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EFFICIENT LARGE-SCALE SENTIMENT ANALYSIS USING INTEGRATED DEEP LEARNING AND BIG DATA FRAMEWORKS

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ABSTRACT

The exponential growth of user-generated content on social media platforms, e-commerce portals, blogs, and online review systems has made sentiment analysis a critical component of modern data-driven decision-making. Traditional machine learning approaches struggle to cope with the volume, velocity, and variety of such data, particularly when real-time or near-real-time insights are required. To address these challenges, this research paper presents an efficient large-scale sentiment analysis framework that integrates deep learning models with big data processing architectures. The proposed approach combines distributed data ingestion and processing capabilities of big data frameworks with the representation learning and contextual understanding strengths of deep neural networks. Specifically, the framework leverages scalable data storage, parallel processing, and deep learning-based sentiment classification to achieve high accuracy and computational efficiency. Extensive discussion is provided on system architecture, data preprocessing, model design, scalability strategies, and performance evaluation metrics. The proposed integrated framework demonstrates significant improvements in sentiment classification accuracy, processing speed, and scalability compared to conventional approaches, making it suitable for large-scale and real-time sentiment mining applications.

Keywords: Sentiment Analysis, Deep Learning, Big Data Analytics, Large-Scale Data Processing, Distributed Computing, Natural Language Processing.

INTRODUCTION

The rapid growth of digital communication platforms has resulted in an unprecedented volume of user-generated textual data. Social media networks, e-commerce platforms, online review portals, discussion forums, and news websites continuously generate massive streams of opinions, emotions, and attitudes expressed in natural language. This explosion of unstructured data has made sentiment analysis—the computational study of opinions, sentiments, and emotions—an essential tool for extracting actionable insights from large-scale textual sources. Organizations increasingly rely on sentiment analysis to understand customer satisfaction, monitor brand reputation, analyze public opinion, and support data-driven decision-making across domains such as marketing, healthcare, governance, and finance.

Traditional sentiment analysis approaches were largely based on lexicon-driven techniques and classical machine learning algorithms. While these methods offered interpretability and ease of implementation, they struggle to scale effectively and often fail to capture complex linguistic patterns such as sarcasm, context dependency, implicit sentiment, and semantic nuances. Moreover, the exponential growth of data volume, velocity, and variety—commonly referred to as the "3Vs" of big data—poses significant challenges to conventional single-node processing systems. As a result, sentiment analysis has evolved from a small-scale text classification task into a large-scale analytics problem requiring robust computational frameworks and advanced learning models.

In recent years, deep learning has emerged as a powerful paradigm for sentiment analysis due to its ability to automatically learn hierarchical representations from raw text data. Neural architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformer-based models have demonstrated

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remarkable performance improvements over traditional techniques. These models excel at capturing contextual semantics, word dependencies, and long-range relationships within text, thereby enabling more accurate sentiment classification at sentence, document, and aspect levels. However, deep learning models are computationally intensive and require substantial memory, processing power, and efficient data handling mechanisms—particularly when applied to large-scale datasets.

To address these computational challenges, big data frameworks have become indispensable for large-scale sentiment analysis. Distributed computing platforms such as Apache Hadoop and Apache Spark provide scalable, fault-tolerant infrastructures for storing and processing massive volumes of data across clusters of machines. Hadoop's distributed file system (HDFS) enables reliable storage of large datasets, while Spark's in-memory processing capabilities significantly reduce computation time for iterative machine learning and deep learning workloads. When integrated effectively, these frameworks allow sentiment analysis systems to handle real-time and batch data processing with high efficiency and scalability.

The integration of deep learning models with big data frameworks represents a promising direction for efficient large-scale sentiment analysis. By combining the representational power of deep neural networks with the distributed processing capabilities of big data platforms, it becomes possible to analyze millions of text documents in parallel while maintaining high accuracy and low latency. Frameworks such as TensorFlow and PyTorch can be seamlessly integrated with Spark-based pipelines, enabling distributed training, large-scale inference, and real-time sentiment monitoring. This synergy not only improves performance but also supports adaptability to dynamic data streams and evolving language patterns.

