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Battery Performance Evaluation through Decision Tree

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Abstract – This study addresses the pervasive concern surrounding battery performance degradation in electronic devices. While some attribute this decline to device aging, a significant portion of the population lacks awareness of the precise factors contributing to diminished battery efficiency. Consequently, the research investigates the factors related to battery performance, aiming to identify the determinants of reduced efficiency. Decision trees are used to meticulously analyze the intricate relationships between variables and discern the factors that respondents perceive as causative of diminished battery performance. This algorithm is chosen since, in predicting high-capacity lithium-ion battery performance, the decision tree outperforms other algorithms in machine learning in accuracy. The study elucidates diverse user preferences, with 55.38% favoring Android and 44.62% expressing a preference for iOS, indicating disparate perceptions of battery health: 61.54% consider their batteries as "Good," while 38.46% acknowledge a decline. The decision tree analysis of 195 participants underscores the pronounced impact of prolonged usage on battery health, revealing that 95% maintain good battery performance. In contrast, 27.69% of Android users face reduced battery performance, emphasizing the need for targeted user education and Android manufacturers to prioritize device longevity. The ultimate objective is to give readers a comprehensive understanding of the dynamics of battery performance in the context of device aging and its contributing factors and give some input to manufacturers and service providers.

Keywords – Android, Battery Performance Evaluation, Decision Tree, iOS.

I. INTRODUCTION

The rapid advancement of information and communication technology has significantly influenced human activities in daily life, often without being consciously recognized [1]. With the continuous evolution of information technology, accessing the necessary information has become increasingly effortless. Technology is crucial for individuals engaged in professional work by facilitating data exchange and communication tasks. Similarly, technology is integral for students as it aids in completing school assignments and tasks. Data exchange, communication, and task execution typically require electronic devices.

Electronic devices serve specific purposes or functions. In the present era, many people own electronic devices [2], with even young children having their own. This prevalence is driven by the inherent enjoyment derived from using such devices. Individuals of all ages can find various forms of entertainment through these electronic devices. Electronic devices prove particularly helpful where remote work and learning have become prevalent [3]. Virtual meetings are still a common practice, highlighting the crucial role of electronic devices in daily life. The importance of electronic devices becomes even more evident when considering the declining battery performance. Many individuals seek new devices due to the decreasing battery performance, especially during the pandemic, where reliance on electronic devices for work and study has increased. While there is speculation that the age of device usage influences the decline in battery performance, some people still do not adequately maintain their devices. Additionally, some are unaware of the various factors affecting battery performance, including the age of device usage [4]. The decision tree algorithm has been applied for public awareness. In this context, the decision tree likely contributes by providing a structured analysis of the factors influencing the decrease in public awareness regarding the application of health protocols [5]. In the context of a decision tree-based user-centric security solution for critical IoT infrastructure, the decision tree contributes by offering a systematic framework to analyze and respond to security-related events or conditions [6]. The decision tree contributes to analyzing impact factors for smartphone-sharing decisions by providing a structured and interpretable model that helps identify critical variables influencing the decision-making process [7]. In addition, among machine learning algorithms, a decision tree is particularly notable for its interpretability [8]. When it comes to predicting the electrical performance of high-capacity lithium-ion batteries, decision tree regression often outperforms other commonly used algorithms such as Linear Regression, k-nearest Neighbors Regressor, and Random Forest Regressor in terms of R-squared (R2) accuracy metric [9].

Hence, we are intrigued to conduct a study on the relationship between the age of device usage and battery performance. The research aims to determine the strength of the correlation between the age of device usage and battery performance. Furthermore, the factors contributing most significantly to the decline in battery performance are identified as perceived by the general populace.

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II. METHODS

In this particular research endeavor, the focus is directed toward three key elements: the age of electronic devices, the performance of their batteries, and the myriad factors that contribute to the diminishing efficiency of these batteries. The age of electronic devices serves as a fundamental aspect of investigation. Understanding how the longevity of these devices may impact their overall functionality, particularly in terms of battery performance, is crucial. Factors influencing battery performance may come from operating system software [10] and device age [11].

