Machine Learning Workforce Development Programs on Health and COVID-19 Research

Andreas Spanias, *Fellow, IEEE*
SenSIP Center, School of ECEE, Arizona State University

***Abstract*—**This paper accompanies the keynote speech at IISA-2020 and describes federally funded workforce development research grants and supplements in the area of sensors and machine learning. These programs operate under the auspices of the Sensor Signal and Information Processing (SenSIP) center which is also an Industry University Cooperative Research Center (I/UCRC) sponsored by the National Science Foundation (NSF) and I/UCRC industry members. The first program is an NSF REU site which has trained more than 30 students working on sensor hardware design and machine learning algorithm development. The second program is the NSF IRES site which is collaborative with the University of Cyprus and is focused on sensors and machine learning for energy systems. The most recent program funded by NSF is a Research Experiences for Teachers (RET) program that started in June 2020. This program embeds teachers and community college faculty in SenSIP machine learning projects. Another state funded program in which SenSIP is a partner is MedTech ventures. Our partner MedTech works on training medical technology students, entrepreneurs and engineers to create smart medical solutions for preventive healthcare. SenSIP also received NSF supplements to train students in using machine learning for COVID-19 detection.

I. Introduction

The Sensor Signal and Information Processing (SenSIP) center initiated several workforce research training programs in sensors and machine learning supported by a series of grants and supplements from the National Science Foundation (NSF). SenSIP is an NSF supported Industry-University Cooperative Research Center (I/UCRC) with several industry members which is on its 11th year. Industry members in the last 10 years included Freescale, Intel, LG, Lockheed Martin, National Instruments, NXP, ON Semi, Qualcomm, and Sprint. A series of small (SBIR size) companies also supported the center as associate or in kind members. The center received a grant from NSF, titled Research Experiences for Undergraduates (REU) [1], which in the last three years trained more than 30 undergraduate students (Fig. 1) from several universities in sensor devices and machine learning (ML) algorithms. The students produced sensor designs and developed algorithms for health and other applications. In 2019, the center received a second program titled International Research Experiences for Students (IRES) [2] that embeds graduate and undergraduate student researchers at the University of Cyprus (UCy) labs. This three year program trained six students in 2019 and 2020 that were co-advised by ASU and UCy faculty. The most recent program, titled Research Experiences for Teachers (RET) [3], was awarded by NSF in 2020 and will train approximately 30 teachers and community college faculty in ML. SenSIP also received a series of REU supplements for research on ML including studies on the identification of COVID-19 hotspots using networking theory and also detection of COVID-19 coughing patterns. In addition, to the above programs, SenSIP is partner in the MedTech ventures program [4] which has been funded by the Maricopa county. MedTech works on training medical technology students, entrepreneurs and engineers to create smart medical solutions for preventive healthcare. In this program, SenSIP has launched a series of training lectures in ML for health related applications.

Fig. 1 REU and IRES participants on a site visit and lecture/demo at the MTW clean room.

In this paper, we describe each of these programs and we briefly cover select projects addressing sensors and machine learning research for health applications. The next section, describes basics of machine learning. Section 3 describes the REU program and select projects during 2017-2019. Section 4 describes the IRES program, and section 5 the RET program. Sections 6 and 7 describe research on COVID-19 hotspot detection and audio analysis. Section 7 presents conclusions.

II. Machine Learning basics

Machine learning [5-8] is an area within the artificial intelligence field and some of the basic work was initiated in computer science. A typical signal analysis framework that employs ML is shown in Fig. 2.

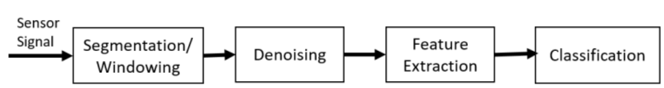

Fig. 2. Basic signal processing / ML framework including pre-processing, feature extraction and classification.

The signal processing block diagram [5] in Figure 2 shows signal acquisition and segmentation using windows such as the Hamming window or specialized application-specific overlapping windows. Noise removal and feature extraction follow. Data denoising can be done with several methods including wavelet and adaptive techniques [9-11]. The feature

978-1-6654-2228-4/20/$31.00 ©2020 IEEE

extraction stage typically involves parameterization and compression of the data into a vector of few parameters. For example in voice processing Mel Frequency Cepstral Coefficients (MFCCs) are used to represent the frequency spectra of voiced frames [12]. In other applications, often used are parameters from principal component analysis (PCA) which are obtained from the autocorrelation matrix of the signal. PCAs are very common as they tend to provide information on the properties and dimensionality of the signal and also in some frameworks they are optimal in terms of compactness. Following feature extraction, we have the ML algorithm which can be trained to cluster features and hence identify the signal and its properties. In Electrical Engineering some of the initial efforts have been developed in voice compression [13] where vector quantization methods [14,15] were used to design codebooks for source coding.

