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AI-Enhanced Repair Management and Electronic Lifecycle Techniques

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ABSTRACT- This research integrates the outcomes of various research conducted on electronic maintenance, repairability, and gadget lifespan within the past few years to design the GadgetCare platform. Recent research has shown how digital reminder systems and booking systems can increase the efficiency of gadget servicing. Big data research has demonstrated how the performance of gadgets remains constant over time while the interest of consumers in repairing the gadget decreases. Repair tracking systems and smart care systems have emphasized the importance of transparency in the gadget servicing process. Technical research has proposed the importance of gadget repairability while discussing the tradeoffs between gadget reliability and repairability. Predictive maintenance systems have proposed the importance of predictive health checking of gadgets. This research has proposed a GadgetCare system based on the integration of all the above research outcomes. This system is designed to increase the lifespan of gadgets while addressing the issue of gadget obsolescence. This research has proposed the evaluation metrics for the GadgetCare system.

KEYWORDS- Gadget Maintenance, Repair Tracking Systems, Predictive Gadget Maintenance Systems, Gadget Repairability, Circular Economy, Iot, User Behavior, E-Waste.

I. INTRODUCTION

The maintenance of gadgets involves a complex interplay of technical, usability, and human factors, and therefore requires a delicate balance between the three aspects, which include behavior, expectations, and transparency in the device's lifecycle. In the past, the only way to effectively communicate the need for gadget maintenance has been through the use of cumbersome and time-consuming methods, such as manual logs and complex workshop management systems, which require a high level of technical know-how and time to update [1], [2]. This has resulted in a barrier for the average consumer and non-technical repairers, which has led to a situation where gadget maintenance and repair are delayed, fragmented, and lack transparency in device health [1]. In recent times, the use of data-based approaches, especially in relation to IoT sensing and machine learning diagnostics, has revolutionized the approach to gadget maintenance and repair, moving away from the use of manual inspections and moving towards automated monitoring and early warning systems [1][2][3]. These simple monitoring approaches allow for scalable health checks based on battery patterns, but a challenge that relates to pixel-level alignment, where the algorithmic outputs respect the device's physical limitations and safe operating context [4]. This paper proposes a novel approach to gadget maintenance and repair, where we consider three integration approaches, namely, prediction and fine-tuning of the device failure modes for better fault recognition, context integrity, where the algorithmic outputs are anchored in safe and constrained inference, and automated [4], [6].

II. LITERATURE SURVEY

Recent studies emphasize the significant shift from reactive and time-based maintenance paradigms to data-driven predictive maintenance (PdM) models [5]. The conventional Reactive Maintenance (RM) and Preventive Maintenance (PM) models have shown limitations in terms of failure response or scheduled time-based interventions, resulting in machine downtime or wasteful maintenance practices [2]. Although the early models of predictive maintenance ensured business continuity in the face of failure or scheduled downtime, they have shown to be counterproductive in terms of increased repair costs and inefficiencies in resource utilization. Predictive maintenance models have shown to overcome the shortcomings of conventional models by providing real-time interventions based on machine health estimation and subsequent maintenance before actual failure or component degradation [1] [10], [13]. Cloud-based predictive maintenance models have shown to be an improvement on conventional models by providing an integrated framework with data acquisition, processing, and decision-making capabilities through various layers of system models [5]. The Internet of Things (IoT) technology has shown to be instrumental in collecting large-scale sensor data from various industrial environments, while machine learning and deep learning models have shown to be effective in fault diagnosis and estimation of useful life with higher accuracy levels [1], [3]. In addition, digital repair models have shown to be effective in improving business efficiency and user trust in terms of service transparency and efficiency through mobile integration with real-time tracking and service portals [4]. A study on consumer electronic device performance based on big data analysis showed that device performance tends to remain consistent in the face of time, suggesting that device transparency and predictive models could reduce wasteful device replacements based on perceived obsolescence rather than actual failure [3], [7]. Although prior studies have shown positive outcomes in terms of predictive maintenance models in industrial environments and digital repair models, they have shown to be limited in terms of focused industrial or service portal models [9], [12]. There is a need to develop an integrated model that addresses the gap in terms of predictive maintenance models with transparent repair models and user-driven scheduling models in a unified framework [9]. The proposed GadgetCare solution is based on an integrated framework with conventional predictive maintenance models and digital repair models to provide a sustainable solution to gadget repair and maintenance models [7].

