to the performance results acquired, the used pre-trained ResNet50 paradigm achieves the peak performance with 99.2% accuracy outperforming all compared methods.

Keywords: Chest X-ray Radiographs; Convolutional Neural Network; Coronavirus; Pneumonia; ResNet50 Model

1 Introduction

COVID-19 evolution, started at December 31, 2019 for the first time with respiratory infection in China (Wuhan) as a result of unexplained reasons, and dramatically converted to become a global disease [22]. The virus was designated as SARS-CoV-2, and the disease as COVID-19. The infection spreads from the center of the storm to most of China in 30 days. Animals affected with most coronaviruses, on the other side these coronaviruses can be contagious to people because of their zoonotic environment. COVID-19 symptoms include cough, fever, headache, sore throat, muscle pain, shortness of breath, and exhaustion [21,22]. Total number of coronavirus infections exceed 152 million and more than 3 million of them died while 129 million were recovered. More than 95% of the number of infected patients in Mild Condition, and the reminder infected people have a critical or serious condition [2,10,18].

Chest radiological picture such as X-ray and CT have a significant impact on early detection and cure of this coronavirus. According to the researchers, combining laboratory findings with chest imaging can aid in the fast identification of COVID-19. Radiologic photographs obtained from COVID-19 patients provide valuable information for diagnostics and detection [5,7,26,27].

Deep learning (DL) is a crucial artificial intelligence (AI) research area that enables end-to-end models to be launched to meet convinced outcomes based on received data with automatic extraction of features. In various problems such as skin cancer classification, arrhythmia detection, pneumonia diagnosis, lung segmentation, and breast cancer detection, DL techniques have been successful [12, 20, 24]. The rapid growth of the COVID-19 epidemic has called for expertise and specialist criteria in this area. Therefore, there is an interest in obtaining AI-powered automatic detection systems. Because of the small number of radiologists, it is a difficult mission to bring professional clinicians to each hospital. Quick, simple and precise AI models may therefore be helpful in order to resolve this issue and provide patients with timely assistance. In radiology, AI techniques can be helpful in obtaining precise detection. In addition, AI approaches can be helpful in excluding drawbacks such as test fees and time elapsed to achieve outcomes. Fast improvement in artificial intelligence-based automated diagnostic technique for COVID-19 patients is introduced in [4, 19, 28, 29].

In this paper, an automated identification of COVID-19 using enhanced deep transfer model is presented. Also, the ConvNet model has standalone structure without selection of methods and manually feature extraction. Also, amongst other pre-trained techniques, the ResNet50 model is a valuable pre-trained model [8, 23]. Chest X-ray images are considered to be among the most satisfactory COVID-19 diagnostic instruments. In small datasets (150 COVID-19 vs. 500 Negative), the ResNet50 pre-trained model has been shown to yield highly accurate performance with federated and distributed machine learning models [3, 9].

Also, using swarm intelligence algorithms can enhance the accuracy and generalization ability of standard machine and deep learning models [13–17]. Hybrid machine and deep learning models can enhance the accuracy of traditional models [1, 6, 11, 25].

The rest of this paper is arranged as follows: Dataset description, transfer learning method are described in Section 2. Simulation Results and analysis are discussed in Section 3. Section 4, is devoted for conclusion as well as the future work.

2 Material and Methods

2.1 X-ray Images Dataset

In this research, chest X-ray images were utilized for the detection of COVID-19 virus. The dataset for COVID-19 X-ray has been acquired from the open-source GitHub source [5]. This dataset is regularly updated with pictures published by researchers from various counties. The proposed research-initiated dataset with chest X-ray pictures of 150 COVID-19 infected persons and 500 regular persons (No-findings) (650 pictures in dataset). All pictures in this dataset were reshaped to 256x256 pixel size. Samples of dataset images for positive and negative cases, are shown in Figure 1.

