Cross-Validated Machine Learning Models for Smartphone Battery State-of-Health Classification

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ABSTRACT

This study investigates the application of Machine Learning (ML) classification models for assessing smartphone battery State-of-Health (SoH) using temperature, usage, environment, and device-related parameters. A dataset comprising 675 observations and 15 attributes was obtained from ten smartphones, with battery SoH categorized as Poor, Fair, or Good. Eight ML algorithms: Naïve Bayes (NB), Decision Tree (DT), Logistic Regression (LR), Gradient Boosting (GB), Support Vector Machine (SVM), Random Forest (RF), CN2 Rule Induction (CN2-RI), and k-Nearest Neighbour (kNN), were evaluated using 10-fold cross-validation. The results indicate substantial differences in model performance across battery-SoH and smartphones, with notable difficulty in correctly identifying Good and Fair SoH and a tendency among several models to classify these conditions as Poor. LR achieved a high number of correct Poor-SoH predictions, while DT and NB showed comparatively more balanced performance across the SoH. The findings demonstrate the potential of ML for smartphone battery-SoH classification but also highlight the effects of SoH imbalance and the need for SoH-sensitive evaluation when selecting reliable predictive models.

Keywords: classification, cross-validation, state-of-health, machine learning and smartphone battery.

INTRODUCTION

Mobile batteries are fundamental components in modern portable devices, particularly smartphones, and they significantly influence the devices' performance and users' experiences. They determine how well the device can function over times while the smooth and responsive interface expected by users will be compromised when the batteries underperform (Mansour et al., 2021). The demand for better performance and longer lifespan in mobile batteries is escalating with the increasing reliance on mobile technology for daily activities. Mobile batteries power many devices, making their reliability and longevity essential for consumers and industries, and their State-of-Health (SoH) is a critical concern for the present technology-driven society. Concerns on the SoH, environmental considerations (Budiman et al., 2025) and users handling (Pramanik et al., 2019) of mobile batteries are consistently increasing. Smartphones combine many applications utilized to achieve various purposes ranging from calls and short messaging services to marketing and scientific measurements. The rate at which each application drains battery energy depends on complexity, frequency and duration of use (Khardim et al., 2020). Video and social media applications are frequently engaged for longer periods by many users compared to few whose major usage are calls and messaging. Understanding the impact of individual applications on battery drain and SoH is invaluable to managing and elongating the life of batteries (Ali et al., 2023). Accurate prediction of a battery's remaining useful life and SoH are vital for preventing failures and the occurrence of thermal runaways (Mansour et al., 2021).

Smartphone batteries are expected to operate within safe voltage and current limits. Unsafe voltage and current could be due to short-circuit of terminals (Naha et al., 2019). Overcurrent can be drawn by multiple high-power applications running simultaneously (Kim et al., 2019), while overvoltage can be due to the increase in the hysteresis of open-circuit voltage of degraded batteries (Ovejas et al., 2019). Smartphone batteries are sensitive to temperature variations and extreme heat. These accelerate aging and degradation of battery materials, which lead to progressive reduction in efficiency, capacity, power and device's overall performance (Leng et al., 2015). Excessive heat leads to thermal runaway, making the battery generate heat uncontrollably and sometimes ending in explosions and fires (Xu et al., 2024; Kim et al., 2019). Uneven heat distribution within the battery creates localized overheating, affecting the device's performance and sometimes damaging hardware (Bandhauer et al., 2011). Generally, elevated temperatures alter the battery's electrochemical reactions, creating side reactions and internal short-circuiting, which degrade the battery's performance and lifespan (Xu et al., 2024).

