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BIG DATA ANALYTICS OPPORTUNITIES AND CHALLENGES FOR THE SMART ENTERPRISE

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Abstract- In the digital world, the quantity of data is progressing in an accelerated manner, so the problem is that how to analyze this large volume and this variety of data in order to extract the values, and explore the patterns and relationships between different business processes to achieve the difference strategic aims. Therefore, the emergence of big data analytics answered the major question and helped to extract information from data using a complicated set of applications, decision algorithms, frameworks as well as predictive models. According to literature, there is no complete framework that can achieve all business objectives, this article presents a literature review explaining how Big-Data analytics help improve business objectives, study some analytics systems used in this goal, and finalize with proposed solutions based on deep learning, which present solutions to known problems of big-data analytics.

Keywords: Big-Data Analytics, Business Analytics, Smart Enterprise, Deep Learning.

1. INTRODUCTION

Organizations handle and collect a large volume of data and exploit it to achieve their business goals. Therefore, it makes data passed through several organizational, strategical and procedural stage. Over the years, various applications and approaches appeared and helped collect and analyze the relevant data to make the right decisions [1]. Recently big-data analytics appeared as a new approach to analyze a large amount of data or Big-Data [2]. This big-data is collected from various sources, including social networks, digital images, videos, sensors, and sales transaction records, that might be analyzed to provide valuable insights. Within these insights, companies may gain an advantage over their competitors and deliver superior business decisions.

It is difficult to manage the analytics of Big Data using traditional tools; this need has contributed to the emergence of new technologies such as Cassandra, Hadoop, Spark ... and deep learning. These techniques allow new possibilities for data exploration. However, these technical solutions always meet challenges, are always in need of improvement to be suitable for the different types, and sizes of data in real-time.

This paper will identify the opportunities of Big-Data analytics and discuss its frameworks, highlighting the challenges and pressures that the analytics systems face in order to propose solutions for these problems based on a new framework and based on deep learning models.

2. BUSINESS ANALYTICS

Business analytics is an advanced concept that emerged from business intelligence. It is an approach combining different disciplines to extract value from data to make a valuable decision via regular analysis with different plans and strategies [3]. So, BA used by organizations for the aim to develop existing processes, identify new opportunities, discover more product features, change and evolve new services and systems, better understand customers' behavior, and expect problems before they happen [4]. These disciplines are machine learning, deep learning, data science, statistics methods, data management, decision science, and other scientific research methods.

2.1. Existing Type of Analytics

To clarify this idea of "analytics", it is important to comprehend it through its three sorts [5], which abbreviate its job and purposes:

2.1.1. Descriptive

Descriptive analytics is a sort of examination and analytics presented as a business detailing and data communication tool (reporting). It gives a translation and extrapolation of the chronicled information and helps comprehend the enterprise's critical change [6]. Its primary outcome is making the crude information reasonable and understandable for the different parts of the association (representatives, administrators, financial backers, provider…).

This sort empowers the organization to respond to the inquiries of "what occurred" as well as "what's going on" [7]. It provides the possibility to know:
- Stocks had been conveyed a year ago.
- The payment for the overall costs a year ago.
- The sort of items returned a month ago.
- The total of deals in recent years.
- Clients subscribed a month ago.

This type of analytics utilizes numerous techniques, such as data aggregation and data mining, extract information, and make a report of accessible data to set it up for additional preparation. That gives experiences and expectations (insights), which help to get why and how some occasion occurred and clarify why a few outcomes happen, all while attempting to improve representative commitment and efficiency.

2.1.2. Predictive

A type of analytics that is a part of the investigation come to support modelling and displaying requires a few factual techniques that can dissect current and chronicled events to give experiences and make expectations about unknown occasions about the future [8]. Specialists utilize this sort to convey future business wanting and objectives to foresee the issues before they occur, find new tasks, new services and opportunities to lessen the time, increment efficiency and limit risks. Its main result is to address the question «what will occur? » or/and «for what reason will it occur? », as examples, we can cite:

- The income if there should be an occurrence of a blacklist for a certain time.
- The income if deals administration diminishes by a certain percentage.
- Expectations if provider costs develop by a certain percentage.
- The most probable worker to leave our association.
- The risk of losing cash on new venture speculation.
- Payment for several services for the following year.

