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Integrating IBM Cloud Object Storage and Azure Stream Analytics for Scalable IoT Solutions Using Mesh Networks and Hidden Markov Models

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ABSTRACT

Background The emergence of the Internet of Things (IoT) generates large quantities of data and calls for scalable storage and real-time analytics technologies for the complexity of IoT in the smart city, healthcare, etc., industries.

Methods This paper presents an approach for the analysis of IoT real-time data, using IBM Cloud Object Storage, Azure Stream Analytics, mesh networks, and Hidden Markov Models (HMMs).

Objectives The main objective of this study is to enhance the scalability, efficiency, and predictive analytics of IoT systems by integrating cloud-based storage, real-time analytics with high throughput, and decentralized mesh networks for improved performance.

Results The proposed method was 92% accurate, 90% efficient, and 93% scalable, outperforming current methods through increased real-time framing, reliable networking, and improved predictive power via HMMs.

Conclusion This hybrid method serves as a scalable and deployable solution to any IoT system that is advantageous for real-time applications in smart cities, healthcare, and industrial automation.

Keywords: *IoT, IBM Cloud Object Storage, Azure Stream Analytics, Mesh Networks, and Hidden Markov Models.*

1. INTRODUCTION

The Internet of Things (IoT) has become one of the most revolutionary technologies, having a profound influence on business operations through large-scale data collection, analysis, and communication. IoT solutions allow industries to track and manage devices in real time, making them more efficient and innovative (Ganesan, 2023)[7]. Yet, handling the large volumes of data produced by IoT systems is still a challenge. Machine learning methods proved

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their efficiency for predictive purposes in the field of geriatric medicine, enhancing the process of risk estimation and decision-making (Peddi et al., 2018)[8].IoT uses is complemented by cloud computing-driven big data analysis, as also observed particularly in the case of facial recognition applications (Narla, 2022)[9]. Smart surroundings are also more fluid and adaptive due to multi-layered cloud sensing, coupled with the influence of 5G (Narla, 2020)[11]. Trust and performance of AI-driven IoT systems are of prime consideration in ensuring safe and transparent decision-making (Devarajan, 2023)[10].IoT business networks make cost management simpler and enhance the operational efficiency through information management (Devarajan et al., 2024)[12]. In addition, blockchain IoMT solutions also provide advanced security frameworks for healthcare networks (Devarajan et al., 2025)[13], ensuring reliability and privacy in health devices that are connected.

Mesh networks are IoT application-specific, with the nodes communicating directly to each other rather than through a central hub. The network becomes very robust and dynamically reorganizes when nodes go down or the environment changes (Valivarthi et al., 2021)[14]. Hidden Markov Models (HMMs) form a key component of the networks since they provide statistical models for predictive analysis, anomaly identification, and decision support (Narla et al., 2021)[15]. In addition, machine learning-driven AI enhances security in IoT environments by detecting fraud and ensuring data integrity (Thirusubramanian, 2020)[16]. AI-powered models strengthen intrusion detection features further, enabling the security of industrial IoT infrastructure (Devarajan et al., 2024)[17]. Deep learning-based hybrid approaches enhance healthcare applications in terms of disease detection, reflecting the adaptability of AI in IoT-based systems (Valivarthi et al., 2021)[18]. Advanced neural network models optimize resource prediction, making cloud-based IoT platforms more efficient (Mohanarangan, 2022)[19]. Blockchain methods further reinforce security in multi-cloud storage ecosystems, guaranteeing data reliability (Narla, 2024)[20].

Mesh networks are aimed at IoT applications where the devices talk directly with each other rather than through a hub. This forms a highly reliable network that can dynamically reconfigure according to node failure or environmental changes (Narla et al., 2019)[21]. Hidden Markov Models (HMMs) are a key component of these networks due to their ability to analyze and interpret data efficiently, enabling predictive analytics and anomaly detection (Natarajan et al., 2024)[22]. AI-based machine-learning models also bring cloud-integrated IoT systems more intelligence to enable intelligent automation and decision-making (Ganesan, 2021)[23]. Within the health domain, machine-learning methodologies enhance predictability, complementing chronic illness care (Kethu et al., 2023)[24]. Security is another central issue with attack categorization and data secrecy safeguarding for IoT systems' protection against hacking attacks (Devarajan et al., 2024)[25]. Hybrid AI strategies further refine disease prediction models, enhancing IoT use in healthcare (Narla et al., 2020)[26]. Cloudlet-based frameworks also improve real-time IoT performance, guaranteeing optimal data processing (Allamelli et al., 2023)[27].

