International Journal of Advanced Engineering, Management and Science (IJAEMS)
Peer-Reviewed Journal
ISSN: 2454-1311 | Vol-9, Issue-8; Aug, 2023
Journal Home Page: https://ijaems.com/
Article DOI: https://dx.doi.org/10.22161/ijaems.98.5

Application and Methods of Deep Learning in IoT

Chirag Kumar Dilipbhai Patel[1], Dr. Prasadu Peddi[2]

[1]Research Scholar, Sunrise University, Alwar, Rajasthan, India
[2]Professor, Sunrise University, Alwar, Rajasthan, India

Received: 15 Jul 2023; Received in revised form: 11 Aug 2023; Accepted: 21 Aug 2023; Available online: 26 Aug 2023

Abstract— *In this talk, we provide a comprehensive overview of how to use a subset of advanced AI techniques, most specifically Deep Learning (DL), to bolster analytics as well as learning in the IoT URL. First and foremost, we define a development environment that integrates big data designs with deep learning models to promote rapid experimentation. There are three main promises made in the proposal: To begin, it illustrates a big data engineering that facilitates big data assortment in the same way that businesses facilitate deep learning models. Then, the language for creating a data perspective is shown, one that transforms the many streams of large data into a format that can be used by an advanced learning system. Third, it demonstrates the success of the framework by applying the tool to a wide range of deep learning use cases. We provide a generalized basis for a variety of DL architectures using numerical examples. We also evaluate and summarize major published research projects that made use of DL in the IoT context. Wonderful Internet of Things gadgets that have integrated DL into their prior knowledge are often discussed.*

Keywords— ***Deep Learning, IOT.***

I. INTRODUCTION

One definition of artificial intelligence (AI) is when computers can mimic human intelligence by doing activities normally done by humans with little to no human intervention. In the 1950s, experts in the field of programming design started to wonder whether they might teach computers to recognize, marking the beginning of the field of study today known as artificial intelligence. Initially, experts believed that AI could be programmed with great programs using a comprehensive strategy of clear set coding principles shown by human managers. This kind of artificial intelligence is mostly agent-based and was the dominant AI approach from the 1950s until the late 1980s. While this viewpoint is useful for solving problems that can be simply depicted, like playing chess, it is not equipped to solve problems that are more complex and require more nuanced analysis, such as those involving the representation of images, the localization of objects, the confirmation of verbal claims, or the clarification of linguistic concepts. Throughout the 1990s, ML emerged as a perfect technique that was quickly supplanting significant AI, and it has since become the most widely utilized, best field of AI.

Machine learning (ML) is a broad discipline, but deep learning (DL) is an area that has been growing in popularity over the last several years. DL combines frameworks for learning representations at several levels of detail (...) by creating fundamentally indirect modules that successively transform the representation at a given level into a representation at a more pressing, somewhat logically distinct level. DL's structure is fundamentally different from that of conventional ML systems, which gives it a great deal of adaptability. While just a handful of layers are actually in use, DL enables a computer to analyze raw data and quickly assess systems for depiction. DL does this via the use of artificial neural networks (ANN), with features like dynamic ability sorting and several caretaking layers that provide automated learning of constraint chains of relevance. Because DL estimates can swiftly complete tasks like resolving dependencies and recreating data from raw data (feature structuring), ML is inherently more efficient. As Google's AI defeated a human in the chaotic game Go, ANN received a few expressions of open enthusiasm. In order to filter through data and address comprehension, we apply a variety of enhancements at varying levels.

II. LITERATURE REVIEW

Zeng et al. (2017) have proposed a scalable big data integration architecture based on meta-synthesis for analyzing massive amounts of data. The foundation of the suggested framework is the notion of meta synthesis, which is based on the coordination of meta synthesis' structural style, intelligence, and comprehension. Data categorization, data creation, data finding, data attainment, and data inquiry have all been made possible via the employment of a variety of big data processing equipment and technologies, multi criteria decision making designs, and artificial smart procedures. Human factors in big data, big data preparation methods, cultural features of big data, big data components, big data executives, and data ambiguity are all areas where the suggested framework places special emphasis on finding solutions.

