

A Metaheuristic-based Machine Learning Approach for Energy Prediction in Mobile App Development

Seyed Jalaeddin Mousavirad and Luís A. Alexandre

Abstract—Energy consumption plays a vital role in mobile App development for developers and end-users, and it is considered one of the most crucial factors for purchasing a smartphone. In addition, in terms of sustainability, it is essential to find methods to reduce the energy consumption of mobile devices since the extensive use of billions of smartphones worldwide significantly impacts the environment. Despite the existence of several energy-efficient programming practices in Android, the leading mobile ecosystem, machine learning-based energy prediction algorithms for mobile App development have yet to be reported. Therefore, this paper proposes a histogram-based gradient boosting classification machine (HGBC), boosted by a metaheuristic approach, for energy prediction in mobile App development. Our metaheuristic approach is responsible for two issues. First, it finds redundant and irrelevant features without any noticeable change in performance. Second, it performs a hyper-parameter tuning for the HGBC algorithm. Since our proposed metaheuristic approach is algorithm-independent, we selected 12 algorithms for the search strategy to find the optimal search algorithm. Our finding shows that a success-history-based parameter adaption for differential evolution with linear population size (L-SHADE) offers the best performance. It can improve performance and decrease the number of features effectively. Our extensive set of experiments clearly shows that our proposed approach can provide significant results for energy consumption prediction.

Index Terms—Energy prediction, mobile App, differential evolution, histogram-based gradient boosting classification, sustainability.



1 INTRODUCTION

DEVELOPERS are very concerned about how their Apps affect the battery life of phones. One of the most common reasons Apps receive bad reviews in App stores is excessive energy consumption [6], [14]. Developers are aware of the energy consumption and often ask for help fixing it, even though they rarely get satisfactory advice [16], [24]. In addition, mobile device manufacturers publish guidelines for developers with the aim of increasing energy efficiency. Also, energy consumption is one of the critical elements affecting mobile device consumers' pleasure. Battery life is identified as the most crucial aspect influencing smartphone purchase decisions in a recent poll of 1898 smartphone users in the US [6], [14]. Energy consumption by a smartphone has become a concern in recent years. For instance, it has been estimated that 9 out of 10 consumers experience low battery anxiety [16], [24].

From a sustainability perspective, finding ways to make mobile devices use less energy is essential. Also, the billions of phones that are used today have a significant impact on the world. For instance, our use of digital devices, like smartphones and tablets, will likely considerably affect global warming more than the aviation industry [9].

Optimising, or even just analysing, how much energy mobile devices use is a complicated and time-consuming

task for users and/or developers. Keeping track of how much energy an App uses requires many tests in different situations and on several devices, which is a time-consuming task. Developers might use several monitoring tools, often leading to context-specific findings. Android is also a heterogeneous platform. There are likely 3,3 billion Android smartphone users in 190 countries around the world¹. Developer's perception of how hardware works is limited to their own devices and without the right tools and skills, they cannot compare how their Apps use energy or see how Apps work on other devices or in different settings and situations. Also, the energy behaviour of the same App changes depending on how it is used, such as in different OS versions or with varying components of hardware turned on. This is something that has to be taken into account when making a comparison.

In the past few years, several studies [2], [10], [11], [19], [27], [34] have considered energy-aware programming trends in Android and tried to find better alternatives, while automatic energy consumption prediction has not been seriously discussed. For instance, [20] used proxy metrics, such as CPU usage and the number of bytes written to memory, to investigate their suitability as predictors for the energy consumption of a music streaming application on a mobile device. They examined several experiments on two Apps, Spotify music and podcast App, to find how these proxies were affected by the energy consumption. In another study [21], a large-scale user study was performed

• Seyed Jalaeddin Mousavirad is with the Universidade da Beira Interior, Covilhã, Portugal.

• Luís A. Alexandre is with Universidade da Beira Interior and NOVA LINCS, Covilhã, Portugal.

Manuscript received ...; revised ...

1. <http://www.bankmycell.com/blog/how-many-android-users-are-there>

to measure the energy consumption characteristics of 15500 BlackBerry smartphone users. By making a large-scale data set, they made the Energy Emulation Toolkit (EET), which lets developers compare the energy needs of their Apps to real user energy traces. In another work, [15] used machine learning (ML) and smartphone environment data to determine if a smartphone's next unlock event can be predicted. They showed that it is possible to predict when the next unlock event will happen by doing a 2-week field study with 27 people, leading to improve accuracy and saving energy by using only software-related background data. They suggest reducing energy consumption by using short-term predictions to reduce needless executions or starting computation-intensive tasks, like OS updates, when the phone is locked. For example, by guessing when the next phone open will happen, smartphones can collect sensor data or prepare content in advance to improve the user experience for the next time the phone is used. In one recent study, [18] indicated two proxies based on image properties for energy consumption: image file size and image quality. In other words, increasing image file size and image quality can elevate energy consumption. They then proposed a multi-objective approach to address this issue. However, they ignored the user's opinion. Therefore, [17] included the user opinion by changing the encoding representation. Thus, despite several works, the literature review shows no report on predicting energy consumption using machine learning algorithms.

This paper proposes a metaheuristic-based machine learning approach for the prediction of energy consumption in smartphones. Our proposed algorithm benefits from a histogram-based gradient boosting classification machine (HGBC) for the modelling process and a metaheuristic-based approach for the hyper-parameter tuning and feature selection process. HGBC is an ensemble machine learning algorithm that uses the data histogram for a gradient boosting-based model. We selected the HGBC classifier since this method provided the best results in our initial experiments and compared it to 25 classification algorithms. Our proposed metaheuristic-based machine learning algorithm has two different tasks: finding adequate features (feature selection) and hyper-parameter tuning. In the feature selection step, we aim to find suitable features because they can enhance the prediction performance and reduce the number of features that form the state of a smartphone. To this end, we proposed a two-part real-valued encoding representation. The first part is dedicated to the feature selection process, while the second is assigned to the HGBC hyper-parameters. Since our proposed metaheuristic-based machine learning algorithm is algorithm-independent, we selected 12 well-established and state-of-the-art algorithms for the search strategy. Among them, a success-history-based parameter adaption for differential evolution with a linear population size reduction (L-SHADE) performs best and is selected as the final approach.

Therefore, the main contributions of this paper are as follows:

- We proposed a machine learning-based approach for energy prediction in mobile App development. This work is the first study for energy prediction in mobile App development.

- Our machine learning algorithm benefits from an ensemble algorithm to boost the results (HGBC algorithm).
- We introduced a new metric, energy consumption per minute (ECPM), for assessing the energy consumption of a smartphone.
- We proposed a metaheuristic approach for simultaneous feature selection and hyper-parameter tuning.
- Since our proposed metaheuristic approach is algorithm-independent, we applied our approach to 12 different search strategies. Among them, L-SHADE is selected as the final algorithm.
- We proposed a novel representation for our proposed metaheuristic approach so that it can perform both tasks effectively, feature selection and hyper-parameter tuning, and in a parallel way.
- To the best of our knowledge, the LSHADE algorithm, the best-performing PBMH algorithm compared to others, has yet to be applied for the feature selection problem and parameter-tuning for the HGBC classifier. Therefore, this paper is the first attempt to examine the effectiveness of the LSHADE algorithm for these two problems.
- From a sustainability perspective, this approach can play a vital role in green computing.

