FEEDFORWARD

The Flagship Publication of IEEE COMPUTER SOCIETY Santa Clara Valley Chapter

olume 1, Issue 2 | From the heart of the Silicon Valley | Apr – Jun 2022

ICADS 2022 Conference Special

Fuzzy Loss Functions for Generative Adversarial Neural Network

Next Generation Artificial Intelligence and Energy Sustainability

Applied Data Science in Education

Website & Media

- https://r6.ieee.org/scv-cs/
- https://www.linkedin.com/company/78437763/
- https://www.linkedin.com/groups/2606895/
- https://www.facebook.com/IEEEComputerSocSCVchapter
- https://twitter.com/IEEEComputerSoc

Mailing List

http://listserv.ieee.org/cgi-bin/wa?SUBED1=cs-chap-scv&A=1

From the Editor's Desk

Dear Readers,

Greetings! We had an eventful quarter with the first in-person event after the pandemic era taking place on Tuesday, June 14 at noon at SEMI in Milpitas, CA. It was an Open House with pizza and drinks featuring a technical talk and a presentation of the state of the chapter. The talk on "Machine Learning, the Mortar of Modernization" generated good questions and discussion in the room and was well-attended by the online participants on YouTube and Zoom as well. Check out the video recording on IEEE.tv if you haven't already.

True to its international vision, this issue of Feedforward too features researchers from Romania, UK, and India who will be speaking at the ICADS '22 conference on Tuesday, July 12, 2022, on cutting-edge topics in Applied Data Science. Articles for future issues are welcome on all topics related to the IEEE Computer Society charter and if possible, relate to the Silicon Valley. One of the aims of this magazine is to encourage hobbyists who may not have time for full-fledged research but are still interested in publishing on leading technical topics. Please submit your articles on our website here: https://r6.ieee.org/scv- cs/?p=2036.

Preparations are underway for the NFIC (New Frontiers in Computing) virtual conference on Saturday, Aug 13, 2022, from 4:00 PM – 8:00 PM (PDT) in collaboration with North America Taiwanese Engineering & Science Association (NATEA, https://natea.org/). Speakers from Taiwan, USA, and possibly other countries will be talking on emerging trends. The September events are planned to be in-person as well. The talks will be collocated with IEEE GHTC conference at Santa Clara University from 6 - 8pm on both September 8 and September 9. Please watch out for the details on our chapter website and consider registering on Eventbrite when they are posted, to attend the talks.

We organized and cosponsored several events this year already and as you see, more are in the pipeline. We will host the next in the popular "Ask Me Anything (AMA)" series in October or November. Please subscribe to the chapter mailing list and follow the chapter social media pages and groups to get timely updates and take advantage of the events. Most of the past events of our chapter are available on IEEE.tv https://ieeetv.ieee.org/search?search_q=scv-cs and on YouTube, where they are live broadcasted: https://www.youtube.com/playlist?list=PLLsxQYv4DdJlYcGPwqUJsnHmfqMtB3eSJ

We are looking for more volunteers to help in various roles. You can help as a reviewer of the articles, papers, be a guest editor for special issues, help organize conferences and events, help with the publicity for our events, and more. Please consider being part of the success story by signing up here: https://r6.ieee.org/scv- cs/?p=2039. With the onset of the bright and warm summer season, let's continue to Feedforward the chapter to a bright new future. Hope you are all with me in my efforts. Happy reading and happiness always!

With every best wish,
Vishnu S. Pendyala

Sunday, June 26, 2022
San Jose, California, USA

ICADS '22 Invited Talk

Fuzzy Loss Functions for Generative Adversarial Networks

Dr. Priti Srinivas Sajja
Department of Computer Science
Sardar Patel University
Vallabh Vidyanagar, Gujarat, India

***Abstract*— Generative Adversarial Networks (GAN) are very popular for medical image analysis. The paper presents an innovative fuzzy loss function for the GAN in the domain of image analysis. The GAN architecture presented here uses two convolutional neural networks, one of which is a generator and the other is a discriminator. Besides the loss function, the training algorithm is also presented in the paper. The proposed approach is generic and can be used for many domains pertaining to medical image analysis and diagnosing. The proposed work with the modified loss function is experimented on the Covid-19 image set. The results achieved are discussed in brief. In the end, the paper presents limitations and future enhancements possible based on the work.**

