European Journal of Computer Science and Information Technology 11 (5), 50-60, 2023
Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

A Smart Campus Internet-of-Things (IoT) Model for Smart Classroom Conditioning Using a Hybridized Technique

Amiefamonyo B. F[1]., Anireh, V.I.E.[2], Matthias, D.[3]
[1,2,3]Department of Computer Science, Rivers State University, Nkpolu, Rivers State, Nigeria.
Corresponding Author: anire.ike@ust.edu.ng Tel.: +234 8033229172

doi:https://doi.org/10.37745/ejcsit.2013/vol11n55060 Published November 19 2023

Citation: Amiefamonyo B. F., Anireh, V.I.E., Matthias, D. (2023) A Smart Campus Internet-of-Things (IoT) Model for Smart Classroom Conditioning Using a Hybridized Technique, *European Journal of Computer Science and Information Technology*, 11 (5), 50-60

ABSTRACT: *This research study presents Smart Campus (SC) Internet-of-Things (IoTs) enabled systems model that will support end-user and automatic functions for proper air conditioning of SC classrooms environment. It consists of a hybrid data learning predictor system using an emerging variant of Artificial Neural Network (ANN) called Neuronal Auditory Machine Intelligence (NeuroAMI) and a Linear Regressor (LR) of polynomial-order-of-1.The system was initially applied separately to the automated coordination of a smart bed in a laboratory sized classroom environment at a University Campus, and simulated using the high-level programming language – MATLAB, while end user interaction model was developed in the Java2ME programming language. Simulations results considering several trial runs showed that the ANN predictor generally performed better than the LR model with over 80% classification accuracy. While considering limited training data points, the LR predictor was found to be superior at one of the simulation trial runs. At 20% data point, the LR was activated while the NeuroAMI remains inactive, but above the 20% level, the NeuroAMI performed better. One advantage of this proposed hybrid system is the ability to deal with continuous data; exactly the same way human brains functions. This feat has not been possible in conventional ANN systems, especially in this area dealing with small data points*.

KEYWORDS: smart campus, internet-of-things, artificial neural network (ANN), neuronal auditory machine intelligence, predictor system, linear regressor.

INTRODUCTION

Comfortable environment for teachers and students plays a key role in effective teacher and (positive) learner outcomes. One key area to achieve effective student comfort in campus is in the area of environmental conditioning such as maintaining proper classroom temperatures considering the prevailing ambient temperatures. Thus, smart campus classrooms (SCCs) are needed in order to reduce the risk of learner failure.

In both cold and tropical regions, the use of fossil fuels for powering air conditioning systems is common, which is costly and environmentally unfriendly. It also warrants efficient energy use management whereby a room air conditioner system needs to be repeatedly turned on or off in order to assure appropriate temperature settings depending on the prevailing temperature conditions in order to maximize the comfort of students as well as optimising energy usage (Osegi et al., 2021).

In an Internet-of-Things (IoTs) based smart campus network, internet-enabled embedded devices offer automated services to support the teaching and learning operations at school. These device services provide a seamless interaction over a variety of platforms (platform technologies) including computing devices with people and their ambient environment. Thus, it is an essential ingredient of the semantic Web, since the future web must allow software agents to make use of one another's services without the need for continued user intervention (Berners-Lee, 2001).However, some obvious challenges still exist particularlyin the matter of arriving at a consensus considering several input agents requirements e.g. as an agent may decide a temperature setting of 25^0C to be comfortable for a relaxed classroom study while another may prefer a 30^0C setting. In this research study, a model design and implementation of a smart campus using an internet-of-things paradigm is researched upon considering thermal conditioning in a typical classroom environment.

Related Works

In particular, related researches bordering on the optimal thermal conditioning configuration of SCCs using the Internet-of-Things is rare in the public domain. In this section, an overview of related works in the domain of smart campus is presented to provide sufficient background validating our proposed approach. Subsequently the research gap is identified to provide more clarity to the need for our proposed technology.

REVIEW OF RELATED RESEARCH STUDIES

There is indeed an emerging interest in smart conditioning for classroom environments in campuses of higher learning. In MacLeod et al (2018), the efficacy of smart classrooms for improving learning experiences had been investigated. They reported good improvement in the learning rate of students when adequate environmental conditioning was implemented.Shen *et al.* (2014) investigated how Near Field Communication (NFC) devices can be applied in the Smart

Classroom context for classroom attendance management automation. The benefits of such systems include real time student feedback, intelligent location, intelligent monitoring of learning progress, name visualization and remote course performance monitoring. Uzelac *et al.* (2018), proposed a smart classroom system that allows the classification of student's satisfaction against lecture quality based on certain physical parameters.

