Deep Learning and Current Trends in Machine Learning

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***Abstract*— Academic interest and commercial attention can be used to identify how much potential a novel technology may have. Since the prospective advantages in it may help solving some problems that are not solved yet or improving the performance of readily available ones. In this study, we have investigated the Web of Science (WOS) indexing service database for the publications on Deep Learning (DL), Machine Learning (ML), Convolutional Neural Networks (CNN), and Image Processing to reveal out the current trend. The figures indicate the strong potential in DL approach especially in image processing domain.**

Keywords*— *DL, ML, Image Processing, Convolutional Neural Networks, Current Trends

I. Introduction

Deep Learning (DL) applications has got considerable academic interest in the last decade, since its intrinsic characteristic to exploit more complex and human-imperceptible relations in between the input variables [1, 2]. DL is a novel Machine Learning (ML) method which produces better results on complex ML problems when compared with the previous ones. DL mainly utilizes deep Artificial Neural Network (ANN) infrastructure to discover the interdependencies in between the input variables and the observed outputs [3]. From an abstract perspective, DL approach differs from that of ANN considering the derivative of the input variables, each hidden-layer receives a derivative of previous level inputs. Significant number of scientific studies, which employ DL method, were conducted on image processing problems and reported better classification results with respect to classical ML ones [4, 5, 6, 7, 8, 9].

There is a strong tendency in contemporary scientific researches and marketed–applications towards DL approaches in ML domain. Although backpropagation and gradient calculation were known earlier and well used in trainable decision networks, using cascaded derivatives of input in successive layers brought a different perspective to ML, which was inspired by DL approach [10]. However, depending on the computation power in hand, the learning phase of DL may require intolerable length of time, since wide range of inputs, large number of layers and complexity in backpropagation calculation [11, 12]. Since a typical DL application employs 5 to 15 network layers and 15 to 30 in Very Deep DL applications it requires to process quite a large number of sample data in training phase when it is compared with traditional ML algorithms [13]. Happily, recent improvements in available computation power, usage of GPU in matrix arithmetic and perfection in parallel processing environments provide satisfactory computation resources and enable viable DL applications in the last decade [14, 15]. Moreover, a novel technique, called Transfer Learning, enables an already-trained DL network to be adapted in a similar problem with less number of training data in a shorter training time. Such that, the number of scientific experiments and installed applications which make use of this novel approach, is prominent, especially in image, video, speech and audio processing domains.

Convolutional Neural Network (CNN) is a term to refer a kind of DL network that convolve the previous layer input with a filter to calculate the derivative to form the input for the next layer [16]. CNN performs better where the input has a matrix representation and the referential positions of the features in the input are important. Alternatively, Recurrent Neural Network (RNN) is used to refer a decision network that utilize the sequence pattern of the input signals [17]. RNN is proved to yield better results on sequential data such as text and speech [18, 19].

In this paper, with a purpose to emphasize the importance of the DL approach in solving ML problems, we summarize and analyze the current researches conducted on image processing, CNN, ML, and DL domains between 2010 and 2017. Comparative figures and percent ratios are given in order to gain a view on present-day scientific trend in ML researches. In the following section, number of published researches in image processing, DL and ML are presented and analyzed. In the conclusion section, current trends in ML researches are discussed.

II. DL, Image Processing, Convolutional Neural Networks and ML in the Literature.

As the new approaches to ML problem solving, specifically in automatic calculation, are introduced scientific and sectoral interest get eager to exploit its potential. Concerned scientists initiate researches on the novel method and examine how to apply it on different problem domains, while the sector companies engage in utilizing it in their production. So that the number of scientific research-projects and publications may safely be used to specify how much prospective the new method is.

In this study, we surveyed the academic literature to determine and point how much the DL approach is important

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in ML and, specifically, in image processing. We have investigated the WOS scientific publication indexing service database to identify the number of researches conducted on DL, ML, Convolutional Neural Networks and Image Processing between the years 2010 and 2017. Recent number of the publications indexed by WOS indexing service are given along with respective ratios, in order to help readers to comprehend current trends by relative comparison.

In order to find the number of publications related to the DL, ML and CNN; the publications indexed by WOS service are searched as of May 2018. In the search, keywords, "Deep Learning", "Machine Learning" and "Convolutional Neural Networks" are scanned in "topic" of the articles. As it is reported in the WOS web site, the "topic" item search includes Title, Abstract, Author Keywords and Keywords-Plus. So in order to make an exclusive search, the "topic" search is used with the years as the search boundary.

First of all, we examined the number of publications related to ML, DL and both of them are between 2010 and 2017. The number of publications are given in Table I and shown as graph in Fig. 1.