The Central Processing Unit (CPU) is the most power-consuming component which significantly influences temperature and subsequently the health of the smartphone's battery (Mansour et al., 2021). When a smartphone's CPU operates under heavy load, it generates more heat, which raises the device's internal temperature and that of the battery. High temperatures accelerate the degradation of the battery chemistry by increasing the rate of chemical reactions inside the cells leading to faster capacity loss and potential safety hazards such as thermal runaway (Leng et al., 2015). The battery performs optimally within a range of temperature range, beyond which degradation accelerates significantly due to increased internal resistance and electrolytic breakdown (Ali et al., 2023; Razi et al., 2021). High CPU usage contributes to high temperatures and negatively impacting the battery's SoH. Moderate CPU activity leads to battery wear when smartphones are used for extended periods without cooling. In contrast, operating a smartphone's CPU under light loads with efficient cooling mechanisms helps maintain an optimal temperature that preserves battery longevity. Lower CPU usage translates to reduced power draw and less heat generation, mitigating the risks associated with aging battery (Rumi et al., 2025). The power-saving modes and optimized software settings in smartphones regulate temperature and extend battery life. Smartphone batteries are highly sensitive to environmental temperature, humidity, and seasonal variations which are critical external factors influence performance, safety, and lifespan. Bandhauer et al. (2011) emphasize that elevated environmental temperatures accelerate degradation mechanisms by increasing the rate of unwanted side reactions within the cell. This promotes electrolyte decomposition, solid-electrolyte interphase instability, and gas generation, which reduces capacity and impairs safety (Xu et al., 2024). In hot climates, prolonged exposure to ambient temperatures, such as leaving a smartphone in a parked car, can accelerate internal heating during charging and discharging. This creates thermal stress that reduces performance and elevates internal temperatures. High humidity accelerates corrosion of metal contacts, infiltrate seals, and compromises electrolyte stability (Budiman et al., 2025). Users have the crucial role of manually monitoring battery SoH and longevity through precise charging process control, effective thermal management, intelligent power consumption strategies, and predictive maintenance capabilities.

METHODOLOGY

Data Collection

A set of temperature, usage, environment, and device-related data for this study comprises 675 instances and 15 attributes (2 categorical and 13 numerical), were collected through mobile applications installed on the smartphones. These devices were chosen from different brands and were randomly labelled with letters A to J to protect their integrity. The applications and the physical quantities measured are presented in Table 1. Some quantities, like battery temperature, were measured by more than one application, and the values from different sources were compared to ensure consistency. There is no separate column for battery mode because Ampere indicates the charging and discharging modes by making the current value positive and negative, respectively. SoH namely good, fair and poor were assigned to the smartphone battery based on their usage and performance history.

Table 1: Applications and the Measured Quantities

Application	Device Model	Battery Capacity (mAh)	Battery Status	Battery Level (%)	Battery Voltage (mV)	Battery Current (mA)	Battery Temperature (°C)	CPU Usage (%)	CPU Temperature (°C)	Memory Usage (%)	RAM Usage (%)	Phone Usage	Ambient Temperature (°C)	Humidity (%)	Wind Speed (m/s)	Battery Health
Ampere	1	1	1	1	1	1	1									1
Phone Temperature	1	1	1	1		1	1									1
Battery Temperature			1	1	1	1	1									1
Battery Monitor			1	1	1		1	1	1	1		1				1
CPU Monitor	1		1	1	1		1				1					1
CPU X		1	1	1	1	1	1					1				1
AccuWeather													1	1	1	

Classification

The data classification was performed in Orange Data mining with an array of models. The cross-validation technique, a resampling strategy was utilized along with Naïve Bayes (NB), Decision Tree (DT), Logistic Regression (LR), Gradient Boosting (GB), Support Vector Machine (SVM), Random Forest (RF), CN2 Rule Induction (CN2 RI), and k-Nearest Neighbor (kNN) models for the analysis. The process begins with loading data from the data file, which is then provided as input to various classification models before it is cross evaluated.

Cross Validation

The most common form is the k-fold cross-validation method, where the dataset is split into k equal folds. The model is trained on k-1 folds and tested on the remaining fold. This process is repeated k times, with each fold used once for testing. In this study, k is 10. This is a robust method in which the results are averaged to produce stable performance and generalization estimate (Djuazva et al., 2023).

RESULTS

The model confusion matrix, correct classification based on device and overall instances and accuracies across SoH and models are presented in Figures 1, 2 and 3, respectively.

Figure 1 presents a set of confusion-matrix heatmaps for the classification models. The collection of heat maps provides a visual narrative of how the ML algorithms predict the SoH. At a glance, the ideal scenario for any model is a deeply colored diagonal stripe running from the top-left to the bottom-right, representing instances where the predicted SoH aligns perfectly with the actual SoH. In these visualizations, dark navy blue indicates high numbers of predictions, while pale, almost white blues represent low counts. Across the board, we see varying shades of blue, but the overall visual footprint confirms that none of these models are perfect. LR and NB emerge as some of the stronger performers by sheer volume of correct predictions, with LR boasting the darkest single cell in the grid: 126 correct predictions for the Poor SoH. However, a deeper look reveals that

