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# ANALYZING AND RATING GREENNESS OF NATURE-INSPIRED ALGORITHMS

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# 1. INDEX:

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## 2. ABSTRACT:

Nature-inspired optimization algorithms (NIOAs) are modelled after natural phenomena such as the behavior of birds, bees, and other animals. These algorithms are designed to mimic the way that nature optimizes solutions to problems, and they can be used to find the optimal solution to a wide range of problems in fields such as machine learning, computer science, and engineering.

This study aims to objectively evaluate energy use and the associated carbon footprint for a few well-known NIOAs. To measure the energy utilized by each algorithm, we used Microsoft Joulemeter. The associated carbon footprint is determined using the recommendations of the Central Electricity Authority of India. According to the study's findings, each algorithm uses varying amounts of energy to accomplish the same task.

This study aims to enhance our knowledge regarding the energy consumption behavior of different NIOAs and aid software designers in selecting greener NIOAs for their task implementation from the available options. The aim is to bring more focus toward greener software solutions to combat growing energy demands and climate change. Future studies might consider more NIOAs and their modifications for energy consumption analysis to identify the most environmentally friendly NIOAs. Additionally, further investigation into the potential effects of different CPU architectures on the efficiency and power usage of the NIOAs may be taken into account.

## 3. INTRODUCTION:

Optimization is the process of modifying an existing system to improve the chances of achieving desired outcomes and reducing the risk of undesirable ones. This concept is widely applied in various fields, including engineering, business operations, industrial design, and many more. Optimization problems may have different objectives such as reducing energy consumption and increasing performance or efficiency. In machine learning, an optimizer is an algorithm or technique to adjust the various parameters of a model in order to minimize the loss function (in simpler terms, the error). The majority of traditional optimization algorithms used to address real-world problems are highly non-linear, have several local optima, and involve complex nonlinear constraints. Nature Inspired Optimization Algorithms (NIOAs) are better at avoiding local optima in comparison to conventional optimization algorithms (H. Li et al., 2020). NIOAs are population-based metaheuristics that replicate a wide range of natural phenomena (X.-S. Yang, 2021). Therefore, they are utilized extensively across a wide range of sectors, including manufacturing, environmental engineering, finance, biology, data mining, and more, to tackle complex and nonlinear optimization problems.

More than a hundred NIO algorithms and their variations are now known and available in the literature (H. Li et al., 2020). The Bat Algorithm (BAT), Camel Algorithm (CAM), Cuckoo Search (CS), Firefly Algorithm (FIR), and Particle Swarm Optimization (PAR) are some of the regularly utilized NIO algorithms that will be the subject of this study's examination of energy consumption and associated carbon footprint. These algorithms were taken into account for this study due to the wide range of applications for them. This work aims to demonstrate how one may experimentally assess the energy consumption of different algorithms. Future research may concentrate on different NIO algorithms or methodologies to eliminate architectural biases.

The objectives of this study are as follows:

- Conducting an analytic review of existing literature on
  - Global Energy usage by Information and Communications Technology (ICT)
  - Effects of Information and Communications Technology (ICT) on the environment,
  - Green or energy-efficient programs,
  - Effects of software's power usage on hardware,
  - Analysis of software's consumption of electricity in algorithm implementations,
  - Current state of Energy-efficient algorithms
  - Nature-inspired optimization algorithms
  - Bayesian Optimization
- Implement the NIO Algorithms in Python programming language using NatureInspiredSearchCV provided by the sklearn_nature_inspired_algorithms library and NiaPy for nature-inspired algorithms.
- Performing Hyper-parameter tuning on NIOAs using Bayesian Optimization.
- Determine the Energy each algorithm consumes using Microsoft Joulemeter.
- Based on how much energy each algorithm consumes, calculate its equivalent carbon footprint.

The results of this study (as well as other studies in this field) can help in many ways:

- Choosing Energy efficient options: By understanding the energy consumption of these algorithms, one can make more informed decisions on which algorithm to use in energy-constrained systems, such as mobile and embedded devices, which will lead to the development of more energy-efficient algorithms.
- Cost reduction: More efficient algorithms will consume less energy which will also help in reducing the operating costs of mobile and embedded devices, benefiting both individuals and Organizations that utilize these devices.
- Improved performance: By selecting the most appropriate algorithm for a given task, the performance of mobile and embedded systems can be improved, which will have a positive impact on various fields, such as machine learning, computer vision, and control systems.
- Environmental Impact: By reducing the energy consumption and thus in turn carbon footprint of mobile and embedded devices, this study can help lower environmental impact due to the growth of the given technologies.