By addressing these inquiries, the enterprise looks at the outcomes to recognize new examples and connections to improve their exhibition through its diverse business process: Strategy Planning, Marketing, Finance, and Management.

2.1.3. Prescriptive

This type is the last advanced analytics interaction that characterizes the actions to interpret future danger and risk and exploit a trend pattern. It utilizes additionally chronicled information and outside data because of the idea of factual algorithms to recognize opportunities and distinguish the purposes for disappointment or achievement. Prescriptive analytics utilizes modern apparatuses and advancements, similar to AI, algorithms and business rules. It addresses the topic of «what I ought to do? » and «for what reason ought to I get it done? » [9]; here is some information that this type can obtain:

- The elective intends to keep up the extreme benefit if a certain number of employee leave.
- The number of items does we need to offer to amplify income.
- The ideal approach to limit expenses and charges.

This handling's appropriate responses assist the enterprise with setting new measures for progress and disappointment to reproduce the business with dependable expectations to create productivity and lessen costs. Figure 1 beneath shows the analytics stages of analytics with its three sorts; it explains that Descriptive Analytics give experiences and insights into the past. Predictive Analytics help to comprehend the future and Prescriptive Analytics exhort possible results and give interpretations.

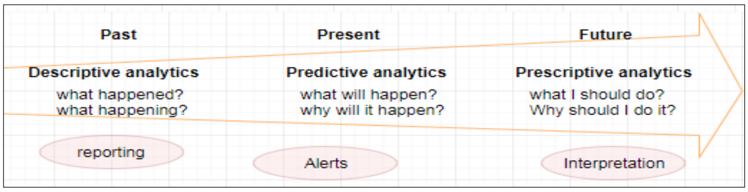

Figure 1. The different types of business analytics [4]

3. BIG-DATA ANALYTICS FOR SMART ENTERPRISE

3.1. Big-Data

Big data is a large collection of data which is difficult for it to be managed and analyzed with traditional tools, this data has different size and formats, companies are trying to exploit this data for its own benefit depends on their needs, for that a set of methods and tools appeared which facilitates the use of this big data to analyze, filter, process, present, discover the different relationships between their processes, the need to analyze and explore Big-Data makes it a necessity and an important data science topic.

From all existed definitions for "Big-Data", we can choose that Big-Data is data that's "too big", "too hard", and "too fast" [10], this 'too big' indicates the large available quantities of data, known as 'volume'. 'too hard' related to the different type and several formats of data a variety of sources, that need some analysis and some tools to process, that known as 'Variety'. 'Too fast' means that data need a high speed to process and that refers to 'velocity', these three Vs shown in Figure 2, are the Big-Data dimensions and attributes (volume, velocity, variety) [11].

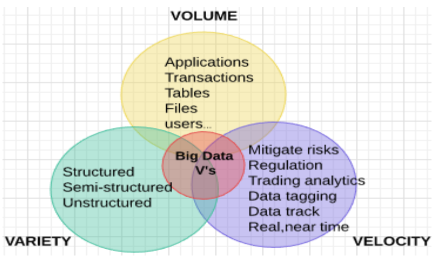

Figure 2. The three Vs of big-data [4]

3.2. Big-Data Analytics

The definition known in scientific research is "big data analysis" this is where advanced analytical methods emerged to analyze this large volume of data, to process it and extract value from it, as shown in the Figure 3 [12], this analytics adoption drives potential benefits; it is the key for the enterprises to exploit data-dependent capabilities, provide insight and direction to enhance and help making-decision. Big-Data analytics unit different tools and disciplines using statistical algorithms, predictive models, data mining, and various other tools to provide valuable information from a large amount of data.