Keywords*— *Generative Adversarial Network (GAN), Loss Function, Fuzzy Logic, Medical Image Analysis, Covid-19

1. Introduction

Artificial intelligence and machine learning have become essential instruments in many domains and have been used ubiquitously. The traditional knowledge-based systems need to collect knowledge, pre-process and represent knowledge prior to utilizing the knowledge. This is a tedious process, particularly when the domain is big, dynamic, and deals with a large amount of multimedia data. Due to this, machine learning methods have become popular, particularly for image analysis and diagnosing. Machine learning models such as Artificial Neural Network (ANN) are widely used to learn from data. However, ANN requires feature identification besides the good quality training data set.

Deep learning models such as Convolutional Neural Network (CNN) and Generative Adversarial neural Network (GAN) overcame the limitation beautifully and are used widely when there is a requirement to jump to a decision from the images. However, like with many advantages and utilities, these models have some limitations too. Some of the limitations are due to the learning architecture (such as vanishing gradients, mode collapse, etc.) and paradigm. Some come from the domain (imbalanced, noisy, un-sufficient data, etc.) This paper tries to solve the limitations by proposing an innovative loss function with the GAN.

Section 2 of the paper introduces the necessary background, applications, and limitations of the existing solutions. Section 3 presents the method, training algorithm, and modified loss function. Section 4 presents an experiment using the proposed network by taking Covid-19 chest CT scanned images. The section 4 also discusses the results achieved. In the end, the paper presents limitations and possible future enhancements to the proposed work.

2. BACKGROUND AND LITERATURE SURVEY

The GAN, as proposed by [1], typically contains two models. These models are generally two neural networks, as the neural network is a versatile generic model which learns many things. One network is a discriminator, and another is a generator network. Both machine learning models require training with sufficient good quality data. The data can be multimedia. The discriminator model takes the training data and tries to learn the possible

classification. The generator, on the other hand, starts with random noise and tries to generate fake data. Both the networks are trained in an adversarial manner. The discriminator's objective is to learn perfect classification with minimum error, and the generator's objective is to fool the discriminator by producing realistic and challenging data and thus making the discriminator more robust through such hard training. Therefore, a generator is often referred as an 'artist', and a discriminator is referred as a 'critic'. Figure 1 illustrates the working of a typical GAN.

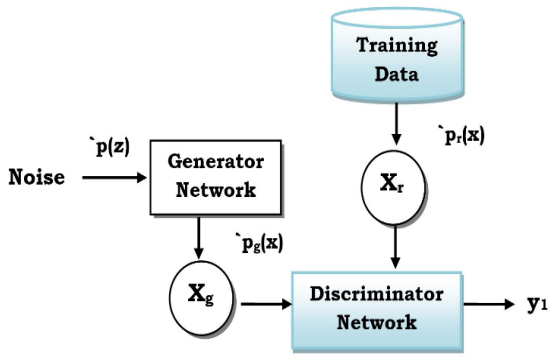


Figure 1: Typical GAN

The GAN applications are versatile and can be used with multimedia data. The most popular use of GAN is in the image domain. Face styling (hair, makeup, picture quality/beauty-enhancing, etc.), ageing and de-ageing, reconstructing pics, removing noise (background, de-raining, day to night conversion, etc.), face reconstruction and criminal face generation & identification, re-colouring images, and 3d object generation. The GAN are also useful in converting satellite images to maps and text to image translation.

When it comes to medical image analysis and classification using machine learning techniques, deep Convolutional Neural Networks (CNN) are popularly used [2], [3], [4], and [5]. The CNN offer the benefits of automatic feature extraction from images. Researchers [3], [6], [7], [8], [9], [10], [11], [12], and [13] have used CNN for medical image analysis. Unanimously, such CNN requires good quality images for analysis. Due to many reasons, such images are not available. Prominent reasons for not getting the medical images are laboratory setups, patients' willingness and discomfort. The images might contain noise also. Besides getting sufficient images, a well-balanced image set is also a problem. Here GAN helps in getting a sufficient and balanced data set containing good quality data images for further analysis and diagnosis.

