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Machine Learning-based Prediction of Remaining Useful Life of Mobile Devices for Circular Economy E-Waste Management

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Abstract: This paper presents a Machine Learning (ML) approach for predicting the Remaining Useful Life (RUL) of mobile phone devices to support circular economy strategies aimed at reducing e-waste. The study addresses the challenge of premature device disposal by developing a prediction model that estimates how long a device can continue functioning before reaching end of life. A synthetic dataset representing 1,000 devices operating over 1,460 days was generated using mathematical degradation equations, and four ML models were evaluated: Random Forest, Gradient Boosting, Support Vector Regression and a Long Short-Term Memory (LSTM) network. The LSTM achieved the best performance, with a Mean Absolute Error (MAE) of 153 days and an R^2 (coefficient of determination) of 0.47. The results show that RUL prediction can support repair, refurbishment and recycling decisions, enabling more sustainable device lifecycle management.

Keywords: Circular Economy, E-waste Management, LSTM, Machine Learning, Predictive Maintenance, Remaining Useful Life.

1. Introduction

As consumers worldwide continue to buy and replace their phones more frequently, the amount of electronic waste keeps increasing globally. In 2022, global electronic waste was reported to be more than 62 million tonnes, and only a portion of it (22.3%) was recycled in a safe and responsible manner [1]. Mobile phone devices (handheld smartphones and feature phones) contribute a significant portion to this problem, with estimates showing that they account for more than 10% of small e-waste streams [2].

The problem addressed in this study is the premature disposal of mobile phone devices while they still have useful life remaining. This situation is more challenging in regions where formal recycling systems are limited, and many devices are handled informally, which may harm the environment and community health [3]. This highlights the need for a tool that can estimate how much useful life a device still has, quantified by the Remaining Useful Life (RUL). Knowing the RUL of a device can help users, technicians, and organisations decide whether the device should be repaired, reused, refurbished, or recycled.

Although Machine Learning (ML) is used in many areas to predict the RUL, such as machines and batteries, there is still limited research on its usage for RUL predictions for mobile phone devices [3]. Some studies focus only on battery health when estimating RUL, which ignores other important indicators of device condition [4]. This does not give a complete picture of how a device ages over time. Another challenge is that long-term device data is not publicly available, which makes it difficult for researchers and decision-makers to develop solutions that fit different local environments [5]. These issues make it harder to use data-based methods to manage electronic waste and support circular economy practices. These gaps show a need for a multi-indicator RUL prediction approach that considers broader device behaviour.

This paper responds to these issues by using ML to estimate the RUL of mobile phone devices. The study uses a synthetic dataset that simulates long-term mobile phone device behaviour because real device-level datasets are not available. The contribution of this study is twofold: (1) to demonstrate a multi-indicator ML-based RUL framework for mobile devices, and (2) to show how predicted RUL values can support circular economy decision-making.

1.1 Related Work

Mobile phone devices gradually lose performance over time due to battery ageing, high temperature, long screen usage, and general wear of the hardware. Battery ageing is one of the main reasons a device becomes slow or shuts down, because the battery cannot store or deliver energy as effectively as before [4]. When this happens, users often assume that the device has become faulty or has reached the end of its useful life, even though it may still operate with reduced performance [4]. Understanding how a device changes over time helps predict when it is approaching the end of its usable life.

The circular economy model promotes sustainable waste management through interventions such as repair, reuse, refurbishment, and recycling of devices. These actions help reduce waste and protect the environment. Circular economy practices can be more effective when users and organisations know the condition of a device and how long it can still be used. Accurate RUL prediction can provide this information and help identify devices that should be repaired, or refurbished and sold again, or devices that should just be recycled [7].

Many existing RUL studies focus only on battery health or a single indicator of ageing. For example, Martinez-Laserna et al. [4] focus on lithium-ion battery degradation and prediction. This usage of one dominant parameter for data-driven RUL prediction limits the ability to represent the full condition of a device [8]. While these approaches perform well in controlled industrial environments, they may not fully capture the complex usage behaviour of consumer mobile devices.

Very few studies combine multiple indicators such as temperature, screen-on time, brightness, charge cycles, and battery capacity. As a result, full-device RUL prediction for mobile phones remains underexplored, particularly in the context of circular economy decision-making [8]. This study addresses this gap by integrating multiple degradation indicators into a comparative ML framework.

1.2 Objectives

The aim of this study is to investigate how ML can be applied to predict the RUL of mobile phone devices and how these predictions can support circular economy actions.

