

Editorial cloud collaborative service improves authorized industrial server database performance

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ABSTRACT

The E-commerce platform for the automotive industry has various obstacles regarding product distribution and sales marketing. Problems such as identifying the product's low defect rate and mapping failure features to the product's existing quality set, both of which occur in the actual world, are included in this category. With the help of an editorial cloud collaborative service, this study will focus primarily on identifying the core causes of product failure. The machine learning confidential (MLC) protocol is used to authenticate the editor's identity when accessing the industrial server's database. A cloud-based collaborative editing service can also be used to extract the root cause of a specific problem from customer complaints. There may be some product flaws that can be remedied with extra features gathered from the end-user to understand real-world practicality better and ensure product accuracy reaches 100% target.

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1. INTRODUCTION

E-commerce has grown greatly beyond the imagination in this digital era, influencing different sectors to expand and enhance their business growth with the support of cloud computing and web service apps [1]. These technologies have greatly influenced digital marketing for promoting new digital items, media advertising, e-trading, and announcing recent sales offers, among other things [2]. Cloud collaborative editing services provide the most recent changes in the industry mentioned [3], [4]. It is a separate module that runs beyond every digital marketing campaign and maintains a data warehouse for each product on the cloud. Specifically for online buying and trading, a cloud collaborative editing solution continuously monitors event progress and updates product sales offer before mega deals [5], [6]. Because of these functionalities, cloud collaborative editing service has gained popularity and exposed their duties to multiple tasks, further improving their position [7].

Product distribution and marketing in the automobile E-commerce business, on the other hand, face several challenges [8], [9]. These include analyzing whether the product has a low defect rate throughout its warranty period and mapping failure features to the device's existing feature set [10]. Failures frequently occur due to the pressure to meet manufacturing deadlines and product counts as rapidly as possible [11], [12]. This is common with third-party sellers to sustain the supply chain; nevertheless, certain commodities have significant root cause issues (i.e., roughly around 100 product outlets, 10% of product may come out with the least accuracy difference in terms of functionality and shapes). It's a natural evolution but should be halted [13].

Currently, the machine learning method is used to automatically choose test input from the machine database [14], [15]. As a result, providing characteristics adjustment is carried out in some mechanical defects, but not all. A new type of failure is unavoidable, but the cause is determined by the customer's product usability [16]. Every product must be covered by a warranty or guarantee period to ensure the buyer receives a new product. However, the sensitive outcome is predicted to fail within its time frame. Collecting those failure attributes may lead to additional testing options for future developments, boosting their accuracy.

The modern manufacturing industry cannot avoid the inevitable trend of smart manufacturing, which is described as a man-machine integrated smart system that includes machines and human professionals [17]. The rapid development of Industrial Internet technologies has attracted great academic interest in industrial data security in the last few years [18]. The industrial production process generates many sensitive data, including manufacturing processing data, production expenditure data, operations data, marketing method, intellectual property protection, and user details [19]. When this private information is made public, it could significantly impact a company's reputation. Predictive maintenance data in today's smart factories must be examined in today's real-world conditions to prevent information leakage [20].

With the rapid advancement of cloud computing, data storage and retrieval are rapidly changing [21]. As a result, many businesses are turning to the cloud to store their sensitive data because it provides them with easy access to the storage capacity that an SP has requested. Using cloud computing in a pay-as-you-go model results in low security for users and their data. Users can access this cloud from any location at any time [22]. Cloud fraud is made easier with this feature's unfettered use of the cloud. Many financial institutions have been impacted by internet criminals stealing large sums of money [23]. Economic sectors such as healthcare, medical, and business data are frequently lost due to insured individuals [24], [25]. Therefore, a highly secure framework is required for cloud computing apps to communicate with each other, exchange data, and conduct financial transactions.

2. THE MAJOR CONTRIBUTION OF THIS WORK

Adopt a cloud-based collaborative editing solution to separate the causes of consumer complaints. Voting ensures the editor's access to the industrial server database. Machine learning technique takes the failure feature dataset from the faulty product management cloud to extract and train the equipment to assure 100% quality goods. Create a second XLM page in the current document with failed product root cause. Thus, boosts mega-deal offerings.

