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Data Driven Decision making Framework for Businesses

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ABSTRACT

Digital technologies have revolutionized the way businesses are built and managed, requiring the development of new solutions and a diverse set of applications. Massive volumes of data are now easily accessible and database capacity has risen tremendously and data collection methods have altered. As a result, while mining big data, issues with regression, the analytical process, and the complexity of the large data all arise.To cope with the aforementioned issues a data analysis framework is proposed for various business decision-making processes which collects the data and saves in Hadoop, a java-based data management system that allows enormous amounts of data to be handled in parallel clusters without failure. Generally, node failures are not concentrated in data storage management systems. Consequently, data mining techniques are used in the design phase to obtain pertinent and essential vital information. Thus, the proposed framework efficiently provides data analytics for various decision making processes with improved accuracy.

Keywords: Data Analysis, Big Data, Business Decision, Management, Analytics tools

1. INTRODUCTION

In today's rapidly evolving business landscape, organizations are increasingly reliant on data to drive decision-making and gain a competitive edge[1]. The integration of both internal and external data sources is essential to navigate the complexity of modern business environments. However, reliance on data introduces several key challenges that companies must address Identifying and Accessing the Right Open/Public Data Sources, Data Integration and Synchronization, Data Quality and Regular Updates, Data Security and Privacy Concerns, Data Analytics and Interpretation, Agility and Real-Time Decision-Making. Indeed, the ability to effectively manage and leverage big data has become a critical factor in gaining a competitive edge in today's business world. Big data provide a useful framework for understanding the complexities and challenges associated with big data[2].Variety of techniques and disciplines including statistics, data mining, machine learning, social network analysis, signal processing, pattern recognition, optimization methods, and visualization approaches, can all contribute to unlocking the full potential of Big Data Analytics (BDA)[3,4]. The ability to harness and integrate these methods is what allows businesses to derive meaningful insights and drive value from large, complex datasets.While the promise of Big Data Analytics (BDA) is clear from improving customer service and developing new products to enhancing operational efficiency and enabling strategic decision-making many organizations still face significant hurdles in implementing BDA effectively[5,6,7]. People, culture, process, and technical challenges all need to be addressed to fully capitalize on BDA opportunities. As you mentioned, corporate leaders play a pivotal role in overcoming these obstacles, creating a data-driven culture, and ensuring that BDA initiatives deliver tangible value for the business. With the right leadership, investment in talent, and commitment to data-driven practices, companies can unlock the full potential of big data and gain a competitive advantage in their industry[8,9].

While Big Data Analytics (BDA) has enormous potential to improve business operations and decision-making, its successful implementation depends on multiple interrelated factors, such as organizational capability, technological infrastructure, analytics expertise, human talent, and information quality[10,11].Assessing the impact of BDA implementation remains a complex challenge, but it is essential for companies to understand how their investments in BDA are affecting performance. A conceptual model for evaluating BDA implementation, which includes setting clear objectives, establishing benchmarks, involving cross-functional teams, and using predictive models[12,13,50], can help businesses make better decisions and ensure that their BDA efforts deliver long-term value.Ultimately, the role of corporate leadership is critical in setting the vision, investing in the necessary capabilities, and ensuring that the organization remains aligned with its data-driven goals. With the right approach, businesses can maximize the value derived from Big Data Analytics and gain a significant competitive advantage.

The shift to data-driven decision-making (DDDM)[14,15] offers organizations a powerful approach to improving operational efficiency, gaining competitive advantage, and fostering innovation. By developing a structured framework that integrates data collection, analysis, and action, businesses can use data to guide decisions at every stage. However, for DDDM to succeed, it requires leadership that actively promotes a culture of data use, invests in the necessary capabilities, and ensures that data-driven decisions are aligned with broader business objectives.With the right framework in place, organizations can maximize the value derived from data and move from being reactive to proactive in their decision-making, ultimately achieving better business outcomes and sustained growth[51].

2. LITERATURE SURVEY

Hu, et al. [40] Indeed, research highlights the importance of integrating data acquisition and administration with the subsequent interpretation of information through creativity. As a result, Data-Driven Decision Making can help to frame big data analysis in the entire decision-making process (from data collection through information extraction and, finally, the development of new knowledge), as outlined in marketing management study.

Gutman et al.[41] emphasize that management decisions differ significantly from everyday individual decisions due to their complexity and the multitude of factors involved. They argue that the substance of managerial decisions, particularly in the context of big data, is shaped by a combination of economic, organizational, legal, technological, and social considerations.