2.2 Deep Transfer Learning

In the recent pandemic COVID-19, many kinds of research have been going on. Deep learning (DL) is a subset of the machine learning (ML) field. DL allows formation of models to fulfil outcomes using input data, with automatic feature extraction capability. DL methods facilitated in latest years continue to illustrate an extraordinary accomplishment in image processing especially in medical applications. Medical imaging technologies such as CT and X-ray can be adopted DL models to automatically detect diseases [4, 8]. In the assessment of medical data and information, the limited dataset resources available represent one of the most obstacles. DL models usually need a huge dataset. The labeling methodology necessitates the use of specialists and is labor intensive. The most significant benefit of using the transfer

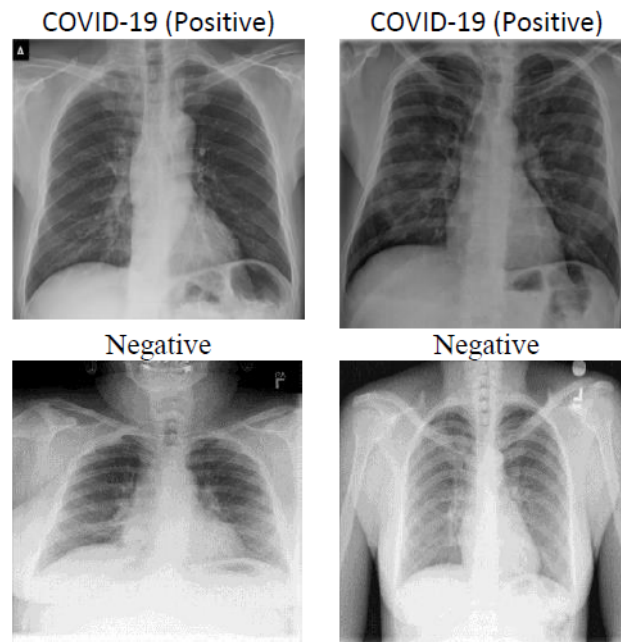


Figure 1: Chest X-ray positive and negative samples of COVID-19

learning approach is that it allows for the processing of information and data with less datasets and requires fewer computation costs.

A standard CNN setup includes a convolution layer that isolates feature from the input image using the filters it employs, a pooling layer to minimize size for statistical and computational performance, and a fully linked neural network layer. This model is completed by the Softmax and Avgpool layers, which produce the outputs. A ReLU activity used to save neurons from dying. Figure 2 depicts a CNN model.

2.3 Proposed COVIDRes-Net50

In this work, a CNN based on ResNet50 model is presented for the recognizing of COVID-19 presence or absence. The schematic performance of CNN containing pre-trained ResNet50 paradigm for the categorization of COVID-19 images to positive and negative.

The enhanced version of CNN (ResNet) model appends shortcuts among layers to solve a problem. It removes the fragmentation that occurs as the network deepens and becomes more dynamic [21]. ResNet50 composed of 50- layer network trained on the ImageNet dataset. In the final stage, it includes a fully connected neural network.

The overall workflow of our proposed COVIDRes-Net50 built on ResNet50 paradigm is described in Figure 3. Starting with reading dataset, preprocessing, applying resnet50 with transfer learning, classification, and finally performance evaluation.