According to the different definitions explored in the state of the art, the main objective of big data analytics is the search for value from big data, this value is a set information that can be used by organizations to produce insights and making the right decision, and as we mentioned above, the variety of this data in terms of format and size, quick information scattering, dependability of the examination, information quality, uncategorized and unaided information, quick data recovery, information labeling and information stockpiling, are the fundamental difficulties confronting Big-Data analytics.

Figure 3. Big data analytics for enterprises

3.3. Smart Enterprise

Mellote affirms that a smart enterprise is an organization exploiting technology to answer critical challenges and also to manage and extract meaning from the diversity & volume of data that is available to them. The second group of definitions emphasis that "smart enterprise" is an organization that offer an integration of all recent analytics technological advances to acquire, transfer, interpret, and analyze the information [13].

A third definition focuses on the insights aspect and accord that a smart enterprise is an organization that embed analytics to transform information into insights and predictions and then into action [14]. From all those definitions, we can conclude that 'Smart enterprise is a new enterprise performance optimization strategy, enable some methods and approaches defined under a solution which is Big-Data analytics. It turns information into value to decide and affect all smart enterprise areas to enhance competitiveness as shown in Figure 4.

Figure 4. Decision in enterprise areas

3.4. Enterprise Big-Data Sources

Contingent upon the enterprise's kind and type, the accessible data differs essentially in the speed of processing, volume and format and speed [15]. Data join information usually oversaw by the HR division, consumer loyalty and operational information. This information extended, connected and analyzed with a few devices to discover what genuinely occurring in the association and find what will occur and how should the association respond. Examples of data are depicted in Table 1.

Table 1. Several information sources used by enterprise

Information source	Description	Examples
HR database	Collection of information contains data about employees, clients, products, etc., Like personal details, execution and, advancement subtleties…	Database: Oracle, Informix, SAP-Sybase… Data: age, gender, pay, office, execution rating, location, absence, area, group, price ...
Customer satisfaction survey data	Put away in surveys and gives data about clients inclinations, clients encounters, clients fulfilment…	Client rating, client devotion, inclinations, satisfaction, purchases and buys probability of additional business…
Operational performance data	Data alludes to the association's effectiveness; it is tied in with estimating the fruitful running of the business.	Several grumblings settled, several calls exited, several inquiries settled, and time devoured in specific tasks.
Employee attitude survey data	Scope of data typically put away in surveys and sent out to records (attitude of employees, their commitment information, as a rule, dealt with suppliers association).	Employee commitment, work strain level, employee execution and performance, fulfilment, the impression of equity, anxiety...
Sales performance data	Data usually possessed by the business work, recording subtleties of deals execution and incomes, it is a valuable data help to decide how the enterprise arrived at the business objective.	Deals of month, new buys, income accomplished, top of the line, items attributes.

4. CHALLENGES AND OPPORTUNITIES

Big-Data Analytics has become a crucial choice that promotes business and provides a meaningful service over competitors. For innovative enterprises that are skilled in "Big-Data analytics" can exploit this opportunity to make the right decision. Decision-making is a significant challenge given the many changes in all enterprise areas [16]; to this end, Big-Data analytics has emerged as a set of strategies, tools and methods to facilitate decision-making. It makes the enterprise ensure the following benefits:

- Trending for market sentiments and segmentation of the customer base.
- Discover new details about their competitors and their consumers.
- Understanding of business change trending for market sentiments.
- Better planning and forecasting, and detection of fraud.
- Using click-streams to understand consumer behaviour.
- Identification of businesses and exchange occasions.
- More numerous and accurate business insights.
- Quantification of risks and real-time decisions.
- More suitable targeted social influencer selling.
- More excellent leverage and ROI for Big-Data.
- Classification of root causes of charge.
- Production yield improvements.

Data generated through many sources of "Big-Data analytics" can help companies to understand their performance than previous technologies [17]; Big-Data offers technological challenges due to its quantity, variety, and velocity. Volume only is a showstopper for many enterprises. Most of these organizations face: the genuine risk of information overload generated by the different systems, the complexity of data, the lack of experts in this field, and the systems costs. There is not yet a comprehensive and a complete framework that can offer a critical solution to these problems to help transform them into a smart business that transforms analytics to value data and make the right decision.

