Survey on EcoSense: Intelligent Tagging System for SDG-Oriented Product Profiling

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Abstract— EcoSense is an AI-based tool designed to help users identify whether a product is environmentally sustainable based on short text inputs such as “plastic toothbrush” or “snack packet.” Using Natural Language Processing (NLP), the system extracts material-related information, classifies the product’s sustainability level, and suggests eco-friendly alternatives .It works fully offline, so users don’t need internet access to get results—making it useful even in remote or low connectivity areas .By helping people better understand the environmental impact of their purchases, this tool makes it easier to choose more sustainable options, supporting the goal of responsible consumption outlined in Sustainable Development Goal 12.

Keywords—Sustainability, Conscious Consumption, NLP, EcoFriendly Choices, Offline AI, SDG 12, Material Impact

I.INTRODUCTION

In the face of accelerating climate change and environmental degradation, achieving sustainable consumption patterns is a pressing global necessity. The UN Sustainable Development Goal 12 emphasizes the need for responsible consumption and production, which hinges not only on how industries operate, but also on how individual consumers make daily product choices. Yet, for most individuals, evaluating whether a product is environmentally sustainable remains a guessing game — lacking transparency, interpretability, and accessible tools at the moment of sale.

Here's where AIML are beginning to step in. A growing body of research suggests that smart systems can support sustainability efforts by helping consumers, businesses, and policymakers better understand the ecological implications of products and behaviors. Machine learning, for example, has been used to classify environmental attitudes [1], detect unethical sourcing [14], and support green marketing decisions [13]. These studies provide a spotlight on how technology can help not just analyze sustainability but actively influence behaviour.

Some works focus on large-scale societal behaviour.[2] examine how reducing non-biodegradable waste in Nigeria requires not only community awareness but also smarter tools that help people make environmentally conscious decisions. Similarly, [4] show how AI can
assist consumers in altering food choices based on environmental and health indicators. Others, like [7], tackle the problem post-consumption through waste segregation tools. However, these applications, while impactful, are limited to specific domains or require highly structured input.

In more technical domains, studies like [3] demonstrate the power of deep learning models such as Efficient Net in product classification within e-commerce platforms. These classification capabilities, while primarily

focused on business use, could also serve sustainability scoring systems with the right tuning. [8] go a step further by proposing multi-modal fusion of structured and unstructured product data, which is particularly relevant for building systems that interpret packaging, labelling, or even product descriptions to infer sustainability impact.

From a consumer psychology angle, green marketing has been extensively explored. [13] as well as [10] illustrate how strategic environmental messaging influences consumer preferences. While such work is often marketing-driven, its insights are crucial for designing AI tools that resonate with public values. [11] further reinforce this by analyzing the psychological impact of eco-labels and awareness campaigns.

However, despite the progress, a recurring limitation across most papers is the lack of real-time, user-centered applications. Many models operate on pre-labelled datasets or industry-level data, which do not reflect the spontaneous, minimal-input decisions of everyday consumers. As emphasized in [6] and [9], integrating intelligent systems into daily purchase decisions remains a challenge — not because the models are unavailable, but because they're not yet accessible, explainable, or deployable at the point of need.

This survey aims to bridge that gap. By reviewing papers across domains of sustainability classification, eco-aware branding, product recognition, and user behavior modelling, we highlight how various ML approaches can be adapted and unified into practical, consumer-facing sustainability tools. Our work also identifies patterns, gaps, and opportunities for building smarter systems — ones that are not only accurate, but lightweight, real-time, and human-centered.

II.LITERATURE REVIEW

In recent years, the intersection of artificial intelligence and the use of sustainable consumption has greatly academic attention. Researchers across domains have explored how machine learning can identify patterns in consumer behaviour, automate waste classification, evaluate product sustainability, and promote eco-conscious decision-making. These efforts stem from a collective recognition that technological intervention can act as a catalyst in speeding up the fulfillment of achieving Sustainable Development Goal 12.

While some studies emphasize backend analysis, such as unethical sourcing detection or green marketing optimization, others focus on front-facing applications like mobile apps for waste segregation or intelligent food assistants. Yet, across the spectrum, the overarching aim remains the same: to bridge the gap between sustainability awareness and actionable choices. This section reviews and compares such research efforts, analyzing their objectives, methodologies, tools used, and relevance to building consumer-focused sustainability tools like the one envisioned in our project.

