Interdisciplinary Project Based Learning Approach for Machine Learning and Internet of Things

Muhammad Khan, Mohamed Ibrahim, Nansong Wu*, and Rajvardhan Patil
Arkansas Tech University, mkhan3, mibrahim1, rpatil @atu.edu
*Sonoma State University, Rohnert Park, CA, wun@sonoma.edu

Abstract - **This paper reports on the use of an interdisciplinary project-based learning approach for undergraduate engineering education in machine/deep learning, and the internet of things (IoT). Machine learning has evolved from pattern recognition and is an important element of artificial intelligence. IoT has also seen rapid growth in multiple application domains including embedded systems, wireless sensor networks, control systems, automation, and sensors. A challenge for traditional electrical/computer engineering curriculum is to effectively educate students in these areas through hands-on activities and projects. There is a need to develop a project-based learning approach to involve undergraduate students in real-world problem solving to develop use cases of machine learning and IoT. This paper reports on the implementation of an interdisciplinary project-based learning approach followed in the undergraduate electrical/computer engineering curriculum. The students were involved in solving real-world problems through machine/deep learning. They also developed IoT applications in multiple domains to address the limitations of existing systems and to go through the engineering design process. The qualitative results indicate that the PBL approach was highly effective in improving their learning outcomes.**

Index Terms – Project Based Learning, Machine Learning, Internet of Things, Problem Solving, Engineering Design Process.

INTRODUCTION

Today's students are required to learn in a climate of continual technological change and innovation. To meet this challenge and prepare them for the future workplace, students are trained to be content experts, highly skilled problem solvers, and team players. This is especially true for students in the field of engineering. Therefore, and in order to prepare students for the 21st-century school environment, instructors are striving to create learning activities that help students develop content expertise, problem-solving, and collaboration to meet workplace challenges. One of the strategies used to help students achieve these skills is project-based learning.

The term project-based learning (PBL) refers to instructional approaches that use the "real world," problems of practice to focus, and initiate content learning and skill development [1]. This learning strategy helps students acquire the knowledge and skills required in the workplace and prepare them for real-life problem-solving. Engaging students in this type of activities gives future teachers the opportunities to apply their content knowledge and teaching skills while working on authentic problems facing classroom teachers. Furthermore, PBL allows students to become actively involved in researching and learning from problem introduction, process reflection to solution implementation.

Project-based learning (PBL) is a teaching strategy that focuses on student-directed investigation [2, 3]. The main foundation of PBL is the constant interaction and active participation with peers. Through this strategy, students engage in projects by articulating questions for investigation, designing plans, collecting and analyzing information, and creating a product of their understanding [2]. The core emphasis of PBL learning is on enabling students to interact and communicate with their peers while working on their projects and to engage in reflective and critical thinking about what is being learned [4-6]. Therefore, project-based learning is considered an important learning approach that may also support the improvement of students' communication skills during projects execution [2, 3, 7].

In recent years there have been rapid developments in applications of machine learning especially neural networks and deep learning frameworks to model functioning of human brain for recognizing patterns. Neural networks are a set of paradigms that interpret sensory data through machine perception, labeling, and clustering of raw inputs. Deep learning includes techniques used by neural networks to progressively extract higher level features from raw inputs. Neural networks and deep learning applications are currently a major focus of research to solve problems in image recognition, speech recognition, natural language processing, and data analytics.

Similar to machine learning, the IoT has also evolved from the rapid convergence of traditional research areas of embedded systems, wireless sensor networks, control systems, automation, and sensors. It is a self-configuring and adaptive system of interconnected, intelligent, and programmable networks of sensors. IoT has been an evolutionary progression of the internet, enabled through the deployment of connected devices for humanitarian, environmental, industrial, and smart city use-cases and applications. Projections for the impact of IoT indicate 100 billion connected devices with a global economic impact of more than $11 trillion by 2025 [8]. This rapid technological evolution has impacted the daily lives of people through expected IoT services. IoT has especially influenced big changes in cities and urban areas with a push towards an embrace of technology and social reorganization through the "Smart City" paradigm to provide better services and solutions to the citizens [9].

