İSTANBUL UNIVERSITY CERRAHPAŞA

RESEARCH ARTICLE

Electrica 2021; 21(2): 203-208

Artificial Intelligence–Based COVID-19 Detection Using Cough Records

Alpaslan Gökcen[1], Bulut Karadağ[1], Cengiz Riva[2], Ali Boyacı[1]

[1]Department of Computer Engineering, İstanbul Commerce University, İstanbul, Turkey
[2]Department of Electrical Electronics Engineering, İstanbul Commerce University, İstanbul, Turkey

Cite this article as: A. Gökcen, B. Karadağ, C. Riva, A. Boyacı, "Artificial Intelligence–Based COVID-19 Detection Using Cough Records", Electrica, vol. 21, no. 2, pp. 203-208, May, 2021.

ABSTRACT

In 2019, with the emergence of coronavirus disease 2019 (COVID-19) and its spread all over the world, many people were directly affected by the pandemic. As its spread increases, it is difficult to diagnose who is actually infected. In addition to continuing vaccination studies, some technological solutions are being used to try to control the virus. One of these technological solutions is presented in this study. The disease is detected using cough data through artificial intelligence (AI). To do this, an open source data set was used from the opensigma.mit.edu website. More than 20,000 cough records representing age, gender, geographic location, and COVID-19 status are available from this site. The AI model trained on cough detection achieved 79% COVID-19 accuracy with an F1 of 80%. With the designed AI-based mobile application, COVID-19 can be detected and monitored.
Keywords: COVID-19, deep learning, cough detection

Introduction

Coronavirus disease 2019 (COVID-19) is an outbreak that first occurred in Wuhan, China. It was reported to the World Health Organization (WHO) on 31 December 2019 by the Chinese authorities [1]. It is a viral disease that is transmitted person to person. The pandemic first started in China; however, in four months, it spread to 2.5 million people in 120 countries. Death can result from severe disease onset, major alveolar damage, and progressive respiratory failure [2]. WHO has reported that 152,551 people have died by 19 April 2020 [3]. Governments have taken some measures to prevent the pandemic. Curfews, wearing masks, working from home, and international travel prohibition are the leading ones. Although these measures slow down the pandemic rate, the spread of the virus can continue through people in circulation. In addition, although some of those suffering from the virus survive the disease in the form of normal flu, elderly individuals especially experience respiratory failure [4]. Patients with a mild flu condition are sent to their homes and kept under surveillance. In patients with respiratory failure, intensive care respiratory failure treatments are generally based on the principle of applying positive pressure and oxygen with the help of a tube placed in the main trachea (intubation) or a mask placed on the face (non-invasive mechanical ventilation) and resting the respiratory muscles in this way [5].

With the inclusion of smartphones in our lives, we do many of our jobs on mobile devices. Internet banking is an information technology system that emerged with the World Wide Web and offers people's financial needs virtually [6]. Internet banking is a new type of innovation related to both product and process [7]. Most banking transactions are done on mobile phones. However, in the field of health, mobile phones are not used at a sufficient level. Most applications (apps) concern diet and physical activity. It is estimated that, by 2017, 50% of mobile phone users have downloaded at least one health-related app [8]. In the majority of academic studies, there are apps that require external sensors. For example, flex sensors [9] and Novelda's Ultra Wideband Impulse Radio [10] can be used for respiration measurement.

Corresponding Author:
Ali Boyacı

E-mail:
aboyaci@ticaret.edu.tr

Received: January 19, 2021

Accepted: April 15, 2021

DOI: 10.5152/electrica.2021.21005

Patients who experience COVID-19 with mild symptoms and are sent home are kept under the supervision of a family physician. Family physicians follow the patients' symptoms, such as fever, respiration, and pulse, at certain intervals. Family physicians are in constant communication with patients during this process. It is important to find a quick solution in outbreaks, such as the COVID-19 pandemic, without requiring external hardware. In this study, in the artificial intelligence (AI)-based mobile app using cough detection, it can be determined whether people have COVID-19. The disease process of the patient will be followed for a certain period. In cases where the current test approach is insufficient, COVID-19 can be detected using a quick solution. These data can also be shared with, and followed up by, the family doctor. If the course of the disease worsens in the future, it is important to monitor patients from home in this way instead of hospitalization, because the intensive care and bed capacities of hospitals are limited.