The specific objectives of the study are listed below.

1. To generate a synthetic dataset that simulates long-term degradation behaviour of mobile phone devices in the absence of publicly available device-level datasets.
2. To develop, train, and compare different ML models including Random Forest (RF), Gradient Boosting (GB), Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) for predicting the RUL of mobile phone devices.
3. To evaluate how predicted RUL can support circular economy action such as repair, refurbishment, reuse, and recycling.

2. Methodology

This study followed a structured process to estimate the RUL of mobile phone devices using ML. The methodology consisted of five main steps: data generation, data preparation, model development, model training, performance evaluation and deployment mapping. A visual overview of the entire process is shown in Figure 1.

2.1 Data Generation

Reliable long-term device-level datasets containing complete operational histories and labelled RUL values are not publicly available for mobile phones. To address this limitation, a synthetic dataset was generated using Python to simulate the lifecycle behaviour of 1,000 mobile devices over a maximum of 1,460 operational days (approximately four years). For each device, daily records were generated until either end-of-life (EOL) was reached or the maximum lifetime was completed.

Each device was assigned an initial battery capacity sampled from a predefined range and a device-specific quality factor drawn from a normal distribution to introduce variability across devices. For each simulated day t, where t represents the device age in days, operational variables were generated, including CPU temperature Tt , daily charge cycles $cycles\_t$, screen-on time, screen brightness percentage $brightness\_t$, CPU load, and memory usage. These variables were used to model realistic daily device behaviour and battery degradation.

Battery capacity was updated recursively according to:

$$Ct=Ct-1-\Delta Ct$$

where Ct represents the battery capacity at day t, and ΔCt represents the daily degradation term. The daily degradation was defined as:

$$\Delta Ct=[(\alpha\cdot cyclest)+(\beta\cdot \max(0,Tt-50))+(\gamma\cdot brightnesst\cdot cyclest)]\times C0$$

where C0 is the initial battery capacity, $cycles\_t$ represents the number of charge cycles on day t Tt represents CPU temperature in degrees Celsius, and $brightness\_t$ represents screen brightness as a percentage. The term $\max(0, Tt-50)$ ensures that temperature contributes to degradation only when exceeding 50°C, reflecting accelerated ageing under thermal stress. The coefficients $\alpha, \beta,$ *and* γ are simulation parameters controlling the influence of charge cycling, elevated temperature, and brightness-related usage, respectively. These equations were designed as part of the synthetic simulation framework to generate realistic ageing trajectories, consistent with general battery degradation trends reported in lithium-ion ageing studies.

EOL was defined using two mechanisms. A device was considered to have reached EOL if its capacity fell below 80% of its initial capacity, that is, $Ct/C0<0.80$. In addition, a stochastic failure process was included, where the daily probability of failure increased gradually with device age to simulate age-related hardware faults independent of battery degradation. The first day on which either condition occurred was recorded as the EOL day.

The RUL at day t was then calculated as:

$$RULt=EOL\_day-t$$

Where EOL_day represents the first day on which a failure condition was triggered. After simulation, a post-processing step ensured consistent RUL computation across all device records.

The synthetic dataset generation framework was implemented in Python. Generative AI tools were used to assist during code refinement This controlled simulation environment enables the modelling of diverse degradation trajectories influenced by usage intensity, thermal exposure, brightness behaviour, charge cycling, and stochastic ageing effects, thereby providing a structured foundation for evaluating ML models for RUL prediction.

2.2 Data Preparation, Modelling and Evaluation and Deployment

After dataset generation, preprocessing was performed to ensure temporal consistency and prevent information leakage. Missing values were checked (none detected), and numerical variables were standardised using statistics derived from the training set only. The dataset was split by device into 80% training, 10% validation, and 10% test sets to ensure that models were evaluated on unseen devices.

This study follows a quantitative comparative research design, where multiple ML models were evaluated under identical conditions. Four models were implemented: RF, GB, SVR, and LSTM.

The RF and GB models were implemented using ensemble decision trees, while SVR was implemented using a radial basis function (RBF) kernel. These three models were trained using tabular features including battery capacity, temperature, charge cycles, screen-on time, and brightness.

The LSTM model was trained using sequential data constructed with 20-day sliding windows to capture temporal degradation behaviour. The network consisted of one LSTM layer followed by a dense output layer. The model was trained using the Adam optimiser with mean squared error as the loss function. Early stopping was applied based on validation performance to reduce overfitting.