Table 2.1 Literature survey

S.No	Paper Title	Methodology Used	Outcomes / Results	Applications / Use Case
1	Classifying Environmental Attitudes Using Explainable ML Models	Logistic Regression, SVM, XGBoost with SHAP	94% accuracy in classifying environmental attitudes	User profiling, environmental awareness modeling
2	Sustainable Consumption in Kwara State, Nigeria	Survey-based qualitative analysis	Identified need for public awareness and waste policies	Policy framing, community engagement
3	E-Commerce Image Classification Using EfficientNetB5	EfficientNetB5, Transfer Learning	High-accuracy image classification	E-commerce tagging, potential for eco-tagging
4	Food Assistant Using AI and Citizen Science	NLP, dietary modeling, feedback learning	Enhanced food decision-making via AI prompts	Personalized food recommendations
5	Trash Detection via ML Techniques	CNN-based image classification	Real-time accuracy in classifying waste materials	Smart bins, waste sorting systems
6	Eco-Friendly Branding & Consumer Decisions	Data analytics, logistic regression	Identified direct link between branding and eco-purchase intent	Sustainable marketing strategies
7	AI-Enabled Material Segregation App	Mobile app, CNN, image processing	Classifies materials as biodegradable or not	Waste management apps, real-time segregation
8	Product Selection via Multi-Modal Data Fusion	Feature-level fusion of text and structured data	Improved product relevance and selection	Product scoring, e-commerce systems
9	Sustainable Development through Innovation	Thematic review, systems thinking	Identified challenges in implementation	Roadmaps for SDG-aligned innovation
10	Green Marketing & Consumer Decisions	Survey + regression modeling	Green campaigns improve product preference	Marketing impact assessment
11	Green Marketing Communication Effectiveness	Statistical analysis, Likert scale surveys	Eco-labels affect purchase behavior positively	Labeling design, consumer psychology
12	Green Branding & Consumer Attitudes	Behavioral data + sentiment analysis	Positive attitudes correlate with green branding	Branding strategies, consumer research
13	Green Marketing Communication Impact	SVM-based sentiment analysis	SVM achieved high precision in classification	Sentiment tracking, campaign design
14	ML for Detecting Unethical Product Sources	Decision trees, ensemble ML	Detected unethical suppliers with 87% accuracy	Supplier vetting, regulatory compliance
15	LLM Prompts for Ecological Texts	Large Language Models + prompt tuning	Improved classification through augmented training data	Ecological report analysis, data annotation
16	Green Purchasing in Indonesia via SEM	Structural Equation Modelling (SEM)	Green product trust affects consumer intention	Awareness studies, policy research

III. COMPARATIVE ANALYSIS

Table 3.1 Comparison table for model outcomes

Parameter	Observations from Survey
Best Accuracy Achieved	94% (environmental attitude classification using logistic regression – [1])
Real-time Tools	Found only in a few studies like mobile segregation [7] and food assistant [4]
Most Complex Model	LLM-based ecological classifier with data augmentation [15]
Most Applicable to Our Goal	Feature-fusion product profiling [8], image classification [3], behavioral predictors [1], [11]
Gaps Identified	Lack of lightweight, generalized, text-based tools for real-time sustainability feedback
Underused Areas	NLP-based product tag scanning, eco-label interpretation, embedded tools for mobile users

The reviewed literature presents a diverse set of approaches to tackling sustainability challenges through artificial intelligence and machine learning. Although the goals of the various studies range from predicting consumer attitudes to classifying trash and doing eco marketing analysis, a comparison analysis identifies important patterns, areas of strength, and research gaps that aid in determining the course of our suggested system.A number of studies focus on consumer psychology and behavior, using models like logistic regression and SVM as well as sentiment categorization techniques (e.g., [1], [11], [12], and [13]).

According to these studies, eco-friendly branding and marketing greatly impact consumer behavior and accurately predict eco-conscious sentiments.However, these models are primarily retrospective in nature and do not provide real-time feedback or tools to aid in decision-making around purchases. Several studies ([3], [5], [7], and [8]) address product recognition or garbage classification by combining multi-modal learning techniques with picture classification.

CNNs and EfficientNetB5 offer strong accuracy in visual data settings, but they are mostly post-consumption (smart bins, for example) and not designed for pre-purchase product evaluation.

Interestingly, the study [8] is one of the few that looks at feature-level data fusion, which makes it extremely pertinent to our objective of combining product descriptions and features for sustainability evaluation. Other research, like Gabriel et al. [2] and Lodi et al. [9] focus on policy-driven or systemic changes, offering valuable insights for long-term strategic planning. However, their contributions are less technical and not immediately applicable for real-time tools or apps.