Shamim et al. [42] and Ghasemaghaei et al.[43] distinguish between the micro-environment which the company can influence and the macro-environment which external forces that cannot be directly controlled. As Ghasemaghaei et al.[43] suggest, management's competence in understanding these environmental factors and preparing for change is critical. BDA, by providing real-time, predictive, and trend-based insights, allows firms to adapt more efficiently to changes in both their micro- and macro-environments.

Visinescu et al.[44] expand on the importance of assessing decision-making performance in terms of effectiveness and efficiency. These two dimensions—effectiveness and efficiency—are crucial for decision support systems (DSS) used in BDA. By integrating real-time data, advanced analytics, and predictive modeling, companies can make faster, more informed decisions while minimizing resource wastage.

Sun et al.[45] introduce the challenge of integrating multiple components in a traditional decision support system (DSS), where the database, model base, and knowledge base are typically handled separately. They suggest that integrating these components into a unified data processing platform using Data Mining Framework Systems (DMFS), particularly in the context of IoT and market big data.

Wamba et al.[46] define Big Data Analytics (BDA) as a holistic strategy for processing and analyzing large datasets to develop value.Akhtar et al. [47] emphasize that big data-savvy teams are essential for leveraging the full potential of BDA. They discuss how organizations benefit from diverse teams with varied skills and knowledge, as it is unlikely that any single individual can possess all the expertise required to handle complex big data challenges.

Mikalef et al.[48] found that BDA capabilities—including tangible, intangible, and human skills—are positively associated with innovation. They argue that the ability to innovate through BDA is facilitated by dynamic capabilities, which allow organizations to adapt to changing environments.

Agarwal et al. [49] point out that while business analytics has existed as long as business itself, its definition and application can vary. Generally, analytics involves the use of data to make better decisions, whether these decisions are in a personal or professional context. This sets the stage for understanding how data is integrated into decision-making, especially when organizations aim to make decisions that are data-driven rather than based on intuition or less sophisticated methods.

Researchers emphasize that organizations with basic BDA capabilities and simple data are more likely to fail when compared to companies that have robust analytics infrastructure and sophisticated data processing systems. This points to the critical importance of having advanced analytics capabilities to improve decision-making outcomes.

As discussed by Gutman et al. [41], management decisions differ from everyday decisions made by individuals because they incorporate a broader set of factors, including Economic factors (costs, profits, investments),Organizational factors (resources, capabilities, culture),Legal factors (compliance, regulations),Technological factors (tools, systems),Social factors (customer preferences, societal impact)

Ghasemaghaei et al. [43] highlight the importance of the macro-environment, which includes factors that can significantly impact business decisions but are outside the control of the organization. The ability to anticipate and adapt to these external factors is critical for businesses. Big Data Analytics (BDA) provides tools for forecasting and scenario planning, enabling companies to make better-informed decisions based on real-time or predictive data. According to Wamba et al. [45], BDA is a critical tool for improving both strategic and operational efficiency.At the strategic level, BDA helps organizations uncover market trends, identify competitive advantages, and optimize resource allocation. For instance, in marketing, BDA can reveal customer behavior patterns, which can inform targeted marketing strategies. On an operational level, BDA can help optimize day-to-day processes, reduce costs, and improve efficiency in areas like supply chain management, logistics, and customer service. Real-time data analytics ensures that companies can act quickly to respond to changes and opportunities.

Akhtar et al. [47] emphasize that diverse, big-data-savvy teams are essential for making the most out of Big Data Analytics. These teams combine diverse skills and expertise across domains to ensures that data is analyzed in ways that are aligned with the company's business objectives and no single expert can be aware of all the nuances in a complex data ecosystem, teams with diverse skills—ranging from data engineering to business strategy.This underscores the idea that BDA is not just a technological challenge, but also a people challenge—requiring the right teams, collaboration, and organizational structure to succeed.

Mikalef et al. [48] argue that companies with an organizational culture that uses evidence-based decision-making (driven by BDA) can achieve competitive performance gains. Their research suggests that the deployment of resources synergistically (across departments, teams, and technologies) is key to achieving successful BDA implementation.Given the various challenges highlighted by the authors, ranging from macro-environmental factors to the need for advanced BDA capabilities, big-data-savvy teams, and a synergistic organizational structure, the need for a novel solution to improve business decision-making is clear.This solution might involve:

- Integrating technology and people: Combining advanced data analytics technologies with skilled, cross-functional teams to interpret data and implement strategies.
- Developing an agile decision-making framework: Leveraging BDA to continuously gather and analyze data, forecast trends, and adapt decisions in real time.
- Building a data-driven culture: Encouraging an organizational culture that values evidence-based decision-making at every level, from operational to strategic decisions.

Such a solution could lead to more efficient, effective, and resilient decision-making processes, enabling businesses to stay competitive in an increasingly data-driven world.