Initially, the generator might produce low quality data/images; but later, it learns to produce realistic images. If the discriminator cannot distinguish the fake images from the real ones, the equilibrium is reached. However, there are many limitations of the approach. There is a constant oscillation between both the generator and discriminator losses because the generator tries to maximize the loss and the discriminator tries to minimize the loss. Further, there is a problem of vanishing gradients too. Here the discriminator is too good so that the generator fails to provide good competition, hence yielding better results.

If the discriminator becomes too strong, then eventually, the generator gradient vanishes and cannot help much. On the other hand, it introduces the mode collapse, where the generator smartly learns what to generate. As a remedy, many loss functions have been designed. Popularly used loss functions are Wasserstein loss [14], min-max loss [1], adversarial loss [15], least square loss [16], unrolled GANs [17], etc. To some extent, these remedies work well. Wasserstein GANs are comparatively less vulnerable; however, if the discriminator traps itself in the local maxima, the Wasserstein loss might not help much. For the unrolled GANs, as per the claim of authors [17], better update rules are required.

Above all, the GAN often fail to converge. As partial solutions adding random noise and penalizing the discriminator weights can be used as suggested in [18]. However, the work only regularizes the discriminator weights.

This paper proposes a modified loss function by identifying popular and suitable losses and integrating them in a necessary and sufficient manner using fuzzy weights. To prove the utility of the modified loss function, an algorithm is designed and used to analyze lung images for COVID-19.

3. METHOD

This section discusses the improved fuzzy loss function to overcome the research gap identified in section 2. The general format of the proposed loss function is as follows.

$$LFZ = \alpha 1.Loss1 + \alpha 2.Loss2 + \ldots + \alpha n.Lossn ;$$

Where αi is a fuzzy linguistic value.

To make the model generic, n numbers of loss functions are considered in the proposed function. As per the nature of the application and domain selected, a few loss functions can be considered. The fuzzy membership functions take Low, Medium, and High values on a scale of 0 to 9. The loss function used in the training algorithm as shown in Figure 2.

Input: Training data total T, Noise samples Z
For each T_i, where T_i belongs to T do
For K number of steps do
  Retrieve k noise samples $z_1, z_2, ...z_k$, where z belongs to Z
  Retrieve m examples from $p_{data}(x)$
  Calculate L = (Loss1, Loss2, Loss3, …, Lossn)
  Derive A= (α1, α2, α3, …, αn)
  Update discriminator using L_{FZ} = α1.Loss1 + α2.Loos2 +…+ αn.Lossn
End for
Retrieve m noise samples $z_1, z_2, ...z_m$, where z belongs to Z
Retrieve m examples from $p_{data}(x)$
Update discriminator using L_{FZ}
End for

Figure 2: Training Algorithm

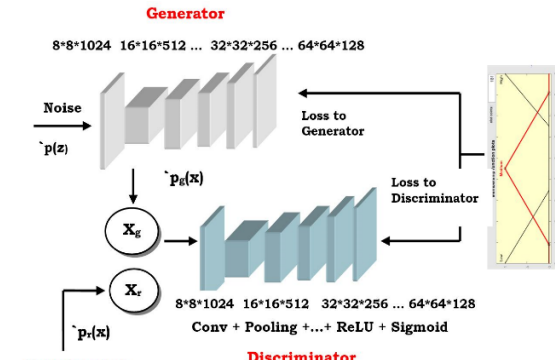
The algorithm outlined in Figure 2 uses many loss functions instead of only one loss function with fuzzy weights. Instead of selecting any one loss function or applying the loss function to only the discriminator, a weighted sum of multiple loss functions is used. Typically, adversarial loss [15], loss in visual perception [15], and traditional mean square error loss are used for the GAN based medical analysis. These loss functions are described below.