2.1. Background

End-user complaints about defective products are discussed in this section, which outlines the steps involved in resolving them.

- Step 1: Assign somebody to pick up returned items after they have been verified: A consumer buys something online and wants to return it. They must utilise the original package and label sheet. All returns need an RMA number. Electronics and automobiles are especially sensitive to product returns. If it doesn't work, demand internet receipts and other documentation. Sometimes they might deny a return.
- Step 2: Make a return request: Once the collector has scanned the product receipt, a record is immediately created in the database for each refund desk. That contains information on the product, such as the order and product numbers, customer profiles, timestamps, and responses to customer feedback.
- Step 3: A refund and a new product will be provided: Point-on-sale (POS) systems play a significant part in payment refunds since they enable consumers to pick from three distinct POS systems. If the customer bought the merchandise online, the auto refund mechanism might reimburse the money to their bank account within two working days. It's called original payment method.
- Step 4: Product returns must be completed in-store: When a consumer requests a product exchange, the process begins. The POS system looks for the necessary information by scanning the product receipt or the order number. The same consumer will receive a fresh delivery order for a different product. It is automatically updated with new product data in the corresponding refund column.
- Step 5: Return the item to the inventory: The faulty product is returned to the warehouse, where a new one is procured from an industrial source and restocked. The SAP warehouse is where this information is kept up to date.

3. ARCHITECTURE

This section provides a description of the block diagram of the collaboration editing service, which can be seen in Figure 1. This service is used to extract failure elements from customer complaint products that are stored in the cloud. The following descriptions highlight the purpose and capabilities of each block.