Training was conducted using the 80% training set. The 10% validation set was used for hyperparameter tuning and early stopping. Final model performance was evaluated on the separate 10% test set, which was not used during training or tuning. Performance was measured using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

Following evaluation, the predicted RUL values were mapped to circular economy decisions. Devices with higher predicted RUL were considered suitable for refurbishment or resale, devices with moderate predicted RUL were recommended for repair, and devices with low predicted RUL were directed toward recycling. This step links the technical model outputs to practical circular economy decision-making.

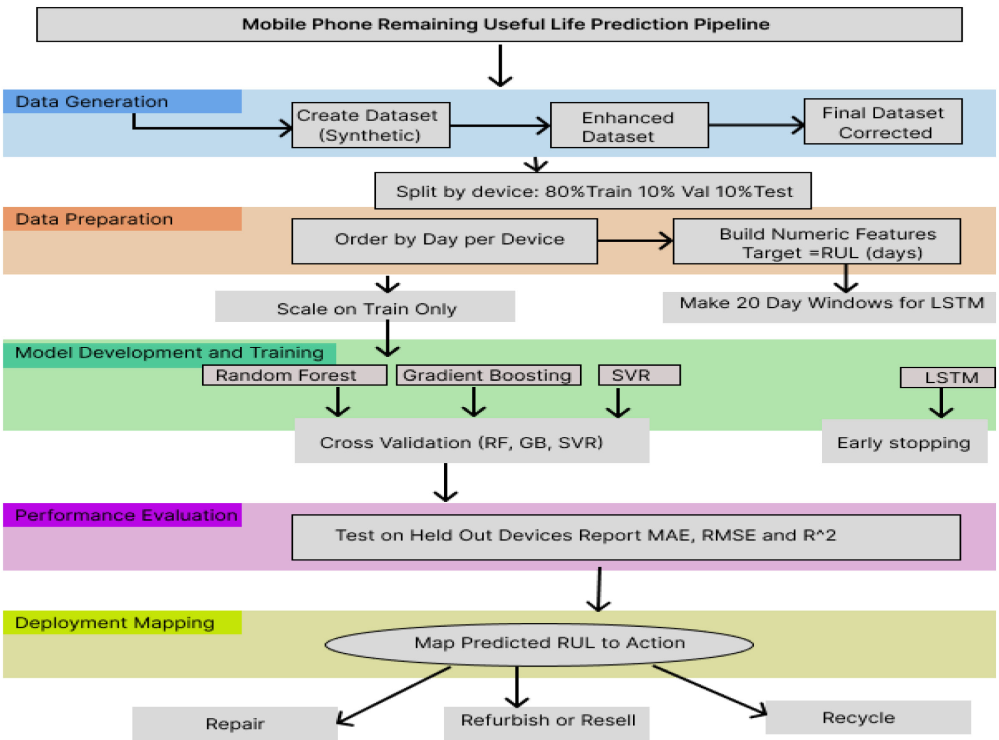

Figure 1: Mobile phone Remaining Useful Life prediction pipeline.

3. Results

This section presents the results of the ML models used to predict the RUL of mobile phones.

3.1 Model Performance Summary

The numerical performance of all models is quantified through the numerical evaluation metrics shown in Table 1. The table includes the MAE, RMSE, and R^2 score for each model. A lower MAE and RMSE indicate smaller prediction errors, while a higher R^2 means the model fits the data better. The LSTM model achieved the best overall performance.

Table 1: Summary of model performance results.

Model	MAE (days)	RMSE (days)	R^2
RF	176.00	247.52	0.405
GB	181.38	247.72	0.404
SVR	219.69	249.02	0.163
LSTM	**153.09**	**230.60**	**0.469**

A visual summary of model performance is shown in Figure 2. The figure presents the MAE, RMSE, and R^2 scores for all evaluated models. Consistent with Table 1, the LSTM model achieved the lowest prediction errors and the highest R^2 value.