The remainder of the paper is organised as follows. Section 2 briefly describes the background knowledge, while Section 3 explains our proposed algorithm. Section 4 provides results and discussion. Finally, Section 5 concludes the paper.

2 BACKGROUND KNOWLEDGE

This section provides background knowledge regarding histogram-based gradient boosting classification machine, feature selection, and the L-SHADE algorithm.

2.1 Histogram-based Gradient Boosting Classification Machine

Histogram-based Gradient Boosting Classification Machine (HGBC), Figure 1, is an approach for building a classification model that combines a gradient boosting machine with a histogram-based algorithm. Gradient boosting is the name given to a group of machine learning models that use simple models, here decision trees, as base learners. A succeeding tree in an ensemble depends on its ancestors. This is so that the later tree aims at decreasing the misclassified instances performed by the former. During the model training phase, the loss function, which measures the misclassification rate of the entire ensemble, is slowly reduced through this process. After the training phase, a strong committee can be built based on several weak classifiers.

In addition, the histogram-based approach, Figure 2, is a method for gradient boosting-based model training, leading to discretising the ranges of continuous features into small bins. These bins are then handled to construct histograms representing the distribution of features' values. The statistical information about the histogram allows for determining the optimal split points for training the base learners. Because the training stage of a decision tree does

not necessitate scanning the whole range of features for split point evaluation, the histogram-based technique can significantly lower the computing cost [13]. Additionally, because the training phase is less vulnerable to noise, the histogram-based technique can also improve generalisation [23].

2.2 Feature Selection for Classification Tasks

Feature selection aims to select suitable features for a given data set. Assume that a data set includes D features (F_1, \dots, F_D) . The feature selection techniques seek to minimise a specified performance function (H) by obtaining a feature subset S with d features chosen from the initial feature set ($d \leq D$). H typically reflects the classification error rate when selecting features for a classification task.

Mathematically speaking, feature selection aims to find a subset of features $S^* \subseteq \mathbb{R}^D$ among all possible combinations so that

$$H(S^*) \leq H(S_j), \forall S_j \in \mathbb{R}^j \quad (1)$$

where $1 \leq j \leq D$.

Generally speaking, feature selection methods are divided into three leading categories: wrapper, filter, and embedding. Filter methods employ a statistical analysis (e.g. the correlation among features and classes) for selecting the optimal features. In contrast, wrapper methods select a subset of features based on the results of classification algorithms. In addition, embedding methods perform the feature selection task as a part of the learning process. PBMH algorithms such as genetic algorithm (GA) [26], particle swarm optimisation (PSO) [28], and differential evolution (DE) [1] can be used as a wrapper-based feature selection. More details of existing PBMH-based feature selection can be seen in [36].

2.3 L-SHADE Algorithm

In this paper, we applied our strategy to 12 PBMH algorithms. Since the L-SHADE algorithm outperforms other algorithms and is selected as the final algorithm, we explain this algorithm in detail here, while for other algorithms, more details can be seen in the cited publications.

Differential Evolution (DE), proposed by Storn and Price [29], is one of the most effective PBMH algorithms. The DE algorithm uses three leading operators: mutation, crossover, and selection. Crossover moves the mutant vector and its parent, whereas mutation tries to produce mutant vectors based on the differences among possible solutions. The selection operator makes a greedy choice between the newly produced trial and its parent to pass on the best candidate solution to the subsequent generation. Moreover, the DE method contains three distinct control parameters: F , CR , and NP . These three parameters represent the scaling factor in the mutation operator, crossover rate, and population size, respectively. The problem-dependent parameter values significantly influence the DE algorithm's performance. One of the state-of-the-art variants of the DE algorithm, success-history-based parameter adaptation for DE (SHADE) [31], has demonstrated excellent performance over DE. The SHADE algorithm changes the parameters F and CR adaptively, while the NP is fixed. SHADE with

Linear Population Size Reduction (L-SHADE) [32] algorithm, the winner of CEC2017 Evolutionary Computation Challenges, adds an adaptive population size to the SHADE algorithm. The main components of the L-SHADE algorithm are described below.

2.3.1 External Archive

In order to maintain diversity, SHADE uses an external archive (A). To this end, parent vectors inferior to the trial vector, $u_{i,G}$, are preserved. Then, the combination of the external archive and the current population ($A \cup P$) is employed in the mutation strategy for updating the position.

2.3.2 Mutation Strategy

The SHADE algorithm uses the *current-to-pbest/1* strategy method to update each candidate solution as

$$v_{i,G} = x_{i,G} + F_i(x_{pbest,G} - x_{i,G}) + F_i(x_{r1,G} - x_{r2,G}) \quad (2)$$

where $x_{pbest,G}$ is a randomly selected candidate solution from the top $N \times p$ candidate solutions, and $p \in [0, 1]$, where p specifies the greediness of the strategy. In addition, F_i denotes the F parameter value by x_i . $x_{r1,G}$ is a random candidate solution selected from the population, P , while $x_{r2,G}$ is a candidate solution selected randomly by $A \cup P$. The size of the Archive is matched to the population size.

Moreover, the SHADE method uses an adaptive technique to adjust the parameter p such that each candidate solution has a unique p that is set as

$$p_i = rand\left[\frac{2}{N}, 0.2\right]. \quad (3)$$

2.3.3 History Based Parameter Adaptation

A historical memory containing H entries helps the SHADE algorithm maintain control over the parameters CR and F . First, the entire contents of memory are set to $0.5(M_{CR}$ and $M_F)$. In each iteration, a random integer number, indicating a random entry, r_i , should be chosen in the range of $[1, H]$. Then, the parameters CR_i and F_i are defined as

$$CR_i = randn_i(M_{CR,r_i,0.1}) \quad (4)$$

$$F_i = randc_i(M_{F,r_i,0.1}) \quad (5)$$

where $randn_i(\mu, \sigma^2)$ and $randc_i(\mu, \sigma^2)$ are responsible for generating random numbers, with mean μ and variance σ^2 using the normal and Cauchy distributions, respectively. CR and F produced values should be constrained to $[0, 1]$.

The CR_i and F_i values used by good candidate solutions are kept in S_{CR} and S_F . In other words, S_{CR} and S_F included the CR_i and F_i values that successfully generate a trial vector superior to the parent individual. The memory contents should be updated at the end of each iteration as

$$M_{CR,K,G+1} = \begin{cases} mean_{WA}(S_{CR}) & \text{if } S_{CR} \neq 0 \\ M_{CR,K,G} & \text{otherwise.} \end{cases} \quad (6)$$

$$M_{F,K,G+1} = \begin{cases} mean_{WL}(S_F) & \text{if } S_F \neq 0 \\ M_{F,K,G} & \text{otherwise.} \end{cases} \quad (7)$$

where K shows an index, initialisation by 1, indicating the memory location between 1 and H . Furthermore, $mean_{WA}$ and $mean_{WL}$ denote the weighted arithmetic and weighted Lehmer means.

