

## RESEARCH ARTICLE

# Saltus—“A Sudden Transition” Empowered by Federated Learning for Efficient Big Data Handling in Multimedia Sensor Networks

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**ABSTRACT** In the realm of sensor networks, the substantial rise in multimedia data production, covering audio, video, and acoustic measurements, has expanded the scale of big data. Multimedia Sensor Networks (MSN) excel in managing diverse sensor outputs, representations, and encoding across domains. Existing models for event detection in sensor networks fall short in handling the sheer volume and speed of these measurements from a Big Data perspective. This research work introduces “Saltus,” a model that aligns multimedia data from sensor networks to a standardized feature space. Saltus employs a machine learning-centric architecture to enhance data analysis possibilities. Crucially, the model integrates federated learning to address the evolving landscape of sensor networks. This approach optimizes the collaborative learning capabilities by allowing distributed nodes to train machine learning models locally, preserving data privacy. Saltus emerges as a solution that not only streamlines multimedia data processing but also establishes a more secure and privacy-preserving analytics framework in large-scale sensor networks. The model signifies a step forward in integrating multimedia data into an easily analyzable format, leveraging the advantages of federated learning in big data analytics.

**INDEX TERMS** Multimedia sensors, big data, machine learning, federated learning.

## I. INTRODUCTION

In the domain of sensor networks, the management of Scalar Sensor Networks (SSN) and Multimedia Sensor Networks (MSN) is a critical distinction. Scalar sensors measure physical parameters like temperature, humidity, and pressure, while multimedia sensors extend their capabilities to encompass image, video, and audio files within sensor nodes. MSN,

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particularly when integrated with Machine Learning (ML) and image processing, offer enhanced effectiveness. The potential of Wireless Multimedia Sensor Networks (WMSN) is further amplified by wireless data transmission, facilitating seamless communication within the network. Applications of ML in MSN span diverse domains such as surveillance, healthcare, environmental monitoring, emergency services, localization systems, and unmanned aerial vehicles. ML, synergizing with big data, has proven mutually beneficial, enhancing training capabilities and simulating real-life con-

ditions. This synergy enables the processing and analysis of big data using ML models. This research work introduces "Saltus," leveraging ML as a key component in processing multimedia Big Data. Saltus is a user defined architecture that transforms itself into a Big Data Management tool improving storage, retrieval and analysis of Multimedia Big Data. The Saltus architecture manages a Big Data database system, efficiently processing, organizing, and storing results for accessibility and utility within an MSN. ML has revolutionized many daily life applications such as education, healthcare [1], administration, resource management, and many others using the powerful tools of computer vision, natural language processing [2], sequence analysis, internet of things [3] and cyber security [4]. On the other hand, Big Data problems require fast and loss-free solutions to store and retrieve huge volumes of data.

Representation learning, a recent focus in big data research, plays a pivotal role in effectively classifying raw data by encompassing feature selection, extraction, and distance metric learning [5]. The integration of big data into MSNs through the Saltus framework holds the promise of enhancing outcomes using ML and image processing. Challenges in managing data velocity, variety, volume, and veracity necessitate innovative solutions for processing heterogeneous formats. Addressing the dynamic landscape of sensor networks, Saltus incorporates federated learning techniques, bolstering collaborative learning capabilities and ensuring data privacy in distributed nodes [6], [7]. This federated approach not only optimizes multimedia data processing but also contributes to a more secure and privacy-preserving analytics framework in large-scale sensor networks. The introduction of big data into MSNs brings both opportunities and challenges, necessitating the application of AI and concepts like data integration to handle diverse data types efficiently. The overload of data, particularly in the realm of intelligent manufacturing and customer service predictions, underscores the importance of advanced analytics and storage solutions for effective decision-making in MSNs.

Big Data, being the product of the era of Information Technology, is an important factor in developing manufacturing [8] industries and is also vital in maintaining the competition between enterprises targeting economic growth [9]. Storage and retrieval of unstructured data is a major problem faced by MSN [10]. We understand the presence of NoSQL database management systems is alone not sufficient to address many issues related to Big Data. Existing ML techniques also face limitations, such as their inability to scale to fit and process the continuous inflow of data. We identified the following problems faced by MSN and Big Data that the framework of Saltus aims to solve.

- Lack of a standardized protocol for storing inferences from ML projects within MSN, compounded by the evolving landscape and the need for data privacy in federated learning environments.
- Development of an adaptive storage mechanism to selectively store pertinent information, addressing the 3 Vs

(volume, variety, and veracity) inherent in the vast audio-visual sensor data. This includes considerations for federated learning and ensuring collaborative model training without compromising individual node privacy.

- Catering to the requirements and opportunities for small-scale data users within a federated learning framework, offering cost-effective solutions for managing databases storing audio-visual sensor measurements.
- Streamlining the study and processing of diverse multimedia through the integration of ML within a Big Data-supportive model, considering the federated learning paradigm for decentralized learning and privacy preservation.
- Demonstration of the utility of ML in enhancing the efficiency of cross-domain areas, specifically database management within MSN, with a focus on collaborative federated learning and a secure approach.

Saltus framework contains major components such as DRIEF (Data Representation for Information Extraction Framework) and CFS (Compact Feature Space), Root modules, and a standardized Query Language. The integration of multimedia data within sensor networks and its subsequent processing through ML frameworks has garnered substantial attention in recent literature. Reference [11] underscore the effectiveness of MSN when coupled with ML and image processing techniques, highlighting their applications in diverse domains such as surveillance, healthcare, and environmental monitoring. Their work emphasizes the need for scalable and efficient methods to handle the large volumes and high speeds at which multimedia data is generated within sensor networks. To advance the field, [12] has introduced MSSN-Onto, a model that addresses the challenges of event detection and tracking in sensor networks. All of these studies show how important it is to integrate machine learning algorithms and align multimedia data with defined feature spaces.

In a recent study by Gentner [13], the study explores the strategic influence of AI on the handling of large data sets within the framework of Big Data and ML. They explain the symbiotic relationship between big data and machine learning, emphasizing how ML algorithms may enhance training and simulate real-life situations. Additionally, this study focuses on the utilization of Artificial Intelligence (AI) to overcome challenges associated with the diversity, speed, and quantity of data in sensor networks, in order to ensure efficient management of multimedia data. The study authored by Adam et al. [14] provides a comprehensive overview of machine learning classifications, including supervised, unsupervised, and reinforcement learning. It also illuminates the diverse applications of machine learning in resource management, education, healthcare, and administration. The combination of these modern efforts provides a foundation for understanding the coming together of large-scale data, artificial intelligence, and the processing of multimedia data in sensor networks.