Machine learning algorithms are typically taxonomized as supervised, unsupervised and semi-supervised. Supervised algorithms are trained based on labeled data or features. In supervised learning, true labels of the dataset are used to train the ML algorithm. Algorithms for training are typically iterative and during the training process they optimize a cost function. The cost function is typically a measure of the error between desired or actual output and the algorithm estimates. By minimizing the cost function, we train our model to produce estimates that are close to the correct values (ground truth). Minimization of the cost function is usually achieved using gradient descent techniques [16-20].

The focus of all the workforce programs described in this keynote speech is to embed participants in sensors and ML research with the focus on health and sustainability applications. In most workforce projects we considered use of sensors, signal processing and ML for health diagnostics and more recently for COVID-19 detection. In the following we describe the ASU SenSIP REU program.

III. REU IN SENSORS DEVICES AND ML ALGORITHMS

One of the goals of this REU workforce program is to embed students in sensors and ML research and motivate participants to pursue research careers. We recruited students from several fields including Electrical and Computer Engineering, Physics, Biology, Mathematics and other STEM related disciplines. The program attracted participants from community colleges and from several universities. The students examined several sensor and ML applications including health, security, and Internet of Things (IoT). One of the training objectives is for students to understand integrated sensing and ML (Fig. 3). An additional objective is to create a program where algorithm developers are trained to also understand sensor device limitations and sensor designers understand basic ML and signal/data analysis algorithms. The REU program immersed students in both tasks through sensor related lab work and algorithm and software hands-on modules. The program required students to first attend a boot camp and receive online training in signal processing, ML and sensors. To accelerate learning we started the training in signal processing and ML using the object oriented J-DSP software [21-24] which has built in modules for k-means (Fig. 4) and other clustering methods. Participants came from several universities and community colleges.

Fig. 3. Integrated sensor device design and ML algorithm development for health related applications.

A special effort was made to build awareness in the research field and in interdisciplinary application areas. In the last 3 years approximately 30 students have been trained through this program. About 30% of the students produced publishable results [25-33] and two students participated in patent disclosures [34-35]. The recruitment demographics of the program were exceptional and details have been reported in NSF annual reports [36]. REU projects included sensors for cancer detection, audio processing, breathing sensors, ion channel sensors and signal processing, activity detection, object detection [33], Crowd Sourced Environmental Monitoring, and Monitoring Childhood Asthma.

Several assessments were documented in all three years of the REU program [36]. These consisted of assessing the effectiveness of the ML modules and the overall research experience. The research experience was analyzed in terms of problem solving, skill building, creativity and collaboration.

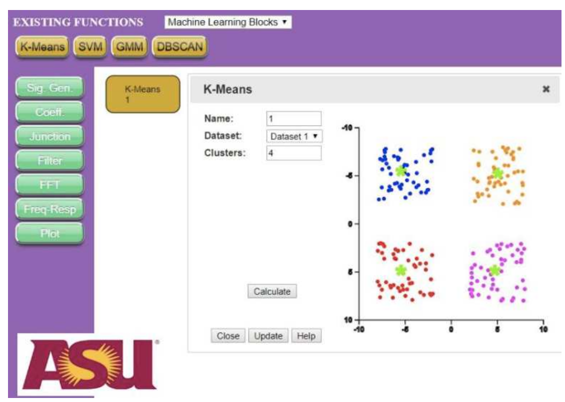

Fig. 4. Hands-on training sessions in Machine Learning with J-DSP [23].

IV. THE IRES PROGRAM ON MACHINE LEARNING

The International Research experiences for students (IRES) program also embeds graduate and undergraduate students in sensors and ML research for energy applications [2,37,64,65, 66]. The program is collaborative between the UCy KIOS center and the ASU SenSIP center. The UCy KIOS center hosted four students (three undergraduates and one graduate) at the KIOS facilities (Fig. 5) in Nicosia Cyprus in 2019. The students were initially pre-trained at ASU by taking modules and hands on sessions on ML and signal processing. They have also received training in deep leaning techniques [64,67].

