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# A Holistic Architecture for a Sales Enablement Sensing-as-a-Service Model in the IoT Environment

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**Abstract:** Sales enablement sensing-as-a-service (SESaaS) is an organisation's future process management for any sales management operation. With an expanding base of dynamic customer demands and the adoption of multiple technological advancements, there is a high possibility that human-centric sales management will be transformed into a fully automated form aimed at increasing productivity and being able to cater to effectively a broader customer base. A review of the relevant literature demonstrates that machine learning is one of the most prevalent techniques in analytics for predicting sales behaviour. However, SESaaS includes many features beyond the sales component. Internet-of-Things (IoT) can additionally be used for networking and data analytics to enrich sales data. Therefore, the proposed scheme introduces a novel SESaaS model capable of balancing the sales team's needs with those of the customers to maximise profits. The proposed model also presents a novel learning scheme in the IoT environment that aids in projecting the service quality score to the final customer, thereby positively influencing the customer to pay a service fee for a superior and desired quality of experience. Unlike any existing sales management scheme, the proposed scheme offers a novel research methodology for improving sales enablement practices, emphasising service scalability, and forecasting company profit. In contrast to any existing system for sales management, the proposed scheme provides greater accuracy, higher service quality, and faster response time in its predictive strategy for projecting the cost of the adoption of SESaaS, which is not reported in any existing studies. In an extensive testing environment, it is determined that the proposed scheme achieves accuracy and service quality of approximately 98.75% and 92.91%, respectively. In addition, the proposed SESaaS model has a significantly faster response time of 1.256 s. These quantifiable outcomes were validated after being compared with commonly adopted learning programs.

**Keywords:** Internet-of-Things; machine learning; profit; quality of experience; sales enablement as a service; sales management



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## 1. Introduction

With the evolution of cloud computing and its effective penetration in various fields of application, there is a growing list of different mechanised processes in the form of services [1]. With this motivation, sales enablement is a comparatively novel concept in enterprises. This drive is inspired by software operations related to sales provided in the form of services; hence, it is named sales enablement sensing-as-a-service (SESaaS) [2]. However, it is a complex process that includes various sales-related contents and sophisticated transactions. The primary goal of SESaaS is to offer a supportive platform for organisational sales running to promote process management [3]. The secondary purpose of SESaaS is to potentially impact the prospective customer's decision regarding service adoption with a sole target of magnifying the arena of revenue [4]. SESaaS also involves various cross-functional applications to elevate sales, including product/service information, sales contents, supporting deal closure, practical product/service training to the sales team, tools and knowledge management, etc. [5]. However, to date, such mechanisms are entirely human-centric and can only be deployed on a small or medium scale with few complexities. The challenges start to evolve when the customer base increases with various sophisticated organisational sales strategies. This section offers compact insights into the background of the study, problems encountered, and the recommended solution to mitigating the identified problems.

### 1.1. Background

The term 'sales enablement' essentially means the conglomeration of all the essential processes required for nurturing the information demanded by a sales organisation including supportive content and the adoption of specific tools. This facilitation of sales enabled within an organisation is meant to improvise sales targets [6]. It also demonstrates the importance of necessary information, tools, training, and analytical knowledge for upgrading sales scores [7]. The complete sales enablement process is carried out in the form of multiple team structures allocating discrete roles and responsibilities [8]. However, it is always practical to consider the deployment of sales enablement in the form of services so that they can be reached and managed by multiple teams in a distributed manner [9]. With the proliferation of cloud-based services, the adoption of customized services has significantly increased with evolving new names of services [10].

Similarly, the concept of sales enablement can also be offered in the form of services by the cloud service provider [11]. However, the core challenge in such a service proposition will be the accessibility and availability of on-demand information for making better decisions. There is a good chance that such implementation of the sensing process will be incorporated within the sales structure, and this could be made possible using the Internet-of-Things (IoT) [12].

Therefore, the concept of SESaaS with the adoption of an IoT could facilitate the proper control and management of sales services. With more usage of cost-effective sensing devices in IoT, the sales team could significantly benefit [13]. An IoT device using location-based services could generate field reports that bridge communication between the service provider and customer [14]. Various forms of temporal-based information, viz. duration needed to dispatch the product/sales, time required to cater to a client's request/demand, and period necessary for transmitting real-time information of services using IoT sensing devices, could be furnished using SESaaS. Analytical operation in IoT when deployed over SESaaS could generate a predicted list of prospective customers as leads or forecast a suitable environment for making a profit or resisting risk [15]. SESaaS could also be used for tracking the real-time performance of any sales representation, saving tedious effort and time in the current system. Therefore, a next generation of sales services could be introduced via SESaaS.

As the SESaaS targets mainly automation, it is necessary to ensure that complete internal process information, its associated linkages, and its dependencies are well known. It will also mean that SESaaS consists of a more significant generation of sales-related details, which would be highly unstructured and cluttered. This is where natural language processing and machine learning can contribute to data structurisation and enrich the informative contents of complex data [16]. Various learning-based techniques have evolved toward business processes [17–20], with claimed beneficial outcomes.

### 1.2. Insights to Issues

The real-time concept of SESaaS demands a specific environment for working with IoT and distributed cloud services that is not present in this perspective as an integrated solution.

There are also multiple challenges associated with such approaches that include:

(i) Adopting an IoT will structure and channel the services associated with sales and introduce various analytical operations to give clear and predictive insights into the sales information. Such analytical operations are carried out using multiple learning-based approaches [21]. With the availability of various machine learning approaches, the selection of an appropriate learning scheme is still uncertain.
(ii) The majority of existing studies on business process management, sales, and costing are associated with solving one part of the sales problem that does not apply to the complete process.
(iii) Applying machine learning can assist in better decision making, but it still cannot offer a suitable environment for data dissemination on a massive scale.

### *1.3. Presented Solution*

Therefore, the importance of deploying IoT comes into the picture. With the wide-scale progressive adoption of IoT in various commercial applications, it is possible to use it in the business process for sales and services [22]. Another reason for IoT's higher applicability is the provision of effective data management using analytics, which could be used for sales. Different devices of IoT can be mounted on terminals right from the sales-enabled (SE) application, where additional sales data can be extracted which, when subjected to analytics, will offer decision-making towards the deal. However, this concept is novel, and at present, SESaaS has never been tested with learning or IoT platforms; hence, various challenges are involved.

Thus, the prime idea of the proposed system is to develop a computational model for SESaaS in the form of a fully automated system that targets enhancing sales productivity in the IoT ecosystem. The core contribution of the proposed scheme is its integrated sales service in one unit with the target of increasing the profit for an organisation that offers SESaaS to its customers. All the effective decisions towards relaying services with optimal quality with optimal subscription charge are managed by the service provider, thereby saving time and effort for a customer. This study makes the following contribution:

- Reviews existing SE management approaches to emphasise the strengths and limitations of existing learning schemes.
- Presents an analytical scheme in which SESaaS is computationally modelled considering IoT attributes and a unique learning scheme.
- Develops an integrated model towards maximising profit for IoT service providers and levying optimal service charges from customers.
- Benchmarks the system to exhibit that it offers better outcomes than existing sales management schemes.

The rest of the paper's organisation is as follows: Section 2 presents a discussion of existing schemes for sales management, followed by highlights of the identified problem in Section 3. Section 4 discusses the adopted methodology, while Section 5 discusses the system implementation. Section 6 highlights the discussion of outcomes, while Section 7 summarises the conclusion by including novel features presented by the proposed scheme.

## 2. Existing Approaches

This section discusses the availability of recent schemes in which IoT and machine learning have been utilised. The core agenda is to realise the effectiveness and applicability of such systems in sales and marketing.

### *2.1. Studies on Sales Management*

There are various predictive techniques associated with sales performance connected with customer usage. These studies implement strategies that can directly forecast various indicators and assess their impact on an organisation's sales. Different research-based approaches that fall under this category are as follows: an integrated strategy for data bundling using big data [23], analysing the value of patents for the manufacturing sector using deep learning in IoT [24], predicting sales using a k-nearest neighbour algorithm [25], sentiment analysis for forecasting sales of vehicles [26], a decision support system for enterprise data in IoT using ensemble decision trees and deep neural network [27], management of power demands using artificial neural network [28], churn prediction using game analytics [29], random forest [30], and Bayesian analysis [31] that predicts using business intelligence [32], specifically prompter the customers to give responses for marketing product using game theory and embedding model [33].