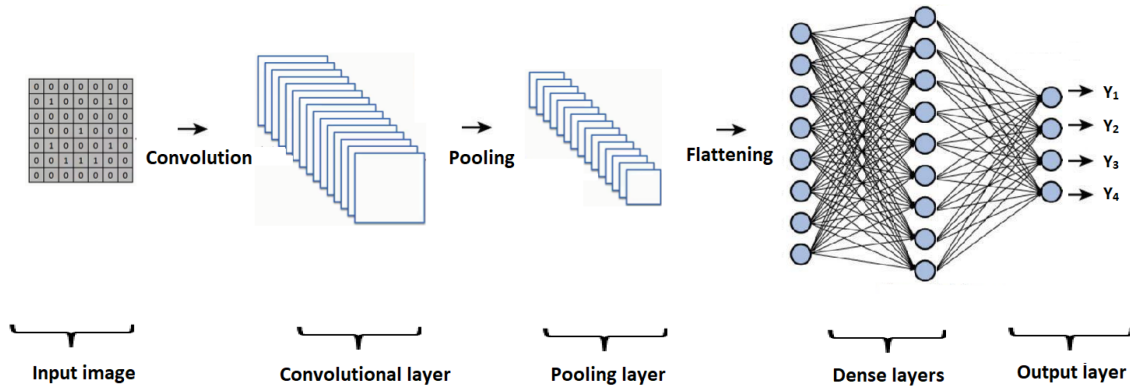


Figure 2: CNN layers operations

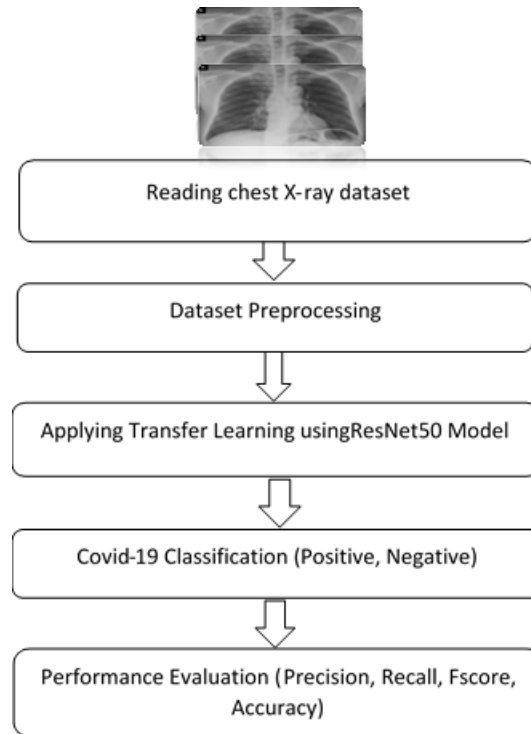


Figure 3: The proposed COVID Res-Net50 model for classification using transfer learning

3 Results and Discussions

3.1 Experimental Setup

Firstly, all images are scaled to the size of 256×256 pixels. The COVIDRes-Net50 framework containing DL classifier Res-Net50 has been implemented using Python programming language on AMD A6-2.0 GHz CPU. Moreover, the experiments were performed utilizing the GPU performed on Kaggle.

For assessing the execution of proposed DL classifier, 80 percent of X-ray images including Negative and Positive covid_19 cases are arbitrarily chosen for training, i.e., 500 images of the dataset and 20% for validation, i.e., 150 images. CNN model (ResNet50) was pre-trained with the Adam optimizer for weight updates. We used learning rate, batch size, cross entropy loss function, and count of epochs were experimentally set to 32, $3e-3$ and 100. Lastly, the layer parameters and layer details of the model are presented in Table 1.

Table 1: The layers and layer parameters of the proposed model

Layer (Type)	Output Shape	Param #	Trainable
Conv2D	[64, 128, 128]	9408	False
BatchNorm2D	[64, 128, 128]	128	True
ReLU	[64, 128, 128]	0	False
MaxPool2D	[64, 64, 64]	0	False
Conv2D	[64, 64, 64]	4096	False
BatchNorm2D	[64, 64, 64]	128	True
Conv2D	[64, 64, 64]	36864	False
BatchNorm2D	[64, 64, 64]	128	True
Conv2D	[256, 64, 64]	16384	False
BatchNorm2D	[256, 64, 64]	512	True

3.2 Results analysis

ResNet50 has been trained and tested on X-ray images. Training precision and loss values of (train loss and valid loss) of the pre-trained model are given in Table 2. Also curve of training loss, validation loss, and accuracy is shown in Figure 4.

The result of confusion matrix obtained using Res_Net50 pre-trained model is shown in Figure 5. In addition, recall, precision, and accuracy results are given in Table 3, and Table 4.

The proposed model has reached the best performance as a precision of 99.2%, average recall of 97.5%, average f1-score value of 98.5%, and average precision of 99.5% for ResNet50 pre-trained model.

Figure 6 presents the performance evaluation for proposed model. Figure 7 presents the performance average of proposed model.

There have been several studies published in the literature as a result of the advent of the COVID-19 virus disease. These kinds of experiments are summarized, and we obtained better results as compared to these studies in the literature, as seen in Table 5 and Figure 8.

