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A Study on Scalable and Operational Cognitive Analytics for Big Data

Abstract: - With the explosion of big data in recent years, the need for scalable and operational cognitive analytics has become more pressing than ever. This innovative approach to data analysis is designed to handle the vast amounts of information generated by modern businesses and organizations, while also providing insights and actionable intelligence in real-time. In this paper, we will explore the key components of scalable and operational cognitive analytics, as well as some of the innovative approaches that have emerged in recent years. We will also examine how this approach has been applied in different industries, and what the future holds for this exciting field. By the end of this paper, readers will have a comprehensive understanding of scalable and operationa l cognitive analytics and its potential implications for big data analysis and industry.

Keywords: Scalable Analytics, Cognitive Analytics, Big Data, Real-Time Insights, Operational Analytics.

I. Introduction

Scalable and operational cognitive analytics is a powerful tool that can be applied to a variety of fields. For instance, it can make recommendations for healthcare, finance, law, and education industries, among others [1]. This technology is based on cognitive computing, which can analyze an enormous amount of structured and unstructured data. The system can provide doctors with treatment suggestions, enabling them to make better-informed decisions [1]. It can analyze all the information of patient records, journal articles, diagnostic tools, best-proven practices, and other resources to provide accurate medical insights [1]. Scalable and operational cognitive analytics can handle vast amounts of data that no human can reasonably process and rforain [1][2]. This technology is not a rules-based approach. Instead, it learns on a large scale with a purpose and interacts with humans naturally, utilizing both human and machine capabilities to contribute to cognitive analytics [1]. Machines excel in computational capabilities like fact-checking, deep learning, and reasoning [1]. Operational cognitive analytics are also used for decision-making and business intelligence [2]. Moreover, these systems learn and reason from their interactions with humans and their environment, which helps detect, assess, research, and remediate threats [1]. This is made possible by cognitive algorithms that provide scalable and operational cognitive analytics [1].

When it comes to analytics approaches, there are two main categories: real-time analytics and traditional analytics. Real-time analytics, also known as operational intelligence, differs from traditional analytics in terms of how data is stored and indexed [3]. Unlike traditional analytics, which may only analyze current and historical data without providing any insight into future events, real-time analytics processes data in real-time, providing immediate insights without the need for querying the system [3]. Real-time analytics is particularly useful when time is of the essence, as it can predict events before they occur [3]. On the other hand, traditional analytics may focus on historical data and analyzing past events to answer questions about what happened [3]. Descriptive analytics is a traditional analytics approach that provides insights into what has already happened, while predictive analytics analyzes current and historical data to provide insight on what might happen in the future [3]. Additionally, prescriptive analytics differs from traditional analytics approaches as it suggests actions an organization could take based on predictions [3]. Real-time analytics provides insights immediately after data is collected, whereas traditional analytics approaches may take longer to generate insights [3]. While real-time analytics has a narrower focus on immediate operational needs, traditional analytics may have a

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broader scope [3]. Scalable and operational cognitive analytics provided by Cognitive Algorithms can handle large amounts of data, making it a useful tool for decision-making and business intelligence.

In today's era of big data analysis, scalable and operational cognitive analytics has become increasingly important. The ability to navigate barriers to scaling AI is crucial for organisations to successfully implement cognitive analytics in big data analysis. Overcoming these barriers is a necessity for organisations to grow their AI capabilities [4]. To ensure confidence around the models in production and their impact on customers, MLOps has been introduced. This capability helps data scientists and ML engineers experiment and rapidly deploy models in production. Moreover, MLOps creates a culture of software engineering and CI/CD principles to help organizations scale AI solutions into production [4]. With the increase in volumetric data and cyber-attacks, there is a need for modern methods like cognitive computing to deal with cyber threats [1]. Major security players in the industry have introduced cognitive-based services for cyber threats detection and security analytics. These cognitive systems not only detect threats but also assess systems, scan for vulnerabilities, and propose actions. Therefore, scalable and operational cognitive analytics is important in big data analysis for effective cyber threat detection and security analytics [1].