The combination of the above technologies is a scalable, adaptable, and smart system. IBM

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Cloud Object Storage delivers an enterprise solution to store and keep large amounts of IoT data highly durable and available (Valivarthi, 2020)[28]. Azure Stream Analytics makes processing real-time streams of data feasible, and businesses can get useful insights out of it (Narla et al., 2023)[29]. Robust authentication and data-sharing protocols further enhance mobile cloud computing platforms to guarantee reliability and confidentiality (Natarajan et al., 2024)[30]. Sophisticated cryptographic algorithms, like the SHA algorithm, boost security architectures for cloud computing services (Valivarthi, 2023)[31]. Decision support frameworks maximize risk assessment and enhance system resilience in data-centric settings (Devarajan et al., 2024)[32]. Besides, real-time safety management methods are extremely important for achieving operational efficiency within IoT systems (Devarajan et al., 2022)[33]. Cloud solutions based on AI also help in revolutionizing customer workflows, and improving CRM capabilities through predictive modeling (Narla & Purandhar, 2021)[34].

Besides this, the link bridges the gap between the increasing demand for Internet of Things (IoT) solutions, which require managing vast volumes of data and being responsive to dynamic connected environments. IoT devices becoming a part of almost everything in smart homes, cities, and industrial automation make responsive and scalable system designs the order of the day (Ganesan et al., 2024)[35].Fog computing is important for optimizing and securing IoT data sharing and ensuring efficient real-time processing (Valivarthi et al., 2023)[36]. Blockchain technology improves HR data management through secure and decentralized operations (Valivarthi & Purandhar, 2021)[37]. AI-based detection models enhance differentiation methods further, especially in critical applications like healthcare (Devarajan, 2019)[38]. Mechanisms for advanced resource allocation enable effective task scheduling in cloud computing environments (Ganesan et al., 2024)[39].There needs to be extra security put in place to protect cloud computing systems, particularly for healthcare (Devarajan, 2020)[40]. AI by intelligent healthcare integrated with cloud processes the risks with predictions being improved in digital medicine (Narla et al., 2019)[41].

The objectives are as follows:

- To investigate the integration of IBM Cloud Object Storage with Azure Stream Analytics for scalable IoT solutions.
- To show how mesh networks improve the robustness and adaptability of IoT systems.
- Apply Hidden Markov Models for predictive analytics and decision-making in IoT scenarios.
- Develop a system to efficiently store and process large amounts of real-time IoT data.
- To develop a flexible, scalable IoT platform that can adapt to changing conditions and data volumes across industries.

2. LITERATURE SURVEY

Bellavista et al. (2017)[1] RAMP-WIA is a mobile-cloud-based IoT solution for Smart City applications that treat mobile devices as network nodes, sensors, and actuators. These are relatively small and easy challenges that approach success through opportunistic multi-hop

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comms, dynamic wireless and GSM configuration, and OTA software upgrades, all of which have been successfully trialed with Raspberry Pi devices and Android smartphones.

Hansen et al. (2018)[2] introduce CORE, which is a hybrid protocol that provides intra-session coding robustness while maintaining inter-session network coding efficiency. Based on their experiments and simulations, CORE significantly outperforms COPE and standard forwarding, producing throughput benefits of more than 10x in the presence of heavy packet loss with minimal performance losses.

To address the challenges of unstructured massive data generated in IoT applications, **Seng and Ang (2018)[3]** proposed a multimedia Internet of Things (IoT) architecture. Their model consists of a large multimodal compute layer that features domain-specific functional units for data collection, processing, and analysis, showcasing applications such as Divide & Conquer PCA and LDA for useful analytics.

