Support Vector Machine Algorithm Optimization for Sentiment Analysis using Bayesian Optimization

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Abstract — ***This study investigates the application of Bayesian Optimization to enhance the performance, efficiency, and sustainability of Support Vector Machine (SVM)-based Aspect-Based Sentiment Analysis (ABSA). A dataset comprising 988 Borobudur Temple reviews, annotated into six aspects (Attractiveness, Facilities, Accessibility, Visual Image, Price, and Human Resources), was employed to compare a baseline SVM with an optimized SVM. Evaluation metrics included accuracy, training time, energy consumption, and CO_2 emissions. The results indicate accuracy improvements across all aspects, with the most substantial gains observed in Facilities (0.7294 to 0.8682) and Price (0.8047 to 0.9576). The most challenging aspect, Visual Image, also improved from 0.6729 to 0.72. Bayesian Optimization reduced training time, particularly for Visual Image (13.04 seconds to 9.4 seconds), and decreased energy consumption and CO_2 emissions, supporting sustainable machine learning practices. The study contributes by (1) demonstrating the effectiveness of Bayesian Optimization in improving both accuracy and efficiency, (2) incorporating energy and emission reporting into ABSA evaluation, and (3) providing aspect-specific insights that reveal heterogeneous improvements. These findings establish Bayesian Optimization as a robust, efficient, and environmentally responsible enhancement to SVM-based ABSA.***

Keywords— **ABSA; *Accuracy*; *Bayesian Optimization*; *Energy Efficiency*; SVM.**

Optimasi Algoritma *Support Vector Machine* untuk Analisis Sentimen dengan *Bayesian Optimization*

Abstrak — **Studi ini menyelidiki penerapan *Bayesian Optimization* (BO) untuk meningkatkan kinerja, efisiensi, dan keberlanjutan Analisis Sentimen Berbasis Aspek (ABSA) berbasis Support Vector Machine (SVM). Kumpulan data yang terdiri dari 988 ulasan Candi Borobudur, yang dianotasi ke dalam enam aspek (Daya Tarik, Fasilitas, Aksesibilitas, Citra Visual, Harga, dan Sember**

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Daya Manusia), digunakan untuk membandingkan SVM dasar dengan SVM yang dioptimalkan. Metrik evaluasi meliputi akurasi, waktu pelatihan, konsumsi energi, dan emisi CO_2. Hasilnya menunjukkan peningkatan akurasi di semua aspek, dengan peningkatan paling substansial diamati pada Fasilitas (0,7294 menjadi 0,8682) dan Harga (0,8047 menjadi 0,9576). Aspek yang paling menantang, Citra Visual, juga meningkat dari 0,6729 menjadi 0,72. BO mengurangi waktu pelatihan, terutama untuk Citra Visual (13,04 detik menjadi 9,4 detik), dan menurunkan konsumsi energi serta emisi CO_2, yang mendukung praktik pembelajaran mesin yang berkelanjutan. Studi ini berkontribusi dengan (1) menunjukkan efektivitas BO dalam meningkatkan akurasi dan efisiensi, (2) mengintegrasikan pelaporan energi dan emisi ke dalam evaluasi ABSA, dan (3) memberikan wawasan spesifik aspek yang mengungkap berbagai peningkatan heterogen. Temuan ini menetapkan BO sebagai penyempurnaan ABSA berbasis SVM yang tangguh, efisien, dan ramah lingkungan.

***Kata kunci*— ABSA; Akurasi; Bayesian Optimization; Efisiensi Energi; SVM;.**

I. INTRODUCTION

The rapid development of Machine Learning (ML) has transformed various domains, including conducting data sentiment analysis on detecting tourist emotions at tourist attractions and detecting identity card leaks [1], [2]. A novel sentiment analysis technique, known as Aspect-Based Sentiment Analysis (ABSA), has recently been created, offering a more nuanced evaluation of sentiments on certain features of a product or service[3], [4]. The escalating computing requirements of machine learning models have led to considerable energy usage and carbon emissions, presenting difficulties in reconciling this technology with sustainability principles [3], [5], [6]. The expansion of machine learning in sentiment analysis underscores the necessity to consider its environmental consequences, particularly the carbon emissions associated with training intricate models like SVM [7], [8]. ABSA is a subset of Natural Language Processing (NLP) that disaggregates input into components and retrieves sentiment information [4], [9]. This method offers more comprehensive insights than conventional document-level or sentence-level sentiment analysis.

Notwithstanding the efficacy of SVM in ABSA tasks, two major concerns emerge. The computational expense associated with hyperparameter adjustment to enhance model performance presents a significant challenge [3], [4]. Secondly, the energy consumption and carbon emissions resulting from the substantial computational requirements of SVM models provide a notable environmental issue [3], [5], [6]. This requires the use of Green Machine Learning, which seeks to enhance the energy efficiency of machine learning models without sacrificing their effectiveness. Enhancing the hyperparameters of SVM models through effective optimization techniques can mitigate both computational expenses and environmental repercussions [5], [6], [7]. Numerous studies have investigated the application of optimization methods, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Bayesian Optimization, for the tuning of hyperparameters in SVM models. These methodologies have exhibited enhanced classification accuracy and diminished computing time relative to conventional grid search or manual tuning techniques [5], [6], [10]. Nevertheless, the current literature predominantly emphasizes the enhancement of SVM model performance, with insufficient attention given to the environmental implications of the optimization process. Incorporating sustainability principles into the hyperparameter optimization of SVM models for ABSA tasks is essential to link this technology with overarching environmental sustainability objectives [3], [11], [12].

