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EDITORIAL

SPECIAL SECTION

Computational Intelligence in engineering practice

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Computational Intelligence (CI), strictly associated with artificial intelligence, is a collection of nature-inspired computational methodologies and approaches to deal with complex real-world problems that are very difficult to solve utilizing standard mathematical approaches to modeling. Computational intelligence is based on a few main pillars: artificial neural networks, especially of deep structure, fuzzy systems, evolutionary computation, and machine learning theory [1–3]. The methods used by CI are close to human reasoning. Based on the registered data, they can find adaptively hidden relationships existing between the particular items of the database.

Artificial neural networks can analyze the experimental data in a way similar to biological systems. Their characteristic features include regular multilayer structure and nonlinearity in the data processing as well as a special adaptation of parameters based on the learning data [4, 5]. Classical neural networks are composed of a limited number of hidden layers (most often three, including the input signal layer). On the other hand, deep neural structures are composed of many locally connected layers (sometimes exceeding a hundred), which perform the role of feature extraction and selection. Therefore, deep neural networks perform at the same time the function of automatic feature generation and the final task of classification or regression. Nowadays, they are most often used in different areas of signal and image processing [5]. Their efficiency in data analysis is significantly higher than traditional neural structures.

Fuzzy systems [2, 6] are based on fuzzy reasoning and analyze analog input signals in terms of logical variables (membership values) that take on continuous values between 0 and 1 (in contrast to Boolean systems, which operate on two discrete values, either 0 or 1). The crisp measured variables are transformed first into their fuzzy membership values, based on which the fuzzy inference if-then rules are formulated. A collection of fuzzy rules creates the so-called knowledge base, representing the acquired knowledge in approximate reasoning. The fuzzy systems have their advantages over classical Boolean approaches to problems in which the measured values are incomplete or imprecise. They have found many applications in control, identification, and decision support [6].

Evolutionary computation is a family of algorithms for global optimization inspired by biological evolution in nature [2]. It starts with an initial set of many candidate solutions, which are iteratively updated using the operations typical for biological evolution. The evolution process creates a new generation of solution vectors by applying reproduction, selection, mutation, and crossover operators. Candidate solutions represent the individuals in a population. The fitness function defines the quality of the solutions and is inversely related to the loss function in the optimization process. The evolution of the population is applied subsequently from generation to generation. As a result, the total population will gradually evolve to increase its fitness, defined appropriately to the problem being solved.

Machine learning theory creates computer algorithms that improve automatically, iteration after iteration, the performance of the analyzed system [1, 2, 7, 8]. Specialized algorithms are developed for neural networks, fuzzy systems, and evolutionary computation. However, all of them apply the optimization algorithms on a large scale. Machine learning is also closely related to computational statistics. The mathematical model of the analyzed process based on sample training data is built to make predictions without going into details of the real mechanisms of the system acting. The loss function representing the difference between the expected and actual values of the model is defined and is subject to minimization using different approaches to an optimization problem.

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Machine learning algorithms are usually divided into three broad categories: supervised learning, unsupervised learning, and reinforcement theory. In the first category, the target is explicitly known and used in the definition of a loss function. Unsupervised learning can also take different forms. One is the so-called self-organization, which facilitates modeling the probability density over multidimensional input data. The other one is the blind signal separation, i.e. the separation of signals from a set of mixed signals, without information (or with very little information) about the source signals or the mixing process [9].

Reinforcement is the process of shaping the behavior of the system by controlling its consequences [5]. A combination of rewards and/or punishments is used to reinforce the desired behavior or extinguish an unwanted behavior of the system.

CI plays a significant role in developing intelligent systems, including computer vision, early diagnosis of some diseases, drug discovery, biomedical informatics, prediction, natural language processing, recommender systems, robotics, gaming, and artificial creativity, to name just a few.

Recent advances in the field of CI and machine learning theory have greatly accelerated the research in all areas of engineering. They are well-suited now to different types of problems because of the ability to process a wide range of factors and generalize to unseen or new situations. They have provided many advantages in these applications, to the extent that the performance of CIs in multi-class classification and verification tasks can be sometimes even better than what is achievable by humans.