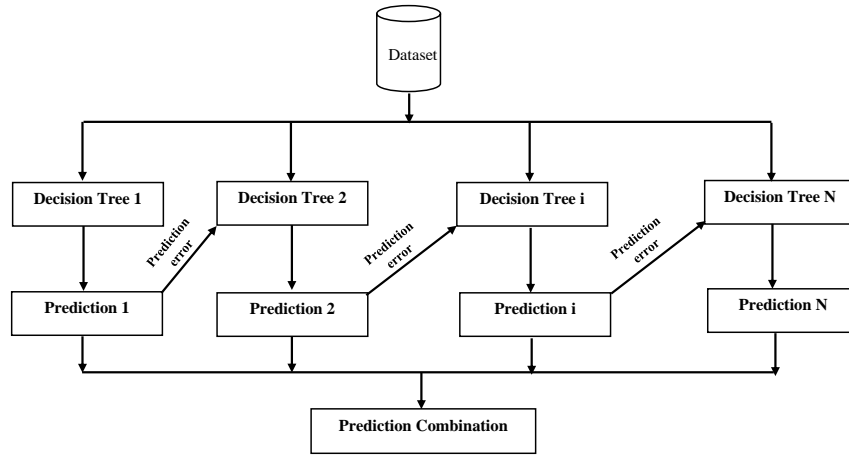


Fig. 1: General structure of a gradient boosting ensemble.

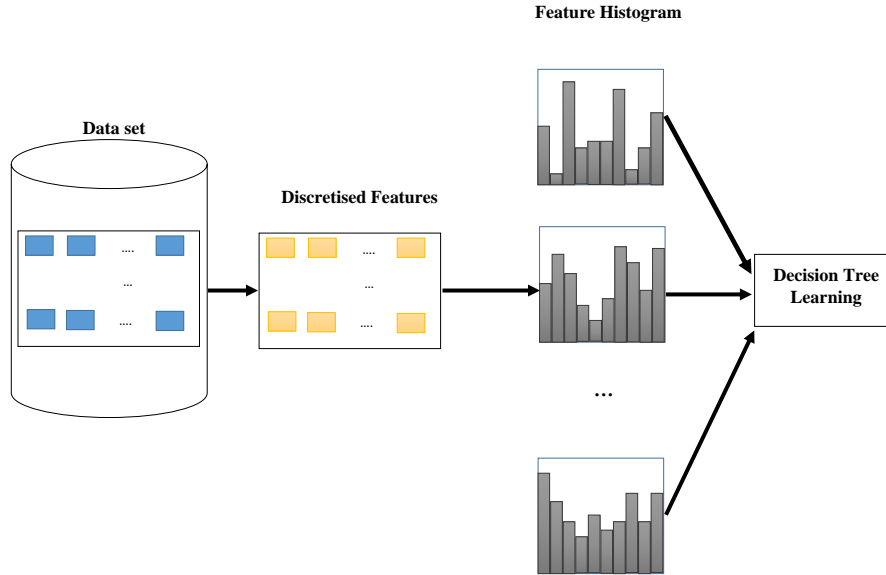


Fig. 2: Illustration of the histogram-based algorithm.

2.3.4 LPSR Technique

The population size, P , is not altered by the SHADE method, but the parameters F and CR are. Smaller populations tend to converge more quickly, while larger populations tend to explore more and slow the convergence rate. In order to reduce the population size throughout the optimisation phase, L-SHADE uses a Linear Population Size Reduction (LPSR) technique, defined by the number of function evaluations. To put it another way, the population size is continuously decreased using LPSR using a linear function as

$$P_{G+1} = \text{round} \left[\frac{P^{min} - P^{int}}{Max_{NFE}} \cdot NFE + P^{int} \right] \quad (8)$$

where P^{min} is the minimal population size, which here is 4 because *current-to-pbest/1* strategy calls for a minimum of 4 candidate solutions, P^{int} shows the initial population size in the first iteration, Max_{NFE} is the maximum number of function evaluations, and NFE is the current number of function evaluations. Also, P_{G+1} denotes the population size in the next generation.

3 THE PROPOSED ALGORITHM

This paper proposes a novel metaheuristic-based machine learning algorithm for energy prediction in mobile App development. To this end, our proposed algorithm employs an HBGC classifier for the modelling process and proposes

a metaheuristic algorithm for selecting the relevant features as well as hyperparameter tuning. Our ML-based energy prediction approach can be deployed for android App development in different techniques:

- Clung-App technique: the ML component is part of an App, which causes this component to exist in a smartphone as many Apps on the same smartphone, which is redundant.
- Clung-Android technique: in this technique, the ML component is a part of Android as a built-in component. While this technique might be the best, it would require major backers, such as Google, to decide that such a built-in component is a viable option, which is currently not feasible.
- Independent-App technique: the ML component is presented as an independent App. It is challenging to persuade a user to install an additional App on top of the App required by the user.
- Web service technique: the ML component acts as a web service in this technique. Therefore, whenever an application intends to use this component, it can send a request to the web service and receive a recommendation. This method works well until major Android backers decide that a built-in ML-based component for energy consumption is necessary.

3.1 Data set

We have used the GreenHub data set [22]. This data set includes more than 23 million instances, from over 900 brands and 5,000 models, across 160 countries. It consists of three types of information, including sample data set, device data set, and App processes data set. The sample data has several details on different smartphone settings, while the device data set includes several device features such as brands. In addition, the App processes data set has features related to the installed Apps in each smartphone.

In this paper, we only used the sample data set and ignored App processes and device data sets. We disregarded App processes because we aim to propose a predictive algorithm independent of the installed applications. In addition, since each geographical region has its native applications, it will make the predictive process challenging. For example, while the popular messenger software in China is *Wechat*, it is *WhatsApp* in Portugal. Therefore, if these features are used, the data set will be sparse. Also, ignoring this data set will make the results independent of the geographical area. The same circumstances also are applicable to the device data. Therefore, we can say that the results are only dependent on the Android settings.

The sample data set has seven types of features, from which we selected 32 features. The features are listed below, while more details can be seen in [22]:

- Battery details: charger (unplugged or plugged), health, voltage, and temperature,
- CPU states: usage, uptime, and sleep time,
- Network details: network type, mobile network type, mobile data status, mobile data activity, roaming enabled, wifi status, wifi signal strength, wifi link speed,
- Samples: battery state, battery level, memory free, memory user, network status, screen brightness, screen on,

- Settings: Bluetooth enabled, location enabled, power saver enabled, flashlight enabled, NFC enabled, developer mode
- Storage Details: free, total, memory active, and memory inactive.

3.2 Preprocessing

This step is responsible for transforming or encoding the existing data set so that the machine learning algorithms can easily work on it. The steps are listed below.

3.2.1 Instance Elimination

In this step, we eliminated the instances including “battery-state=charging” since our goal is to predict the energy consumption in the discharging state. Also, the instances with missing values are removed from the data set.

