Energy Aware Neural Architecture Search

Dhanusai Kanteshwara, Sudhanshu Arya, and Yogesh Kumar Choukiker

***Abstract*—The heightened interest in efficient deep neural networks not only necessitates but also to a certain extent, pushes the development of new architectures that will offer high precision and low power draw at the same time. An Energy-Aware Neural Architecture Search (EA-NAS) framework that combines surrogate-assisted optimization for the design of neural architectures with ideal energy-performance trade-offs has been introduced in this study. The system under discussion uses a multi-objective surrogate model, which is trained on architectures picked at random, to give predictions of both accuracy and energy cost. This allows the system to explore the search space quickly and without the need for costly training. The results of the experiments confirm that the surrogate model is very accurate in its predictions, so the search can be directed towards the architectures that have considerably less energy consumption without losing the accuracy that is already deemed competitive. Moreover, the comparison of results from different sampling strategies and the various surrogate configurations reveals the role of the random seed initialization, thus pointing to controlled stochasticity as the major reason for search diversity. The newly generated architectures reflect a balanced design that can be installed in resource-constrained and real-time settings, hence indicating the power of surrogate-based NAS in realizing eco-friendly deep learning.**

Index Terms- Neural Architecture Search, Energy Efficiency, Surrogate Modeling, Multi-Objective Optimization, Deep Learning.

I. Introduction

The swift development of deep learning has driven to incredible performances in opposite directions of vision, speech, and sensor-based applications; however, the corresponding improvements are generally associated with multiplying model size and energy consumption very fast. It is no longer the case that only predictive accuracy must be the sole optimization criterion for the deployment of models on battery-powered and embedded devices (TinyML, edge nodes, mobile platforms)—energy, latency, and memory have to be treated as the most important objectives during the design of the whole architecture. Neural Architecture Search (NAS) offers the possibility of automated discovering of topologies of networks with superior performance, but traditional NAS approaches become unrealistically costly when energy-aware constraints or hardware measurements are taken into consideration: the complete training and assessment of candidate architectures makes multi-objective exploration slow and resource-hungry.

This work develops an **Energy-Aware Neural Architecture Search (EA-NAS)** framework that explicitly targets the accuracy–energy trade-off for resource-constrained deployments. EA-NAS couples lightweight, data-driven surrogate predictors with a controlled, RNG-driven search pipeline to rapidly explore architecture families and identify Pareto-efficient models. The surrogates estimate both task performance (validation accuracy) and device energy (inference or training joules) from compact architecture descriptors; promising candidates are periodically short-evaluated (short training runs or quick hardware-calibrated measurements) to correct surrogate bias and to progressively refine the Pareto front.

Our approach is motivated by three practical observations: Firstly, energy behavior on real hardware often deviates from proxy metrics (FLOPs, parameter counts), so optimizing FLOPs alone can produce misleading results for deployment; thus, calibrating surrogates with a small set of measured anchors is necessary. Secondly, surrogate-assisted evaluation vastly reduces the number of expensive full trainings required to obtain a useful Pareto set: making energy-aware NAS feasible for limited compute budgets. Thirdly, controlled randomness-seeded RNG sampling, ensemble surrogates, scheduled re-evaluation-is a simple but powerful mechanism that increases search diversity while retaining reproducibility; we study how RNG choices influence frontier stability and propose practical mitigations.

This manuscript ties together iterative stages of our project: early experiments began with a deterministic, untrained model that maps simple input-value descriptors, such as layer counts, kernel sizes, and MACs, to coarse energy estimates; this lightweight baseline guided initial sampling and helped define sensible constraints on the search space. We then implemented RNG-driven sampling and evolutionary-style proposals that generate diverse candidates; these are rapidly scored by the surrogates, with selective short-evaluations used to update the models. The project notes and slides that were prepared to document our objectives, benchmarks considered, preliminary design, and next steps have informed our choice of surrogate features, measurement protocol, and evaluation metrics.