- Beneficial Factor: The approaches are capable of offering accurate predictive outcomes considering the adopted case studies.
- Shortcoming Factor: The complete emphasis is on achieving sales accuracy without considering various practical constraints linked with business processes in the practical world.

Viable Solution: Effective modelling can be carried out by considering all the essential practical constraints associated with the sales operational setup. This adoption can offer higher applicability in an actual setup. Further, adopting machine learning can ensure that models provide reduced iterative operation and faster execution with less error margin.

### *2.2. Studies Involving Learning in Sales*

This study emphasises machine learning approaches focusing on explicit knowledge extraction. The core idea of such techniques is to develop a deployable learning scheme to establish a better learning environment in sales and marketing. Different learning-based approaches used are as follows: analytical modelling for evaluating the credibility of customers using integrated machine learning approach, i.e., random forest, AdaBoost, Bagging, decision tree, and support vector machine [34]; cost prediction for fault identification using feed-forward neural network [35], predicting product backorder using gradient boosting and random forest [36], harnessing extracted knowledge for customer prediction using regression [37], artificial intelligence in forming business strategy [38], and predictive modelling for customer loyalty using integrated machine learning approach [39]. Brief remarks on the effectiveness of such schemes are as follows:

- Beneficial Factor: Such models offer robust platforms for assessing different learning algorithms, increasing the product analysis scope.
- Shortcoming Factor: The majority of such schemes are potentially dependent on training data to perform analysis. Furthermore, such methodologies are heavily iterative, time-consuming and not meant for instantaneous response generation.

Viable Solution: One of the feasible solutions will be to carry out the integration of various sales units which can perform data integration. This adoption will result in the aggregated data being cost-effectively analysed with reduced time consumption and fewer iterations. Further, the abundance of heterogeneous sales data maintained in a well-structured form will offer more solutions towards achieving convergence scores catering to multi-objective functions.

### *2.3. Studies on Negotiation/Cost*

Fundamentally, negotiation is a human-centric task that is usually not outsourced to machines. The prime rationale behind this is that negotiation involves considering various nonlinear parameters and higher vertical knowledge, which is computationally challenging for machines. Cost is another essential attribute connected with negotiation that encounters similar challenges. In response, developing a negotiation model and cost factors based on decision making is an increasing area of interest. Such studies' implementation would emphasise extracting prime knowledge that could assist in decision making from sales representatives and customers. Various methodologies being implemented on sales-based negotiation in different variations of service/product are as follows: negotiation models using a fuzzy controller [40], decision making using a stochastic model [41], a broker negotiation model using re-federation scheme [42], consumer perception modelling for negotiation using Big Data [43], distribution optimisation in logistics using Big Data [44], decisions for pricing using game theory [45], analytical cost modelling for cloud transaction using cloud uncertainty model [46], cost management modelling for manufacturing [47], cost uncertainty modelling using dynamic pricing [48] and optimising resource integration in retail sector using ant colony optimisation [38]. The overall degree of effectiveness from these studies is as follows:

- Beneficial Factors: The primary benefit of such approaches is the higher scope of decision-making considering various attributes on practical ground. The secondary benefit is their application towards multiple products and services associated with sales.
- Shortcoming Factors: The major drawback of such methodologies is that they largely depend on rules formulated by humans. At the same time, the machine-based rule formulating system is also controlled by humans. Hence, the systems are not automated and cannot take the entire decision to negotiate in dynamic environments.
- Viable Solution: There is a need to carry out a novel cost estimation module which can project the beneficial advantage toward service adoption of sales by customers, unlike any existing approaches. Also, there is a need for the customer to be given more control over their selection of sales services in distributed form. The cost factor can be further controlled using an appropriate learning-based scheme.

The beneficial features and limitations associated with the existing approaches are highlighted in Table 1.

**Table 1.** Summary of analysis of existing approaches.

| Authors | Problem | Methodology | Advantage | Limitation |
|---|---|---|---|---|
| Zhang et al. [23] | The ineffective pricing model for sales data-as-a-service | Strategy for integrated bundling service, contract theory | Applicable for any form of sales product | Doesn't consider the backend sales team |
| Trappey et al. [24] | Knowledge extraction from intellectual properties | Principal component analysis, deep neural network | High predictive accuracy score | Accuracy depends upon the quantity of trained data |
| Palacios et al. [25] | Autonomous forecasting of sales | Machine learning | Enhances forecast accuracy | Doesn't consider the practical constraints |
| Pai et al. [26] | Prediction of vehicle sales | Least square support vector regression, time series | Enhances forecast accuracy | The model is highly sensitive to outliers |
| Nguyen et al. [27] | Prioritization of customer service | IoT, decision support system | Simplified predictive model | Not applicable for the larger scale of IoT |
| Mahmud et al. [28] | Reducing prediction error | Artificial Neural Network, autoregressive moving average | Enhanced management of power demand | Highly iterative, not cost-effective for practical application |
| Lee et al. [29] | Churn analysis (gaming industry) | Feature engineering, k-means clustering | Effective identification of loyal customer | Doesn't consider the heterogeneity of data |
| Ullah et al. [30] | Churn analysis (telecom industry) | Random forest | Better churn classification | Not applicable for real-time prediction |
| Wu et al. [31] | Churn management (telecom industry) | Analytical framework, multiple machine learning | Random forest exhibited better performance | Increased data makes the model run slow |
| Khan et al. [32] | Demand forecasting | Machine learning | Higher accuracy for real-time data | Demand modelling doesn't consider the practical constraints |

**Table 1.** *Cont.*

| Authors | Problem | Methodology | Advantage | Limitation |
|---|---|---|---|---|
| Bai et al. [33] | Prediction of early review | Quantitative modelling, game theory | Effective predictive scores | Narrow scope of applicability, complex modelling |
| Aniceto et al. [34] | Evaluation of credit risk | Multiple machine learning | Adaboost & random forest perform better | Accuracy dependent on training data size |
| Boateng et al. [35] | Cost prediction of fibre optic cable | Linear regression, feed-forward neural network | Effective predictive scores | Highly iterative |
| Islam & Amin [36] | Product backorder forecasting | Gradient boosting machine, distributed random forest | Higher applicability in sales management | Overfitting, longer duration for training |
| Jamjoom [37] | Knowledge extraction from churn data (insurance industry) | Decision tree, k-means, neural network, logistic regression | Multiple scopes of applicability of the model | Impractical assumption of linearity on conceptual variables |
| Mishra & Tripathi [38] | Business model innovation | Machine learning, artificial intelligence | Comprehensive discussion | Doesn't offer insight into the technical implementation |
| Wassouf et al. [39] | Churn management (telecom industry) | Descriptors, classification | Effectively perform loyalty prediction | Doesn't offer an instantaneous response |
| Adabi et al. [40] | Formulation of negotiation strategy | Fuzzy logic | Simplified modelling with a faster outcome | Model entirely depends upon ruleset |
| Araujo et al. [41] | Decision-making | Stochastic modelling | Considers constraints for customer service | Not benchmarked |
| Bhattacharya et al. [42] | Handling negotiation (cloud service) | Simulation model | Offers balanced state | Computationally extensive process |
| Chaudhary et al. [43] | Consumer behaviour prediction | Big data analytics, mathematical model | Enriched data processing | Doesn't address the inherent problems with big data |
| Chen [44] | Optimising logistic distribution | Big data analytics | Satisfactory execution time | Human-centric mechanism |
| Ke et al. [45] | Supply chain pricing decision | Numerical analysis | Reduces uncertainty of payment | Not completely automated system |
| Makhlouf [46] | Cost of transaction in cloud services | Cost theory | Identifies some practical issues | Low scale of applicability to large environment |
| Rounaghi et al. [47] | Addressing cost stickiness | Strategic cost management | Accurate pricing | Applicable to the manufacturing sector only |
| Song & Wang [48] | Uncertainty in sales | Pricing strategy with optimality | Offers practical suggestion | Not benchmarked |
| Yang & Yao [49] | Resource integration in retail | Dynamic service modelling, ant colony optimisation | Offers a collaborative service framework | Outcome not benchmarked |