The division of Battery performance into "Good" and "Decline" categories reflects the dual states of satisfactory and diminishing battery health, offering insights into the overall condition of device batteries. Simultaneously, the segmentation of Battery Health Percentage into 65%, 75%, 85%, and 95% provides a nuanced classification of battery health, ranging from significant decline to optimal performance. These categorizations serve as crucial indicators for users, manufacturers, and service providers, guiding decisions on troubleshooting, user education, and future device improvements. The precise delineation allows for targeted interventions based on individual batteries' specific health and performance needs, promoting informed decision-making and proactive measures to enhance overall device satisfaction and longevity. In comparison, factors affecting the decline in battery performance include Charging while playing [12], overcharging [13], and frequent use of power banks [14].

Data collection in research aims to obtain valid and accurate information that can be responsibly used as a basis for seeking solutions and addressing existing issues. This process represents the initial stage in conducting research before delving into the analysis of the acquired data. In this study, the researcher employs a quantitative data collection method by distributing structured questionnaires to respondents who meet specific criteria. The questionnaires are designed with closed-ended questions, signifying that the researcher has provided predefined response options. Consequently, respondents are required to select one of the provided answers.

The researcher employs two research methods in this study. First, the correlational research method enables the researcher to identify or uncover relationships between variables or multiple variables with other variables. This method is chosen because the researcher aims to explore the relationship between the age of device usage and battery performance variables. Additionally, the researcher seeks to determine the factors influencing the decline in battery performance. Afterward, the quantitative research method involves numerical data, which is processed and analyzed using specific statistical criteria and presented as mathematical calculations [15]. The researcher utilizes the quantitative research method through a survey, distributing questionnaires to respondents who meet the specified criteria.

Based on the problem above, the researcher utilized the Decision Tree. The Decision Tree constitutes a hierarchical framework where localized regions are recognized through a sequence of iterative divisions facilitated by decision nodes within the testing function [16]. The decision tree is a popular method for prediction or classification due to its ease of interpreting results and human-friendly nature [17]. Additionally, this algorithm is effective in discovering relationships between variables. The Decision Tree structure is easy to remember as it resembles a tree consisting of root, internal, and leaf nodes [18]. The root node is the topmost node with one or more outgoing edges but no incoming edges. Internal nodes have one incoming edge and one or more outgoing edges. Leaf nodes are the bottommost nodes with only one incoming edge and no outgoing edges, representing the outcomes of the process [19]. Advantages of the Decision Tree algorithm include its simplicity, specificity, results easily understandable by humans, accurate calculations, and the ability to process numeric and categorical data [20]. However, it has disadvantages such as overlap, lack of tree growth, and increased decision-making time and memory usage in the presence of extensive classes and criteria [21].

A decision tree model is shown in Figure 1. A decision tree algorithm starts with the whole dataset at the central part of the tree, called the root node. It then repeatedly picks the best feature to group the data based on factors like how well it is separated or how much information it can give. At each step, it splits the data into smaller parts called decision nodes and keeps splitting until it reaches "leaf nodes." These leaf nodes have a predicted value or a label based on the most common value or average value of the data in the node.

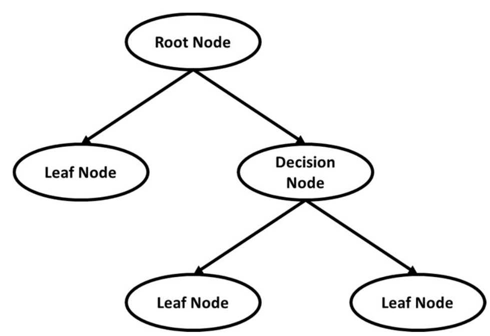

Fig 1 Decision Tree Model

III. RESULTS AND DISCUSSION

This study gathered responses from 195 participants, as shown in Table 1. Firstly, the analysis of OS Software preferences revealed that among the surveyed respondents, 55.38% preferred Android, while 44.62% preferred iOS. Specifically, 108 respondents opted for Android, constituting the majority, while 87 chose iOS. This breakdown provides insights into the distribution of operating system choices among the surveyed individuals. This distribution suggests that the studied population is diverse regarding the age of their devices, providing a

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comprehensive snapshot of the different stages of battery aging. Understanding this diversity is crucial for device manufacturers, service providers, and researchers in tailoring solutions, support, and innovations that cater to the varying needs and challenges associated with distinct phases of battery life. It also emphasizes the importance of considering a wide range of user experiences and expectations related to battery performance in developing technology and services.