Artificial intelligence within the consumer, enterprise, government, and defense sectors is migrating to an essential technology driving improvement in quality, efficiency, and speed. The predicted artificial intelligence revenue is growing very quickly every year. Figure 1 depicts the growth in revenue from artificial intelligence for the enterprise application market worldwide from 2015 to 2024 (in millions of US dollars).

Deep neural networks play a very special role in CI [4], in particular different forms of convolutional neural networks

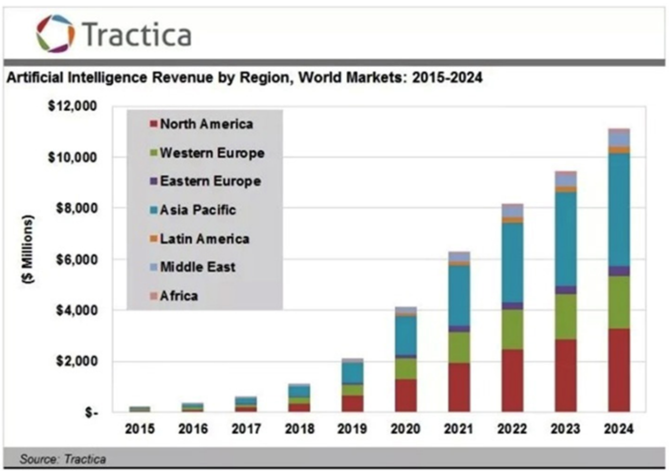

Fig. 1. The predicted growth of revenue from artificial intelligence for the enterprise application market worldwide (according to Tractica)

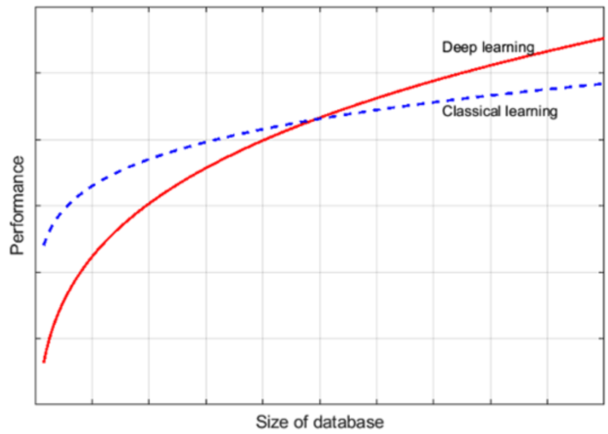

Fig. 2. The performance of deep learning over classical learning algorithms used in computational intelligence applications

(CNN). Their advantage over classical neural solutions is the increased ability to generalize. This is well seen in Fig. 2, presenting the performance of classical learning algorithms and deep learning algorithms with the increasing amount of data. This is the reason why so many different solutions to deep neural networks have been proposed nowadays [10]. They are available in the form of pre-trained structures ready to use for everybody in the form of so-called transfer learning. To such examples belong Alexnet, Resnet, Inception, Unet, R-CNN, Segnet, and many others [8–10].

Nowadays, deep learning has become the most important method in computational and artificial intelligence. Moreover, the increasing computational power of computers has greatly accelerated the research in this area and facilitated its practical application in different areas of our life.

The examples of applications of CI and deep learning include the recognition and classification of objects existing in images, photo descriptions, image restoration, real-time multi-person pose estimation, computer games, translation, voice generation, natural language processing, automatic machine translation, music composition, transferring style from famous paintings, colorization of black and white images, etc.

The application of CI in self-driving cars or mind-controlled wheelchairs is very famous (a mind-machine interfacing device that uses thought to command the motion of a motorized wheelchair [9]).

CI was found especially useful in bioengineering, in which we deal with very difficult problems of medical image and signal analysis (RTG, ECG, USG, CT, PET, OCT, and others). CI copes well with the increasing amount of data, input data sizes, and greater complexity of the objective real-world medical problems.

This Special Section of Bulletin of the Polish Academy of Sciences, Technical Sciences is devoted to the practical applications of CI in different areas of engineering, especially signal and image processing in bioengineering. It will contain the selected extended versions of the papers that have been presented at the International Online Conference of Computational Problems in Engineering in 2020.

The papers included in the presented issue of Bulletin represent a few categories: applications of CI in biomedical image processing [11–14], signal analysis [15–17], and application in game theory [18].