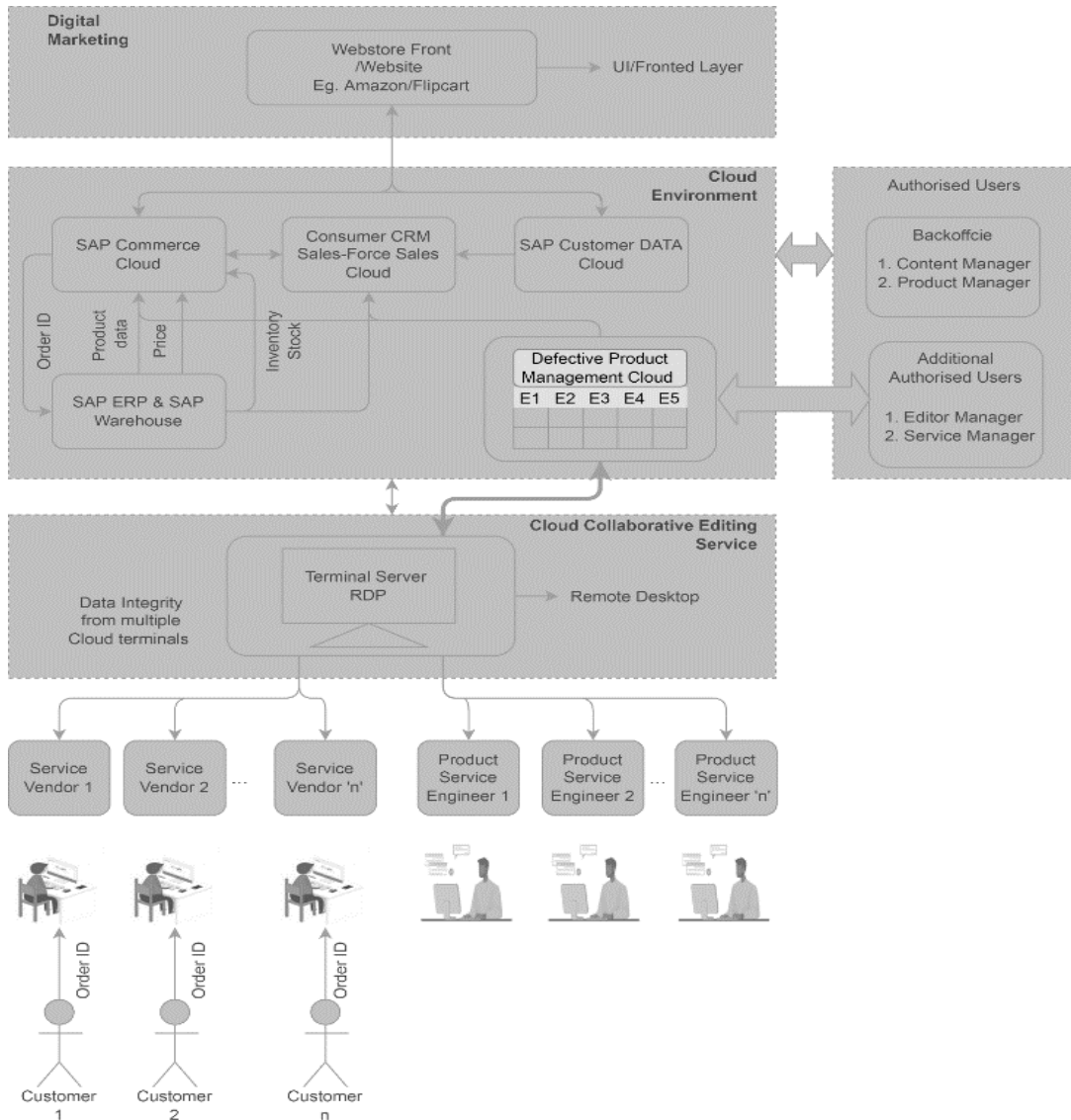


Figure 1. Block diagram of collaboration editing service for extracting failure elements from customer complaint product in the cloud

3.1. Frontend/Website

If customers want to buy the product, they may easily get it by registering their profile and defining a user interface layer that shows all the product details. Once registered with a unique email address, they can access the buying cart. Examples: flip kart, amazon, and other e-commerce applications.

3.2. SAP commerce cloud

SAP commerce cloud simply shows customers product photos. This list has a category and subcategory for unusual items. On each side of the product picture are the current price and any discounts. Next, the consumer adds and removes things from the shopping cart. Cloud-based space offers products, payment, order placing, tracking, and delivery. Tax validation is computed for each ordered goods, and payment information are recorded in an excel column.

3.3. Customer relationship management (CRM) sales force

Customer interaction (phone call, email, and gift voucher) is the primary method for promoting the purchase of the goods. Product promotion and gift card offer based on previous purchases, for example, may be facilitated by obtaining customer data via a cloud-based customer data repository. This block has a direct impact on the company's profitability.

3.4. SAP customer data cloud

The user's profile is immediately updated in the cloud whenever a customer registers at the front-end layer by providing a one-of-a-kind email address. Customers have the ability to directly use SAP commerce cloud to search for products, monitor their thoughts, and create a separate column in their customer profile specifically for the purpose of storing this information. The consumer CRM sales force receives promotions based on previous purchases. Some examples of these promotions include gift cards.

3.5. SAP, ERP and SAP warehouse

Most of the available cloud storage space is taken up by product and stock inventory. This cloud area provides an overview of all product particulars, such as their dimensions, prices, colors, delivery locations, and stocks that are currently available. In addition, the stock inventory keeps track of the product stock, distributes it through the industrial outlet, receives stock requests from SAP commerce in this cloud space, and carries out order placements.

3.6. Defective product management cloud

The e-commerce cloud computing platform has a new capability. Separate table for failure feature extraction matches failure product data to product data. Only authorised users may access this (editor service and industrial engineers). When customers notice a product issue, they may work together to remedy it. The editing service classifies the complaint feature based on the input. Because the equipment training sample has been changed, a service engineer may be able to see the change. The supply chain has 100% quality goods.

4. METHOD

4.1. Overview

Figure 2 shows the flowchart of the proposed novel framework of correct authentication of failure product and extracts a new failure feature to obtain training samples for the machinery database. The overview of the working operation of the proposed cloud collaborative editing service framework is described as follows. When a customer initiates a product return, if it is an electronic or vehicle device, the system connects to a service vendor portal where the customer can directly file their product failure concerns. Next, they will enter the product's fault complaint into the defective product management cloud. Only the authenticated service provider can make changes to the corresponding document already prepared by the manufacturer detailing the product information via the terminal server. Before it, a specific step must be taken.