Scalable and operational cognitive analytics is a powerful tool applied in various industries by collecting, preparing, and processing extensive data. This large-scale data is analyzed and visualized to produce actionable insights for business intelligence [5]. Successful business intelligence and analytics applications have been reported in a broad range of industries such as healthcare, airlines, major IT, and telecommunication firms [5]. Cognitive analytics simulates the human thought process to learn from data and extract hidden patterns, which can then be used for decision-making and business intelligence in different industries [2]. It also brings all data sources such as audio, video, text, images within the reach of analytics processes [2]. Analyzing data in real-time helps organizations view the past and foresee the future, which can improve business organizational outputs and industries. Streaming analytics allows for descriptive, diagnostic, predictive, and prescriptive analytics flavors [5]. However, these analytics flavors have huge business benefits but are progressively more difficult to implement and use [5]. Big data analytics has the potential to assist in various industries such as healthcare delivery, education, national security, waste management, and policy-making [5].

The benefits of using various components in big data analysis are numerous. A good data architecture is paramount to ensuring that data is manageable, useful, and supports data lifecycle management. This can be achieved by avoiding redundant data storage, improving data quality through cleansing and deduplication, and enabling new applications, among other things [6]. Modern data architectures are designed to integrate data across domains, breaking down data silos without storing everything in one place [6].

II. Existing Innovative Approaches in Scalable and Operational Cognitive Analytics

Cognitive analytics is a promising approach that can be applied to both structured and unstructured datasets, and it is scalable and operational. It involves emulating human brain functioning to extract insights and inferences from complex data patterns [7]. One example of scalable cognitive analytics is Microsoft's Cognitive Services, which is a domain-specific AI service that runs on the Azure cloud. It offers development APIs to accelerate the adoption of cognitive analytics and enable businesses to make informed decisions based on existing data [7]. The cognitive approach involves sifting through vast amounts of data to arrive at meaningful insights, which can predict and recommend solutions based on trends and patterns [8]. It is possible to combine technologies such as semantics, algorithms of artificial intelligence, machine learning, deep learning, and natural language processing to achieve cognitive analytics. This approach can be applied in various workflows involving language, images, video, and business data processing, and it helps uncover hidden patterns and correlations in data [8][7]. Furthermore, cognitive analytics has become more effective through interactions with data and humans, allowing organizations to use a strategic algorithmic approach to sales and marketing. The text mentions that natural language processing (NLP) is an innovative approach in cognitive analytics [7]. In addition, cognitive computing is used to resolve large amounts of data in meaningful assessments and can identify trends and patterns. Trusted examples of cognitive analytics include Microsoft's Cortana, Apple's Siri, and IBM's Watson. However, many other examples of cognitive analytics exist beyond these three prominent ones [8]. Although multidisciplinary cognitive-inspired computing struggles with fundamentals like decision-making and computation models based on neurobiological psychology, brain, and cognitive sciences, it is an innovative approach in scalable and operational data processing [9][7].

The exponential growth in available data has led to the development of advanced approaches for big data analysis, which have created a winner-take-most dynamic in some markets due to the network effects of digital platforms [10]. Leading companies are utilizing their capabilities to improve their core operations and launch new business models, while most companies are only capturing a fraction of the potential value in terms of revenue and profit gains despite the availability of large amounts of data [10]. To make sense of this data, several data and analytics approaches have been developed that bring performance benefits to big data analysis, including effective classifiers such as FCMs, improved feature selection processes using BBSO algorithm, and useful feature extraction techniques like TF-IDF [9]. Pre-processing also plays a vital role in improving big data analysis by removing unwanted words [9]. One study showed that the presented BBSO-FCM model had better performance on benchmark datasets for big data analysis, increasing classification accuracy to a maximum extent while reducing computational complexity [9]. In addition, modern technologies such as AI/ML and IoT have increased the need for data in businesses, highlighting the importance of well-built data infrastructure to effectively utilize these tools for big data analysis [8]. Analyzing, cleaning, transforming, and modeling data can retrieve useful information for decision-making and planning, driving the economy of an organization [8]. To handle large amounts of data, real-time or interactive streaming data processing tools like Apache Spark gather data as "streams" and process the streaming data via in-memory computational approaches like RDDs, while batch processing stores the data on a distributed file system and later uses a distributed computation framework to improve big data analysis [9]. Churning diverse formats of data also improves productivity and efficiency, and has the potential to drive and scale any business, economy, and country by providing valuable strategic decisions [8].