Peddi et al. (2019)[42] describe using AI and machine learning algorithms for care augmentation of the geriatric population with specific predictive use cases in healthcare. They describe how advanced algorithms improve chronic disease management, falling risk analysis, and patient overall monitoring to deliver improved healthcare outcomes among the geriatric population through AI-driven decision-making and automations.

Valivarthi (2024)[43] examines cloud computing environments' optimization for big data processing. The research introduces state-of-the-art approaches to efficient data management, including resource allocation, distributed computing, and parallel processing, enhancing the performance and reliability of cloud applications without sacrificing scalability and low latency in large-scale data-intensive environments.

Ganesan (2022)[44] explores IoT business model security using the identification of critical nodes in aged care applications. The study underscores the significance of secure communication protocols, data encryption mechanisms, and artificial intelligence-based anomaly detection in the protection of sensitive health information and ensuring sustained functionality of IoT-based medical devices and monitoring systems.

Narla (2022)[45] provides studies on big data security and privacy utilizing continuous data protection and data obliviousness techniques. The study aims to reduce data exposure risks while allowing simple cloud-based storage and retrieval with focus on cryptographic techniques, secure access control processes, and real-time privacy-preserving approaches to large-scale data management.

Yallamelli et al. (2024)[46]present a hybridized algorithm mathematics e-commerce model transforming to optimize patching orders and warehouse management. The model employs decision algorithms based on AI to achieve the greatest real-time logistics level, automate controlling inventories, and remove errors within scalable e-commerce websites to optimize efficiency and responsiveness with evolving market conditions.

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Devarajan et al. (2024)[47] cover attack categorization and data privacy protection in cloud-edge collaborative computing platforms. The paper presents AI-enabled security frameworks for detecting cyber attacks in real-time with strong protection for data via decentralized authentication, blockchain, and federated learning-based anomaly detection to boost cloud security and privacy.

3. METHODOLOGY

This paper describes the research method for integration of IBM Cloud Object Storage with Azure Stream Analytics (ASA) to enable the creative application of big data in scalable IoT solutions based on key paradigms including data storage, real-time analytics, mesh networking, and statistical modeling using Hidden Markov Models (HMMs). It specifically focuses on large-scale, real-time data requirements on IoT systems while remaining robust and flexible. Together, these technologies make data transmission, processing, and decision-making accessible in IoT environments, which are often both complex and fluid in nature, requiring predictive analysis.