## 3. Research Problem

From the prior section, it has been noted that the existing implementation schemes for sales management are characterised by both beneficial and limiting factors. However, in brief, it can be seen that such models do not encompass the complete business model required to give the shape of SESaaS. The prime reasons for the pitfalls serve as the research problems, which are as follows:

- Incomplete modelling of sales enablement: Sales enablement consists of various attributes ranging from sales content to deal closure and productivity. It also consists of understanding future customer demands. Unfortunately, existing studies favour the sales team ignoring the importance of interactivity with the customer. Though the adoption of machine learning can assist in prediction based on historical data, this is not enough without encapsulating a supportive customer environment.
- Lack of emphasis on service scalability: The majority of existing studies were carried out considering a specific case study of a business process. Hence, irrespective of a better learning approach, such models fail to adapt when the business process is altered. This leads to a decline in scalability performance when different dynamic variables associated with sales enablement are included. The existing system also fails to explain the applicability of such models when run on a bigger scale. The inclusion of IoT assists in this regard; however, existing approaches to sales enablement using IoT focus on the networking aspect and less on data analytical aspects.
- Does not project profit to customers: Irrespective of various cost model approaches in sales, they are mainly associated with evaluating the cost involved in their process without any provision for attracting clients. An eagerness to pay by the customer entirely depends upon the quality of service and the cost involved in the complete process. Unfortunately, the existing methodologies do not project any beneficial features for customers if they adopt any services associated with sales enablement. Hence, this model fails on the practical ground of technology adoption.
- More human-centric and less automated: With the rising demand for standard automation in Industry 4.0, none of the existing systems offers a complete automation process for sales management programs. The sales team manually manages the entire application control upon receiving a machine's predictive outcomes. The same situation applies to customers, who rely on the sales team to understand their benefits and risks.

The proposed system identifies and addresses all the above-stated concerns. The following section outlines an integrated solution where unique machine learning and IoT offer a novel SESaaS model.

## 4. Proposed Methodology

Before discussing the proposed solution, it is essential to understand the best possible way to address the identified research problem in the prior section. The first research problem of incomplete modelling of sale enablement can be mitigated by capturing the unbiased set of real-time information associated with clients' and service providers' demands. The second research problem of lack of emphasis on service scalability can be addressed when the complete business processes involved are integrated with a particular device which can capture business-/operation-intensive information without much re-engineering. The third research problem of does not project profit to customers demands an automated system to capture the data, subject it to an appropriate analytical operation, and forward the analysed outcome user-friendly to customers. The fourth and final research problem of more human-centric and less automated can be addressed by adhering to the automation standard of Industry 4.0, where IoT, cloud computing, and analytics are essential technology pillars. Therefore, the solution to all the above is to consider the adoption of a sensing device that can perform the seamless capturing of information integrated with analytical processing.

Considering that sensing devices are now available in the commercial market at a more cost-effective price, such devices can be integrated with various operational setups in an enterprise system. For this purpose, the proposed scheme considers four different operational setups: sales content, sales training, deal support, and sales productivity. The proposed study also considers that all these operational setups can be integrated with a specific form of sensor, RFID device, or other data capturing device that does not require human intervention. Overall, it constitutes a topology mapped with an IoT system where different entities involved in the sales enterprise can interact. These aggregated data can be suitably subjected to a novel analytical scheme. Hence, the proposed system introduces a sales enablement sensing-as-a-service (SESaaS) model by harnessing the potential of IoT and machine learning. The core contribution of the scheme is computational modelling, where the existing sales team of an organisation can automate the complete process with their end customers using the sensed information that is analytically processed and delivered to customers.

Adopting this scheme introduces various actors of an IoT as well as learning formulation, which will call for an additional service charge. Hence, the novelty of this scheme is that it reflects the beneficial aspect of adopting the proposed IoT-based SESaaS scheme for an enriched service experience for the clients. At the same time, the scheme also offers better profit to third parties and the sales team equally as a win-win situation. According to Figure 1, the proposed implementation consists of three essential modules: Sales enabled (SE) attributes, IoT attributes, and machine learning. Different sensing devices are utilised to capture data from various operational setups involved in sales enterprises. The captured sensed data are then subjected to integration and management per the sensing data related to overall sales. Notably, the proposed system is designed to cater to any enterprise system irrespective of its products and services. This phenomenon will further ensure the processing of all the characteristic data considering the IoT environment with available network devices.

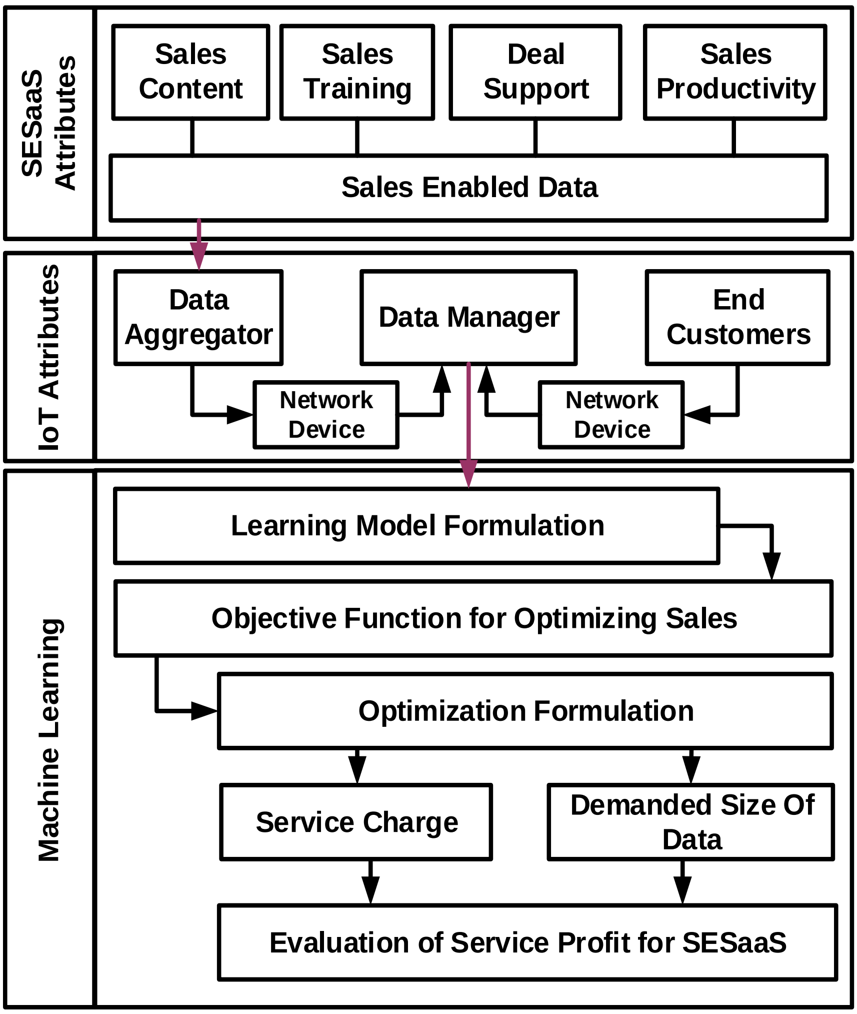


**Figure 1.** IoT-based SESaaS schematic diagram.

The idea is to collect all the relevant SE data followed by the third parties managing the data over an IoT platform, the data aggregator and manager, connected by network devices.

The agenda is to structure all essential data for deciding on sales and service support. The machine learning model is responsible for constructing a learning model using a definitive objective function for optimising sales. Further, it targets profit maximisation based on service charge and demanded data size by the end-user. The fundamental goal of the approach is to offer competitive costing for the customers where the service charges they pay come with value for money. Hence, the study outcome is sales-enabled sensed data that offers specific information towards a higher degree of knowledge as a service when subjected to the proposed algorithm. It also showcases cost-effective modelling practices using machine learning in the proposed scheme.