The rapid development in artificial intelligence (AI) related technological areas requires future engineers to learn and master the essential elements of these domains during their undergraduate curriculum. However, the engineering curriculum is still catching up with the rapid growth in technology especially applications of machine learning and IoT in real-world problem-solving. Many engineering schools lack adequate laboratory facilities and expert faculty in these areas. The PBL has evolved as an effective hands-on based problem-solving approach to deliver the content knowledge while engaging the students to maximize learning. This paper looks at applying the essential elements of PBL approach to engaging the students in active learning through projects that are primarily driven by real-world problem-solving. The projects were carefully designed to include technical problems that needed engineering intervention. The students went through the engineering design process and develop solutions that were tested in the field. The students also worked in teams and learned essential communication, problem-solving, and logical thinking skills in addition to other hands-on engineering skills.

The rest of the paper is organized as follows: Section II covers the details of the project selection, team formulation; and engineering design process that they followed while undertaking PBL; Section III includes a detailed description of example projects which can be tailored by other educators for implementation; Section IV covers the student feedback and resulting changes in the pedagogical model to improve student learning; Section V presents the conclusions from this study.

PROJECT SELECTION AND TEAM FORMULATION

A team of researchers has been working together at Arkansas Tech University (ATU) to promote student collaboration and interdisciplinary research on problem-solving through PBL. The team members comprise faculty researchers from Electrical and Computer Engineering, Mechanical Engineering, Computer and Information Systems, Biological and Physical Sciences, Curriculum and Instruction, and Business and Finance. The primary objective of the team has been to identify undergraduate student projects that are interdisciplinary and collaborative in nature while emphasizing on applications of emerging technological areas such as machine/deep learning, and IoT. The university has been a very supportive environment for this work through undergraduate research, and interdisciplinary research grants. The team identifies projects through needs analysis based on input from various stakeholders including local industry and advisory boards. A principal investigator (PI) is identified and the team works on a grant proposal to arrange funding for the project. The grants are submitted every cycle to ATU Undergraduate Research, and Interdisciplinary Research Offices. The grants are funded after a competitive peer-review process. An essential element of each grant is the identification and inclusion of an interdisciplinary team of undergraduate students that works under the mentorship of PI and Co-PIs from their respective disciplines. Before the start of work on a project, the team is briefed on the engineering design cycle that includes: problem definition, background research, requirement specification, brainstorming and evaluation of options, developing and prototyping of a solution, testing and validation, and design review for improvement.

The students are mostly upper-division (Junior and Senior) in their respective programs and work as a team with the support and mentorship from the PI and their respective Co-PIs. So far, the student teams have worked on the following projects:

- IoT based water quality monitoring system for Lake Dardanelle, AR. [10]
- Industrial IoT implementation for machine condition monitoring. [11]
- Wildfire detection system with distributed sensors and IoT. [12]
- Deep Learning and Robotics for structural health monitoring applications. [13]
- IoT based system for monitoring feeding patterns of migratory birds.
- Machine Learning for Quantitative Analysis of Financial Data.
- Application of machine learning algorithms for crack detection in pipes. [14]
- Convolutional neural networks for processing and analysis of underground utility pipe images.

As an example of the team formulation process, in a project on design and implementation of an IoT based water quality monitoring system for Lake Dardanelle, an interdisciplinary student team was formed as a first step to start the project. The team comprised of two students from Electrical Engineering (EE), two from Computer Science (CS), and one each from Biology, Chemistry and Mechanical Engineering. During the team formulation process, the PI sought help of Co-PIs to identify and recruit students from their respective departments. The students were assigned responsibilities as follows. The Co-PIs and students from Physical and Biological Sciences, due to their experience of working on the lake (as part of their course projects), helped to identify the types of sensors and monitoring locations around the lake. EE students researched existing microcontroller technologies and IoT modules to select a suitable microcontroller and IoT module for this application. The EE students designed the power budget, researched potential solutions, and worked on the interface and wireless communication issues between sensors and IoT module.