Creating precise and energy-efficient ABSA models is essential for promoting sustainable AI. Although SVM is a strong algorithm for sentiment classification, its effectiveness is significantly dependent on the careful tuning of parameters, which can be resource intensive. Bayesian Optimization presents an effective approach for automating hyperparameter tuning, leading to significant reductions in both computational time and energy consumption. This method can effectively tackle the simultaneous issues of model efficacy and ecological footprint linked to the training of intricate machine learning models for ABSA tasks [3], [8], [10]. A number of investigations have examined the application of Bayesian Optimization for tuning the hyperparameters of SVM models, showing enhanced classification accuracy and decreased computational requirements in comparison to conventional approaches [5], [6], [12], [13]. Nonetheless, the current body of work mainly emphasizes enhancing the performance of SVM models, while giving insufficient attention to the environmental implications of the optimization process. Incorporating sustainability principles into the hyperparameter optimization of SVM models for ABSA tasks is essential to ensure that this technology aligns with the overarching objectives of environmental sustainability. This study focuses on enhancing SVM models to improve both performance and energy efficiency, thereby contributing to the advancement of sustainable and ethical AI solutions in sentiment analysis.

Current studies primarily emphasise enhancing the accuracy of ABSA models, frequently overlooking their environmental implications [3], [4], [5], [7]. Few studies have investigated the incorporation of green optimization methods in ABSA. Bayesian Optimization has been employed to improve the efficiency of SVM models across multiple domains; however, its use in Green Machine Learning for ABSA tasks is still insufficiently investigated. The current literature predominantly emphasises the enhancement of SVM model performance, while giving insufficient attention to the environmental implications of the optimization process [3], [12], [14], [15]. Incorporating sustainability principles into the hyperparameter optimization of SVM models for ABSA tasks is essential for aligning this technology with overarching environmental sustainability objectives. Moreover, current research on Green Machine Learning predominantly emphasises enhancing the energy efficiency of deep learning models, while there is comparatively limited focus on optimising traditional machine learning algorithms, such as SVMs, which are extensively utilised in ABSA tasks.

This study seeks to enhance SVM models in terms of both performance and energy efficiency, thereby contributing to the development of sustainable and responsible AI solutions in sentiment analysis. The rapid growth of machine learning highlights the urgency of addressing its environmental implications, particularly the carbon emissions generated during the training of complex models such as SVM. Accordingly, this study proposes a Green Machine Learning approach for ABSA by employing Bayesian Optimization to improve SVM performance while reducing computational costs, energy consumption, and carbon footprint. Empirical evaluations are conducted to assess improvements in accuracy, training efficiency, and sustainability. Thus, the following research question is addressed: How can Bayesian Optimization improve the energy efficiency and performance of Support Vector Machine models for Aspect-Based Sentiment Analysis while lowering their carbon footprint?

II. RESEARCH METHODOLOGY

This section outlines the methodological approach utilized to evaluate the impact of Bayesian Optimization on improving the accuracy, training efficiency, and energy consumption of an SVM-based ABSA model. The tests evaluated the efficacy and ecological consequences of a baseline SVM model, retrained without optimization, in comparison to an optimized SVM model developed by Bayesian Optimization. The research employed the identical dataset as previous studies [16], comprising 988 customer reviews of Borobudur Temple. The dataset is categorized into six dimensions: Attractiveness, Amenities, Accessibility, Visual Image, Price, and Human Resources, with sentiment labels designated as Positive (1), Neutral (0), Negative (−1), or No Mention (-). Our study directly utilizes these annotations for classification tasks; these aspect labels were pre-defined in the dataset and were not produced by aspect extraction techniques. For clarity, the following are samples of annotated reviews: "Pelayanan petugas sangat ramah, tetapi harga tiket terlalu mahal" (Price = Negative; Human Resources = Positive) and "Pemandangan candi indah sekali, namun toilet kurang bersih" (Visual Image = Positive; Amenities = Negative). Attractiveness and Visual Image predominate in the dataset's unbalanced distribution, which creates further difficulties for model evaluation and training. Figure 1 illustrates the overall research flow.