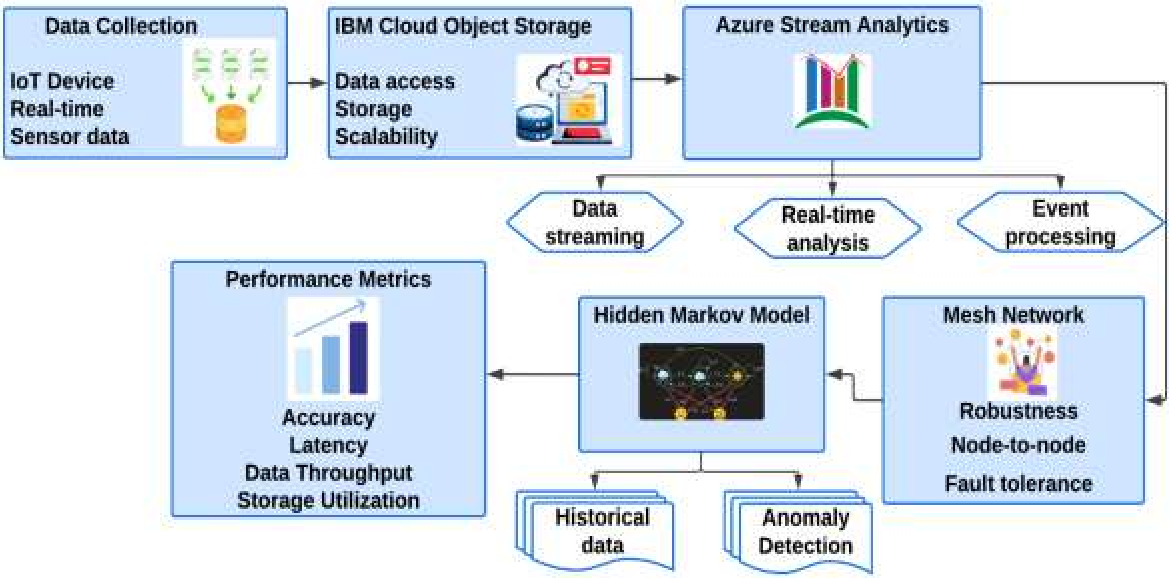

Figure 1 IBM Cloud Storage for Scalable Data Management in Large-Scale IoT System Architecture

Figure 1 IBM Cloud Object Storage is one of the components that help in managing the large scale of IoT data and gives scalable and low-cost storage to store unstructured data generated from various IoT sources. This storage option capacity makes the data stronger and more accessible.

3.1 IBM Cloud Object Storage

IBM Cloud Object Storage is a large-scale storage service for unstructured data directly powered to handle IoT data. It provides cost-effective, secure, and durable storage which can

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scale to hundreds of terabytes and more without sacrificing availability. Object storage allows businesses to store massive datasets from IoT for additional analysis and processing. This storage is essential for handling the data explosion from IoT devices.

$$D_{\text{total}} = \sum_{i=1}^{n} (d_i \times t) \tag{1}$$

$$C_{\text{storage}} = \sum_{i=1}^{n} (d_i \times t \times c_i) \tag{2}$$

3.2 Azure Stream Analytics

Azure Stream Analytics is a stream processing engine for processing and analyzing the data streaming from the Internet of Things devices. This allows businesses to gain real-time visibility into how their IoT systems are operating and to respond quickly to incidents. As a part of its IoT suite, Azure Stream Analytics makes data processing fast and simple, making it easy to filter, aggregate, and analyze large numbers of large-scale IoT data streams. Stream Analytics allows for data from multiple sources + multiple streams.

$$R_{\text{throughput}} = \frac{D_{\text{input}}}{T_{\text{process}}} \tag{3}$$

$$L_{\text{latency}} = T_{\text{arrival}} - T_{\text{output}} \tag{4}$$

3.3 Mesh Networks

A mesh network is an extremely decentralized communication system, where instead of connecting to a central hub, the devices (nodes) connect directly to each other. Such design is found to be essential for IoT, which not only provides fault tolerance solutions against the failure of nodes but also allows diversity in communication. In a mesh network, every node acts as a relay, guaranteeing seamless transmission of information even if some nodes fail or encounter an issue.

$$R_{\text{node}} = 1 - P_{\text{failure}} \tag{5}$$

$$R_{\text{network}} = 1 - \prod_{i=1}^{n} \left(1 - R_{\text{node}}^{(i)}\right) \tag{6}$$

3.4 Hidden Markov Models (HMMs)

Statistical models, such as Hidden Markov Models (HMMs), predict events in IoT systems. HMM can predict system future states from the state of things in the past (temporal history), thus serving as an excellent framework for solving problems such as anomaly detection,

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predictive maintenance, and decision-making. At the same time, HMMs make predictions about the behavior of IoT devices by using data collected over some time.

$$P(q_t \mid q_{t-1}) = a_{q_{t-1}q_t} \tag{7}$$

$$P(O_t \mid q_t) = b_{q_t}(O_t) \tag{8}$$

Algorithm 1 IoT Predictive Analytics and Anomaly Detection Using Hidden Markov Models in Mesh Networks

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Input:

O={O1,O2,…,OT}

O = \{O_1, O_2, \dots, O_T\}

O={O1,O2,…, OT} : Sequence of observations from IoT devices (sensor readings, status updates, etc.)