$$L_{Adv} = E_{x\sim P_G}[D(x)] - E_{x-p_{data}}[D(x) + \lambda E_{x\sim penalty}[(\| \nabla_x D(x) \| - 1)^2]$$

$$L_{Per} = \frac{1}{W_{ij}H_{ij}} \sum_{x=1}^{W_{ij}} \sum_{y=1}^{H_{ij}} (\emptyset^{ij}(I^{HR})_{x,y} - \emptyset^{ij}(G(I^{LR}))x,y)^2$$

$$L_{MSE}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \| I_i^H - G(I_i^L, \theta) \|^2$$

For the possible weights of the combined loss function LFZ triangular fuzzy membership functions are used on scale of 0 to 9. Figure 3 illustrates the working mechanism of the proposed approach. Besides handling vagueness and uncertainty within the weight factors, the fuzzy linguistic provide increased naturality while designing an interface of the system for medical professionals which are non-computer professionals.



$L_{FZ} = \alpha 1.\ L_{Adv} + \alpha 2.L_{Per} + \alpha 3.\ L_{MSE}$ where

$L_{Adv} = E_{x\sim P_G}[D(x)] - E_{x-p_{data}}[D(x) + \lambda E_{x-penalty}[(\| \nabla_x D(x) \| - 1)^2]$

$L_{Per} = \frac{1}{W_{ij}H_{ij}} \sum_{x=1}^{W_{ij}} \sum_{y=1}^{H_{ij}} (\emptyset^{ij}(I^{HR})_{x,y} - \emptyset^{ij}(G(I^{LR}))x,y)^2$

$L_{MSE}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \| I_i^H - G(I_i^L, \theta) \|^2$

Ai, i={1,2,3} → {Low, Medium, High}

Figure 3: Proposed GAN with Fuzzy Loss Function

4. EXPERIMENT AND RESULTS

The world is fighting with many variants of the SARS-CoV-2 virus, popularly known as coronavirus. Due to the inability to visit the hospital and other infrastructural and physical constraints, getting a balanced dataset of good quality lung images is challenging. Here the proposed GAN with the modified fuzzy loss function algorithm is used to (i) generate a balanced image set of CT scanned lung images and (ii) diagnose the disease. The data set used in this experiment is the covid-19 image set [19]. The dataset contains more than 1000 images. Other data sets, which can be used for the experiment are Covid-CT, Covid-19 image collection [20], and Covid CS (21). The Covid CT contains approximately 300 images from 200 patients. The images are available freely, being open source along with necessary metadata. The Covid-CS includes a really big amount of mages, approximately 70000 images from about 400 patients. However, essential metadata are not available, and the images are not freely available too.

The generator and discriminator networks used in the experiment are basically the typical convolutional neural network. The noise distribution taken into account for the experiment is normal. The original, as well as generated images, are split into training and testing sets in the ratio of 70:30. The Figure 4 illustrates the results achieved.

Measure	Batch Size	100	200	500	1000
Sensitivity	TPR = TP / (TP + FN)	0.84	0.85	0.88	0.91
Specificity	SPC = TN / (FP + TN)	0.76	0.78	0.84	0.88
Precision	PPV = TP / (TP + FP)	0.78	0.79	0.85	0.88
Negative Predictive Value	NPV = TN / (TN + FN)	0.83	0.84	0.87	0.91
False Positive Rate	FPR = FP / (FP + TN)	0.24	0.22	0.16	0.12
False Discovery Rate	FDR = FP / (FP + TP)	0.22	0.21	0.15	0.12
False Negative Rate	FNR = FN / (FN + TP)	0.16	0.15	0.12	0.09
Accuracy	ACC = (TP + TN) / (P + N)	0.80	0.81	0.86	0.89
F1 Score	F1 = 2TP / (2TP + FP + FN)	0.81	0.82	0.86	0.90
Matthews Correlation Coefficient	TP*TN - FP*FN / sqrt((TP+FP)*(TP+FN)*(TN+F) * (TN+FN))	0.60	0.63	0.72	0.79

Figure 4: Results Achieved

As shown in the Figure 4, the results improve as the batch size improves. After training first 100 samples, the accuracy is 0.80 and the F1 score is also 0.81, which is comparable with the work done by [22] with accuracy up to 0.73 and an F1 score up to 0.68. The accuracy after training 1000 samples has reached to 0.89, and the F1 score has reached to 0.90. Given bigger size of the image set, the results can be further improved.