3.2.2 ECPM Metric

In this paper, we defined a new metric to show the amount of energy consumed per minute by a smartphone. Energy Consumption Per Minute (ECPM) is defined as

$$ECPM = \frac{BT_{state1} - BT_{state2}}{TS_{state1} - TS_{state2}} \quad (9)$$

where BT_{state1} is the battery level in state 1, while TS_{state1} means the time stamp in state 1. In addition, State 1 and State 2 are two consecutive states. State of a smartphone here means the current settings of a smartphone, such as Bluetooth and Wifi states (on/off). Also, we have two assumptions. First, the current state of a smartphone is not dependent on the earlier states, and second, the smartphone settings have not changed between the consecutive states. ECPM can be used as a metric for energy consumption. Lower values of ECPM show a lower energy consumption. Since we assumed that there are no smartphone settings changes in two consecutive states, if “battery-state=charging” state is between two “battery-state=discharging” states, the corresponding instance is not considered for our new metric.

3.2.3 Histogram Analysis

Since this research considers the energy prediction as a classification problem, here we have assigned each instance to a class based on ECPM metric. The number of selected classes is three, namely safe, warning, and critical status. Assigning each sample into a class depends on the mobile App developer, for example, for one developer, $ECPM=0.5$ may be high, but for another developer, this value is in a safe state. Since we have no knowledge of developer interest, here, we used a histogram analysis to select classes, although this could easily change later. From the histogram, instances with $ECPM < 0.5$ are assigned to the first class, while instances with $ECPM > 1.5$ are set to another class. Also, the remaining instances belong to the third class.

3.3 Metaheuristic-based HGBC Algorithm

This paper proposes a metaheuristic-based HGBC algorithm for the modelling process. For this, three issues to be determined are the structure of each candidate solution (representation), the objective function, and the search strategy, which we define in the following.

3.3.1 Representation of Solutions

Our proposed PBMH aims to find the optimal features, numbers, and parameters for the HGBC classification algorithm. Therefore, we proposed a two-part candidate solution: a real-valued vector of length $N_D + N_P$. The first N_D elements are in the interval $[0,1]$ and are employed for selecting the features. The remaining elements indicate the N_P parameters of the HGBC classification algorithm.

The first part of our proposed representation is dedicated to the feature selection process, which is a string with a length equal to the number of features (here, it is 32). The vector's cells are initialised at random with real values between 0 and 1. Despite the use of this representation in continuous search space [35], we used this representation since the operators in the employed search algorithms are designed for the continuous search space, and the goal of this paper is not to define new operators for discrete search spaces. Therefore, a feature is used when a cell's value is above 0.5. Thus, the feature set can be defined by the following notation: The value of the corresponding cell changes to 1 when a feature is selected and to 0 otherwise. As a result, the string is transformed into a binary vector, where 0 denotes the feature's rejection, and 1 denotes its selection.

The second part of our representation is assigned to the HGBC parameters, learning rate (lr), minimum leaf nodes ($MnLN$), maximum leaf nodes ($MxLN$), L2 regularisation, and maximum bins (mb). The boundary of the search space in these parameters is different from the first part of the representation. The lr parameter is set as a number between 0.001 (as a negligible number close to 0) and 1, while L2 regularisation is a number between 0 and 3. Other boundaries for $MnLN$, $MxLN$, and mb are set as [1,29], [30,100], and [2,255]. Since $MnLN$, $MxLN$, and mb should be integer numbers, after each continuous operation in the search strategy, they are rounded to the nearest integer.

Therefore, the total length of our used representation is $(32+5=37)$. In addition, this paper aims to find both the optimal number of features and the parameters of the HGBC classification algorithm simultaneously using only one representation strategy.

It is worth mentioning that the search space size is large in our proposed representation. The solution space of the first part of our problem is 2^{32} . In addition, assume points are located equally with a distance of 0.01 in lr and L2 regularisation parameters. Therefore, the solution space size in this problem is at least $2^{32} \times 100 \times 300 \times 29 \times 71 \times 254$ which is a large number, and makes this a challenging process for the optimisation algorithms.

3.4 Objective Function

The objective function here is responsible for hyper-parameter tuning, and feature selection, simultaneously, which is calculated in three following steps:

- 1) In the first step to compute the objective function, the features corresponding to the representation should be selected. In other words, the input to the training phase will be only the features that have a value of one in the corresponding representation.

- 2) HGBC classification algorithms should be trained based on the selected features and the hyper-parameters available in the second part of the representation.
- 3) The objective function here is calculated based on a classification error, which is defined as

$$\text{Classification error} = \frac{100}{P} \times \sum_{p=1}^P \xi(x_p) \quad (10)$$

with

$$\xi(x_p) = \begin{cases} 1 & \text{if } o_p \neq d_p \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

where P is the number of instances, and for each input vector in training data, the corresponding desired output is d_p , and o_p is the predicted output.

This objective function can simultaneously measure both the feature quality and the adequacy of the hyper-parameters. To have robust results, the objective function is calculated using a k -fold cross-validation.

3.5 Search Strategy

This paper aims to find suitable features and hyper-parameters for the HGBC classification algorithm for energy prediction in mobile App development. Since the problem is novel, there is no research on this issue. Therefore, we selected 12 metaheuristic algorithms, including both base and state-of-the-art variants, as follows:

- Random search (RS),
- Genetic algorithm (GA) [5],
- Artificial bee colony (ABC) [12],
- Covariance matrix adaptation evolution strategy (CMA-ES) [8],
- Evolution strategy (ES) [37],
- Differential evolution (DE) [29],
- Hierarchical PSO Time-Varying Acceleration (HPSO-TVAC) [25],
- Phasor Particle Swarm Optimization (P-PSO) [7],
- Adaptive Differential Evolution With Optional External Archive (JADE) [38],
- Success-History Adaptation Differential Evolution (SHADE) [31],
- Linear Population Size Reduction Success-History Adaptation Differential Evolution (LSHADE) [32].

Our experiments (available in Section 4) showed that LSHADE outperforms other algorithms. Therefore, we focus on the LSHADE search strategy and propose LSHADE-HGBC as our final prediction approach, while the details of other strategies can be seen in the cited publications.

LSHADE-HGBC aims to find the optimal features and hyper-parameters of HGBC classification algorithms using the LSHADE algorithm. To this end, like other population-based algorithms, it starts with a set of randomly candidate solutions, and its structure is explained in Section 3.3.1. Then, the quality of each generated solution is evaluated by Eq. 10. The LSHADE algorithm is responsible for finding the optimal solutions based on the operators introduced in Section 2.3. The final solution is an array including both the features selected by the LSHADE-HGBC algorithm and the optimal hyper-parameters for HGBC classifier. These

Input : D : dimensionality of problem; NFE_{max} : maximum number of function evaluations; NP_{max} : maximum population size; NP_{min} : minimum population size; H : Memory size