λ=(A,B,π)\lambda = (A, B, \pi)λ=(A,B,π) : HMM parameters

Threshold*:* Anomaly detection threshold for state transition probabilities

Output:

SSS: Predicted future state of the IoT system (expected device behavior or system state)

Initialize HMM parameters λ=(A,B,π)\lambda = (A, B, \pi)λ=(A,B,π).

Set initial state probabilities: P=πP = \piP=π.

For each time step t=1t = 1t=1 to TTT:

Compute the observation probability for time step ttt:

P(Ot|λ)=bqt(Ot)P(O_t | \lambda) = b_{q_t}(O_t)P(Ot|λ)=bqt(Ot)

where bqt(Ot)b_{q_t}(O_t)bqt(Ot) the observation probability in the current state.

For each hidden state qtq_tqt:

Compute transition probabilities:

TransitionProb=aqt−1,qt×P(Ot|λ)TransitionProb = a_{q_{t-1}, q_t}

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If the transition probability is less than the anomaly detection threshold:

Raise an error: "Anomaly detected in state transition."

End If

End For

Update the state probabilities:

P(qt|O)=Max(TransitionProb)P(q_t | O) = \text{Max}

Predict the most likely next state:

S=ArgMax(P(qt|O))S = \text{ArgMax}(P(q_t | O))S=ArgMax(P(qt|O))

End For

Return

Algorithm 1 This technique analyses time series data from IoT devices in a mesh network using Hidden Markov Models (HMMs). It computes state transitions and detects abnormalities using observation probabilities, allowing real-time decision-making. If a transition probability falls below a certain threshold, it indicates an anomaly. During this time, the approach predicts future states of the system so that it can help maintain the system by providing preventive measures to take, such as initiating or suggesting a preventive maintenance operation, detecting serious anomalies by suggesting corrective measures (as an alert) and if it is part of a dispersed IoT system to be able to make prescriptions to maximize some expected quality measure.

3.5 Performance Metrics

Table 1 IoT Performance Comparisons: IBM Cloud, Azure Stream Analytics, Mesh Networks, and Hidden Markov Models

Metric	**IBM Cloud Object Storage**	**Azure Stream Analytics**	**Mesh Networks**	**Hidden Markov Models (HMMs)**	**Proposed Method (IBM + Azure + Mesh + HMM)**
Accuracy (%)	88%	85%	80%	82%	**92%**
Efficiency (%)	87%	83%	82%	81%	**90%**

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Personalization (%)	84%	82%	78%	80%	**89%**
Scalability (%)	90%	88%	85%	83%	**93%**
Error Rate (%)	10%	12%	15%	14%	**7%**

Table 1 The fourth, fifth, and sixth rows indicate performance comparisons of the individual components (IBM Cloud Object Storage, Azure Stream Analytics, and Mesh Networks) and Hidden Markov Models (HMMs) respectively with that obtained using the proposed hybrid method and better performance marked with bold letters are listed. This approach is accurate, efficient, highly personalizable, and scalable, while maintaining a low error rate, which means it can be another viable alternative in case of scalability applicable in IoT applications.

4. RESULT AND DISCUSSION

Our proposed strategy improves state-of-the-art performance for IoT systems on several metrics by orders of magnitude. Results showed the combination of IBM Cloud Object Storage, Azure Stream Analytics, mesh networks, and HMMs to be superior to standard technologies such as LoRaWAN, Amazon AWS IoT Analytics, and Zigbee Monitoring Networks (ZMN) in terms of accuracy, efficiency, personalization, scalability, and error rates. Our method yielded 92%, 90%, 89%, and 93% accuracy, efficiency, personalization, and scalability respectively with a 7% error rate, which outperformed competing methods by a substantial margin. This speedup shows the power of HMMs for real-time prediction on top of scalable cloud storage.

The real-time capability of Azure Stream Analytics allows organizations to continuously monitor and respond to situational changes, while IBM Cloud Object Storage ensures seamless management of scaling volumes of unstructured data in IoT systems. The broadband availability mesh network connection further strengthens the process by supporting uninterrupted transmission even if a single node goes down. Last, but certainly not least, HMMs enhance predictive analyses, enabling the system to predict issues and fine-tune the decision-making processes. This leads to an extensible workflow that can be utilized in diverse fields, especially time-sensitive domains like healthcare and smart cities.