In Sutjarittham *et al.* (2019), a very interesting smart campus system application for the prediction of classroom attendance and for optimally allocating classes so as to resolve the classroom underutilization problem was developed. Their proposed system used several machine learning artificial intelligence (ML-AI) techniques including Multiple Regression, Support Vector Regression for course attendance data prediction and a Constrained Programming (CP) optimization AI technique for optimal classroom allocation.

Bakken *et al.* (2017) studied the benefits of a smart classroom based Natural Text-to-Voice and Voice-to-Text software systems for supporting learners with disabilities. The authors reported better learning and understanding, as well as positive ratings for students with disabilities interacting with such natural smart sensing software compared to comparable Windows and Google Docs voice/text software.

Notwithstanding the existing and well applied body of research in this area of study, there are still issues affecting the various implementations pertaining smart classroom applications for smart campuses. Thus, there still room for improvement and research is still ongoing. One particular growing area of interest is in the area of smart classroom air-conditioning using automated tools and techniques (Aghniaey et al., 2019). This in turn have given rise to a number of key research studies in thermal conditioning such as in (Alberti et al., 2018a, Alberti et al., 2018b) where Non-linear Autoregressive Neural Networks (NARX-NETs) were used for precise air temperature prediction utilizing a combination of real and synthetic sequential temperature datasets obtained from the existing building structures of classrooms and in Paudel et al (2019) where the Long Short-Term Memory (LSTM) neural technique was used for the predicting some conditioning variables within a classroom such as temperature, humidity and luminance and in a context-aware energy saving system.

Osegi and Anireh (2020) presented results of experiments using a new biologically constrained machine intelligence algorithm based on neural processing in the auditory cortex called auditory machine intelligence (AMI). The algorithm is an online learning technique for predicting sensory time series data, data that comes in streams or in a sequential order. The AMI algorithm was particularly inspired by the mismatch negativity effect (Osegi and Anireh 2016) which provided important evidence that the brain learns a statistical structure of the world it senses. The results of their experiments when compared with two very popular techniques used for time series predictions were adjudged to be better. It has also been subsequently applied in the smart bed context for classroom conditioning automation (Osegi *et al*., 2021).

Identified Research Gap

The current challenge with the existing neural prediction techniques such as the NARX-NET and LSTM is the need for very large datasets, the requirement of training and test procedures, and the excessive hyper-parameter tuning requirement.These requirements are often not feasible in practice and there is always a challenge in developing more affordable and less complex system solutions in the world of embedded smart systems.Also, most if not all existing research works on smart campus conditioning do not implement continual learning systems. For real world smart based systems, the need for this very important requirement cannot be overemphasized.Thus, it is the purpose of this research to develop an IoT capable Smart Campus (SC) based system solution model exploiting hybridized techniques including a continual learning neural strategy.

PROPOSED METHODOLOGY

One of the most important aspects of any smart systems device is the communication method and channel of the devices. We are proposing a novel method of communicating with IoT devices for intelligent conditioning using real time thermal (temperature) data from a smart bed.The ANN-LR Smart Campus Activity Learning Architecture is incorporated into an embedded simulation model to emulate real smart control and conditioning in classroom environments. This trains the system on expected behavioural patterns which can be obtained from an IoT capable devices.

The proposed system (hybrid) model is an improvement on the typical Deep-Learning Smart classroom systems architecture proposed in the literature and is used to tackle the aforementioned constraints by employing an advanced and emerging auditory inspired Artificial Neural Network (ANN) called the Neuronal Auditory Machine Intelligence (NeuroAMI) and a Linear Regressor (LR) model of polynomial-order-of-1 in a hybrid context.

The AI technique - NeuroAMI-ANN has been developed in (Osegi & Anireh, 2020) and also used successfully in a number of research studies such as found in (Osegi et al., 2021; Osegi et al., 2023); this research study will design and implement and simulate a Smart classroom system that models a hybridized NeuroAMI-ANN-LR machine learning model that is very much less data-hungry than the conventional solutions but as efficient.

The proposed architecture of our IoT capable smart campus classroom model is as shown in Figure 1.

