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A Systematic Review of Social Media Analytics Pipelines: Verification, Optimization, and Scalable Computing Perspectives

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| Peer Review Information | Abstract |
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| <p><i>Submission: 05 Sept 2025</i> <i>Revision: 23 Sept 2025</i> <i>Acceptance: 16 Oct 2025</i></p> | <p>Social media platforms generate vast volumes of dynamic, heterogeneous, and real-time data, making them valuable for analytics in domains such as marketing, healthcare, disaster management, and public policy. To extract meaningful insights, organizations rely on social media analytics pipelines that integrate stages including data acquisition, preprocessing, storage, analysis, and visualization. However, the growing scale and complexity of such data introduce challenges related to verification, optimization, and scalability. This paper presents a systematic review of 30 studies published between 2018 and 2023, examining key architectural components, processing frameworks, and emerging technologies for efficient pipeline design. It highlights verification mechanisms such as misinformation detection, fact-checking, and trust-aware systems to ensure data reliability. The review also explores optimization strategies, including data reduction, indexing, hybrid batch-stream processing, and AI-driven tuning, which improve efficiency and reduce latency. Furthermore, it analyzes scalable computing approaches like distributed systems, cloud and edge computing, and microservices architectures. While tools such as Apache Spark and Hadoop enhance performance, challenges remain in real-time verification, energy efficiency, data privacy, and integration of multi-modal data, indicating important directions for future research.</p> |
| <p>Keywords</p> <p><i>Social Media Analytics, Big Data Pipelines, Verification, Optimization, Scalable Computing, Data Processing.</i></p> | |

Introduction

Social media platforms have transformed the way information is generated, shared, and consumed. Platforms such as Twitter, Facebook, and Instagram produce massive volumes of data every second, making them valuable sources for analytics in domains such as marketing, healthcare, politics, and disaster management. The analysis of such data requires structured pipelines capable of handling large-scale, heterogeneous, and dynamic data streams. A social media analytics pipeline typically consists of several stages, including data collection, preprocessing, storage, analysis, and visualization. These stages form a continuous workflow that enables organizations to extract insights from raw data. However, the complexity of social media data introduces significant

challenges. According to research, social media data exhibits characteristics of Big Data, including high volume, velocity, variety, and veracity, which complicate processing and analysis.

One of the primary challenges in social media analytics pipelines is verification. Social media platforms are prone to misinformation, fake news, and unreliable content. Therefore, verifying the authenticity and accuracy of data is critical. Recent studies have proposed automated verification pipelines that include steps such as claim detection, evidence retrieval, and fact-checking. These pipelines leverage machine learning and natural language processing techniques to identify credible information sources and validate content. Another key aspect is optimization. Social media analytics pipelines

often involve processing large volumes of data in real time, which can lead to high computational costs. Optimization techniques such as data reduction, parallel processing, and efficient storage mechanisms are essential to improve performance. Technologies like Apache Spark and Hadoop have been widely used to optimize data processing tasks by enabling distributed computation.

Scalability is also a critical requirement for social media analytics pipelines. As the volume of social media data continues to grow, systems must be capable of scaling horizontally across distributed environments. Cloud computing and edge computing have emerged as important solutions for handling large-scale data processing. These technologies allow systems to dynamically allocate resources based on workload requirements, improving efficiency and reducing latency. The integration of multiple data sources further complicates the design of analytics pipelines. Social media data includes text, images, videos, and network interactions, requiring advanced data fusion techniques. Modern systems often use multi-model data architectures to handle these diverse data types efficiently. For example, recent research has introduced tri-store systems that combine relational, graph, and text analytics to improve scalability and performance.

Despite these advancements, several challenges remain. Data privacy and security are major concerns, as social media data often contains sensitive information. Additionally, real-time processing requirements demand low-latency systems capable of handling continuous data streams. Ensuring data quality and reliability is another challenge, as social media data is often noisy and unstructured. This paper aims to provide a comprehensive review of social media analytics pipelines, focusing on verification, optimization, and scalability. By analyzing 30 studies published between 2018 and 2023, the paper identifies key trends, challenges, and future research directions in this field.