In this study, we benefited from the data set of open sources [11]. The cough signal classification has been used successfully to diagnose a variety of respiratory conditions. With this project in our mind, algorithms of deep learning were processed to supply COVID-19 screening globally. The COVID-19 dataset includes more than 20,000 crowd-sourced cough records displaying a wide variety of ages, genders, geographic locations, and COVID-19 conditions. These data included more than 2,000 tagged records.

Related Work

Cough analysis is a well-studied topic for identifying numerous respiratory diseases. However, COVID-19 does not share the typical symptoms and signs with these diseases [12-14].

Laguarta et al. [15] extracted biomarkers and trained a convolutional neural network–based model using over 5,000 records, achieving very high accuracy and precision to detect COVID-19.

Imran et al. [16] developed a mobile application using the classification approach. After cough is identified, it is forwarded to three parallel independent classifications.

Using phone recordings of coughs, a group of scientists utilized four different classification algorithms and compared the results of these algorithms [17]. To distinguish healthy and COVID-19–infected coughs, principal component analysis was executed to indicate the results visually.

Another study using cell phone cough recordings was performed by Pahar et al. [18], using various classifier machine learning methods that are able to discriminate COVID-19.

Pal and Sankarasubbu [19] used a deep neural network with symptom embeddings and cough embeddings.

Brown et al. [20] showed that a simple binary machine learning classifier was able to detect healthy and COVID-19 sounds correctly.

Some of the researchers [21-25] who are described shortly analyzed X-ray and computed tomography (CT) images to diagnose COVID-19; however, cough is much easier than taking X-ray images or CT scans of patients.

Ezz El-Din Hemdan et al. [23] applied deep learning classifiers over two-dimensional X-ray images and proposed the best performer models.

A group of Chinese researchers demonstrated that, using chest CT scans, they were able to identify COVID-19, developing a three-dimensional deep learning framework [24].

Similar work was also performed by another group of scientists using chest CT and several machine learning algorithms, of which multilayer perceptron appeared to be the best performer [25].

Methodology

Data Gathering

To compose the Massachusetts Institute of Technology (MIT) Open Voice data prepared for COVID-19 cough distinction certified by the MIT Committee on the Use of Humans as Experimental Subjects Institutional Review Board, data collection was started with the contact of the website (opensigma.mit.edu) in April 2020 [26]. Ten test questions with multiple options for recognizing the disease, overview of the matter, and audio records of coughs changing in length were gathered from this site. Candidates found suspicious for the disease were asked if they felt fever, fatigue, sore throat or any problem in their respiratory system, persistent chest pain or pressure, diarrhea, or coughing. After the output was made anonymous, it was collected on reliable servers and specimens were registered in unzipped WAV format (16 kb bitrate, single channel, opus codec). Every COVID-19–positive sample in the dataset was utilized, and occasionally, the same number of COVID-19–negative subjects were chosen for equality in ranges.

Preprocessing

The MIT COVID-19 data set was used to feed the model, which included cough sounds, gender, respiratory condition, fever, muscle pain, and COVID-19 status [15].

The cough sounds in the data set included initial sounds and gaps. As can be seen in Figure 1, there are gaps between sound recordings. In the preprocessing step, cough sound was cleaned using a filter that eliminates noise below 400 MHz. Each sound file was sampled in the first 9 seconds after cough starts. Gaps were removed after filtering, as seen in Figure 2. Features were extracted from these files using the Mel-frequency cepstral coefficient, which is mostly used in audio recognition and modeling frequency content of the audio signal [27-29], and added other information related to sound files, such as gender, respiratory condition, fever, muscle pain, and status. The data set has the following features: uuid, datetime, cough_detected, latitude, longitude, age, gender, respiratory_condition, fever_muscle_pain, status, quality_1, cough_type_1, dyspnea_1, wheezing_1, stridor_1, choking_1, congestion_1, nothing_1, diagnosis_1, severity_1, quality_2, cough_type_2, dyspnea_2, wheezing_2, stridor_2, choking_2, congestion_2, nothing_2, diagnosis_2, severity_2, quality_3, dyspnea_3, wheezing_3, stridor_3, choking_3, congestion_3, nothing_3, cough_type_3, diagnosis_3, and severity_3. However, only four of these were used because of null values as a proposed model feature. To match features with audio files, uuid was used.