First and foremost, identify the verified service vendors who can be subjected to service modification based on registered client complaints. It is accomplished through the use of the voting mechanism idea. Initially, interested service suppliers are allocated individual trust values, which are then used to construct a service vendor access list. Later, this access list is updated based on the trust value for each successful product transaction. Furthermore, the voting process generates the verified service providers based on feedback responses and the number of access requests. It examines the service vendor's trust value at the access request time. If it exceeds the previous trust value, access to the terminal server for editing service is authorized. Otherwise, the access request is denied. The feedback response is generated based on the product's selling ratio.

Similarly, if they fail to sell the product within the period specified, their trust value is reduced. When it surpasses the maximum timestamp, the trust value associated with that service vendor is set to zero. Following that, their access request is constantly disabled. This method generates an authenticated service vendor access list.

On the other hand, once the failure complaint is registered, they may determine the authenticity of the product purchased using the purchase order number or product ID. Once satisfied, label the product failure based on the customer complaint and cross-reference it with the pre-existing failure cluster group. If it is matched, simply replace the product in the related purchase order with a new one. It is subjected to failure feature generation using a machine learning technique if not. It will build a new test feature if the product truly experienced a recent failure due to the customer's firsthand experience in various external scenarios. As a result, if the test feature is not generated, it is mapped to existing cluster groups. Otherwise, it is assigned to a new cluster group. Service engineers can uncover novel failure features and collect test and training samples from machines. As a result, when the client uses the product in their style, the risks of product failure are reduced. For upgrading product failure in the selected failure cluster groups, the cloud collaborative editing service is now turning to the service vendor. As a result, it is extremely beneficial for industry service engineers to identify a new failure root cause and extract a new training feature for machineries to teach the machinery to maintain the maximum accuracy point.

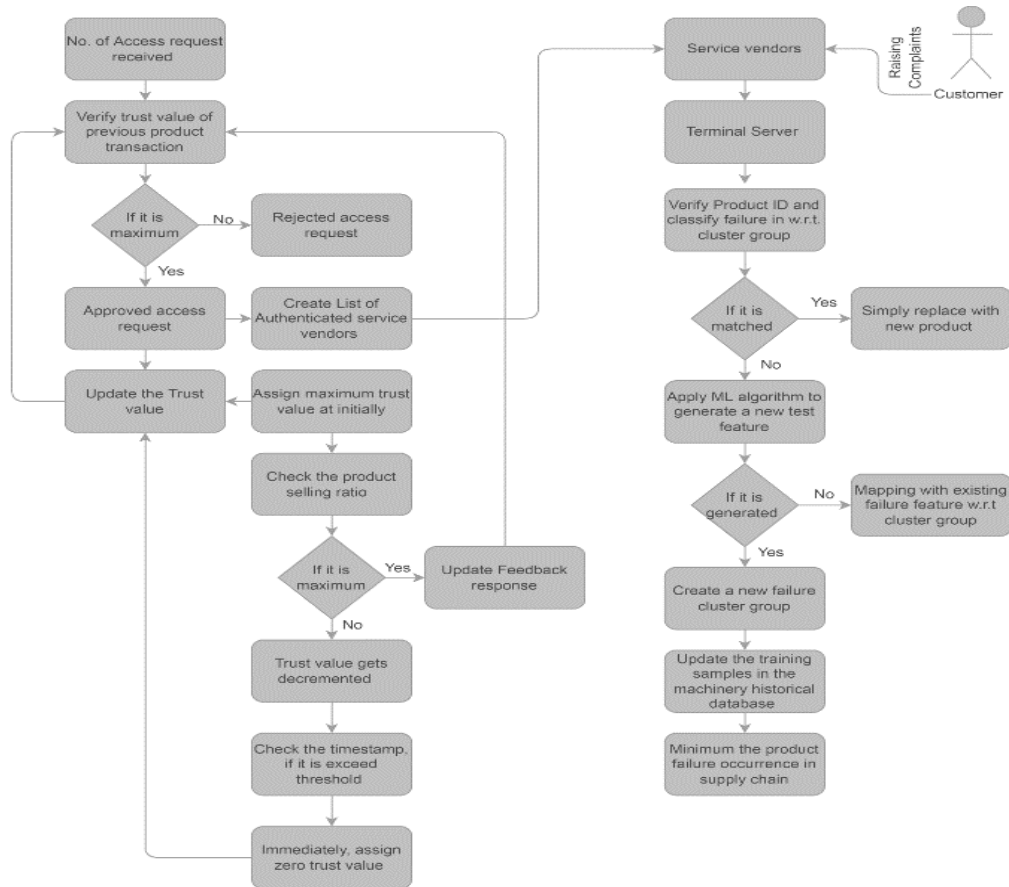


Figure 2. An operational flow to ensure effective verification of failure products and extract a new failure characteristic