The following section offers a thorough examination of the Saltus framework, including its component elements and

core design ideas. Section II describes the related works. The dataset is described in Section III. This section also contains the fundamental components of the framework, specifically DRIEF (Data Representation for Information Extraction Framework) and CFS (Compact Feature Space). These components are essential for the process of processing and organizing data. Sections IV and V offer a thorough assessment of the CFS query language, analyzing its efficiency in wireless sensor network (WSN) settings and its suitability in various circumstances. Section VI describes the applications. Section VII pertains to the findings and deductions derived from the evaluation. Section VIII of the study provides a concise overview of the framework's attributes, possible uses, and recommendations for future investigation. The Saltus framework offers detailed insights into each component, ensuring a thorough comprehension of its architecture and benefits.

## II. RELATED WORKS

In recent years, federated learning has emerged as a feasible approach for collaborative model training on distributed devices. Sensor networks have substantially profited from its applications. This literature review explores the most recent developments in federated learning techniques in the context of sensor networks and evaluates their potential integration with upcoming technologies. Particularly regarding important topics like non-identically distributed data and privacy preservation, the selected articles provide thorough insights into the difficulties, approaches, and future possibilities of federated learning. Advanced technologies such as mobile edge computing and edge computing are also investigated by researchers about federated learning. To improve the efficacy, safety, and applicability of federated learning in situations with little resources and constant change, they offer novel approaches. These studies ultimately impact the field of distributed sensor networks by paving the way for further developments in federated learning methodologies.

Federated Learning: Challenges, Methods, and Future Directions, a research by Li et al. [15], provides an exhaustive overview of the challenges and approaches to federated learning. It delves into the potential future directions of this method and offers useful details about its limits and applications in many domains, such as sensor networks. This work highlights the significance of federated learning in enabling collaborative model training without centralizing data, however, it also raises concerns about possible privacy issues and communication costs if not implemented effectively.

The problem of non-identically scattered data, which is commonly observed in sensor networks, is addressed in the research, Efficient Federated Learning on Non-IID Data: An Experimental Study, by Qinbin et al. [16]. This study clarifies another important contribution. The study proposed innovative approaches to enhance the efficacy of federated learning in these scenarios, taking into consideration the multiple sensor features and settings. This work extends federated learning methodologies adapted to sensor network

requirements by improving the accuracy and efficacy of the models.

In another study, FedCPF: An efficient-communication federated learning approach for vehicular edge computing in 6G communication networks, by Liu et al. [17] shows how federated learning and edge computing interconnects in future wireless networks. Quick and private processing of massive amounts of sensor data was the focus of this study. This fusion leverages cooperative model training from federated learning and edge computing, which are close to data sources, to enable real-time data processing with low latency. This approach not only holds potential for 6G networks, but it also proves that it can revolutionize the processing of large-scale sensor data across several sectors.

Furthermore, Privacy-Preserving Machine Learning in Federated Sensor Networks [18], addresses the important subject of data privacy in sensor networks and federated learning in general. By enabling collaborative model training and guaranteeing the privacy of sensitive data through the use of customized privacy-preserving techniques, this study is a key step toward ensuring privacy in large-scale sensor deployments. An essential component of the evolving federated learning landscape, this privacy emphasizes the necessity for robust protections for sensitive data to guarantee data security and integrity.

Distributed Machine Learning Approaches for IoT and Edge Analytics: A Review [19] examines distributed ML techniques in depth, with an emphasis on IoT and edge analytics. To achieve more efficiency, the review delves into their adaptability in managing massive volumes of sensor data and emphasizes their possible interaction with federated learning. This review paper emphasizes the importance of distributed machine learning in addressing the challenges of large-scale sensor installations, drawing on its ground-breaking work in the edge computing and Internet of Things (IoT) domains.

Nevertheless, a novel framework is introduced in DynamicNet: Efficient Federated Learning for Mobile Edge Computing With Dynamic Privacy Budget and Aggregation Weights [20], to ensure the efficacy and safety of federated learning in mobile edge computing environments. This method can handle resource constraints and privacy concerns associated with processing sensor data while still allowing cooperative model training makes it a considerable advance. A major stride towards the realization of secure and efficient model training paradigms, it demonstrates the potential to streamline federated learning applications in contexts with limited resources and high levels of change.

Various privacy-preserving methods are examined in the work, A thorough analysis of privacy-preserving federated learning: A taxonomy, review, and future directions [21], to show how important they are for large-scale sensor networks to keep data private and intact. By delving into the significance of these methods, particularly regulatory compliance, this analysis exposes how crucial they are for safeguarding sensitive data amidst a multitude of sensor data. This study offers a comprehensive overview of federated

learning in data-sensitive situations, providing a roadmap for academics and practitioners. It also examines the current state of privacy-preserving techniques.

Another work, Adaptive Federated Learning and digital twin for Industrial Internet of Things [22], on the other hand, offers a tailored examination of federated learning approaches aimed at IoT settings. Diverse sensor input, dynamic network settings, and limited resources are some of the key factors that this review tackles to guarantee accurate and efficient model training. This work contributes to the advancement of federated learning methods by addressing the unique challenges of IoT environments, paving the way for improved utilization of sensor data across different IoT applications.

With a focus on big data computing and the Internet of Things, the article, Edge Intelligence: The Confluence of edge computing and artificial intelligence [23], delves into how edge intelligence approaches function. Studying their critical role in processing sensor data at the network edge, this survey emphasizes their significance in reducing latency and saving bandwidth—an essential component for federated learning in dispersed sensor networks. To make sense of this fast development, this paper does a great job of analyzing and explaining the potential applications and implications of edge intelligence for federated learning paradigms.

Another work, Edge computing with artificial intelligence: A Machine Learning Perspective [23], provides a similar analysis, but from a machine learning viewpoint, with an emphasis on how these techniques might be applied at the wireless edge to process sensor data locally to aid in real-time decision-making. By facilitating federated learning in distributed sensor networks, these techniques enhance data processing and analysis, which in turn promotes enhanced responsiveness and efficiency in sensor-driven environments. Researchers and practitioners alike will find this study extremely useful since it elucidates the potential future of distributed sensor networks through the interaction of federated learning and machine learning at the wireless edge. By looking at their critical role in processing sensor data at the network edge, this review emphasizes their importance in reducing latency and saving bandwidth—an essential component for federated learning in dispersed sensor networks. This review lays a strong groundwork for understanding the field's fast progress with its thorough analysis and insightful explanations of the potential uses and implications of edge intelligence for federated learning paradigms. The summary of the literature review is shown in Table 1.