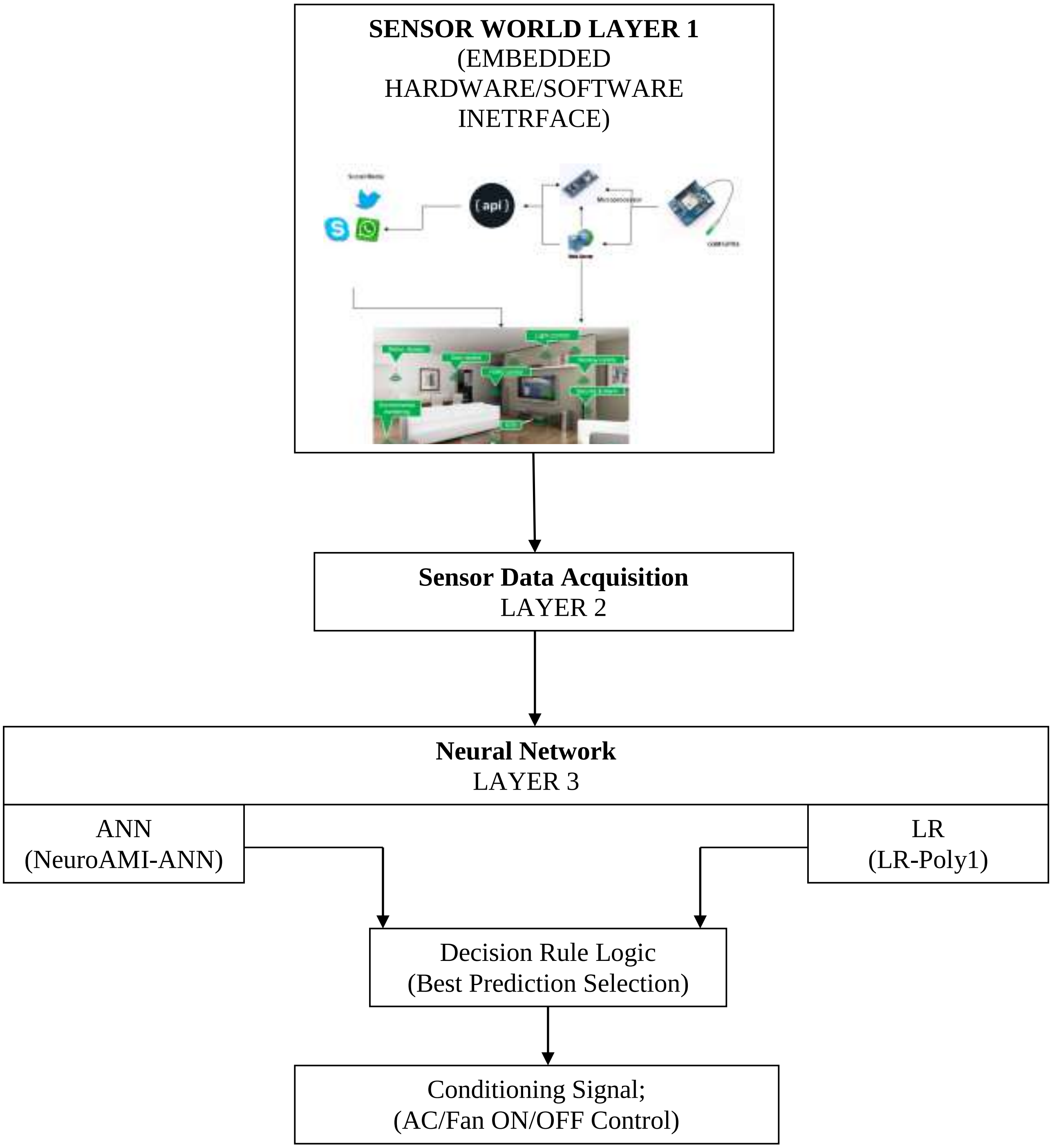

Figure 1: Proposed Smart Classroom Architecture

Simulation Experiment

Simulation experiments were performed to gain insight into how the actual system may operate; they helped to save costs and time as any error can be fixed in application before deployment on the actual physical board. The research study simulated the proposed systems model for three different trial runs of 10, 50 and 100 points (duration settings). Simulation results were obtained using the Variable step ode23t (Mod.stiff/Trapezoidal) solver set in the configurations parameter of the SIMULINK system and comparisons were made between the Neuronal Auditory Machine Intelligence (NeuroAMI) based Artificial Neural Network (ANN) model and an equivalent Linear Regression (LR) Model. It is important to note that the simulation data point settings are different from the generated data points during simulation. The linear algebra solver of the Physical Signal (PS) model is set to sparse to improve the overall system resilience.