3. PROPOSED WORK

The Data Analytics-BDM is based on design science, where the proposed framework is constructed and evaluated using a three-stage design science approach (Intellect phase, Design phase, and Evaluation phase). As a consequence, an artefact (DA-BDM framework) was created using the applicable knowledge from the knowledge repository and business demands of the domain. Following that, after DA-BDM framework has been built, it is assessed and shown by applying BDA to support decision making. Whereas, framework was evaluated by looking at how successfully it applied BDA across the decision-making process to support making better decisions. In addition, the smoothness of the procedure and the framework applicability in various scenarios were observed. The below section explains the description of method in more detail.

3.1 Intelligent Platform Design for DA-BDM

In big data analytics, advanced analytic techniques are applied to enormous data sets. As an outcome, analytics based on a huge data sample can expose and exploit business transformation. Therefore, advanced analytics may assist you in making better decisions, reducing risk, and uncovering valuable insights from data that might otherwise be ignored.Consequently, the first phase of the decision-making process is when data from internal and external data sources is gathered that can be used to identify problems and possibilities. Where the source of big data must be identified, and gathered from many sources, processed, stored, and moved to the enduser throughout this phase. As a result, the framework first phase is to identify the big data that will be used in the analysis.To store and process the gathered data across a high-speed network, the big data storage and management systems can be employed.Also, the data collected can then be saved in Hadoop, a java-based data management system that allows massive amounts of data to be processed in parallel clusters without failure, whereas traditional data storage management systems do not concentrate node failures. The data is then processed with Apache Spark, which leverages in-memory caching and improved query execution for speedy searches against any size of data, whereas the old method worked at a very slow speed for large-scale data processing. Such tools, as well as others, can assist in the identification and preparation of huge amounts of data for analysis.

3.2 Design phase for DA-BDM

The design phase of the decision-making process plays a critical role in shaping and analyzing various possible courses of action. During this phase, a conceptual model or representation of the situation is developed, which serves as the foundation for exploring different solutions. The framework for this phase is divided into three steps: model planning, data analytics, and analysis. In the model planning step, a conceptual framework or model of the decision-making scenario is created. This model helps define the problem and identify the different variables involved, setting the stage for further analysis. The goal here is to establish a clear understanding of the situation to inform the next steps.The data analytics step involves applying techniques that enable organizations to analyze large datasets and extract meaningful insights. In this context, data mining and machine learning techniques are used to enhance the accuracy and effectiveness of the analysis. One of the key methods employed is classification analysis, which organizes data into different categories or classes. This technique allows for identifying important and relevant features of the data.

- Gradient Boosting Decision Trees: These are used for predictive analytics and can significantly improve the accuracy of the analysis. This machine learning method builds decision trees one at a time, with each tree attempting to correct the errors of the previous one. This iterative approach helps address the complexities of big data and regression issues commonly found in large datasets.
- Data Mining and OLAP: Data mining tools, such as Online Analytical Processing (OLAP), are employed to help analysts explore multidimensional views of the data. OLAP enables quick and reliable data exploration, helping users uncover patterns and trends. Additionally, in-memory processing is used to enhance the speed of data analysis by keeping data in RAM, thus speeding up access and improving model performance.

Once the data has been processed and analyzed, the results are evaluated using the company's dataset (e.g., the 2019 dataset). This is where the outcomes of the various potential solutions proposed in the design phase are assessed. The choice phase follows, where the decision-makers review the evaluated results and choose the best course of action based on the analysis.The decision tree is a key model used in the analysis. It is built by recursively selecting the most relevant features of the data and splitting it based on those features. The goal is to create partitions that lead to "pure" child nodes—nodes that contain data from only one class. This reduces the number of splits required and helps in building an efficient and accurate model.

- Information Gain is the key measure used to determine which attributes should be used for splitting the data. It quantifies how well an attribute separates the data into distinct classes. The attribute with the highest information gain is selected for the split.
- Tree Building Algorithm: The pseudocode below illustrates the process of building a decision tree using information gain:

After the decision tree is constructed and the data has been analyzed, the next step is to evaluate the results of the analysis. The company dataset (e.g., 2019 dataset) is used to assess the effectiveness of the model. Based on the evaluation, decision-makers assess the proposed solutions and select the one that best addresses the problem at hand.

Tools like Pentaho play an important role in the decision-making process by offering features for data visualization, reporting, and dashboard creation. These tools allow for better communication of the results, providing clear and actionable insights from the data.

Algorithm 1: Decision tree algorithm

Input:P,Where P=group of instances that have been classified.