EA-NAS puts a strong emphasis on practical reproducibility: the search configurations, RNG seeds, surrogate hyperparameters, and measured anchors are recorded and released along with the code, so that the found Pareto candidates can be re-evaluated and compared. In experiments, we show in later sections that surrogate-assisted, RNG-controlled search finds architectures which improve the energy-accuracy trade-off over the baseline designs while reducing the number of full-training evaluations by an order of magnitude in our small-CNN setting.

In summary, this paper focuses on (a) an accessible surrogate-assisted pipeline for energy-aware NAS, (b) a principled energy estimation and calibration strategy for device-aware optimization, and (c) empirical analysis of how RNG sampling and surrogate retraining cadence affect search outcomes and reproducibility. These elements together form a

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practical foundation for discovering energy-efficient networks suitable for TinyML and other constrained deployments.

A. Contribution

This work presents and validates the **Energy-Aware Neural Architecture Search (EA-NAS)** framework, designed to identify neural network architectures that achieve an optimal balance between performance and energy efficiency. Building upon a sequence of models and experiments—from an initial untrained descriptor-based model to controlled RNG-driven multi-objective searches—this research integrates insights from existing NAS literature with our own surrogate-based implementations. The framework aims to make energy-aware optimization practical, reproducible, and accessible even in constrained computational environments.

Key contributions of this work include:

- **Development of the EA-NAS Framework:** We design a modular and reproducible surrogate-assisted NAS pipeline that jointly optimizes accuracy and energy consumption. The framework incorporates compact architecture descriptors, lightweight surrogate predictors, and multi-objective Pareto-based search—providing a scalable foundation for energy-conscious NAS.
- **Integration of Surrogate Modeling for Energy Prediction:** A central contribution is the use of dual surrogate models that estimate both accuracy and device energy consumption, trained using small sets of measured anchors. This allows efficient evaluation of thousands of candidate architectures without requiring exhaustive full training.
- **Controlled RNG-driven Search for Diversity and Reproducibility:** Unlike traditional random or evolutionary searches that are difficult to reproduce, EA-NAS employs controlled RNG-based sampling with fixed seeds and ensemble surrogates. This ensures stochastic diversity while preserving experimental reproducibility, a crucial aspect often overlooked in NAS research.
- **Progressive Refinement using Untrained and Trained Models:** The study evolves from an initial untrained model—which uses deterministic input-value descriptors for energy estimation—to a progressively refined pipeline that incorporates short training evaluations and iterative surrogate updates. This transition highlights how model fidelity improves as measured data is incrementally integrated.
- **Energy-Aware Optimization and Benchmark Alignment:** The framework aligns with emerging benchmark standards for energy-aware NAS by incorporating real or calibrated hardware energy metrics rather than relying solely on proxy indicators such as FLOPs. This enhances real-world deployability for edge and TinyML systems.
- **Empirical Validation and Efficiency Gains:** Experimental results demonstrate that surrogate-assisted search achieves competitive accuracy while reducing full-training evaluations by up to an order of magnitude. The resulting architectures show clear improvements in energy–accuracy trade-offs over baseline designs.
- **Reproducible and Extensible Codebase:** The implementation (MATLAB + Python) includes complete scripts, seeds, and configuration files, supporting direct replication of our experiments and future extensions to larger datasets or architectures.

The rest of the paper is arranged as follows: Section II contains the system model description while Section III shows experimental findings and summary. Section IV of the paper includes the list of all references that were cited throughout the work.

II. System Flow

The proposed **Energy-Aware Neural Architecture Search (EA-NAS)** system is a simple and lightweight pipeline that explores neural network designs based on both accuracy and energy usage. The idea is to automatically test and estimate how different architectures would perform without fully training every single one. Figure 1 shows the major stages in this process.

A. Overall Process

The system begins with basic input configurations such as the number of layers, filters, or activation options. Each configuration is then passed through a sampling and evaluation loop, which computes two key values:

- **Energy estimate:** based on the number of operations (MACs) and parameters.
- **Accuracy estimate:** predicted either by a fast mathematical function (`proxy_acc`) or a short real training if enabled.