Oussous et al. (2018) spoke about how crucial data mining methods are in a few specific fields. Finding patterns and extracting value from massive datasets is a crucial use of data mining methods. Traditional data mining techniques, such as association mining, clustering, and classification, are incorrect and inefficient when applied to massive data. Such data is unfit for long-term storage and analysis due to its volume, velocity, and variability. In light of this, several data mining methods have included detection tactics that account for the data environment.

Haider and gandomi (2015) demonstrates that several meanings of big data are used in practice and research. Actually, these big data definitions vary depending on the understanding of the user, with some focusing on the characteristics of big data in terms of volume, assortment, and speed; others focusing on precisely what it accomplishes; and yet others categorizing it based on their business's requirements. Harris Interactive conducted an online survey of 154 C-suite corporate officials in April 2012 for the benefit of SAP, and Figure 7 displays the many interpretations of the term "big purchased."

Garca et al. (2016) highlights the rise of data pre handling inside distributed computing and how its use has altered the landscape of insight discovery from data. This is shown by looking at how data mining strategies and pre handling have evolved as a result of the widespread adoption of big data structures for storing, preparing, and analyzing data. The provided solution included a wide variety of data pre-handling strategy families, with considerations like optimal size support studied in terms of big data and data pre-preparing across the board of systems. Hadoop, Spark, and Flink, among other amazing large data systems, have also been discussed**.**

Pouyanfar et al., (2018) Artificial intelligence (AI) is rapidly approaching what many believe will be its moment of supremacy as deep adaptation gradually takes its place at the forefront of its field. Deep learning employs several levels of abstraction to have computational conversations with data reflections. Our view of data management has been revolutionized by a few key enabling agent deep learning calculations such generative adversarial networks, convolutional neural networks, and unit movements. By the way, there is a lack of knowledge about the history of this very active region since it has not been lately discussed from a broad perspective. These persuasive techniques as discovery tools are produced by a lack of central knowledge, which impedes fundamental progress. Additionally, deep learning has frequently been portrayed as a silver bullet to various obstacles in AI, which is far from the truth. This report begins with an extensive overview of the documented as well as the most recent best-in-class techniques in visual, sound, and content preparation, informal organization investigation, and common language handling, and then moves on to an in-depth analysis of the revolving as well as earth-shattering improvements in deep learning applications. It was also anticipated to deal with problems related to major learning, such as performance learning, disclosure structures, and online learning, and to discover how these problems may be transformed into fruitful future avenues for research.

III. METHODOLOGY

Proposed Approach

- Data Pre-Processor: It processes data in a variety of ways before it's used.
- Data Trainer: It's what you use to get your deep learning models trained.

Scope Of the Study

Many different areas of research and design make use of deep learning processes, such as speech recognition, image classification, and language processing. Traditional data preparation methods also have their limitations when it comes to dealing with massive amounts of data. Researchers have also recently combined a number of deep learning techniques with mixed learning in order to build very fast data-handling frameworks. The reliance of many of these approaches on vector space means they perform poorly outside of their intended context, which includes things like big data learning capabilities. Furthermore, one of the main causes of that dissatisfaction is the increased role that humans play in configuring new and better computations thanks to deep learning methods and machine learning.

IV. DATA ANALYSIS

Successful DL solutions have been shown with top-tier outcomes in a variety of settings, including banner planning, trademark language care, and image verification. The IoT industry is moving upwards. Models of brain systems vary greatly in terms of where they excel. In the realm of vision-related applications, convolutional networks tend to perform better overall, whereas AEs excel in irregularity disclosure, data denoising, and dimensional reduction for data depiction. Connecting the kind of neural framework model that works best across all of the different application domains is crucial.

In this section, we discuss the useful applications of DL in IoT environments. Our research has shown that many Internet of Things (IoT) applications rely on visual or image recognition for critical functions like validating traffic signs or maybe even diagnosing illnesses. Human stance differentiating evidence is only one example of an extra organization that may be put to use in both smart home applications and smart vehicle support. We consider many of these businesses to be foundational platforms upon which other Internet of Things (IoT) applications may be built. Rather than storing their data for future analyses, most businesses should focus on taking care of their regular operations as they arise. It's possible that there are other, less important groups present in each location. Organizational essentials and other IoT use cases are shown in Figure 1.