Paper [11] co-authored by A. Osowska-Kurczab, T. Markiewicz, M. Dziekiewicz, and M. Lorent is dedicated to building a multi-feature ensemble model for the recognition of 8 subtypes of renal neoplastic lesions. The presented model associates two independent methods of image description: textural features and deep learning strategy. Many different algorithms of classification were applied to single-phase computed tomography images containing 8 subtypes of renal neoplastic lesions. The final ensemble of classifiers includes a textural description combined with a support vector machine and various configurations of convolutional neural networks, including Alexnet, Resnet, and Inception. The results of experimental tests have proved that such a model can achieve 93.6% of the weighted F1-score in 10-fold cross-validation mode of 8 classes of renal lesions.

Paper [12] of E. Kot, Z. Krawczyk, K. Siwek, P. Czwarnowski, and L. Królicki is devoted to brain tumor detection and segmentation using deep learning methods. A universal and complex framework for two parts of the dose control process – tumor detection and tumor area segmentation in medical images is proposed. This framework implements methods to detect glioma tumors from CT and PET scans. Two deep learning pre-trained models: VGG19 and VGG19-BN were investigated and utilized to fuse CT and PET examination results. Mask R-CNN (region-based convolutional neural network) was used for tumor detection – the output of the model binds box coordinates for each tumor object in the image. U-Net was used to perform semantic segmentation – to segment malignant cells and tumor areas. Data augmentation methods were applied to generate and increase the number of training samples. The results presented in the paper may be used by radiologists for tumor detection during screening tests, thereby decreasing the time of diagnosis while increasing the accuracy.

Paper [13] by Z. Krawczyk and J. Starzynski studies the suitability of deep neural networks in automatic bone structure segmentation of the CT data series of the pelvic region. Four different models of neural networks (FCN, PSPNet, U-net, and Segnet) were trained to perform the segmentation task of the three following classes: background, patient outline, and bones. The mean and class-wise intersection over union measures were evaluated for each network outcome. The most exact segmentation results correspond to the use of U-net model, with the mean intersection union value equal to 93.2%. The results were further improved by introducing ResNet50 as the encoder in the U-net model.

Paper [14] by T. Leś presents an automatic system for generating kidney boundaries in computed tomography (CT) images. The U-Net network was used for image segmentation. Several improvements to the standard U-net have been proposed in the paper. Among them, there is an innovative solution for framing the input data, precision-recall analysis to calculate the optimal image threshold value, and the volumetric analysis of coherent areas to eliminate false-positive errors. The developed system facilitates a fully automatic generation of kidney boundaries as well as a generation of a three-dimensional kidney model. It is very helpful in increasing the accuracy of the performed medical diagnosis and reducing the time in preparation of the final medical description.

Paper [15] co-authored by M. Kołodziej, A. Majkowski, P. Tarnowski, R. Rak, and A. Rysz presents the application of 1D convolutional neural network in cardiac sympathetic index (CSI) estimation based on ECG recordings. It is known that CSI increases before the seizure of epilepsy, therefore, its estimation is of practical importance. The paper presents a new approach to CSI estimation using a deep learning approach. The experiments have shown the good performance of the method on the example of 40 epilepsy cases. The 1D-CNN results were compared with the regression methods, based on the application of multilayer perceptron, support vector machine, and linear regression. The results proved that the proposed 1D-CNN method is characterized by much better resistance to the noise and artifacts existing in the ECG signal.

Paper [16] by E. Majda-Zdancewicz et al. compared the application of selected signal processing methods and machine learning algorithms for the taxonomy of acquired speech signals representing the vowel *with* prolonged phonation in patients with Parkinson's disease and healthy subjects. The problem was solved by using different statistical description methods of speech signals as well as the deep learning approach based on the processing of images of spectrograms in different time and frequency resolutions. The discriminatory ability of feature vectors was evaluated using the SVM technique, while the spectrogram images were processed by AlexNet convolutional neural network with the application of transfer learning. The accuracy of the best method reached the value of 97% with the specificity no worse than 93%.