# 4. LITERATURE REVIEW:

## 4.1. Global Energy Usage by Information and Communication Technology (ICT)

Due to the rapidly increasing demand for Communication Technology devices and the establishment of the Internet of Things (IoT), most devices are interconnected nowadays (Albrecht & Michael, 2013). Be it cloud computing (Berl et al., 2010), thin clients like smartphones (Maga et al., 2013), or highspeed network access (Ajmone Marsan & Meo, 2011), they all have had a disruptive impact on the ICT sector. While efficiency improvements have both been made in computations (Kudtarkar et al., 2010) and mass-storage operations (Baliga et al., 2011) but still the growth of electricity usage has outweighed these improvements (Neves & Krajewski, 2012). As this trend continues (A. S. G. Andrae & Edler, 2015) and more and more applications utilizing computation power develop over time, the necessity for reliable electricity increases. It is predicted that energy usage increase might become completely unsustainable by 2040 if nothing is done to tackle the issue (A. Andrae, 2019; Barlage & Shoute, 2021). The growing electricity usage will increase carbon emissions, may it be in production or expanding the energy delivery network. This is not good for the environment for obvious reasons thereby steps need to be taken to make the process and devices more efficient on every scale and frontier possible.

## 4.2. Effect of ICT on the Environment

Between 2008 and 2021, the ICT sector has grown responsible for almost 1.9 increased percent of the world's carbon emissions, with the remaining 97.9 to 96.1% coming from other industries including the transportation and agricultural industries (Freitag et al., 2021; Webb, 2008). The environment and the economy suffer as a result of the rise in carbon emissions brought on by Greenhouse Gases and other causes (Murugrsan, 2007). The ICT sector can significantly contribute to lowering global carbon emissions by reducing the carbon footprints of its products and services because there is growing global demand for ICT goods and services. Energy-efficient hardware and other embedded systems have been the subject of extensive study (Hosangadi et al., 2005; Schmitz et al., 2005; Shiri et al., 2020; Simunic et al., 1999), but software and application development should also receive significant attention (Capra et al., 2012; D'Agostino et al., 2021).

## 4.3. Green Software

Green or energy-efficient software is defined as using less energy for effective computing while causing little environmental harm (Naumann et al., 2011). The energy efficiency of web-based software applications and software features has been the subject of numerous research (Kor et al., 2015; Olaoluwa et al., 2015). The software can easily be estimated to use between 25% and 40% of the total energy used by a device, depending on the laptop or mobile battery (Engel, 2015). However, because it is correlated with the host device's life cycle, the indirect impact of software is more challenging to measure (Dastbaz et al., 2015). Only when both the positive and negative impact is taken into consideration throughout the design and deployment phases can the energy efficiency of software be truly accomplished. In light of this, optimizing ICT application services is essential to lowering harmful environmental effects.

4.4. Software's Impact on Hardware-Related energy consumption

The software's energy usage patterns strongly impact how much energy hardware uses and how long a device's battery lasts (Ardito et al., 2015). A device's energy usage may eventually increase if software or application that is poorly built disables various hardware-based energy-saving capabilities (Murugesan, 2008). For instance, it can prevent hardware from using energy-saving features and impact how the hardware is used, which could ultimately increase indirect energy usage (Ferreira et al., 2013). One of the trickiest tasks during the design stage of an embedded system is the development of energy-efficient software that enhances the energy efficiency of a piece of hardware. Various trade-offs between productivity and sustainability will need to be considered to increase software and application productivity while maintaining energy efficiency (Bener et al., 2014).

## 4.5. Analysis of Energy Consumption in algorithms implementations

**Table 1 – Comparative analysis of energy consumption in algorithmic implementations in existing studies.**

| Year | Title | Author | Description | Result | Remarks |
|---|---|---|---|---|---|
| 2015 | Energy Consumption Analysis of Algorithms Implementations | Mohammad Rashid, Luca Ardito, Marco Torchiano | Experimented measuring energy consumption of different soring algorithms implementations using various programming languages on an ARM device | ARM Assembly and Counting sort are most efficient respectively | Energy Consumption is determined by the computational complexity |
| 2018 | Analysis of Energy Consumption of Sorting Algorithms on Smartphones | Mutlidhar Verma, K.R. Chowdhary | Implemented and tracked energy consumption of different sorting algorithms on smartphones | Quick sort is the most efficient | Concept of energy-complexity to track energy demand of algorithm |
| | Time and Energy Efficiency: A Comparative Study of Sorting Algorithms Implemented in C | T. Deepthi, Antoinette Mary J Birunda | Tracked time and energy efficiency of sorting algorithms when implemented in C | Quick sort is the most efficient | A lot of similar studies are taking place due to numerous factors that can affect energy consumption like programming language, device, etc. |

Table 1(contd.) – Comparative analysis of energy consumption in algorithmic implementations in existing studies.