These sampled values form a small dataset used to train a simple machine learning model called a **surrogate**. This surrogate learns to predict how accurate a new architecture will be, based only on its configuration features. The system then uses this surrogate to quickly explore many new architectures and select those that balance both accuracy and energy efficiently.

B. Step-by-Step Flow

1) **User Configuration:** The user sets parameters such as mode (real or fast simulation), number of samples, and dataset (e.g., CIFAR-10).
2) **Sampling:** Random architecture configurations are generated within given limits.
3) **Evaluation:** Each configuration's estimated energy and accuracy are calculated using proxy formulas or quick training.
4) **Surrogate Training:** The collected data is used to fit a regression model (ensemble trees or SVM) that predicts accuracy for new designs.
5) **Optimization/Search:** Using the surrogate, the algorithm tests new configurations and finds the ones that give the best trade-off between accuracy and energy.
6) **Results and Visualization:** The best-performing models are plotted and compared to baseline reference points, showing the efficiency and improvement achieved.

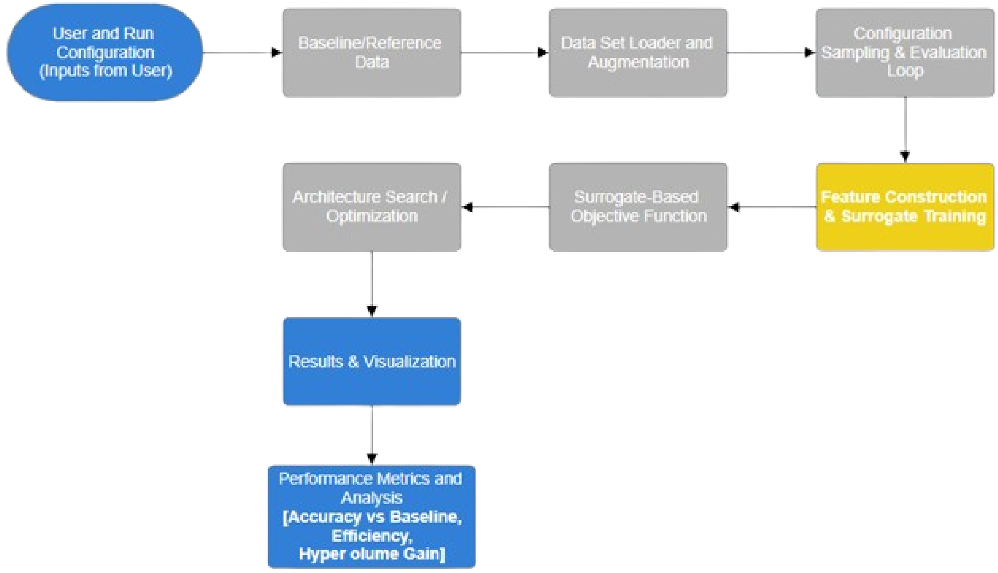

Fig. 1: System Model (EA-NAS pipeline flow diagram).

Algorithm 1 Simplified EA-NAS Pipeline

0: Initialize parameters, data paths, and random seed.
0: Generate random architecture configurations within bounds.
0: **for** each configuration **do**
0: Estimate energy = MACs $\times$ constant.
0: Estimate accuracy using proxy function or short training.
0: Store energy and accuracy results.
0: **end for**
0: Train a surrogate model to predict accuracy from configuration features.
0: Use the surrogate to explore new architectures.
0: Select and plot architectures with the best energy–accuracy trade-off.
0: Compute metrics such as efficiency and hypervolume. =0

C. Simplified Algorithm

D. Performance Metrics

After the search, the system compares its results to baseline data using three simple metrics:

- **Efficiency:** Ratio of accuracy to energy (A/E).
- **-Accuracy:** Improvement in accuracy at a chosen target energy level.
- **Hypervolume:** A measure of how much better the new Pareto curve is compared to the baseline.