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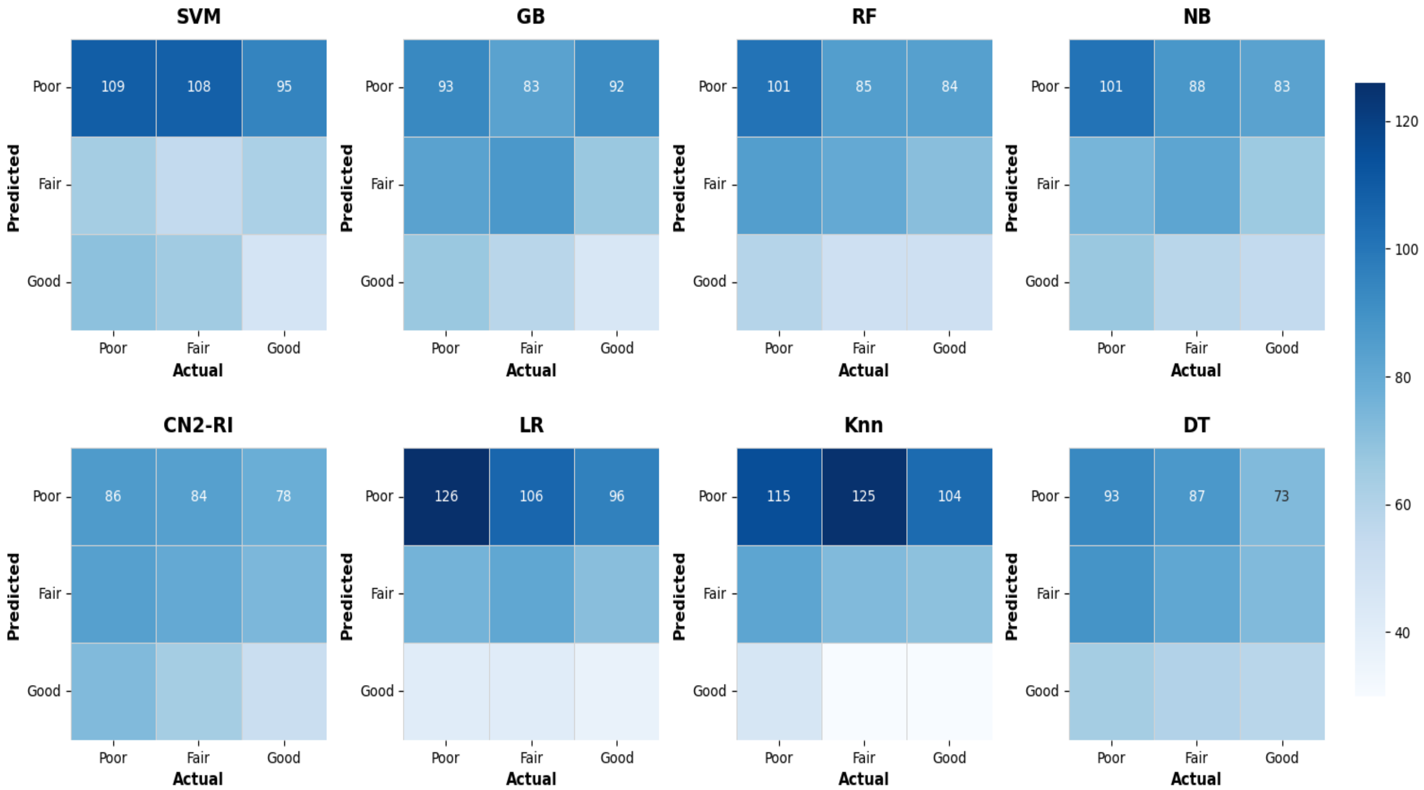
this strength is often heavily skewed, and high performance in one SoH frequently masks severe weaknesses in others.