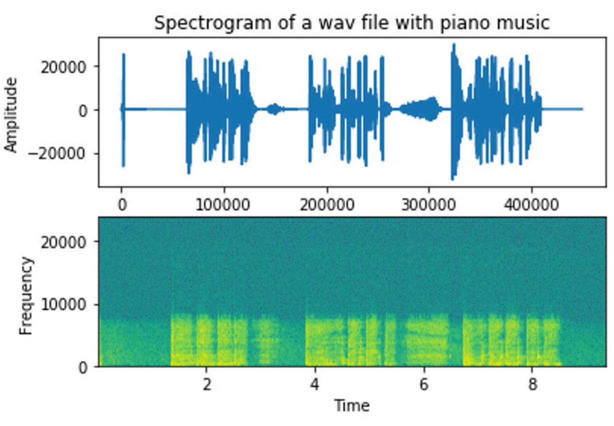

Figure 1. Original cough signal

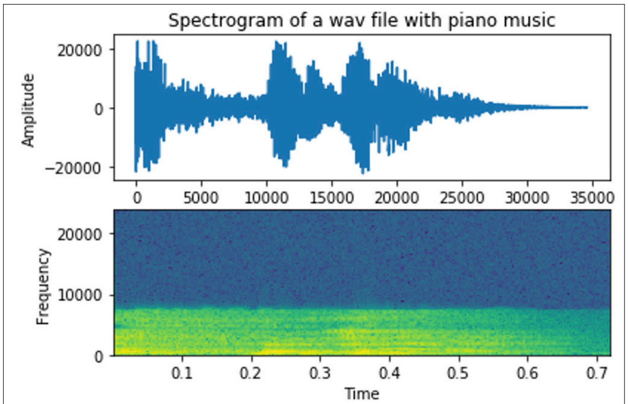

Figure 2. Filtered cough signal

Modeling

A total of 822 recording samples were selected equally from healthy and COVID-19–infected groups. Each sample's cough detected values were >80%, and these values were present in the data set. Figure 3 shows the steps taken when detecting deep learning–based cough.

Accuracy, precision, recall, and F1 scores were measured as shown below in equations (1)–(4), where TP is true positives, TN is true negatives, FP is false positives, and FN is false negatives.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FN+FP) \quad (1)$$

$$\text{Precision} = TP/(TP+FP) \quad (2)$$

$$\text{Recall} = TP/(TP+FN) \quad (3)$$

$$F1 = (2 \text{ x Precision x Recall})/(\text{Precision}+\text{Recall}) \quad (4)$$

A deep learning model was created that had an input layer with 256 neurons, two fully connected hidden layers with 128 and 64 neurons, and an output layer with 1 neuron. Relu was used as an activation function for all neurons except the output layer, where sigmoid was used instead of the softmax activation function because of the nature of the binary classification problem [30]. Relu function is given in equation (5), where z is the output of the neural network.