A. Predictive Maintenance Architectures.

The proliferation of connected consumer gadgets and smart appliances has led to the development of a new paradigm in predictive maintenance architectures, which aim to ensure that unexpected failures are averted and the longevity of gadgets and appliances is maximized. Unlike other approaches, such as reactive and preventive maintenance, PdM architectures use constant monitoring, data acquisition, and estimation of the health of a system to ensure that maintenance occurs before a failure occurs [1]. Modern PdM architectures utilize IoTenabled sensing, data processing in the cloud, and machine learning algorithms for fault diagnosis and RUL prediction [1,8]. These architectures are based on a number of principles, including industrial standards, system layers, and decision support, which aim to optimize cost and reliability [1]. Research indicates that, although PdM improves accuracy in detecting failures, the use of user interface and repair tracking portals is essential in ensuring that consumers are aware of the condition of the gadgets and appliances they use [4, 9]. Research on repair tracking portals and smart care dashboards indicates that consumers are more likely to cooperate with the system if they are aware of the condition of the gadgets and appliances they use [4, 9]. This architectural approach, which combines data acquisition, intelligent analysis, and decision support, provides a conceptual foundation for the GadgetCare system, which draws on PdM principles in industrial settings [1, 8].

B. Cloud-Enabled Predictive Maintenance and Digital Service Integration

Recent research demonstrates a transition from reactive and time-based maintenance strategies toward data-driven Predictive Maintenance (PdM) frameworks. PdM systems operate by continuously collecting operational data through sensors and connected devices, enabling real-time condition monitoring and early fault detection [8]. These architectures typically follow layered system models such as PdM 4.0 and OSA-CBM, integrating modules for data acquisition, preprocessing, analysis, decision support, and maintenance execution [8]. Technically, PdM relies on condition monitoring, fault diagnosis, and fault prognosis to estimate equipment health and remaining useful life. Data from IoT-enabled sensors are processed using machine learning and deep learning techniques to identify degradation trends and optimize maintenance schedules [8]. This structured pipeline allows organizations to reduce unplanned downtime and balance cost with reliability objectives [8]. Beyond industrial machinery, similar digital architectures are increasingly applied to consumer electronics repair ecosystems. Online repair tracking portals demonstrate that integrating cloud services, mobile technologies, and real-time tracking systems enhances transparency, operational efficiency, and customer trust [4]. Reminder-based maintenance systems further support proactive servicing by notifying users about planned or emergency maintenance needs, thereby extending equipment usability [1]. Complementary big-data analyses highlight that device performance often remains stable over time, suggesting that timely diagnostics and transparent service visibility can counter premature replacement behaviours [2]. Drawing from these validated system architectures and digital service models, the GadgetCare platform adopts a cloud enabled monitoring and service orchestration framework that combines lightweight data inputs, structured diagnostics, and transparent repair tracking to support sustainable gadget lifecycle management [8], [9], [11], [14].

III. METHODOLOGY

A. Model Adaptation and Predictive Calibration

It was found that generic predictive models are not effective in learning the operational characteristics of specific categories of devices. To address this issue, various model adaptation and transfer learning strategies are employed to improve the accuracy of the predictive model. For instance, recent studies have found that deep learning models can be adapted for predictive maintenance to improve the accuracy of fault recognition while retaining the ability to perform device diagnostics [8], [10], [11].

The process of adapting the model for specific device categories involves the following steps:

- Data Preparation: Data related to device operations can be extracted from user input and Internet-of-Things monitoring, which includes various features like usage time, battery status, temperature trends, and failure records. Such data needs to be cleaned, normalized, and processed for feature extraction to ensure consistency between devices of different types [8].
- Hyperparameter Optimization: Model parameters are optimized using grid search combined with k-fold cross-validation to prevent overfitting and ensure robust generalization across varying device usage scenarios. Key parameters such as tree depth, learning rate, and number of estimators are tuned for optimal performance [7].

- Training and Transfer: Faults can be classified through supervised machine learning algorithms like Random Forest and Gradient Boosting using past maintenance data. The concept of transfer learning is incorporated into the process through the fine-tuning of models built from similar classes of equipment to predict faults in different equipment classes [8].

The structured model adaptation process allows the predictive system to recognize specific trends in device failures and device anomalies that the baseline model may not be able to recognize. This improves the accuracy of the predictive system and allows for reliable maintenance scheduling within the GadgetCare framework [4], [7].

B. Layered System Architecture for Structural Integrity

One of the major limitations of existing predictive models, in isolation, is the possible disconnect that may develop between the results of the analytical process and the actual implementation of the maintenance process in the real world [3]. To address this, modern predictive maintenance systems have adopted the use of layered system architectures, including the OSA-CBM and cloud-based PdM system frameworks, that have been designed to include additional structural components that help maintain system integrity in the execution of the condition monitoring and decision support process [8].

The process generally involves the following steps:

- Data Acquisition: The process begins with the use of sensor networks and IoT devices to collect system parameters, which are then transferred to storage devices for processing [8].
- Condition Processing: The acquired data is then preprocessed to generate the required inputs to the diagnostic algorithm, ensuring the integrity of the inputs to the system [8].
- Decision Support and Execution: The results of the diagnostic process are then translated into optimized system maintenance plans, which are then executed through digital service platforms and cloud-based interfaces [8], [4].