In the sections that follow, we'll first examine some of the most prominent IoT firms that rely on DL as their intelligence engine, before expanding our scope to include IoT applications as a whole.

Foundational Services

1) Image Recognition: The majority of IoT applications deal with scenarios where images or videos serve as the input data for DL. The widespread availability of high-quality cameras in smartphones has encouraged people all around the world to start shooting movies and taking images. Additionally, smart camcorders are employed in a wide variety of settings, including factories, sports stadiums, and savvy households. Among the most essential uses of such devices are picture confirmation/request and object ID.

When evaluating the overall success of IoT-related activities, it might be problematic to rely on just a small subset of available stock statistics. In order to train their models, several of these methods make use of publicly available normal image datasets like the MNIST collection of hand-written digits, the VGG face dataset, the CIFAR-100 and CIFAR-10 tiny pictures dataset, etc. Despite the fact that these statistics are great for general evaluation purposes near different processes, they do not reflect the unique qualities of IoT systems. Examples include situations when the data image is at night or maybe in a foggy or stormy environment state, and analysis for the system of vehicle acknowledgment in clever linked automobiles, which isn't often a prominent picture. Cases like this aren't controlled by the readily available datasets, hence the models suggested by those datasets don't cover all bases.

2) Speech/Voice Recognition: Minute chat confirmation is genuinely changing into a clearly dynamically typical and uncomplicated approach for people to assist out their contraptions, especially with the massive rise of wonderful mobile phones and wearables. In addition, the modest components of modern smartphones and wearables lessen the need for consoles and touch displays as a method of cooperative effort and dedication.

Several researchers have reported developing a low-force DL chip designed specifically for automated discourse recognition. The new, specialized chip uses just 0.2 to 10 milliwatts of power, which is far less than the power required to run a speech recognition program on a modern smartphone. DNNs for discourse recognition have been implemented in the spic and span chip. Three distinct neural networks, each with a different level of complexity, are used to create three distinct levels of vocal exercise recognition in service of energy conservation. Presumably Discourse movement may be distinguished from other types of motion by keeping an eye on the resistance presented by the natural world around it. If the system's administration determines that a voice has been detected, the chip will then execute an associated complexity sum acknowledgment structure, the operation of which is acoustic displaying to determine whether or not the voice seems to be discourse. If this system's output is more likely, the third network, which has the greatest practical use, is triggered to quickly decide on individual words.

3) Indoor Localization: Offering location-aware services like indoor navigation and store advertising is quickly becoming the norm in enclosed spaces. The Internet of Things (IoT) may find use for confined spaces in areas as diverse as smart homes, fairgrounds, and even buildings. Input data from these applications often comes from a variety of sources, including vision, obvious light correspondence (VLC), infrared, ultrasound, WiFi, RFID, ultra-huge band, and Bluetooth, to name a few. The vast majority of the writing in this review relied on mobile phones to acquire fingerprint-like markers broadcast by stationary transmitters (i.e., entry or maybe iBeacons) connected through Bluetooth or WiFi. Many projects have employed DL models to predict the area fingerprinted, and DL has also been put to use to locate interior conditions with remarkable accuracy. DeepFi is a system that uses a DL technique beyond fingerprinting WiFi channel declaration data to detect client locations. This approach incorporates both online and offline phases of preparation. In reality, DL is misused in the off-line preparation step to prepare all of the loads using the previously spared channel pronouncing information fingerprints. There are a number of reports in the literature that use somewhat different DL models in relation to various learning procedures in order to extract capabilities for use as assessment positions. These studies demonstrate that the limiting precision of DL models is directly impacted by the number of hidden layers and devices included inside the models. A convolutional neural network (CNN) may be used for in-house confinement by combining visual and appealing detecting data. CNN has also been tasked with deciphering owners' interiors by analyzing images captured of their immediate environments.