$$Relu(z) = \max(0, z) \quad (5)$$

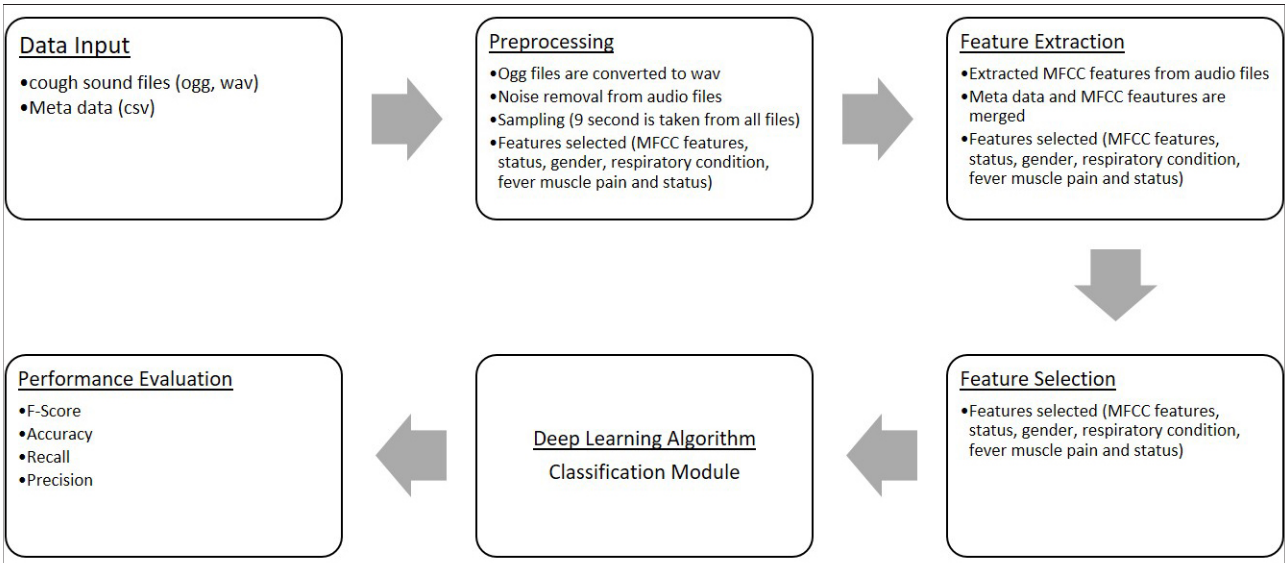

Figure 3. Deep learning based cough detection model. MFCC, Mel-frequency cepstral coefficient

Sigmoid function is shown in equation (6), where *e* is Euler's number and z is the output of the neural network.

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (6)$$

For classification, binary cross-entropy is shown in equation (7),

$$BCE = -(y\log(p) + (1-y)\log(1-p)) \quad (7)$$

where y is the target label for the training example, p is $h_\theta(x)$, $h_\theta(x)$ is a model with neural network weights θ, and x is the input for the training example.

The training part is used to deter probabilistic false negatives. For example, for a training example where the output is 1 and the model output is 0.55, probabilistic false negative is 45%, meaning that the model has 45% confidence in the wrong result. As a result, this function penalizes the case 45% by value of -log(0.55) = 0.25. If the model output is 1, it is completely accurate for the given case, and function output is -log(1) = 0. The second term of the function is used for false positives with the same logic.

All methods were implemented on a computer with 16 GB of RAM, NVIDIA Cuda 1050TI GPU, and Intel i7 7700HQ CPU. There are six multiprocessors and 128 Cuda cores in each multiprocessor on NVIDIA 1050Ti. The method was implemented in Python Programming Language.

A total of 100 epochs were used for each training step. Table 1 shows that 79% accuracy, 75% recall, 86% precision, and 80% F1 score were achieved. The output of the study is intended to be used for a mobile application. As seen in Figure 4, COVID-19 cough detection can be made via a mobile application.

Table 1. Comparison of accuracy, precision, recall, and F1 scores

Accuracy	Recall	Precision	F1
79%	75%	86%	80%

Figure 4. Mobile App UI Mock-Up

Conclusion

A public data set was used for data input from the opensigma.mit.edu website. First, this data set was used for preprocessing. In the preprocessing stage, file conversion to wav, noise removal from audio files, and feature selection process were completed. In the next stage, feature extraction and appropriate features were selected. A deep learning classification algorithm was applied for selected and extracted negative and positive cough data. In the last stage, the improved AI model provided 79% accuracy, 75% recall, 86% precision, and 80% F1 score.

An AI-based mobile application can be designed with this model to detect patients with COVID-19 by real-time cough measurement. In case of doubt, they will be able to do their own pretests. In this way, people with suspected illness will be able to do their own COVID-19 tests without leaving home. Conducting such a study reduces the time and cost spent for the COVID-19 test.

Cough is a symptom that occurs not only with coronavirus but also in other respiratory diseases, including cold, flu, pharyngitis, bronchitis, and laryngitis. Because COVID-19 is present all over the world, we were able to access COVID-19 cough data. However, if data from other respiratory diseases are also obtained, AI studies can be carried out for other respiratory diseases. By presenting these studies on a single platform, different types of respiratory diseases can be detected. In this way, a preliminary determination can be made before going to the hospital.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – A.B.; Design – A.G., A.B.; Supervision – A.B.; Resources – A.G., B.K.; Materials – A.B.; Data Collection and/or Processing – A.G., B.K.; Analysis and/or Interpretation – A.G., B.K., C.R., A.B.; Literature Search – B.K., C.R.; Writing Manuscript – A.G., B.K., C.R., A.B.; Critical Review – A.G., B.K., C.R., A.B.; Other – A.G., B.K., C.R., A.B.

Conflict of Interest: The authors have no conflicts of interest to declare.

Financial Disclosure: The authors declared that this study has received no financial support.

References

1. W. H. Organization, "Novel Coronavirus (2019-nCoV) SITUATION REPORT - 1," World Health Organization, Geneva, 2019.
2. C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan, J. Xu, C. X. Gu, Z. Cheng, T. Yu, J. Xia, Y. Wei, W. Wu, X. Xie, W. Yin, H. Li, "Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China," The Lancet, vol. 395, no. 10223, pp. 497-506, 2020.
3. W. H. Organization, "Coronavirus disease 2019 (COVID-19) Situation Report - 90," World Health Organization, Genova, 2020.