The use of the layered system architecture helps to address the possible disconnect that may develop between the results of the analytical process and the actual implementation process in the real world, ensuring that the results of the predictive process remain aligned with the system structure at all times.

C. Automated Maintenance Scheduling and Repair Orchestration:

Once the focus shifts to the scheduling of the maintenance rather than just visualizing it, the digital service systems come into the picture to automate the scheduling of the repairs. Recent research in the predictive maintenance and repair tracking has highlighted the development of an organized pipeline where the operating data and the service requests are converted into an actual maintenance schedule through the platforms provided in the cloud. Such systems have the ability to translate the device diagnostics and the user issues into an organized service request, thereby providing an opportunity for the efficient assignment of the repair tasks [2], [5], [15], [16].

Different methods have been proposed for the scheduling of the repairs, which have been discussed below:

- Reactive Scheduling: This method has the potential to start the maintenance only once the failure is detected. Such an approach has the potential to create service bottlenecks.
- Preventive Time-Based Scheduling: This method has the potential to rely on the regular intervals for the servicing of the devices. Such an approach has the potential to result in the scheduling of the unnecessary maintenance tasks.
- Predictive Maintenance: This method has the potential to integrate the condition monitoring of the devices, fault diagnosis, and decision support to create well-organized and efficient maintenance actions.

To enhance the reliability of the automated recommendations provided for the scheduling of the repairs, the post-processing steps have the potential to validate the raw diagnostic outputs and translate them into the service workflows [1], [9], [11], [14].

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

A. Web-based application framework:

To ensure that predictive maintenance and repair services are accessible to a broad range of users, these services are now made available as web and mobile apps. The general architecture for maintenance and repair services [1], [4], which is also applicable to the GadgetCare platform, is as follows:

- Frontend Layer: This layer consists of mobile and web apps developed using cross-platform app development frameworks. This layer provides interactive apps to users to facilitate maintenance services and repair services [1], [4]. The overall look and feel of this layer are designed to ensure user engagement in maintenance and repair services by making the services transparent to the users.
- Backend Layer: This layer consists of backend services that use application frameworks to facilitate user interaction and integrate services with various modules for maintenance and repair operations. The backend layer also provides connectivity to predictive maintenance models and manages communication between the frontend, database, and analytical modules [1], [4].
- Database Management: This layer consists of relational database management systems such as MySQL for managing user information, device records, maintenance history, and repair logs. It provides structured and reliable data storage for maintenance and repair services.
- Model Integration and Cloud Support: This layer integrates predictive maintenance models with cloud computing infrastructure to ensure scalability, efficient processing, and real-time accessibility. Cloud support enables the system to handle predictive analytics, device monitoring, and maintenance scheduling effectively while supporting large-scale service integration [1], [4] [2], [3], [9].

B. System Architecture Diagram:

Figure 1: GadgetCare System Architecture

As shown in Figure 1, the proposed GadgetCare system comprises a modular and cloud-enabled architecture that includes a user interface, backend services, and a predictive maintenance core. Users interact with the system through the frontend interface, where they can register gadgets, upload diagnostic logs or images, and request maintenance or repair services [1].

The backend service handles request validation, session management, notification services, and the routing of diagnostic data to the predictive engine. The predictive maintenance core performs condition monitoring, anomaly detection, and fault prognosis while maintaining alignment with realistic maintenance constraints and operational requirements [6], [11].

The proposed architecture follows a layered approach, which aligns with the existing predictive maintenance architecture, where data acquisition, preprocessing, analysis, and decision support are incorporated into a scalable cloud environment [8]. The User Input Module will allow users to input the details of the gadget, such as brand, model, usage category, and symptoms, which will then be passed on to the processing module, where device-specific operating features will be extracted [9], [11].

The proposed system will follow a similar approach, where digital repair tracking systems allow users to report repair issues, which will then be analyzed [4].

In the Data Processing and Diagnostic Module, the collected inputs are validated, normalized, and features are extracted, which are then used in the predictive inference process. In the predictive maintenance framework, the importance of the data preprocessing step is emphasized, as accurate fault detection and reliable RUL estimation are critical in the process [8].

The Predictive Analytics Module utilizes various machine learning and deep learning algorithms to diagnose faults and optimize the maintenance process. These algorithms analyze the usage and degradation trends of the gadgets and provide prioritized repair recommendations and maintenance alerts [8]. In the process, the condition monitoring and decision support are integrated, which enables the system to provide proactive intervention instead of reactive maintenance.

Finally, the Service Orchestration and Tracking Module maps the output of the predictive analytics process and executes the workflows, including booking, dispatch, and tracking. Digital repair portals have shown the efficiency of the tracking process in ensuring the smooth operation of the system and the trust of the user in the process. This architecture, which includes the user interface, data processing, predictive analytics, and structured service execution, is the basis of the GadgetCare system in providing sustainable gadget lifecycle management solutions [8], [9].