The following section elaborates on the internal operations and implementation aspects of the proposed SESaaS scheme in IoT.

## 5. System Design

Given that the proposed system is the first of its kind in presenting a computational model that integrates SESaaS with IoT in the area of research, it is essential to define and illustrate the mechanism adopted to arrive at the proposed architecture. The complete discussion of the system design is carried out with respect to SESaaS architecture and integration of SESaaS with IoT as follows.

### *5.1. Modelling SESaaS Architecture*

The modelling of the SESaaS was carried out initially with the original concept of the arena of sales and marketing. It consists of all the services that a service provider associated with sales and marketing is required to offer to leverage the customer experience. Usually, this is carried out by third parties; hence, this sensed sales management is provided in the form of service. There is another reason for relaying this sensed sales management in the form of service: it is one of the most sophisticated processes for implementation. SESaaS is a platform that involves financial payments by business clients to third parties. Third parties are responsible for offering their cost management, protocols, and policies to implement SESaaS effectively.

Figure 2 highlights the critical attributes that potentially influence SESaaS operation.

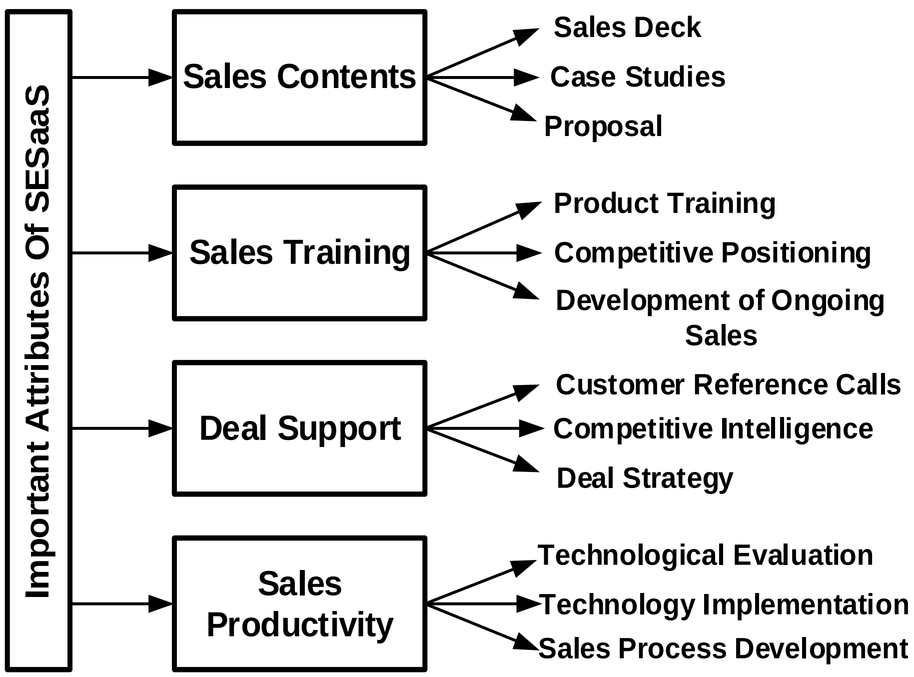


**Figure 2.** Essential attributes for SESaaS.

The first attribute, content, consists of informative case studies by the sales team to improve impressions and customer engagement. The second attribute, training, refers to imparting proper guidance and teaching about the service and product details to the sales representatives so that their communication with the client is effective. The third attribute, dealing, could be human and non-human-based techniques that call for implementing competitive intelligence and strategies to create an effective communication bridge between the customer and the negotiation team. The fourth and final attribute is technology, where various technological advancements using sensing devices are adopted to automate and involve much productive performance for the sales team to benefit the parent company. The existing practices call for a standard procedure to implement SE for different recurring variants of services in SESaaS. Following are the steps of implementation for sales enablement:

- Preliminary configuration: This is the first part of the implementation that mainly emphasises assessing the effectiveness of various existing sales processes. This is carried out to find the loopholes in the existing practices by understanding the target audience and configuring the workflows of the routine as well as exploring mechanisms to monitor the prime indicators of sales performance. This primary implementation stage acts as a foundation for the upcoming sales management.
- Maintenance: The maintenance of the SESaaS is not a one-time process: it undergoes various stages of improvement depending upon the customers' demands. A successful SESaaS calls for progressive maintenance work along with the inclusion of optimisation. All the internal processes associated with the sales operation, competitive intelligence, and training undergo a dynamic change in this implementation stage.
- Campaigning: This is the final stage of the implementation of SESaaS, where the idea is to cater to customers' demands by responding to their queries. It also calls for measuring the success and analysing the degree of success obtained by the existing implementation.

However, the prime target of any form of SESaaS is to ensure better control of the pricing system for the customer to guarantee the best delivery of services. Notably, this is an entirely human-centric operation, whereas it needs to be automated for the large-scale deployment of SESaaS. The discussion carried out in this section highlights the consideration of an essential attribute for modelling SESaaS.

### *5.2. Integrating SESaaS with IoT*

From the prior section, two sets of information are obtainable. These include:

(i) The inclusion of four essential attributes of SESaaS;
(ii) The need to improve the commercial SESaaS structure to fit in a bigger deployment scenario of IoT.

It is also notable that a practical decision regarding better pricing management for many customers is the critical demand for improving SESaaS. Therefore, the proposed system considers the inclusion of IoT to address the problem associated with extensive deployment, pricing, and an effective sensing-as-a-service system. To integrate SESaaS with IoT, the proposed system constructs three further essential modules as follows:

- Data aggregator: This module represents a sensing device responsible for gathering, storing, and processing all the sensed data. A typical IoT device capable of sensing the target signal from the individual operational sales setup can be used for this purpose. In the preliminary configuration step, all the sensors are assigned a unique identity before deployment. The aggregated data are time-stamped and forwarded for integration with other sensor data. For simplification, the study considers a specific enterprise template which organises all the sensed data in a highly structured form. The sensed data are then reposited in cloud-storage units in indexed form. The maintenance block is responsible for acting as a bridge of communication between the raw sensed data and the template. This module performs all the pre-processing of the sensed data to remove any possible artefacts. The campaigning block is responsible for launching any alteration in the sensing process in the case of any new inclusion of sensed data or exclusion of existing data. This module assists in fine tuning the sensing process per the business requirement. By incorporating an IoT system on computing devices and sales management platforms, such forms of data can be obtained easily. However, it should be noted that the inclusion of this process also demands that financial data be structured and annotated by humans to accomplish the objective of processing them. This results in detecting anomalies and any form of missing financial data. The sales team can levy the cost of this operation from the customer to provide them with enriched data.

- Data manager: The sensed data aggregated from the sales team and the customer are rather raw. Its quality can only be realised when some effective analytical operation is applied. The data manager is a discrete module in an IoT system that obtains sensed data from multiple sensed data aggregators (IoT devices) and subjects them to machine learning. This module offers everyone profit, from the sales team to the customers, who obtain better experience in the contract period, and the third parties, who can levy costs benefitting them. However, it is optional to take this service.
- End customer: The study considers the presence of a specific number of independent entity customers. Each customer has the right to choose from the maximum threshold of service payment towards SESaaS fixed by the data manager. Customers' choice to pay this cost depends upon their demand for such a service and self-evaluation.

Figure 3 highlights the proposed architecture, which exhibits the integration of IoT devices with a sales management system to evolve as an IoT-enabled SESaaS scheme. The contribution of this architecture is that it emphasises costing involved in relaying sensing-as-a-service and offers options to almost all entities to opt for this sensing service to improve the productivity of sales and customer experience.