| Year | Title | Author | Description | Result | Remarks |
|---|---|---|---|---|---|
| 2019 | A Comparative Analysis of Quick, Merge and Insertion Sort Algorithms Using Three Programming Languages II: Energy Consumption Analysis | Oluwakemi Sade Ayodele, Bamidele Oluwade | Measured Energy consumption of sorting algorithms for different implementation styles and languages | Iteratively Merge sort is most efficient and Recursively Quick sort is most efficient. C is most energy efficient language for sorting algorithmic implementations | Energy consumption scales up with increasing data size. |
| 2022 | Analyzing energy consumption of nature-inspired optimization algorithms | Kor Green, Mohammad Newaj Jamil, Ah-Lian Kor | Measured Energy consumption of some Nature-inspired optimization algorithms using benchmark functions. | Differential Evolution is the most efficient algorithm among their suite. | Need to test NIOAs when applied to real world problems to extend the picture regarding their energy consumption behaviour. |

4.6. Current state of Energy-efficient algorithms:

As seen from the previous subsection, the current state of energy-efficient algorithms mainly focuses on comparing sorting algorithms in different implementations, platforms, and languages. While this type of research provides valuable insights for specific use cases, it does not provide a comprehensive understanding of the general energy efficiency of algorithms across different fields of software development. Additionally, most of the existing literature deals with creating specific energy-efficient algorithmic solutions for use cases such as flow time minimization (Albers & Fujiwara, 2007), RFID estimation problem (T. Li et al., 2010), or cloud computing algorithms (Zhou et al., 2020). However, the field is still in its early stage and more research is needed to better understand the energy efficiency of different types of algorithms in different application fields. This can help to identify the most energy-efficient algorithms for various use cases and to reduce energy consumption in software development.

4.7. Nature-inspired optimization algorithms:

Current research on nature-inspired algorithms primarily focuses on the following areas: optimization (Barontini et al., 2017; H. Li et al., 2020; X. S. Yang, 2020; X.-S. Yang, 2021) utilizing metaheuristics (Abdollahzadeh et al., 2021) or heuristic methods (Mohanty et al., 2022); improving environmental sustainability, such as optimizing supply chain processes (Sadrnia et al., 2014), managing energy resources intelligently (Nguyen et al., 2020), and increasing energy efficiency in data centers (Usman et al., 2019); and energy efficiency (Sharma et al., 2019) and optimization (Agbehadji et al., 2021) in wireless sensor network clustering.

### 4.8. Bayesian Optimization:

Bayesian optimization (BO) is a powerful technique used to find the optimal set of parameters for a given model. BO is widely adopted in various fields, such as machine learning, computer vision, and control systems, due to its ability to effectively handle high-dimensional parameter spaces. It is useful in a situation where traditional optimization methods may be computationally expensive or impractical (Frazier, 2018). In the context of energy efficiency, Bayesian optimization is used to optimize the energy consumption of different algorithms by searching for the optimal set of parameter values that minimize energy consumption. A study conducted in 2016 demonstrated the suitability of Bayesian optimization as a tool for tuning parameters in Evolutionary Algorithms (Roman et al., 2016). This study will also utilize Bayesian optimization to perform Hyper-Parameter tuning for the algorithm implementations.