V. ALGORITHM

The GadgetCare concept is based on the idea of predictive maintenance, abbreviated as PdM. This is a technique in which a device's health is measured using a data-driven approach to identify problems before they occur. There are two main steps in the predictive maintenance process. First, the current condition is monitored, and the next action to be taken is determined. In the monitoring process, the current condition is observed by collecting device operation data through sensors or user input [3], [5], [8], [10].

In the decision process, the collected data is analyzed using a variety of analytical models to identify the presence of wear and tear in the device. Once the problems are identified, the best course of action is determined. In the case of cloud-based predictive maintenance, the process is made more efficient and effective. In this case, the process is integrated into a single framework, making the process easier to execute. In the traditional process, a device is only maintained after it has broken down. However, in the predictive process, the estimated rate at which the device is likely to break down is determined, which reduces the number of times the device is maintained.

Although the process is effective. In some instances, the results obtained from the process do not reflect the actual situation. This drawback is addressed by adding repair tracking and service orchestration modules and preparation for the next task or the upcoming operation in the queue [3], [5].

Furthermore, Figure 2 shows that the system design permits modularity in integrating new elements into its structure. Additional analytical modules or services can thus be integrated in the framework without compromising the core functionality of the algorithm.

In terms of uncertainty handling and data imprecision, the algorithm uses probabilistic and statistical approaches. The analysis process will rely on patterns and insights obtained from previous analyses to generate accurate predictions when sensors provide unreliable readings [4].

As far as security issues and data protection are concerned, all user data and device information will go through encrypted channels to preserve their confidentiality and safety during the transmission process. This will prove particularly important in the case of cloud integration, where data transfers occur in numerous layers.

Lastly, the algorithm allows for an optimal allocation of maintenance resources. Based on repair priorities, urgency, and risk of failure of particular devices, the system ensures sure that time & manpower are used in an efficient way [5].

In conclusion, the use of the suggested algorithm will not only increase the precision of the prediction but also promote scalability, security, and resource optimization [1], [4].

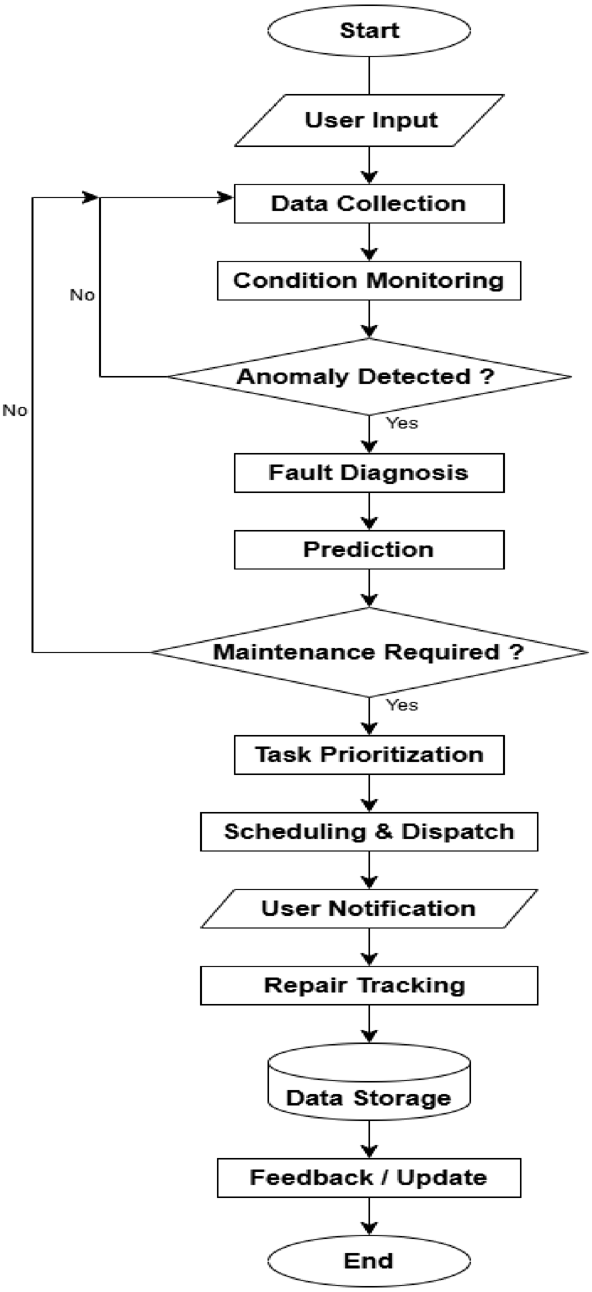


Figure 2: GadgetCare Algorithm

VI. RESULTS, DISCUSSIONS AND FUTURE SCOPE

The GadgetCare system promises to deliver significant benefits in terms of the efficiency of the maintenance process and the overall effectiveness of the diagnostic system [1]. Consider the predictive maintenance research. Data-driven condition monitoring has been shown to detect issues before they occur and minimize unexpected downtime compared to waiting for issues to occur [4]. This is especially true when integrating the diagnostic system with the repair tracking system. Predictive analytics and digital service orchestration have been shown to outperform traditional maintenance methods like manual checks and service intervals.