Literature Review

Sebei et al. (2018) conducted a comprehensive review of social media analytics processes and Big Data pipelines. The study identified key pipeline stages, including data collection, preprocessing, analysis, and visualization. It highlighted challenges such as data heterogeneity, scalability, and real-time processing.

Stieglitz et al. (2018) proposed a structured framework for social media analytics consisting of discovery, tracking, preparation, and analysis stages. The study emphasized the need for

systematic pipeline design to address data complexity.

Batrinca & Treleaven (2019) analyzed social media analytics tools and techniques, focusing on data extraction and sentiment analysis. The study highlighted the importance of scalable architectures for handling large datasets.

Chen & Zhang (2019) explored Big Data processing frameworks such as Hadoop and Spark in social media analytics. The study demonstrated how distributed computing improves pipeline efficiency.

Barrón-Cedeno et al. (2020) introduced a verification pipeline for social media claims, including steps such as claim detection, evidence retrieval, and validation. The study showed the effectiveness of machine learning models in detecting misinformation.

Zhang et al. (2020) proposed a real-time social media analytics pipeline using Apache Spark Streaming. The study focused on processing high-velocity Twitter data streams for sentiment analysis and event detection. The pipeline integrates data ingestion, preprocessing, and real-time analytics using distributed computing. Experimental results showed that Spark-based architectures significantly reduce latency compared to traditional batch-processing systems.

Khan et al. (2020) introduced an optimized social media analytics pipeline using data reduction techniques, including feature selection and dimensionality reduction. The study demonstrated that reducing data dimensionality improves computational efficiency without significantly affecting analysis accuracy. The approach is particularly useful for large datasets where processing time is critical.

Ahmed et al. (2021) developed a cloud-based social media analytics framework designed to handle large-scale datasets. The system uses distributed storage and parallel processing to improve scalability. The study highlighted the advantages of cloud computing, including elastic resource allocation and cost efficiency. Results showed improved performance compared to on-premise systems.

Li et al. (2021) proposed a graph-based social media analytics pipeline for analyzing user interactions and network structures. The model uses graph processing frameworks to identify communities, influencers, and information diffusion patterns. The study demonstrated that graph-based approaches provide deeper insights compared to traditional analytics methods.

Wang et al. (2021) introduced a machine learning-based verification pipeline for detecting misinformation on social media. The system integrates natural language processing and

classification models to identify false information. Experimental results showed high accuracy in detecting fake news, highlighting the importance of automated verification systems.

Yang et al. (2021) proposed a deep learning-based social media analytics pipeline that integrates neural networks for sentiment analysis and topic modeling. The pipeline processes unstructured text data using word embeddings and recurrent neural networks (RNNs).

The study demonstrated that deep learning models significantly improve accuracy in sentiment classification compared to traditional machine learning methods. However, the increased computational cost requires optimized hardware and distributed processing.

Sun et al. (2021) introduced a hybrid analytics pipeline combining batch and stream processing. The system leverages both real-time and offline analytics to balance performance and accuracy. The study showed that hybrid architectures can efficiently handle both historical and real-time data, making them suitable for dynamic social media environments.

Zhang et al. (2022) developed a multi-modal social media analytics pipeline that integrates text, image, and video data. The system uses deep learning models for feature extraction across different data types. Results showed that multi-modal analytics improves insight generation and decision-making compared to single-modal approaches.

Liu et al. (2022) proposed a blockchain-based verification pipeline for social media data. The system uses blockchain to store and verify data provenance, ensuring transparency and trust. Smart contracts are used to validate data authenticity, reducing the spread of misinformation. The study demonstrated improved trustworthiness but noted increased computational overhead.

Kumar et al. (2022) introduced an edge computing-based social media analytics pipeline. The model processes data closer to the source, reducing latency and improving real-time analytics capabilities. The study showed that edge computing significantly reduces response time and network load, making it suitable for applications requiring immediate insights.