Another important challenge was to handle and manage data collected by the sensors. The CS student helped in application programming and web interface design for real-time data access to users. Co-PIs and students from Physical and Biological Sciences also helped in data collection and analysis in the validation phase of the project.

DETAILED PROJECT EXAMPLES

This section will include details of the example projects which were undertaken by the students. In many cases, the student teams made significant progress to develop a prototype and test it in the field. In few cases, the students made significant progress on the project and the work was continued by a second team of students. These projects have been an opportunity for students to learn about the latest advancements in AI technologies and helped the faculty sustain their research agenda by promoting undergraduate research.

I. IoT based water quality monitoring system (WQMS) for Lake Dardanelle, AR.

This project was motivated by the need to monitor the water quality parameters of Lake Dardanelle, AR. The lake is located close to the campus of Arkansas Tech University. The latest annual water quality assessment report published by the Arkansas Department of Environmental Quality (ADEQ) highlights that the water quality data from the majority of Arkansas Lakes is sparse [15]. Lake Dardanelle is a major tourist destination for game fishing and is classified as a large lowland lake (Type E) within the Arkansas River Valley ecoregion. The lake's watershed includes areas with industrial/manufacturing units, intensive row-crop agriculture, small farms, pastures and timberlands [15]. The drainage from watershed has the potential to change the physio-chemical and biological parameters of the lake water. The ADEQ quarterly monitoring program only includes 16 of Arkansas's large public lakes [16] and Lake Dardanelle is not part of this program. The lack of any routine monitoring system and potential for contamination from industrial and human activities motivated the researchers to develop an IoT based real-time WQMS. The initial focus was on the system design to measure physio-chemical parameters of the lake water important for game fish such as temperature, turbidity, dissolved oxygen (DO), and power of Hydrogen (pH).

The multidisciplinary project team of students was assigned for the system design and deployment. The team overcame several challenges including the selection of appropriate wireless data communication technology, microcontrollers, sensors and sensor calibration, data flow architecture, user interface design, and platform selection for system implementation. The overall diagram of the system

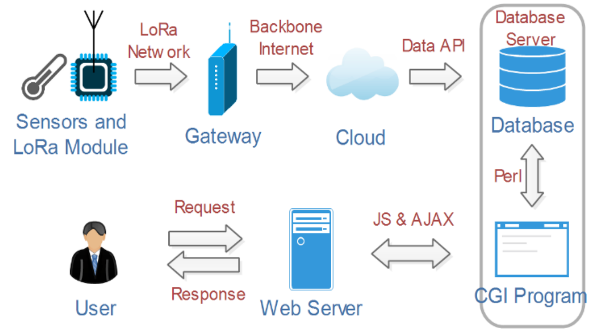

FIGURE I
DIAGRAM OF DATA FLOW, STORAGE, AND RETRIEVAL

including data flow is shown in Figure I. The students selected LoRa (Long Range) technology for Low-Power Wide-Area Network (LPWAN). In this water quality monitoring system project, we chose LoRa was selected because of its open MAC layer, free Industrial Scientific and Medical band operation (915 MHz), low power consumption, and low channel capacity which are suitable for distributed sensors. LoRa also provided a large coverage area with a single gateway with adequate security for IoT application.

The student team selected four sensors to measure water quality parameters and mounted them on a center hull of an Unmanned Surface Vehicle (USV) which was a catamaran for increased stability and shallower draft as shown in Figure II. These features were considered ideal for the lake environment of this application. The sensors are shown in Figure II. These include pH (SEN0169), turbidity (SEN0189), DO (Atlas Scientific), and digital temperature (DS18B20) sensors. The students used standard solutions available in the Chemistry lab to calibrate the sensors by comparing their readings with those from Vernier sensors on a Labquest 2 data-collection device [19]. The CS students selected GoDaddy service to host the project website. They used JavaScript andAJAX to design the webpage, and MySQL database to store the data. Perl script was used to get the real-time data. API Eclipse Mosquito was used to fetch the data from cloud storage and keep the database updated. On the backend, the data was