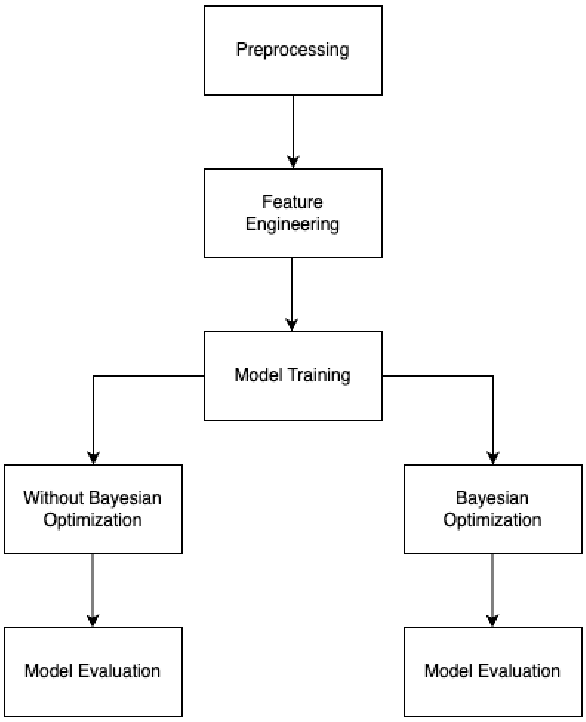

Figure 1. Research Flow

There will be four major stages carried out in two study scenarios, which are described in greater detail below.

A. *Pre-processing*

The pre-processing phase is essential for ensuring the quality and consistency of input data for the SVM model. Pre-processing converts raw, unstructured textual data into a clean and standardised format, essential for machine learning tasks, particularly sentiment analysis. This research employed the subsequent pre-processing treatments:

1) *Text Cleansing*

Text cleaning involves the elimination of irrelevant components, including special characters, punctuation, numeric values, and excess whitespace from raw text, thereby minimising noise. This step guarantees the text is devoid of extraneous artifacts that may obscure the machine learning model's performance. Eliminating extraneous noise allows the model to concentrate on significant patterns in the data, enhancing its learning efficiency. Text cleaning is crucial for sentiment analysis, as unclean data can distort classification results and impair model performance. Eliminating irrelevant elements standardises the input text and prepares it effectively for subsequent pre-processing stages, thereby improving accuracy and reliability.

2) *Tokenization*

Tokenisation refers to the process of segmenting text into distinct words or tokens. This is generally accomplished through the use of natural language processing libraries, such as the tokenizer from NLTK. Tokenisation is crucial for subsequent tasks, as it establishes the basic units of analysis for machine learning models.

3) *Stopword Removal*

Stopword are frequently occurring words that lack substantial semantic value, including terms like "the," "a," "and," and "is." Eliminating these stopword from the text enhances the analysis by concentrating on more significant terms, thereby improving the performance of the ABSA model. Researchers frequently employ predefined stopword lists or custom-curated stopword sets tailored to specific domains or languages.

4) *Normalization*

Normalisation refers to the conversion of non-standard or slang terms into their standard forms. This step is crucial in user-generated content, including online reviews, where the language tends to be informal and varied. Normalising the text enhances the ABSA model's ability to comprehend the intended meaning and sentiment conveyed in the data.

5) *Stemming and Lemmatization*

Stemming and lemmatisation are methods employed to reduce words to their base forms, referred to as stems or lemmas, respectively. This process organises related words, enhancing the model's capacity to understand semantic relationships among terms. Stemming generally entails the removal of suffixes, whereas lemmatisation takes into account the context and part of speech to ascertain the appropriate root form.

B. *Feature **Engineering***

Feature engineering is an essential step in the preparation of textual data for machine learning models, especially in sentiment analysis applications. This study employs two feature extraction techniques, CountVectorizer and TF-IDF Transformation, to convert pre-processed text data into a numerical format appropriate for SVM classification. These methods are commonly utilised due to their effectiveness in capturing key text features and facilitating efficient training of machine learning models.

1) *Count Vectorizer*

Count Vectorizer is a simple and commonly employed technique for representing text data in a bag-of-words (BoW) format. The method involves tallying the frequency of each word within a document and creating a matrix based on these frequencies, with rows representing documents and columns representing unique words. The Count Vectorizer is noted for its computational efficiency and interpretability, rendering it appropriate for high-dimensional datasets, especially when word context is not a primary concern. One limitation of the Count Vectorizer is its equal treatment of all words, disregarding their relative importance within and across documents. This can lead to suboptimal performance in text classification tasks, particularly when common words dominate the dataset.

2) *TF-IDF*

To overcome the limitations of Count Vectorizer, the Term Frequency-Inverse Document Frequency (TF-IDF) transformation is utilised. TF-IDF is a sophisticated method that accounts for word frequency within a document while also diminishing the weight of terms that are prevalent across multiple documents, as such terms tend to provide less informative value. TF-IDF quantitatively assigns a weight to each word w in a document d according to the following formula (1):

$$\text{TF-IDF}(\boldsymbol{w}, \boldsymbol{d}) = \text{TF}(\boldsymbol{w}, \boldsymbol{d}) \cdot \mathbf{log}\,(\frac{\boldsymbol{N}}{\text{DF}(\boldsymbol{w})}), \tag{1}$$

C. *Model* ***Training***

1) Support Vector Machine (SVM)

SVM is a supervised machine learning algorithm primarily used for classification tasks, but it can also handle regression problems. SVM works by finding an optimal hyperplane that separates data points into distinct classes with the maximum margin between them. Given a dataset of n n labelled training samples $\{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{i=1}^{n}$ where $\boldsymbol{x_i}$ represents the input features and $\boldsymbol{y_i} \in \{-\mathbf{1}, \mathbf{1}\}$ denotes the class labels, the SVM optimization problem is formulated as shown in formula (2):

$$\text{minimize } \frac{\mathbf{1}}{\mathbf{2}}||\boldsymbol{w}||^2 \text{subject to } \boldsymbol{y_i}(\boldsymbol{w} \cdot \boldsymbol{x_i} + \boldsymbol{b}) \geq \mathbf{1} - \boldsymbol{\xi_i}, \boldsymbol{\xi_i} \geq \mathbf{0}. \tag{2}$$