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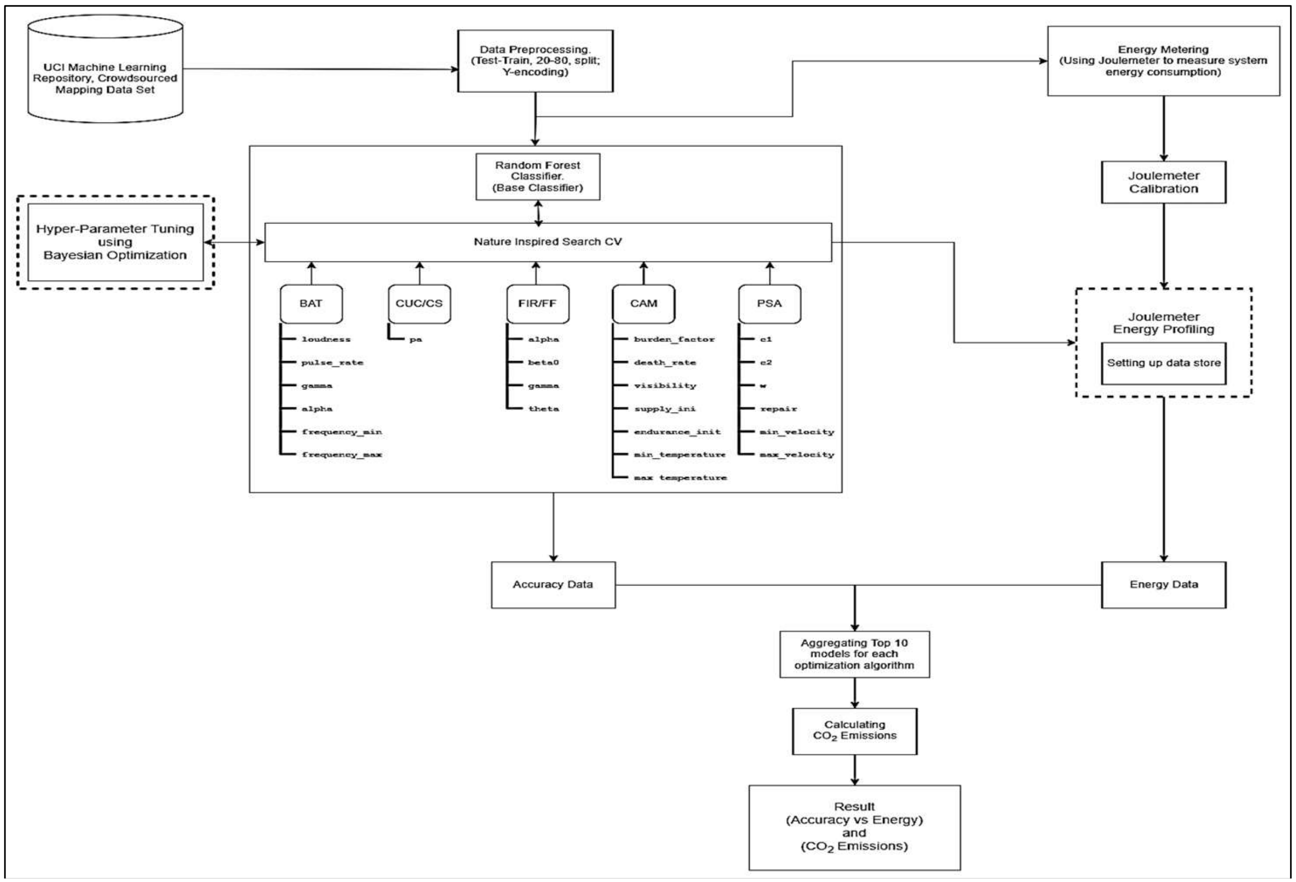
# 5. RESEARCH GAPS:

It is important to note that the present study has certain limitations that should be considered when interpreting the results.

- The results are specific to the problem type and algorithm implementations that were examined and may not be generalizable to other scenarios.
- The study may be influenced by the characteristics of the input data and the hardware utilized.
- Energy consumption was measured using the Microsoft Joulemeter software, which has a resolution of 0.1J per reading.
- It is acknowledged that energy efficiency varies among different hardware, operating systems, and CPUs, thus energy consumption may vary depending on the device and configuration used.

# 6. PROPOSED METHODOLOGY:



# 7. RESULTS & DISCUSSION:

Using Bayesian Optimization we have created the 50 parameter sets that will be trained and then ranked according to their performance (accuracy). From them the details of energy consumed by each optimization algorithm for the top 10 parameter sets are shown in Table 2-6 in order:

- Bat Algorithm
- Camel Algorithm
- Cuckoo Search Algorithm
- Firefly Algorithm
- Particle Swarm Optimization Algorithm

Table 2 – Energy Consumed by top 10 parameter sets of Bat Algorithm

| Keys | Time Taken (s) | Total Energy (J) | CPU Energy (J) | Disk Energy (J) | Base Energy (J) | Power Consumed (W) |
|---|---|---|---|---|---|---|
| BAT-0042 | 100 | 323.20 | 177.20 | 0.0 | 150.0 | 3.232 |
| BAT-0034 | 793 | 2728.30 | 1561.6 | 0.1 | 1189.5 | 3.440 |
| BAT-0008 | 76 | 247.1 | 136.40 | 0.0 | 114.0 | 3.251 |
| BAT-0029 | 230 | 761.90 | 427.20 | 0.0 | 345.0 | 3.313 |
| BAT-0011 | 78 | 251.80 | 138.5 | 0.0 | 117.0 | 3.228 |
| BAT-0017 | 533 | 1741.1 | 964.30 | 0.0 | 799.5 | 3.267 |
| BAT-0003 | 306 | 980.20 | 535.40 | 0.0 | 459.0 | 3.203 |
| BAT-0040 | 150 | 490.00 | 270.80 | 0.0 | 225.0 | 3.267 |
| BAT-0016 | 115 | 371.60 | 204 | 0.0 | 172.5 | 3.231 |
| BAT-0020 | 9 | 29.4 | 16.4 | 0.0 | 13.5 | 3.267 |