RESULTS

The graphical results of the simulation showing the actual vs. predicted response for 10, 50, and 100 trial points are presented in Figures 2 to 4 in that order. Also presented in Tables 4.1 and 4.2 are the classification accuracies of NeuroAMI based smart classroom thermal control system for different percent training examples (data points) compared with the LR method.

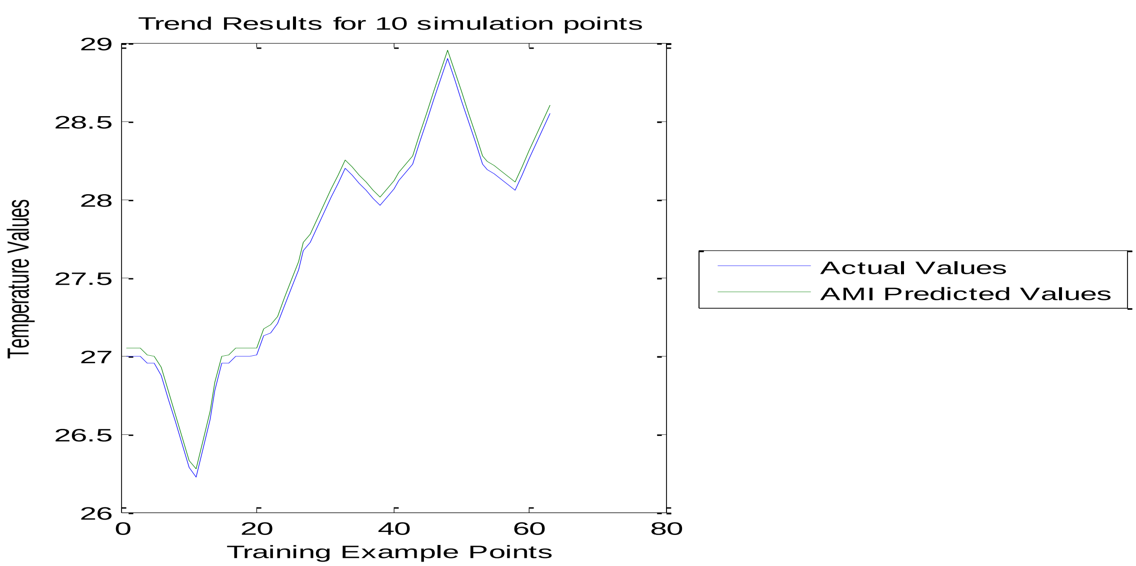

Figure 2: Predicted vs. actual temperatures using ANN Model smart bed for 10 simulation trial points.

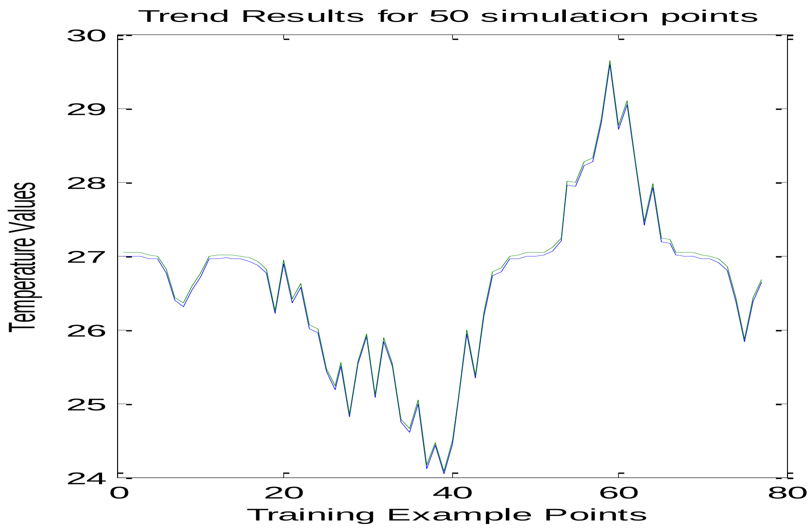

Figure 3: Predicted vs. actual temperatures using ANN smart bed for 50 simulation trial points.