Output : Decision Tree

Require $\mathbf{P = \emptyset, \mathit{num\_attributes} > 0}$

Function Buildtree

repeat

$\mathbf{0 \rightarrow max\ Gain}$

$\mathbf{null \rightarrow Split\ B}$

$\mathbf{C \rightarrow Entropy}$

for all Attributes a in P

do

Information Gain(a,c) → gain

if gain> **max Gain then**

gain → max Gain

a → **split B**

endif

endfor

Partition(P, split B)

until every partition has been processed

end function

3.3 Evaluation phase for DA-BDM

The Evaluation phase evaluates impacts of the proposed solution by using the Pentaho tool that provides data integration, OLAP services, reporting, information dashboards, data mining, andload (ETL) capabilities to overcome the memory scalability issues whereas the data is stored in the cloud.Also, the evaluated impacts of the proposed solution can be processed to select the best option using the line-up matrix, which compares alternatives based on multiple criteria with varying levels of importance and assigns a ranking to each alternative combination to reduce decision fatigue and subjectivity in decision making.Finally, the recommended solution from the preceding phase is put into effect during the implementation phase of the decision-making process. Furthermore, in the last phase of the data analytics lifecycle, the results of the choice are operationally defined, or actualized, in this step. As a result, big data tools and technologies can be used to track the decision outcomes and provide real-time or periodic feedback on the implementation consequences.Thus, the proposed framework provides the best option for action that must be taken to improve business outcomes.

4. RESULT AND DISCUSSION

This segment provides a detailed description of the implementation results as well as the performance of the proposed system. This work has been implemented on Companies sorted dataset. 7+ million companies are represented in this database, which spans 237 countries. Linkedin URL, domains, company size (1-10,000+ employees), company location, and employee count are provided and explain the methodology in a detailed manner. The simulation results are discussed below-

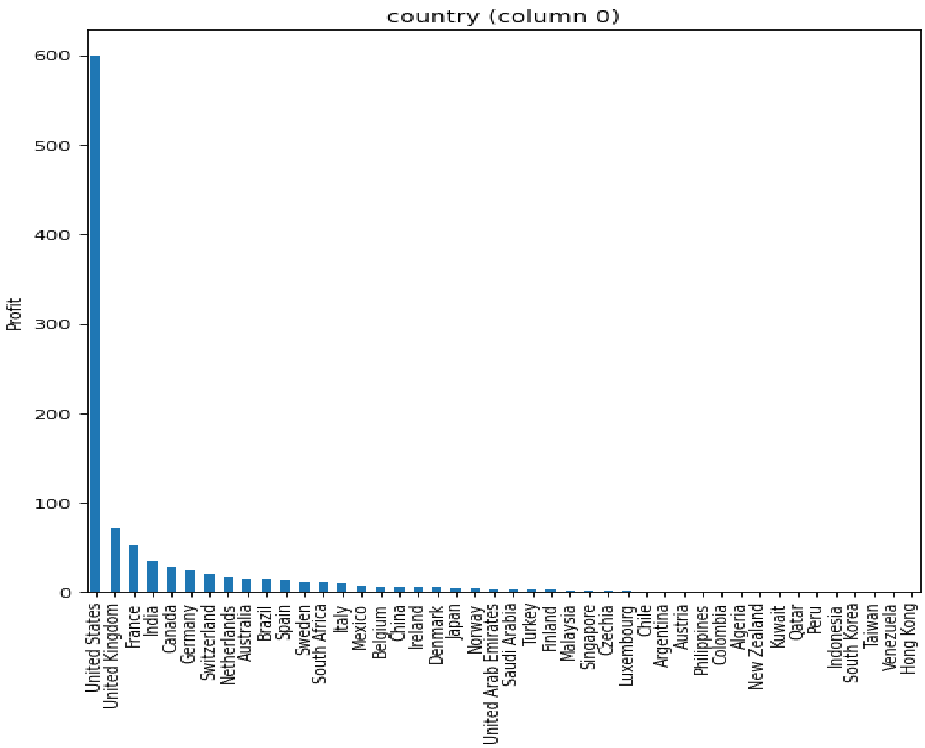

Fig.2.Companies_Sorted dataset

The Companies_sorted dataset that is quite unbalanced after looking at the profit in this dataset: More than 59% of the data belongs to the United States, 80% of the data to the United Kingdom, 50% of the data to France, and 30% of the data belongs to India.