4.2. Machine learning strategy

In the proposed cloud collaborative editing service framework, machine learning (ML) is used to improve the detection of anomalies in the product and machine process deviations. An optimistic dataset obtained by the defective product management cloud is the primary focus of this control signal whenever new product failure root causes are discovered. For this reason, the suggested system has two important components.

Service vendor: the verification of individual service vendors before accessing the cloud server, which delivers genuine failure cluster groups, and the service engineer, who can evaluate the machine and product performance. Date flow: It is the process of identifying a failure feature from a defective product management cloud. It is clearly shown in Figure 3.

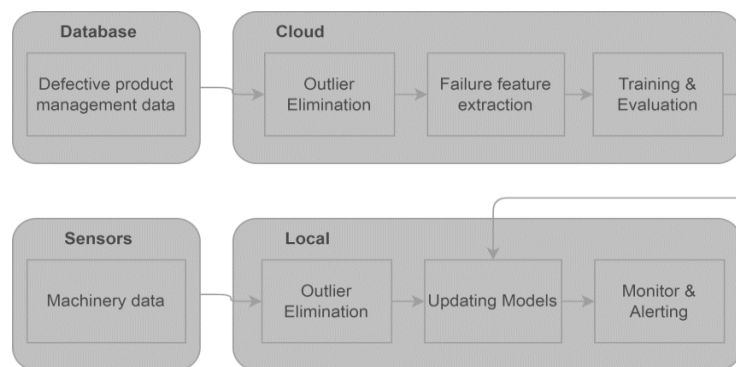


Figure 3. A processing failure feature from a defective product management cloud

Before the product exits the production line, the equipment module's failure feature dataset must be updated to assure high-quality output. Conclusion considers sensitivity, specificity, and accuracy. When comparing data sets, use the historical database. New process deviation data is contributed to the cloud-based historical dataset. Unsupervised learning is used to gather data. When datasets arrive from a local server, supervised learning is possible. Unsupervised learning algorithms are used to give soft classes since future datasets may include unknown characteristics. Classifier input may discover machine processing problems before they are visible. After receiving immediate machine input, supervised learning models incorporate a rigid class assignment. Supervised learning employs the product ID as a labelled value, therefore feature comparisons are typical. Authenticated service providers may access the maintenance system after validating a random identification code. Current and historical database data are integrated to discover product faults before they occur. Customers may utilise the feature extraction module to monitor a product's shape, weight, and value locally and in the cloud. This section summarises both levels' data analytics and defines each module mathematically.

Defective product management cloud generates new cluster groups, subject to extracting test training sample features for machinery training sample data. The cloud management cloud. It is denoted as F_{ut}^{cloud} . These datasets are used to train the machinery manufacturing functions through supervised learning. After that, it's sent for data stream analysis, where parameters' quality estimates are performed.

As a result of the values, extract labeling and product Ids are assigned to each dataset and kept in the central cloud. Long-term use of this method is possible since it allows for precise adjustment of the processing parameters to get the desired result.

The failure feature evaluation is done by (1):

$$\xi_{nl} = \frac{D_l F_{ut}^{cloud}(S_n | \vartheta_l, \Sigma_l)}{\sum_{j=1}^L D_j F_{ut}^{cloud}(S_n | \vartheta_j, \Sigma_j)} \quad (1)$$

where $D_l = \frac{F_N}{F_T}$ be the ratio of similar feature mixing between different failure classes is denoted as standard mean of the individual failure class after execution for a long duration. Were, F_T is the total number of failure classes indicated by the service provider F_N is the specific failure type that was randomly selected at l^{th} the timestamp.