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| Table 3 – Energy Consumed by top 10 parameter sets of Camel Algorithm | | | | | | |
|---|---|---|---|---|---|---|
| Keys | Time Taken (s) | Total Energy (J) | CPU Energy (J) | Disk Energy (J) | Base Energy (J) | Power Consumed (W) |
| CAM-0000 | 164 | 527.00 | 287.30 | 0.3 | 264.0 | 3.213 |
| CAM-0049 | 704 | 2264.00 | 1241.10 | 0.0 | 1056.0 | 3.215 |
| CAM-0024 | 222 | 708.40 | 384.10 | 0.0 | 333.0 | 3.191 |
| CAM-0003 | 164 | 529.00 | 289.40 | 0.0 | 246.0 | 3.226 |
| CAM-0026 | 97 | 313.80 | 172.60 | 0.0 | 145.5 | 3.235 |
| CAM-0008 | 19 | 61.3 | 33.5 | 0.0 | 28.5 | 3.226 |
| CAM-0041 | 38 | 123.7 | 69.10 | 0.0 | 57.0 | 3.255 |
| CAM-0033 | 840 | 2695.80 | 1475 | 0.6 | 1260.0 | 3.209 |
| CAM-0025 | 124 | 398.60 | 218.50 | 0.0 | 186.0 | 3.214 |
| CAM-0006 | 53 | 172.80 | 95.70 | 0.0 | 79.5 | 3.260 |

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| Table 4 – Energy Consumed by top 10 parameter sets of Cuckoo Algorithm | | | | | | |
|---|---|---|---|---|---|---|
| Keys | Time Taken (s) | Total Energy (J) | CPU Energy (J) | Disk Energy (J) | Base Energy (J) | Power Consumed (W) |
| CUC-0009 | 16 | 51.10 | 27.70 | 0.0 | 24.0 | 3.194 |
| CUC-0031 | 264 | 852.80 | 468.30 | 0.0 | 396.0 | 3.230 |
| CUC-0010 | 84 | 269.3 | 146.50 | 0.0 | 126.0 | 3.206 |
| CUC-0042 | 678 | 2185.10 | 1198.30 | 0.0 | 1017.0 | 3.223 |
| CUC-0035 | 40 | 130.0 | 71.90 | 0.0 | 60.0 | 3.25 |
| CUC-0040 | 612 | 1978.50 | 1086.70 | 0.1 | 918.0 | 3.233 |
| CUC-0041 | 258 | 832.00 | 455.3 | 0.0 | 387.0 | 3.225 |
| CUC-0039 | 63 | 206.30 | 114.50 | 0.0 | 94.5 | 3.275 |
| CUC-0046 | 84 | 273.6 | 151.30 | 0.0 | 126.0 | 3.257 |
| CUC-0048 | 69 | 222.40 | 122.40 | 0.0 | 103.5 | 3.223 |

| Table 5 – Energy Consumed by top 10 parameter sets of Firefly Algorithm | | | | | | |
|---|---|---|---|---|---|---|
| Keys | Time Taken (s) | Total Energy (J) | CPU Energy (J) | Disk Energy (J) | Base Energy (J) | Power Consumed (W) |
| FIR-0042 | 340 | 1045.90 | 551.20 | 0.0 | 510.0 | 3.076 |
| FIR-0037 | 218 | 709.10 | 388.80 | 0.0 | 327.0 | 3.253 |
| FIR-0003 | 933 | 3013.40 | 1654.10 | 0.0 | 1399.5 | 3.230 |
| FIR-0049 | 93 | 288.2 | 152.8 | 0.0 | 139.5 | 3.099 |
| FIR-0043 | 527 | 1623.00 | 855.80 | 0.0 | 790.5 | 3.080 |
| FIR-0041 | 129 | 397.70 | 209.50 | 0.0 | 193.5 | 3.083 |
| FIR-0014 | 74 | 238.5 | 131.50 | 0.0 | 111.0 | 3.223 |
| FIR-0009 | 119 | 386.5 | 212.30 | 0.0 | 178.5 | 3.248 |
| FIR-0012 | 86 | 280.20 | 154.70 | 0.0 | 129.0 | 3.258 |
| FIR-0000 | 92 | 295.70 | 162.2 | 0.0 | 138.0 | 3.214 |

| Table 6 – Energy Consumed by top 10 parameter sets of Particle Swarm Optimization Algorithm | | | | | | |
|---|---|---|---|---|---|---|
| Keys | Time Taken (s) | Total Energy (J) | CPU Energy (J) | Disk Energy (J) | Base Energy (J) | Power Consumed (W) |
| PAR-0016 | 186 | 609.60 | 338.9 | 0.0 | 279.0 | 3.277 |
| PAR-0043 | 21 | 67.90 | 37.8 | 0.0 | 31.5 | 3.233 |
| PAR-0030 | 75 | 269.00 | 157.5 | 0.3 | 112.5 | 3.587 |
| PAR-0003 | 168 | 551.70 | 307.70 | 0.0 | 252.0 | 3.284 |
| PAR-0022 | 116 | 380.20 | 211.10 | 0.1 | 174.0 | 3.278 |
| PAR-0004 | 87 | 285.70 | 159.30 | 0.0 | 130.5 | 3.284 |
| PAR-0045 | 64 | 207.2 | 114.4 | 0.0 | 96.0 | 3.238 |
| PAR-0044 | 61 | 200.80 | 111.80 | 0.0 | 91.5 | 3.292 |
| PAR-0032 | 153 | 493.50 | 270.90 | 0.0 | 229.5 | 3.224 |
| PAR-0015 | 33 | 107.9 | 59.50 | 0.0 | 49.5 | 3.270 |