Here, w w is the weight vector, b is the bias, and $\xi\ i$ represents slack variables to account for non-linearly separable data. The parameter C regulates the balance between margin maximisation and classification error minimisation. Support Vector Machines (SVM) utilise various kernel functions, such as linear, polynomial, radial basis function (RBF), and sigmoid, to map data into higher-dimensional spaces, facilitating easier separation. SVM demonstrates superior performance in text classification and sentiment analysis tasks characterised by high feature space dimensionality.

2) Scenario 1: Baseline SVM Training

In the Baseline SVM Training scenario, the SVM model is retrained with hyperparameters that match those from the referenced study [16]. The hyperparameters include: C = 0.5 (regularisation strength), Degree = 2 (degree of the polynomial kernel), Gamma = Scale (automatic scaling based on feature variance), and Kernel = Sigmoid. The parameters guarantee that the model upholds baseline performance, facilitating a fair comparison with the optimised version. The training process is carried out independently for the six components: Attractiveness, Amenities, Accessibility, Visual Image, Ticket Price, and Human Resources. The baseline scenario seeks to replicate initial performance results while assessing energy consumption and environmental impact through CarbonTracker, a tool developed to monitor and report energy usage and carbon emissions during model training. Monitoring energy consumption is essential for aligning machine learning practices with sustainable AI goals, as emphasised by [17]. This scenario functions as the control setup, establishing a benchmark for comparison with the introduction of Bayesian Optimization in Scenario 2. This experiment quantifies the environmental trade-offs linked to SVM hyperparameter configurations through systematic measurement of model accuracy and energy consumption.

3) Scenario 2: Bayesian Optimization for Hyperparameter Tuning

In Bayesian Optimization, the training process is enhanced through the automatic tuning of SVM hyperparameters to optimise validation accuracy. Bayesian Optimization is a probabilistic technique that effectively explores the parameter space by developing a surrogate model, such as a Gaussian Process, to estimate the objective function. This method is especially beneficial for machine learning models that incur high training costs, as it minimizes the number of evaluations needed for optimization. The parameter search space comprises:

1) C: [0.1, 10.0] to investigate a broad spectrum of regularisation strengths.
2) Degree: [1, 5] for polynomial kernel degree.
3) Gamma: {Scale, Auto} to optimize kernel coefficient scaling.
4) Kernel: {Linear, Polynomial, RBF, Sigmoid} for flexible decision boundaries.

The Optuna library, a cutting-edge framework, is utilised to execute Bayesian Optimization for efficient hyperparameter search. Optuna conducts repeated assessments of various parameter combinations utilising the validation set and determines the configuration that produces the optimal performance for each aspect classification and sentiment classification task. Optuna expedites hyperparameter optimization while preserving high accuracy in text classification tasks, as shown in [18]. Upon determining the appropriate hyperparameters, the SVM models are retrained utilising these configurations for each aspect and sentiment classification task. This enhanced training procedure is anticipated to augment model precision and efficacy relative to the baseline scenario. CarbonTracker is utilised to assess the environmental impact of the optimization process by monitoring energy consumption and calculating the carbon footprint of both the Bayesian Optimization and the subsequent model training. This stage is essential for assessing the trade-off between enhancing accuracy and resource expenditure, as minimising energy consumption is consistent with green AI concepts. Strubell et al. [19] underscored that optimising energy consumption is crucial for the sustainability of machine learning processes.

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The Bayesian Optimization process in Optuna follows a structured three-stage workflow. **In the input stage**, the search space is defined and includes SVM hyperparameters such as the regularisation parameter C, polynomial kernel degree, kernel coefficient gamma, and kernel type (linear, polynomial, RBF, sigmoid). Validation accuracy obtained during training is used as the objective function to maximise. **During the process stage**, Optuna utilises the Tree-structured Parzen Estimator (TPE) as a surrogate model to guide the search. At each iteration, candidate hyperparameter sets are sampled and evaluated, and the results are used to update the surrogate distribution. This iterative cycle balances exploration of less-tested regions in the search space with exploitation of regions that demonstrate higher performance. **In the output stage**, the optimization process identifies the best-performing hyperparameter configuration, supported by performance metrics and trial logs to ensure reproducibility and transparency. This structured approach enhances both the efficiency and robustness of training SVM-based ABSA models.

*D. Model **Evaluation***

This study evaluates the performance and energy efficiency of the SVM model through a combination of performance metrics and energy efficiency metrics. These metrics facilitate a thorough evaluation of model accuracy and environmental impact, consistent with sustainable and efficient machine learning practices.