4. N. Health, "The Official Website of the City of New York," 15 04 2020. [Online]. Available: https://www1.nyc.gov/assets/doh/downloads/pdf/imm/covid-19-daily-data-summary-deaths-04152020-1.pdf. [Accessed 08 01 2021].
5. T. T. Dernegi, "Turk Toraks Dernegi," 18 11 2016. [Online]. Available: https://www.toraks.org.tr/site/news/3402. [Accessed 08 01 2021].
6. Y. Y. Shih, K. Fang, "Effects of network quality attributes on customer adoption intentions of Internet banking". Total Quality Management, vol. 17, no 1, page, 61-77, 2006. [Crossref]
7. R. DeYoung, W. W. Lang, D. L. Nolle, "How the Internet affects outputs and performance at community banks", Journal of Banking & Finance, vol. 31, no 4, pages 1033-1060, 2007. [Crossref]
8. E. Leroux, H. Rivas, "Mobile health without borders, evidence-based mHealth", Stanford University; 2014.
9. I. K. Mahardika, T. Hamzah, T. Rahmawati, L. Soetjiatie, "Measuring Respiration Rate Based Android", IJEEEMI, vol. 1, no. 1, pp. 39-44, Aug. 2019. [Crossref]
10. Y. J. Park, H. S. Cho, H. K. Lyu, "A method of detection of respiration rate on android using uwb impulse radar", ICT Express, vol. 2, no. 145, pages 83149, 2016. [Crossref]
11. L. Orlandic, T. Teijeiro, D. Atienza, "The COUGHVID crowdsourcing dataset: A corpus for the study of large-scale cough analysis algorithms (Version 1.0) [Data set]", Zenodo, 2020. [Crossref]
12. R. X. A. Pramono, S. A. Imtiaz, E. Rodriguez-Villegas, ''Automatic cough detection in acoustic signal using spectral features. In: 2019 41st annual international", Conference of the IEEE Engineering in Medicine and biology society. EMBC, pages 7153-7156, 2019.
13. I. D. Miranda, A. H. Diacon, T. R. Niesler, ''A comparative study of features for acoustic cough detection using deep architectures", In: 41st annual international Conference of the IEEE Engineering in Medicine and biology society. EMBC), pages. 2601-2605, 2019.
14. M. Solinski, M. Łepek, Ł. Kołtowski, ''Automatic cough detection based on airflow signals for portable spirometry system", Informatics in Medicine Unlocked, pages 100313, 2020. [Crossref]
15. J. Laguarta, F. Hueto, B. Subirana, "COVID-19 Artificial Intelligence Diagnosis using only Cough Recordings," IEEE Open Journal of Engineering in Medicine and Biology, doi: 10.1109/OJEMB.2020.3026928.[Crossref]
16. A. Imran, I. Posokhova, H. N. Qureshi, U. Masood, S. Riaz, K. Ali, C. N. John, I. Hussain, M. Nabeel, "Ai4covid-19: Ai enabled preliminary diagnosis for covid-19 from cough samples via an app," Informatics in Medicine Unlocked. ArXiv preprint arXiv, 2004.01275 (2020). [Crossref]
17. B. Subirana, F. Hueto, P. Rajasekaran, J. Laguarta, S. Puig, J. Malvehy, O. Mitja, A. Trilla, C. I. Moreno, J. F. M. Valle, E.M. González, B. Vizmanos and S. Sarma, "Hi sigma, do I have the coronavirus?: Call for a new artificial intelligence approach to support health care professionals dealing with the covid-19 pandemic," arXiv preprint arXiv:2004.06510, 2020.
18. M. Pahar, M. Klopper, R. Warren, T. Niesler, "COVID-19 Cough Classification using Machine Learning and Global Smartphone Recordings", arXiv: 2012.01926, Dec 2020.
19. A. Pal, M. Sankarasubbu, "Pay Attention to the cough: Early Diagnosis of COVID-19 using Interpretable Symptoms Embeddings with Cough Sound Signal Processing", arXiv: 2010.02417, 2020.
20. C. Brown, J. Chauhan, A. Grammenos, J. Han, A. Hasthanasombat, D. Spathis, T. Xia, "Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data", In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 3474-3484, Aug. 2020. [Crossref]
21. L. Wang, A. Wong, ''COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images", arXiv preprint arXiv:2003.09871vol. 1., 2020. [Crossref]
22. A. Narin, C. Kaya, Z. Pamuk, ''Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks", arXiv preprint arXiv:2003.10849, 2020.
23. E. E. D. Hemdan, M. A. Shouman, M. E. Karar, "COVIDX-Net: a framework of deep learning classifiers to diagnose COVID-19 in x-ray images", arXiv preprint arXiv:2003.11055, 2020.
24. L. Li, L. Qin, Z. Xu, Y. Yin, X. Wang, B. Kong, J. Bai, Y. Lu, Z. Fang, Q. Song, ''Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT", Radiology 200905, 2020.
25. X. Mei, H. C. Lee, K. Y. Diao, M. Huang, B. Lin, C. Liu, Z. Xie, Y. Ma, P. M. Robson, M. Chung, "Artificial intelligence-enabled rapid diagnosis of patients with covid-19", Nature Medicine, volume 26, pages 1224-1228, 2020. [Crossref]
26. B. Subirana, F. Hueto, P. Rajasekaran, J. Laguarta, S. Puig, J. Malvehy, O. Mitja, A. Trilla, C. I. Moreno, J. F. M. Valle, A. E. Mercado González, B. Vizmanos, S. Sarma, "Hi sigma, do I have the coronavirus?: Call for a new artificial intelligence approach to support health care professionals dealing with the COVID-19 pandemic," arXiv:2004.06510, 2020.
27. J. Lyons, D. Yow-Bang Wang, G. H. Shteingart, E. Mavrinac, Y. Gaurkar, W. Watcharawisetkul, S. Birch, L. Zhihe, J. Hölzl, J. Lesinskis, H. Almér, C. Lord, A. Stark, (2020, January 14). jameslyons/python_speech_features: release v0.6.1 (Version 0.6.1). Zenodo. http://doi.org/10.5281/zenodo.3607820
28. N. Chigozie, I. Winifred, A. Gachagan, S. Marshall, "Activation Functions: Comparison of trends in Practice and Research for Deep Learning", 2020.
29. M. Xu, L. Y. Duan, J. Cai, L. T. Chia, C. Xu, Q. Tian. "HMM-Based Audio Keyword Generation". In: Aizawa K., Nakamura Y., Satoh S. (eds) Advances in Multimedia Information Processing - PCM 2004. PCM 2004. Lecture Notes in Computer Science, vol 3333. Springer, Berlin, Heidelberg, 2004. [Crossref]