TABLE-I THE NUMBER OF PUBLICATIONS RELATED TO ML AND DL

Year	# ML Papers	# DL Papers	# DL & ML Together Papers
2010	3603	653	56
2011	4079	722	58
2012	4503	823	84
2013	5747	1040	142
2014	7237	1438	278
2015	10077	2846	537
2016	12736	4608	1020
2017	14591	7444	1738
TOTAL	**62573**	**19574**	**3913**

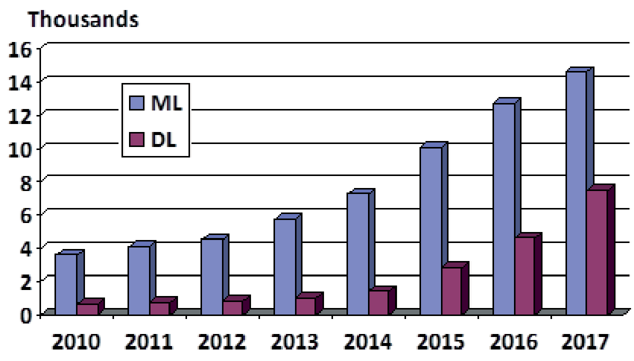

Fig. 1. Number of WOS Indexed Publications with respect to years.

As seen at Table 1, the total number of publications related to ML is 62573. It is clear that there is an increase about on the number of publications related to ML between 2010 and 2017. Especially there is nearly 50% increase between the years 2014 and 2015.

If we examine the number of publications related to DL (column3 of Table 1), we notice that the total number of publications related to DL is 19574 and it is increasing year by year. While there were 653 publications in 2010, this number is 7444 for 2017. Thus, during 7 years, the number of publications increased more than 10 times. The number of publications about DL was 1438 in 2014, and this number is nearly doubled in 2015 (a total of 2846 publications in 2015). Table 1 clearly shows that there is an increasing interest towards DL in academic world. Another interesting point about Table 1 is that the total number of publications related to DL in 2017 is 7444, which is 38% of the total publications.

We have also included the number of publications related to both DL and ML at the last column of the Table 1. As can be seen from that column, there are 3913 publications related to DL and ML in total. Since DL is a special type of ML and ML and DL are highly correlated topics, it is not surprising to see that there are publications including both of the topics.

A. Trends about image processing using DL approaches

It is shown in Table II, a cumulative total of 5766 articles on using DL in image processing have been indexed by WOS out of 19574 articles on DL only between 2010 and 2017. This simply calculates to 29% of DL articles were on image processing problems. However, this ratio is the average figure for 8 years. The one of the important points in Table II is the regular increasing ratio in the number of publications on image processing problems that are utilizing DL approach over that of DL only. The ratio is about 5% seven years ago (in 2010) and it reached to 40% in year 2017, ten times higher than the earlier.

TABLE II. NUMBER OF PUBLICATION ON DL + IMAGE PROCESSING AND DL ONLY.

Year	# DL and image processing papers		# DL **ONLY** papers		% of image processing publications
	Number	*Change %*	*Number*	*Change %*	
2010	32	-	653	-	4,90
2011	47	46,88	722	10,57	6,51
2012	51	8,51	823	13,99	6,20
2013	108	111,76	1040	26,37	10,38
2014	231	113,89	1438	38,27	16,06
2015	764	230,74	2846	97,91	26,84
2016	1538	101,31	4608	61,91	33,38
2017	2995	94,73	7444	61,55	40,23
	5766 Total	**101,12 Ave.**	**19574 Total**	**44,37 Ave.**	**29,46 Total Ave.**

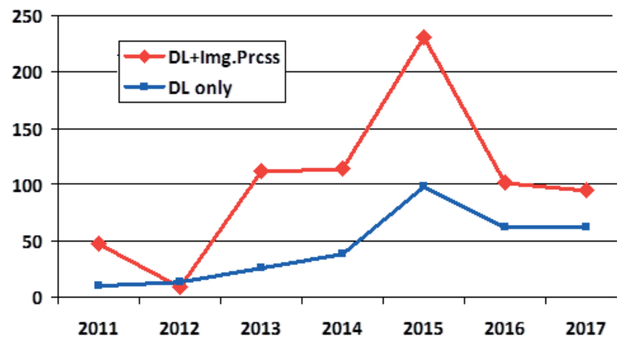

Fig. 2. DL+Image Processing and DL only publications Change % variations by years.

Fig. 2 indicates that except the year 2012 the percent ratio is on regular rise in the last 8 years, making it almost the half of the DL publications in 2017 are on DL and Image Processing. Although the number of indexed publications on DL only are on a constant rise in each year and having a yearly average increase 44%, that of on DL and image processing is also on rise and yearly average (101%) is more than two times higher than DL only. Year 2015 was an exceptional for DL and image processing publications with an increase ratio of 230 %.

Instead of image processing, when WOS indexing database is searched for the publications on Convolutional Neural Network (CNN) during the same period, the number of publications has been found as in Table III. In line with image processing publications, the increasing ratio in the number of publications on CNN displays an exceptional case (415%) in 2015. However, the average the ratio of increase in the number of publications on convolutional neural network is more than half than that of image processing with average increase values about 155% and 101% respectively. Interestingly in 2017 the publication number on CNN is observed to be on a respective decline with a rise ratio of 98% when the figure is compared with that of previous year. Although a decline in the rise ratio is also witnessed in 2017 for the number of DL and image processing article number, it is not as distinctive as in convolutional neural networks.