Zhao et al. (2022) proposed a distributed social media analytics pipeline using Apache Hadoop ecosystem tools. The framework integrates HDFS for storage and MapReduce for large-scale data processing. The study demonstrated that distributed storage and parallel computation significantly improve scalability when handling massive datasets. However, batch-processing

limitations reduce its effectiveness for real-time analytics.

Alqahtani et al. (2022) introduced an optimized pipeline using data caching and indexing techniques to improve query performance in social media analytics systems. The study showed that efficient indexing reduces query latency and enhances system responsiveness, particularly in interactive analytics scenarios.

Wang et al. (2023) developed a scalable social media analytics pipeline using microservices architecture. The system decomposes the pipeline into independent services that can be scaled individually. This approach improves flexibility, fault tolerance, and maintainability. Experimental results showed better performance compared to monolithic architectures.

Gupta & Verma (2023) proposed an energy-efficient social media analytics pipeline designed for large-scale distributed systems. The model optimizes resource utilization by dynamically allocating computing resources based on workload. Results showed reduced energy consumption without compromising performance.

Liu et al. (2023) introduced an adaptive analytics pipeline that dynamically adjusts processing strategies based on data characteristics. The system selects appropriate algorithms and processing methods depending on data type and volume. This improves efficiency and ensures optimal performance under varying workloads.

Patel et al. (2023) proposed a hybrid social media analytics pipeline combining cloud and edge computing. The model distributes computation between centralized cloud servers and edge nodes to balance performance and latency. The study demonstrated that latency-sensitive tasks (e.g., real-time event detection) are handled at the edge, while large-scale data processing is performed in the cloud. This hybrid approach significantly improves system efficiency and scalability.

Ahmed & Khan (2023) introduced a large-scale social media analytics pipeline for smart city applications. The system processes data from multiple sources, including social media, sensors, and public data platforms. The study highlighted the importance of integrating heterogeneous data sources and demonstrated that the pipeline supports urban planning, traffic management, and emergency response systems.

Kim et al. (2023) developed a low-latency analytics pipeline optimized for real-time streaming platforms. The system uses in-memory processing and efficient data structures to reduce processing time. Experimental results showed that the pipeline achieves near real-time

performance, making it suitable for applications such as trend detection and live monitoring.

Reddy & Kumar (2023) proposed a decentralized social media analytics pipeline using blockchain technology. The system ensures data integrity and transparency by recording transactions on a distributed ledger. This approach improves trust and security but introduces additional computational overhead and latency.

Fernandez et al. (2023) introduced a user-centric analytics pipeline with privacy and consent management features. The model allows users to control how their data is collected and analyzed, improving transparency and compliance with data protection regulations. The study highlighted the importance of ethical data usage in analytics pipelines.

Zhang et al. (2023) proposed an AI-driven optimization pipeline for social media analytics that automatically tunes processing parameters using machine learning. The system monitors pipeline performance and dynamically adjusts resource allocation and algorithm selection. Results showed improved efficiency and reduced processing time compared to static configurations.

Singh et al. (2023) introduced a lightweight social media analytics pipeline for mobile environments. The model uses compressed data representations and efficient algorithms to reduce computational overhead, making it suitable for mobile and low-resource devices.

Chen et al. (2023) developed a secure multi-party social media analytics pipeline that enables collaborative analysis without sharing raw data. The system uses encryption and distributed computation techniques to ensure privacy and security. The study demonstrated strong data protection but noted increased computational complexity.

Omar et al. (2023) proposed a trust-aware analytics pipeline that evaluates the credibility of data sources before processing. The system assigns trust scores to users and content, improving the reliability of analytics results. Experimental results showed reduced misinformation impact.

Das & Roy (2023) introduced an energy-efficient scalable analytics pipeline using optimized workload distribution techniques. The system balances computational loads across distributed nodes, reducing energy consumption while maintaining high performance.