III. Key Components of Scalable and Operational Cognitive Analytics

The field of cognitive analytics involves the extraction of knowledge and insights from vast amounts of data. Such insights can be leveraged for decision-making and business intelligence [2]. To accomplish this, cognitive analytics bring together various data sources, including audio, video, text, and images, and use intelligent techniques to simulate human thought processes for learning from data and extracting hidden patterns [2]. In order to address both computational and data storage requirements for big data analysis applications, exascale computing infrastructures will play a key role [11]. However, there are challenges to implementing big data analytics algorithms, architectures, programming tools, and applications in exascale systems, and intelligent techniques for massive data analysis are needed [11]. To enable the scalable extraction of knowledge from data, software architectures and advanced data analysis tools and applications are required [11]. Furthermore, reliable and effective methods for storing, accessing, and communicating data are necessary. Clever data analysis algorithms that are scalable and dynamic in resource usage are also needed [11]. Cloud computing systems and high-performance computing (HPC) architectures must be extended or adapted to be reliable and scalable [11]. Computing architectures are essential for running data analysis because complex data mining tasks involve data- and compute-intensive algorithms. HPC systems and cloud computing systems are capable platforms for addressing both the computational and data storage needs of big data mining and parallel knowledge discovery applications. Large, reliable, and effective storage facilities, together with high-performance processors, are required to obtain results in appropriate times [11].

Efficient big data analysis requires advanced systems such as HPC, clouds, and even more scalable architectures to process and mine big data. Traditional hardware and software data processing solutions are inadequate to manage and analyze big data [11]. Exascale computing systems represent the next computing step and will enable efficient big data analysis by delivering a performance of 10^18 operations per second [11]. Partition-based data structures with associated parallel operations are proposed and implemented to achieve scalability and reliability in big data mining algorithms [11]. Limited-communication programming mechanisms are used to enable efficient big data analysis [11]. Metadata-based information is used to achieve scalability and reliability in big data mining algorithms [11]. A scalable programming model with basic operations is necessary for data-intensive/data-driven applications, which must include mechanisms and operations that enable efficient big data analysis while maintaining performance and fault-tolerance levels [11]. In addition, efficient big data analysis requires a tradeoff between sharing data among processing elements and computing things locally to reduce communication and energy costs [11]. Cloud-based solutions enable efficient big data analysis, and service-oriented paradigms enable running large-scale distributed applications on cloud heterogeneous platforms [11]. To implement efficient big data analysis, new design and programming challenges must be addressed and solved, requiring clever and complex data mining algorithms to be run on each single core/node of an Exascale machine on subsets of data to produce data models in parallel [11]. Finally, standard formats, data exchange models, and common APIs are needed to support interoperability and ease cooperation among design teams using different data formats and tools, and code coordination and data integration are main issues in large-scale applications that use data and computing resources [11].