TABLE III. NUMBER OF PUBLICATION ON CONVOLUTIONAL NEURAL NETWORK AND DL ONLY.

Year	# CNN papers		# DL **ONLY** papers		CNN papers %
	Number	*Change %*	*Number*	*Change %*	
2010	21	-	653	-	3,22
2011	15	28,57	722	10,57	2,08
2012	28	86,67	823	13,99	3,40
2013	77	175,00	1040	26,37	7,40
2014	178	131,17	1438	38,27	12,38
2015	918	415,73	2846	97,91	32,26
2016	2289	149,35	4608	61,91	49,67
2017	4550	98,78	7444	61,55	61,12
	8076 Total	**155,04 Ave.**	**19574 Total**	**44,37 Ave.**	**44,37 Total Ave.**

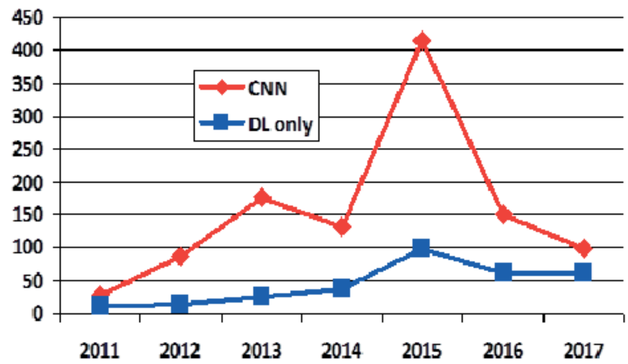

Fig. 3. CNN and DL only publications Change % variations by years.

B. *Trends in image processing applications*

DL based Image Processing applications can be divided into three groups. In this first group, the inputs are images to the DL, and DL tries to identify the object that the image has. This is known as classification. In the second group the inputs are images again, and the system try to find if the image has the object that it tries to find. For example, this system tries to find if the input image has a car inside it or not. This approach is known as detection. The last group, which is known as localization, tries to find the location of the searched object in the image.

As it is obvious each approach has its own requirements and own methodologies. In order to determine the current trends about those groups, the WOS based number of publications are listed in Table IV. Please note that in this study “DL” and “image processing” keywords also included in addition to classification, detection and localization terms in the search in order to filter the DL and image processing related papers.

TABLE IV. NUMBER OF PUBLICATION RELATED TO CLASSIFICATION, DETECTION AND LOCALIZATION

Year	# of papers related to classification and DL	# of papers related to detection and DL	% of papers related to localization and DL
2010	4	1	-
2011	7	3	3
2012	15	7	1
2013	37	13	3
2014	97	33	6
2015	326	139	33
2016	653	382	60
2017	1337	780	151
TOTAL	**2476**	**1358**	**257**

As can be seen from Table 4, most of the publications focus on image classifications problems using DL. The second most popular group is the detection group. As a relatively new application area localization has the least number of publications.

Another important point about Table 4 is that the number of publications for all groups have an increasing trend and we believe that the number of publications will increase in the near future.

III. CONCLUSIONS

Academic and sectoral interest can be used to point how much the method is prospective and important. Since if the potential of a method is evident to many scientists, they would exploit this method in their researches. On the other hand, if a method is to increase the performance or decrease the fabrication cost of a product, then it will surely attract commercial attention as well. Therefore, the level of interest in academia and production market can be used to indicate the potential of a novel methodology.

In this present study, we focused on the WOS indexing service database to find out how much an academic interest has been attracted by DL approach in ML domain during the last 8 years. Current figures for the number of publications on DL, ML, CNN, and İmage Processing are obtained by executing key word searches. We analyzed the collected publication numbers in order to recognize the recent trend and incline in academia in ML domain.

The figures and relative percent ratios reported in this study show that there is a strong drift towards DL approach on ML problems between the years 2010 and 2017. Considerable number of researches out of the ones on ML have studied DL methodology in researches with an indisputable average ratio of 50%. Results in this study apparently indicate the strong academic interest on DL methodology.

Alternatively, major technology companies such as Google, Facebook, Microsoft, IBM, Yahoo, Twitter and Adobe have already initiated researches and disseminated several (at least beta version) products, especially on image understanding. Such that, computers successfully identify the objects with their behavioral and locational relative-interrelations and understands the content of any given image. There are experimental automated solutions to produce captions for the images [20].

Additionally, educational initiatives have already been taken to cover DL fundamentals and its applications in higher educational curriculums, in order to equip the graduates with fundamentals of DL and related skills. A multinational curriculum development project for higher educational institutions to teach DL in undergraduate level was submitted to EU Erasmus+ Strategic Partnership program [21]

In conclusion, with its rising abstraction, achieved by increasing derivatives, on each level and high number of levels DL seems to be dominant in ML for the close future. Its potential in image, voice, video processing, medicine, genetics, physics problems and particularly natural language understanding have already been proven, but many others are still pending.

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