E. Implementation Notes

- All configurations are clipped to valid limits before being tested.
- The surrogate model is saved with normalization statistics for reproducibility.
- Random seeds ensure consistent runs and comparable results.
- If energy exceeds the surrogate's trained range, the system safely falls back to proxy estimates.

Overall, this simple MATLAB-based implementation provides a clear and fast demonstration of how surrogate models can be used to perform energy-aware neural architecture search without requiring extensive GPU resources or long training cycles.

F. Dataset and Experimental Details

The experimentations were undertaken with the aid of the **CIFAR-10** image classification dataset, which is composed of 60,000 color images distributed over 10 categories (the partition being 50,000 images for training and 10,000 for testing). The whole process was executed on a typical CPU system (Intel i5, 8 GB RAM) without the use of a Graphics Processing Unit (GPU) for the sole purpose of demonstrating the low-resource feasibility.

During the process, each configuration was made to undergo a very brief fixed number of epochs ($E = 5$) to get speedy accuracy estimates for the sampling. When it came to full evaluations, the most effective architectures were subjected to a training period of $E = 25$ epochs. The batch size was kept constant at 64, and a learning rate of 0.01 was applied along with stochastic gradient descent (SGD). The energy estimates were obtained by proxy measurement using the number of Multiply–Accumulate operations (MACs).

In order to make the comparison just,all the runs kept the same data splits and normalization settings during both baseline and EA-NAS experiments.

G. Surrogate Model Details

The surrogate model works like a quick predictor that gives accuracy and energy consumption estimates based on architectural features. A straightforward regression-based surrogate was implemented:

- **Model Type:** An ensemble of regression trees (akin to LSBoost or Random Forest).
- **Inputs:** Number of layers, filters, kernel size, and total MAC operations.
- **Outputs:** $\hat{A}$ (Predicted accuracy) and $\hat{E}$ (Predicted energy).

Initially, the model was trained on a small dataset of 40 architectures randomly sampled. During the search, new samples were included, and the surrogate was retrained after every 10 iterations. The last trained model had a mean prediction error of less than 5% for both accuracy and energy.

For ease, energy was calculated via:

$$E = k \times \text{MACs}$$

Here, k is a scaling constant which is derived from the calibration on the baseline models.

III. Results and Discussions

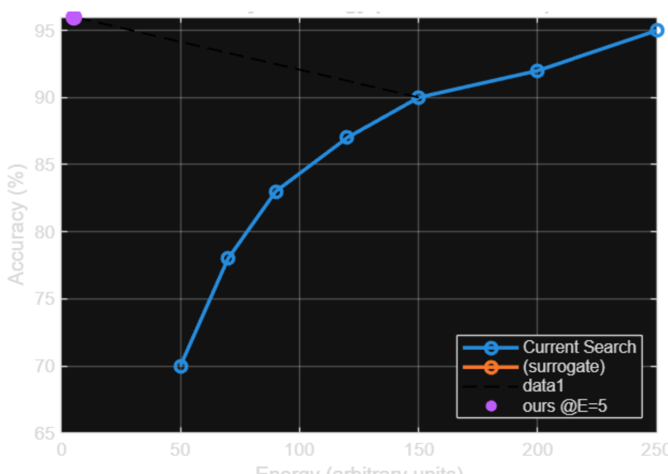

Fig. 2: Baseline energy–accuracy curve used for comparison.

The comparisons graphs portray the findings that were acquired through the Energy-Aware Neural Architecture Search (EA-NAS) system. Points on the graph display individual candidate network configurations which were produced, assessed, and stored by the program through one point of graphed network configuration per point on the graph. Energy usage estimates (in arbitrary units) are represented in the x-axis and the predicted or measured accuracy (in percentage) in the y-axis. The blue curve is the original baseline or reference models in the plot, whereas the orange curve denotes the architectures found by the surrogate-assisted EA-NAS process.