V. RESEARCH EXPERIENCES FOR TEACHERS

Another workforce program on sensors and ML is research experiences for teachers [3] which embeds teachers and community college faculty in SenSIP research projects. The program has as objectives: a) train teachers in ML and sensors for health and other applications, b) advance the science of ML for use in health and other systems, c) transition research experiences into lesson plans for use in high schools and community colleges. This strategy also contributes to attracting more students in the STEM field. Teachers and community college faculty have been recruited. Teachers have gone through a boot camp in ML that included modules, hands on Python software sessions, and daily teleconferencing.

Fig. 5. IRES participants at the UCy KIOS center in Nicosia.

VI. Research On COVID-19 Hotspot Determination

One of the key issues in detecting COVID-19 hotspots is to estimate the number of people in a specific location (e.g. a church, a shopping mall) and their distance from one another. Research in consensus estimation [38-41] has previously been successful in estimating network area/size and node locations. Such methods rely on distributed processing which leads to enhanced accuracy and efficiency in terms of power consumption. The research [68] seeks to create high precision algorithms for smart phones for COVID-19 hotspot size estimation. Mobile devices are used by most people and hence locations and network size can be used to estimate the number of users and their proximity to each other.

VII. COVID-19 Sound Spectral Analysis

The research is based on the premise that coughing and breathing patterns [42] can be used to detect COVID-19. The idea is to use databases formed from various conversations on cell phones or teleconferencing systems to extract appropriate sound features for COVID-19 detection. Prior research [42] has shown promise in terms of determining spectral features for COVID-19. This research explores several tools for feature extraction and pattern matching. Audio features and related methods previously used in speech compression [43-47], voice recognition [48-51], and speech disorder detection [52-53] will be explored. In addition, a variety of ML approaches [54-58, 62-63] will be explored with the emphasis on sparse deep learning methods including Graph Models and Multi-layer Embeddings (GrAMME) [61]. The main advantage of GrAMME is that it requires fewer labels to train a neural network model. Another efficient method is the use of sparse neural networks including pruned and dropout architectures. By posing this problem as a multi-class classification problem, we can use the lottery ticket hypothesis [69] method to derive a sparse neural network for identifying the different classes of features. Efficiency and avoidance of over fitting are advantages of these methods. Pruned and dropout neural networks [64] have been used in our previous ML studies (Fig. 6) and will be explored with audio features to classify sound patterns. Feature classification may require diarization pre-processing [59,60]. In addition to the above methods, deep attention models will be explored to learn robust audio representations.

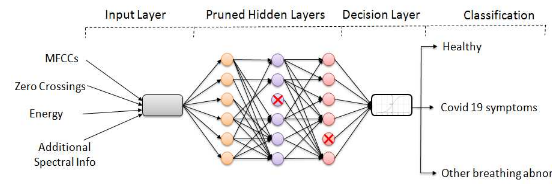

Fig. 6. Pruned neural network for sound classification.

VIII. Conclusion

This paper is associated with the keynote speech at IISA 2020 and describes research programs that have been supported by workforce development grants. All programs train students in machine learning for sensor and health related applications. Several of the participants in the workforce development programs were able to publish some of their results and two participants have submitted patent pre-disclosures. The programs were assessed in terms of: a) enablement of the participants to produce new research results, b) the skill-building components in terms of ML and its applications, c) inclusiveness and diversity. Communications with most program participants have been maintained through emails, LinkedIn and social media. The most recent programs, supported through NSF supplements, are on COVID-19 research addressing networks and on sound analysis.

Acknowledgment

We acknowledge the support of NSF through the REU award 1659871, RET award 1953745, IRES award 1854273 and also supplements through NSF awards 1540040. We also acknowledge the partnership with MedTech Ventures.

References

[1] A. Spanias and J. Blain Christen, "A STEM REU Site On The Integrated Design of Sensor Devices and Signal Processing Algorithms'," *Proc. IEEE ICASSP 2018,* Calgary, April 2018.

[2] K. Jaskie, J. Martin, S. Rao, W. Barnard, P. Spanias, E. Kyriakides, Y. Tofis, L. Hadjidemetriou, M. Michael, T. Theocharides, S. Hadjistassou, and A. Spanias,, IRES Program in Sensors and Machine Learning for Energy Systems, *Proc. IEEE 11th IISA 2020,* Piraeus, July 2020.