Fig. 2 compares the energy usage of each method for clarity, and Fig. 3 displays the average accuracy of the five algorithms for the top 10 epochs.

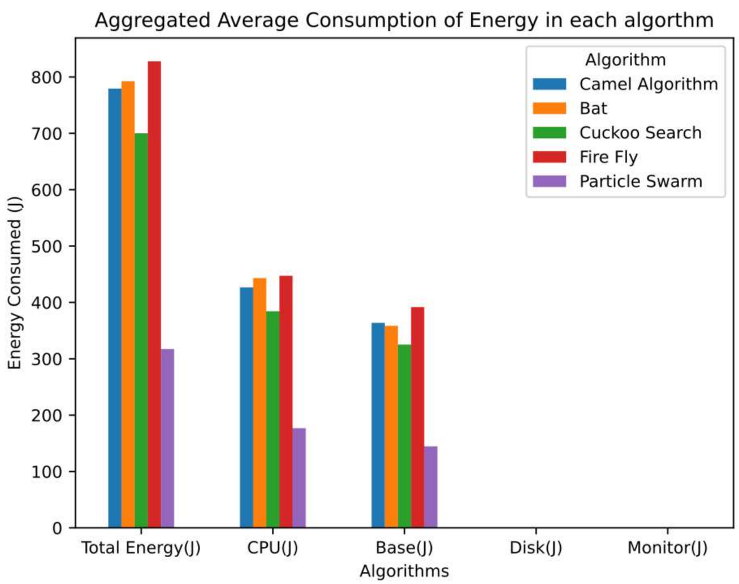


Fig. 2 - Aggregated Average consumption of Energy in each Algorithm

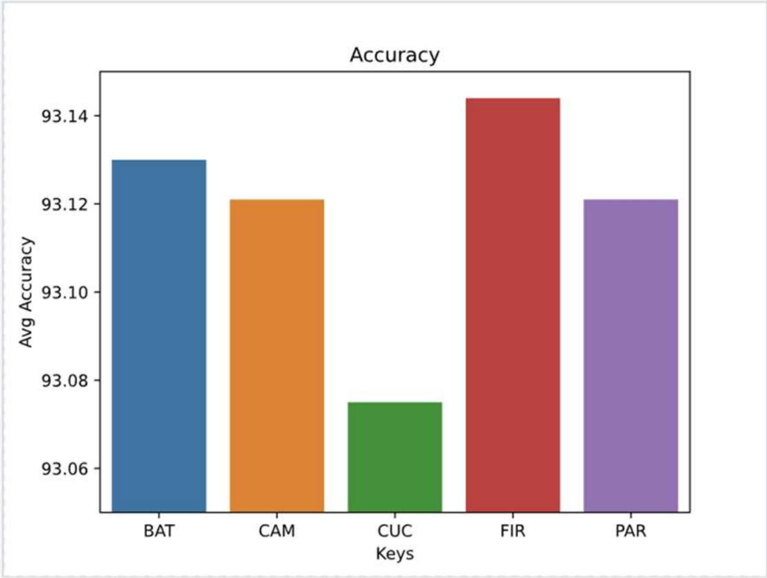


Fig. 3 - Average Accuracy of top 10 epochs achieved for each of the five nature-inspired algorithms

Table 7 depicts the average power, accuracy, and CO2 emission of selected models.