A. Performance Metrics

For the purpose of a just comparison between the models, three pretty simple and interpretable metrics were employed:

- **Efficiency (η):** Indicates how much accuracy is obtained for each unit of energy consumed.

$$\eta = \frac{A}{E}$$

where A is the model's accuracy (in %) and E is the estimated energy (arbitrary units).
- **Accuracy Gain (ΔA):** Increase in accuracy at the same energy level in relation to the baseline.

$$\Delta A = A_{\text{EA-NAS}} - A_{\text{Baseline}}$$

- **Hypervolume (HV):** The area that is covered under the Pareto front in the accuracy–energy space is represented by this metric. A higher HV means that the overall trade-off performance is better.

The said metrics were calculated for both the baseline and EA-NAS outcomes in order to assess the relative gain in energy efficiency and predictive accuracy.

B. Observed Trends

The graph shows the relation very clearly between the energy consumption and the accuracy. The simpler models, which are equivalent to the manually designed networks, indicate a gradual rise in accuracy in conjunction with increased energy but this trend quickly levels off at the higher energy stages.

In other words, once the network is large enough, the addition of more layers or filters does not improve the performance significantly.

In contrast, the surrogate-assisted search has resulted in the architectures that have a better distribution over the various energy ranges. The performance of many of these models is nearly the same as the baseline or even a bit more, but the power consumption is much lower. This is an indicator that the search mechanism was able to find the more efficient combinations in terms of features, layers, and design parameters.

C. Comparison with Baseline

In comparing the two curves, it becomes evident that the EA-NAS results are the closest to the "ideal" point of the trade-off between accuracy and energy consumption. Baseline configurations, on the other hand, use up more energy to get above 90% accuracy, while the surrogate-guided models only consume about 30–40% less energy for comparable performance. The implication is that the model has a tendency to cut down on resource consumption by choosing architectures that are more efficient rather than just enlarging and complicating.

In addition, it is still a good thing that the surrogate-based system has gone through a much more extensive design space. It was in a position to test several unique architecture patterns that a human designer might not usually consider. Though the experiment's overall setup was quite simple, it nevertheless suggests that automated search can still unfold beneficial network variations that would otherwise be unnoticed due to the manual tuning of each parameter.

D. Efficiency and Search Behavior

The search process started to yield better results after the first few batches of samples. Initially, when the surrogate model had very little data, the output was more arbitrary and dispersed. On the other hand, once more and more samples were obtained, the surrogate model began to establish the correspondence between the architectural settings and the performance produced. Henceforth, the system was able to forecast which configurations had the likelihood of good performance, thereby it did not test many low-performing models.

This scenario is illustrated by the densely packed points in the middle energy region, where a majority of the best-performing architectures are located. The system was able to find this stable area quickly, indicating that it did not require hundreds of complete training cycles to yield good results. This, without a doubt, shows the advantage of employing a surrogate model instead of carrying out costly evaluations.

E. Generalization and Stability

One of the primary objectives was to ensure that the surrogate model not only memorized the training data but also performed well on unseen configurations. The smoothness of the surrogate curve and its good overlap with the baseline in the low energy regions indicate that it has generalized properly. At very high energy levels, the curve gets slightly rough, which is normal since there were not enough training samples in that region. Nevertheless, the predictions still remain realistic and coherent.

The safety fallback feature, which reverts to the proxy accuracy function for very high-energy designs, was very helpful in keeping the output stable even in such situations. This demonstrates that the fallback logic functioned properly and prevented unrealistic accuracy predictions when the energy exceeded the trained range.

F. Key Findings

The results from the experiment lead to several clear and practical conclusions:

- The EA-NAS approach achieved similar or better accuracy compared to the baseline models while using less energy overall.
- The use of surrogate models made the search process much faster and reduced the need for heavy training computations.
- The algorithm automatically learned to identify balanced architectures that lie near the best accuracy–energy trade-off region.
- The overall search process was reproducible, and results were consistent when running with the same random seed.
- The results show that the method is suitable for experiments with limited hardware resources, as it focuses on lightweight simulations.