Alpaslan Gökcen graduated with an M.Sc. degree in Computer Engineering from European University of Lefke in 2018. His research interests are machine learning, parallel processing, and real-time image processing. Currently, he is a Ph.D. student at Istanbul Commerce University in Computer Engineering.

Bulut Karadağ received a B.S. degree in Electronics and Telecommunication from Marmara University, İstanbul, Turkey, in 2009 and completed an M.Sc. degree in Computer Engineering from Ahmet Yesevi University. He is currently a Ph.D. student in Computer Engineering at Istanbul Commerce University. He worked as a software developer at Piworks between 2010 and 2013 and at Kuveyt Turk Participation Bank between 2013 and 2016. He has been an R&D developer at Vakıf Participation R&D Center since 2016. His current research interests include digital fintech, blockchain, and machine learning.

Cengiz Riva received a B.S. degree from İstanbul Teknik University and an M.Sc. degree from Boğaziçi University, İstanbul, Turkey, in 1993 and 1996, respectively, in Electrical Electronics and Communication Engineering. He worked as a mobile communication expert at Alcatel SEL GmBh from 1996 to 2001 in the Asia-Pacific region. Later, he continued his career at Avea Mobile Com. Company as Central Op. Manager between 2001 and 2015. Currently, he is a Lecturer with the Department of Electrical-Electronics Engineering, İstanbul Commerce University, İstanbul. His current research interests include digital system design, embedded systems, and machine learning.

Ali Boyacı received B.S. and M.Sc. degrees in computer science from İstanbul University, İstanbul, Turkey, in 2007 and 2010, respectively, and a Ph.D. degree from Yıldız Technical University, İstanbul, Turkey, in 2015. He worked as a software engineer at Nortel Networks and Huawei from 2007 to 2012. Currently, he is an Assistant Professor with the Department of Computer Engineering, İstanbul Commerce University, İstanbul. His current research interests include computer networks, embedded systems, and machine learning.