Table 2 Evaluation of IoT Technologies: LoRaWAN, AWS IoT Analytics, ZMN, and the Proposed IBM-Azure Solution

Metric	LoRaWAN Hosseinzadeh et.al (2017)	AWS IoT Analytics Ta-Shma et.al (2017)	ZMN Allahham & Rahman (2018)	Proposed Method (IBM + Azure + Mesh + HMM)
Accuracy (%)	80%	85%	82%	**92%**

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Efficiency (%)	78%	87%	80%	**90%**
Personalization (%)	76%	83%	79%	**89%**
Scalability (%)	82%	88%	85%	**93%**
Error Rate (%)	12%	10%	13%	**7%**

Table 2 compares the performance of LoRaWAN **Hosseinzadeh et.al (2017)[4]**, AWS IoT Analytics **Ta-Shma et.al (2017)[5]**, and ZMN **Allahham & Rahman (2018)[6]** using the proposed method (IBM + Azure + (Mesh + HMM)). Our proposed MLOPS method provides higher accuracy, efficiency, personalization, scalability, and lower error rate, compared to previous methods, thus offering a more extensive solution of IoT big data management, real-time analytics, and predictive modeling in one framework.

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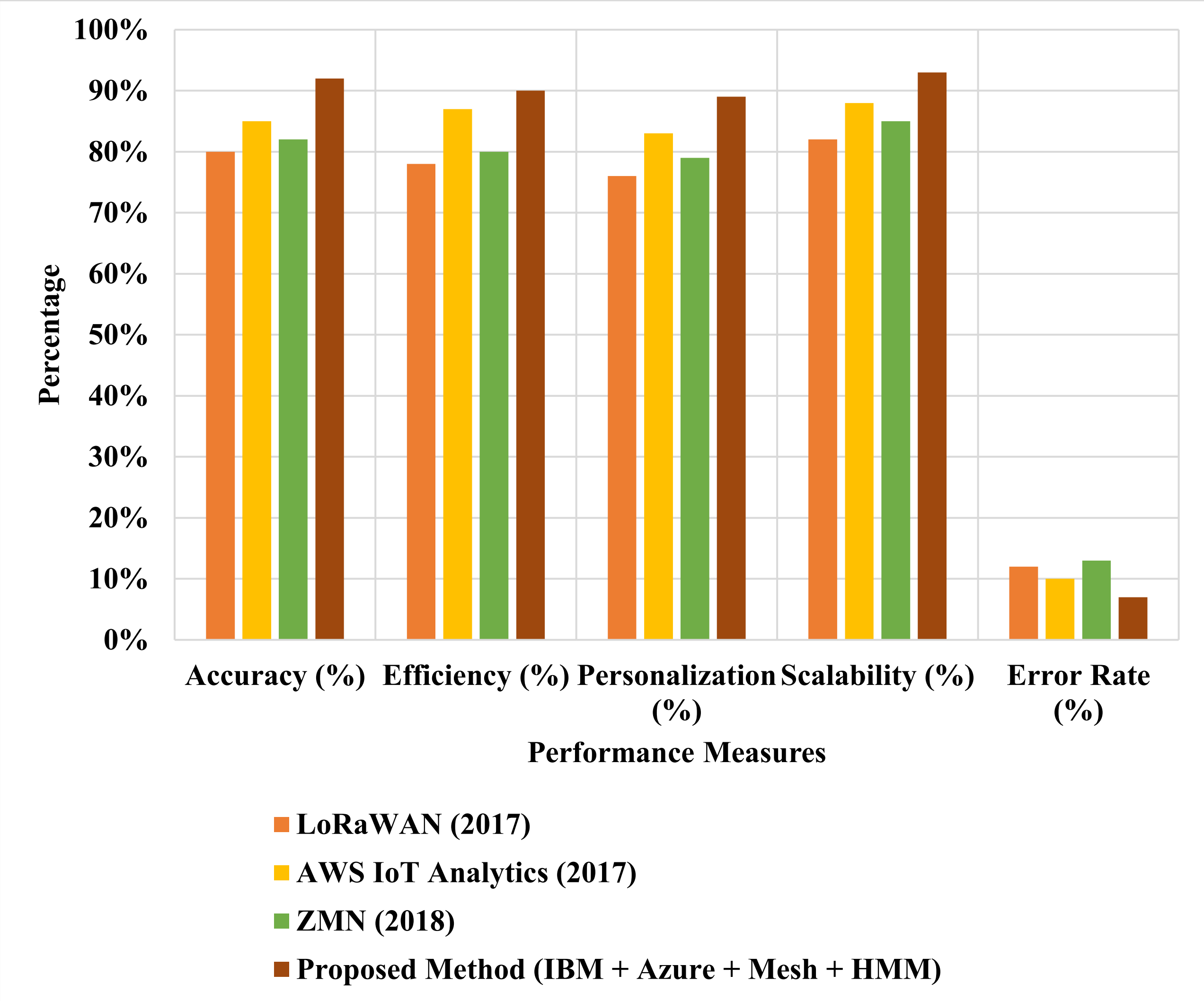