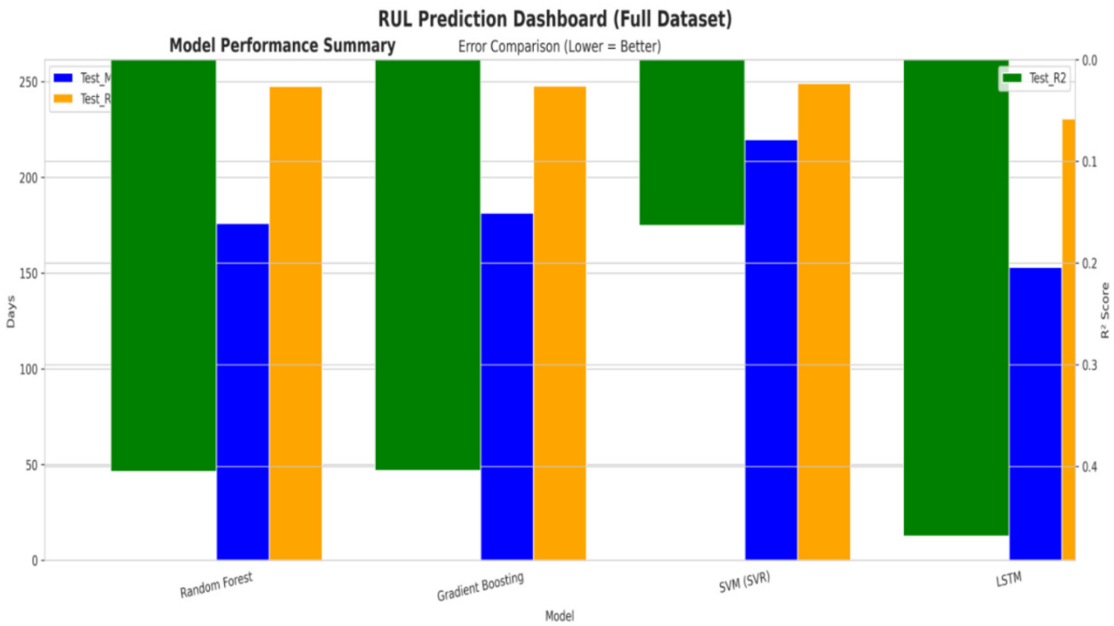

Figure 2: Top: Model performance summary. Bottom: Random Forest results.

3.2 LSTM Results

Figure 2 compares the performance of all evaluated models using MAE, RMSE, and R^2 metrics. Lower MAE and RMSE values indicate smaller prediction errors, while higher R^2 values indicate better model fit. The LSTM model achieved the lowest MAE and RMSE and the highest R^2 among all models, indicating the strongest predictive performance in this study.

The detailed behaviour of the LSTM model is shown in Figure 3. The left plot illustrates the relationship between true and predicted RUL values, with the diagonal line representing perfect prediction. While the model captures the general degradation trend, predictions are compressed within a narrower range and tend to underestimate higher true RUL values.The right plot presents the distribution of absolute prediction errors. Most errors are concentrated at lower values, although a tail of larger errors is observed. These results are consistent with the moderate R^2 value and suggest that while LSTM performs best among the evaluated models, there remains room for improvement in prediction accuracy.