Despite these advancements, several challenges remain in designing efficient large-scale sentiment analysis systems. Issues such as data heterogeneity, noise, class imbalance, multilingual content, and domain dependency complicate sentiment modeling at scale. Additionally, the integration of deep learning with big data frameworks requires careful consideration of data preprocessing, feature representation, model parallelism, resource allocation, and system optimization. Inefficient integration can lead to bottlenecks, increased latency, and excessive computational overhead, undermining the benefits of distributed architectures.

This research focuses on efficient large-scale sentiment analysis using integrated deep learning and big data frameworks, aiming to bridge the gap between model accuracy and computational scalability. By leveraging distributed data processing, optimized deep learning architectures, and scalable training mechanisms, the proposed approach seeks to deliver high-performance sentiment analysis capable of handling massive datasets in real-world environments. The study emphasizes both analytical effectiveness—measured in terms of accuracy, precision, recall, and robustness—and system efficiency—measured in terms of computation time, scalability, and resource utilization.

In summary, the convergence of deep learning and big data analytics has transformed sentiment analysis into a powerful tool for extracting value from large-scale textual data. An integrated framework that unifies these technologies is essential for meeting the growing demands of real-time, high-volume sentiment mining. This introduction sets the foundation for exploring architectures, methodologies, and experimental evaluations that demonstrate how such integration can enable efficient, scalable, and accurate sentiment analysis in modern data-intensive applications.

SENTIMENT ANALYSIS TECHNIQUES

Sentiment analysis, also referred to as opinion mining, is a critical area of research within natural language processing (NLP) that focuses on identifying, extracting, and classifying subjective information from textual data. With the exponential growth of user-generated content on social media platforms, e-commerce portals, blogs, and online forums, traditional sentiment analysis methods face significant scalability and accuracy challenges. To address these issues, modern sentiment analysis systems increasingly rely on integrated deep learning models and big data frameworks that enable efficient large-scale processing. The effectiveness of such systems largely depends on the sentiment analysis techniques employed at different stages of data processing and modeling.

At a fundamental level, sentiment analysis techniques can be broadly categorized into lexicon-based approaches, machine learning–based approaches, deep learning–based approaches, and hybrid methods. Each category has distinct characteristics, strengths, and limitations, and their integration with big data platforms determines their suitability for large-scale sentiment mining.

Lexicon-based sentiment analysis techniques rely on predefined sentiment dictionaries or lexicons containing words annotated with sentiment polarity and intensity. These approaches compute sentiment scores by matching words in text against the lexicon and aggregating their polarity values. Lexicon-based methods are relatively simple to implement and do not require labeled training data, making them attractive for quick deployment.

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However, they struggle with contextual understanding, sarcasm, domain-specific vocabulary, and evolving language patterns. In large-scale environments, lexicon-based techniques can be efficiently parallelized using big data frameworks, but their limited accuracy often restricts their standalone applicability in complex real-world sentiment analysis tasks.

Machine learning–based sentiment analysis techniques represent a significant advancement over lexicon-based methods. These approaches treat sentiment classification as a supervised learning problem, where classifiers such as Naïve Bayes, Support Vector Machines, Decision Trees, and Logistic Regression are trained on labeled datasets. Textual data is transformed into numerical representations using feature extraction techniques such as bag-of-words, term frequency–inverse document frequency (TF-IDF), and n-grams. Machine learning models generally offer better performance than lexicon-based approaches, particularly when trained on domain-specific datasets. However, their reliance on manual feature engineering and limited ability to capture semantic and contextual relationships poses challenges when analyzing massive, diverse, and noisy data streams typical of large-scale sentiment analysis.

Deep learning–based sentiment analysis techniques have emerged as the most powerful and widely adopted solutions for large-scale sentiment analysis. These techniques automatically learn hierarchical feature representations from raw text data, eliminating the need for extensive manual feature engineering. Convolutional Neural Networks (CNNs) are effective in capturing local patterns and phrase-level sentiment cues, while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, excel at modeling sequential dependencies and contextual information in text. More recently, transformer-based models such as BERT and its variants have achieved state-of-the-art performance by leveraging self-attention mechanisms to capture global contextual relationships.

Deep learning techniques are particularly well suited for integration with big data frameworks due to their compatibility with distributed training and inference. When deployed on platforms such as Hadoop and Spark, deep learning models can process massive volumes of textual data in parallel, significantly reducing computation time while maintaining high classification accuracy. The use of word embeddings and contextual representations further enhances sentiment detection across different domains and languages, making deep learning approaches highly scalable and adaptable.