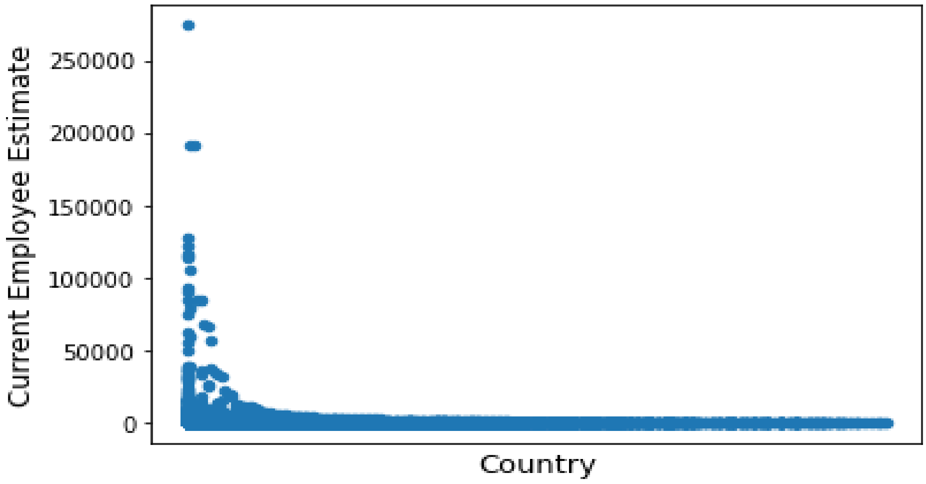

Fig.3.Estimating Current Employee details(Dataset)

The above fig.3. is plotted between Current Employee Estimated details with respect to country. More than 250000 current employees belong to the United States, 140000 current employees belong to the United Kingdom, and 25000 current employees belong to India.

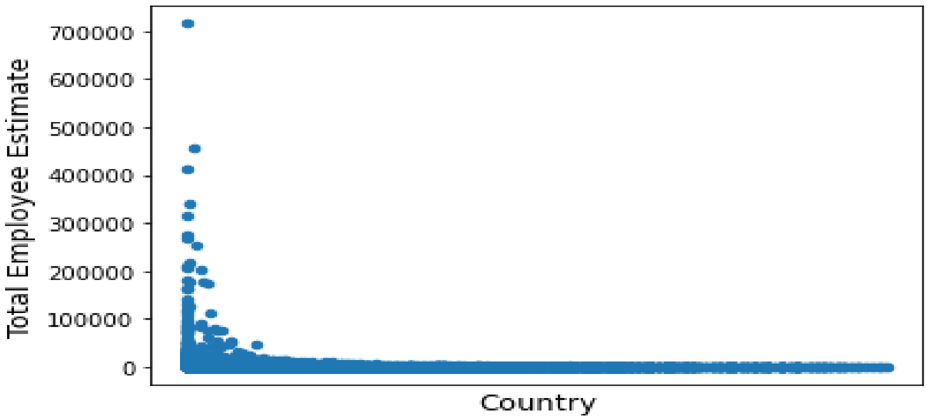

Fig.4.Estimating Total Employee details

The above fig.4 is plotted between the Total Employee Estimated details with respect to country. More than 700,000 total employees belong to the United States, 450000 of current employees belong to the United Kingdom, and 100000 current employees belong to India.

4.1 Simulation Outputs and Performance Evaluation:

In this section, the simulation outputs of the proposed framework as well as the performance evaluation metrics are presented. The performance of the proposed framework has been evaluated with the related evaluation metrics such as accuracy, precision, recall, sensitivity, F-measure, execution time.

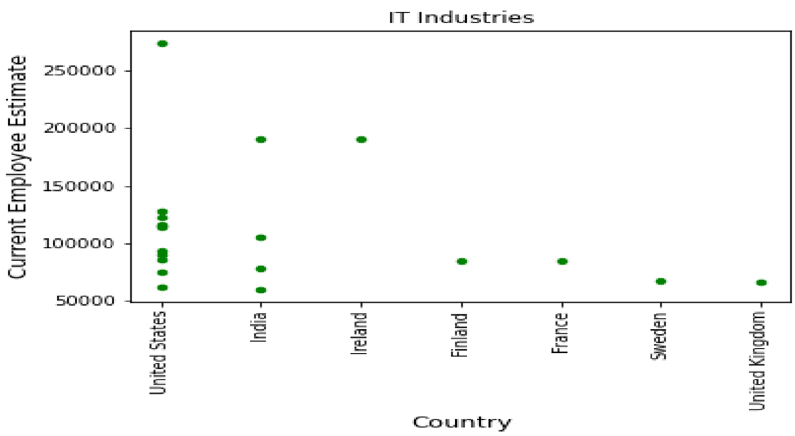

Fig.5.Estimating Current Employee details in IT Industries

The above fig.5 is plotted between current employee estimates in the IT industry with respect to country. More than 250000 current employees belong to the United States, 120000 current employees belong to India, and 60000 current employees belong to the United Kingdom.