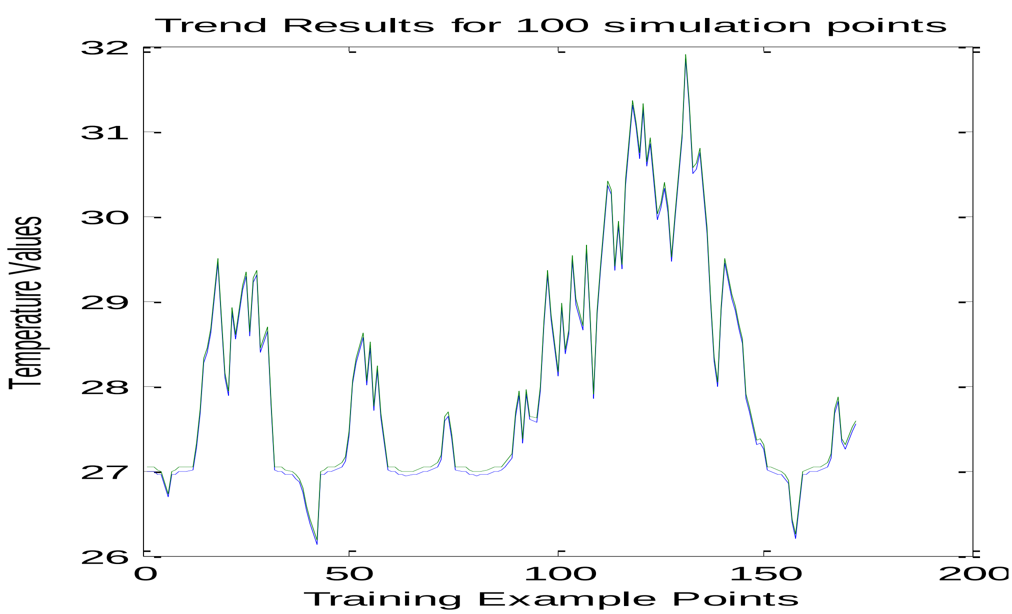

Figure 4: Predicted vs. actual temperatures using ANN smart bed for 100 simulation trial points.

Table 1: Classification of NeuroAMI-ANN vs. LR Models for Smart Classroom Applications (50 data points)

Simulation Trial Training Data Points (%)	**NeuroAMI-ANN-CA$_{test}$ (%)**	**LR-CA$_{test}$ (%)**
20	00:00	40.00
30	52.94	Error
40	72.41	53.33
50	50.00	Error
60	94.74	60.00
Mean:	**54.02**	**35.36**

Table 2: Classification of ANN vs. LR Models for Smart Classroom Applications (100 data points)

Simulation Trial Training Data Points (%)	**NeuroAMI-ANN-CA$_{test}$ (%)**	**LR-CA$_{test}$ (%)**
20	18.99	30.00
30	79.71	37.14
40	61.02	26.67
50	40.82	28.00
60	33.33	55.00
Mean:	**46.77**	**35.36**

Considering the Figures 2 to 4 (see Section 3), it is obvious that the ANN predictions clearly follow the actual generated patterns and this is a clear indication of its good error matching and continual learning property.

From Table 1, apart from the first data point, the classification accuracies (CA) show clearly that the NeuroAMI-ANN prediction is much better than LR models. But in the hybridized context there is still a need to adapt the LR approach to the solution process since in certain circumstances the accuracy may be higher than ANN part (see data points 1 and 5, Table 2). This therefore validates the need for hybridized solutions as in the case where the LR becomes better than the NeuroAMI-ANN, it performs the air-conditioning controllability function in the smart campus classroom.

CONCLUSION

In this research study, the modeling of smart classroom in smart spaces is successfully researched using simulation logic and based on a hybridized Artificial Neural Network (ANN) – Linear Regressor (LR) approach.

The proposed system was developed to have intelligent and proactive capabilities that the home can use to adaptively control its environment especially in the area of thermal conditioning. An emerging and advanced form of Artificial Neural Network (ANN) inspired by intelligence processing in auditory cortex called the Neuronal Auditory Machine Intelligence (NeuroAMI) and standard Linear Regressor (LR) of polynomial-order-of-1 was used for the predictions of a sample IoT sensor device thermal conditioning data obtained from classroom.

Simulations were conducted and the results showed promising accuracies for the ANN part but there is still need to improve the LR-part to enhance the overall system resilience. This research has also looked at the issue of the need for smart conditioning particularly as it pertains to smart classrooms in smart campuses. In many institutions, electronic equipment and lights are left on when there is no need for them. This often results in power wastage or under-utilization which incurs additional costs to the institution.

To provide a solution to this problem, this research provided a prototype model of an IoT capable hybridized technique for controlling the home devices within a smart campus environment. This can provide end-users with the much needed programming capability for handling their needs of controlling appliances directly or allowing the system to automatically condition the environment.