Figure 1: Models' confusion matrix



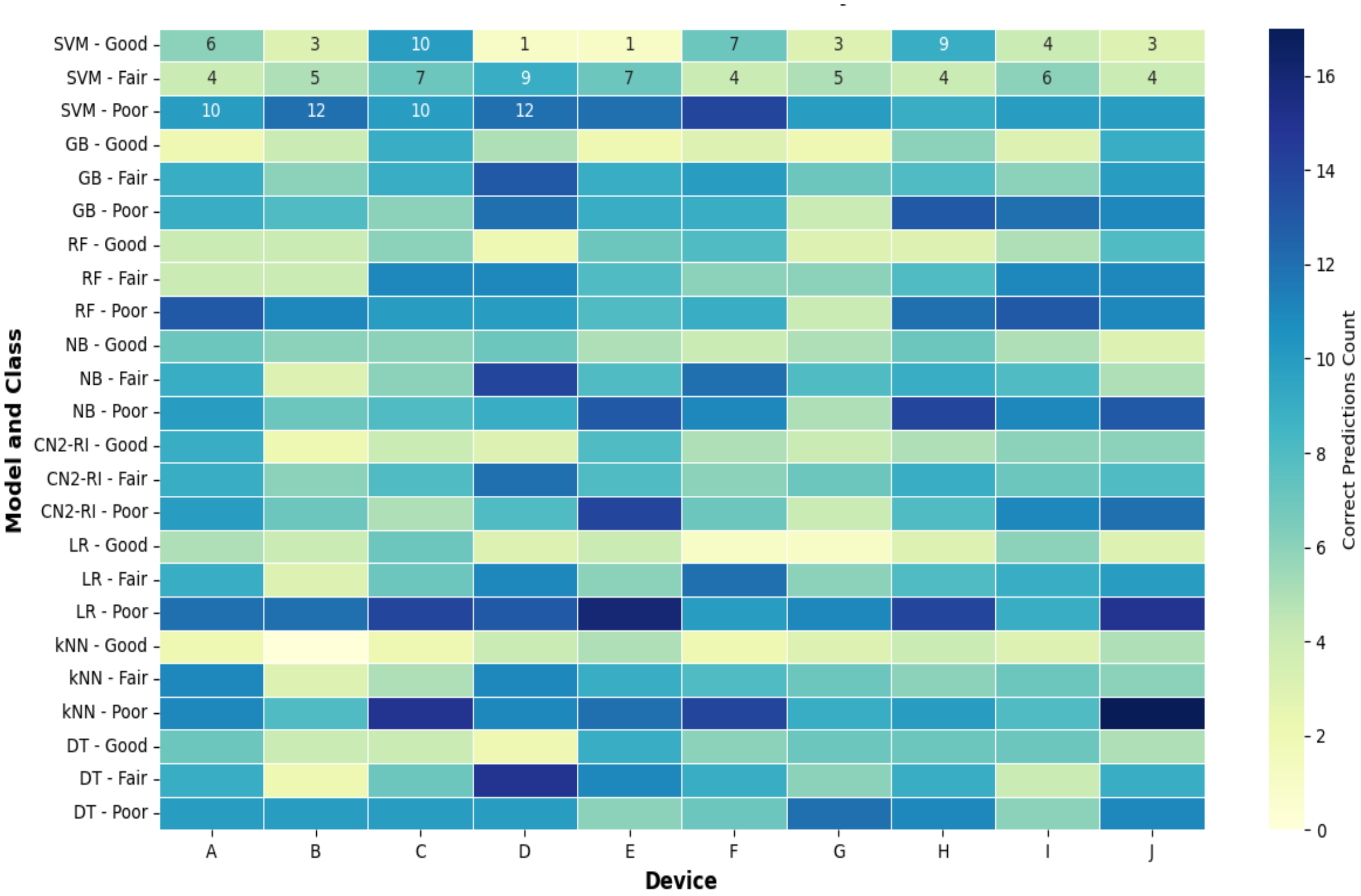
The heatmaps illustrate a widespread and systemic struggle across nearly all the algorithms with the tendency to misclassify Fair and Good SoH as Poor. Visually, this manifests as dark blue appears heavily into the top row of the matrices. For instance, kNN model shows a severe bias toward the Poor SoH. While it correctly predicts Poor 115 times, it glaringly misclassifies 125 Fair SoH and 104 Good SoH as Poor. This creates a dark, error-heavy top row that severely undermines the model's overall reliability. Similarly, SVM and LR suffer from this same affliction. In the LR heatmap, the cell representing Predicted Poor / Actual Fair is almost as dark as its correct Poor diagonal, with 106 errors. This tells us that while these models are highly sensitive to Poor SoH, they do so at the direct expense of misreading the Fair and Good SoH.

When shifting focus to the bottom-right of the matrices, representing the Good SoH, the colors rapidly fade to pale blue across almost all models, signifying that correctly identifying Good SoH is a significant challenge. The DT and NB models offer some of the better visual performances here, managing to correctly identify Good 58 and 55 times, respectively, keeping their off-diagonal errors slightly more balanced than their peers. In contrast, models like GB and kNN struggle significantly with the Good class, capturing only 45 and 30 correct predictions, respectively. Their Good diagonal cells are pale, while the off-diagonal cells indicating Good instances misclassified as Poor are noticeably darker, highlighting a systematic failure to distinguish Good SoH from poor ones. The heatmap of LR reveals a bias toward the Poor SoH, essentially guessing Poor for almost everything. NB and DT present a slightly more visually balanced matrix, spreading their correct predictions more evenly across all the SoH.