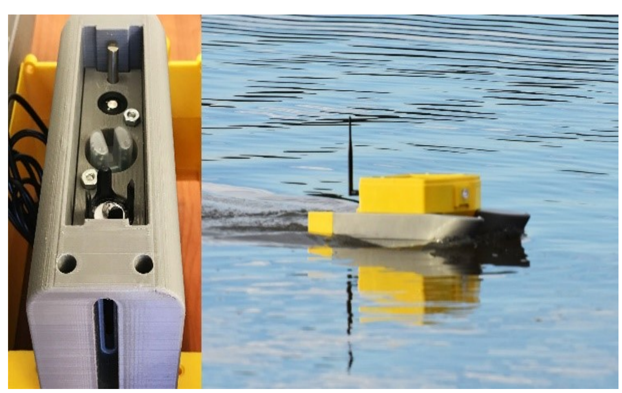

FIGURE II
SENSORS MOUNTED ON CENTER HULL AND USV UNDERWAY

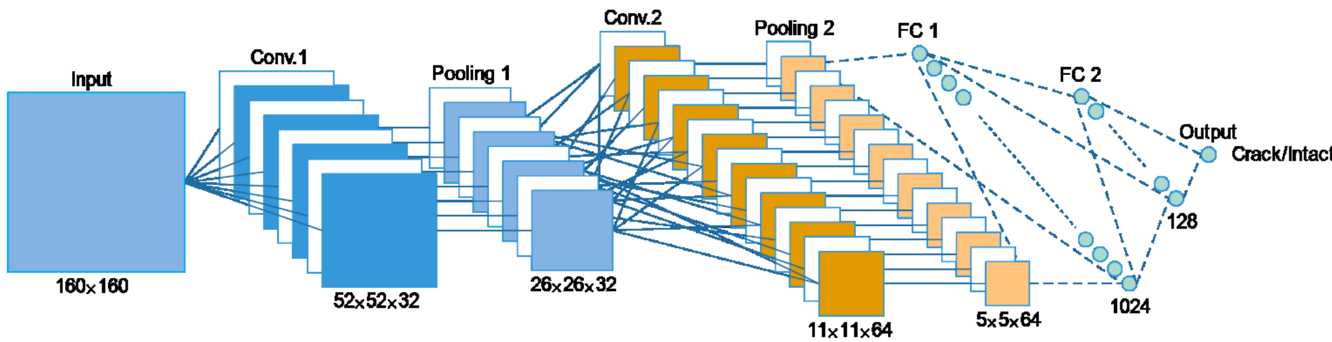

FIGURE III
CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

pulled every 2 minutes from the cloud, and the JavaScript refreshed the webpage after the same interval.

II. • Deep Learning and Robotics for structural health monitoring applications.

The motivation for this project was drawn from the need to monitor the structural health of underground sewer piping networks. Polyvinyl chloride (PVC) pipes are extensively used in sewer installations due to their low-cost, longer life, and easier installation. However, these pipes are prone to structural failure due to poor installation and engineering, faulty operation, internal and external contamination, manufacturing defects and abuse by the users [17]. These failures can lead to leaking sewers with adverse effects on public health and environment. The existing pipeline condition monitoring system is based on passing a robot-mounted closed-circuit television (CCTV) camera through the pipe. These systems are expensive, have a complicated deployment, and man-hour intensive. There is a need to develop an economical and easily deployable system for automated defect detection process without the need for an onsite operator to visually observe the CCTV video. In this project, an autonomous robot mounted with a camera was passed through the pipe to record the video of inside the pipe. The recorded images were processed using convolution neural networks (CNNs) to detect the presence of cracks and other structural defects.

The student team comprising three students from EE, one student from CS, and two students from ME researched existing work on using image processing for defect detection in pipes. They investigated intelligent classification algorithms such as conic fitting, and multilayer perceptron (MLP) using neural networks. They also researched computer vision techniques, and deep learning based on using faster region-based convolutional neural network (faster R-CNN). They based the design of the pipe crack detection system on CNNs due to their excellent performance in applications of computer vision, such as image classification, object detection, and image segmentation.