Table 2: Sample of training and loss values of the pre-trained model

Epochs	Training Loss	Validation Loss	Accuracy
1	0.818035	0.215299	0.904000
2	0.655854	0.108407	0.960000
3	0.582863	0.037355	1.000000
4	0.496495	0.016691	1.000000
5	0.419247	0.018139	1.000000
6	0.379116	0.010196	1.000000
7	0.320826	0.008791	1.000000
8	0.276221	0.020114	1.000000
9	0.234684	0.009855	1.000000
10	0.207661	0.019936	0.992000
11	0.184298	0.021269	0.992000
12	0.157956	0.025135	0.984000
13	0.138604	0.071454	0.992000
14	0.128936	0.025364	0.992000
15	0.118417	0.028702	0.984000
16	0.100699	0.006527	1.000000
17	0.080904	0.020330	0.992000
18	0.075333	0.043874	0.992000
19	0.073052	0.092359	0.976000
20	0.062135	0.078228	0.992000

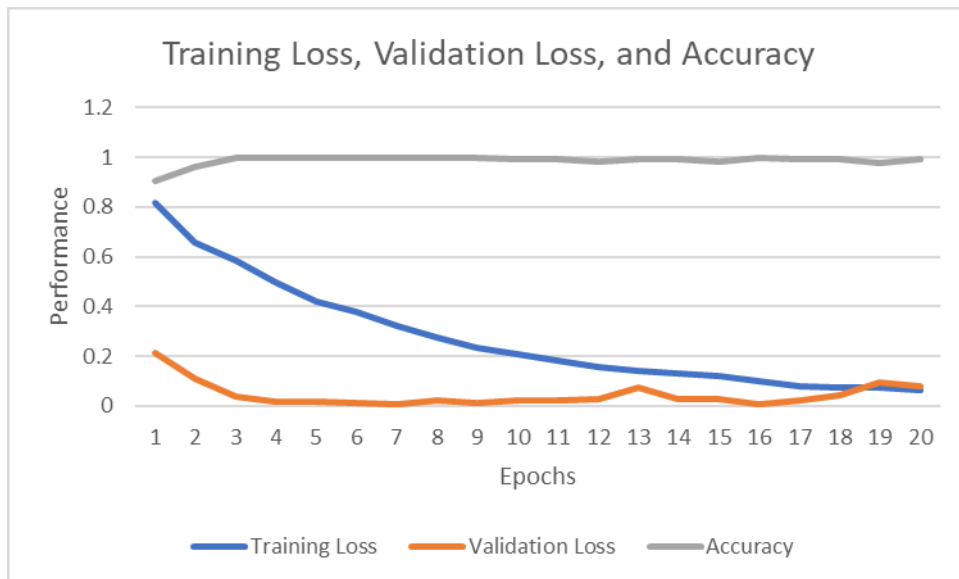


Figure 4: Curve of training and loss values of the pre-trained model

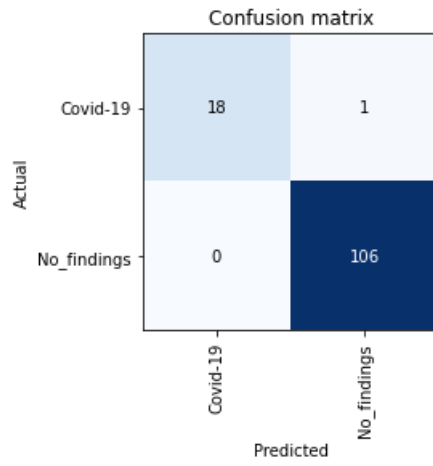


Figure 5: The confusion matrix obtained using Res_Net50 pre-trained model

Table 3: Recall, precision, F1-score, and accuracy results obtained using Res_Net50 pre-trained model

	Precision	Recall	F1-Score	Support
Covid-19 +ive	1.00	0.95	0.97	19
Covid-19 -ive	0.99	1.00	1.00	106