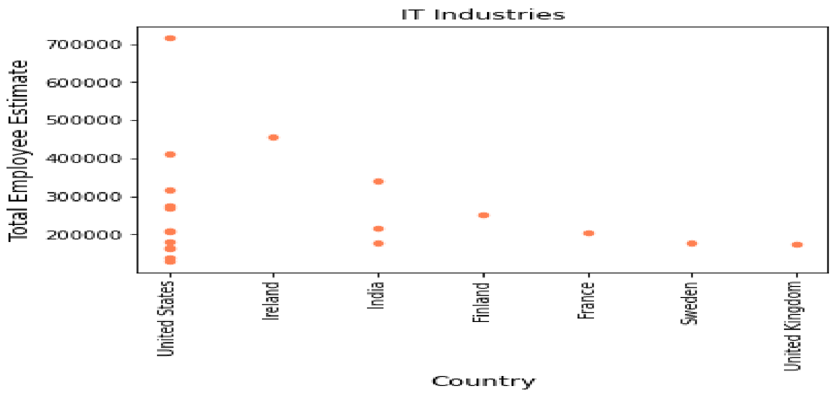

Fig.6.Estimating Total Employee detailsin IT Industries

The above fig.6. is plotted between the total employee estimated details in the IT industry with respect to country. More than 700000 total employees belong to the United States, 450000 of total employees belong to Ireland, and 350000 of total employees belong to India.

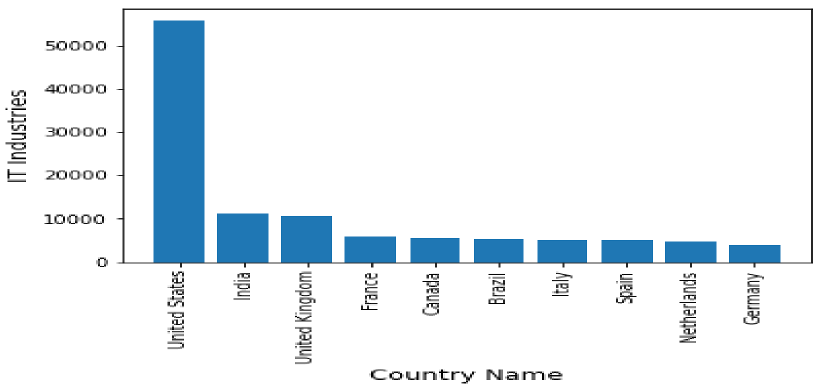

Fig.7.Country name Vs IT Industries

The above fig.7 shows the IT industry with respect to the country. More than 60000 IT industry jobs belong to the United States, 11000 belong to India, and 10000 in the UK.

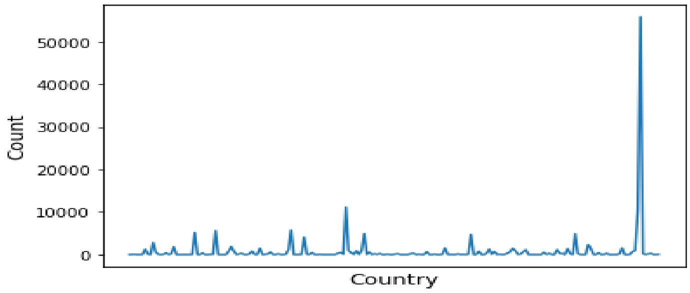

Fig.8.Country name Vs Count

The above fig.8 shows the IT industry countconcerning the country. More than 50000 IT industry jobs belong to the United States, and 10000 belong to India.

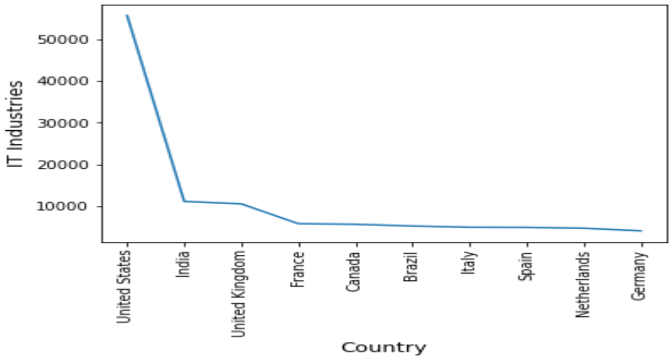

Fig.9.Country name Vs IT Industries

The above fig.9. shows the IT industry with respect to the country. More than 60000 IT industry jobs belong to the United States, 11000 belong to India, and 10000 in the UK.