[3] Research Experiences for Teachers https://sensip.engineering.asu.edu/ret/

[4] MedTech Ventures https://medtech.asu.edu

[5] U. Shanthamallu, A. Spanias, C. Tepedelenlioglu, M. Stanley, "A Brief Survey of Machine Learning Methods and their Sensor and IoT Applications," *Proc. 8th IEEE IISA 2017,* Larnaca, August 2017.

[6] K. Jaskie and A. Spanias, "Positive and Unlabeled Learning Algorithms and Applications: A Survey," *IEEE 10th IISA 2019,* Patras, July 2019.

[7] S. Theodorides, Machine Learning, A Bayesian and Optimization Perspective, 1st Edition, Academic Press, December 2015.

[8] P. Warden, D. Situnayake, TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers, O'Reilly, 2019.

[9] K. Ramamurthy, J. Thiagarajan, P. Sattigeri, M. Goryll, A. Spanias, T. Thornton, S. Phillips, "Transform domain features for ion-channel signal classification." Biomedical Signal Processing and Control, 219-224, 2011.

[10] P. Sattigeri, J. J. Thiagarajan, K. Ramamurthy, A. Spanias, M. Goryll and T. Thornton, , “Robust PSD Features for Ion-Channel Signals,” *Proc. IEEE SSPD 2011*, London, Sep. 2011.

[11] M. Deisher and A.S. Spanias, "Practical Considerations in the Implementation Frequency-Domain Adaptive Noise Cancellation," *IEEE Trans. CAS*, Part II, Vol. 41(2) pp. 164-168, Feb. 1994.

[12] A. Spanias, T. Painter, V. Atti, Audio Signal Processing and Coding, Wiley, March 2007.

[13] A.S. Spanias, "Speech Coding: A Tutorial Review," *Proceedings of the IEEE*, Vol. 82, No. 10, pp. 1441-1582, October 1994.

[14] Gersho, Allen, and Robert M. Gray. *Vector quantization and signal compression*. Vol. 159. Springer Science, 2012.

[15] J. Makhoul, S. Roucos, and H. Gish. "Vector quantization in speech coding." *Proceedings of the IEEE*- 73, 1551-1588, 1985.

[16] S. Amari, "Backpropagation and stochastic gradient descent method", Neurocomputing, vol. 5, no. 4-5, pp. 185-196, 1993.

[17] H. Blockeel, ML and knowledge discovery in databases, Springer, 2013.

[18] A. Spanias, “A Brief Survey of Time- and Frequency-Domain Adaptive Filters,” Proc. 7th *IEEE IISA 2016*, pp. 1-7, Halkidiki, July 2016.

[19] A. Spanias, "Block time and frequency domain modified covariance algorithms for spectral analysis," in *IEEE Transactions on Signal Processing*, V. 41, no. 11, pp. 3138-3152, Nov. 1993.

[20] B. Widrow , S. Stearns, Adaptive Signal Processing, Prentice Hall, 1985.

[21] A. Spanias and V. Atti, “Interactive On-line Undergraduate Laboratories Using J-DSP,” *IEEE Trans. on Education,*. 48, pp. 735-749, Nov. 2005.

[22] H. Kwon, V. Berisha, A. Spanias, V. Atti, "Experiments with Sensor Motes and Java-DSP*," IEEE Tran. Educ.,* v. 52, pp. 257-262 , 2009.

[23] J-DSP, Available online at: http://jdsp.asu.edu.

[24] A. Dixit, S. Katoch, M. Banavar, H. Song, A. Spanias, "Development of Signal Processing Online Labs using HTML5 and Mobile platforms," *2017IEEE FIE*, Indianapolis, Oct. 2017.

[25] D. Ramirez, D. Rajan, P. Curtis, M. Banavar, H. Braun, C. Pattichis, A. Spanias, “Android Signal Processing for Mobile Health Monitoring,” *38th IEEE EMBC 2016*, Orlando,. 2016.

[26] P. Curtis, M. Banavar, S. Zhang, A. Spanias, V. Weber,”Android acoustic ranging,” *5th IISA 2014,* pp. 118- 123, Crete, July 2014.

[27] Lisa Kreigh, Hany Arafa, and Jennifer Blain-Christen “Autonomous System for Continuous Measurement of pH for the Assessment of Cancer Cell Proliferation” *36th Annual EMBC'14,* Chicago, Aug. 2014.

[28] C. Snyder, J. Blain Christen, H. Ross, “Human Factors Engineering for Mobile Health Applications,”*2017 IEEE HI- POCT conf.*, Nov. 2017.