Comparative Table

| Study | Year | Technique | Focus | Key Feature | Application |
|-------|------|---------------|------------------|------------------|-------------|
| 1 | 2018 | Survey | Pipeline | Big Data | General |
| 2 | 2018 | Framework | Structure | Analytics stages | General |
| 3 | 2019 | Tools | Extraction | Sentiment | Marketing |
| 4 | 2019 | Hadoop/Spark | Processing | Scalability | Big Data |
| 5 | 2020 | ML | Verification | Fake news | Media |
| 6 | 2020 | Spark | Streaming | Real-time | Twitter |
| 7 | 2020 | Reduction | Optimization | Efficiency | Big Data |
| 8 | 2021 | Cloud | Scalability | Elasticity | Cloud |
| 9 | 2021 | Graph | Network analysis | Influence | Social |
| 10 | 2021 | ML | Verification | Fake detection | Media |
| 11 | 2021 | DL | Analytics | Accuracy | NLP |
| 12 | 2021 | Hybrid | Processing | Flexibility | Big Data |
| 13 | 2022 | Multi-modal | Integration | Rich data | Media |
| 14 | 2022 | Blockchain | Verification | Trust | Security |
| 15 | 2022 | Edge | Real-time | Low latency | IoT |
| 16 | 2022 | Hadoop | Storage | Scalability | Big Data |
| 17 | 2022 | Indexing | Optimization | Speed | Queries |
| 18 | 2023 | Microservices | Architecture | Flexibility | Systems |
| 19 | 2023 | Energy | Efficiency | Sustainability | Systems |
| 20 | 2023 | Adaptive | Optimization | Dynamic | Systems |
| 21 | 2023 | Hybrid | Cloud-edge | Performance | IoT |
| 22 | 2023 | Smart city | Integration | Multi-source | Urban |
| 23 | 2023 | Streaming | Real-time | Low latency | Media |

| | | | | | |
|----|------|------------|------------------|--------------|---------------|
| 24 | 2023 | Blockchain | Decentralization | Trust | Security |
| 25 | 2023 | Consent | Privacy | User control | Ethics |
| 26 | 2023 | AI | Optimization | Automation | Systems |
| 27 | 2023 | Mobile | Lightweight | Efficiency | Mobile |
| 28 | 2023 | SMPC | Security | Privacy | Collaborative |
| 29 | 2023 | Trust | Verification | Reliability | Media |
| 30 | 2023 | Energy | Scalability | Efficiency | Distributed |

Analysis

The analysis reveals the following key trends:

1. Verification Evolution
 - Early focus: Fake news detection
 - Recent: Blockchain & trust-based systems
2. Optimization Techniques
 - Data reduction and indexing
 - AI-driven optimization
 - Hybrid architectures
3. Scalability Approaches
 - Hadoop & Spark
 - Cloud and edge computing
 - Microservices
4. Emerging Trends
 - Multi-modal analytics
 - Real-time streaming pipelines
 - Privacy and user control
5. Challenges
 - Data heterogeneity
 - Real-time processing constraints
 - Energy consumption
 - Verification accuracy

Discussion

The systematic review of social media analytics pipelines highlights the rapid evolution of technologies designed to process large-scale, dynamic, and heterogeneous data. Over the past decade, social media platforms have become major sources of real-time information, necessitating robust analytics pipelines capable of handling vast amounts of structured and unstructured data.

One of the most significant findings is the growing importance of verification mechanisms. With the rise of misinformation and fake news, ensuring the credibility of social media data has become a critical requirement. Early approaches focused on machine learning-based classification models for fake news detection. However, recent advancements have introduced more sophisticated verification methods, including blockchain-based systems and trust-aware frameworks. These approaches enhance transparency and accountability but often introduce additional computational overhead. Optimization is another key area of focus in social media analytics pipelines. The increasing volume

of data requires efficient processing techniques to minimize computational costs and improve performance. Traditional optimization methods such as data reduction and indexing have been complemented by advanced techniques like AI-driven optimization and hybrid processing architectures. These approaches enable dynamic adjustment of system parameters, improving efficiency under varying workloads.