| Name Of Algorithm | Keys | Avg. Accuracy | Avg. Time Taken (s) | Avg. Energy Used (J) | Avg. Equivalent $CO_2$ Emission (mg) |
|---|---|---|---|---|---|
| Bat Algorithm | ['BAT-0042', 'BAT-0034', 'BAT-0008', 'BAT-0029', 'BAT-0011', 'BAT-0017', 'BAT-0003', 'BAT-0040', 'BAT-0016', 'BAT-0020'] | 93.13047 | 239.0 | 792.46 | 187.10861 |
| Camel Algorithm | ['CAM-0000', 'CAM-0049', 'CAM-0024', 'CAM-0003', 'CAM-0026', 'CAM-0008', 'CAM-0041', 'CAM-0033', 'CAM-0025', 'CAM-0006'] | 93.12125 | 242.5 | 779.44 | 184.03444 |
| Cuckoo Search | ['CUC-0009', 'CUC-0031', 'CUC-0010', 'CUC-0042', 'CUC-0035', 'CUC-0040', 'CUC-0041', 'CUC-0039', 'CUC-0046', 'CUC-0048'] | 93.07515 | 216.8 | 700.11 | 165.30375 |
| Firefly Algorithm | ['FIR-0042', 'FIR-0037', 'FIR-0003', 'FIR-0049', 'FIR-0043', 'FIR-0041', 'FIR-0014', 'FIR-0009', 'FIR-0012', 'FIR-0000'] | 93.14431 | 261.1 | 827.82 | 195.45750 |
| Particle Swarm Optimization | ['PAR-0016', 'PAR-0043', 'PAR-0030', 'PAR-0003', 'PAR-0022', 'PAR-0004', 'PAR-0045', 'PAR-0044', 'PAR-0032', 'PAR-0015'] | 93.12125 | 96.4 | 317.35 | 74.92986 |

Fig. 4 shows the average energy consumed by the five algorithms for the top 10 epochs, while Fig. 5 shows the average CO2 emitted by the five algorithms for the top 10 epochs.

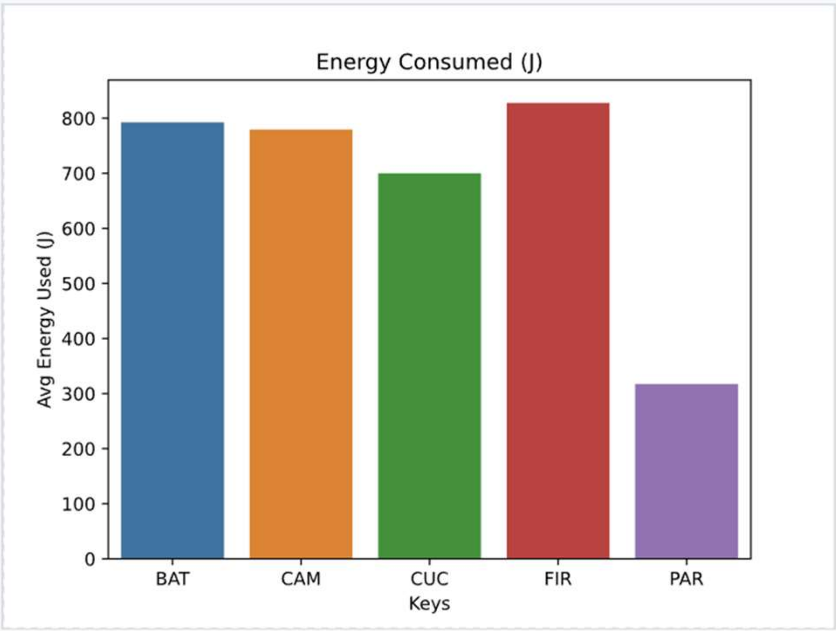


Fig. 4 - Average Energy Consumed of top 10 epochs achieved for each of the five nature-inspired algorithms

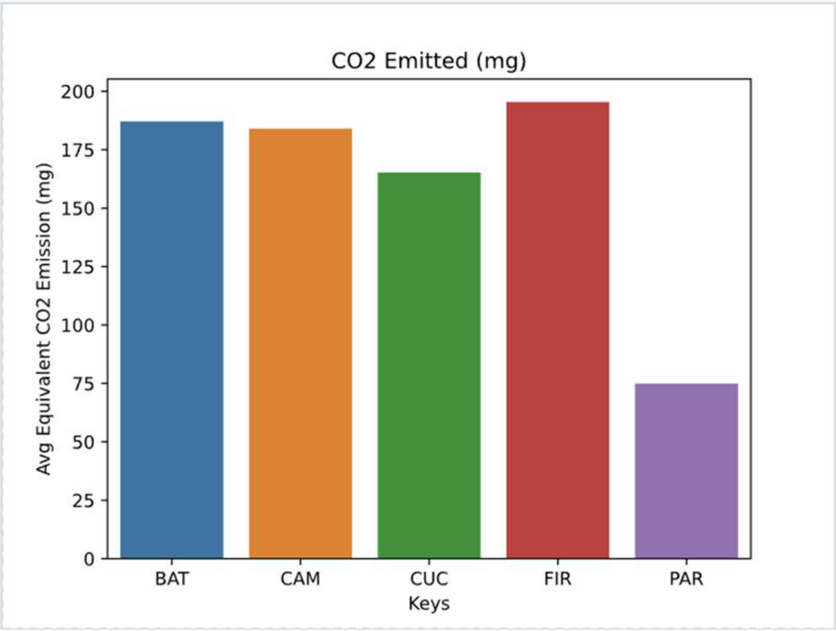


Fig. 5 - Average Equivalent CO2 emissions of top 10 epochs achieved for each of the five nature-inspired algorithms