The proposed design was based on deep CNN architecture to detect cracks in the PVC pipes. The network architecture is described in Figure III. A single video frame captured by a camera from inside the pipe was used as input to the network. The network generates a probability of the crack in that single frame. The 3-dimensional color images are converted to 1-dimensional gray-scale images to reduce the computational requirements. The network includes two phases for image classification: a feature learning phase and classification phase. The feature learning phase has two sets of convolutional layers, max-pooling layers, and a flattened convolutional layer. The classification phase includes two fully connected layers and a sigmoid classifier layer. As crack detection is posed as a binary problem between the presence and absence of a crack, the sigmoid function was appropriate for this application.

The project team also set up an experiment to obtain empirical data from cracked and clean pipe sections. They used two 3.048-m long sections of 0.1-m diameter Schedule 40 PVC pipes. One pipe had a 2-mm circumferential crack midway along its length. The other pipe section was intact

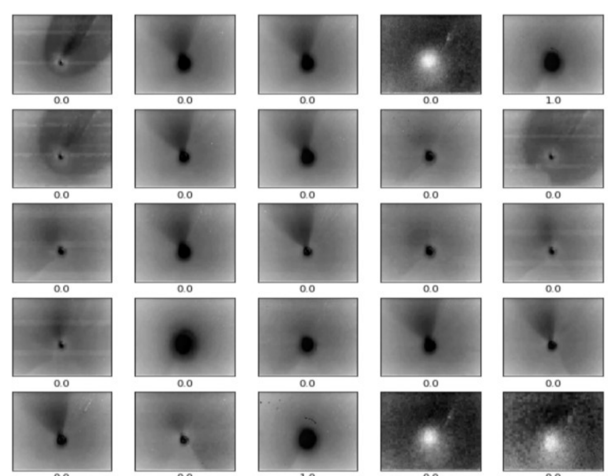

FIGURE IV
SAMPLE DATA

with no cracks. To receive video from inside the pipe a wireless camera was mounted on a robot dolly. The video was recorded in a frame width of 640 and a frame height of 480 at the rate of 30 frames-per-second. The team collected 627 effective frames from the recorded videos. Figure IV shows the sample data. The data was split into 80:20 for training and validation. The CNN model was trained on 501 frames and validated with 126 frames. The team achieved a classification accuracy of 89.42% in training and 83.33% in validation.

III. Application of Machine Learning Algorithms for crack detection in pipes.

In this project, a team of students used machine learning algorithms for condition classification of the pipes based on acoustic data. The team comprising two ME students, two EE students, and one CS student conducted experiments on clean and cracked PVC pipe samples to collect data. They used audio tones at one-third octave band frequencies within a band of 50-Hz to 10.0 kHz. The frequency range was divided into three sub-bands: a low-frequency band between 50 Hz to 200 Hz; a mid-frequency band between 250 Hz to 2,000 Hz; and a high-frequency band between 2,500 Hz to 10,000 Hz. Each tone was transmitted for 5.0 seconds and a pilot tone of 1.0 kHz pilot tone was used to indicate the start and end of the tonal sequence. The test set up is shown in Figure V. The tests were conducted in the laboratory on 3.3 m long PVC pipe sections with one section having a 2-mm circumferential crack. The raw data was collected with two microphones: one microphone was used to record the reference signal, and the second microphone was placed near the end of the pipe section to measure the signal at the output.

The team analyzed the collected data with Python using the Machine Learning (ML) algorithms: Decision Tree, K-Nearest Neighbor (KNN), and Naïve Bayes. The team had to do filtering and transformation of the raw data before applying the ML algorithms. The data was labeled by adding a column “Label” with binary values to the dataset. Before running the ML analysis, the data was standardized using StandardScalar Method which normalized its probability distribution with a mean of 0 and a standard deviation of 1. Data was then split into 80% for training and 20% for validation of the algorithms and determine their accuracy/score.