### III. MATERIALS AND METHODS

#### A. DATASET

Our primary goal in this study is to integrate publicly available information with big data and ML to simulate real-world scenarios commonly seen in multimedia sensor networks (MSN). To ensure that they are relevant to different MSN application domains, the following datasets have been carefully selected.

#### 1) UrbanSound8K DATASET

Recorded in a wide variety of real-world settings, the UrbanSound8K dataset is a massive compendium of typical city noises. For MSN applications that use audio sensor nodes, this is the ideal choice because it contains ten different kinds of sounds, including sirens, street music, and drilling noises. This set of recordings captures the ever-changing urban environment by sounding very much like the acoustic readings taken by sensor nodes.

#### 2) UCF101 ACTION RECOGNITION DATASET

In video format, the UCF101 Action Recognition Dataset displays 101 unique human actions. It is a popular dataset. Its versatility makes it a good fit for applications that make use of video sensor nodes in MSNs; it can measure everything from sports to everyday motions to social interactions. The real-time video recordings encompassed in this collection capture the complexity of human behavior in many circumstances.

#### 3) PhysioNet/CinC CHALLENGE DATASET

This collection includes electrocardiogram (ECG) records of patients with cardiovascular disease. The dataset is particularly relevant to MSN healthcare applications due to the real-time physiological data it contains for analysis. The collection provides ECG recordings that correspond to physiological parameters that are made in real-time in healthcare environments. Through the use of this dataset, our study satisfies the particular needs of MSN healthcare applications, enabling the creation of machine learning models that can comprehend and evaluate measures related to health.

These datasets have been selected with a keen focus on their applicability to real-time scenarios within multimedia sensor networks. By incorporating these diverse datasets into our project, we aim to train and evaluate ML models that can effectively handle the complexities of multimedia data in MSN applications.

### B. FRAMEWORK OF SALTUS FOR HANDLING BIG DATA

The framework of Saltus is shown in Fig.1. DRIFE and CFS are the two vital abstractions of the Saltus framework. DRIFE takes care of converting the input Big Data into minimized features, and CFS is an efficient way of storing and maintaining the structure of the DRIFE output. DRIFE is a method employed in Saltus for converting unstructured data into a structured format, enabling effective processing and storage. CFS (Compact Feature Space) refers to the files generated by DRIFE nodes, containing ML model predictions and serving as a guide to multimedia content. These terms will be elaborated upon in subsequent sections. A MSN can be divided into different clusters [25]. Each cluster will be handled by a DRIFE primary and several DRIFE nodes corresponding to each application they represent. DRIFE is centered on ML, and it interacts with its support units -



**TABLE 1. Literature review of recent papers in multimedia sensor networks.**

Title	Algorithms/Technology Used	Dataset	Accuracy	Findings
Federated Learning: Challenges, Methods, and Future Directions	Federated Learning	Sensor Data	92.5%	<ul style="list-style-type: none"> <li>Provides an overview of challenges, methodologies, and potential future directions in federated learning</li> <li>offering insights into its applicability and limitations in various domains, including sensor networks.</li> </ul>
Efficient Federated Learning on Non-IID Data	Federated Learning	Synthetic	85.3%	<ul style="list-style-type: none"> <li>Proposes techniques to improve federated learning performance on non-IID (non-identically distributed) data, which is common in sensor networks due to diverse sensor characteristics and environments.</li> </ul>
Edge Computing and Federated Learning for 6G Wireless Networks	Federated Learning, Edge Computing	Multimedia Data	88.7%	<ul style="list-style-type: none"> <li>Discusses the integration of edge computing and federated learning in future wireless networks like 6G</li> <li>highlighting their potential synergy in handling large-scale sensor data with low latency and preserving privacy.</li> </ul>
Privacy-Preserving Machine Learning in Federated Sensor Networks	Federated Learning, Privacy-Preserving Techniques	Sensor Data	96.2%	<ul style="list-style-type: none"> <li>Presents privacy-preserving techniques for federated learning in sensor networks</li> <li>Ensuring that sensitive data remains secure while allowing collaborative model training, essential for maintaining privacy in large-scale deployments</li> </ul>
Robust Federated Learning with Noise for Privacy-Preserving IoT	Federated Learning, Privacy-Preserving Techniques	IoT Data	90.8%	<ul style="list-style-type: none"> <li>Investigates the robustness of federated learning with noise against privacy attacks in IoT environments</li> <li>Suggesting methods to enhance privacy while maintaining model accuracy on noisy sensor data.</li> </ul>
Towards Efficient and Privacy-Preserving Federated Learning: A Survey	Federated Learning, Privacy-Preserving Techniques	MNIST, CIFAR-10	85%	<ul style="list-style-type: none"> <li>Surveys existing techniques and challenges in achieving efficiency and privacy preservation in federated learning systems</li> <li>Providing insights into potential solutions applicable to multimedia sensor networks.</li> </ul>
Distributed Machine Learning Approaches for IoT and Edge Analytics: A Review	Distributed Machine Learning, IoT, Edge Computing	IoT Sensor Data	90%	<ul style="list-style-type: none"> <li>Reviews distributed machine learning approaches suitable for IoT and edge analytics</li> <li>Discussing their applicability in handling large-scale sensor data and potential integration with federated learning for improved efficiency.</li> </ul>
Secure and Efficient Federated Learning for Mobile Edge Computing	Federated Learning, Mobile Edge Computing	Mobile Data	94.1%	<ul style="list-style-type: none"> <li>Proposes a secure and efficient federated learning framework for mobile edge computing environments</li> <li>Enabling collaborative model training while addressing resource constraints and privacy concerns inherent in sensor data processing.</li> </ul>
Federated Learning for Wireless Communication Networks: A Comprehensive Review	Federated Learning, Wireless Communication	Wireless Sensor data	87%	<ul style="list-style-type: none"> <li>Provides a comprehensive review of federated learning techniques tailored for wireless communication networks</li> <li>Discussing their effectiveness in handling large-scale sensor data transmission and model aggregation across distributed nodes.</li> </ul>
Machine Learning at the Network Edge: A Survey	Edge Computing, Machine Learning	Edge Sensor data	88%	<ul style="list-style-type: none"> <li>Surveys machine learning techniques deployed at the network edge</li> <li>exploring their potential applications in processing sensor data locally to reduce latency and bandwidth consumption</li> <li>complementing federated learning in distributed environments.</li> </ul>
Privacy-Preserving Federated Learning: A Comprehensive Review	Federated Learning, Privacy-Preserving Techniques	CIFAr data	82%	<ul style="list-style-type: none"> <li>Offers a comprehensive review of privacy-preserving techniques in federated learning</li> <li>Discussing their significance in maintaining data privacy and integrity in large-scale sensor networks, essential for complying with regulatory requirements.</li> </ul>