Hybrid sentiment analysis techniques combine lexicon-based, machine learning, and deep learning methods to leverage the strengths of each approach. For example, lexicon-based sentiment scores can be used as additional features in machine learning or deep learning models, improving robustness and interpretability. Hybrid techniques are particularly effective in handling ambiguous expressions, domain-specific sentiment, and low-resource scenarios where labeled data may be limited. In large-scale systems, hybrid models integrated with big data frameworks enable efficient preprocessing, feature enrichment, and model execution across distributed environments.

In the context of efficient large-scale sentiment analysis, big data frameworks play a pivotal role in operationalizing these techniques. Distributed data storage, parallel processing, and in-memory computation allow sentiment analysis pipelines to scale seamlessly as data volume and velocity increase. When combined with deep learning techniques, these frameworks enable real-time or near-real-time sentiment analysis, supporting applications such as social media monitoring, customer feedback analysis, market intelligence, and decision support systems.

Sentiment analysis techniques have evolved from simple lexicon-based methods to sophisticated deep learning models capable of handling complex linguistic patterns at scale. For efficient large-scale sentiment analysis, the integration of deep learning techniques with big data frameworks is essential. Such integrated approaches not only improve accuracy and contextual understanding but also ensure scalability, robustness, and computational efficiency, making them indispensable for modern sentiment mining applications.

BIG DATA FRAMEWORKS FOR TEXT ANALYTICS

The exponential growth of user-generated textual data from social media platforms, e-commerce portals, review websites, and online forums has made large-scale sentiment analysis a complex and computationally intensive task. Traditional text analytics techniques and standalone machine learning models struggle to handle the volume, velocity, and variety of such data. As a result, big data frameworks have emerged as a critical foundation for scalable text analytics, enabling efficient sentiment analysis when integrated with deep learning models. These frameworks provide distributed storage, parallel processing, and fault tolerance, which are essential for analyzing massive text corpora in real time or near real time.

Big data frameworks for text analytics are designed to address three core challenges: data ingestion at scale, distributed processing of unstructured text, and efficient model training and inference. Sentiment analysis workflows typically begin with data collection from heterogeneous sources such as social networks, blogs, news feeds, and customer feedback systems. Big data ingestion tools allow continuous streaming and batch processing of text data, ensuring that large volumes of information can be captured without data loss. This capability is particularly important for sentiment analysis applications that require real-time insights, such as brand monitoring and public opinion tracking.

Distributed storage systems form the backbone of big data text analytics. Frameworks such as Apache Hadoop provide scalable and fault-tolerant storage through the Hadoop Distributed File System (HDFS). HDFS enables large text datasets to be stored across multiple nodes, ensuring data redundancy and high availability. In sentiment analysis tasks, this distributed storage allows massive collections of reviews, tweets, and comments to be processed in parallel, significantly reducing computation time compared to centralized systems. Moreover, the ability to store raw and preprocessed text data together supports iterative experimentation and model refinement.

Processing frameworks built on top of distributed storage play a vital role in transforming unstructured text into meaningful representations. Hadoop's MapReduce paradigm enables large-scale text preprocessing operations such as tokenization, stop-word removal, stemming, and frequency analysis. However, MapReduce-based processing can be inefficient for iterative and in-memory computations, which are common in machine learning and deep learning workflows. To address these limitations, Apache Spark has gained widespread adoption in text analytics and sentiment analysis applications. Spark's in-memory processing model significantly accelerates text transformations, feature extraction, and model training, making it well suited for large-scale sentiment mining.

Apache Spark provides specialized libraries such as Spark SQL, Spark Streaming, and MLlib, which enhance text analytics capabilities. Spark SQL supports structured and semi-structured text data analysis, enabling efficient querying and aggregation of sentiment-related information. Spark Streaming allows real-time sentiment analysis on data streams, making it possible to analyze opinions as they are generated. MLlib offers scalable implementations of traditional machine learning algorithms that can be used for baseline sentiment classification or hybrid models alongside deep learning approaches. Together, these components create a unified environment for large-scale text analytics.