The Figure 5 present the issues for establishing Big-Data analytics in enterprises. So, finding a way to exploit the data at their disposal and leverage them to improve business and organizational performance becomes a necessity [18]. This can only be achieved when analytical techniques are connected and coupled to be integrated into a structured and rigorous framework; this aggregate can identify new opportunities for promotion or propose innovative ideas to address past challenges.

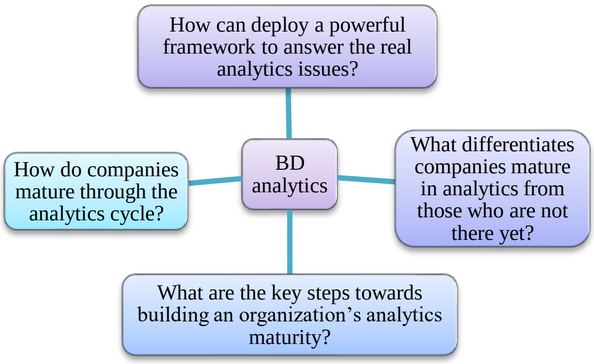

Figure 5. Big-data analytics issues in enterprise

4.1. Technical Details

This section describes the current analytics arrangements and solutions, which can be a significant key to making and conveying a proficient prescient logical administration model that creates expectations and experiences (insights, predictions). All that help the manager make a decision and settle on better choices for the organization. The vast majority of these solutions are costly; however, there is a load of closeness between the bundles, and analysis, produce similar outcomes. Along these lines, analytics techniques and abilities are the most important, and it is feasible to apply them in different frameworks depend on their diversity. Table 2 shows the most mainstream analytic frameworks subtleties.

Table 2. Details of big-data analytics systems

Software system	Details
APACHE ZOOKEEPER	Apache zookeeper is a framework that can federate the communications between distributed systems [19]; it functions by providing a memory space shared by all the instances of servers, these several machines connected solve problems and process a large quantity of data together that accelerates the processing, offers real-time access and handling system breakdown problems.
APACHE STORM	Apache Storm project started in December 2010 by Nathan Marz to produce a stream processing method. It was designed as an open-source system and adopted by Apache on 17 September 2014 [20]. This system offers real-time, distributed processing methods to prepare and treat unbounded data streams more agile than ever [21]. It is easy to use and provide low latency with guaranteed data processing. It promotes interaction across a JSON-based protocol. It offers services of filtering, aggregation, join, read/write to and from several sources.
KAFKA	The Kafka project used to build real-time data pipelines and streaming applications [22]. It is a distributed, partitioned and replicated service. It supports parallel data loading provide by various producers (Frontend web applications, services, adapters...), consumed by real-time consumers (filter and sift information in databases and trigger alert), near real-time consumers (save data in any NoSQL system) and offline consumers (storing information in customary and traditional data-warehouse for disconnected (offline) analysis). The following diagram shows a typical big-data analysis and investigation and aggregation scenario supported by the Apache Kafka system.
SPARK	Apache Spark is a robust open-source framework for intelligent data processing, developed by AmPlab, in 2009, adopted by apache in 2010 [23]; it makes sophisticated analysis and designed for speed and ease. It has several advantages over other technologies. It is an efficient solution for intelligent data analytics, offers text and graphics visualization, and supports streaming requests.
HADOOP	Apache-Hadoop created as an open-source system for the distributed processing of many data sets across clusters of computers using simple programming models [24], built to scale up from single servers to lots of machines, each offering local storage and computation. It is composed of several components that work commonly to prepare and analyze data: HDFS (distributed file system layer that adjusts storage and replication across the cluster nodes), MapReduce (batch processing core for Hadoop) and YARN (cluster coordinating component of the Hadoop stack).
CASSANDRA	Apache Cassandra is a robust distributed database of the NoSQL family designed to collect a large amount of data from multiple sources [25]. Data stored is automatically replicated to multiple physical instances: nodes offering no downtime and offers high availability and scalability. This database's architecture constitutes nodes that use the peer-to-peer connection and clusters, data centres, and partitions.