## 8. Comparative Analysis

As was previously said, different hardware specs would produce various outcomes. As a result, the outcomes will alter if the trials are carried out on a laptop with different specifications. PAR is used as the foundation to explore the energy consumption ratio of other algorithms, which is presented in Tables 8 & 9 for CPU energy consumption and Total energy consumption respectively because it is discovered to have the lowest energy consumption.

| Algorithm | CPU Energy Consumption(J) | Ratio Comparison to PAR |
|---|---|---|
| Bat Algorithm | 443.18 | 2.505 |
| Camel Algorithm | 426.63 | 2.412 |
| Cuckoo Search | 384.29 | 2.172 |
| Firefly Algorithm | 447.29 | 2.529 |
| Particle Swarm | 176.89 | 1.0 |

Table 8 - CPU Energy Consumption Ratio of each algorithm relative to Particle Swarm Optimization

| Algorithm | Total Energy Consumed(J) | Ratio Comparison to PAR |
|---|---|---|
| Bat Algorithm | 792.46 | 2.497 |
| Camel Algorithm | 779.44 | 2.456 |
| Cuckoo Search | 700.11 | 2.206 |
| Firefly Algorithm | 827.82 | 2.609 |
| Particle Swarm | 317.35 | 1.0 |

Table 9 - Total Energy Consumption Ratio of each algorithm relative to Particle Swarm Optimization

Energy usage for each optimization algorithm varies greatly. But as the number of decision trees increases, it is observed that the Particle Swarm Optimization algorithm has the highest accuracy to energy consumption ratio of 0.29343. Firefly Algorithm performs the worst with the accuracy to energy consumption ratio of 0.11252 (Fig 6).

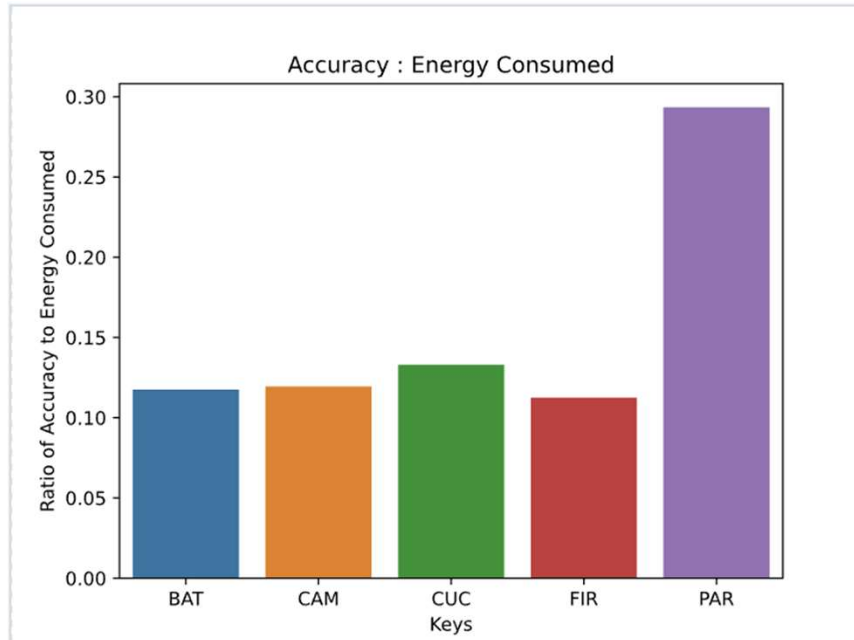


Fig. 6 - Ratio of Accuracy to Energy Consumption of top 10 epochs achieved for each of the five nature-inspired algorithms

# 9. CONCLUSION & FUTURE WORK :

## 9.1. Conclusion

In the present experiment, it was found that the Particle Swarm Optimization algorithm exhibited the least energy consumption while maintaining relatively high accuracy. As such, it can be concluded that it is the most energy-efficient algorithm among the ones evaluated in this study. The purpose of this study was to emphasize the significance of energy efficiency in technology and the capabilities of nature-inspired optimization algorithms to decrease energy consumption. This will aid in enhancing the energy efficiency of various systems, thereby contributing to a more sustainable future.

## 9.2. Future Scope

The potential for further research in this field includes the possibility of incorporating other optimization algorithms and applying them to various real-world problems. Additionally, the study can be extended to optimize the algorithms on different hardware platforms to minimize the effects of architectural differences, thus allowing for a comprehensive examination of the energy characteristics of algorithms. Furthermore, there is scope for further research on other methods of hyper-parameter tuning to provide even more optimal and energy-efficient results.

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