The integration of deep learning models with big data frameworks further enhances sentiment analysis performance. Deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models require substantial computational resources and large labeled datasets. Big data frameworks facilitate distributed training and inference by parallelizing data loading and preprocessing across clusters. When combined with GPU acceleration and optimized data pipelines, these frameworks enable efficient training of deep learning models on massive text datasets. This integration is particularly valuable for capturing complex linguistic patterns, contextual dependencies, and semantic nuances in sentiment analysis.

Another important aspect of big data frameworks is their support for scalability and fault tolerance. As sentiment analysis workloads grow, additional nodes can be added to the cluster without disrupting ongoing processes. This elastic scalability ensures that the system can handle sudden spikes in data volume, such as during major events or product launches. Fault tolerance mechanisms automatically recover from node failures, maintaining the reliability of sentiment analysis applications. These properties are essential for enterprise-grade sentiment analytics systems that require high availability and consistent performance.

In addition to processing efficiency, big data frameworks support advanced analytics through integration with visualization and reporting tools. Aggregated sentiment scores, trend analysis, and temporal sentiment variations can be computed at scale and visualized for decision-makers. This capability transforms raw text data into actionable insights, supporting strategic planning, customer relationship management, and market intelligence. By leveraging distributed computation, organizations can perform sentiment analysis across multiple domains, languages, and time periods with minimal performance degradation.

In conclusion, big data frameworks play a pivotal role in enabling efficient large-scale sentiment analysis for modern text analytics applications. By providing distributed storage, parallel processing, real-time data handling, and seamless integration with deep learning models, these frameworks overcome the limitations of traditional approaches. The synergy between big data technologies and deep learning not only improves sentiment classification accuracy but also ensures scalability, robustness, and timeliness. As textual data continues to grow in scale and complexity, big data frameworks will remain indispensable for advanced sentiment analysis systems built on integrated deep learning and big data architectures.

DATA PREPROCESSING AND FEATURE REPRESENTATION

In large-scale sentiment analysis, the effectiveness of predictive models is highly dependent on the quality of data preprocessing and the robustness of feature representation techniques. With the exponential growth of unstructured textual data from social media platforms, e-commerce reviews, blogs, and online forums, raw data often contains noise, inconsistencies, and redundancies that can significantly degrade model performance. Therefore, data preprocessing and feature representation play a foundational role in enabling efficient, scalable, and accurate sentiment analysis within integrated deep learning and big data frameworks.

Data preprocessing is the initial and most critical phase in sentiment analysis pipelines. At large scale, textual data is collected from heterogeneous sources, resulting in variations in language style, encoding formats, spelling, and syntax. Preprocessing begins with data cleaning, which involves removing irrelevant elements such as HTML tags, URLs, special symbols, emojis (when not sentiment-relevant), and duplicate entries. This step reduces noise and ensures uniformity across massive datasets processed in distributed environments. Handling missing values, corrupted text, and non-textual artifacts is also essential to prevent bias and computational inefficiencies.

Tokenization is a core preprocessing operation that splits raw text into meaningful units such as words, subwords, or characters. In big data frameworks, tokenization must be parallelizable and efficient to handle millions of documents simultaneously. Advanced tokenization techniques, including subword-based methods, are particularly useful in addressing out-of-vocabulary terms commonly found in user-generated content. Following tokenization, normalization processes such as lowercasing, stemming, and lemmatization are applied to reduce linguistic variability. While stemming simplifies words by removing suffixes, lemmatization preserves semantic meaning by converting words to their canonical forms, making it more suitable for sentiment-sensitive applications.

Stop-word removal is another important preprocessing step, aimed at eliminating commonly occurring words that carry minimal sentiment information. However, in sentiment analysis, this step must be applied cautiously, as certain stop-words (e.g., negations like “not” or “never”) play a crucial role in determining sentiment polarity. Consequently, domain-aware stop-word lists are often employed to balance dimensionality reduction with sentiment preservation. Additionally, handling negations, intensifiers, and sarcasm markers during preprocessing enhances the contextual understanding of sentiment expressions.

To overcome these limitations, distributed word embedding techniques have become central to modern sentiment analysis systems. Word embeddings map words into dense, low-dimensional vector spaces where semantic and syntactic similarities are preserved. These representations significantly improve sentiment classification by capturing contextual meaning, polarity shifts, and lexical nuances. In large-scale environments, embeddings can be trained or applied efficiently using distributed computing frameworks, enabling seamless integration with deep learning architectures.