Secondly, the distribution of battery age among surveyed respondents reveals a balanced representation. Approximately 50.77% of participants reported using devices with batteries aged two years or more, while the remaining 49.23% indicated devices with batteries less than two years old. This even distribution offers insights into the varied timelines of battery aging within the surveyed population. This even distribution signifies a diverse representation of devices at different stages of battery aging within the surveyed population. The implication is that the study captures a comprehensive view of various timelines in the life cycle of batteries. This diversity is crucial for drawing robust conclusions about the factors influencing battery performance and devising targeted strategies for maintaining or enhancing battery efficiency. Additionally, it underscores the need for tailored solutions and support that consider the unique challenges associated with distinct phases of battery life experienced by users.
Furthermore, the survey results reveal notable factors influencing the decline in battery performance among respondents. The majority, accounting for 55.38%, identified "Charging while playing" as a significant contributor to reduced battery efficiency. Additionally, 27.69% highlighted "Overcharging," and 16.92% pointed to the "Frequent use of power banks" as a factor impacting battery performance. These insights comprehensively understand prevalent user practices contributing to decreased device battery efficiency. These findings hold important implications for user behavior and device usage patterns. Understanding these general practices allows device manufacturers, service providers, and users to address these factors proactively. It emphasizes the importance of designing devices resilient to these common practices for manufacturers. Service providers can offer guidance on optimal charging habits, and users can adopt practices contributing to prolonged battery health. Overall, this comprehensive understanding aids in formulating strategies to mitigate battery performance decline, enhancing user experience and device longevity.

The analysis of battery performance perceptions among respondents reveals that 61.54% of participants reported their devices' batteries as "Good," indicating satisfactory health. In contrast, 38.46% acknowledged a decline in battery performance. These insights provide a comprehensive overview of user perspectives on the condition of their device batteries, shedding light on the prevalence of both satisfactory and deteriorating battery health among the surveyed population. The implication lies in the need for targeted interventions and support mechanisms tailored to both groups. For users with satisfactory battery health, highlighting positive experiences can contribute to brand loyalty and user satisfaction. Meanwhile, addressing the concerns of those experiencing declining battery performance becomes imperative for device manufacturers and service providers. Strategies could include offering troubleshooting assistance, optimizing software updates, or providing information on battery maintenance practices.

Table 1. Questionnaire Results

Factors	Answers	Total	Percentage
OS Software	Android	108	55.38%
	IOS	87	44.62%
Device Age	Two years or more	99	50.77%
	Less than two years	96	49.23%
Factors affecting the decline in battery performance	Charging while playing	108	55.38%
	overcharging	54	27.69%
	frequent use of power banks	33	16.92%
Battery Performa	Good	120	61.54%
	Decline	75	38.46%
Battery Health Percentage	95%	120	61.54%
	85%	27	13.85%
	75%	42	21.54%
	65%	6	3.08%

Finally, a high % Battery Health Percentage of 95% indicates optimal battery conditions. However, a noteworthy proportion of respondents (21.54%) have a Battery Health Percentage of 75%, suggesting a decline in battery health. Additionally, 13.85% report a Battery Health Percentage of 85%. The presence of varied Battery Health Percentages emphasizes the diverse experiences of users, highlighting the need for targeted interventions. Manufacturers and service providers can address the specific concerns of users with lower Battery Health Percentages, offering support, guidance, or potential solutions to enhance overall battery performance. This breakdown aids in tailoring strategies for maintaining and optimizing battery health, contributing to improved user satisfaction and prolonged device lifespan.

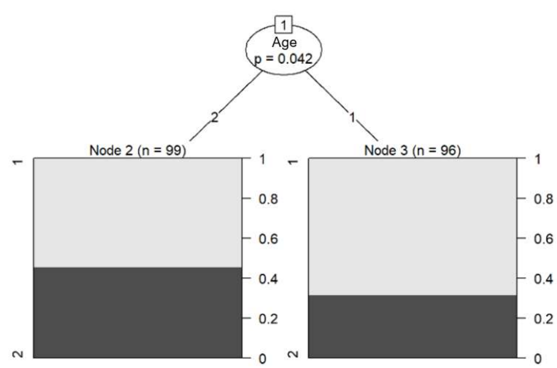

Fig. 2 Decision Tree of Device Age

The utilization of the decision tree, as depicted in Figure 2, meticulously examines the correlation between the duration of device usage (less than two years or at least two years) and the consequent battery performance. The Figure reveals that 99 individuals have been utilizing their devices for at least two years, while 96 have used them for less than

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two years. Notably, users who have been using their devices for at least two years experience a more pronounced decline in battery performance than those who have used them for less than two years. This observation underscores the potential impact of prolonged device usage on battery health, signaling a critical consideration for manufacturers regarding product durability and user satisfaction. Addressing this trend may involve developing technologies that better withstand extended usage periods or implementing strategies to optimize battery performance over an extended device lifespan.