### 5.3. Learning Model Formulation

The study first carries out the model's mathematical formulation to develop a concrete model for the proposed IoT-based SESaaS scheme. Considering analytical operations in IoT, machine learning is applied to the sales sensed data, and the proposed system constructs the mathematical variables accordingly. The model considers two essential variables with $a_i$ attributes and $b_i$ sensed data index, where the variable $i$ represents a number of buffers $t$ in a table $(i = 1, 2, \ldots t)$. This means that the dataset $\phi$ required for training must consist of these variables, i.e., $\phi = [a_i, b_i]$. The buffer $t$ was constructed to reposit all the linked attributes, while the data index was considered to be present in regression and classification problems in machine learning. The study also considers that all the attributes of sales sensed data $a_i$ consist of $\psi$ attributes of both sales and service data. Hence, the proposed study formulates this in the form of the problem of optimising sensed sales-enabled data from the perspective of machine learning as follows:

$$Ob\_func \rightarrow arg_{min}(s) \cdot g(H_1) + g(H_2) \quad (1)$$

Expression (1) exhibits a discrete objective function $Ob\_func$ for the proposed scheme that is meant to cater to two integrated demands in order to accomplish the proposed functionality of the SESaaS model. The first functional demand of the proposed scheme, i.e., $arg_{min}(s) \cdot g(H_1)$, is meant to offer minimisation of the training process in order to control the computational complexity associated with the learning operation, while the second functional demand $g(H_2)$ is to ensure that the proposed scheme meets the training goal associated with the quantified sales model along with discrete weight factor. The above Expression (1) pertains to the objective function $Ob\_func$, $s$ represents the sensed sales model, and $g$ represents the training goal for machine learning in IoT. The variable $H_1$ represents a matrix consisting of ($\phi$ sensed dataset and $s$ sales model) while $H_2$ represents a matrix consisting of $w$ weight and $s$ sales model. It should be noted that the complete model formulation of the proposed IoT-based SESaaS scheme is based on applying machine learning to make better decisions on IoT services. In such a case, the raw input data are subjected to filtering and pre-processing followed by machine learning to obtain an analytical model. This is further subjected to assessment and validation to justify its quality of service and data utilisation in the SESaaS model.

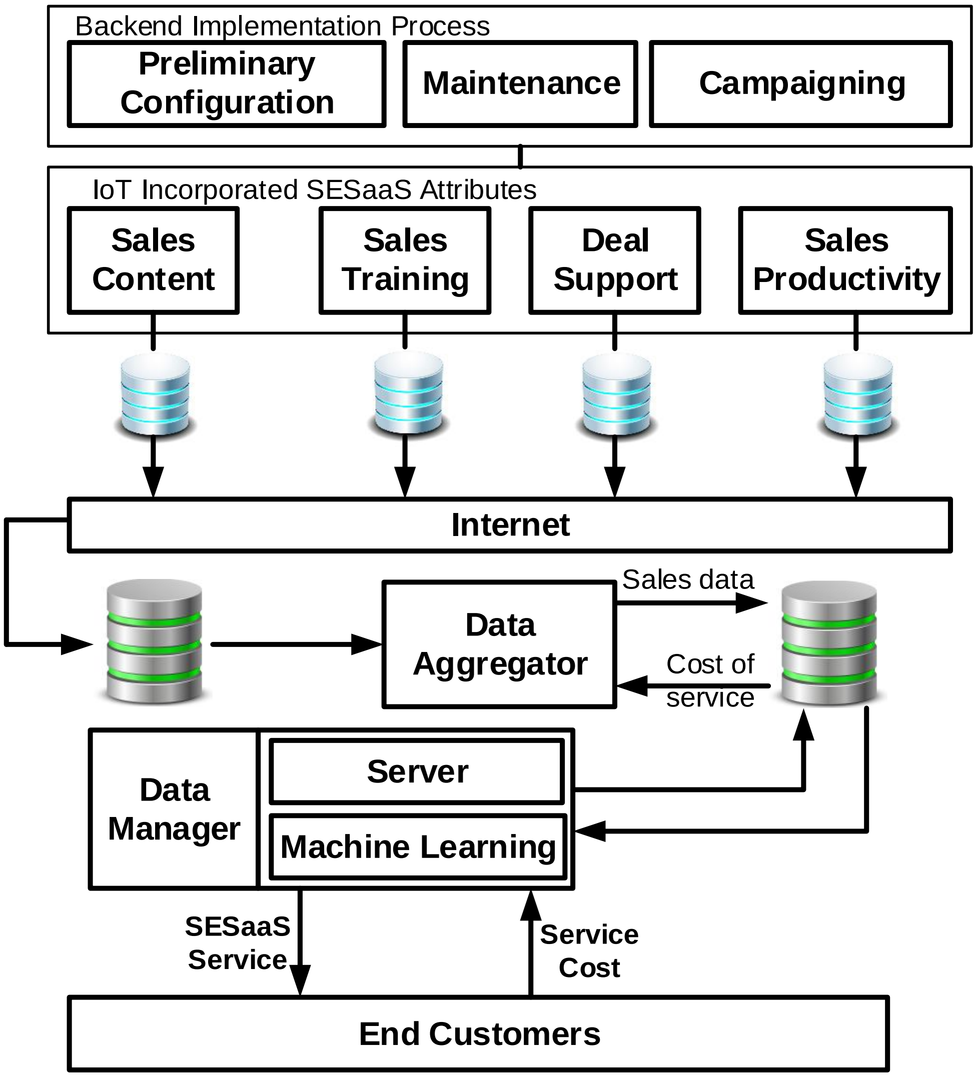


**Figure 3.** Proposed architecture of IoT-based SESaaS.

Thus, the proposed system is an analytical model of IoT-based SESaaS that is meant for automating the complete sales management service with a particular emphasis on costing on practical ground. The complete target is to enhance the profit for the data manager in SESaaS and offer customers the benefits of quality of experience. The study considers that there are $N$ customers with a varied scope of inclination to pay $\mu$ for the sensing services towards adopting the proposed SESaaS-based application. A conditional constraint is formulated, which states that if the inclination to pay $\mu$ is found to be maximised than service charge $\lambda$ based on delivery quality $\varphi$, i.e., $\mu > \lambda$, then it confirms the customer's registration to adopt the service of SESaaS by an organisation's sales team. This conditional constraint essentially indicates that the evaluation carried out by the customer for the services as well as benefits obtained after adopting it is the prime decision factor of inclination to pay $\mu$ by the customer. More customer acquisition and retention are ensured on the ground of enhanced service quality of the sales team. To better understand and formulate the proposed model of SESaaS, it can be said that the inclination to pay $\mu$ is a form of uniform point of distributed sensed data. Therefore, a mathematical representation of the profit acquired upon the adoption of SESaaS by the sales team can be empirically represented as follows:

$$\delta(H_3) \rightarrow H_4 - H_6 \tag{2}$$

In Expression (2), the variable $\delta$ represents a function of profit for the data manager considering the input argument of $H_3$, such that $H_3 = \{\lambda, d_s\}$. This profit function is obtained by differentiating revenue parameter $H_4$ and cost of data parameter $H_6$ such that $H_4 = (N{\cdot}\lambda{\cdot}Prob)$, where $Prob$ refers to the probability that the clients will enrol themselves for adopting SESaaS. The last variable, $H_6$, is a dot product of the size of sales sensed data $d_s$ and unit cost $u_c$ of an IoT device. The constructed first variable of revenue parameter $H_4$ of the Expression (2) is only valid for the applicable conditional constraint $\mu > \lambda$. Hence, the Expression (2) can now be modified as,

$$\delta(H_3) = (N{\cdot}\lambda{\cdot}c) - H_6 \tag{3}$$

In Expression (3), the variable $c$ represents the probability of profitable quality $prob_q$ of the sensing service, mathematically represented as follows:

$$c = 1 - prob_q \tag{4}$$

In Expression (4), the variable $prob_q = 1 - (\lambda/\varphi)$ is an essential parameter for defining the practical aspect of cost as it represents the likelihood of payment by the customer to acquire SESaaS-based on positively projected sensing service quality by the sales team using IoT infrastructure. On the other hand, it should be noted that the cost of sensed data parameter $H_6$ is considered to be the cumulative cost of sensed data to be paid by the customer to the data aggregator, which is equivalent to the size of the sensed data being demanded by the customer $d_s$ with respect to $u_c$. Therefore, this part of the expression mainly deals with constructing the profit factor for adopting the SESaaS scheme by the customer based on probability computation; however, it is equally imperative to construct a condition for enhancing this profit for the data manager.