Interestingly, [15] experiment with Large Language Models (LLMs) to enhance ecological text classification. This novel approach demonstrates potential for applications in product labeling,
eco-tag parsing, or sustainability content validation—but requires significant computational power and curated data.

Furthermore, applications like the food assistant tool [4] and the material segregation mobile app [7] are excellent examples of AI being integrated into consumer tools. However, these tools are domain-specific (i.e., food or waste), while our project aims for a generalized, product-agnostic eco-detection tool.

Table 3.2 Comparison table(based on comparing papers their models, solutions, insights)

S.No	Paper Title	Algorithm / Model Used	Type of Solution	Interesting Insights
1	Classifying Environmental Attitudes Using Explainable ML Models	Logistic Regression, SVM, XGBoost + SHAP	Behavioural classification	SHAP values showed key behavioural drivers; logistic regression outperformed deep models
2	E-Commerce Products Image Classification Using EfficientNetB5	EfficientNetB5, Transfer Learning	Image-based product recognition	Demonstrated high performance on real e-commerce images; adaptable to product tag scoring
3	Trash Detection – Advanced Classification of Waste	CNN	Real-time image classification	Built for smart bin automation; good field accuracy with minimal hardware
4	Product Selection Using Feature-Level Fusion	Feature fusion of structured + unstructured data	Multi-modal recommendation system	Integrated numeric + text data for better product matching; could inform eco-scoring
5	Green Marketing and Consumer Behavior via SVM	Support Vector Machine	Sentiment-based behavior modeling	Achieved reliable sentiment classification accuracy; good for real-time trend tracking
6	Food Assistant Through AI & Citizen Science	NLP + personalization + user feedback loops	Recommendation engine	Included real-world dietary adjustments; combines health + sustainability concerns
7	AI-based Material Segregation via Mobile App	CNN, Mobile Image Recognition	Classification app	First of its kind app in the study; capable of guiding users in real-time
8	Evaluating LLM Prompts for Ecological Texts	Large Language Models (LLMs)	Data augmentation & text classification	Explores prompt engineering for multi-label classification; pushes NLP limits

IV. RESULT

Relevant insights into the present applications of AI and machine learning to promote sustainable production and consumption are offered by the review and comparative analysis of research papers. From computer vision systems and recommendation tools to behavioral categorization models, every topic included in the reviewed literature contributes in a different way to SDG 12. According to our research, most papers consistently exhibit great accuracy and inventiveness. Strong performance, frequently over 90% accuracy, was reported by models such SHAP-empowered behavioral predictors [1] and EfficientNetB5 for product classification [3].

These results demonstrate how well-developed ML methods are in regulated settings using clean datasets. But only a small number of studies addressed end-user accessibility or real-time deployment, which is particularly noticeable in studies that otherwise shown good predictive performance. The rise of user-facing technologies, like smartphone apps for classifying waste materials [7] or AI-powered food assistants [4], is one positive trend. These studies show that implementing AI systems in a sustainable manner is not only possible but also has an effect on consumers.Regretfully, these technologies are often domain-specific and inflexible when it comes to managing a wider range of products or situations.

A number of studies were notable for their creative approaches, such as rapid engineering using Large Language Models (LLMs) [15] along with multi-modal and data fusion [8]. Although these methods demand a lot of computing power, they pave the door for scalable systems that can decipher complicated product data, which is necessary for any all-purpose sustainable product detector.