Table 1: Comparison of Traditional and Predictive Maintenance

Parameter	**Traditional Maintenance**	**GadgetCare System**
Maintenance Type	Reactive / Time-Based	Predictive (Data-Driven)
Fault Detection	After failure	Before failure
Downtime	High	Reduced
Maintenance Cost	Higher (Unexpected repairs)	Optimized
User Awareness	Low	High (alerts & tracking)
Repair Tracking	Limited	Real-time tracking
Efficiency	Moderate	High
Resource Utilization	Poor	Optimized

As can be seen in Table 1, there are several crucial differences between conventional maintenance techniques and the suggested predictive GadgetCare system for maintaining machinery. The first difference is associated with the fact that while conventional techniques employ either reactive maintenance, which is implemented only when the machine breaks down, or preventive maintenance, which involves regular replacement of components at specified time periods, both types result in high downtime, excessive costs, and poor resource management. The GadgetCare system, however, applies a predictive maintenance strategy, allowing detecting faults at an early stage and scheduling maintenance properly.
Predictive methods have been shown to minimize the time it takes to perform the repair while maximizing the overall resources used. Reminder systems have also been shown to maximize the overall benefits of the system [8]. Future enhancements to the system could involve the integration of more advanced remaining useful life estimates. This could involve the integration of adaptive learning to better generalize the device. Integration of real-time IoT telemetry could also maximize the overall benefits of the system. This would especially be true for the condition monitoring system. Integration of the system with digital repair marketplaces could also maximize the overall benefits of the system [3] [4].

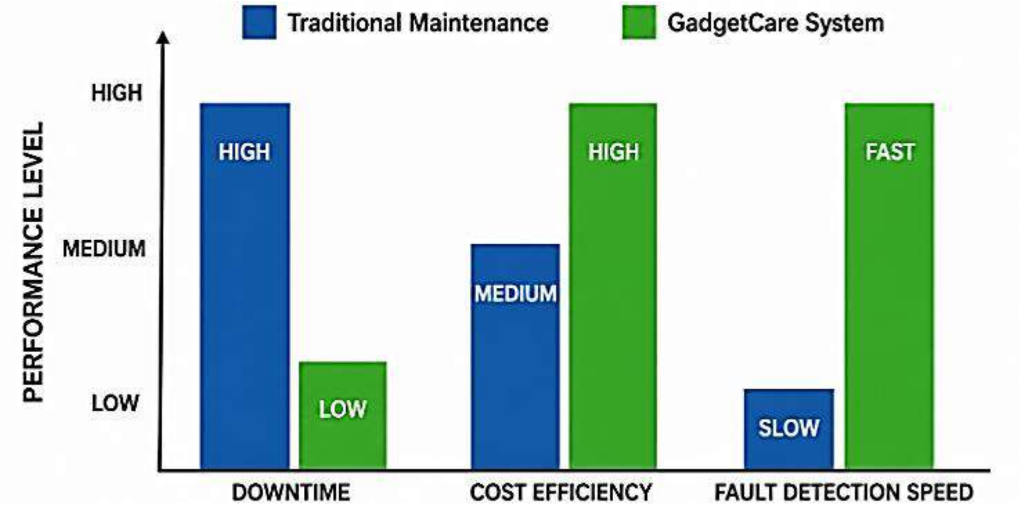


Figure 3: Performance Comparison

Figure 3 illustrates a comparative analysis between traditional maintenance approaches and the proposed GadgetCare system across key performance metrics. It is observed that the GadgetCare system significantly reduces downtime, improves cost efficiency, and enables faster fault detection. This highlights the effectiveness of predictive maintenance over conventional reactive methods.