For the quantitative evaluation of performance, the following metrics are used: Precision, Accuracy, Recall, F-measure, and Sensitivity:

$$\text{Accuracy} = \left[\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}\right] * 100 \qquad \text{---------(1)}$$

Where, TP- True Positive Value

TN-True Negative Value

FP-False Positive Value

FN-False Negative Value

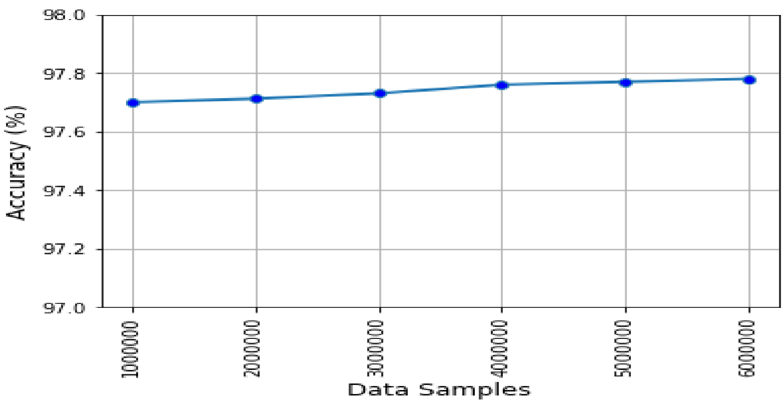

Fig.10. Accuracy Comparison

Fig.10.shows that the accuracy of data analytics and business decision-making is compared with the accuracy of the various data samples, which are presented in figure 10. From the graph, it is clear that by increasing the number of samples, the output achieves 97.7% at 6000000 data samples.

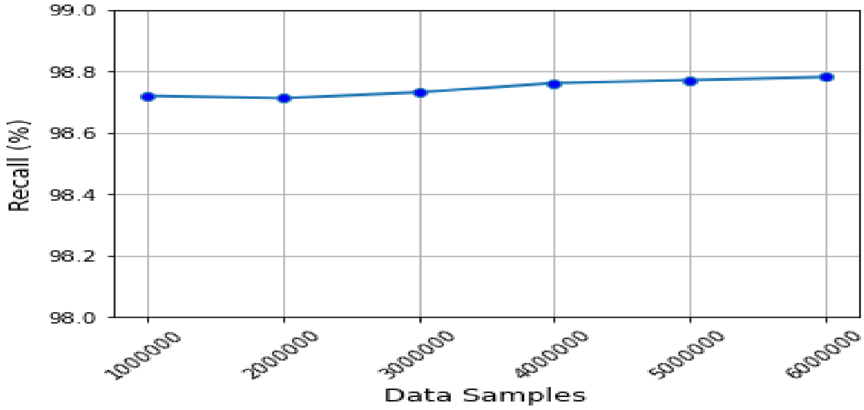

Fig.11.Recall Comparison

Fig.11. shows that the recall of data analytics and business decision-making is compared with the various data samples. From the graph, it is clear that by increasing the number of samples, the output achieves 98.7% at 6000000 data samples.

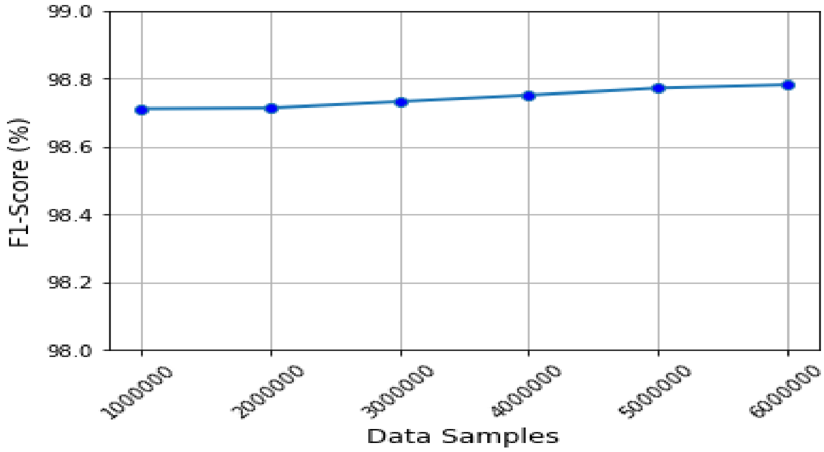

Fig.12.F1-Score Comparison

Fig 12 shows that the F1-Score of data analytics and business decision-making is compared with the various data samples. From the graph, it is clear that by increasing the number of samples, the output achieves98.7% at 6000000 data samples.