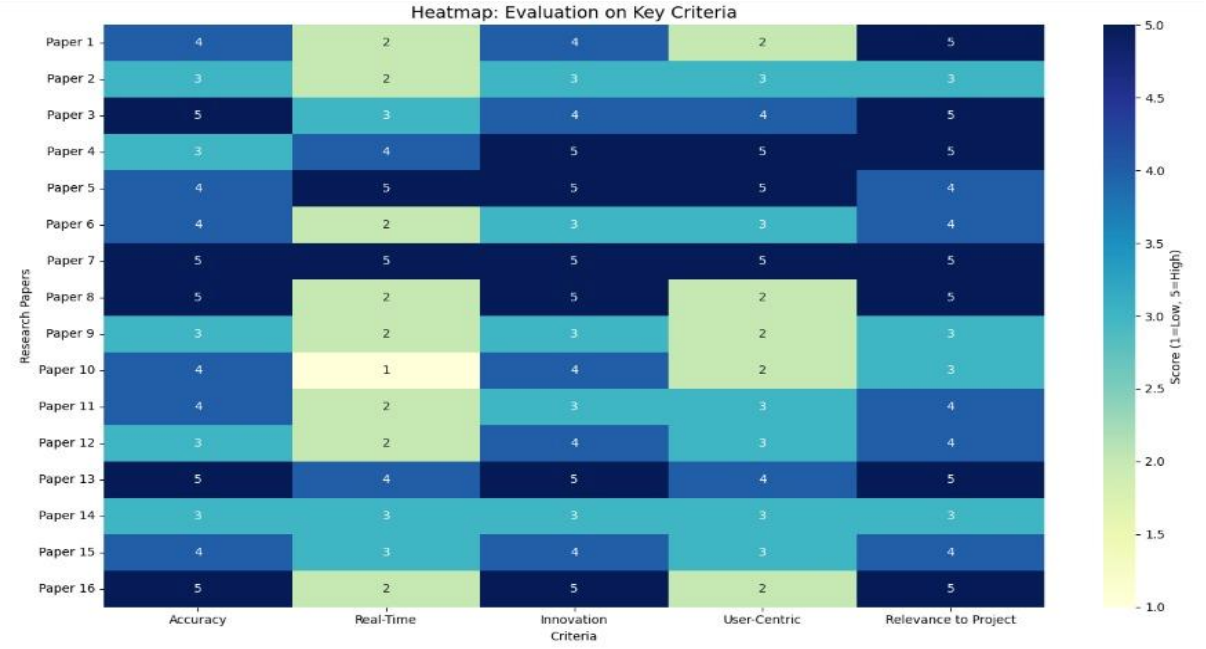


Fig 4.1 Heatmap comparing all the papers

4.1.1 Discussions

Three significant limitations are revealed by the literature despite technological advancements. Absence of comprehensive assessment instruments. The majority of models are not made for full-cycle sustainability profiling, but rather for specialized tasks like sentiment analysis and waste classification. Limited capacity to explain Few studies, with the exception of [1], used interpretable AI, which is crucial for increasing user confidence in sustainability scores. Lack of mobile-friendly, lightweight solutions Real-time use in typical consumer scenarios is limited by the resource-intensive nature of many high-performing models. These gaps demonstrate how unique and pertinent our suggested idea is. By combining text-based NLP models, explainable outputs, and a mobile-ready design, we aim to provide consumers with real-time sustainability feedback without needing barcodes or scanning devices. Our approach takes inspiration from multiple works — [3], [4], [7], and [8] — yet moves a step further by unifying their best elements into a generalized and scalable tool.

Implications and Future Directions:
This review suggests that future research should prioritize:

Model lightweighting for mobile deployment, Interpretable AI frameworks to enhance transparency. Unified scoring mechanisms that consider multiple sustainability factors (packaging, sourcing, nutrition, etc.), more real-world testing with noisy or incomplete product data to validate robustness.

As consumer awareness grows, there is a pressing need for smart assistants that do more than just analyze—they must guide, explain, and adapt in real time. Our future work aims to contribute to this emerging class of eco-intelligent systems.

V. CONCLUSION

This survey paper explored the role of artificial intelligence and machine learning in promoting sustainable consumption, with a focus on models that help assess product sustainability, influence eco-conscious consumer behaviour, and support responsible decision-making. Across 16 reviewed papers, we observed a diverse range of methodologies—from classical classifiers like SVM and logistic regression to more advanced systems using deep learning, multi-modal fusion, and LLMs. While many studies demonstrate strong accuracy and domain-specific innovation, only a handful offer real-time or user-centric solutions suitable for everyday consumer use.

Our comparative analysis highlights a crucial research gap: the absence of lightweight, explainable, and mobile-friendly tools capable of offering real-time sustainability insights based solely on product names or descriptions. This gap informs the direction of our proposed model, which aims to combine the strengths of NLP, interpretable AI, and minimal user input to build a Sustainable Product Detector that is both practical and impactful.

The findings from this review reinforce the idea that AI is a powerful ally in achieving Sustainable Development Goal 12. However, future systems must prioritize transparency, usability, and adaptability if they are to truly empower individuals and drive widespread behavioural change. We recommend future work focus on real-world deployment, user interface design, and the integration of localized sustainability databases to support global scalability.

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