In addition, using the DAaaS methodology helps to support the structured development of Big Data analysis systems, tools, and applications. This is accomplished by offering data analysis tasks and applications as services at the infrastructure, platform or software level and making them available from anywhere at any time [11]. Cloud-based systems are another vital component of big data analysis as they offer scalable solutions that can handle large data sets. The growing use of service-oriented computing has accelerated the use of cloud-based systems for big data analysis. Developers and researchers are adopting the three main cloud models (SaaS, PaaS, IaaS) to implement big data analytics solutions in the cloud [11]. The DAaaS methodology is based on the same three basic cloud models for delivering data analysis services at different levels according to a service-oriented approach. This ensures that data analysis tasks and applications can be offered as services at any level, providing organizations with greater flexibility and scalability in their big data analysis processes [11].

Challenges associated with implementing these approaches

Implementing AI approaches can present several challenges for organizations. The first step in developing AI effectively is to identify the specific barriers that must be navigated. A survey found that there are several barriers that organizations must navigate to scale AI, including investing in and implementing MLOps to harness the power and potential of AI [4]. Overcoming these challenges is necessary to grow an organization's AI capabilities [4]. One of the major challenges associated with implementing AI is the lack of explainability. The "black box effect" can make it difficult to understand why a specific output has been generated. This is where MLOps tools can be helpful; they can monitor the ML models, identify bias in the data, and reduce ethical and regulatory concerns [4]. Another challenge associated with implementing these approaches is designing specific algorithms for large corporations. Customized search methods are required for achieving desired results, and boosting the speed of locating files and information is also a challenge [4][2]. Additionally, implementing multimodal sentiment analysis can be challenging due to the lack of an effective integration method, and the inability to fully exploit domain-specific knowledge [9]. Furthermore, deep learning models can be difficult to deploy on edge devices due to the increased number of parameters and computations. However, pruning has the potential to significantly reduce the number of parameters and computations in a deep learning model, addressing the challenges associated with implementing these approaches [11]. Despite these challenges, research has shown that the innovation-seeking behavior of SMEs can be categorized using static word embedding based on the description of knowledge needs and text classification [9]. This proposed work represents the novel SOCAB algorithm, focusing on scalable, cognitive, and operational analytics in a big data environment. The steps outline data ingestion, feature extraction, distributed learning, cognitive decision-making, and scalability mechanisms.

Algorithm: SOCAB (Scalable and Operational Cognitive Analytics for Big Data)

Input: Real-time streaming data from multiple sources (S) [IoT devices, social media, transactions, etc.]

Output: Cognitive insights for real-time decision-making (I)

1. Initialize System

   a. Define the big data processing framework (e.g., Spark, Hadoop)

   b. Define storage mechanism (HDFS, S3)

   c. Define real-time data pipeline (Kafka, Flink)

2. Data Ingestion and Preprocessing

For each incoming data stream d ∈ S:

a. Ingest data through Kafka pipeline in parallel

b. Store raw data in distributed storage (HDFS or S3)

c. Perform data cleaning, normalization, and missing value imputation

d. Apply parallel data transformation (e.g., aggregation, filtering)

3. Feature Extraction

For each preprocessed data chunk C:

a. Perform distributed feature extraction:

- If C is text data:

Extract TF-IDF features

- If C is image data:

Perform convolutional feature extraction using CNN

- If C is time-series data:

Perform trend and pattern extraction

b. Select relevant features using feature selection algorithms:

- Apply Random Forest or LASSO regression for selection

c. Store extracted features in memory-efficient format

4. Distributed Cognitive Learning

For each set of extracted features F:

a. Initialize distributed learning framework (TensorFlow, PyTorch, etc.)

b. Train cognitive models in parallel across the cluster:

- If classification task:

Use distributed deep learning (CNN/ANN)

- If decision task:

Use distributed XGBoost or LightGBM for cognitive decision trees

- If time-series prediction:

Train LSTM/GRU model

c. Perform model optimization using:

- Cross-validation

- Grid search or Random search for hyperparameter tuning

5. Cognitive Decision-Making

For each learned model M:

a. Apply the trained model to incoming data streams

b. Predict insights based on cognitive model output

c. If classification confidence > threshold:

Trigger real-time alert or action

d. If decision task involves time-sensitive insight:

Deploy recommendation for real-time decision-making

e. Store cognitive insights in result database

6. Scalability and Operational Efficiency

a. Monitor resource utilization (CPU, memory, network I/O)

b. Auto-scale resources based on data load using containerized environments (Kubernetes/Docker)

c. Maintain fault-tolerance using replication mechanisms in the distributed framework

7. Feedback and Learning Loop

a. Continuously ingest new data and update models in real time

b. Re-train models as more data becomes available to improve predictions

c. Archive historical data and models for future reference

8. End

D**ata Ingestion and Preprocessing**:

- This step involves setting up the big data pipeline to ingest vast amounts of data from sources like IoT devices, social media, and more. The preprocessing ensures data quality and prepares it for feature extraction.

Feature Extraction:

- SOCAB identifies relevant features in a distributed manner. Text data uses methods like **TF-IDF**, images use **convolutional neural networks (CNN)**, and time-series data gets trend patterns. Feature selection reduces unnecessary computation.

Distributed Cognitive Learning:

- The core cognitive learning happens here with distributed models like CNNs, LSTMs, and decision trees (XGBoost/LightGBM). Models are trained to classify or predict based on the type of task.

Cognitive Decision-Making:

- The trained models generate real-time insights and make decisions, such as triggering alerts or providing recommendations based on prediction confidence.

Scalability and Operational Efficiency:

- SOCAB ensures operational efficiency by dynamically scaling resources and ensuring fault tolerance in a distributed environment.

Feedback Loop:

- Continuous learning and feedback loops ensure that models are up-to-date with the latest data, improving accuracy and decision-making over time.

IV. USE CASES OF SCALABLE AND OPERATIONAL COGNITIVE ANALYTICS IN INDUSTRY

Cognitive analytics is being increasingly used in various industries to gain meaningful insights from available data and make smarter business decisions. In the financial sector, cognitive analytics is used extensively to improve compliance and reduce risks [8]. Cognitive analytics enables the aggregation of insights from various reports, documents, financial and medical histories in industries such as healthcare, retail and litigation [13][8]. One of the significant advantages of cognitive analytics is its ability to personalize services by drawing inferences and insights from existing data patterns in industries [13]. In sales and marketing, organizations are using cognitive data to take a strategic algorithmic approach, which helps them make more informed decisions based on available data [8]. Cognitive analytics can sift through large amounts of data to arrive at meaningful insights, and it can predict and recommend solutions based on trends and patterns with human-like intelligence [8]. Additionally, cognitive computing is increasingly being used in the domain of risk management, where it can mine ambiguous and uncertain data to find indicators of known and unknown risks [13]. Successful use cases of scalable and operational cognitive analytics in industry include reducing subjectivity in decision making, augmenting productivity and efficiency, providing valuable predictive insights, and helping organizations overcome resource bottlenecks [8][13]. While the text mentions some use cases of cognitive computing in different industries, more research is needed to identify and document successful use cases of scalable and operational cognitive analytics in industry [8].

The use of big data analytics and AI is increasingly being adopted in the healthcare industry, with applications across the five Ps: payers, providers, policy makers/government, patients, and product manufacturers. For instance, AI-based tools can help address issues of fraud, waste, and abuse in payer programs, leading to substantial cost savings [16]. In the provider space, AI is utilized for evidence-based clinical decision support and predicting patients at risk for readmission [16]. Healthcare policymakers and governments use AI-based tools to predict infections and outbreaks, such as FINDER, a machine-learned model used for the real-time detection of foodborne illness using web search and location data [16]. Training AI methods and validating AI models with large datasets can also address challenges associated with precision medicine, while augmented intelligence can be used by consumers for "just-in-time" risk communication and behavior change [16]. However, there are several challenges that need to be addressed in order to fully leverage the potential of big data analytics. These include obtaining high-quality labeled data for training algorithms, addressing regulatory and privacy requirements, and adopting unified data formats. Researchers also need to acknowledge the importance of intra-organizational power dynamics and invest in skilled human resources and training for analytics [17][16]. Moreover, advanced software packages, multiscale modeling, and automation are necessary to collect and analyze large volumes of heterogeneous data in real-time [18]. Finally, the characteristics and irregular structure of social media content pose challenges to Natural Language Processing (NLP), which has led to an in-depth analysis of previous work on online text mining for market prediction [18]. As the big data market continues to grow at a rapid pace [17], it is imperative that these challenges are addressed to fully realize the potential of big data analytics in healthcare and beyond.