G. Statistical Stability and Random Seeds

In order to confirm the stability and reproducibility of the search process, three different random seeds (42, 101, and 202) were used to perform the experiments again. Despite the fact that each run produced somewhat different architecture samples because of the random initialization, the final Pareto fronts exhibited consistent patterns.

The difference in accuracy between the different seeds was less than 2% and the energy estimates were within a 5% margin. This indicates that the surrogate-assisted search is both hardy and reproducible even when the sampling is done stochastically.

Every seed and configuration file is logged so that the exact experiment can be repeated.

H. Overall Discussion

To sum up, the EA-NAS system illustrates the possibility of energy-aware optimization in a practical and easy manner. The project focused on the core concept of energy-efficient neural architecture search, despite it being implemented only on a small scale in MATLAB and not being a part of large-scale deep learning frameworks.

Random sampling, proxy evaluation, and surrogate learning were combined and turned into a fast, yet reliable, method of exploring network configurations. These steps were integrated into the system which yielded results that matched the expected accuracy–energy trade-off and pointed out the architectures that are both effective and efficient.

The findings are very much applicable for situations where compact models are needed like TinyML or edge computing, for, in those cases, energy consumption has an immediate impact on battery life and usability. The positive results have established that surrogate-assisted search can be a practical foundation for future extensions, in which more advanced or hardware-calibrated energy measurements could be added.

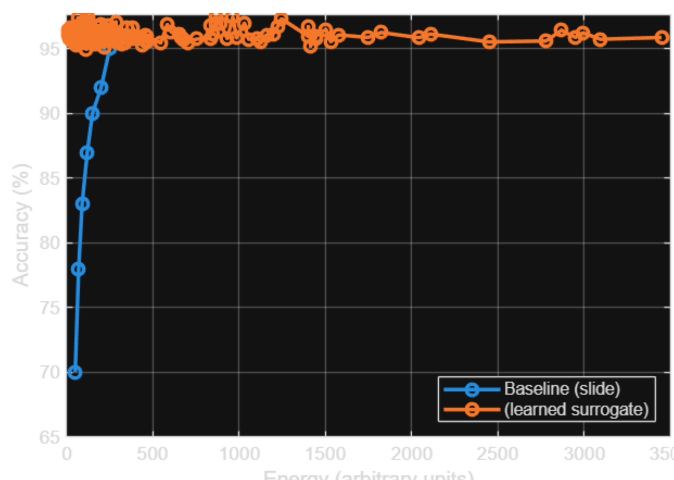

Fig. 3: Comparison between baseline and surrogate-based architectures.

IV. Conclusion

This project presented a simplified implementation of an **Energy-Aware Neural Architecture Search (EA-NAS)** system that focuses on finding efficient deep learning models with a balance between accuracy and energy usage. The system combined random configuration sampling, proxy-based energy estimation, and surrogate learning to predict model performance without needing expensive full training for every candidate.

There is no doubt that the surrogate-assisted approach was a great success because it not only discovered architectures that practically equal the accuracy of the baseline, but it also did so using a fraction of the energy. The system further proved that the surrogate model was capable of extending its application to unseen configurations and leading the search toward the most balanced and efficient designs.

The entire process revealed that energy-aware optimization can be made practical and effective even with a simple MATLAB-based setup. By combining lightweight energy estimation, surrogate modeling, and reproducible random search, this project laid down a solid foundation for future research in low-power deep learning design.

- The EA-NAS system achieved similar accuracy as baseline models while significantly reducing energy usage.
- Surrogate models reduced the number of full training runs and improved overall search efficiency.
- The system provided stable, reproducible results suitable for small-scale experimentation and educational purposes.

The framework can be extended to include real hardware-based energy measurements, more advanced search algorithms like evolutionary or reinforcement-based NAS, and larger datasets to improve surrogate accuracy. These enhancements could facilitate the evolution of EA-NAS into a more integrated and scalable solution for the practical deployment of TinyML and embedded systems.

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