4) Physiological as well as Psychological State Detection: The Internet of Things (IoT) in conjunction with DL techniques is also utilized to observe a variety of human physiological and mental states, including the present, the work at hand, and emotional state. Most Internet of Things applications (smart houses, smart cars, entertainment (e.g. XBox), guidance, recovery similarly to health aid, sports, and current gathering) integrate a module for human attitude estimate or maybe practice confirmation to pass on their firms. For instance, smart houses' organization of beneficial apps is informed by an analysis of residents' attitudes. The cameras feed the occupant's video feed into a DNN, which analyzes the data to determine the person's position and then executes the most appropriate action. Toshev describes a framework that makes use of a CNN model to do this. This kind of company may also be used in the classroom to gauge students' interest and in stores to simulate consumers' purchasing habits.

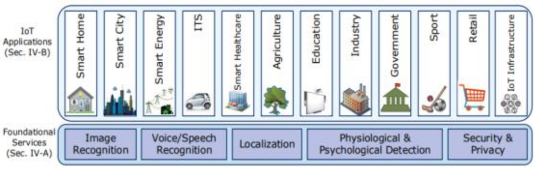

Fig. 1: IoT applications and the foundational services

V. APPLICATIONS

1) Smart Homes: With the help of the Internet of Things (IoT), smart houses may centralize a wide range of tasks that improve residents' convenience, income, and quality of life. Devices used inside the nuclear family may now link to the internet and provide additional intelligent services. Cortana DL is being used by Liebherr and Microsoft in a joint effort to analyze data collected from within the cooler. When combined with other external data, these analytics and hypotheses may be utilized to assess and predict general prosperity patterns in the home and to help the homeowner have a far better handle on the expenses and supplies of maintaining their household.

Using three DL models—LSTM, LSTM Sequence-to-Sequence (S2S), and CNN—Hyper conducted an evaluation study on weight comparing for domestic imperativeness usage. Their results show that LSTM S2S is superior to other methods for predicting best-in-class performance, with CNN coming in second and LSTM third. They also distinguished between the unknown dataset and a baseline ANN, and all of the most recently cited models ultimately prevailed over the ANN.

2) Smart City: Organizations in forward-thinking cities consider a wide range of Internet of Things (IoT) fields, including transportation, agriculture, urgency, etc. Also, from an AI standpoint, this region is becoming more and more satisfying, as the disparate datasets collected from numerous locations ultimately form a large dataset that, when evaluated with DL models, will inspire tremendous productivity gains. The progress made in one area helps the city of splendor as a whole in terms of its resourcefulness. Getting plans and analytics out of open transportation activities, for instance, is useful for local professionals since it helps the open transportation structure and provides new redesigned organizations.

Together with Dell Technologies, Toshiba has recently developed a DL testbed for use in analyzing the data collected by a community center in Kawasaki, Japan. The testbed's operation is meant to evaluate the ease of applying DL models in IoT natural frameworks and choose the most optimal approaches for business redesign, which incorporates expanding machine accessibility, enhancing monitoring receptors, and decreasing maintenance expenses. The massive data which maintains the demonstration site was compiled through official construction, air conditioning, and security measures.

Predicting the construction of new public buildings and the ways in which they will be used for public transit is a crucial problem for any genuinely magnificent city. To achieve this objective on a metropolitan scale, Song developed a method that relies on DNN models. Their strategy is based on a four-layer recurrent long short-term memory (LSTM) neural architecture to discover from GPS data on people and their various modes of transportation. Instead of working together to overcome these limitations, they split the mobility of the population and the transportation industry into separate sectors.

Table 1 Typical Iot-Based Services in Smart City

Service	Input data	DL model
Crowd density/ transportation prediction	GPS/ transition mode	LSTM
	Telecommunication data/CDR	RNN
Waste management	Garbage images	CNN
Parking lot management	Images of parking spaces	CNN

Liang proposed a method for measuring crowd density at transit hubs that makes use of information about mobile phone users' media transmissions -- also known as a "visitor detail record," or CDR. CDR data are genuinely obtained whenever a client makes a media transmission move on the telephone (i.e. a call, SMS, MMS, or Internet access), and they often include information on the customer's ID, geographic location, and time, in addition to their telecommunications activity. Similarly to how they found that logically precise wishes differed from nonlinear autoregressive neural system models, they constructed their system based on an RNN model for metro stations. Waste management and refuse collection are two sides of the same coin for thriving metropolitan areas. In the past, deep convolutional neural networks (CNNs) have been used for vision-based automation leadership. One more route for organized control is monitoring air quality and anticipating pollution. By using a stacked AE for single trademark extraction and a determined backslide model for the final gauges, Li was able to create a DL-based air quality want model.