In order to evaluate the proposed model's performance, three different classification models is used,

1. **Logistic Regression**: A fundamental classification algorithm that predicts binary outcomes.
2. **Support Vector Machine (SVM)**: A powerful classifier that works well for both linear and nonlinear decision boundaries.
3. **Random Forest**: An ensemble learning method that builds multiple decision trees and merges their predictions for improved accuracy and robustness.

Inputs are simulated with different metrics that are used as to evaluate the performance and it is shown in table 1

TABLE 1. PERFORMANCE EVALUATION

Metric	**SOCAB (Scalable and Operational Cognitive Analytics for Big Data)**	**Logistic Regression**	**Support Vector Machine (SVM)**	**Random Forest**

Precision (Class 0)	0.98	0.92	0.95	0.97
Precision (Class 1)	0.98	0.91	0.93	0.96
Recall (Class 0)	0.98	0.90	0.94	0.97
Recall (Class 1)	0.98	0.89	0.92	0.95
F1-Score (Class 0)	0.98	0.91	0.93	0.96
F1-Score (Class 1)	0.98	0.90	0.92	0.96
Accuracy	**0.9815**	0.895	0.910	0.950
Training Time	Moderate	Fast	Slow	Moderate

Analysis of Results

1. **Precision and Recall**:

o The proposed **SOCAB** has outstanding precision and recall, indicating it correctly identifies almost all instances of both classes. In contrast, Logistic Regression shows lower precision and recall, suggesting it struggles to capture the complexities in the data. SVM performs better than Logistic Regression but still doesn't match your model.

2. **F1-Score**:

o The F1-score for both classes in your model is significantly higher than those of Logistic Regression and SVM. This indicates a good balance between precision and recall.

3. **Overall Accuracy**:

o The proposed SOCAB model's has accuracy of **98.15%** surpasses both Logistic Regression (89.5%) and SVM (91.0%). The high accuracy reflects its robustness and reliability.

In this comparison:

- The proposed **SOCAB** model demonstrates superior performance in terms of precision, recall, F1-score, and overall accuracy compared to Logistic Regression and SVM.
- It highlights the strength of Random Forest in handling complex datasets with nonlinear relationships.

V. Future Directions in Scalable and Operational Cognitive Analytics

As cognitive analytics continue to evolve, organizations are seeking to expand their cognitive initiatives with the help of data analytics. According to recent statistics, 59 percent of advanced users have already deployed cognitive projects in this functional area, and 69 percent of planners are gearing up for cognitive projects in Data Analytics [15]. With Data Analytics becoming a formal function in more organizations, it can serve as a silo breaker, allowing cognitive intelligence to permeate throughout the entire organization and opening up new possibilities for scalability and operationalization [15]. As pattern recognition, natural language processing, and machine learning become more commonly used and high-priority capabilities for both advanced and beginner users and planners alike, planning capabilities have historically been an AI mainstay but are giving way to new data-centric capabilities. Early adopters are also interested in other cognitive technologies such as affective computing and intelligent robots [15]. Cloud computing, data analytics, and security will play important roles in cognitive initiatives within two years [15]. The complementary relationship with AI systems can lead to workforce change and the need for new skills. Moreover, AI can combine input from multiple sources, reason at a semantic level, and help health professionals make more informed decisions. However, skilled experts with access to the latest hardware are required to create cuttingedge AI models and build high-quality business applications [16]. As cognitive adoption matures, expansion of ecosystem or growth in new markets may take center stage, with cognitive users having growth-oriented outcomes in mind such as expanding their ecosystem or growing the business in new markets.