1) Model Performance Metrics

The accuracy metric evaluates the ratio of correctly classified instances to the total number of test samples. Accuracy is mathematically defined as shown at formula (3):

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\%. \tag{3}$$

Accuracy serves as a commonly utilised evaluation metric in sentiment analysis tasks, owing to its clear interpretation and significance for classification issues. The model demonstrates effectiveness in accurately predicting labels across six dimensions: Attractiveness, Amenities, Accessibility, Visual Image, Ticket Price, and Human Resources. Accuracy is a primary benchmark for evaluating text classification models such as SVM, as it measures the overall correctness of predictions, which is essential for practical applications in sentiment analysis. Accuracy alone fails to account for imbalanced class distributions, necessitating the integration of supplementary insights from energy efficiency evaluations.

2) Energy Efficiency Metrics

Energy efficiency is assessed by evaluating training duration, energy usage, and carbon emissions, which indicate the environmental impact of model development. The importance of these metrics grows as machine learning applications expand in size and complexity.

1) Training Time
The training time represents the total duration required to train the SVM models, quantified in seconds or minutes, and serves as a direct indicator of computational resource utilisation. Shorter durations signify greater efficiency in models, which is crucial for practical applications. Strubell et al. [19] emphasise the importance of minimising training time while maintaining accuracy for energy-efficient machine learning systems, noting that Bayesian Optimization facilitates a more efficient hyperparameter search.
2) Energy Consumption
Energy consumption, expressed in kilowatt-hours (kWh), quantifies the energy utilised in the process of model training. Tools such as CarbonTracker facilitate the monitoring of usage, thereby ensuring precise reporting. Henderson et al. [17] highlight the significance of energy-efficient models in mitigating the environmental impact of machine learning, especially within resource-constrained systems.
3) Carbon Emissions
Carbon emissions, expressed in kilograms of CO_2 equivalent ($kgCO_2eq$), are derived from energy consumption data utilising CarbonTracker. Lacoste et al. [20] emphasise the importance of monitoring emissions for sustainable AI, advocating for environmentally friendly practices such as Bayesian Optimization to reduce ecological impact.

This study offers a thorough evaluation of SVM models by analysing accuracy in conjunction with training time, energy consumption, and carbon emissions. The findings emphasise the equilibrium between enhancements in performance and resource efficiency, confirming that machine learning solutions can be both effective and environmentally sustainable.

III. Results And Discussion

This section presents the experimental results and a comprehensive discussion of the findings for two scenarios: the baseline SVM model without hyperparameter optimization and the SVM model optimised using Bayesian Optimization. This comparison examines three key performance metrics: accuracy, computation time, and carbon footprint and energy usage, which collectively offer a comprehensive evaluation of the model's effectiveness and efficiency. The findings indicate that hyperparameter tuning enhances accuracy and computational efficiency while reducing energy consumption, aligning with the principles of sustainable machine learning. Each facet of feeling is analysed individually to elucidate the model's behaviour, strengths, and limitations. The discussion proposes avenues for enhancement, particularly in regions exhibiting suboptimal performance, and examines the wider consequences of employing Bayesian Optimization for ABSA.

Table 1 presents the results of Bayesian optimization for SVM hyperparameters across six dimensions: Attraction, Amenities, Accessibility, Visual Image, Price, and Human Resources. The optimised C values vary between 0.89 and 2.45, effectively balancing regularisation strength across different dimensions. Most aspects exhibit a degree of 1, indicating that linear relationships are adequate, with the exception of Visual Image, which has a degree of 5, suggesting increased complexity. The gamma parameter primarily employs "scale" for automatic scaling, with the exception of Amenities, which utilises "auto." Kernel selection exhibits a linear relationship for Attraction, Amenities, and Visual Image, a sigmoid relationship for Accessibility and Price, and a polynomial relationship for Human Resources. The results underscore the significance of aspect-specific hyperparameter tuning, demonstrating that Bayesian optimization effectively improves performance through tailored configurations, thereby enhancing accuracy and ensuring computational efficiency.

TABLE 1.
PARAMETERS RESULTING FROM BAYESIAN OPTIMIZATION

Aspects	Parameters Based on Bayesian Optimization Result			
	C	degree	gamma	kernel
Attraction	2.253353671	1	scale	linear
Amenities	1.18730165	1	auto	linear
Accessibility	1.361852376	1	scale	sigmoid
Visual Image	0.8920207877	5	scale	linear
Price	2.226360565	1	scale	sigmoid
Human Resources	2.445368319	1	scale	poly

Table 2 presents the SVM baseline results (scenario 1), assessing computation time, accuracy, and environmental impact via energy consumption, CO_2 emissions, and car-equivalent distances. Of the six aspects analysed, Human Resources demonstrates the highest accuracy at 0.9341, accompanied by the lowest computation time of 4.041 seconds, minimal energy consumption of 0.000013 kWh, and CO_2 emissions of 0.0062 grammes, reflecting both efficiency and superior performance. In contrast, Visual Image exhibits the lowest accuracy (0.6729) alongside the highest computation time (13.042s), energy consumption (0.000053 kWh), and CO_2 emissions (0.0252 g), indicating a level of complexity and inefficiency in its processing capabilities. Accessibility shows high accuracy (0.8353) and low resource usage, while Amenities has moderate accuracy (0.7294) but requires greater computation time and energy consumption. The results demonstrate variability in SVM performance across different aspects, suggesting that areas such as Visual Image necessitate further optimization to enhance efficiency and accuracy, whereas aspects like Human Resources exhibit baseline efficiency with minimal environmental impact.