4.2. Components of Big-Data Analytics

Figure 6 shows a set of layers of abstraction, which represents the Big-Data analytics levels shows that it is composed of a group of blocks and stacks linked together. The distributed file system layer constitutes the core of Big-Data-centric application, but this is not always the case.

5. PROPOSED SOLUTIONS

In this section, we will propose solutions to the problems described above, the first solution based on a new framework and the second based on deep learning models.

5.1. Solution 1: Designed Framework

In the socio-economic world, the decision-making challenge turn around the type and the quality of data, the people, the business planning, the business objective, that give us the impression that the technical side is not the only critical side. That is why necessary to think about a comprehensible multidimensional framework that project on all the dimensions that can extract value from a large amount of data and help to turn this value into action to take the right decision. We proposed a simple framework based on the existed ones that are relatively limited in scope as presented in Figure 7, this system presents a total model that combine a few measurements, and several dimensions connect:

- Actors: include software developers, personnel, customers, managers.
- Interaction models: Interface between user and system aspects.
- Computing infrastructure: devices and the software required.
- Communication: Workflow process of business process as a joint effort that requires a substantial two-way correspondence.
- Enterprise content: information data disposition of employees, personnel subtleties and their exhibition, advancements subtleties, client's data.
- Data sources: the source frameworks such as Data-warehouses, production network frameworks, and other operational frameworks, reviews.
- Internal hierarchical arrangements, strategies and culture: acquisition of equipment and programming, information reinforcements.
- External powers: outer standards, guidelines force that place requirements or support the sending.

Original data	Storage systems	Task trackers	High-level language	Security and management	Modeling	Loading analytics databases	Analytics applications	Presentations
Files External data bases Surveys Business apps Medias	Hadoop				ETL Modeling tools	e.g green-plum, Netezza…	Merced	Reports
	File system, e.g HDFS	MapReduce engine	Hive	Cascading			ClickFox	Dashboards
	NoSQL Db, HBbase		Pig	Kerberos				Alerts

Figure 6. Big-data analytics components

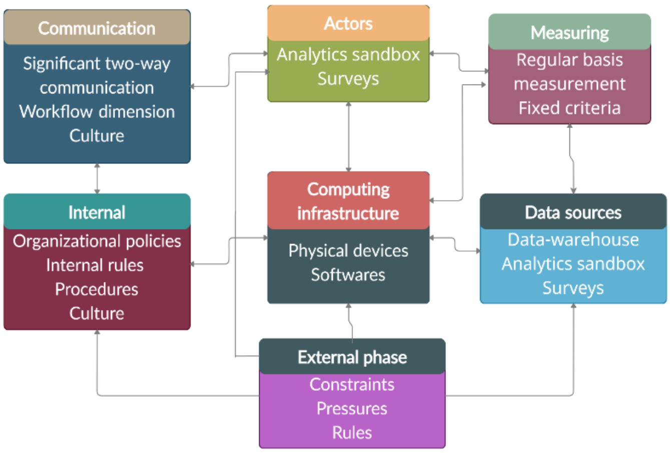

Figure 7. Proposed analytics framework

What makes this a robust model is its hierarchical decomposition of these different components. Likewise, the chance of separating an unpredictable process, framework or device into its parts offers the likelihood to study and understand them and afterwards incorporate the outcomes attempting to comprehend the total working framework. The interaction between this model's different components presents the objective set of Big-Data analytics with these three types.

It can offer dashboards and reporting; it can make insights and predict future performance. There is always a gap between analytics development and analytics within enterprises the challenge, so the first challenge is finding a complete framework. The second is to implement and use it correctly to make the decision [26]. We can also say that analytics deployment confronted by the following barriers:

- Lack of experienced individuals that can comprehend the analytics frameworks.
- Turn data and bits of knowledge into choice requires a colossal encounter.
- Distrust of the data and gaps to separate correct information.
- Models are costly and complex to convey.