CONCLUSION

The paper uses a generative adversarial neural network using two convolutional neural networks to generate, balance, and analyze medical images. The proposed method uses the weighted loss functions with fuzzy weights. The approach is used in the domain of CT scanned lung images for analysis and diagnosis of COVID-19 to get satisfactory results. After the successful prototype testing, many more aspects of the approach have opened up. The first one is about the use of fuzzy logic. The application of fuzzy logic is limited to determining weight factors only. It can be further enhanced to take its true advantages in inferencing as well as in the graphical interface development for the non-computer professionals in the medical domain.

Further, the hybrid loss function can be optimized just like an ordinary loss function using genetic algorithms. Besides this, instead of taking simple fuzzy membership functions, type 2 fuzzy membership functions can also be considered. The proposed method and algorithm are generic in the true sense and hence can be utilized for any image analysis and diagnosis with minor modifications.

References

[1] Generative adversarial nets. Goodfellow, I, et al. 2014. Proc. Adv. Neural Inf. Process. Systems. pp. 2672–2680.

[2] An Introduction to Neural Computing. Morton, H. and Aleksander, I. London: Int Thomson Comput Press, 1995.

[3] Dermatologist-level classification of skin cancer with deep neural networks. Andre, Esteva, et al. 7639, 2017, Nature, Vol. 542, pp. 115–118.

[4] Application of Machine Learning for the Detection of Heart Disease. Snig, Nagrale, Shivajirao, Jadhav and Yadav, Samir. 2020, pp. 165-172.

[5] Application of Fuzzy Convolutional Neural Network for Disease Diagnosis: A Case of Covid-19 Diagnosis Through CT Scanned Lung Images. [book auth.] Mayuri Mehta et al. TRacking and Preventing Diseases with Artificial Intelligence. s.l. : Springer, 2021, Vol. 206.

[6] A Convolutional Fuzzy Neural Network Architecture for Object Classification with Small Training Database. Hsu, M, Chien, Y and Wang, W. 2020, Intrernational Journal of Fuzzy Systems, Vol. 22, pp. 1-10.

[7] A Convolutional Fuzzy Neural Network for Image Classification. Korshunova, K. P. Vladivostok : s.n., 2018. 2018 3rd Russian-Pacific Conference on Computer Technology and Applications (RPC). pp. 1-4.

[8] ImageNet classification with deep convolutional neural networks. Krizhevsky, A, et al. 6, 2017, Communications of the ACM , vol. 60, no. 6, pp. 84–90, 2017, Vol. 60, pp. 84-90.

[9] Automatic segmentation of MR brain images with a convolutional neural network. Moeskops, P, et al. 5, 2016, IEEE Trans Med Imaging, sVol. 35, pp. 1252–1261.

[10] Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural network. Narin, A, Kaya, C and Pamuk, Z. 2021, Pattern Anal. Applications, pp. 1-14.

[11] Evolutionary pruning of transfer learned deep convolutional neural network for breast cancer diagnosis in digital breast tomosynthesis. Ravi, K Samala, et al. 9, 2018, Physics in Medicine & Biology, Vol. 63.

[12] COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19. Wang, L and Wong, A. 2020, Cases from Chest Radiography Images. In Arxiv.

[13] How Convolutional Neural Networks Diagnose Plant Disease. Yosuke, Toda and Fumio, Okura. Article ID 9237136, 2019, Plant Phenomics, Vol. 2019 , pp. 1-14.

[14] Wasserstein GAN. Arjovsky, M, Chintala, S and Bottou, L. 2017, arXiv preprint arXiv:1701.07875.

[15] Generative Adversarial Network for Image Super-Resolution Combining Texture Loss. Yuning, Jian and Jinhua, Li. 1729, 2020, Applier Science,, Vol. 10.

[16] Multi-class Generative Adversarial Networks with the {L2} Loss Function. Xudong, Mao, et al. 2016, CoRR, arxiv.org/abs/1611.04076), Vol. 1611.04076.