Output: x^* : the best individual

```

 $M_F = 0.5, M_{CR} = 0.5, NFE = 0, t = 1, NP = NP_{max}$ 
Randomly generate initial population  $Pop$ 
Evaluate objective function value of each individual using Eq. 10 and
the new data set generated by the selected features and the
hyper-parameters embedded in an individual
 $x^* \leftarrow$ : the best candidate solution from the current population;
while  $NFE < MAX_{NFE}$  do
     $S_F = 0, S_R = 0$ 
    for  $i \leftarrow 1$  to  $NP$  do
        Generate random index  $r_i = rand(1, H)$ 
        Generate  $CR_i^t$  as  $randn_i(M_{CR}, r_i, 0.1)$ 
        Generate  $F_i^t$  as  $randc_i(M_F, r_i, 0.1)$ 
        Generate  $p_i^t$  as  $rand[p_{min}, 0.2]$ 
        Select  $x_{r1}$  randomly from current population
        Select  $x_{r2}$  randomly from combination of current population
        and archive
        Generate trial vector as
         $v_i^t = x_i^t + F_i^t(x_{best}^t - x_i^t) + F_i^t(x_{r1} - x_{r2})$ 
        for  $j \leftarrow 1$  to  $D$  do
            if  $rand_j[0, 1] < CR_i$  or  $j == j_{rand}$  then
                 $u_{i,j} = v_{i,j}^t$ 
            else
                 $u_{i,j} = x_{i,j}^t$ 
            end
        end
    end
    end
    for  $i \leftarrow 1$  to  $NP$  do
        if  $f(u_i^t) \leq f(x_i^t)$  then
             $x_i^{t+1} \leftarrow u_i^t$ 
        else
             $x_i^{t+1} \leftarrow x_i^t$ 
        end
        if  $f(u_i^t) < f(x_i^t)$  then
             $A \leftarrow x_i^t$ ;
             $S_{CR} \leftarrow CR_i^t$ 
             $S_F \leftarrow F_i^t$ 
        end
    end
    end
    When size of archive exceeds  $|A|$ , randomly delete individuals so
    that  $|A| \leq |P|$ 
    if  $S_{CR} \neq 0$  and  $S_F \neq 0$  then
        Compute  $M_{F,K}^{t+1} = mean_{WL}(S_F)$ 
        Compute  $M_{CR,K}^{t+1} = mean_{WA}(S_{CR})$ 
    end
    Perform LPSR as
     $NP = round[\frac{NP_{max} - NP_{min}}{MAX_{NFE}} \cdot NFE + NP_{max}]$ 
     $t = t + 1$ 
     $x_{best} \leftarrow$ : the best candidate solution from the current population
    if  $f(x^*) > f(x_{best}^t)$  then
         $x^* \leftarrow x_{best}^t$ 
    end
end
 $N\_Data \leftarrow$  select the optimal features based on  $x^*$  and create a new
data set
 $Opt\_param \leftarrow$  select the optimal parameters for HGBCM
classification algorithms
Apply HGBCM on the  $N\_Data$  data set by using the optimal
parameters ( $Opt\_param$ )

```

Algorithm 1: LSHADE-FS-HGBCM algorithm in the form of Pseudo-code.

parameters are used for the final evaluations. The proposed algorithm in the form of Pseudo-code is described in Algorithm 1.

3.6 Strength and Limitations

This paper examined a wide range of classification algorithms and PBMH algorithms to find the best predictive combination. One of the most important properties of the proposed algorithm is that it can predict effectively without any knowledge regarding the applications installed in a smartphone. This is important because it is much more challenging to ask a user for permission to know all the

Apps installed on the smartphone than to obtain an App's settings. Also, the number of Apps for Android is huge, and more Apps are provided daily. Providing a predictive algorithm by ignoring installed software can solve this problem to a large extent. Also, the proposed prediction algorithm is independent of the device. In other words, it can be applied on all brands and models.

Despite the strength of the proposed method, this research needs to address one crucial limitation: permission. Some of these features require permission from a user, so a user may not grant all these permissions to an App. In other words, the value of some features might not be present in the feature set. This case can not be handled by the proposed approach.

4 EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we provided an extensive set of experiments to assess our proposed algorithm. To this end, we selected two main criteria, accuracy and F-measure. For the experiments, we used k -fold cross-validation (kCV) So that a data set is divided into k almost equal parts. Each time, one part is used as test and the rest as training. This is repeated k times and the statistical results including mean and standard deviation (std.) are reported. The details of the data set we used are available in Section 3.1.

4.1 Performance Analysis

In this paper, we proposed 12 PBMH-based HBGC algorithms. All representation and objective functions are selected the same, and only their search strategy differs. The population size and the number of function evaluations, as the stopping criterion, for all algorithms are selected 50 and 800, respectively, while we have used default values for the other parameters given in Table 1.

The results are given in Table 2. From the table, LSHADE-HGBC provides the best results, while DE-HGBC and RS-HGBC perform worst. Most algorithms, including RS, ABC, CMA, ES, GA, PSO, HPSP, and DE, can not achieve better results than the HGBC algorithm with the default parameters, indicating the poor ability of these search strategies to find the optimal solutions. Among all algorithms, only JADE, SHADE, and L-SHADE, all the improved variants of DE, can enhance the results. In particular, LSHADE-HGBC can improve the classification error by more than 5%.

Due to the nondeterministic nature of metaheuristic algorithms, non-parametric statistical methods are required to understand the significance of the results. In this case, the alternative hypothesis H_1 indicates a statistically significant difference among the algorithms, whereas the null hypothesis H_0 asserts no statistical difference among the algorithms. The H_0 is the initial statistical assertion, and if the H_0 is shown to be false, the H_1 is accepted. To statistically compare the results, we applied the Wilcoxon signed rank test [4] at a significance level of 5% based on the 10CV classification results. The Wilcoxon signed-rank test was chosen since it does not presume normal distributions and is, therefore, safer than the t-test. In addition, the Wilcoxon test is less sensitive to outliers than the t-test [4]. Table 3 shows the Wilcoxon signed rank test results based on 10CV

TABLE 1: Parameter settings for the experiments.

Algorithms	Parameter	Value
RS	-	-
GA	PC	0.95
	PM selection	0.05 Tournament
ABC	limit	$n_e \times$ dimensionality of problem
	n_o	50% of the colony
	n_e	50% of the colony
	n_s	1
ES	λ	0.75
CMA-ES	-	-
DE	weighting factor	0.8
	crossover rate	0.9
	Strategy	DE/current-to-rand/1/bin
PSO	C1	2.05
	C2	2.05
	w_{min}	0.4
	w_{max}	0.9
HPSO-TVAC	C1	2.05
	C2	2.05
	w_{min}	0.4
	w_{max}	0.9
	ci	0.5
	cf	0
P-PSO	C1	2.05
	C2	2.05
	w_{min}	0.4
	w_{max}	0.9
JADE	weighting factor	0.8
	crossover rate	0.9
	Strategy	DE/current-to-rand/1/bin
	cr	0.5
	P_t	0.1
	A_p	0.1
SHADE, LSHADE	weighting factor	0.8
	crossover rate	0.9
	Strategy	DE/current-to-rand/1/bin
	Memory size	50

classification accuracy. From the table, we can observe that LSHADE outperforms others significantly since, in all cases, LSHADE is the winning algorithm, while JADE placed in the second rank because it wins against 10 other algorithms. The third rank belongs to SHADE, which was the winner in 9 cases. The overall subsequent best-performing algorithms are GA (7 wins, 1 tie, and 3 fails) and ABC (5 wins, 2 ties, and 3 fails). The worst algorithms are DE (11 fails), and RS (1 win and 10 fails). In addition, the same table is obtained for the results of the Wilcoxon signed rank test based on 10CV F-measure. Therefore, due to the limitation page, we did not include this table in the paper.