REFERENCES

Aliberti, A., Ugliotti, F. M., Bottaccioli, L., Cirrincione, G., Osello, A., Macii, E., ... & Acquaviva, A. (2018, June). Indoor air-temperature forecast for energy-efficient management in smart buildings. In *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)* (pp. 1-6). IEEE.

Aliberti, A., Bottaccioli, L., Macii, E., Di Cataldo, S., Acquaviva, A., & Patti, E. (2019). A non-linear autoregressive model for indoor air-temperature predictions in smart buildings. *Electronics*, *8*(9), 979.

Aghniaey, S., Lawrence, T. M., Sharpton, T. N., Douglass, S. P., Oliver, T., & Sutter, M. (2019). Thermal comfort evaluation in campus classrooms during room temperature adjustment corresponding to demand response. *Building and Environment*, *148*, 488-497.

Bakken, J. P., Uskov, V. L., Kuppili, S. V., Uskov, A. V., Golla, N. and Rayala, N.(2017). Smart university: software systems for students with disabilities. In *International Conference on Smart Education and Smart E-Learning,pringer*, Cham, 87-128.

Berners-Lee, T., Hendler, J., & Lassila, O. (2001). The semantic web. *Scientific american*, *284*(5), 34-43.

Borgia, E., Bruno, R., &Passarella, A. (2018). Making opportunistic networks in IoT environments CCN-ready: A performance evaluation of the MobCCN protocol. *Computer Communications*, *123*, 81-96.

Chen, S. L., Chen, Y. Y., & Hsu, C. (2014). A new approach to integrate internet-of-things and software-as-a-service model for logistic systems: A case study. *Sensors*, *14*(4), 6144-6164.

Keyur K. & Sunil M. (2016). A New Approach toIntegrate Internet-of-Things and Software-as-a-ServiceModel for Logistic Systems: A Case Study.International Journal of Engineering Science andComputing.

MacLeod, J., Yang, H. H., Zhu, S., & Li, Y. (2018). Understanding students' preferences toward the smart classroom learning environment: Development and validation of an instrument. *Computers & Education*, *122*, 80-91.

Osegi, E. N., & Anireh, V. I. (2016) Deviant Learning Algorithm: Learning Sparse Mismatch Representations through Time and Space. arXiv preprint arXiv:1609.01459.

Osegi, E. N., & Anireh, V. I. (2020). AMI: An auditory machine intelligence algorithm for predicting sensory-like data. *Computer Science*, *5*(2), 71-89.

Osegi, E.N., Anireh, V.I., Taylor, & O.E. Taylor. (2021). A Novel Neural Machine Intelligence Algorithm for Temperature Forecasting and Conditioning for Smart Classroom Applications. Journal of Information Science, Systems and Technology, 4(3), 19-31.

Osegi, E. N., Jagun, Z. O., Chujor, C. C., Anireh, V. I., Wokoma, B. A., & Ojuka, O. (2023). An evolutionary programming technique for evaluating the effect of ambient conditions on the power output of open cycle gas turbine plants-A case study of Afam GT13E2 gas turbine. *Applied Energy*, *349*, 121661.

Paudel, P., Kim, S., Park, S., & Choi, K. H. (2019, January). A Context-aware Architecture for Energy Saving in Smart Classroom Environments. In *2019 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1-2). IEEE.

Salman, O., Abdallah, S., Elhajj, I. H., Chehab, A., & Kayssi, A. (2016, June). Identity-based authentication scheme for the Internet of Things. In *2016 IEEE Symposium on Computers and Communication (ISCC)* (pp. 1109-1111). IEEE.

Sintef OV, Friess P (2014) Internet of Things–from research and innovation to market deployment. River Publishers' Series In Communications.

Shen, C. W., Wu, Y. C. J., & Lee, T. C. (2014). Developing a NFC-equipped smart classroom: Effects on attitudes toward computer science. *Computers in Human Behavior*, *30*, 731-738.

Sutjarittham, T., Gharakheili, H. H., Kanhere, S. S., & Sivaraman, V. (2019). Experiences with IoT and AI in a smart campus for optimizing classroom usage. *IEEE Internet of Things Journal*, *6*(5), 7595-7607.

Uzelac, A., Gligorić, N. and Krčo, S. (2018). System for recognizing lecture quality based on analysis of physical parameters. *Telematics and Informatics*, 35(3), 579-594.