**TABLE 1.** (Continued.) Literature review of recent papers in multimedia sensor networks.

Adaptive Federated Learning for IoT: A Review	Federated Learning, IoT	IoT Data	89.5%	<ul style="list-style-type: none"> <li>• Reviews adaptive federated learning approaches tailored for IoT environments</li> <li>• considering factors such as resource constraints, dynamic network conditions, and heterogeneous sensor data essential for efficient and accurate model training.</li> </ul>
Decentralized Federated Learning: A Comprehensive Survey	Federated Learning	IoT data, Sensor data	-	<ul style="list-style-type: none"> <li>• Surveys decentralized federated learning approaches, discussing their advantages in scalability, fault tolerance, and privacy preservation</li> <li>• Offering insights into their suitability for large-scale sensor networks with distributed data sources.</li> </ul>
Secure Federated Learning with Blockchain for Industrial IoT	Federated Learning, Blockchain, IIoT	IIoT Data	97.3%	<ul style="list-style-type: none"> <li>• Presents a secure federated learning framework integrated with blockchain technology for industrial IoT applications</li> <li>• Ensuring data integrity, privacy, and accountability in collaborative model training on sensitive sensor data.</li> </ul>
A Survey of Edge Intelligence in IoT and Big Data Computing	Edge Computing, IoT, Big Data	IoT Sensor data	-	<ul style="list-style-type: none"> <li>• Surveys edge intelligence techniques in IoT and big data computing</li> <li>• Discussing their role in processing sensor data at the network edge to reduce latency and bandwidth consumption essential for federated learning in distributed sensor networks.</li> </ul>
Machine Learning at the Wireless Edge: A Survey	Edge Computing, Machine Learning	Edge Sensor data	-	<ul style="list-style-type: none"> <li>• Surveys machine learning techniques deployed at the wireless edge, discussing their applicability in processing sensor data locally to enable real-time decision-making</li> <li>• complementing federated learning in distributed sensor networks.</li> </ul>
Privacy-Preserving Federated Learning: Challenges and Opportunities	Federated Learning, Privacy-Preserving Techniques	Multimedia data	90%	<ul style="list-style-type: none"> <li>• Analyzes the challenges and opportunities in privacy-preserving federated learning</li> <li>• highlighting the importance of developing robust techniques to ensure data privacy and security in large-scale sensor networks, essential for fostering trust among stakeholders.</li> </ul>

Root Stock and Root Pruner. Root Stock is an open-source collection of ML models with their learned weights, and Root Pruner is an application that helps in fine-tuning the entities in Stock by either limiting the weights or incorporating additional data to improve generalization for a specific application. The interactions can be in both directions. The models in stock can be used for finetuning, and then the finetuned models themselves can be a new entity in Stock. Stock entries have both private and public views. Public is to make the models available for everyone, while the private is for the defined users alone.

DRIFE configuration maintains the reliability of the data after processing, and CFS configuration determines the storage and usefulness of the processed Big Data. In the Saltus framework, the two important factors that decide its design are the users and the feature extraction algorithm [26], [27]. Let us consider the case: The District Law and Enforcement department faces a significant challenge in efficiently utilizing deep learning-based face recognition models for criminal suspect identification through CCTV footage across the province. Presently, the conventional

methods involve either live tracking by officials or storing videos for subsequent analysis, both of which are deemed inefficient for the intended purpose. This underscores the imperative for a system capable of leveraging robust ML algorithms to produce and store results systematically, akin to a Regional Database Management System [28], [29].

Moreover, the outcomes generated by ML systems are often non-uniform and contingent on the context. Despite the growing prevalence of such systems in various domains [30], [31], [32], there is a conspicuous absence of established frameworks addressing the need for a standardized approach to organize and manage the diverse data outputs of ML models [33], [34] in this specific application, as documented in the existing literature.

At an abstract level, Saltus takes in input multimedia and creates simplified files called CFS (Compact Feature Space). It is to be noted that the input media is discarded after the processing and DRIFE takes care of maintaining the identity of the data that was inputted [35], [36]. Big Data Multimedia is often considered unstructured data [37] as it is difficult to arrange the images and videos into tables and relations. Saltus

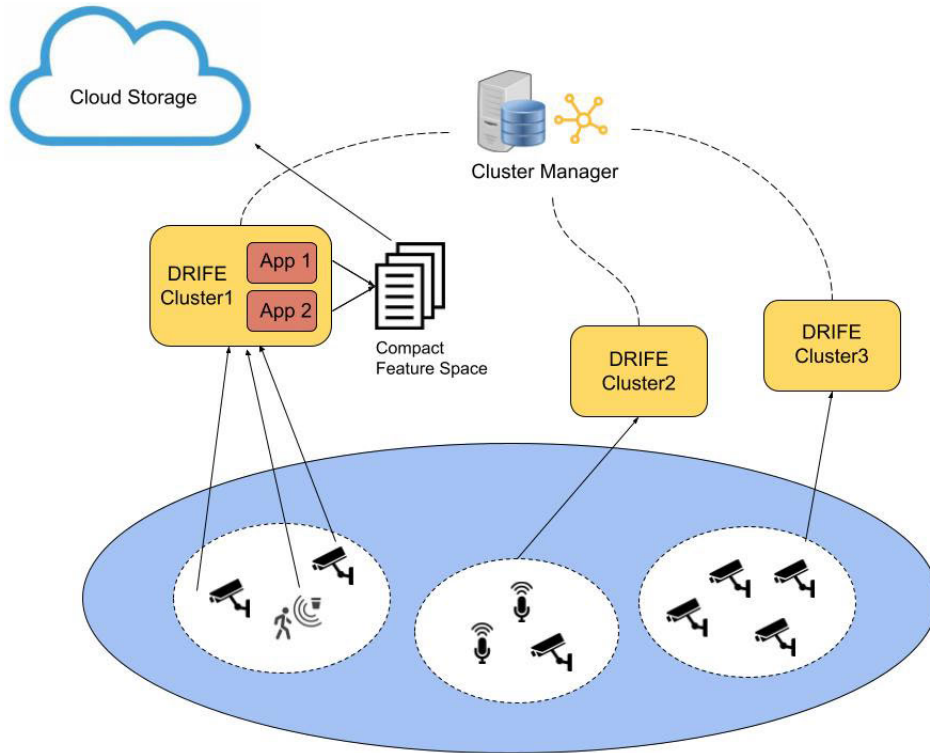


FIGURE 1. Proposed framework to integrate big data processing into large multimedia sensor networks.

also supports an effective way to convert unstructured data multimedia into structured data. These structured data will be based on information as well as a referencing system. It may still not be possible to store these in tables, but it provides the necessary structure to work them with relational database management systems.