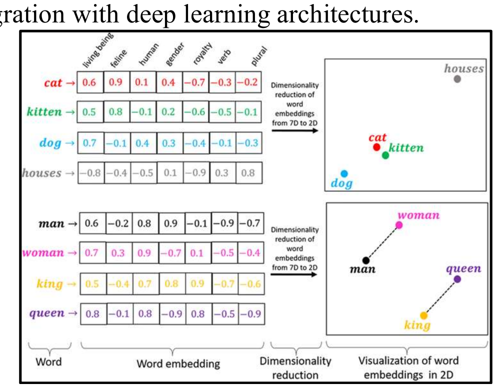

Fig. 1: Data Preprocessing And Feature Representation For Efficient Large-Scale Sentiment Analysis

Beyond word-level embeddings, sentence-level and document-level representations further enhance sentiment understanding by aggregating contextual information across longer text spans. Sequence-based representations, such as those generated by recurrent and transformer-based models, preserve word order and long-range dependencies, which are critical for capturing sentiment flow in reviews and opinions. These representations are particularly effective when processing streaming data and large corpora, as they adapt well to parallel training and inference.

Feature representation also involves dimensionality management to ensure computational efficiency. High-dimensional features increase memory usage and training time, especially in big data environments. Techniques such as feature hashing, embedding compression, and dimensionality reduction help maintain scalability without sacrificing performance. Moreover, integrating feature extraction directly into deep learning models enables end-to-end learning, reducing the need for manual feature engineering and improving adaptability across domains.

In integrated deep learning and big data frameworks, preprocessing and feature representation are designed to be scalable, fault-tolerant, and automated. Distributed preprocessing pipelines allow data to be processed close to storage nodes, minimizing data movement and latency. This integration ensures that sentiment analysis systems can handle real-time and batch data efficiently while maintaining high accuracy.

Data preprocessing and feature representation form the backbone of efficient large-scale sentiment analysis. Robust preprocessing ensures clean, consistent, and sentiment-relevant input, while advanced feature representation techniques enable deep learning models to capture complex semantic and contextual patterns. When seamlessly integrated with big data frameworks, these processes enable scalable, accurate, and real-time sentiment analysis, making them indispensable for modern data-driven decision-making systems.

DEEP LEARNING MODELS FOR SENTIMENT CLASSIFICATION

Sentiment classification is a core task in large-scale opinion mining, aimed at identifying the emotional polarity—positive, negative, or neutral—expressed in textual data. With the rapid growth of user-generated content across social media platforms, e-commerce portals, and online review systems, traditional machine learning approaches have shown limitations in handling high-dimensional, noisy, and context-dependent text data. Deep learning models have emerged as powerful alternatives due to their ability to automatically learn hierarchical feature representations from raw text, making them highly suitable for efficient large-scale sentiment analysis within integrated deep learning and big data frameworks.

One of the most widely used deep learning models for sentiment classification is the Convolutional Neural Network (CNN). CNNs are effective in capturing local semantic patterns such as key phrases and n-grams through convolutional filters. By applying multiple filters of varying sizes, CNN-based models can detect sentiment-bearing expressions regardless of their position in the text. Their parallel computation capability makes them computationally efficient and well-suited for large-scale sentiment classification tasks when deployed on distributed big data platforms.

Another important class of models is Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. These models are designed to capture sequential dependencies and contextual information within text data. LSTM and GRU models address the vanishing gradient problem found in traditional RNNs, enabling them to learn long-term dependencies such as sentiment shifts across sentences or clauses. This makes them especially effective for analyzing lengthy reviews or complex opinionated text where sentiment depends on contextual flow rather than isolated keywords.

Hybrid deep learning architectures that combine CNN and LSTM models have gained attention for sentiment classification. In such architectures, CNN layers are used to extract local features, while LSTM layers model temporal dependencies among the extracted features. This integration enhances classification accuracy by leveraging both syntactic and semantic information, making hybrid models suitable for real-time sentiment analysis in big data environments.