4.2 Comparison of Different Variants

This paper proposes a PBMH-based algorithm for energy prediction in an Android smartphone. The PBMH algorithm is responsible for finding the hyper-parameters of HGBC and feature selection. In this section, we aim to compare different variants of the proposed algorithm. In the first variant (FS-HGBC), the PBMH algorithm is responsible for only the feature selection process. In contrast, our proposed algorithm only can tune the hyper-parameters without any feature selection step in the second variant (THGBC). Also, we selected the LSHADE algorithm since it performs best.

TABLE 2: 10CV classification results for different PBMH-based THGBC algorithms.

Algorithms	Accuracy		F-measure	
	Mean	Std.	Mean	Std.
HGBC	79.33	1.86	79.13	1.88
RS-HGBC	77.95	1.69	77.76	1.74
ABC-HGBC	79.23	1.54	79.03	1.60
CMA-HGBC	78.68	1.69	78.46	1.70
ES-HGBC	79.13	1.43	78.88	1.54
GA-HGBC	79.49	1.81	79.30	1.87
PSO-HGBC	79.23	1.47	79.00	1.49
HPSO-HGBC	78.78	1.76	78.60	1.81
PPSO-HGBC	78.45	0.84	78.23	0.91
DE-HGBC	77.35	1.70	77.06	1.73
JADE-HGBC	80.18	1.40	80.08	1.38
SHADE-HGBC	80.08	1.53	80.00	1.76
LSHADE-HGBC	80.43	1.61	80.23	1.65

For FS-HGBC and THGBC, we changed the representation of solutions. In other words, FS-HGBC only has 32 elements, while THGBC has 5 parameters, which has caused the size of the search space to become much smaller in both variants.

The results can be seen in Table 4. By comparison between FS-HGBC and HGBC, we can observe that the results are almost the same, but it is imperative to mention two points: firstly, the number of features has decreased, which means that with fewer features, the algorithm was able to achieve the same performance, and secondly, the stability of the results, based on the standard deviation, has also improved (from 1.86 to 1.49 for accuracy and from 1.88 to 1.50 for the F-measure). The number of selected features after the feature selection process is 24, and some features, such as wifi signal speed and roaming enabled, are eliminated. Comparison between HGBC and THGBC indicates that the hyper-parameter tuning can enhance the classification error by more than 5%, showing the positive effect of hyper-parameter tuning. In addition, the results of LSHADE-HGBC are better than THGBC and FS-HGBC, meaning that the feature selection process can improve the final performance.

4.3 Comparison of Different Classifiers

In this experiment, we selected several classification algorithms for the modelling process. This experiment aims to find the best classification algorithms and justifies choosing the HGBC classifier as the base classifier of our proposed algorithm. The evaluated classifiers are linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), logistic regression (LR), passive aggressive classifier (PAC), stochastic gradient descent (SGD), decision tree (DT), Naive Bayes (NB), k -nearest neighbour (KNN), multi-layer perceptron (MLP), support vector classification (SVC), and five ensemble classifiers including adaboost, random forest (RF), extra tree classifier (ETC), gradient boosting classifier (GBC), and histogram gradient boosting classifier (HGBC). Also, we used DT with two different splitting criteria, accuracy (DT-AC) and gini-index (DT-GI), three different NBs, including Gaussian NB, Bernoulli NB, and multinomial NB, four different k for the KNN algorithm ($K = 3, 5, 7, 9$), two different structures for the MLP (with 100 and 200 neurons in the hidden layer), four different kernels for the SVC, including, linear, polynomial, RBF, and sigmoid, and two

TABLE 3: Results of Wilcoxon signed rank test based on the 10CV accuracy results. +, -, and = denote that the algorithm in the corresponding row is statistically superior to, inferior to, or equivalent to the algorithm in the corresponding column, respectively. The final column summarises the cumulative wins (w), ties (t), and losses (l) of each algorithm.

	RS	ABC	CMA	ES	GA	PSO	HPSO	PPSO	DE	JADE	SHADE	LSHAD	w/t/l
RS	-	-	-	-	-	-	-	-	+	-	-	-	1/0/10
ABC	+	-	+	=	-	=	+	+	+	-	-	-	5/3/3
CMA	+	-	-	-	-	-	=	=	+	-	-	-	2/2/7
ES	+	=	+	-	-	=	=	+	+	-	-	-	4/3/4
GA	+	+	+	+	-	=	+	+	+	-	-	-	7/1/3
PSO	+	=	+	=	=	-	+	+	+	-	-	-	5/3/3
HPSO	+	-	=	=	-	-	-	=	+	-	-	-	2/3/6
PPSO	+	-	=	-	-	-	=	-	+	-	-	-	2/2/7
DE	-	-	-	-	-	-	-	-	-	-	-	-	0/0/11
JADE	+	+	+	+	+	+	+	+	+	+	+	-	10/0/1
SHADE	+	+	+	+	+	+	+	+	+	-	-	-	9/0/2
LSHADE	+	+	+	+	+	+	+	+	+	+	+	+	11/0/0

TABLE 4: 10CV classification results for different variants of our proposed algorithm.

Algorithms	Accuracy		F-measure	
	Mean	Std.	Mean	Std.
HGBC	79.33	1.86	79.13	1.88
FS-HGBC	79.43	1.49	79.22	1.50
THGBCM	80.43	1.61	80.23	1.65
LSHADE-HGBC	81.02	1.34	80.76	1.42

splitting criteria for the RF algorithm, accuracy (RF-AC) and gini-index (RF-GI). Therefore, we tested 26 different classifiers for this experiment.

The 10CV results can be seen in Table 5. From the table, we can observe that LDA, QDA, linear models, NBs, and SVCs perform worst. In particular, the worst classifiers are SVC with polynomial kernel and PAC classifier. Ensemble classifiers provide the best results. Among the ensemble classifiers, HGBC works best, while adaboost performs worst. It is worthwhile to mention that minimum accuracy/F-measure for HGBC is 77.13/77.00, that is higher than maximum accuracy/F-measure for other algorithms. As a result, according to the merits of HGBC, we selected HGBCM as the final classifier for our proposal.

4.4 Comparison of LSHADE-based Feature Selection Algorithm with the Conventional Algorithms

In section 4.2, we showed that the proposed LSHADE-based feature selection could provide the same results with the HGBC classifier but with less features. This section compares this with several conventional feature selection algorithms, including chi-square (CS) [33], F-classify (FC) [30], and mutual information (MI) [3]. Since one of the input parameters of the conventional algorithms is the number of features, we run the experiments with all features. Figures 3 and 4 show the accuracy and F-measure results for different selected features. From the Figures, the highest accuracy and F-measure are obtained when the number of features is between 28 and 32 and the performance is almost the same. Therefore, we selected 28 features for comparison. The results can be seen in Table 6. However, the results of the proposed feature selection algorithm are the same as the conventional ones; it can find the number of features automatically. In addition, the proposed algorithm can achieve these results with fewer features. Therefore, we can

TABLE 5: Comparison of different classifiers.