### *5.4. Optimisation Formulation*

This part of the implementation emphasises the optimisation of the mathematical model presented in the prior section. The idea is to incorporate more profit towards adopting SESaaS from both perspectives, i.e., sales team and customer. For this purpose, an objective function is formulated as follows:

$$\begin{gathered} Ob_{func} \rightarrow arg_{max}\delta(H_3) = (N{\cdot}\lambda{\cdot}c) - H_6 \\ provided,\ const_1 \rightarrow \lambda > 0\ \&\ const_2 \rightarrow d_s > 0 \end{gathered} \tag{5}$$

Expression (5) is meant to increase data managers' profit considering the dual constraints $const_1$ and $const_2$. The involvement of these two constraints is intended to retain a positive solution for the customer's SESaaS adoption cost and demanded size of data. To carry out optimisation, it is necessary to acquire unconstrained parameters from the mathematical expression of the constrained cost enhancement problem, as shown in Expression (5). For this purpose, the proposed system implements the Lagrangian method for transforming constrained to unconstrained forms, thereby achieving a minimality form [50]. The Lagrangian method $L$ is revised and used in this perspective for the proposed IoT-based SESaaS scheme as follows:

$$L\{inp\} \rightarrow -(\delta(H_3)) - y(\lambda, d_s) \tag{6}$$

In Expression (6), the input argument $inp$ represents a set of service charges $\lambda$, size of demanded sensed data $d_s$, and Lagrangian multipliers $y_1$ and $y_2$ correspond to the dual constraints $const_1$ and $const_2$. The new variable of the Lagrangian multiplier modified for the proposed scheme $y$ can be represented mathematically as $y = (y_1 \cdot \lambda + y_2 \cdot d_s)$. Therefore, applying the derivation of first order with respect to service charge $\lambda$ and size of demanded sensed data $d_s$, the Expression (6) transformed to the following:

$$\frac{dL}{d\lambda} = N\left(\frac{\lambda}{\varphi} - 1\right) + \frac{N\lambda}{\varphi} - y_1 \tag{7}$$

$$\frac{dL}{dd_s} = u_c - y_2 - \left(\frac{N \cdot k_1 \cdot k_2 \cdot \lambda^2 \cdot exp|(k_2 \cdot d_s)|}{\varphi^2}\right) \tag{8}$$

In Expressions (7) and (8), the proposed model considers the Lagrangian multiplier without any constraint, i.e., $y_1 = 0$ and $y_2 = 0$. Therefore, if the derivatives of both Expression (7) and Expression (8) are equivalent to 0, then the proposed scheme obtains the optimal solution as follows:

$$\lambda = \frac{H_7}{H_8} \text{ and } d_s = \frac{1}{k_2} \cdot \log\left(\frac{H_9}{H_{10}}\right) \tag{9}$$

Expression (9) represents the revised form of the empirical expression for service charge $\lambda$ and demanded size of sensed data $d_s$. The variable representations are $H_7 = (N \cdot k_1 \cdot k_2 - 4\varphi)$, $H_8 = 2N \cdot y_2$, $H_9 = N \cdot k_1 \cdot k_2$, and $H_{10} = 4\varphi$. Hence, the conditional statement of $H_7$ must be bigger than $H_{10}$ to offer assurance for nonnegative outcomes for service charge $\lambda$ and the demanded size of data $d_s$. This will also mean that a higher profit $\delta(H_3)$ is obtained for the data manager by replacing the above-mentioned optimal values in Expression (3). This leads to the finally optimised model exhibited in Figure 4, connecting all the actors for managing sales-enabled sensing (SES) service autonomously to the end user along with proper control over profit and the automation of service charges from the customers.

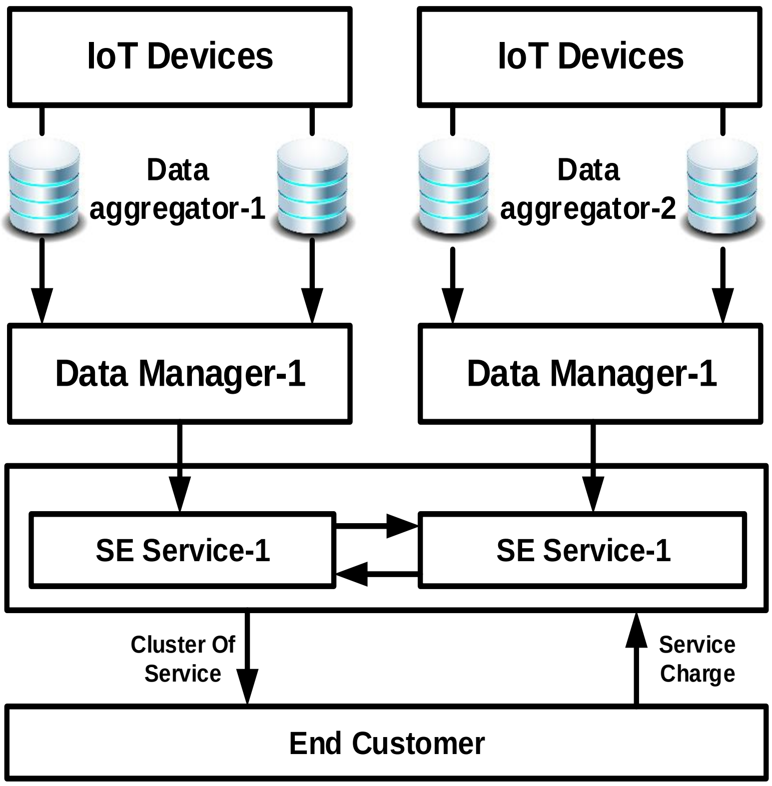


**Figure 4.** Optimised model for IoT-based SESaaS.

## 6. Result Discussion

This section discusses the results obtained after implementing the proposed IoT-based SESaaS scheme. The complete illustration of the result in this section is carried out with respect to the briefing of the dataset, implementation environment, and result discussion. Figure 4 highlights the actual implementation scenario considered for analysing the proposed concept of SESaaS. Following are the steps of operation carried out in order to design this test environment viz. (i) Two domains of IoT device are considered which are capable of sensing different forms of heterogeneous data; all the information is collected and reposited in distributed data units called data aggregators which store unique information followed by identifying and discarding redundant information. (ii) The next process is associated with the accessibility of aggregated data from distributed IoT sources mounted on different service locations by the data manager. The data manager's role is to properly index the core and meta-data from the primary level and forward these to the next level of sales enablement (SE) services. Hence, the data manager acts as an intermediary between IoT devices and SE services. (iii) As there are multiple entities of SE service blocks running collecting aggregated data from various data managers, SE service blocks are required synchronise with each other. This syncing operation further eliminates redundant data and assists the complete model in constructing a virtual topology of sales data. (iv) The final step of this test environment is to apply the proposed algorithm to obtain a cluster of services that are forwarded to the end customer while, in parallel, an appropriate service charge is levied from the end customer. A similar test model is further elaborated in Figure 5.