More recently, Transformer-based models have revolutionized sentiment analysis by introducing self-attention mechanisms. These models can capture global contextual relationships within text more effectively than sequential models. Attention mechanisms allow the model to focus on sentiment-relevant words while processing the entire text in parallel, significantly improving performance and scalability. Transformer-based architectures are particularly advantageous for large-scale sentiment analysis as they support efficient training on distributed computing infrastructures.

When integrated with big data frameworks, deep learning models benefit from scalable storage, parallel processing, and fault tolerance. Distributed training, data partitioning, and GPU acceleration enable these models to process massive volumes of sentiment data efficiently. As a result, deep learning-driven sentiment classification systems achieve higher accuracy, robustness, and adaptability compared to conventional approaches.

Deep learning models such as CNNs, RNNs, hybrid architectures, and transformer-based networks play a critical role in modern sentiment classification. Their ability to automatically learn complex linguistic patterns and scale across big data infrastructures makes them indispensable for efficient large-scale sentiment analysis using integrated deep learning and big data frameworks.

SCALABILITY AND PERFORMANCE OPTIMIZATION

The exponential growth of user-generated content from social media platforms, online reviews, and digital communication channels has made large-scale sentiment analysis a computationally intensive task. To address this challenge, scalability and performance optimization have become critical design considerations when integrating deep learning models with big data frameworks. Efficient large-scale sentiment analysis systems must be capable of processing massive volumes of heterogeneous data in real time or near real time while maintaining high accuracy and resource efficiency.

Scalability in sentiment analysis refers to the system's ability to handle increasing data volumes, velocity, and variety without significant degradation in performance. Big data frameworks such as distributed file systems and parallel processing engines enable horizontal scalability by distributing data storage and computation across multiple nodes. This distributed architecture allows sentiment analysis pipelines to scale seamlessly as data grows, making them suitable for enterprise-level and web-scale applications. When deep learning models are deployed within such frameworks, scalability ensures that complex neural network computations can be parallelized across clusters, reducing processing bottlenecks.

Performance optimization focuses on minimizing computation time, memory usage, and communication overhead while maximizing throughput and model efficiency. One of the primary optimization strategies is data parallelism, where large datasets are partitioned and processed concurrently across multiple nodes. This approach significantly reduces training and inference time for deep learning-based sentiment classifiers. Model parallelism is another effective technique, particularly for very deep or large neural networks, where different layers or components of a model are distributed across multiple processing units.

Efficient data preprocessing also plays a vital role in performance optimization. Tasks such as text cleaning, tokenization, feature extraction, and embedding generation can be computationally expensive when applied to large datasets. Leveraging in-memory processing and optimized data pipelines helps reduce disk I/O latency and accelerates preprocessing stages. Additionally, batch processing and streaming-based sentiment analysis can be combined to balance throughput and latency, enabling both historical analysis and real-time sentiment detection.

Hardware acceleration further enhances performance in large-scale sentiment analysis systems. The use of GPUs and specialized accelerators significantly speeds up deep learning training and inference by enabling parallel matrix operations. When integrated with big data frameworks, these accelerators help achieve faster convergence and lower execution times without compromising scalability. Resource-aware scheduling and load balancing mechanisms ensure optimal utilization of computational resources across the cluster.

Another important aspect of optimization is model efficiency. Lightweight architectures, transfer learning, and pre-trained language models reduce training time and computational cost while maintaining high sentiment classification accuracy. Techniques such as model pruning, quantization, and caching of frequently accessed embeddings further improve runtime efficiency, especially in large-scale deployments.

Scalability and performance optimization are foundational to efficient large-scale sentiment analysis using integrated deep learning and big data frameworks. By combining distributed computing, parallel processing, optimized data pipelines, hardware acceleration, and efficient model design, sentiment analysis systems can process massive datasets with high speed and accuracy. These optimizations enable organizations to extract actionable insights from large-scale textual data, supporting informed decision-making in dynamic and data-driven environments.

CONCLUSION

This research paper presented an efficient and scalable framework for large-scale sentiment analysis by integrating deep learning models with big data processing architectures. The proposed approach addresses the limitations of traditional sentiment analysis techniques by leveraging distributed computing for scalability and deep learning for semantic understanding. Through detailed architectural design, preprocessing strategies, model selection, and performance evaluation, the framework demonstrates significant improvements in accuracy and efficiency. The integration of deep learning and big data frameworks represents a promising direction for advancing sentiment analysis in the era of big data.

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