Algorithms	Accuracy		F-measure	
	Mean	Std.	Mean	Std.
Discriminant Analysis				
LDA	56.83	1.71	56.25	1.79
QDA	50.24	1.87	46.63	2.46
Linear Models				
LR	56.71	1.89	55.74	1.94
PAC	48.23	7.47	45.46	7.41
SGD	55.31	2.20	53.60	2.78
Decision Trees				
DT-AC	67.13	1.40	66.97	1.40
DT-GI	67.06	1.72	66.88	1.74
Naive Bayes				
Gaussian NB	45.04	1.03	37.37	1.32
Bernoulli NB	52.79	1.23	52.12	1.35
Multinomial NB	50.60	1.78	48.87	1.66
K- Nearest Neighbors				
KNN (K=3)	62.41	2.10	62.26	2.06
KNN (K=5)	61.59	1.88	61.35	1.88
KNN (K=7)	60.94	2.18	60.43	2.22
KNN (K=9)	60.30	1.90	59.72	1.89
Multi-layer neural network				
MLP-V1	62.25	1.82	61.70	2.00
MLP-V2	65.26	1.57	64.98	1.76
Support Vector Machines				
SVC (linear Kernel)	56.23	1.84	54.51	1.94
SVC (Polynomial Kernel)	47.48	0.62	36.55	1.26
SVC (RBF Kernel)	55.38	1.50	52.82	1.56
SVC (Sigmoid Kernel)	54.01	1.56	50.76	1.75
Ensemble Classifiers				
Adaboost	63.61	2.36	63.52	2.38
RF-AC	77.16	1.61	76.82	1.70
RF-GI	77.24	1.90	76.83	2.00
ETC	62.61	2.46	62.43	2.38
GBC	70.49	1.79	70.22	1.83
HGBC	79.33	1.86	79.13	1.88

TABLE 6: Comparison of LSHADE-based feature selection with several conventional algorithms.

Algorithms	Accuracy	F-measure	Number of selected features
CS	78.66	78.66	28
FC	78.95	78.76	28
MI	79.33	79.13	28
FS-HGBC	79.33	79.13	24

say that the proposed feature selection performs better than the conventional feature selection algorithms.

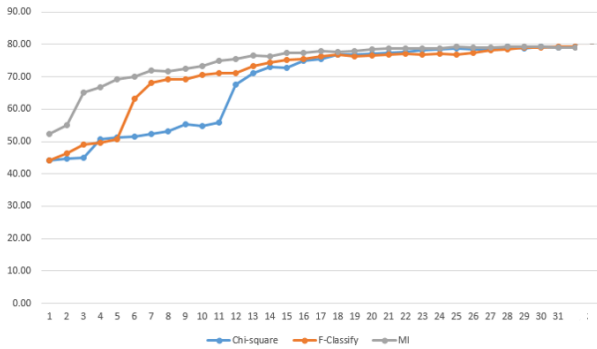


Fig. 3: The effect of conventional feature selection algorithms with different number of features in terms of accuracy.

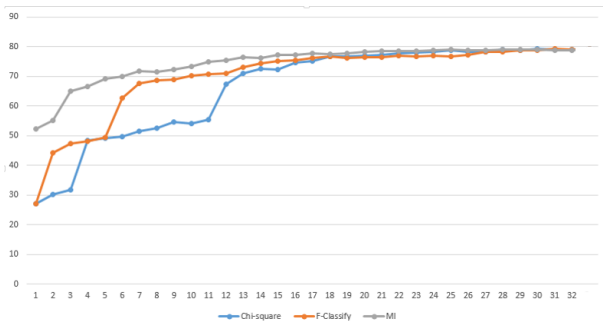


Fig. 4: The effect of conventional feature selection algorithms with different number of features in terms of F-measure.

5 CONCLUSION

Energy consumption is one of the crucial factors for both developers and users of mobile phone Apps, so the quality of an App is associated with the amount of energy it consumes. Knowing information about the future state of a smartphone’s energy consumption can enable the developer to manage energy consumption. Therefore, this paper proposes a metaheuristic-based machine learning for energy prediction in mobile App development. After some preprocessing of the data set, we introduced a new metric called Energy Consumption Per Minute (ECPM) for evaluating the energy consumption in an Android device. Then, we proposed a metaheuristic-based histogram-based gradient boosting classification machine (HGBC) for the modelling process. In this paper, the metaheuristic algorithm tackles two different issues: selecting the proper features (feature selection) and tuning the parameters of the HGBC classifier. Our extensive experiments clearly show that the proposed approach can provide satisfactory results. Also, we suggested deploying this approach in real-world problems in four ways: clung-App, clung-android, independent-app, and web service although currently the latter technique is the best approach. Regarding sustainability, our approach can play a crucial role in green computing since the energy consumption of digital devices, like smartphones, will likely considerably affect global warming further than the aviation industry [9].

Despite the satisfactory performance of the proposed approach, this work can be extended in the future by addressing the following issues:

- The proposed approach employs the combination of the HGBC classification algorithm and LSHADE metaheuristic algorithm for the prediction purpose. However, other algorithms, such as deep learning-based approaches, might have the potential to provide better results.
- This paper assumes that all the values in the used data set are present, while some features might be unavailable in practice. Considering this issue in the future is another direction.
- This paper employs an ensemble algorithm for the prediction, while the ensemble of solutions found by LSHADE is another possible direction to improve the results.

ACKNOWLEDGMENTS

This work was financed by FEDER (Fundo Europeu de Desenvolvimento Regional), from the European Union through CENTRO 2020 (Programa Operacional Regional do Centro), under project CENTRO-01-0247-FEDER-047256 – Green-Stamp: Mobile Energy Efficiency Services.

This work was supported by NOVA LINCS (UIDB/04516/2020) with the financial support of FCT-Fundação para a Ciência e a Tecnologia, through national funds.