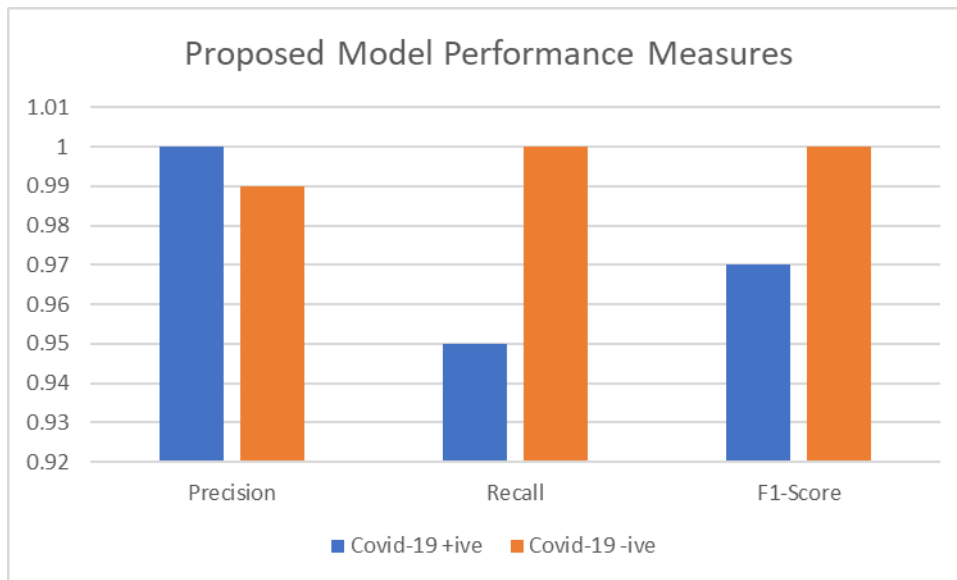


Figure 6: Proposed Model Performance Measures

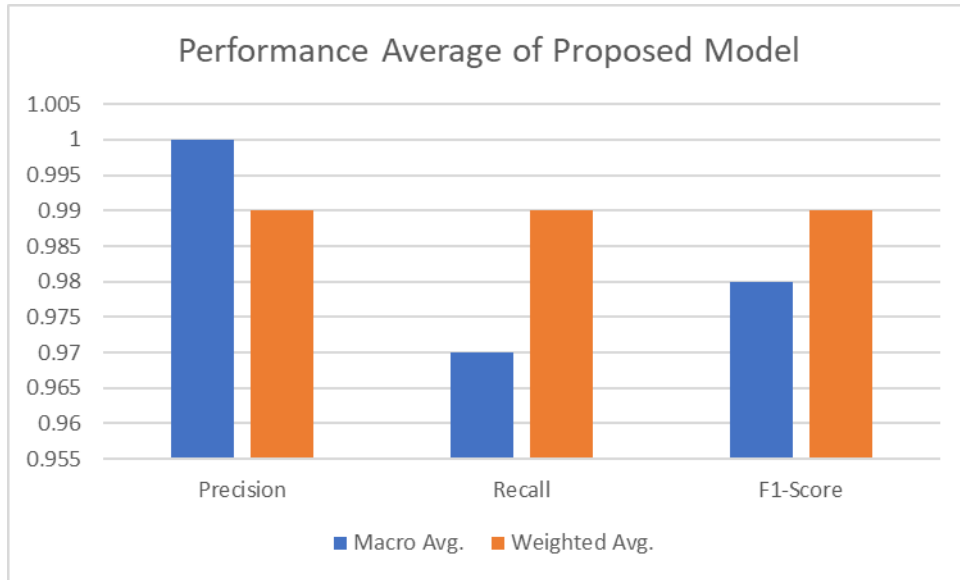


Figure 7: Performance average of proposed model

Table 4: Macro, and weighted average accuracies of proposed model

Avg.	Precision	Recall	F1-Score	Support
Macro Avg.	1.00	0.97	0.98	125
Weighted Avg.	0.99	0.99	0.99	125

Table 5: Comparison of the proposed COVID-19 detection model with other DL models developed utilizing chest X- ray images