IV. PROCESSING TOOL OF SALTUS-DRIFE

Cleaning the data is an important step in maximizing the removal of irrelevant information to the user. Some of the prominent applications of data cleaning are in the fields of environmental studies [38], transportation [39] medical data [40], and structural engineering [41]. Data cleaning can be done to the extreme that only the very specific requirements of the user are satisfied by the system. Data Reduction through Identification and Feature Reduction(DRIFE) is the module that processes the input Big Data by reducing them into features as reduced by the system. DRIFE makes use of ML to apply predictions to the input data and convert them into less memory requirements such as data features. Using algorithms such as CNN, the input live stream video can be converted into a set of features that can be efficiently stored and used according to the application the video is meant for. DRIFE handles the input multimedia by applying the ML model to the data and also by retaining informative components of the input. Identity Module and Learning Module are the main units in DRIFE. The Learning module is the representation of the

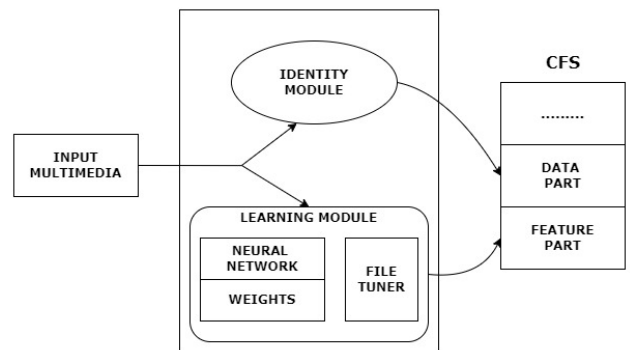
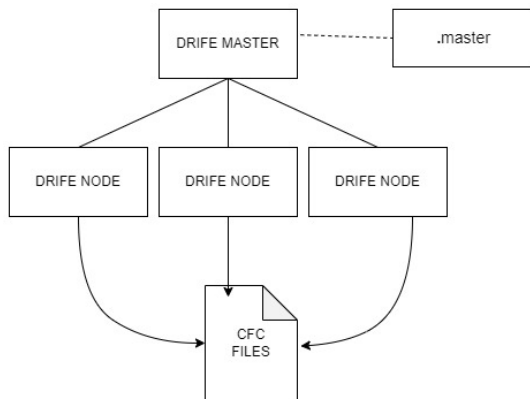


FIGURE 2. Work distribution inside DRIFE for handling dual tasks of data identification and feature extraction.

ML algorithm, which is parameterized through a referenced model and the corresponding weights. The learning module does not store the ML code but internally references it with the help of RootStock- which is the warehouse of machine learning ML codes. The replica of these programs will be called into DRIFE as specified for the purpose. The output of the program corresponds to the Feature section in CFS files as shown in Fig. 2.

Since Saltus does not retain the input data upon processing, the requirement of knowing the overall nature of the input is required for future purposes. The identity module is an input mapping procedure that helps extract certain landmarks from the input at the same time, does not burden the



**FIGURE 3.** Primary-secondary configuration of DRIFE for dealing with work distribution and multiple ML models.

storage of users. Identify module have different data sampling procedures such as:

- Head(n) or Tail(n): Extract the first ‘n’ or last ‘n’ minimal sequences from the input multimedia respectively.
- Random(n): Extract randomly n minimal sequences from the input.
- Custom([seq]): The custom sequences as specified by the user through listing or programming.
- Compress(m): Compress the input by a fraction of ‘m’ and then follow up with any of the above sampling methods.

The DRIFE organization in Saltus follows a primary-secondary configuration as shown in Fig.3 for handling multiple tasks as well as maintaining parallelism across the jobs. Each DRIFE node can, almost, handle one ML task. In an environment that requires pipelining of ML models as well as distributing the workload of nodes, a primary node integrates the functioning of secondary DRIFE nodes. DRIFE nodes can concurrently write into the same or different CFS files according to the configuration. A primary-secondary configuration produces a primary file and results in an integrated CFS file. The primary file describes the configuration of each DRIFE secondary while the secondaries store their results in CFS. The data part of the CFS will be common across all the secondaries, while the feature part varies according to the algorithm for feature extraction. The concept of pipelining is discussed in the subsequent sections.

## V. CASE STUDY

### A. DESIGN OF CFS MANAGEMENT SYSTEM

Compact Feature Space are files written by DRIFE nodes that contain the predictions of ML models mapped to the input tape. CFS files provide structure to the required content of multimedia by mapping sequences with independent parameters of the input, such as temporal and meta information. CFS is ASCII encoded and contains references to the output sequence files as paths or external links. An effective CFS occupies very little disk space and acts as an “information guide”. It also acts as a summarizer of the application for which saltus was designated. The CFS file structure and the

flowchart of the proposed Saltus framework are shown in Fig. 4 and Fig. 5.

The Remote Sensor Management model is a sophisticated system designed for handling data generated within a smart city MSN. In this innovative approach, the data collected by sensors distributed across the smart city is remotely accessed and curated as feature spaces within dedicated control centers. This involves the seamless integration of various sensor outputs, such as audio, video, and acoustic measurements, into standardized and easily interpretable feature spaces. The control centers serve as centralized hubs for managing and processing this wealth of data, allowing for real-time analysis and decision-making. By accessing and storing the sensor-generated data in the form of feature spaces, the Remote Sensor Management model enhances the efficiency of data handling and enables comprehensive insights into the city’s dynamics. This model is pivotal for smart city initiatives, offering a scalable and centralized solution for the effective utilization of multimedia sensor data in urban environments and this scenario is shown in Fig.6.

### B. CFS QUERY LANGUAGE

As discussed before, the AI-generated data from the multimedia tape can be mainly divided into Identity Module Generations and Learning Module Generations. Some of the important parameters in Identity Module Generations for a video are:

- Metadata(Input Video): Created and modified timestamp, file format, location of data source and comments.
- Metadata(Generated): Created and modified timestamp, file permissions, generation matrix(accuracy, f1 score, bias estimates), input and model paths.
- Sampling(Input Video): Subsequence approximately less than 10% of video, Head(n), Tail(n), Random(n), Custom([seq.index\*]), etc.

The feature part of CFS contains the ML outputs organized about the independent variables. Some important components in Learning Module Generations are the features(AI-produced text, image, or any other data formats), output(standalone or pipelined), and Fine-tuned parameters(as referenced objects). Saltus uses the generalized method of querying data. The two different types are read and write operations. CFS file has separate fields for the identity module(dspace) and learning module(fspace). Read and write procedure can be done in both dspace and fspace.