[17] Unrolled Generative Adversarial Networks}. Metz, Luke, et al. 2016, {arXiv}, 2016, https://arxiv.org/abs/1611.02163).

[18] Stabilizing training of generative adversarial networks through regularization. Roth, K., et al. 2017, Advances in neural information processing systems, Vol. 30.

[19] COVID19-CT-dataset: an open-access chest CT image repository of 1000+ patients with confirmed COVID-19

diagnosis. Shakouri, S., Bakhshali, M.A. and Layegh, P. 178, 2021, BMC Res Notes, Vol. 14.

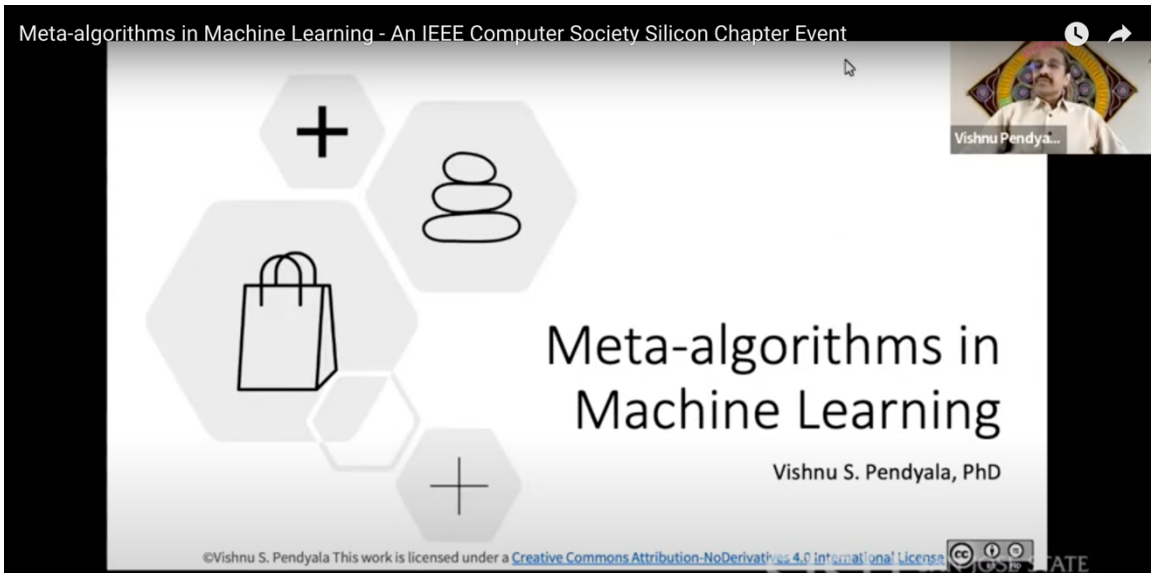
[20] Joseph Paul Cohen, Paul Morrison, and Lan Dao. Covid-19 image data collection. . [Online] 2020. arXiv preprint arXiv:2003.11597, 2020a..

[21] Jcs: An explainable covid-19 diagnosis system by joint classification and segmentation. arXiv preprint arXiv:2004.07054, 2020. Wu, Yu-Huan, et al. 2020, arXiv preprint arXiv:2004.07054, 2020.

[22] Hybrid deep learning for detecting lung diseases from X-ray images. Bharati, S., Podder, P. and Mondal, M. R. H. 100391, 2020, Informatics in Medicine Unlocked, Vol. 20.

***Dr**. Priti Srinivas Sajja has been working at the Post Graduate Department of Computer Science, Sardar Patel University, India since 1994 and presently holds the post of Professor. She specializes in Artificial Intelligence and Systems Analysis & Design especially in knowledge-based systems, soft computing and multi-agent systems. She is author of Illustrated Computational Intelligence (Springer, 2020) and Essence of Systems Analysis and Design (Springer, 2017) published at Singapore and co-author of Intelligent Techniques for Data Science (Springer, 2016); Intelligent Technologies for Web Applications (CRC, 2012) and Knowledge-Based Systems (J&B, 2009) published at Switzerland and USA, and four books published in India. She is supervising work of a few doctoral research scholars while eight candidates have completed their Ph.D research under her guidance. She has served as Principal Investigator of a major research project funded by the University Grants Commission, India and as a member of Indo-Russian Joint Research Project. She has produced 219 publications in books, book chapters, journals, and in the proceedings of national and international conferences out of which five publications have won best research paper awards.*