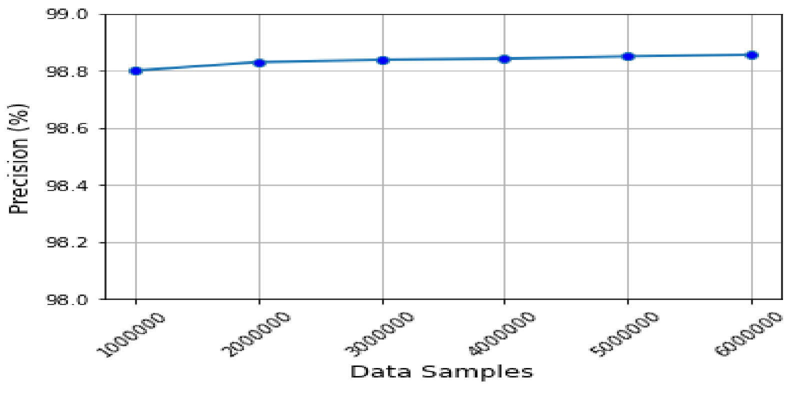

Fig.13.Precision Comparison

Fig.13. shows that the precision of data analytics and business decision making is compared with the various data samples,which are presented in figure 13. From the graph, it is clear that by increasing the number of samples, the output achieves 98.9% at 6000000 data samples.

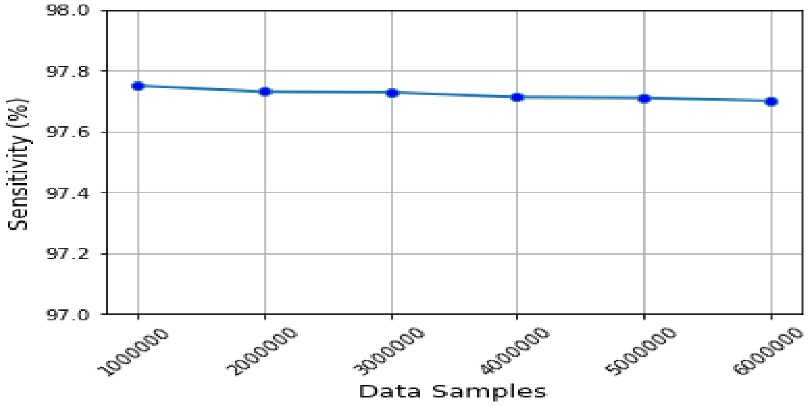

Fig.14.Sensitivity Comparison

Fig.14.shows that the sensitivity of data analytics and business decision making is compared with the various data samples. From the graph, it is clear that by increasing the number of samples, the output achieves97.6% at 6000000 data samples.

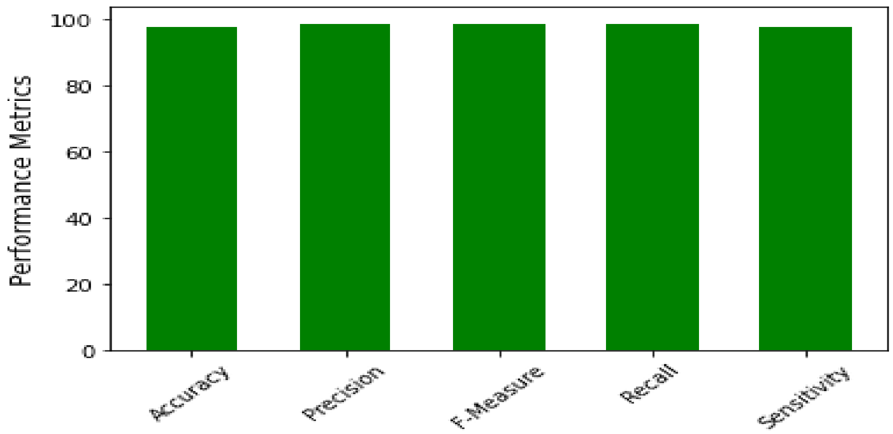

Fig.15.Comparison of Performance metrics

The comparison of performance metrics like Accuracy of 97.7%, Recallof 98.7%, F1 Scoreof 98.7%, Precision of 98.9%, and Sensitivity of 97.6% are shown in fig 15.

5. CONCLUSION

In this research, the novel topic of big data is investigated,which has suddenly gained considerable attention due to its apparent unrivalled prospects and benefits.By applying advanced analytic approaches to huge data and discovering hidden insights and valuable knowledge, big data analytics may be used to leverage business change and improve decision making. Valuable information can be retrieved and used from big data using such analytics to improve decision making and support informed decisions.Consequently, the established and tested DA-BDM framework, which helps us through the decision-making process using big data analytics and other big data tools and approaches, is the research contribution. The DA-BDM framework can be used at work and in businesses. As a result, people and organizations now have access to the DA-BDM framework, which demonstrates how to integrate and apply big data analytics across the decision-making process in order to make better, more accurate decisions.

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