[29] F. Khondoker, T. Thornton,.A. Spanias, U. Shanthamallu, “Optimizing Activity Detection via Sensor Fusion,” *2018 9th IISA,* Zakynthos 2018.

[30] P. Stevenson, H. Arafa, S. Ozev, H. Ross and J. B. Christen, "Toward wearable, crowd-sourced air quality monitoring for respiratory disease," IEEE HI-POCT, Bethesda, 2017.

[31] M. Zhu, U.Obahiagbon, K. Anderson, and J. Blain Christen, “Highly Sensitive Fluorescence-based Lateral Flow Platform for Point-of-Care Detection of Biomarkers in Plasma,” *IEEE HI-POCT Conf.* Nov. 2017.

[32] D. Mohan, S. Katoch, S. Jayasuriya, P. Turaga, A. Spanis, “Adaptive Video Subsampling For Energy-Efficient Object Detection," *IEEE Asilomar Conf. on Sign., Systems and Computers*, Monterrey, Nov. 2019.

[33] O. Iqbal, S. Siddiqui, J. Martin, S. Katoch, A. Spanias, D.Bliss, S. Jayasuriya, 'Design and FPGA Implementation Of An Adaptive Video Subsampling Algorithm For Energy-Efficient Single Object Tracking', *IEEE ICIP 2020*, Abu Dhabi, Oct. 2020.

[34] Paul Curtis (REU Student). M.Banavar, M16-089P Android Acoustic Reflection Mapping, Skysong Innovations, 2015.

[35] S. Jayasuriya, S. Katoch, D. Mohan, A. Spanias, P. Turaga, Adaptive Video Subsampling for Energy-Efficient Object Detection, Skysong Innovations, US Provisional Patent 62/872,902 , July 2019

[36] W. Barnard, CREST Assessment of the SenSIP REU, Dec. 2017.

[37] NSF IRES Program, https://sensip.engineering.asu.edu/nsf-ires-project/

[38] S. Zhang, C. Tepedelenlioglu, M. Banavar A. Spanias, "Distributed Node Counting in Wireless Sensor Networks in the Presence of Communication Noise," *IEEE Sensors J.*, p. 1175, V. 17, Feb. 2017.

[39] S. Zhang, C. Tepedelenlioglu, M.Banavar A. Spanias, "Max Consensus in Sensor Networks: Non-linear Bounded Transmission and Additive Noise," *IEEE Sensors J.*, V.16, pp. 9089-9098, Dec. 2016.

[40] S. Zhang, C. Tepedelenlioglu, A. Spanias, Distributed Network Center Area Estimation, US Patent 10,440,553, Oct. 2019.

[41] S. Zhang, C. Tepedelenlioglu, , A. Spanias, M. Banavar, Distributed Network Structure Estimation using Consensus Methods, Synthesis Lect. on Comm., Morgan & Claypool Publishers, Ed. W. Tranter, Feb. 2018.

[42] Wang, Y. et al, :Abnormal respiratory patterns classifier may contribute to large-scale screening of people infected with COVID-19 in an accurate and unobtrusive manner,” *arXiv preprint arXiv:2002.05534*

[43] T. Painter and A.S. Spanias, “Perceptual Coding of Digital Audio,” *Proceedings of the IEEE*, pp. 451-513, Vol. 88, April 2000.

[44] T. Bäckström,, *Speech coding: with CELP,* Springer, 2017.

[45] K. Ramamurthy, A. Spanias, MATLAB Software for the Code Excited Linear Prediction Algorithm: The Federal Standard-1016, Morgan & Claypool Publ., Synth. Lect. on Algo. & Soft. in Eng., Vol. 2, Jan 2010.

[46] R. Goldberg, *A practical handbook of speech coders*. CRC press, 2019.

[47] J. Thiagarajan, A. Spanias, Analysis of the MPEG-1 Layer III (MP3) Algorithm Using MATLAB, Morgan & Claypool Publi., Synth. Lectures on Algorithms and Software in Engineering, Vol. 3, No. 3, Nov. 2011.

[48] D. Yu, L. Deng, Automatic Speech Recognition, Springer 2016.

[49] P. Loizou, A. Spanias, "Improved speech recognition using a subspace projection approach*," IEEE Trans. on SAP* v. 7, pp. 343-345, May 1999.

[50] P. Loizou and A. Spanias*,* "High Performance Alphabet Recognition," *IEEE Trans. on Speech and Audio,* vol. 4, no. 6, pp. 439-445, Nov. 1996.