The team imported the required ML packages from Python, and applied the fit, transform, and predict methods available in each package. The methods were used to compute scores, precision, and recall values for each algorithm. For all tested algorithms, the k-fold cross-validation value was set to 5. That split the training set into five-folds. The predictions were made and evaluated on each fold using a model trained on the remaining folds. The score, precision, and recall results were produced by the ML algorithms. The results were compared to determine the suitable frequency band and specific tones that could be used for crack detection in pipes.

FIGURE V
TEST SETUP FOR ACOUSTIC BASED PIPE CRACK SYSTEM

STUDENT FEEDBACK AND PEDAGOGICAL CHANGES

There have been 36 junior and senior students who have participated in the projects related to IoT and machine learning over the past four semesters. Qualitative feedback was collected from students through interviews and comments. The students greatly appreciated the opportunity to learn about the latest AI technologies and engage in hands-on PBL for solving real-life problems. The students also showed interest in learning more about these fields and have asked the faculty for formal instruction through courses in these subjects. The faculty is looking into developing a dedicated course on embedded machine learning. The course will consist of hands-on laboratory sessions base on ARM Cortex-M processors. To engage engineering students at an early stage, the faculty is also looking into developing interactive sessions and projects for first-year students. These projects will be based on using STMicroelectronics SensorTile and STM32 processor [18]. This IoT platform comes with MEMs nine degree of freedom (9DOF) sensors, digital microphone, accelerometer, gyroscope, barometer, and wireless connectivity through Bluetooth Low Energy (BLE) and integrated antenna. The students will experiment with connecting sensors and establishing communication with sensors through General Purpose Input Output (GPIO), Inter-Integrated Circuit (I2C), serial, USB data, Pulse Code Modulation, Analog to Digital, and Digital to Analog interfaces. The students will develop solutions in C programming language. The SenserTile platform will also enable students to experiment with signal processing concepts such as discrete-time low and high pass first order IIR filters. Typical projects will include gesture recognition, motion sensing, and inertial sensing.

The SensorTile platform will also be used for machine learning applications at the capstone level projects. The platform is suitable for this level as it provides a very capable processor with a high sample rate and integrated LiPo battery and charger. It also enables wearable wireless sensors and can be integrated with embedded Linux platforms. For machine learning, the system will be used for Fast Artificial Neural Network (FANN) System, and Liquid DSP signal processing. The capstone projects will enable students to develop strong foundations in IoT and machine learning especially data acquisition methods, neural network architecture selection, network design, system deployment, training, testing, and validation.

CONCLUSION

This paper presents an overview of PBL based learning approach implemented at ATU by an interdisciplinary team of faculty. The projects were focused on areas of machine/deep learning, and IoT. They have helped faculty in promoting undergraduate research and collaboration across campus. Projects have also been an important resource for furthering faculty's own research agendas. This approach can work as a model for other institutions where faculty and students can be involved in collaborative interdisciplinary projects for learning new technologies and real-world problem solving. The projects have also helped participating students by giving them opportunities to promote their understanding of the latest technologies and enhance their communication, problem solving, and critical thinking skills. Students also worked in teams and went through the engineering design process for developing prototype systems which are important student learning outcomes for academic programs especially engineering disciplines.

The authors look forward to pursuing these opportunities to involve students in multidisciplinary collaborative projects in the future as well. Efforts are in hand to enhance these collaborations among students during their early years in the programs as well as at the capstone level projects. Authors have received very positive responses from students and school administration to promote this model of learning at all levels. The projects have received funding through undergraduate research and interdisciplinary research avenues to further these collaborative interactions. The authors look forward to advancing this approach through more student and faculty involvement across departments, colleges, and schools.

ACKNOWLEDGMENT

We would like to thank the Office of Sponsored Programs and University Initiatives and Office of Undergraduate Research at Arkansas Tech University for their funding of the projects. We also appreciate the assistance from Drs. Charles Mebi, and Douglas Barron for lab testing of sensors in the WQMS project.