When additional features are added to a dataset, it is referred to as an updated feature dataset S_n (i.e., $S_n \in F_T$). The cloud-based defective product management system can thus be used to choose failure features continuously. The parametric adjustment is carried after the evaluation is being completed concerning failure class:

$$\vartheta_l^{new} = \frac{1}{F_{Tl}} \sum_{n=1}^{F_T} \xi_{nl} S_n \quad (2)$$

$$\Sigma_l^{new} = \frac{1}{F_{Tl}} \sum_{n=1}^{F_T} \gamma_{nl} (S_n - \vartheta_l^{new}) (S_n - \vartheta_l^{new})^T \quad (3)$$

In order to create a new dataset, the greatest likelihood is calculated as (4).

$$\ln Q(S | \vartheta, \Sigma, D) = \sum_{n=1}^{F_T} \ln \{ \sum_{l=1}^L D_l F_T(S_n | \vartheta_l, \Sigma_l) \} \quad (4)$$

the supervised learning modules were used to train the known feature initially using a threshold value of $P[\vartheta_l \in D_{1l}] \geq r$ for parameter evaluation and soft-class assignment for unknown feature extraction. In (3) explicitly categorizes it as a necessary dataset for future use. To begin the generation of new cluster group of product failure feature, a fresh classifier input is generated. After verification of an identity code created at random during product examination, it will be accessible to the service engineers. The product failure dataset can be evaluated as compared with current product feature data with the history database to generate a new set of data called $P[F_T \in C_l](S_t \in D_{2l})$.

It is necessary to use the feature extraction module to keep track of the product's dimensions and weight, $S_n \in D_{1l}(D_1 \cup D_L)$ and to store the updated data in both local and cloud storage in case future customers complain about product failure in (5).

$$\xi_{nl} = \begin{cases} \frac{D_l F_T(S_n | \vartheta_l, \Sigma_l)}{\sum_{j=1}^L D_j F_T(S_n | \vartheta_j, \Sigma_j)} & , v_n \in D_{1l} \\ 1(k = y(n)) & , v_n \in D_{2l} \end{cases} \quad (5)$$

To keep track of the present status of each machine, a digital display is installed on each one. It ensures the quality of both the production machine and the finished product, resulting in increased productivity.

5. RESULT AND DISCUSSION

E-commerce platforms for product distribution and sale promotion are examined in this section, which claims the proposed machine learning confidential (MLC) protocol in qualitative and quantitative aspects. There are two primary aspects to the experimental results. Part A focuses on the additional features of the manufacturing machine module's training ability and production efficiency, which ensures the quality of the product before it leaves the manufacturing line. Quantitative analysis of various quality data with product database is presented in Part B to gain a new collection of data that can be used for a massive sale, which will have a big discount over the stacking product. As input from the editorial cloud collaboration service, the statistical analysis classifies and updates failure product weights in both local and cloud space for future customer claims regarding product failure. The results are maintained in both local and shadow areas. Designing the prototype model of the proposed system using the SimEvent toolbox in MATLAB is utilized for qualitative and quantitative analysis.

Before being launched, many things lack computerised diagnostics at each stage of production. Because choosing the optimal data collection is difficult and time-consuming. Vital product analysis may increase processing time. While calibration allows suspension modification, it's often unable to connect until an advanced cycle time has begun. Many organisations employ a quality control supervisor, yet goods still fail owing to manual interruptions during fault overhauls. Figure 4 shows the performance evaluation of training and testing results to convey the superiority of the proposed method.

Additional failure characteristics limit them to static tests alone. Using the MLC protocol, static and dynamic tests may be run to generate a model with an extra failure feature for automated training samples. The cloud-based editorial collaboration service collects and stores product failure testing data to detect new failure patterns. To handle acquired data, optimise data, and give the simulation unit with the best data, a faulty product management cloud space is constructed. Parallel computing toolboxes run and train analyses on optimal data to enable many computing operations. The suggested MLC protocol via the editorial cloud collaboration service's extra failure feature fared well in simulations. It's in the machine's functioning record to assure high-quality output. The database's dissimilarity feature failing has these added, confined properties. The failure set may alter with usage. A new failure feature will collide with this type's current database. On the other hand, the proposed MLC protocol may be used by industrial engineers to sort out the failing product stack occupancy in the e-commerce purchasing line since it can interface with all the data in the cloud. Machinery Train and test results, model loss and accuracy can be readily seen as mentioned in Figures 4(a) and (b), respectively.