Research Paper	Model	Model Accuracy
Ozturk [22]	DarkCovidNet	98.08%
Narin [21]	ResNet-50	98%
	InceptionV3	97%
	InceptionResNetV2	87%
Hemdan [18]	COVIDX-Net	90.0%
Apostolopoulos [5]	VGG-19	93.48%
Sethy [26]	ResNet50+ SVM	95.38%
Wang [27]	COVID-Net	92.4%
Proposed Study	Deep CNN	99.2%
	ResNet-50	

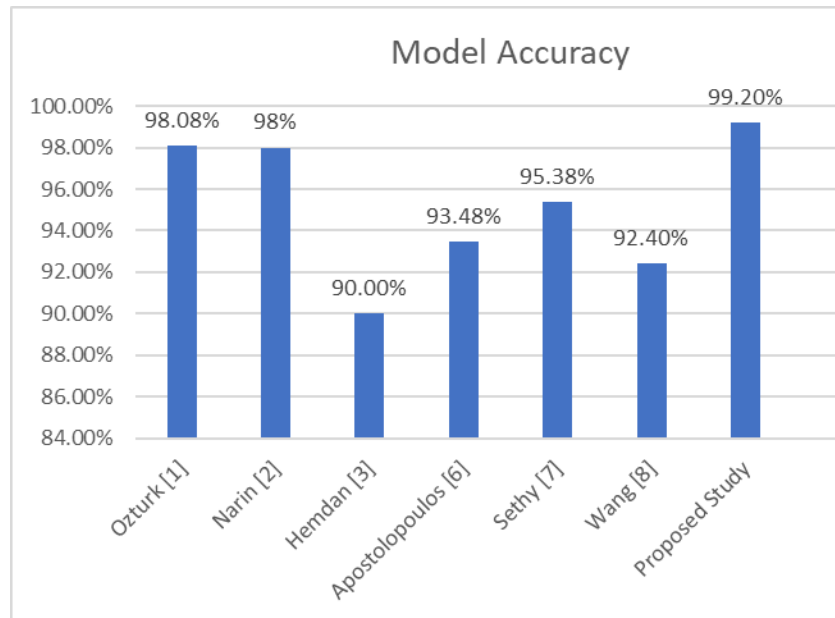


Figure 8: Performance of proposed and compared models

4 Conclusion and Future Work

Early diagnosis of COVID-19 cases is critical to preventing the disease from spreading to other people. Deep transfer learning-based approach was suggested in this study that uses chest X-ray images obtained from COVID-19 cases to predict COVID-19 cases automatically. As compared to other models, the ResNet50 pre-trained model generated the highest accuracy of 99.2%.

Due to the high results, it is expected that it will assist radiologists in automatically diagnosing COVID-19 disease in the scope of our findings.

In the future, we will focus on using swarm intelligence algorithms to optimize CNN model. In addition, a bigger dataset can be used, along with hybrid deep learning models.

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Biography

Mustafa Abdul Salam received the B.Sc. from Faculty of Computers & Informatics, Zigzag University, Egypt in 2003, and obtains master degree in information system from faculty of computers and information, Menoufia university, Egypt in 2009 specializing in Hybrid Machine Learning and Bio Inspired Optimization algorithms. He obtained his Ph.D. degree in information system from faculty of computers and information, Cairo University, Egypt. He is currently an assistant professor in AI department, Faculty of Computers and AI, Benha University, Egypt. He has worked on a number of research topics. Mustafa has contributed more than 30+ technical papers in the areas of neural networks, support vector machines, optimization, time series prediction, extreme learning machine, hybrid AI models in international journals, international conferences, local journals and local conferences. His majors are Machine Learning, Big Data, Stream Data Mining, and Deep Learning.

Mohamed A. Torad received the B.Sc. degree in electrical engineering from Higher Technological Institute (HTI), in 2007. From 2008, he has been a research assistant at communication and electronics department, Higher Technological Institute, received his M.D. from Ain Shams University (ASU) in 2013. and received his PhD degree from Ain Shams University (ASU) of in 2016. He still working at communication and electronics department from 2007 till now, working at Future University at Egypt (FUE) and supervises number of graduation projects at Culture and Science City. Work as reviewer at many conferences (e.g., International Conference on Microelectronics (ICM), IEEE International Multi-Conference on Systems, Signals & Devices).