TABLE 2.
SVM BASELINE RESULT (SCENARIO 1)

Aspects	Computation Time (s)	Accuracy	CarbonTracker		
			Energy (kWh)	CO_2 (g)	Equivalent by Car (km)
Attraction	7.283	0.8141	0.000026885277	0.01265713665	0.000117740806
Amenities	9.626	0.7294	0.000029012803	0.01365874046	0.000127058051
Accessibility	4.529	0.8353	0.000015882135	0.007477042255	0.000069553881
Visual Image	13.042	0.6729	0.00005346176	0.02516889836	0.000234129287
Price	6.535	0.8047	0.000023963053	0.01128140296	0.000104943283
Human Resources	4.041	0.9341	0.00001319315	0.006211113557	0.000057777801

The SVM models optimised through Bayesian Optimization (Scenario 2) demonstrate enhanced accuracy and decreased computational resource requirements relative to the baseline, as indicated in Table 3. Price and Human Resources attain the highest accuracies of 0.9576 and 0.9553, respectively, while demonstrating low computation times of 3.587s and 4.523s,

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along with minimal energy consumption and CO_2 emissions, underscoring their efficiency under optimised parameters. Attraction and amenities exhibit notable performance improvements, achieving accuracies of 0.8659 and 0.8682, while also showing decreased computation times and energy consumption relative to scenario 1. Accessibility enhances accuracy to 0.8918 while sustaining low energy consumption (0.000013 kWh), demonstrating the advantages of optimization. Despite a reduced computation time of 9.401 seconds and lower energy usage, Visual Image continues to underperform, achieving an accuracy of only 0.72, which suggests inherent complexity in this area.

TABLE 3.
SVM WITH BAYESIAN OPTIMIZATION RESULT (SCENARIO 2)

Aspects	Computation Time (s)	Accuracy	CarbonTracker		
			Energy (kWh)	CO_2 (g)	Equivalent by Car (km)
Attraction	6.15	0.8659	0.000021750163	0.01023961142	0.000095252199
Amenities	7.469	0.8682	0.00002520844	0.01186770999	0.000110397302
Accessibility	4.067	0.8918	0.000013373226	0.006295890194	0.00005856642
Visual Image	9.401	0.72	0.000032117104	0.01512019312	0.000140652959
Price	3.587	0.9576	0.000011905935	0.005605114009	0.000052140595
Human Resources	4.523	0.9553	0.000015571126	0.00733062475	0.000068191858

Bayesian Optimization improves model accuracy, decreases training time, and minimises energy consumption and carbon emissions, thereby supporting more sustainable and efficient machine learning processes. The baseline SVM [16] and the SVM optimized with Bayesian optimization are compared in Figure 2 in terms of energy consumption (kWh) across six factors: price, human resources, accessibility, visual image, amenities, and attraction.

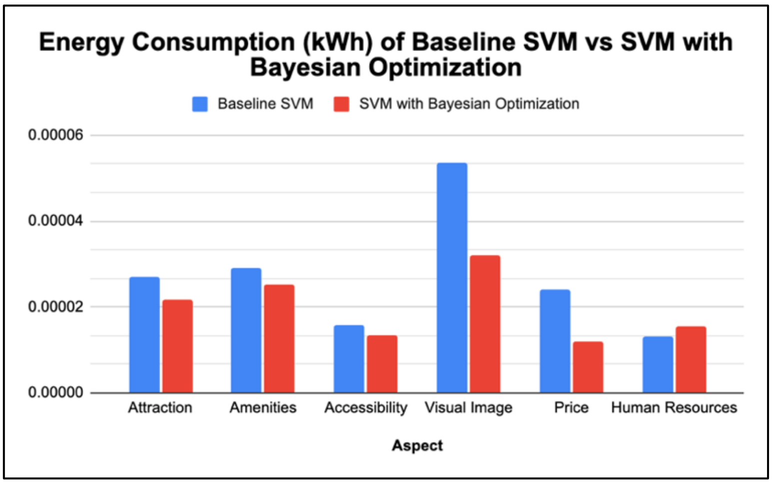

Figure 2. Comparison Scenario 1 vs Scenario 2 Based on Energy Consumption

The findings demonstrate that Bayesian optimization improves training efficiency by lowering energy usage in the majority of areas, but especially in the areas of accessibility, amenities, and attractions. Visual Image shows the biggest decrease, although overall, this component still uses the most energy. Human Resources shows a modest increase, indicating a trade-off between efficiency and accuracy. In general, the results show that Bayesian optimization helps training be more energy-efficient, which is consistent with sustainable machine learning techniques. CO2 emissions (g) are shown in Figure 3 for each of the six factors.