Event Recording from May 31
Meta-algorithms in Machine Learning
Dr. Vishnu S. Pendyala
https://ieeetv.ieee.org/video/meta-algorithms-in-machine-learning



Applied Data Science in Education

ICADS '22 Invited Talk

Dr. Elvira Popescu
Computers and Information Technology Department
University of Craiova, Romania

***Abstract*— Learning analytics (LA) is a growing research area, which aims at selecting, analyzing and reporting student data (in their interaction with the online learning environment), finding patterns in student behavior, displaying relevant information in suggestive formats; the end goal is the prediction of student performance, the optimization of the educational platform and the implementation of personalized interventions. The topic is highly interdisciplinary, including machine learning techniques, educational data mining, statistical analysis, social network analysis, natural language processing, but also knowledge from learning sciences, pedagogy and sociology. Despite its increasing popularity, LA has been applied less in the context of social media-based environments; hence in this talk we focus especially on research in social learning analytics area. In particular, we explore academic performance predictors and the relationships between students' learning styles and their social media use; we also investigate students' collaboration patterns and the community of inquiry supported by social media tools. Four research directions are tackled: analytics dashboards, predictive analytics, social network analytics and discourse analytics. As far as analysis techniques are concerned, we apply various approaches, such as: classification, regression, clustering and PCA algorithms, textual complexity analysis, social network analysis techniques, content analysis based on Community of Inquiry. We thus address the "trinity" of methodological approaches: i) network analysis (representing actor-actor / social relations); ii) process-oriented analysis (based on action logs and pattern detection); iii) content-oriented analysis (based on learner created artefacts); hence a more comprehensive learning analytics perspective is provided.**

Keywords*— *Learning Analytics, Natural Language Processing, Predictive Analytics, Social Network Analysis

■ 1. **Speaker Profile** Elvira Popescu is a Full Professor at the Computers and Information Technology Department, University of Craiova, Romania. Her research interests include technology-enhanced learning, adaptive educational systems, learner modeling, computer-supported collaborative learning, learning analytics, and intelligent and distributed computing. She authored and co-authored over 100 publications, including two books, journal articles, book chapters, and conference papers. In addition, she co-edited six journal special issues, as well as 20 international conference proceedings. She participated in over 15 national and international research projects, three of which as a principal investigator. Prof. Popescu also serves as the Vice Chair for the IEEE Women in Engineering Romania Section Affinity Group and is a board member for the IEEE Technical Committee on Learning Technology and the International Association of Smart Learning Environments. She is also a Distinguished Speaker in IEEE Computer Society Distinguished Visitors Program (2020-2023). She received several scholarships and awards, including five best paper distinctions. She is actively involved in the research community by serving as associate editor for three journals (IEEE Transactions on Learning Technologies, Smart Learning Environments, Frontiers in Computer Science), member of five other journal editorial boards, organizing a series of international workshops (SPeL 2008–2020), serving as a conference chair, program committee chair and track chair for over 20 conferences.

Next Generation Artificial Intelligence and Energy Sustainability

Dr. Celestine Iwendi
School of Creative Technologies
University of Bolton, UK

ICADS '22 Invited Talk

***Abstract*— The industry is on a mission to capture the business value that comes with the Next Generation Artificial Intelligence in the context of Industry 5.0 and Energy 5.0 as regarding the provision of renewable energy production facilities. This has greatly increased the need to address the cyber risk landscape with a secure, vigilant, and resilient response and system in place. This marriage of algorithms, processes, and ingenuity will enable humans and machines work together utilizing human-centric design solutions in collaboration with human resources to enable sustainable, personalized, and autonomous manufacturing through enterprise social networks. This talk will analyse how AI could engender better and more informed decision-making during crisis management scenarios. Furthermore, we shall elaborate how Industry 5.0 actively encourages and enhances the relationship between humans and robots in a cyber-physical domain and in the field of energy consumption, while also relying on advanced five-sense and hologram-based communications.**

Keywords*— *Industry 5.0, Energy 5.0, cyber risk, human-centric design, autonomous manufacturing, enterprise social networks

■ 1. **Speaker Profile** CELESTINE IWENDI is an IEEE Brand Ambassador as well as a visiting Professor with many universities including Coal City University, Nigeria; School of Computing, Faculty of Engineering, BIHER, India; and the School of Computing & Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, India.