Amato created a decentralized system that uses brilliant and deep CNN cameras to choose the empty and included spaces inside designated stopping areas. The experts provided a basic framework for a CNN using smart cameras and the Raspberry Pi 2 computer. In this way, the CNN may be performed on each camera unit, and images of express auto rest stops can be sorted into empty and occupied categories. The cameras would only relay the request's outcome to the rules server. Additionally, Valipour built a framework for detecting parking spaces using CNN and discovered that it produced notably better results compared to SVM baselines. Recent projects are included in Table III.

3) Energy: The two-way dialogue between vitality consumers and the smart system is a treasure trove of Internet of Things big data. Canny meters are the wave of data progress despite acquisition in this extraordinary situation, allowing for granular assessment of energy use. In order to succeed in the market, energy providers must master the next power use designs, foresee the needs, and make sound judgments based on real-time data. Mocanu have developed a kind of RBM to continually recognize and predict the buildings' energy potential. Changes in a family's power consumption that have a little effect on the travelers themselves constitute vitality flexibility. Adaptive power management is expected to be realized within the context of the aforementioned use, duration of use, and performance of selected home appliances.

On the bright side of things, calculating the potential of electrical power from renewable sources like the sun, the wind, and other forms of natural controllable force is an active area of study. The area is seeing a rise in the adoption of DL across a variety of use cases. Take a look at the overall performance of several DL models such as DBNs, AEs, LSTMs, and MLPs while trying to visualize the solar-powered importance of twenty-one different types of photovoltaic plants. An essential aspect of the analysis for sun-based imperativeness is a numerical motivating factor for atmosphere determining in a certain time horizon. Their research shows that when differentiating and comparing models, the combination of LSTMs and AEs (Auto LSTM) produces the best possible outcomes. Since Auto LSTM is able to infer attributes from noisy data, it may be used to validate a high desire score, which isn't the case with MLP. Additionally, ANN In, a web determining structure sensitive to LSTM, is offered to forecast the solar flare strength twenty-four hours in advance.

4) Intelligent Transportation Systems: The data collected by Intelligent Transportation Systems (The) is another example of the increasingly ubiquitous nature of big data. Mother proposed a strategy for assessing the feasibility of DL-based transportation options. For their models of a parallel figuring situation, they've relied on RNN and RBM architectures, with GPS data from intriguing explorations serving as a comparable commitment to the models. Preparing their method to anticipate traffic jam progress from more than an hour's worth of data took no more than six minutes, and it was accurate to within eighty percent. The evaluation of flashing traffic stream desire was also seen. In their study, they found that LSTM was the most effective learning model when compared to a number of other popular options, including as support vector machines, simple feed-ahead neural networks, and stacked AEs.

VI. DEEP LEARNING ON IOT DEVICES

Before the advent of the Internet of Things, the majority of DL studies focused on boosting its count and attempting to transmit practical models on cloud stages in case the problem became too large to handle the massive data. When the scale of the problems reduced to the level of resource-constrained devices, interest in continuous analytics grew in a way that was not possible before the development of IoT.

In some measure, light weight understanding is required to ponder splendid things. Given DL's fruitful results in talk and video applications, which are among the most fundamental services and commonplace uses of IoT, adapting its procedures and models for arrangement on asset-restricted gadgets has been an exceptionally fundamental focus of research. To far, DL methods have been inapplicable in asset constrained gadgets and IoT for educational purposes due to the resource-intensive nature of DL models. There are situations when the readily available resources are inadequate to cope with a pre prepared DL computation for induction assignments. To our relief, it has recently been shown that many of the parameters often used in DNNs might really be detrimental. In certain cases, it may be unnecessary to use several obfuscated layers in pursuit of precision. As a result, these DNNs may become IoT-friendly by effectively removing these parameters and, moreover, layers, which will significantly reduce their sensitivity to noise without significantly reducing their output. The remainder of this section will focus on the techniques and tools that have been developed to achieve these ends, and will demonstrate how they have been put to use in a variety of contexts.