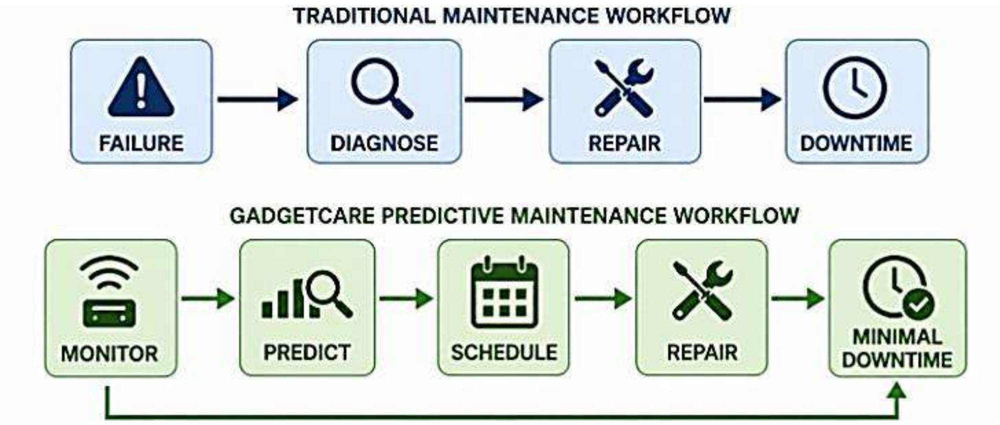
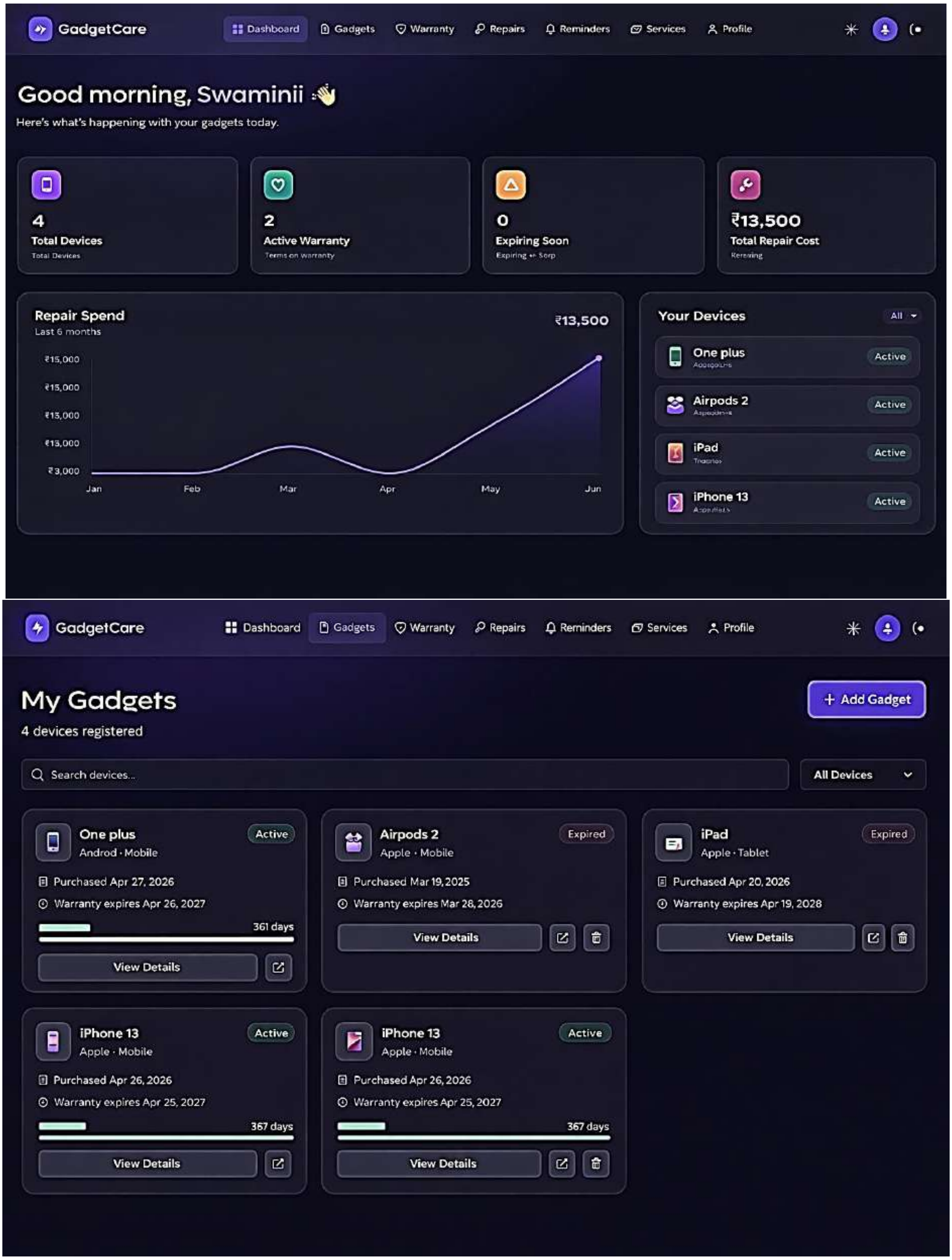


Figure 4: Workflow Comparison

Figure 4 presents a workflow comparison between traditional maintenance and the GadgetCare predictive maintenance approach. Unlike the traditional method, which reacts after failure, the proposed system follows a proactive process involving monitoring, prediction, and scheduled maintenance. This results in reduced downtime and improved system reliability.