[51] U. Kamath et al, *Deep learning for speech recognition,* Springer 2019.

[52] S. Sandoval, R. Utianski, V. Berisha, J. Liss, A. Spanias, "Feature divergence of pathological speech," *JASA.* 134, no.5,4133-4133, 2013.

[53] Fang, S. H. et al. Detection of pathological voice using cepstrum vectors: A deep learning approach. *Journal of Voice*, *33*(5), 634-641.

[54] V. Berisha, A. Wisler, A. Hero, A. Spanias, "Data-driven estimation of density functionals using a polynomial basis" *IEEE Transactions on Signal Processing*, pp. 558-572, Vol. 66, January 2018.

[55] M. Shah, M. Tu, V. Berisha, C. Chakrabarti, A. Spanias, “Articulation Constrained Learning with Application to Speech Emotion Recognition,” *Computer Speech and Language*, Elsevier, 2019.

[56] H. Song, J. Thiagarajan, P. Sattigeri, A. Spanias, "Optimizing Kernel Machines using Deep Learning" *IEEE Trans. on Neural Networks and Learning Systems,* NLS-2017-P-8053.R1, pp. 5528–5540, Feb. 2018.

[57] V. Berisha, A. Wisler, A. Hero, A. Spanias, "Empirically Estimable Classification Bounds Based on a Nonparametric Divergence Measure," *IEEE Trans. on Signal Processing,* vol. 64, no. 3, pp.580-591, Feb. 2016.

[58] I. Goodfellow, Y.Bengio, A. Courville. *Deep learning*. MIT press, 2016.

[59] V. Narayanaswamy, J. Thiagarajan, A. Spanias, "Designing An Effective Metric Learning Pipeline for Speaker Diarization," *IEEE ICASSP 2019*, Brighton, UK, May 2019.

[60] H. Song, M. Willi, J. Thiagarajan, V. Berisha, and A. Spanias. "Triplet network with attention for speaker diarization." 3608-3612, *Interspeech*. Hyderabad, *India, Sept. 2018.*

[61] U. Shanthamallu, J. Thiagarajan, H. Song, A. Spanias, "GrAMME: Semi-Supervised Learning using Multi-layered Graph Attention Models," *IEEE Trans. on Neural Net. and Learning Syst*., pp. 3977 - 3988 , Nov. 2019.

[62] Tsihrintzis, G., Virvou, M., Sakkopoulos, E., Jain, L. (Eds.), Machine Learning Paradigms-Applications of Learning and Analytics in Intelligent Systems, Learning & Analytics In Intellg. Syst. Series, Springer 2019.

[63] G. Tsihrintzis, D. Sotiropoulos, , J., Lakhmi C. (Eds.), Machine Learning Paradigms - Advances in Data Analytics, Intelligent Systems Reference Library series, vol. 149, Springer 2019.

[64] S. Rao, S. Katoch, V. Narayanaswamy, G. Muniraju, C. Tepedelenlioglu, A. Spanias, P. Turaga, R. Ayyanar, and D.Srinivasan, "Machine Learning for Solar Array Monitoring, Optimization, and Control," Synthesis Lectures on Power Electronics, Morgan & Claypool, Ed. J. Hudgins, Book, 91 pages, ISBN: 9781681739076, Aug. 2020.

[65] J. Fan, S. Rao, G. Muniraju, C. Tepedelenlioglu, and A. Spanias, “Fault Classification in Photovoltaic Arrays Using Graph Signal Processing,” *IEEE ICPS 2020,* Tampere, June, 2020

[66] E. Pedersen, S. Rao, S. Katoch, K. Jaskie, A. Spanias, C. Tepedelenlioglu, and E. Kyriakides, “PV Array Fault Detection using Radial Basis Networks”, *Proc. IEEE 10th IISA-2019*, Patras, July 2019.

[67] J. Booth, A. Ewaisha, A. Spanias, A. Alkhateeb, “ Deep Learning Based MIMO Channel Prediction: An Initial Proof of Concept Prototype,” *IEEE Asilomar Conf. Signals, Syst., and Comp., Monterrey,* Nov. 2020.

[68] NSF RAPID (2032114) on COVID-19 Hotspot estimation, April 2020.

[69] J. Frankle, M. Carbin. "The lottery ticket hypothesis: Finding sparse, trainable neural networks." *arXiv preprint arXiv:1803.03635* (2018).