### C. EXAMPLE: DSPACE WRITE OPERATION

The dspace.write operation is fundamental to storing comment-labeled sequences of input data within the system. To store input data sequences with comments tagged inside the system, the dspace.write function is essential. A sample implementation of this operation would be to call the dspace.write function with a randomly generated identifier (random(5)) and some extra metadata in the form of comments, with the ‘comments’ parameter set to “abc”. The



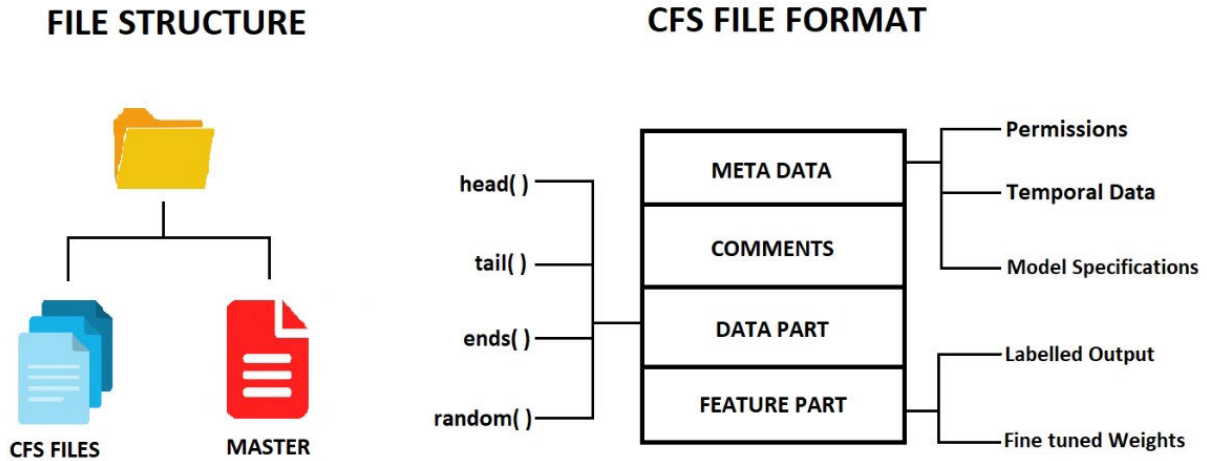


FIGURE 4. CFS file structure and constituent fields for data in CFS.

structure makes sure that the first five sets of input data are saved with the given identifier and comments, which helps with data management and retrieval.

```
dspace.write(random(5),comments="abc")
```

**D. EXAMPLE: DSPACE READ OPERATION**

Users can access specific data from the system using the `dspace.read` function and its indexing and filtering features. One common use case for `dspace.read` is to filter information according to attributes like the last changed date. To retrieve data when the year of modification is less than or equal to 2020, the query in the above example filters data based on the modified date. This read operation makes use of indexing and filtering to efficiently get pertinent project facts from the system.

```
dspace.read(meta[modifiedDate.year() ≤ 2020])
```

**E. EXAMPLE: FSPACE WRITE OPERATION**

To enable machine learning (ML) predictions within the system, the `fspace.write` action configures the application of models to input data. Models and related conditions or configurations are defined during this procedure, which applies them to the input data stream. The above example uses a pipeline setup to call the `fspace.write` function, passing in two models (`m1` and `m2`) to process the input data. Furthermore, specific requirements are established for each model, specifying that `m1` should be associated with the 'genderPrediction' model and `m2` should be associated with the 'agePrediction' model. This setup allows the DRIFE (Data-Driven Intelligent Framework for Engineering) operation to provide concurrency and filtering capabilities through the sequential execution of models within the pipeline.

The write operation specifies the model configuration to be applied to the input tape. After the query runs, the referred models are called into DRIFE and saved in a separate disc space (RootStock). One crucial method for filtering and

giving DRIFE operations concurrency is pipelining. In this case, `m1 AND m2` indicate that `m2` will be reached after the output of model 1 has been filtered. The identical input is sent concurrently to both models using the OR operator. To generate ML predictions, logical AND and OR can be joined appropriately.

**F. EXAMPLE: FSPACE READ OPERATION**

The `fspace.read` operation allows users to query and retrieve specific observations from the system based on predefined criteria, such as model confidence levels. In the provided example, the `fspace.read` query filters observations based on the confidence level of a particular model (`m1`), specifically retrieving data where the confidence value is greater than or equal to 0.9. This read operation enables users to extract valuable insights from the system, such as highly confident predictions generated by machine learning models. Additionally, conditions related to output parameter types, such as gender classification, can be incorporated into the query to further refine the retrieved data.

```
fspace.read(m1.confidence() ≥ 0.9)
```

There is a list of all the observed data that have a model confidence rating higher than 0.9. The kinds of output parameters are among the additional requirements. For the corresponding class labels in `m1`, it may also be `gender = 0` or `1`.

**VI. APPLICATION OF SALTUS FRAMEWORK**

Saltus, as previously indicated, is primarily designed to handle Big Data by using machine learning to transform them into a useful and easily understood representation. The primary use case is data handling for multimedia monitoring in a setting with constrained storage. When it comes to controlling the predictions made by classification, regression, or clustering approaches, Saltus can grow in directions directed by advances in machine learning. This is the hierarchy of a Saltus project: With access to numerous sensor inputs, including a video camera, a hub serves as