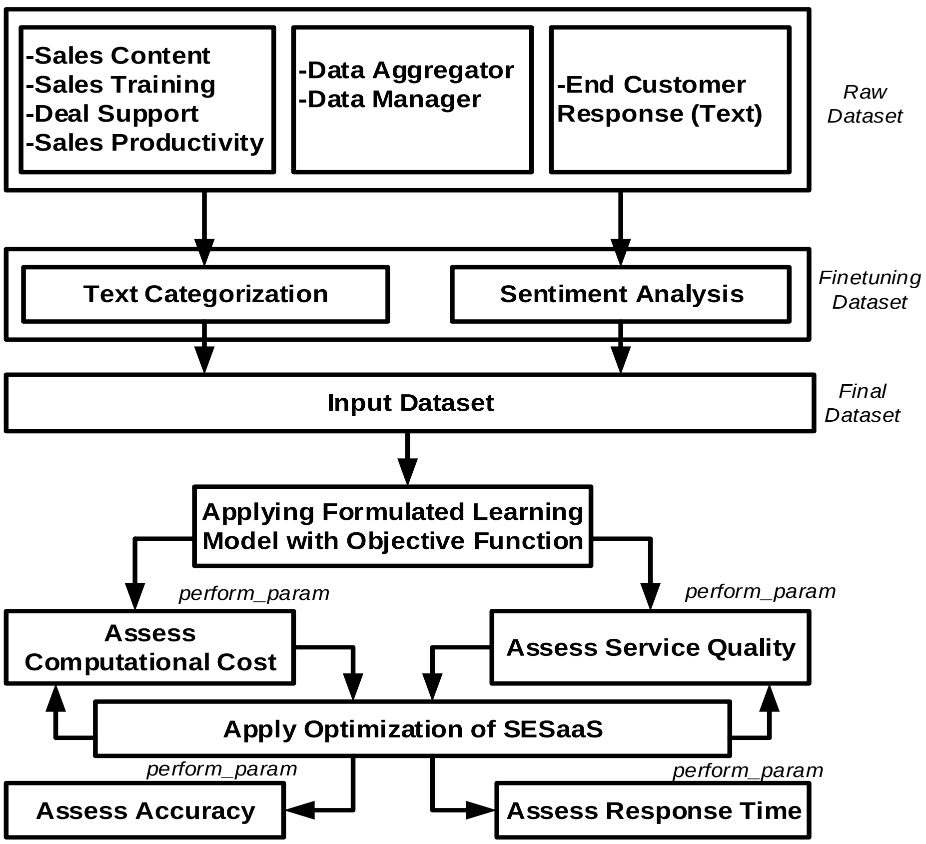


**Figure 5.** Implementation flow for the proposed scheme.

### *6.1. Adopted Dataset*

The dataset required to perform the experiments demands the following characteristics. It should:

(i) Be voluminous and deal with heterogeneous product and service sales.

(ii) Retain all information related to four essential attributes of SES, i.e., sales content, sales training, deal support, sales productivity.
(iii) Retain the response-based information in the form of the English text for both end-users and the sales team.
(iv) Bear all the transactional records for IoT attributes, i.e., data aggregator, data manager, and end-user.

Unfortunately, no publicly available dataset can be directly used for this purpose. Hence, the study considers the sales dataset from Kaggle [51], which consists of 20,000 samples with 20 different product/service categories and 600,000 responses from the end-users. The dataset is slightly modified to include a column for the sales training and sales productivity, which is missing in the original dataset. The input dataset is now complete with all four aforementioned characteristics.

Further, the dataset is fine tuned to ensure its proper applicability in the next series of learning operations. The proposed system uses text categorisation based on occurrences of common and uncommon terms and sentiment analysis to structure the SES attributes. Owing to the usage of an IoT perspective in the proposed SES, various opinions about both the sales team and customers are subjected to sentiment analysis for performing polarity detection. Additionally, the proposed machine learning scheme discussed in Section 5.3 of the prior section is deployed over the dataset to obtain trained data, followed by its validation. The prime objective of the learning module is to compute the degree of customer inclination to pay service charges by evaluating the quality of service offered by the sales team.

### *6.2. Implementation Environment*

The implementation of the proposed scheme in the Python environment is carried out in the following sequential plan, as exhibited in Figure 5.

- Dataset preparation: This is the first step of the proposed implementation, carried out in three processes viz. acquisition of all necessary fields associated with the sales team, third parties in IoT, and customers. All the extracted fields from the Kaggle sales dataset are maintained in rows and columns mapped with sensed data from the IoT device. The second step in this process is fine tuning the dataset, which is carried out in two further steps, viz. (i) preprocessing and (ii) applying natural language processing using text categorisation and sentiment analysis. The advantages of undertaking this step are (i) a reduction in the size of data where all the string and character-based data are now transformed into numeric (excluding the main fields/headers to act as a primary key), and (ii) more refined, contextually informative, and structured data are now available compared with raw data. These fine-tuned data are considered the final input dataset.
- Applying machine learning: A script was written in Python for an objective function to ensure the best fit for the proposed learning scheme towards the formulated constraints. This part of the implementation emphasises evaluating the profit for the data manager to assess the costing based on demanded data size by customers with an indicative service charge. A probability concept was applied towards initialising where for one unit of data, the service charge $\lambda = 0.5$. This stage of operation also assesses the computational cost associated with relaying the sensing service, followed by evaluating the service quality of the proposed SESaaS.
- Optimisation: This is the final step of implementation that optimises the profit to a different level, considering the Lagrangian optimisation approach. The outcome of this step offers a bundled service from the sales team and data manager to the customer. On this basis, it will be feasible to compute the on-the-run service charge paid by the customer. The idea is to balance maximum profit for the data manager cum sales team and enriched service delivery to the customer. Accuracy and response time are computed in this stage, along with re-checking the updated computational

cost and service quality. This completes the whole process of implementation using the four performance parameters to assess the effectiveness of the proposed scheme.

### *6.3. Result Discussion*

The results are evaluated based on the implementation environment discussed in the prior sub-section. In contrast, benchmarking is carried out from the identified machine learning mechanism implemented in the existing literature. From Section 2, it is evident that the most frequently used machine learning schemes applied over sales management schemes are deep learning, gradient boosting, support vector machine (SVM), decision tree, random forest, artificial neural network (ANN), and k-nearest neighbour (KNN) algorithms. Following is the discussion of the results with respect to the adopted performance parameters:

1. Analysis of accuracy: Accuracy is a standard term for assessing the predictive approach toward decision making. The proposed system computes accuracy by dividing the accurately predicted outcomes by the total number of predicted outcomes. The data manager must carry out this operation on behalf of the sales team to project their decision-making accuracy towards the service relay.

The accuracy outcome highlighted in Figure 6 shows that the proposed learning approach offers much better accuracy than the existing schemes. The primary rationale behind this outcome is that the existing learning mechanism made a prediction based on the fitness function defined by the learning algorithms, where constraints are not formulated. Hence, the accuracy dips down when exposed to the customer's dynamic demands of sensed data size. On the other hand, this learning mechanism introduced by the proposed scheme offers multi-objective functions that effectively structure the data. Applying the proposed learning scheme with constraints offers more straightforward decision making with higher accuracy.

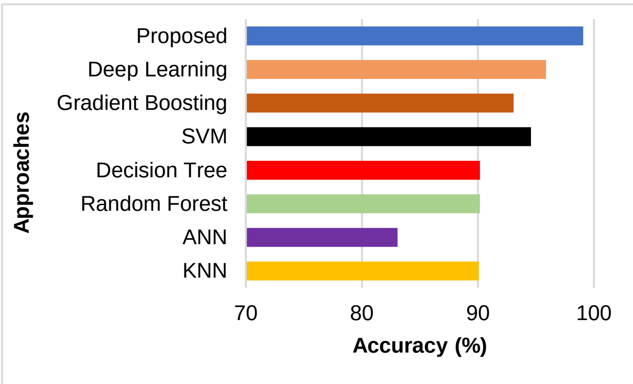


**Figure 6.** Comparative analysis of accuracy.

2. Analysis of service quality: This is one of the most prominent parameters directly controlling the customer's inclination to realise the benefits of adopting SESaaS. The higher the service quality, the higher the profit for both the sales team and IoT attributes (especially the data manager). If the demanded service request is identified accurately (as seen in the prior accuracy outcome), the service quality will be higher. Service quality is defined as data quality when subjected to learning considering all the constraints. The proposed system evaluates service quality considering the assumptions when $\varphi > 0$ and $\varphi < 0$. The first assumption $\varphi > 0$ is a maximisation function where accuracy progressively improves with the size of demanded data. The second assumption, $\varphi < 0$, represents the minimisation function to exhibit accuracy for learning frameworks.

The outcome of service quality in Figure 7 exhibits improved performance of the proposed scheme over the others. The core reason for this outcome is that the existing learning scheme computes the predicted outcome of profit based on stated sales parameters. From this perspective, it should be noted that the data retained by the sales team are rather static, while those recorded for transactions among IoT attributes are rather dynamic. This characteristic suppresses conventional learning techniques to extract features from either sales or IoT attributes or randomly consider partial features from both. This causes an increase in outliers (reducing accuracy) and thus potentially affects service quality scores. Further construction of an objective function in the proposed scheme reduces squared errors and increases service quality for the proposed SESaaS scheme.