Paper [17] by F. Gil and S. Osowski aims to investigate and compare the performance of different selection methods for choosing the diagnostic features in classification problems. The investigated set includes such methods as Fisher criterion, refiefF, nearest component analysis, stepwise fit, Kolmogorov-Smirnov criteria, T2-test, Kruskall-Wallis test, feature correlation with class, and SVM recursive feature elimination. The investigations compare their sensitivity to the noisy data as well as the repeatability of the most important features. Based on this study, the best selection methods are chosen and applied in the process of selection of the most important genes and gene sequences in a dataset of gene expression microarrays in prostate and ovarian cancers. The results of their fusion can be treated in practice as biomarkers of cancer.

Paper [18] co-authored by K. Godlewski and B. Sawicki, presents the development of AI players based on Monte Carlo Tree Search algorithms in the card game "The Lord of the Rings". The main challenge is the complexity of the game mechanism, in which each round consists of 5 decision stages and 2 random stages. The research covered an agent based on expert rules, using a flat Monte-Carlo search, as well as a complete MCTS-UCB. Moreover, different play-out policies have been compared. As a result of the experiments, an optimal (assuming a limited time) combination of algorithms was formulated and successfully tested.

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References

[1] H. Das, J. K. Rout, and S.C.N. Dey, Maharana, *Applied Intelligent Decision Making in Machine Learning*, CRC Press, 2020.

[2] B. Zhang, Y. Wu, J. Lu, and K.L. Du, "Evolutionary computation and its applications in neural and fuzzy systems", *Appl. Comput. Intell. Soft Comput.* 2011, 938240 (2011), doi: 10.1155/2011/938240

[3] M. Injadat, A. Moubayed, A.B. Nassif, and A. Shami, "Machine learning towards intelligent systems: applications, challenges, and opportunities", *Artif. Intell. Rev.* (2021), https://doi.org/10.1007/s10462-020-09948-w.

[4] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*, MIT Press, 2016.

[5] J. Heaton, "Applications of Deep Neural Networks", arXiv: 2009.05673v2 [cs. LG] 2021, Heaton Research, Inc.

[6] E. Kayacan and M.A. Khanesar, *Fuzzy Neural Networks for Real Time Control Applications: Concepts, Modeling and Algorithms for Fast Learning*, Elsevier, 2015.

[7] A. Burkov, *Machine Learning Engineering*, True Positive Inc., 2020.

[8] A. Krizhevsky, I. Sutskever, and G. Hinton, *Imagenet classification with deep convolutional neural networks*, NIPS, 2012.

[9] A. Cichocki, R. Zdunek, A. H. Phan, and S.-I. Amari, *Nonnegative matrix and tensor factorizations: applications to exploratory multi-way data analysis and blind source separatio*n, Wiley, 2009.

[10] A. Khan, A. Sohail, U. Zahoora, and A.S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks", *Artif. Intell. Rev.* 53, 5455–5516 (2020), doi: 10.1007/s10462-020-09825-6.

[11] A. Osowska-Kurczab, T. Markiewicz, M. Dziekiewicz, and M. Lorent, "Multi-feature ensemble system for renal tumour classification", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e136749 (2021).

[12] E. Kot, Z. Krawczyk, K. Siwek, P. Czwarnowski, and L. Królicki, "Deep learning-based framework for tumour detection and semantic segmentation", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e136750 (2021).

[13] Z. Krawczyk and J. Starzyński, "Segmentation of bone structures with the use of deep learning techniques", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e136751 (2021).

[14] T. Leś, "U-Net based frames partitioning and volumetric analysis for kidney detection in tomographic images", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e137051 (2021).

[15] M. Kołodziej, A. Majkowski, P. Tarnowski, R. Rak, and A. Rysz, "A New Method of Cardiac Sympathetic Index Estimation Using 1D-Convolutional Neural Network", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e136921 (2021).

[16] E. Majda-Zdancewicz *et al.*, "Deep learning vs. feature engineering in the assessment of voice signals for diagnosis in Parkinson's disease", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e137347 (2021).

[17] F. Gil and S. Osowski, "Fusion of feature selection methods in gene recognition", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e136748 (2021).

[18] K. Godlewski and B. Sawicki, "Optimisation of MCTS player for The Lord of the Rings: the card game", *Bull. Pol. Acad. Sci. Tech. Sci.* 69(3), e136752 (2021).

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