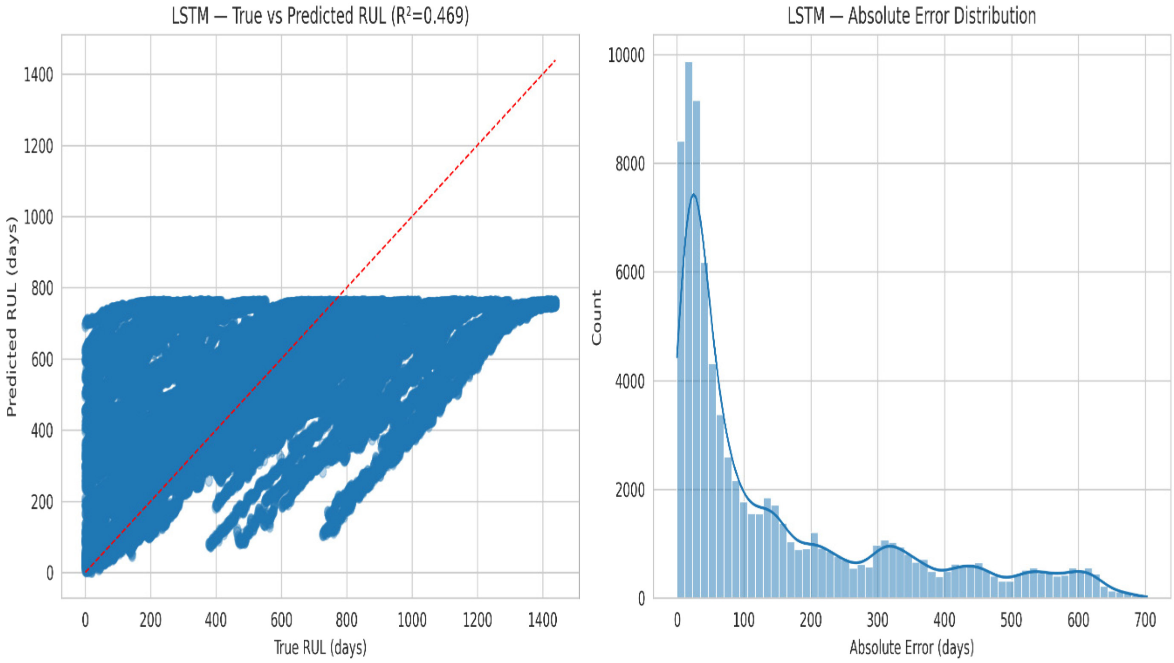

Figure 3: LSTM model results showing true vs predicted RUL and absolute error distribution.

3.3 Limitations of the Results

Although the LSTM model produced the best results, the findings of this study have several limitations. The dataset used in this study was synthetic because real long-term mobile phone device datasets are not publicly available. This means the model was trained on simulated behaviour, which may not fully capture the complexity and variability of real devices. Some indicators, such as app usage patterns or network activity, were not included in the dataset, which may affect the accuracy of real-world RUL predictions. The models were also evaluated on data from the same synthetic source, so their performance may differ when applied to real device data. Finally, although LSTM showed lower errors than the other models, the prediction uncertainty was still noticeable at higher RUL values. These limitations show the need for future work using real device datasets and more detailed indicators.

4. Business Benefits

This work provides practical benefits for organisations managing large numbers of mobile devices, including those operating in repair, refurbishment, and e-waste management industries. By predicting the RUL of mobile phones, organisations can make better decisions about maintenance, repair, resale, or recycling, helping to optimise costs and resource use.

RUL estimates allow businesses to anticipate device degradation and plan actions in advance. This supports more efficient maintenance scheduling, improved inventory planning, and better budgeting. For example, refurbishment companies can prioritise devices with higher remaining life for resale, repair centres can assess whether repair is economically viable, and mobile network operators can plan upgrade programmes more effectively. E-waste management organisations and government agencies can also use RUL estimates to design more targeted reuse and recycling strategies.

From an economic perspective, improved RUL prediction supports better cost control, resale planning, and resource allocation. From a societal perspective, extending device life contributes to reduced electronic waste and supports broader circular economy objectives.

Practical implementation would require access to real device-level data and integration with existing diagnostic systems. Pilot testing with industry partners and validation using real-world datasets would be necessary before full deployment, along with careful consideration of data privacy and system integration requirements.

5. Conclusions

This paper presented a ML approach for predicting the RUL of mobile phones to support better device management and circular economy practices. The results show that synthetic degradation modelling can be used to simulate long-term device behaviour when real datasets are not available. Among the models evaluated, the LSTM model achieved the best performance, demonstrating the importance of capturing temporal degradation patterns.

One important lesson from this study is that incorporating multiple degradation indicators allows device ageing to be analysed from a broader perspective. By combining features such as temperature, charge cycles, screen-on time, brightness, and battery capacity, the framework considers several aspects of device behaviour rather than focusing on a single parameter. This supports more informed decision-making in circular economy contexts.

Compared to previous related work, this study moves beyond single-indicator battery prediction by integrating multiple degradation factors into a comparative machine learning framework specifically designed for consumer mobile devices. This contributes to bridging the gap between industrial predictive maintenance models and consumer electronics applications within a circular economy context.

For projects in similar areas, it is important to clearly define degradation assumptions, validate model performance carefully, and ensure that prediction outputs are linked to practical decision-making processes. Without this connection, technical models may not translate into real-world impact.

Future work will focus on validating the framework using real-world device usage datasets and testing the model in collaboration with refurbishment and repair organisations. Further research may also explore advanced deep learning architectures and uncertainty estimation techniques to improve prediction reliability. From a practical perspective, pilot implementation and industry partnerships would be necessary steps toward real-world deployment and commercial application.

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Declaration of use of content generated by Artificial Intelligence (AI) (including but not limited to Generative-AI) in the paper

The authors acknowledge the use of Artificial Intelligence (AI) tools, including ChatGPT, in the paper entitled *"Predicting the Remaining Useful Life of Mobile Devices to Support Circular Economy Decisions"*. AI was used to generate the synthetic dataset used for the modelling experiments, and to help simplify and clarify written text, as well as improve grammar and readability.

All model development, analysis, training, evaluation, figures, and results were carried out by the author.

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