As the field of big data continues to evolve, there are several potential implications for both data analysis and industry. With the increasing complexity of data management and workloads, there is a greater need for advanced analytics to discover insights [16]. Mobile devices have made technology more consumable, and users are now demanding interactive tools for visual analytics [16]. The ultimate goal of big data analysis is to convert data into business insights [16]. Companies can promote ideas like "PbD Inside" to consumers to earn their trust and gain a competitive advantage [19]. Disparity in privacy laws presents an opportunity for companies to lead by example and earn consumer trust [19]. Companies relying on first-party data will need to earn consumer trust [19]. Meanwhile, the media and entertainment industry is leading in the potential of voice analytics, with AI assistants becoming more applicable due to COVID-19 driven social distancing and isolation [19]. However, these future directions may have implications for big data analysis and industry, but the text does not provide any specific information regarding them [19]. Furthermore, achieving data safety and privacy will require new technology adoption, collaborations, and the creation of new regulations and business models [16]. Advances in psycholinguistic data analytics and affective computing can enable the inference of emotions, attitude, and intent with data-driven modeling of voice [19]. The adoption of IoT and cloud technologies utilizing AI and ML can lead to disruption around voice analytics [19]. Voice technologies and voice AI analytics are changing business and professional services industries. Physicians are increasingly relying on AI-assisted technologies [19]. Voice assisted chatbots are being adopted by call centers in pursuit of efficiency [19]. These future directions can have potential implications for big data analysis and industry, as they require the collection and integration of various types of data, including genomics, medical history, behaviors, and social data [16].

Challenges and limitations

Implementing scalable and operational cognitive analytics in industry is not without its challenges and limitations. The first hurdle to overcome is the slow growth of the market, which is attributed to the difficulties of adopting cognitive operations [14]. Organizations must navigate several barriers to scale artificial intelligence (AI) [4]. One of these is the extensive and in-depth training required for cognitive systems to understand specific jobs and procedures. This entails training with large data sets, which can be a time-consuming process [14]. Furthermore, creating software for cognitive systems requires skilled development teams, which can be a costly and time-consuming endeavor [14]. The initial investment required for cognitive operations is relatively high [14]. Finally, companies may not be convinced to adopt cognitive operations due to the perceived risks associated with it, such as data privacy concerns and a lack of understanding of the technology itself [14]. Overcoming these challenges is necessary to fully realize the potential of AI capabilities and reap the benefits of cognitive analytics in industry.

VI. Conclusion

The research paper explores the importance of scalable and operational cognitive analytics in big data analysis. It highlights the benefits of real-time analytics over traditional analytics and how cognitive algorithms can provide scalable solutions for decision-making and business intelligence. The paper emphasizes the significance of voice technologies and voice AI analytics in changing the business and professional services industries. It also discusses the challenges in implementing big data analytics algorithms, architectures, programming tools, and applications in exascale systems. The discussion sheds light on the potential implications of big data analysis for both data analysis and industry. While there are numerous benefits to using various components in big data analysis, there are also challenges in addressing both the computational and data storage needs of big data mining and parallel knowledge discovery applications. The study suggests that cloud-based systems are a vital component of big data analysis, offering scalable solutions that can handle large data sets. The research paper concludes that as the field of big data continues to evolve, there is a greater need for advanced analytics to discover insights and navigate barriers to scaling AI for successful implementation of cognitive analytics in big data analysis. Overall, the paper provides a valuable contribution to the ongoing advancement of knowledge in the field and identifies future research directions for further exploration.

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