Scalability remains a fundamental challenge in social media analytics. Distributed computing frameworks such as Hadoop and Spark have played a crucial role in enabling large-scale data processing. More recently, cloud computing, edge computing, and microservices architectures have emerged as effective solutions for improving scalability and flexibility. These technologies allow systems to dynamically allocate resources and handle real-time data streams efficiently.

Another important trend is the integration of multi-modal data. Social media content includes text, images, videos, and network interactions, requiring advanced data fusion techniques. Multi-modal analytics pipelines have demonstrated improved performance in extracting meaningful insights, particularly in applications such as sentiment analysis and event detection.

Despite these advancements, several challenges remain. Real-time processing requirements demand low-latency systems capable of handling continuous data streams. Additionally, energy efficiency has become an important consideration, particularly in large-scale distributed systems. Privacy and ethical concerns also play a significant role, as social media data often contains sensitive information.

In conclusion, social media analytics pipelines have evolved significantly, incorporating advanced technologies for verification, optimization, and scalability. However, further research is needed to address existing challenges and develop more efficient and reliable systems.

Conclusion

This systematic review has explored the development and evolution of social media analytics pipelines, focusing on verification, optimization, and scalable computing

perspectives. By analyzing 30 studies published between 2018 and 2023, the paper provides a comprehensive understanding of current trends, challenges, and future directions in this field.

Social media analytics pipelines have become essential tools for extracting insights from large-scale data generated by social platforms. These pipelines consist of multiple stages, including data collection, preprocessing, storage, analysis, and visualization. Each stage plays a critical role in transforming raw data into actionable information.

One of the key findings of this review is the increasing importance of verification mechanisms. The proliferation of misinformation and fake news has highlighted the need for reliable methods to validate social media content. Techniques such as machine learning-based classification, blockchain-based verification, and trust-aware frameworks have been developed to address this challenge. While these approaches improve data reliability, they also introduce additional complexity and computational overhead.

Optimization is another critical aspect of social media analytics pipelines. The large volume and high velocity of social media data require efficient processing techniques to ensure timely analysis. Traditional optimization methods, such as data reduction and indexing, have been enhanced by advanced approaches like AI-driven optimization and hybrid architectures. These techniques enable dynamic adjustment of system parameters, improving performance and resource utilization.

Scalability is a fundamental requirement for social media analytics pipelines. As data volumes continue to grow, systems must be capable of handling large-scale computations efficiently. Distributed computing frameworks such as Hadoop and Spark have been widely used to address scalability challenges. More recently, cloud computing, edge computing, and microservices architectures have emerged as powerful solutions for enabling scalable and flexible data processing.

The integration of multi-modal data represents another significant advancement in social media analytics. By combining text, images, videos, and network interactions, multi-modal analytics pipelines provide richer insights and improve decision-making capabilities. However, this integration also increases system complexity and requires advanced data fusion techniques.

Despite these advancements, several challenges remain. Real-time processing is one of the most critical issues, as social media data is continuously generated at high speeds. Ensuring low-latency processing while maintaining

accuracy is a significant challenge. Additionally, energy efficiency has become an important consideration, particularly in large-scale distributed systems.

Privacy and ethical concerns also play a crucial role in the design of social media analytics pipelines. The use of user-generated data raises issues related to data protection and consent. Future systems must incorporate privacy-preserving mechanisms and ensure compliance with data protection regulations.

Future research directions in this field include the development of more efficient verification mechanisms, advanced optimization techniques, and scalable architectures. The integration of artificial intelligence and machine learning is expected to play a key role in improving system performance and adaptability. Additionally, the adoption of hybrid computing models that combine cloud, edge, and distributed systems will further enhance scalability and efficiency.

In conclusion, social media analytics pipelines represent a rapidly evolving field with significant potential for innovation. While substantial progress has been made, ongoing research is essential to address existing challenges and develop more robust, efficient, and scalable systems.

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