REFERENCES

[1] D. Boud and G. Feletti, The challenge of problem based learning. London: Kogan Page, 1997.

[2] P. C. Blumenfeld, E. Soloway, R. W. Marx, J. S. Krajcik, M. Guzdial, and A. Palincsar, "Motivating project-based learning: Sustaining the doing, supporting the learning," Educational psychologist, vol. 26, pp. 369-398, 1991.

[3] M. C. English and A. Kitsantas, "Supporting student self-regulated learning in problem-and project-based learning," Interdisciplinary journal of problem-based learning, vol. 7, p. 6, 2013.

[4] H. S. Barrows, Problem-based learning applied to medical education: Southern Illinois University School of Medicine, 2000.

[5] C. Bereiter and M. Scardamalia, "Intentional learning as a goal of instruction," Knowing, learning, and instruction: Essays in honor of Robert Glaser, pp. 361-392, 1989.

[6] L. Torp and S. Sage, Problems as possibilities: Problem-based learning for K-12 education: ASCD, 1998.

[7] S. Sungur and C. Tekkaya, "Effects of problem-based learning and traditional instruction on self-regulated learning," The journal of educational research, vol. 99, pp. 307-320, 2006.

[8] Report, "The Internet of Things: An Overview", released October 2015, Internet Society.

[9] A. Arroub; B. Zahi , E. Sabir; and M. Sadik, "A literature review on Smart Cities: Paradigms, opportunities and open problems", Proc. 2016 International Conference on Wireless Networks and Mobile Communications (WINCOM), Oct 26-29, Fez, Morocco.

[10] N.Wu, and M. Khan,"LoRa-based Internet-of-Things A Water Quality Monitoring System", Proceedings of IEEE SoutheastCon 2019, April 11-14, 2019, Huntsville, AL.

[11] H. Barksdale, Q. Smith, and M. Khan, "Condition Monitoring of Electrical Machines with Internet of Things", Proceedings of the IEEE Southeast Conference 2018, April 18-22, 2018, St. Petersburg, Florida.

[12] T. Blalck, D. Ellis, M. Long, C. Brown, R. Kemp, and M. Khan, "Low-Power Distributed Sensor Network for Wildfire Detection", Proceedings of IEEE SoutheastCon 2019, April 11-14, 2019, Huntsville, AL.

[13] M. Khan, N. Wu, K. Zeng, and I. Unwala, "Robotics and Deep Learning for Structural Health Monitoring of Utility Pipes", IEEE International Symposium on Measurement and Control in Robotics (ISMCR), September 19-21, 2019, University of Houston Clear Lakes, Houston, Texas.

[14] M. Khan, and R. Patil, "Application of Machine Learning Algorithms for Crack Detection in Pipes", Proceedings of IEEE SoutheastCon 2019, April 11-14, 2019, Huntsville, AL.

[15] ADEQ, "Integrated water quality monitoring assessment report", WQ16-04-01, 2016.

[16] ADEQ website, available: ww.adeq.state.ar.us/water/planning/surface, Accessed December 20, 2018.

[17] D. Priddy, " Why Do PVC & CPVC Pipes Occasionally Fail?", Plastic Failures Lab, Midland, MI document, availabe at: www.californiasprinklerfitters.org/files/ WhyCPVC-OccasFail.pdf.

[18] STMicroelectronics SensorTile and BeagleBone: Internet of Things and Machine Learning, University of California Los Angeles, available at: https://sites.google.com/view/ucla-stmicroelectronics-iot-ml/home.

AUTHOR INFORMATION

Muhammad Khan, Assistant Professor, Department of Electrical Engineering, Arkansas Tech University.

Mohamed Ibrahim, Associate Professor, Department of Curriculum and Instruction, Arkansas Tech University.

Nansong Wu, Associate Professor, Department of Engineering Sciences, Sonoma State University.

Rajvardhan Patil, Assistant Professor, Department of Computer and Information Systems, Arkansas Tech University.