Figure 3 shows the decision tree used to observe users' devices' battery performance and battery health. According to the decision tree analysis, it can be observed that the majority of individuals still maintain good battery performance. Based on the decision tree analysis presented above, it is evident that 95% of the sample exhibits good battery performance. Conversely, 75 individuals have experienced a decline in their device's battery performance, with battery health percentages ranging from 75% followed by 85% and 65%. This breakdown provides a nuanced understanding of the distribution of battery performance within the sampled population. The implication here is twofold. Firstly, it highlights the need for targeted interventions or support mechanisms for users experiencing declining battery performance. Understanding the factors influencing this decline, as identified in the decision tree, can guide manufacturers and service providers in tailoring solutions to address specific issues such as overcharging, usage patterns, or other contributing factors. Secondly, identifying this subgroup underscores the importance of user education and awareness programs. Users may benefit from guidance on best practices for maintaining battery

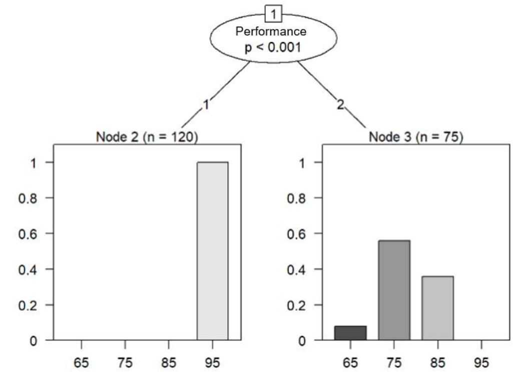

Fig. 3 Decision Tree of Battery Performance

health, thus potentially mitigating issues related to performance decline.

The decision tree analysis in Figure 4, illustrating factors contributing to the decline in battery performance according to respondents' understanding, indicates that the operating system type divided between iOS and Android is the most crucial variable in category separation. The implication is a significant difference in the understanding and habits of iOS and Android users in battery management.

For iOS device users, a specific observation was made regarding battery health at 85%. The battery performance on these devices is primarily influenced by overcharging, followed by device usage while charging. The implication is that managing overcharging practices and discouraging device usage during charging is critical for iOS users in

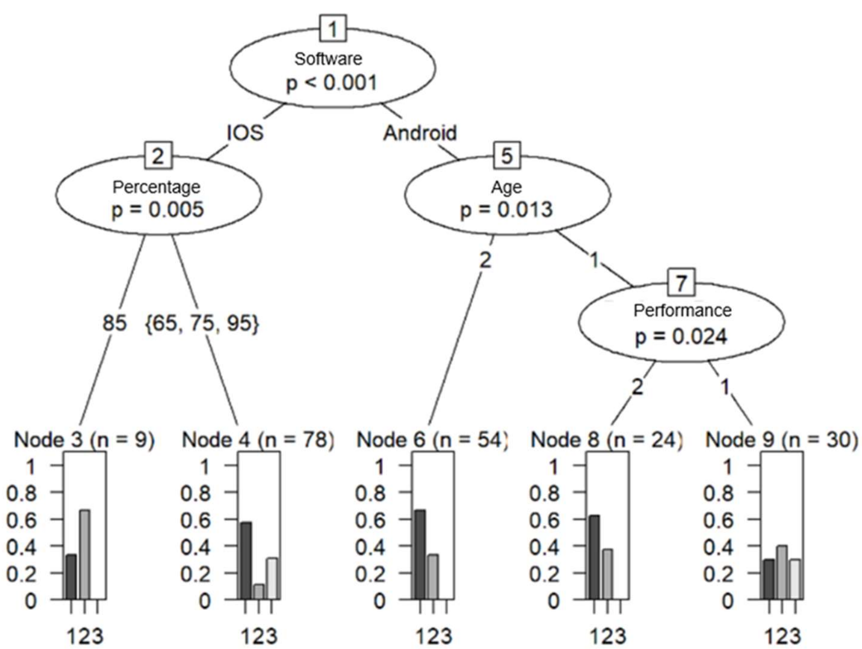

Fig. 4 Decision Tree to show Factors contributing to the decline in battery performance according to respondents' understanding.