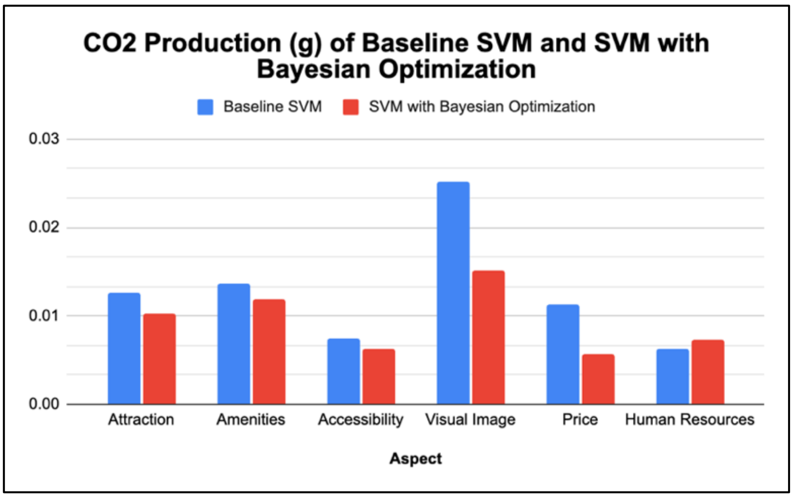

Figure 3. Comparison Scenario 1 vs Scenario 2 Based on CO2 Production (g)

In most situations, Bayesian optimization reduces emissions, with noticeable decreases for accessibility, amenities, and attractions. This is in line with the findings on energy consumption. Visual Image shows the biggest decline, demonstrating that optimization reduces the environmental impact of more computationally intensive operations. Under the optimized model, price records the lowest emissions, while human resources show a slight increase, demonstrating once more the balance between efficiency and performance. These findings show that Bayesian optimization can help promote more environmentally friendly AI techniques and lessen the environmental impact of ABSA models. Computation time (s) for both models across six aspects are displayed in Figure 4.

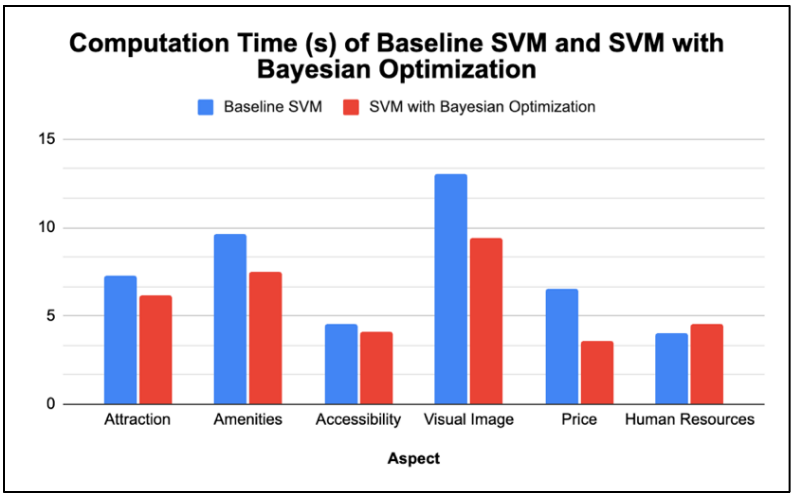

Figure 4. Comparison Scenario 1 vs Scenario 2 Based on Time Computation (s)

With significant reductions for Visual Image (from about 14 seconds to 9 seconds) and Price (almost 50% faster than baseline), the optimized SVM often reduces training time. These enhancements demonstrate how well-adjusted hyperparameters can increase computational efficiency. A slight increase in human resources suggests that accuracy might occasionally take precedence over speed in optimization. Overall, the results indicate that Bayesian optimization helps to achieve more efficient model training without compromising predictive accuracy by cutting down on computation time for resource-intensive jobs. Based on previous research, the results show that the SVM improved with Bayesian optimization performs better than the baseline SVM [16] as shown in Figure 5.

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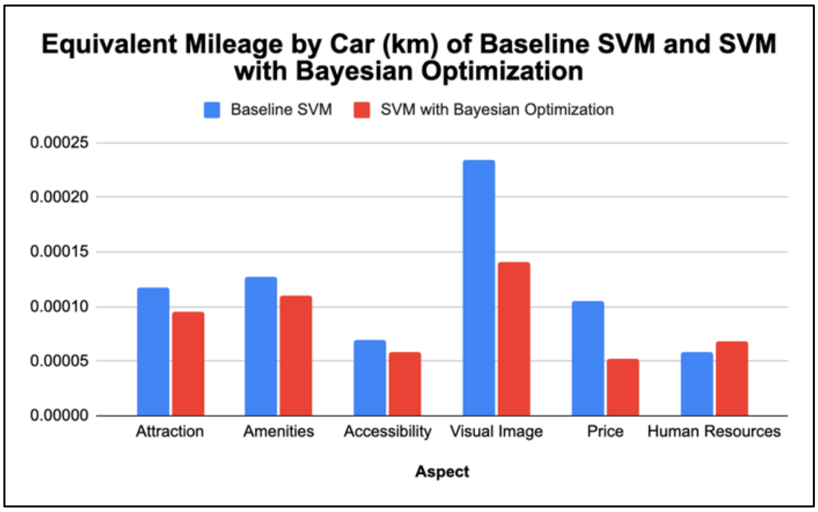

Figure 5. Comparison Scenario 1 vs Scenario 2 Based on Equivalent Mileage by Car (km)

The optimized model consistently improves accuracy in all areas, with the biggest gains in price (from 0.8047 to 0.9576) and amenities (from 0.7294 to 0.8682), underscoring the significance of hyperparameter tuning in enhancing model precision. Also improving to 0.72 is the Visual Image aspect, which had previously scored the lowest accuracy (0.6729). Bayesian Optimization decreases computational cost in most areas of training efficiency, with significant reductions for complicated tasks like Visual Image (from 13.04s to 9.4s) and Amenities (from 9.6s to 7.4s). These findings show that both increased accuracy and increased computing efficiency are facilitated by hyperparameter tweaking. Accuracy comparisons between the baseline and optimized models are shown in Figure 6.