He also serves as an Honorary Adjunct Professor and Investigator in the Center of Excellence in Robotics and Mechatronics, ITM Baroda University, India; Adjunct Professor, Delta State Polytechnic, Nigeria; Honorary Professor in the School of Computing Science and Engineering, Galgotias University, India; and an Associate Professor (Senior Lecturer) in the School of Creative Technologies, University of Bolton, United Kingdom. He is a Fellow of the Higher Education Academy, United Kingdom, and a Fellow of the Institute of Management Consultants.

His past assignments include Associate Professor, Bangor College China; Senior Researcher, WSN Consults Ltd, United Kingdom; Electronics and Sensor Researcher, University of Aberdeen, United Kingdom; and Lead Electronics Engineer, Inscentinel Ltd, United Kingdom. He received his Ph.D. in Electronics from the University of Aberdeen, United Kingdom, his MSc in Hardware Engineering from Uppsala University, Sweden, and his MSc and BSc in Electronic Engineering from Nnamdi Azikiwe University, Nigeria. He supervises/co-supervises several graduate (MSc and Ph.D.) students and mentors ACM student members at SAGE University Indore, India.

His research interests include Artificial Intelligence (AI), Internet of Things (IoT), wireless sensor networks, network/cybersecurity, machine learning, and data networks. He has authored over 60 peer-reviewed articles. He has served as chair (program, publicity, and track) in top conferences and workshops. He has delivered over 65

invited and keynote talks. He is a Distinguished Speaker, ACM; Senior Member of IEEE; Member, ACM; Member, IEEE Computational Intelligence Society; Senior Member, Swedish Engineers; Member, Nigeria Society of Engineers; and Member, Smart Cities Community, IEEE.

He is the Branch Counsellor of the IEEE University of Bolton Student Branch and a Board Member of the IEEE Sweden section. He mentors several Ph.D. students in Artificial Intelligence, robotics, Internet of Things and blockchain. He has developed operational, maintenance, and testing procedures for electronic products, components, equipment, and systems, and has also provided technical support to several organizations. He is a community developer, philanthropist and an international speaker in many top conferences and webinars. Dr. Celestine is listed among the 2% top-scientist list. The list has been prepared by Stanford University and published by Elsevier— https://lnkd.in/gVeV6CjB

Event Recording from June 14
Open House, Machine Learning, The Mortar of Modernization
Dr. Vishnu S. Pendyala
https://youtu.be/0T3DtvsMkK8

Chapter Awards

IEEE COMPUTER SOCIETY

Santa Clara Valley Chapter

Call for Nominations

IEEE Computer Society, Santa Clara Valley chapter is calling for nominations for the following awards:

- Industry Rising Star Award: Given to the professional who shows significant promise to lead substantial efforts in the computer industry
- Outstanding Woman Engineer
- Outstanding Educator
- Outstanding Student

Please feel free to nominate for other award categories not listed above that you believe the nominee deserves

All professionals are eligible – nominee need not be a member of the chapter but should be currently living within the Santa Clara Valley.

Awardees will receive a plaque, an e-certificate and recognition on the chapter website, magazine, and event(s).

To submit your nomination, visit https://r6.ieee.org/scv-cs/?p=2064

Submission deadline: Tuesday, July 12, 2022

Connect with us

https://r6.ieee.org/scv-cs/

https://www.linkedin.com/groups/2606895/

http://listserv.ieee.org/cgi-bin/wa?SUBED1=cs-chap-scv&A=1

http://www.youtube.com/user/ieeeCSStaClaraValley

https://www.linkedin.com/company/ieee-computer-society-scv-chapter/