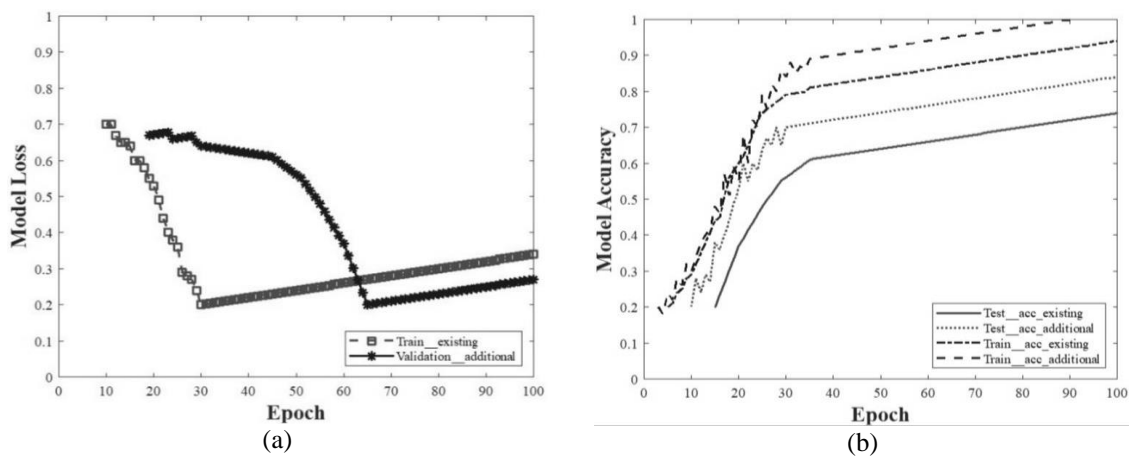


Figure 4. Simulation graphs of the machinery train and test outcome in terms of (a) model loss and (b) accuracy

It is also possible to conduct a statistical analysis of an already-existing product database to determine how much benefit can be gained from adding additional feature extraction as an input received from an editorial cloud collaborative service to classify and update failure product weights. Figure 5 the Comparative analysis of different products performance after editorial engineers' support. Figures 5(a) and (b) demonstrates the comparative analysis of many products, including base, cloth, vehicle, and mobile, and its accuracy following the backing of editorial engineers. Uses an e-commerce product failure dataset from the link provided in the paragraph above to test the suggested method. The suggested technique is more effective than product reshipping into industrial and sales marking after collaborative cloud service. Figure 5 shows that the stackhouse has plenty of area for mobile and vehicular technologies. A reviewer or customer may find a flaw

in a market-impacting model. During major sales, you can sell anything. This shouldn't affect the product model's turnover chart. Golden clients may also get scratch cards or cash vouchers.

The sales marketing unit and industrial engineers effectively use the additional feature extraction to predict. The new failure option, which derives the additional training samples sent to the equipment training dataset to extract new features as shown in Figure 6. It is clearly shown in Figures 6(a) and (b) that the failed product's waiting period is reduced, the industrial productivity lineup is balanced, and the sale marketing of four important qualities, such as the basis, cloth, mobile, and the automobile, are greatly enhanced.