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optimizing battery health and performance. Meanwhile, the revelation that up to 40% of respondents attribute diminished battery performance to usage during charging and reliance on power banks underscores the importance of addressing user behavior and technological limitations. In the context of iOS users, these implications gain specific relevance for Apple and its consumer base. Many respondents, including iOS users, attribute reduced battery performance to charging practices and power bank usage. In that case, Apple may need to tailor its user education efforts, potentially integrating features or notifications that guide users toward optimal charging habits. The findings may also signal a need for continuous innovation in battery technology within Apple devices to ensure resilience against common user behaviors.

The revelation that 27.69% of Android users experience reduced battery performance, primarily linked to devices in use for at least two years and exacerbated by usage during charging and overcharging, underscores the need for Android manufacturers to focus on device longevity. It entails investing in user education on optimal charging practices, refining product lifecycle management strategies to create more durable devices, and exploring ongoing innovation in battery technology. Furthermore, for users whose devices are less than two years old, a significant majority still experience diminished battery performance, primarily attributed to the common usage factors during charging and overcharging. Interestingly, among users who perceive their batteries to be in good condition, the reasons for potential performance decline are evenly distributed across the three factors above. The implications for Android manufacturers are notable, given that most users with devices under two years old report diminished battery performance, mainly due to usage during charging and overcharging. It suggests a need for targeted efforts in user education regarding optimal charging practices, emphasizing the impact of these common behaviors on battery health. Android manufacturers could consider implementing more robust battery management systems and giving users more precise guidelines on charging habits to mitigate premature performance decline. It underscores the importance of integrating innovative technologies into newer Android devices that can withstand and adapt to user behaviors, enhancing overall battery longevity. Addressing these implications is critical for maintaining user satisfaction, improving product longevity, and remaining competitive in the Android market.

IV. CONCLUSION

This study reveals that 55.38% preferred Android, while 44.62% favored iOS. Notably, 50.77% reported devices with batteries aged two years or more, and 49.23% had batteries less than two years old. Factors influencing battery decline included "Charging while playing" (55.38%), "Overcharging" (27.69%), and "Frequent use of power banks" (16.92%). 61.54% perceived their batteries as "Good," while 38.46% acknowledged a decline. Battery Health Percentages varied, with 95% optimal conditions, 21.54% at 75%, and 13.85% at 85%. This diverse data emphasizes the importance of tailored interventions for different user groups, guiding strategies for enhanced battery performance, user satisfaction, and prolonged device lifespan.

The decision tree analysis indicates that out of 195 participants, 99 used their devices for at least two years and 96 for less than two years. Users with over two years of usage experienced a more pronounced decline in battery performance, underscoring the impact of prolonged use on battery health. The decision tree also shows users' device battery performance and health. According to the analysis, 95% of the sample maintains good battery performance, while 75 individuals have experienced a decline, with health percentages at 75%, 85%, and 65%. Furthermore, the decision tree highlights the operating system's crucial role in understanding battery performance, primarily dividing iOS and Android users. For iOS users, managing overcharging and discouraging device usage during charging are pivotal for optimizing battery health, especially at 85%. The revelation that 27.69% of Android users face reduced battery performance emphasizes the need for Android manufacturers to focus on device longevity. Users with devices under two years old still experience diminished performance, highlighting the importance of targeted user education.

Device users are advised to optimize battery performance by monitoring charging habits and avoiding overcharging and excessive use while charging. Limiting the frequent use of power banks, periodically checking battery health, and adhering to manufacturer guidelines for setting practices are crucial. Considering the impact of the operating system on battery performance, understanding the influence of device age and being cautious with devices aged two years or more are also recommended. Education programs by manufacturers and service providers can inform users about best practices while seeking support for declining battery performance is encouraged. These measures aim to enhance user experiences and contribute to prolonged battery life.

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