Methods and Technologies

DL models may include millions or even billions of parameters, necessitating fast computing and a large amount of storage space. In this section, we take a look at a variety of state-of-the-art methods for bringing DL models to IoT-enabled, low-resource gadgets.

1) Network Compression:

Using system pressure, in which a dense network is converted to a sparse one, is one approach of delivering DNNs to resource-constrained devices. When DNNs are used for various forms of distinction on IoT devices, this strategy may assist keep their storage and processing demands to a minimum. One major drawback of these methods is that they can't properly account for a large variety of networks. It's only relevant for sparsity-displaying system models.

The authors conducted tests of the approach on four vision-related models: LeNet5, LeNet-300-100, VGG-16, and Alex Net. Even if the models' precision had been nearly safeguarded, they had been compressed numerous times for AlexNet and many times for VGG 16. The approach is limited in that it can only be used to one specific kind of DNN model.

Table 2 DNN Sizes and Complexities In Different Applications

	Type of DNN	Depth	Layers Sizes	Training Time	Test Time
Transportation analysis	RNN+RBM	2	R(100)-RBM(150)	NA	354 (s), whole test set
Localization	RBM DBN	4 4	500-300-150-50 300-150-100-50	NA	NA
Localization	SdA DBN ML-ELM SDELM	4 3 5 5	26-200-200-71 26-300-71 26-300-300-1500-71 26-300-300-1500-71	451 (s) 110 (s) 14 (s) 24 (s)	NA
Localization	SdA	5	163-200-200-200-91	NA	0.25 (s)
Pose detection	CNN	12	C(55×55×96)-LRN-P- C(27×27×256)-LRN-P-C(13×13×384)-C(13×13×384)-C(13×13×256)-P-F(4096)-F(4096)-SM	NA	0.1 (s)
Human activity detection	CNN+LSTM	7	C(384)-C(20544)-C(20544)- C(20544)-L(942592)-L(33280)-SM	340 (min)	7 (s), whole test set
Human activity detection	LSTM	5	L(4)-FF(6)-L(10)-SG-SM	NA	2.7 (ms)
FDI detection	DBN	4	50-50-50-50	NA	1.01 (ms)
Malware detection	DBN	3	150-150-150	NA	NA
Parking space	CNN	8	C(64×11×11)-C(256×5×5)-C(256×3×3)-C(256×3×3)-C(256×3×3)-F(4096)-F(2)-SM	NA	0.22 (s)
Traffic sign detection	CNN	6	C(36×36×20)-P-C(14×14×50)-P-FC(250)-SM	NA	29.6 (ms) on GPU 4264 (ms) on CPU
food recognition	CNN	22	Used GoogLeNet	NA	50 (s)
Crop recognition	CNN	6	C(96×7×7)-P-C(96×4×4)-P-F(96)-F(96)	12 (h)	NA
Classroom Occupancy	CNN	5	C(6×28×28)-P-C(16×10×10)-P-F(120)	2.5 (h)	2 (s) (4 thread)
Fault diagnosis	AE	4	300-300-300-300	NA	91 (s)
Road damage detection	CNN	8	Used AlexNet [37]	NA	1.08 (s)
Classifying offensive plays	RNN	3	10-10-11	NA	10 (ms)

For use with dense network models, a guessing motor known as EIE was developed using a specialized piece of hardware design similar to SRAMs rather than DRAMs, and its efficacy was shown. This technology allows for the management of redid insufficient lattice vector duplication and industry sharing without compromising the system's overall viability. The engine is made up of a flexible cluster of preparation segments (PEs), each of which does its comparing computations in its own SRAM. Since almost all of a neural network's available power is used up in the process of retrieving data from memory, this artificial speeding agent consumes far less energy than its benchmark system.