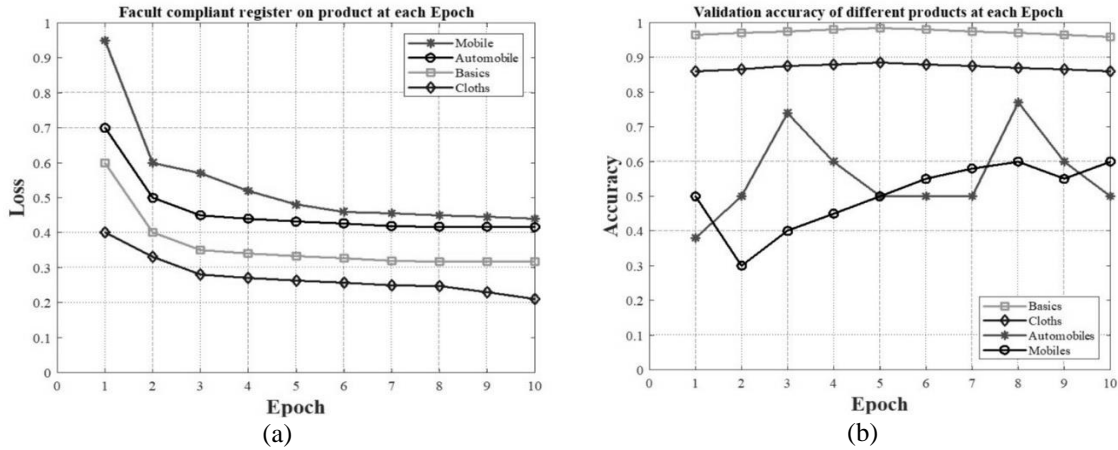


Figure 5. Comparative analysis of different products performance after editorial engineers' support (a) loss and (b) accuracy

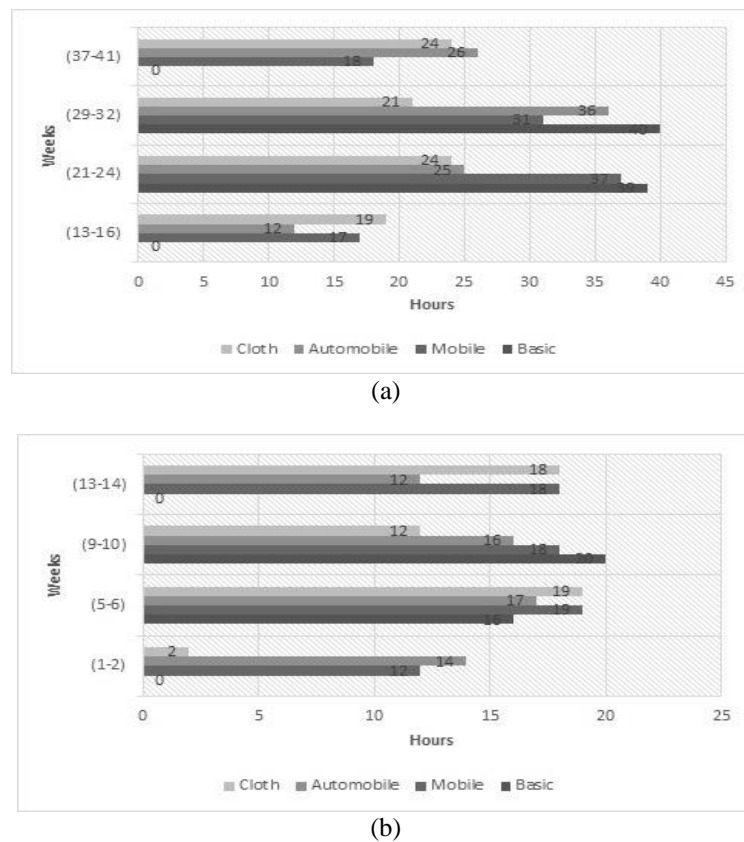


Figure 6. Statistical comparison analysis over additional features induction into machinery process from an editorial cloud collaborative service (a) before induction and (b) after induction

6. CONCLUSION

The editorial cloud collaboration service and the MLC protocol are used well in this paper's additional feature segregation over customer compliance after being deployed in the real world. Product datasheets authenticated by a third-party cloud service are used to create the defective product management cloud. An efficient way for industrial engineers to find new training features is using failure data entered into the editorial cloud collaboration service. It is also supported by an authorized editing service that promotes mega sales offers and effectively fails product shipment without inducing the product waiting period in a warehouse. Further, the MLC protocol is supported by authenticated editing service that promotes the mega sales offers and effective failure product shipment without inducing the product waiting period in the warehouse. A cyclic chart of product replacement with a shorter waiting period in the supply chain has been demonstrated through experimental findings. Thus, shows significant improvement towards automobile gadgets replacement over influenced by the editorial cloud collaboration service before and after, respectively. Nearly, 1/4th of the waiting period is reduced in accordance with the average week/month and maintained equal waiting period for as almost every product.

7. CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest. The manuscript has not been submitted to more than one journal for simultaneous consideration. The manuscript has not been published previously. The research does not involve human participants and animals





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