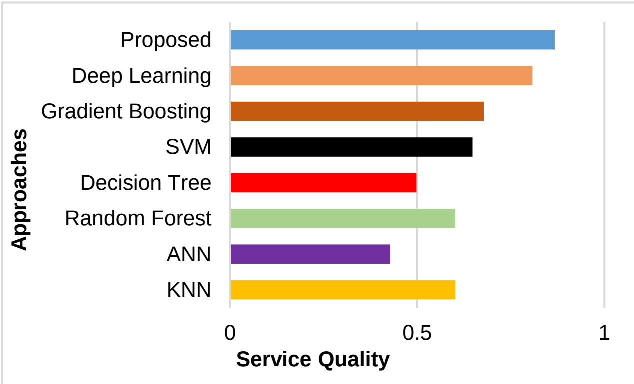


**Figure 7.** Comparative analysis of service quality.

3. Analysis of response time: It is well known that the algorithms associated with machine learning models include training duration and consume a certain amount of time. This is also one of the prime reasons behind the non-applicability of learning schemes on certain processes requiring sensitive instantaneous predictive outcomes. The proposed system defines response time as the total duration between accepting the customer's request and dispatching the service (based on the decision made by the sales team) along with the projected cost. This is the effective duration of time, which also involves negotiation (deal support attribute from the SE model) and profit analysis. The client obtains the estimated time gap between the order being placed and the dispatch of the product or service or query response from the application viewpoint. This performance parameter also contributes to the customer decision-making system. The smaller the time gap, the higher the service quality and the better the system efficiency in relaying the autonomous SESaaS scheme.

The outcome in Figure 8 highlights that the proposed system offers a faster response time than the existing learning schemes. The justification behind this outcome is manifold. Unlike any existing scheme, the proposed system does not provide any iterative scheme; instead, it extracts the benefits of iteration by considering the minimisation of errors and reducing iteration steps. The second reason behind this outcome is the non-inclusion of validation steps in the existing learning scheme. The proposed scheme already includes internal validation by using a multi-objective function and its constraint formulation, which ensures impartial service quality with higher accuracy.

4. Analysis of computational cost: The computational cost was calculated as the number of resources involved in implementing and executing the proposed scheme. It is also a direct representation of the resource burden incurred during the entire operation of SESaaS.
 The outcome in Figure 9 exhibits that the proposed scheme offers much lower computational cost owing to reduced resource inclusion. The conventional learning scheme depends on computing resources for various training operations. However, a closer look into the proposed SESaaS scheme shows that the multi-objective function in the sales model with a specific training goal performs maximum operations without much increment in computing steps. This contributes to the reduced computational

cost of the proposed scheme. Apart from this comparison, the proposed study is also evaluated on the basis of other standard taxonomies of machine learning approaches, as shown below:

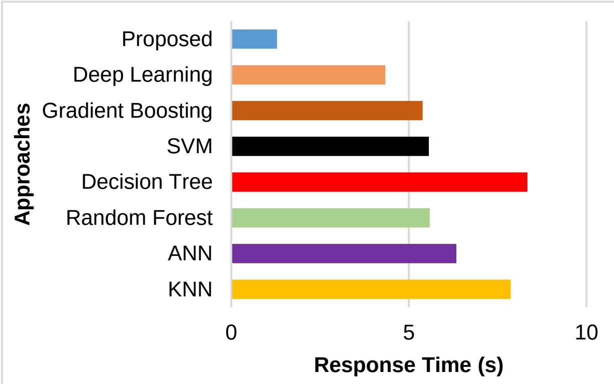


**Figure 8.** Comparative analysis of response time.

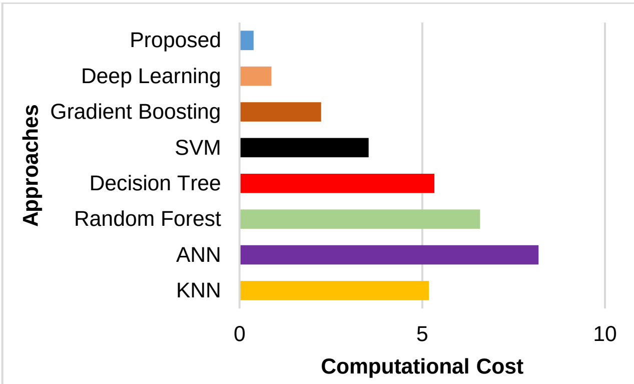


**Figure 9.** Comparative analysis of computational cost.

The complete process of comparative analysis is carried out extensively considering supervised (classification, regression) as well as unsupervised (clustering) learning schemes. The acronyms of the outcome used in Table 2 are as follows: (i) HRT (higher response time) > 10 s, LRT (lower response time) < 3 s, MRT (medium response time)—between 4–10 s. (ii) HA (higher accuracy) > 80%, LA (lower accuracy) < 30%, MA (medium accuracy)—between 50–70%, and (iii) HSQ (Higher Service Quality) > 80%, LSQ (lower service quality) < 30%, MSQ (medium service quality)—between 50–70%. Although the classification-based approach is noted with a medium accuracy score, its response time is quite higher owing to higher dependencies on training. This also affects the performance of service quality. Regression models exhibited much inferior performance in almost every aspect due to collinear problems. On the other hand, clustering-based learning models are exhibited to offer higher complexity; their response time is witnessed to be higher and their service quality degraded. In the discussion carried out in Section 2, it was noted that the existing schemes for improving sales are particular to the case study or domain. Moreover, the studies carried out balance the need for maximising the profit of IoT service providers, and the available customers are few. Hence, based on an accomplished outcome of the study, the following are the strengths of the proposed system:

5. The objective function developed for the proposed system offers higher accuracy with fewer iterations. At the same time, it ensures organisation-based benefits due to its faster processing algorithm.
6. Unlike the frequently adopted learning scheme, the proposed system highly increased service quality with efficient predictive modelling. Owing to maximised data quality

by the proposed IoT modelling in SESaaS, the proposed method benefits its client from the perspective of an efficient service delivery IoT model.

7. The applicability of the proposed SESaaS model is relatively high for any organisation that deals with sales offered in the form of services irrespective of any domain of product/services.
8. The implementation scenario and the architecture developed for the proposed scheme are highly flexible. The scheme can be subjected to any customization to retain better computational cost and superior service quality.

**Table 2.** Extensive comparison.

| Approaches | Response Time | Accuracy | Service Quality |
|---|---|---|---|
| Proposed | LRT | HA | Higher Service Quality (HSQ) |
| Classification-based | Higher Response Time (HRT) | MA | LSQ |
| Regression-based | HRT | LA | LSQ |
| Clustering-based | HRT | MA | LSQ |

## 7. Conclusions

This paper discusses a novel IoT-based SESaaS scheme with multiple objectives achieved in one computational model. The primary novelty of the presented manuscript is offering a unique, adaptable framework for IoT that relays services as a consequence of machine learning approaches to sales data with the target of improvising the complete sales productivity as an integrated system. The study evaluated optimal data sizes and services offered by IoT service providers to optimise their profit scores. At the same time, it also offered a unique balance towards meeting customer interests by levying optimal subscription charges. In a simplified manner, the proposed scheme increases the profit margin for IoT service providers that offer SE as a service using sensing capabilities while presenting an effective sales strategy by integrating IoT services. The novelties of this paper are as follows: (i) Unlike existing learning-based schemes, the proposed learning scheme does not use any form of an iterative or conventional training process; instead, it uses multi-objective functions to meet its goal over the IoT platform; (ii) the proposed unique optimisation scheme is capable of offering better service delivery quality based on demanded data size and service charges to the customer; (iii) the proposed scheme is highly adaptable to any sales-oriented business process; (iv) the model offers benefits to both sales teams and customers equally without using any sophisticated techniques; and (v) the proposed system offers higher accuracy, higher service quality, faster response time, and reduced computational cost than any existing sales management schemes.

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