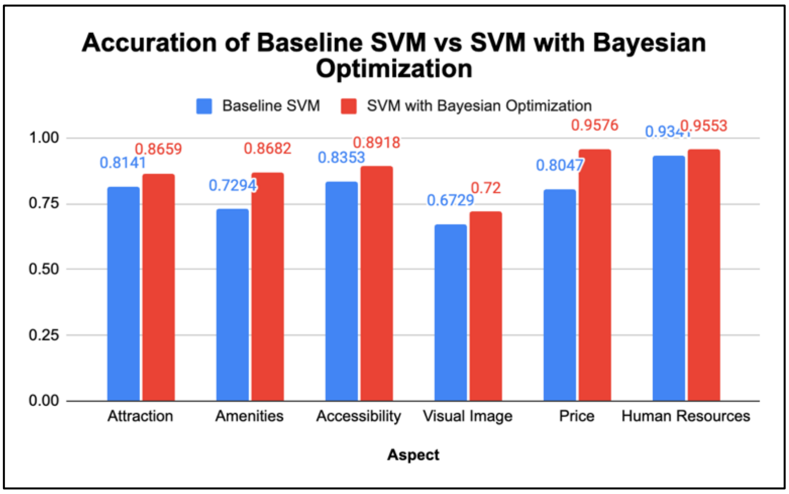

Figure 6. Comparison Scenario 1 vs Scenario 2 Based on the Accuracy Model

Accuracy increases in every way: Price increases from 0.8047 to 0.9576, Visual Image from 0.6729 to 0.72, Amenities from 0.7294 to 0.8682, Accessibility from 0.8353 to 0.8918, Attraction from 0.8141 to 0.8659, and Human Resources from 0.9341 to 0.9553. These improvements are mainly noticeable for the comparably more difficult factors of price and amenities. The optimized model still makes a slight improvement, even though Visual Image is still the least accurate because of the small sample size. These findings imply that Bayesian optimization improves classification accuracy in a variety of ways. All things considered, the optimized SVM consistently outperforms the baseline found in earlier studies [16]. Notably, price increased from 0.8047 to 0.9576 and amenities from 0.7294 to 0.8682, highlighting the significance of hyperparameter adjustment. Additionally, there is a discernible improvement (0.72) in the Visual Image aspect, which had the lowest baseline accuracy (0.6729). The majority of the training time is cut, with notable decreases in Visual Image (from 13.04s to 9.4s) and Amenities (from 9.6s to 7.4s). These results show that Bayesian optimization increases computing efficiency and accuracy.

In addition to improving performance, the optimized models significantly lower energy consumption and CO2 emissions, especially in energy-intensive areas like Visual Image. This fills in the gaps in the earlier study [16], where environmental factors were not evaluated, and is consistent with sustainable machine learning concepts. Since Bayesian Optimization actively modifies parameters (C, kernel, and gamma) to match aspect-specific complexity, the impact of hyperparameter adjustment is clear. For simpler aspects like attraction, linear kernels worked well; for more complex aspects, polynomial and sigmoid kernels worked better. These findings demonstrate that Bayesian optimization reduces baseline constraints and provides an ABSA solution that is more precise, effective, and ecologically friendly.

IV. CONCLUSION

Bayesian Optimization for hyperparameter tuning enhances the performance, computational efficiency, and sustainability of Support Vector Machine-based Aspect-Based Sentiment Analysis models. This is demonstrated by accuracy gains across six aspects of Borobudur Temple reviews, with the most notable improvements observed in Amenities (0.7294 to 0.8682) and Price (0.8047 to 0.9576). Reductions in computation time and energy consumption are also evident, particularly for complex aspects such as Visual Image. The findings confirm that Bayesian Optimization improves predictive accuracy, reduces training overhead, and lowers carbon emissions, thereby supporting the principles of sustainable artificial intelligence. However, the study is limited by the relatively small and imbalanced dataset of 988 reviews, the exclusive focus on a single algorithm without comparison to alternatives such as Logistic Regression or Transformer-based models, reliance on accuracy rather than imbalance-sensitive metrics such as macro-F1, weighted-F1, or AUC-PR, and energy reporting restricted to CPU-based experiments. Future research should expand datasets and balance aspect annotations, incorporate additional algorithms and comprehensive evaluation metrics, extend carbon accounting to GPU or cluster-based environments, and integrate explainability and error analysis to advance more accurate, efficient, and environmentally responsible Aspect-Based Sentiment Analysis solutions.

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