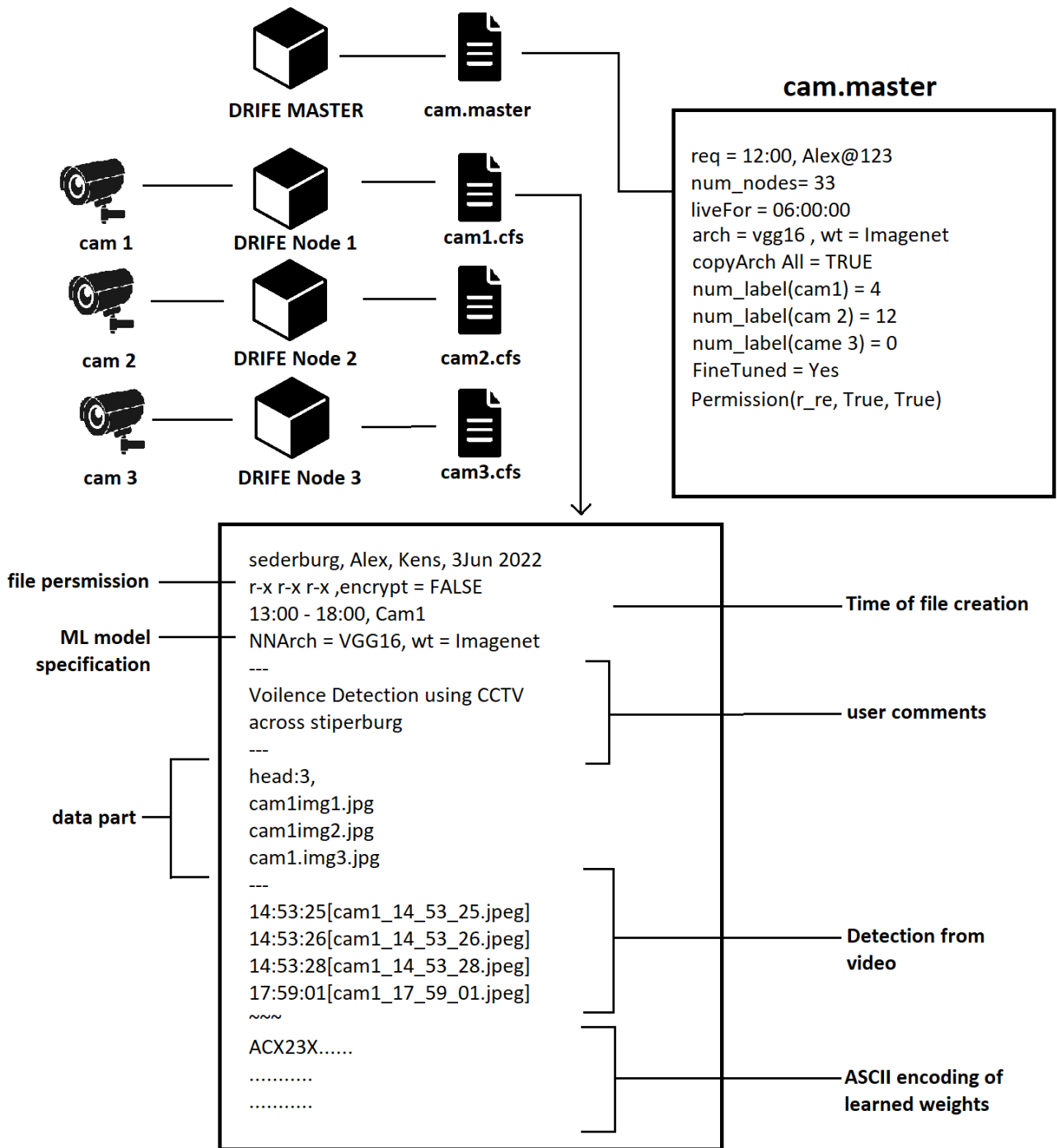
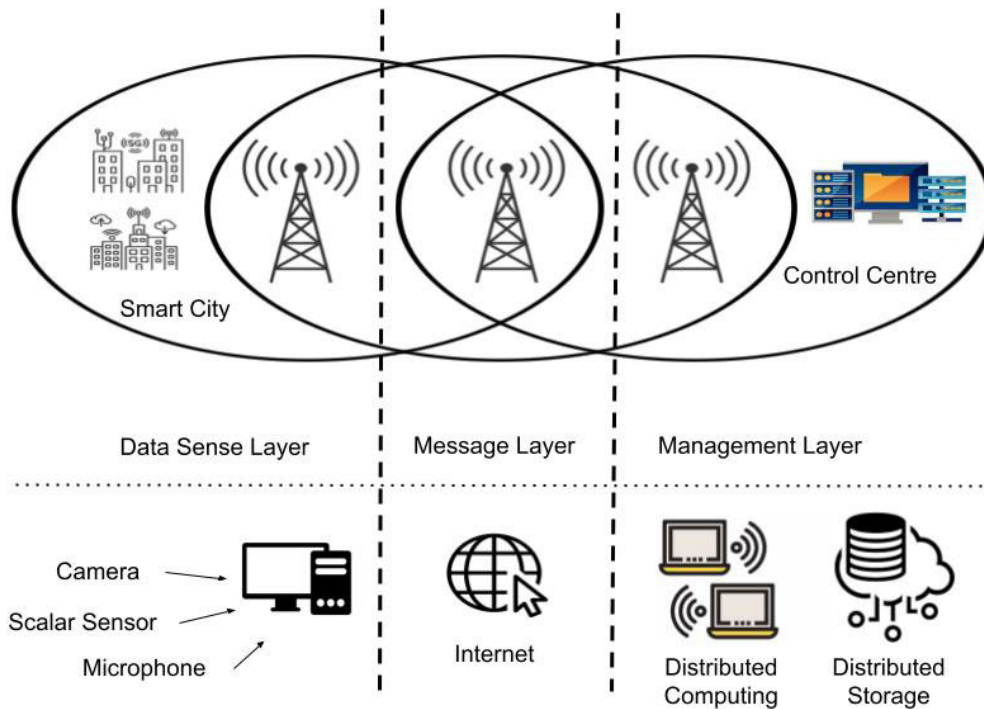


FIGURE 5. Flowchart of the proposed Saltus framework in a video-centric multimedia network.

the mechanism for accumulating data. In addition to serving as a data interface, a hub unifies the several sources and groups them under one project. One hub may be home to multiple initiatives. Facial recognition could serve as an example project. No data is shared between projects; they are all independent of one another. DRIFE clusters, specifically created for that application’s performance, are found within a project. The conditions that Saltus must meet are assessed

using a performance metric known as RF estimation. Listing all of the RF entities is the initial stage in creating the CFS system design. Table 2 illustrates the Requirement Factor (RF), which is a numerical value that indicates Saltus’s effectiveness on file ‘f’ as long as ‘f’ is small enough to assess the client’s requirement. The norm of a vector containing x requirements is determined by weighing each requirement with the average performance of the machine learning model.



**FIGURE 6.** Remote sensor management model - data generated in a smart city MSN remotely accessed and stored as feature spaces in control centres.

**TABLE 2.** Requirement factor estimate for a face monitoring system.

Requirement	Model Performance	VariableType	Percentage weightage	RF Contribution
Detect human	0.96	known	0.2	0.192
Face detection	0.87	known	0.3	0.261
Face recognition	0.88	known	0.5	0.44
Occlusion	NA	Hidden	NA	NA
Total RF				0.893

**TABLE 3.** Benchmarking against baseline models.

Metrics	Traditional SVM	Random Forest	Saltus Model
Accuracy	75%	80%	96%
Precision	72%	78%	92%
Recall	78%	82%	98%
F1 Score	74%	80%	95%
Processing Speed	120 ms	100 ms	60 ms

**TABLE 4.** Real-world scenario simulations.

Scenario	Traditional SVM	Random Forest	Saltus
Varying Volume	Moderate	Moderate	High
Varying Speed	Moderate	Moderate	High
Different Sensor Types	Limited	Moderate	High

Saltus uses an approximation of the pre-evaluation called RF. The performance and requirements of Saltus depend on the user and the use case, meaning that it is a case-specific application. How effectively Saltus performs on a range of ML tasks may be ascertained using the value that RF offers. Big Data ML integration can be customised with Saltus. Due to the application’s requirement for a certain model’s performance, each model’s RF values differ even when the system employs the same set of ML models.