VII. CONCLUSION

When it comes to the automated extraction of obscure data portrayals (features) at deeper levels of reflection, Deep Learning computations are a very promising avenue of research. Such calculations provide a multi-tiered, dynamic structure of learning and addressing facts, in which higher-level (more potent) restrictions are genuinely seen in articulations of more base-level (less imaginary) traits. Artificial intelligence mimics the deep, layered learning technique of the rule sensorial territories of the neo cortex within the human character, which quickly concentrates thoughts similarly as limits from the concealed data, and this dynamic learning structure of Deep Learning counts. Learning from large amounts of isolated data is a strong suit for Deep Learning algorithms, which also tend to uncover data representations in an unendingly layer-wise fashion. Accumulating nonlinear part extractors (as in Deep Learning) has been shown to produce better AI results than other methods, including more recent portrayal illustrating, higher quality conveyed tests by generative probabilistic models, and the invariant property of data depictions.

REFERENCES

[1] Zeng, Z., Xu, X. and Shi, J. (2017), Meta synthesis-based intelligent big data processing paradigm, in ‘Proceedings of the Tenth International Conference on Management Science and Engineering Management’, Springer, pp. 455–466.

[2] Oussous, A., Benjelloun, F.Z., Lahcen, A.A. and Belfkih, S., 2018. Big Data technologies: A survey. Journal of King Saud University-Computer and Information Sciences, pp. 431-448.

[3] Gandomi, A. and Haider, M., 2015. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, Volume 35, pp. 137-144.

[4] García, S., Ramírez-Gallego, S., Luengo, J., Benítez, J.M. and Herrera, F., 2016. Big data preprocessing: methods and prospects. Big Data Analytics Journal, p. 9.

[5] Pouyanfar, Samira & Sadiq, Saad & Yan, Yilin & Tian, Haiman & Tao, Yudong & Presa Reyes, Maria & Shyu, Mei-Ling & Chen, Shu-Ching & Iyengar, S.. (2018). A Survey on Deep Learning: Algorithms, Techniques, and Applications. ACM Computing Surveys. 51. 1-36. 10.1145/3234150.

[6] Qingchen ZhangLaurence T. YangZhikui ChenPeng L (2018) “A survey on deep learning for big data” Information Fusion 42 (2018) 146–157147

[7] Dekhtiar, Jonathan & Durupt, Alexandre & Bricogne, Matthieu & Eynard, Benoit & Rowson, Harvey & Kiritsis, Dimitris. (2018). Deep learning for big data applications in CAD and PLM – Research review, opportunities and case study. Computers in Industry. 100. 10.1016/j.compind.2018.04.005.

[8] Elaraby, Nagwa & Elmogy, Mohammed & Barakat, Shereif. (2016). Deep Learning: Effective Tool for Big Data Analytics. International Journal of Computer Science Engineering (IJCSE). 5. 254-262.

[9] Benuwa, Ben & Zhan, Yong & Ghansah, Benjamin & wornyo, Dickson & Banaseka, Frank. (2016). A Review of Deep Machine Learning. International Journal of Engineering Research in Africa. 24. 124-136. 10.4028/www.scientific.net/JERA.24.124.

[10] Chen, Xue-Wen & Lin, Xiaotong. (2014). Big Data Deep Learning: Challenges and Perspectives. Access, IEEE. 2. 514-525. 10.1109/ACCESS.2014.2325029

[11] Juergen Schmidhuber (2014) “Deep Learning in Neural Networks: An Overview” Neural Networks, 61. 10.1016/j.neunet.2014.09.003.

[12] Elgendy, N. and Elragal, A., 2014. Big data analytics: a literature review paper. s.l., Springer, cham, pp. 214-227.

[13] Marz, N. and Warren, J. (2015), Big Data: Principles and best practices of scalable realtime data systems, Manning Publications Co.

[14] Rathore, M. M. U., Paul, A., Ahmad, A., Chen, B.-W., Huang, B. and Ji, W. (2015), ‘Real-time big data analytical architecture for remote sensing application’, IEEE journal of selected topics in applied earth observations and remote sensing 8(10), 4610– 4621.

[15] Mart´ınez-Prieto, M. A., Cuesta, C. E., Arias, M. and Fernandez, J. D. (2015), ‘The ´ solid architecture for real-time management of big semantic data’, Future Generation Computer Systems 47, 62–79.