Figure 2 presents a heatmap showing substantial variation in the number of correctly classified Good, Fair, and Poor battery SoH cases across A–J devices and eight models. For SVM, the correct Good/Fair/Poor classifications for devices are respectively A (6/4/10), B (3/5/12), C (10/7/10), D (1/9/12), E (1/7/12), F (7/4/14), G (3/5/10), H (9/4/9), I (4/6/10), and J (3/4/10), showing strong Poor prediction but relatively weak Good prediction on several devices. GB records A (2/9/9), B (4/6/8), C (9/9/6), D (5/13/12), E (2/9/9), F

(3/10/9), G (2/7/4), H (6/8/13), I (3/6/12), and J (9/10/11), with comparatively strong Fair predictions, especially for D.

Figure 2: Correct predictions based on device



RF gives A (4/4/13), B (4/4/11), C (6/11/10), D (2/11/10), E (7/8/8), F (8/6/9), G (3/6/4), H (3/8/12), I (5/11/13), and J (8/11/11), again showing a tendency toward stronger Poor and Fair prediction than Good prediction. NB records A (7/9/10), B (6/3/7), C (6/6/8), D (7/14/9), E (5/8/13), F (4/12/11), G (5/8/5), H (7/9/14), I (5/8/11), and J (3/5/13), with notably strong Fair performance for D and F and strong Poor performance for E, H, and J. CN2-RI produces A (9/9/10), B (2/6/7), C (4/8/5), D (3/12/8), E (8/8/14), F (5/6/7), G (4/7/4), H (5/9/8), I (6/7/11), and J (6/8/12), showing particularly strong overall performance for A and E, although its Good predictions are comparatively weak for B and D. LR shows a pronounced tendency toward the Poor class, with A (5/9/12), B (4/3/12), C (7/7/14), D (3/11/13), E (4/6/16), F (1/12/10), G (1/6/11), H (3/8/14), I (6/9/9), and J (3/10/15); its most striking result is the very high number of Poor classifications for E, H, and J, accompanied by very low Good classifications for F and G. kNN records A (2/11/11), B (0/3/8), C (2/5/15), D (4/11/11), E (5/9/12), F (2/8/14), G (3/7/9), H (4/6/10), I (3/7/8), and J (5/6/17), representing the strongest tendency of all the models toward Poor classification, with the highest individual Poor count of 17 for device J, while Good classification is weak, including zero for device B. Finally, DT produces A (7/9/10), B (4/2/10), C (4/7/10), D (2/15/10), E (9/11/6), F (6/9/7), G (7/6/12), H (7/9/11), I (7/4/6), and J (5/9/11), demonstrating relatively strong Good classification across several devices and an especially high Fair count of 15 for device D. Overall, the heatmap indicates that Poor SoH is generally the easiest category for the classifiers to recognize, particularly for LR and kNN, whereas Good SoH is generally more difficult, especially for LR and kNN; Fair SoH tends to occupy an intermediate position, with some models such as GB, NB, and DT showing stronger performance for particular devices. The results also demonstrate that classifier performance is device-dependent: the same model can perform strongly for one smartphone while producing substantially fewer correct prediction for another, suggesting that differences in device characteristics, battery SoH condition, operating behaviour, or measurement conditions may influence classification performance.

CONCLUSION AND RECOMMENDATION

In conclusion, while ML models can be employed to estimate smartphone battery SoH, their reliability is heavily compromised by dataset imbalance, particularly the overrepresentation of Poor SoH instances. Models such as LR and kNN exhibited a strong bias toward the Poor SoH, essentially guessing Poor for the majority of predictions, which led to high misclassification rates for Fair and Good battery SoH. In contrast, DT and NB provided a more balanced performance across all three classes, proving them to be more trustworthy for nuanced SoH prediction. It is therefore recommended that developers and engineers utilizing predictive maintenance for smartphone batteries avoid relying on accuracy metrics alone, and instead adopt balanced models like DT or NB. Future studies should focus on employing data resampling techniques: SMOTE to balance the dataset, and incorporate a wider variety of hardware metrics to improve the generalization and precision of SoH classification across diverse smartphone architectures.

DECLARATION OF CONFLICT OF INTEREST

The author declares no conflict of interest

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