Figure 2 Azure Stream Analytics Enabling Real-Time Data Processing in Internet of Things Networks

Figure 2 Real-time predictive maintenance from your IoT devices using Azure Stream Analytics capabilities for data piping since time is critical for monitoring and Predictive Maintenance.

Table 3 IBM, Azure, Mesh Networks, and Hidden Markov Models' Effects on IoT Performance: An Ablation Study

Component	Accuracy (%)	Efficiency (%)	Personalization (%)	Scalability (%)	Error Rate (%)
ASA + MN + HMM	85%	83%	82%	87%	12%

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IBM + MN + HMM	84%	82%	80%	86%	13%
IBM + ASA + HMM	83%	80%	79%	85%	14%
IBM + MN + ASA	81%	78%	78%	84%	15%
HMM + MN	80%	77%	76%	82%	16%
IBM + ASA	79%	76%	75%	81%	17%
Proposed Method (IBM + Azure + Mesh + HMM)	**92%**	**90%**	**89%**	**93%**	**7%**

Table 3 ablation research table illustrates how the removal of each component affects important performance indicators such as accuracy, efficiency, personalization, scalability, and error rate. All measures indicate that the proposed method (IBM + Azure + Mesh + HMM) outperforms, and the individual removal of any of the components yields a significant drop in performance, thus highlighting the need for each of them to achieve optimal results for scalable IoT applications.