In summary, it can be seen from the findings that the GadgetCare system proposed provides a major breakthrough from the conventional systems by ensuring proactive fault detections, minimal downtimes, and optimization of resources. In addition, the integration of analytical methods with repair and scheduling functions ensures both operational efficiency and satisfaction of customers. The use of adaptive learning, IoT telemetry data, and digital repair ecosystem integration can improve the performance of the proposed system even more [3], [6], [11], [12].



Good morning, Swaminii

Here's what's happening with your gadgets today.

4 Total Devices

2 Active Warranty

0 Expiring Soon

₹13,500 Total Repair Cost

One plus — Active

Airpods 2 — Active

iPad — Active

iPhone 13 — Active

My Gadgets

4 devices registered

One plus — Active
Android · Mobile
Purchased Apr 27, 2026
Warranty expires Apr 26, 2027
361 days

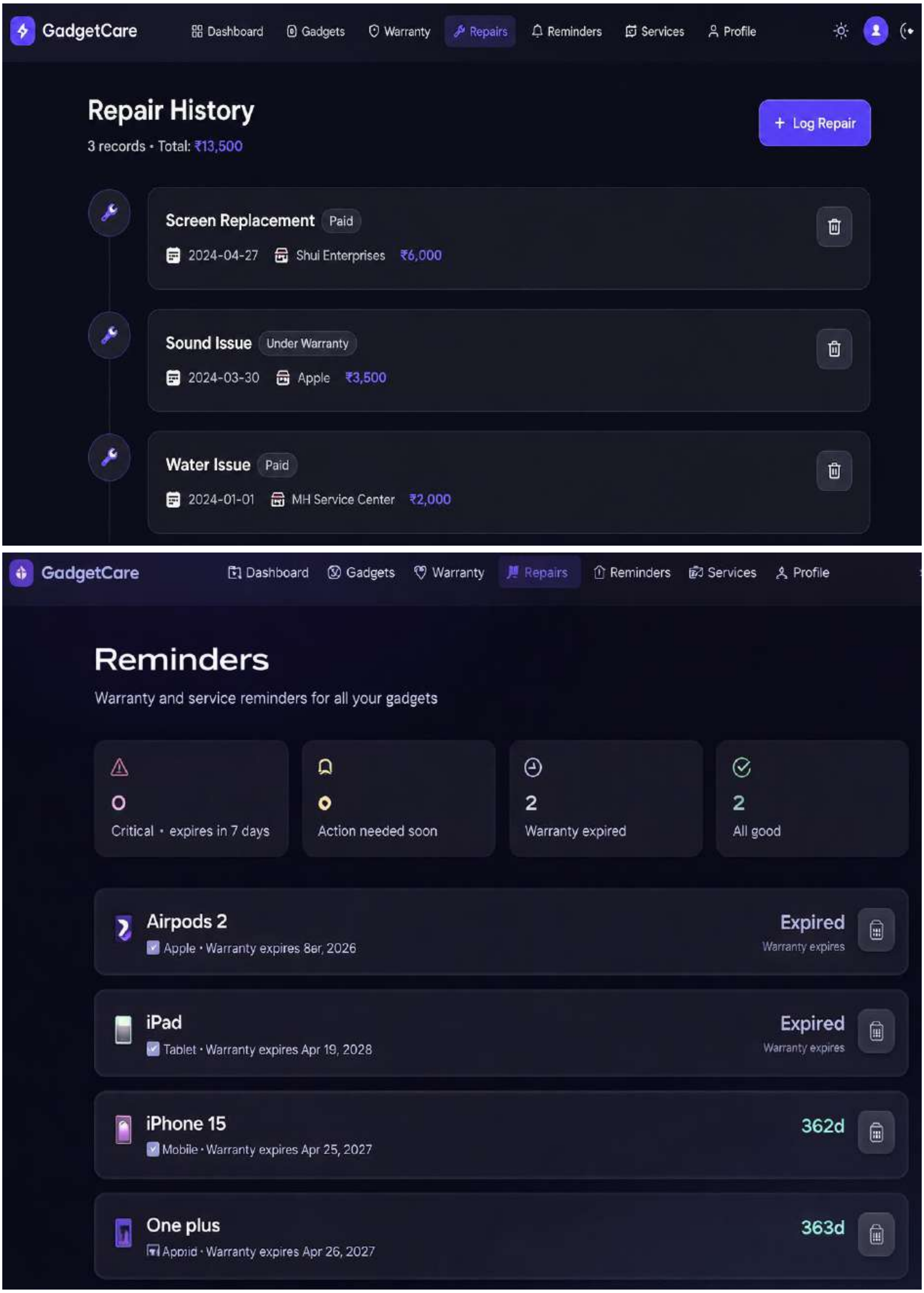
Airpods 2 — Expired
Apple · Mobile
Purchased Mar 19, 2025
Warranty expires Mar 28, 2026

iPad — Expired
Apple · Tablet
Purchased Apr 20, 2026
Warranty expires Apr 19, 2028

iPhone 13 — Active
Apple · Mobile
Purchased Apr 26, 2026
Warranty expires Apr 25, 2027
367 days

iPhone 13 — Active
Apple · Mobile
Purchased Apr 26, 2026
Warranty expires Apr 25, 2027
367 days