REFERENCES

- [1] Wathiq Laftah Al-Yaseen, Ali Kadhum Idrees, and Faezah Hamad Almasoudy. Wrapper feature selection method based differential evolution and extreme learning machine for intrusion detection system. *Pattern Recognition*, 132:108912, 2022.
- [2] Abdul Ali Bangash, Karim Ali, and Abram Hindle. A black box technique to reduce energy consumption of android apps. In *Proceedings of the ACM/IEEE 44th International Conference on Software Engineering: New Ideas and Emerging Results*, pages 1–5, 2022.
- [3] Gavin Brown, Adam Pocock, Ming-Jie Zhao, and Mikel Luján. Conditional likelihood maximisation: a unifying framework for information theoretic feature selection. *The journal of machine learning research*, 13:27–66, 2012.
- [4] Joaquín Derrac, Salvador García, Daniel Molina, and Francisco Herrera. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm and Evolutionary Computation*, 1(1):3–18, 2011.
- [5] Alex S Fraser. Simulation of genetic systems by automatic digital computers ii. effects of linkage on rates of advance under selection. *Australian Journal of Biological Sciences*, 10(4):492–500, 1957.
- [6] Bin Fu, Jialiu Lin, Lei Li, Christos Faloutsos, Jason Hong, and Norman Sadeh. Why people hate your app: Making sense of user feedback in a mobile app store. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1276–1284, 2013.
- [7] Mojtaba Ghasemi, Ebrahim Akbari, Abolfazl Rahimnejad, Seyed Ehsan Razavi, Sahand Ghavidel, and Li Li. Phasor particle swarm optimization: a simple and efficient variant of PSO. *Soft Computing*, 23(19):9701–9718, 2019.
- [8] Nikolaus Hansen and Andreas Ostermeier. Completely derandomized self-adaptation in evolution strategies. *Evolutionary Computation*, 9(2):159–195, 2001.
- [9] J Harris. Our phones and gadgets are now endangering the planet. *The Guardian*, 17, 2018.
- [10] Geoffrey Hecht, Naouel Moha, and Romain Rouvoy. An empirical study of the performance impacts of android code smells. In *Proceedings of the international conference on mobile software engineering and systems*, pages 59–69, 2016.

- [11] Emanuele Iannone, Manuel De Stefano, Fabiano Pecorelli, and Andrea De Lucia. Predicting the energy consumption level of java classes in android apps: an exploratory analysis. In *Proceedings of the 9th IEEE/ACM International Conference on Mobile Software Engineering and Systems*, pages 1–5, 2022.
- [12] Dervis Karaboga and Bahriye Basturk. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *Journal of Global Optimization*, 39(3):459–471, 2007.
- [13] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30, 2017.
- [14] Hammad Khalid, Emad Shihab, Meiyappan Nagappan, and Ahmed E Hassan. What do mobile app users complain about? *IEEE software*, 32(3):70–77, 2014.
- [15] Chu Luo, Aku Visuri, Simon Klakegg, Niels van Berkel, Zhanna Sarsenbayeva, Antti Mötönen, Jorge Goncalves, Theodoros Anagnostopoulos, Denzil Ferreira, Huber Flores, et al. Energy-efficient prediction of smartphone unlocking. *Personal and Ubiquitous Computing*, 23:159–177, 2019.
- [16] Irene Manotas, Christian Bird, Rui Zhang, David Shepherd, Ciera Jaspan, Caitlin Sadowski, Lori Pollock, and James Clause. An empirical study of practitioners’ perspectives on green software engineering. In *Proceedings of the 38th international conference on software engineering*, pages 237–248, 2016.
- [17] Seyed Jalaleddin Mousavirad and Luís A Alexandre. Metaheuristic-based energy-aware image compression for mobile app development. *arXiv preprint arXiv:2212.06313*, 2022.
- [18] Seyed Jalaleddin Mousavirad and Luís A Alexandre. Energy-aware JPEG image compression: A multi-objective approach. *Applied Soft Computing*, page 110278, 2023.
- [19] Sona Mundody and K Sudarshan. Evaluating the impact of android best practices on energy consumption. In *IJCA Proceedings on International Conference on Information and Communication Technologies*, volume 8, pages 1–4, 2014.
- [20] Moa Nyman. Estimating the energy consumption of a mobile music streaming application using proxy metrics, 2020.
- [21] Earl Oliver and Srinivasan Keshav. Data driven smartphone energy level prediction. *University of Waterloo Technical Report*, 2010.
- [22] Rui Pereira, Hugo Matalonga, Marco Couto, Fernando Castor, Bruno Cabral, Pedro Carvalho, Simão Melo de Sousa, and João Paulo Fernandes. Greenhub: a large-scale collaborative dataset to battery consumption analysis of android devices. *Empirical Software Engineering*, 26:1–55, 2021.
- [23] Petra Perner. Decision tree induction methods and their application to big data. *Modeling and Processing for Next-Generation Big-Data Technologies: With Applications and Case Studies*, pages 57–88, 2015.
- [24] Gustavo Pinto and Fernando Castor. Energy efficiency: a new concern for application software developers. *Communications of the ACM*, 60(12):68–75, 2017.
- [25] Asanga Ratnaweera, Saman K Halgamuge, and Harry C Watson. Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients. *IEEE Transactions on evolutionary computation*, 8(3):240–255, 2004.
- [26] Lior Rokach. Genetic algorithm-based feature set partitioning for classification problems. *Pattern Recognition*, 41(5):1676–1700, 2008.
- [27] Jagannath Singh and Arpan Maity. Energy consumption-based profiling of android apps. In *Mobile Application Development: Practice and Experience: 12th Industry Symposium in Conjunction with 18th ICDCIT 2022*, pages 21–32. Springer, 2023.
- [28] Xian-fang Song, Yong Zhang, Dun-wei Gong, and Xiao-yan Sun. Feature selection using bare-bones particle swarm optimization with mutual information. *Pattern Recognition*, 112:107804, 2021.
- [29] Rainer Storn and Kenneth Price. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4):341–359, 1997.
- [30] B Surendiran and A Vadivel. Feature selection using stepwise anova discriminant analysis for mammogram mass classification. *ACEEE International Journal on Signal and Image Processing*, 2(1):17–19, 2011.
- [31] Ryoji Tanabe and Alex Fukunaga. Success-history based parameter adaptation for differential evolution. In *IEEE Congress on Evolutionary Computation*, pages 71–78. IEEE, 2013.
- [32] Ryoji Tanabe and Alex S Fukunaga. Improving the search performance of shade using linear population size reduction. In *IEEE Congress on Evolutionary Computation*, pages 1658–1665. IEEE, 2014.
- [33] Ikram Sumaiya Thaseen and Cherukuri Aswani Kumar. Intrusion detection model using fusion of chi-square feature selection and multi class svm. *Journal of King Saud University-Computer and Information Sciences*, 29(4):462–472, 2017.
- [34] Leonhard Wattenbach, Basel Aslan, Matteo Maria Fiore, Henley Ding, Roberto Verdecchia, and Ivano Malavolta. Do you have the energy for this meeting? an empirical study on the energy consumption of the google meet and zoom android apps. In *Proceedings of the 9th IEEE/ACM International Conference on Mobile Software Engineering and Systems*, pages 6–16, 2022.
- [35] Bing Xue, Mengjie Zhang, and Will N Browne. Particle swarm optimization for feature selection in classification: A multi-objective approach. *IEEE transactions on cybernetics*, 43(6):1656–1671, 2012.
- [36] Bing Xue, Mengjie Zhang, Will N Browne, and Xin Yao. A survey on evolutionary computation approaches to feature selection. *IEEE Transactions on evolutionary computation*, 20(4):606–626, 2015.
- [37] Xin Yao. Global optimisation by evolutionary algorithms. In *Proceedings of IEEE International Symposium on parallel algorithms architecture synthesis*, pages 282–291. IEEE, 1997.
- [38] Jingqiao Zhang and Arthur C Sanderson. JADE: adaptive differential evolution with optional external archive. *IEEE Transactions on Evolutionary Computation*, 13(5):945–958, 2009.