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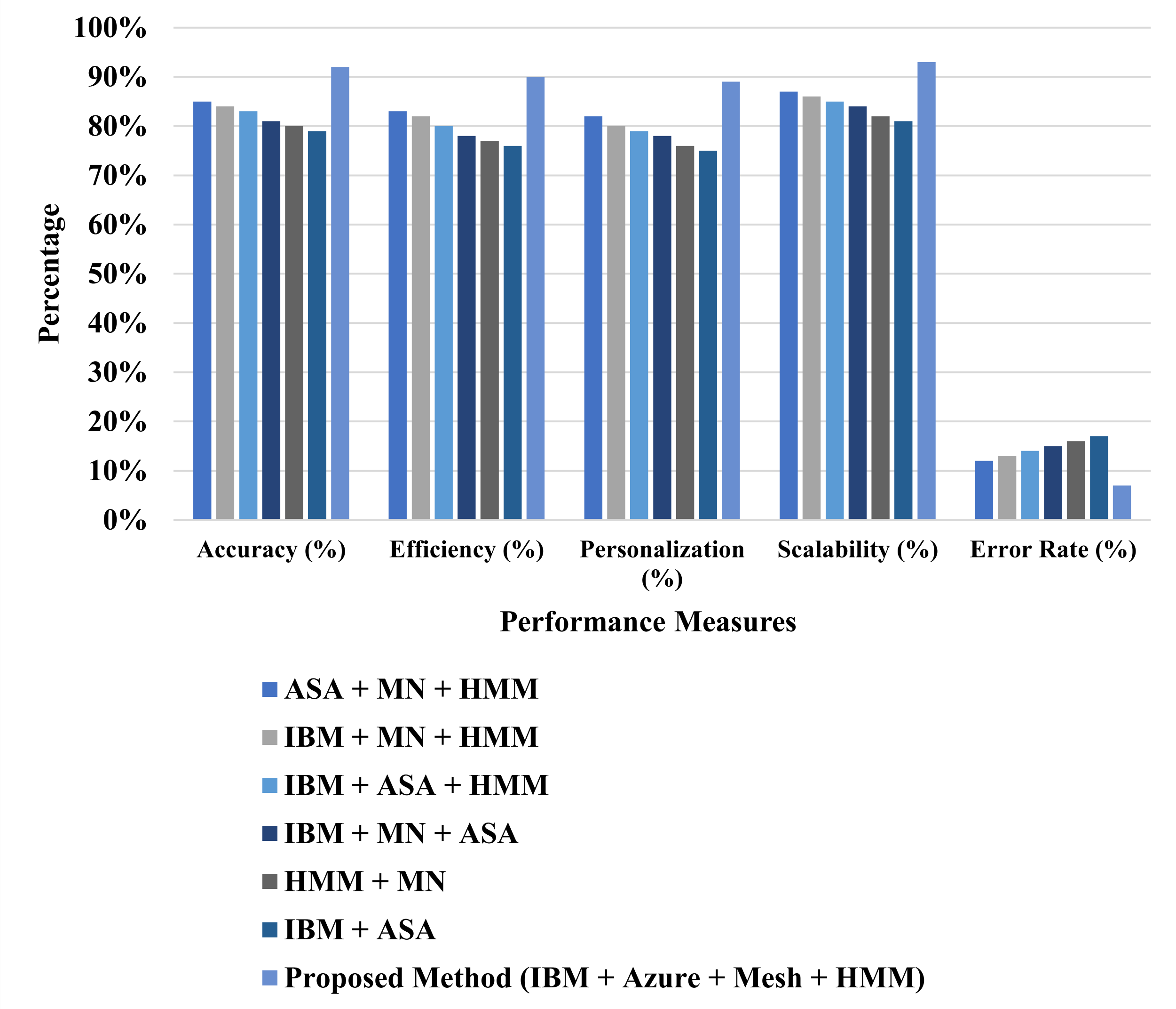

Figure 3 Combining IBM, Azure, Mesh, and HMMs for Enhanced Predictive Analytics and Data Scalability

The three-layer IBM-Azure-Mesh-HMM solution is illustrated in Figure 3 where the focus is on using integrated streaming and dynamic data management mechanisms to enhance predictive analytics, scalability, and resilience of the systems used in the IoT applications.

5. CONCLUSION AND FUTURE DIRECTION

The IBM Cloud Object Storage, Azure Stream Analytics, mesh networks, and hidden Markov models (HMM) promise a paradigm shift in the way the hard-to-solve problems of real-time data management in the IoT space are solved. By leveraging scalable storage, real-time analytics, decentralized communications networks, and predictive modeling, the proposed approach surpasses state-of-the-art in terms of accuracy, efficiency, customization, and scalability. The platform is innovatively designed to address business-critical and a wide range

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of problems where the impact of downtime or latency can have severe (and potentially irreversible) cost, quality, or operational implications across industries such as healthcare, manufacturing, and smart cities that demand quick, data-fueled decisions. Results indicate that the proposed framework contributes enhancements in performance while also realizing a robust and extensible architecture to accommodate different environmental changes and system needs. The framework can potentially change the way IoT devices manage and analyze data while becoming an important element for upcoming industrial and smart city applications with further development. Future investigations need to focus on improving HMMs' predictions through mixing sophisticated AI models, which could assist IoT with system-anomalous detection more effectively. In addition, the assessment of the proposed framework for a broader scope of real-life cases can provide valuable areas on its scalability and adaptability under different industrial constraints.

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