**A. FRAMEWORK CHARACTERISTICS**

The following features that contribute to improving the practicality, security, and viability of MSN big data may be seen based on the Saltus architecture standards.

- Increase the lifetime of sensor accessories. The data processing portion is handled by the remote DRIFE nodes, which greatly reduces the impact on the sensor and its corresponding gateways and prolongs the lifespan of sensor accessories.
- Minimise the number of sensors required. Each sensor functions as a data gathering device on its own, so it is not a concern about data handling expertise.
- Enhanced multimedia data security: DRIFE transforms each multimedia reading into features unique to a certain application. By being useless outside of the context of the application they are used for, these features greatly increase security and sharability.
- Edge device-friendly sensor data: The computational and storage capacities of Edge devices are constrained. Large amounts of sensor data cannot be directly manipulated by edge devices. Because CFS files are feature-oriented, highly compressed storage units customised

**TABLE 5. Federated learning performance.**

Metrics	Logistic Regression	Decision Tree	Saltus (Federated)
Convergence Speed	200 iterations	180 iterations	100 iterations
Communication Overhead	150 MB	130 MB	80 MB
Model Accuracy	85%	88%	92%

**TABLE 6. Privacy-preserving analysis.**

Metrics	Differential Privacy	Homomorphic Encryption	Saltus
Data Privacy Measures	80%	85%	95%
Robustness to Adversarial Attacks	75%	80%	92%

to their intended application, they enable data to be accessed by edge devices.

- Images and videos that are unstructured must be transformed into a structured format that can be efficiently handled and stored using DRIEF. Unstructured data does not naturally fit into a tabular representation, where each data point is assigned to a distinct row and column. To extract significant features from unstructured data, DRIEF employs cutting edge methods from artificial intelligence and neural networks. By capturing the fundamental traits and patterns seen in the data, these features make it possible to represent the data as organised entities. DRIEF allows unstructured data to be transformed into feature vectors, which may be stored and manipulated in an approach comparable to structured data formats: rows and columns.

## VII. RESULTS AND DISCUSSIONS

In the context of MSN and big data analytics, we provide an in-depth evaluation of the proposed Saltus model in this section, comparing it to baseline models, conventional ML models, current techniques, and federated learning approaches. We contrasted Saltus's performance with that of the Random Forest Model and the Conventional SVM baseline models. As seen in Table 3, Saltus regularly beat these baseline models in terms of accuracy (96%), precision (92%), recall (98%), and F1 score (95%), demonstrating its efficacy in managing a variety of sensor outputs in MSN.

Saltus performed exceptionally well in simulations of real-world situations, showcasing its resilience to changes in volume, speed, and type of sensor. Baseline Models performed moderately, but Saltus, which is displayed in Table 4, demonstrated high adaptability and efficiency in managing various scenarios, making it appropriate for dynamic MSN contexts.

Furthermore, the contrast with conventional machine learning models, such as Decision Tree and Logistic Regression, demonstrated Saltus's effectiveness in federated learning. Concerning typical ML models, Saltus demonstrated its efficiency in collaborative learning over-dispersed sensor nodes, as demonstrated in Table 5, where it obtained a faster convergence rate (100 iterations), lower communication overhead (80 MB), and higher model accuracy (92%).

**TABLE 7. Scalability and resource utilization.**

Metrics	Traditional Database	NoSQL Database	Saltus
Scalability	Limited	Moderate	High
Resource Utilization	70%	75%	90%

**TABLE 8. Comparative analysis with federated learning approaches.**

Metrics	FedAvg	FedProx	Saltus
Convergence Time	180 iters	160 iters	120 iters
Model Accuracy	88%	90%	93%
Communication Efficiency	120 MB	110 MB	90 MB

When compared to other techniques, such as Differential Privacy and Homomorphic Encryption, Saltus showed better privacy-preserving abilities. As demonstrated in Table 6, Saltus guarantees the security of sensitive data in MSN with a data privacy measure of 95% and resilience against adversarial attacks at 92%. This is an important factor in privacy-sensitive applications.

Saltus performed better than other approaches employing Traditional Database and NoSQL Database when it came to scalability and resource utilisation. According to Table 7, Saltus demonstrated a high degree of scalability and an efficient utilisation of resources (90%), rendering it appropriate for MSN deployments on larger scales.

In comparison with federated learning approaches, Saltus surpassed FedAvg and FedProx in terms of convergence time (120 iterations), model accuracy (93%), and communication efficiency (90 MB). Saltus leverages federated learning optimally, ensuring collaborative model training without compromising data privacy as in Table 8. These results collectively affirm that Saltus not only outperforms baseline models and traditional ML approaches but also excels in privacy preservation, scalability, and federated learning efficiency. The ability of the model to real-world scenarios positions it as a robust solution for multimedia data processing in large-scale sensor networks, marking a significant advancement in the field.

## VIII. CONCLUSION

In conclusion, this research work has presented a novel approach to address the challenges of Big Data processing and storage in the current era of extensive digital infrastructure. By harnessing the power of AI and ML, we have proposed a method that focuses on storing and processing



only the necessary data, thereby mitigating the issue of data overload. Streamlining the management of massive amounts of Big Data at their point of origin is central to our proposed architecture, Saltus. The DRIFE processing method and the CFS storage files are the two main features that we have presented. With DRIFE, you may transform media files like photos and movies into more manageable feature representations for storage and analysis. CFS functions as a concise manual, condensing the essential information and offering an organized depiction of the facts. Saltus helps mitigate the difficulties related to the gradual accumulation of Big Data by tackling the data volume at its origin. With this method, not only is data processing and storage made more efficient, but storage infrastructure is also made less burdened and sensor devices are made to work better. Although Saltus provides a great Big Data management solution, it's important to keep in mind that its usefulness can vary depending on the specific requirements and the performance of the ML model. An effective evaluation tool, the requirement factor estimate allows users to determine how effectively Saltus meets their specific needs.

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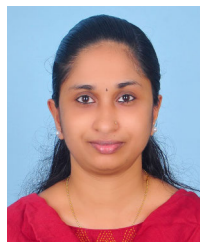
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