5.2. Solution 2: Using Deep Learning

The second proposed solution is about using deep learning to extract value from complex data without the involvement of human to avoid a common problem with traditional means (tagging, indexing, retrieval, reporting and problems of solution one described above) [27]. Given the complexity of the data, the diversity of their format and volume, deep learning is an exciting choice that adapts with supervised or non-supervised data. Deep learning can learn from different data sources (cited above) and extract data representations in real-time with efficiency and high accuracy [28], two deep learning architectures will be discussed here as a solution for traditional data processing techniques: Convolutional Neural Networks and Deep Belief Networks known as CNN and DBN, as the Figure 8 below indicates.

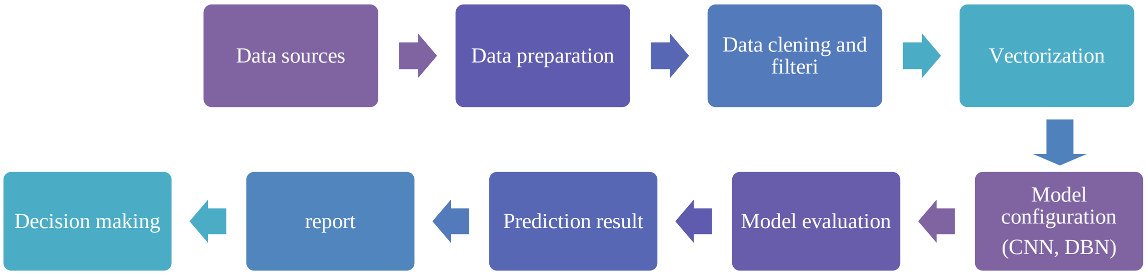

Figure 8. Architecture of the system

• Convolutional Neural Networks for Big-Data

In the world of deep learning, "convolutional neural network" is among the most consistent algorithms, it consists of several layers starting with a convolution layer, and it has a specific hierarchy of other layers which differs between layers of Max pooling, Dense, and fully connected, this level of the algorithm generates feature maps, this architecture receives input data. The output is stored in global memory. The model will be process data after its preparation (cleaning, filtering and vectorization). Once the data prepared, it will be introduced into the CNN model and start learning to get these training metrics. We then evaluate the model by predicting the test data. We also have to adjust a set of parameters for each respective model to increase its accuracy (Width and depth, layer arrangement method, number learning steps, activation function, and runtime environment GPU, CPU…). This deep learning model process data in large volume inefficient and faster and generates data presentations and predictions to help the enterprise make a decision.

• Deep Belief Networks for Big-Data

A deep learning model exploits supervised and unsupervised methods. It comprises of Input-output layers and hidden layers. Two straightforwardly associated layers structures restricted RBM (Boltzmann machine). This RBM has nodes in its two layers, which are entirely associated with each other, and there is no association between nodes inside the same layer. Numerous analysts utilize this Deep Belief Networks separation to deal with large information proficiently. For example, a Graphical Processing Unit (GPU) based compositional model is introduced to handle the enormous measure of information favoring Big-Data.

This strategy should be utilized in a similar style to join a gigantic measure of information with less preparing time to extract value and make a decision.

6. CONCLUSION

This paper describes Big-data analytics for intelligent enterprises. It demonstrates that this concept is a set of analysis of a large amount of data that comes to drive and deploy the future business planning. As well as we proposed a framework that support "Big-Data analytics" and creates expected advantages of the enterprises which the significant key behind the coming of business objectives, The paper also presented deep learning as one the solutions to deal with traditional data processing technique limitations encounter with gigantic data. In our future work, we will implement a deep learning model with a convolutional neural network able to collect data in real-time and train it to generate data presentations with high accuracy and minor error.

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BIOGRAPHIES

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