Figure 5: Dashboard and Gadgets interface



Repair History

3 records • Total: ₹13,500

Screenshot Replacement Paid

2024-04-27 Shui Enterprises ₹6,000

Sound Issue Under Warranty

2024-03-30 Apple ₹3,500

Water Issue Paid

2024-01-01 MH Service Center ₹2,000

Reminders

Warranty and service reminders for all your gadgets

0 Critical • expires in 7 days

0 Action needed soon

2 Warranty expired

2 All good

Airpods 2 — Apple • Warranty expires 8er, 2026 — Expired — Warranty expires

iPad — Tablet • Warranty expires Apr 19, 2028 — Expired — Warranty expires

iPhone 15 — Mobile • Warranty expires Apr 25, 2027 — 362d

One plus — Appıid • Warranty expires Apr 26, 2027 — 363d

Figure 6: Repair History and Reminders interface

The implementation of the user interface for the suggested system GadgetCare is depicted in Figure 5 and Figure 6, showing how the concept of predictive maintenance and digital repair can be realized in practice. As shown in Fig. 5, the dashboard and gadget management modules enable users to have a unified representation of their device information, such as warranty information, repair expenses, activities of devices, and general information about the system. This helps users make more informed decisions based on real-time data. Besides, the gadget management module makes it easy for users to manage many gadgets simultaneously since it displays important attributes of each gadget, including the date of purchase, warranty periods, and lifetime. Furthermore, repair history and reminder modules, presented in Figure 6, provide service records and reminders about upcoming expiration dates of the warranty period. These aspects contribute to the better usability and engagement of users while motivating them to conduct more proactive actions regarding maintenance activities.

Such outcomes correspond well with the findings discussed in Table 1, showing that the application of predictive maintenance offers significant benefits in comparison with the reactive approach and time-based preventive maintenance. Besides, the graph shown in Figure 3 proves that the developed system has sufficient capabilities to increase several important indicators of its operation, including fast detection of faults, economical performance, and efficient use of resources. In addition, the comparative study provided in Figure 4 confirms this conclusion, highlighting how the reactive maintenance cycle can be transformed into the data-driven maintenance process consisting of monitoring, prediction, scheduling, and execution stages. This change will result in considerable reduction of unplanned disruptions and higher reliability. Taken together, the results of the empirical study prove that the designed GadgetCare system is not only theoretically correct but also very applicable in practice.

VII. LIMITATIONS AND CHALLENGES

Despite the advantages of the predictive maintenance and digital repair tools, there are various challenges to be addressed. Some of the challenges include the requirement of high-quality data. In the absence of reliable data, the output of the predictive model will not be reliable, and the system will lose its credibility. In the consumer world, the lack of standardization in the sensing data will affect the reliability of the output of the model [8], [10], [13].

Another major issue in the system is the requirement of computation and infrastructure. Advanced predictive analytics, especially in the areas of fault diagnosis and RUL, require a lot of computation. Although the cloud-based infrastructure will be helpful in overcoming the computation issue, the cost of integrating the system and the infrastructure will be a major deterrent for small service providers and local device repair ecosystems [2], [3].

The system is based on the use of historical data available in the maintenance process [1], [4]. If the data used in the model are not diversified, the output of the model will not be reliable. In addition, studies have shown that the lifespan of the device is determined based on the behavior, economics, and psychology of the user, and the output of the model will not be reliable in overcoming the limitations of the real world.

Another major issue in the system is the user interface. Although the system will be helpful in providing timely maintenance, the lack of clarity in the output of the model will affect the user. This has to be addressed in the digital device repair system.

To address the limitations of the system, the data quality, the use of cloud computing, diversified data, and user interface have to be improved [8], [4], [1], [2].

VIII. CONCLUSION

The suggested research paper presented GadgetCare, an advanced integrated AI-powered repair management and electronic product lifecycle framework aimed at enhancing the performance of gadgets, ensuring effective and efficient maintenance and repairs, and improving the sustainability of gadgets' lifecycle. By introducing predictive maintenance, cloud-enabled service orchestration, and the ability to track repairs and notify users, GadgetCare solves a number of critical issues associated with reactive and periodic maintenance.

Moreover, the research proves that using predictive analytics in conjunction with digital repairs can help to establish a much more effective and transparent maintenance system for consumer electronics. The proposed solution is particularly relevant to home settings, office use, repair centers, as well as digital repair marketplaces online.

Of course, there are still some challenges that have to be faced before further implementation. In particular, they relate to issues related to data quality, computational cost, adaptation of models for different devices, and design. However, the current framework represents a solid basis for further developments. Possible improvements may include introduction of IoT telemetry, adaptive learning, and expansion into a digital repair marketplace.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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