Vision-Language Models for E-commerce: Detecting Non-Compliant Product Images in Online Catalogs

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Abstract: This study explores the use of vision-language models (VLMs) for automated validation of product images in e-commerce, aiming to ensure visual consistency and accuracy without the need for extensive data annotation and specialized training. We evaluated two VLMs, LLaVA and Moondream2, to determine their effectiveness in classifying images based on suitability for online display, focusing on aspects such as visibility and representational clarity. Each model was tested with varying textual prompts to assess the impact of query phrasing on predictive accuracy. Moondream2 outperformed LLaVA in both precision and processing speed, making it a more practical solution for large-scale e-Commerce applications. Its high specificity and negative predictive value (NPV) highlight its effectiveness in identifying non-compliant images. Our results suggest that VLMs like Moondream2 provide a viable approach to visual validation in e-Commerce, offering benefits in scalability and implementation efficiency, particularly where a rapid and reliable assessment of product imagery is critical. This research demonstrates the potential of VLMs as effective alternatives to traditional image validation methods, underscoring their role in enhancing the quality of the digital catalog.

1 INTRODUCTION

In today's digital era, the global e-commerce market is experiencing rapid expansion, making the exchange of digital information an essential component of modern trade. Scholars and industry professionals alike recognize that maintaining high quality data is a key challenge for organizations, and poor data quality can have potentially significant negative effects on business operations (Wang and Strong, 1996; Ballou et al., 2004; Haug et al., 2011). Quality of product data refers primarily to attributes such as accuracy, completeness, timeliness, and consistency of information in online catalogs (Wang and Strong, 1996). Ensuring data quality has become a critical determinant of success or failure for many enterprises, directly influencing the efficiency of business transactions (Cao and Zhang, 2011; Hole et al., 2018).

Product images play one of the most important roles in ensuring high-quality product data in e-commerce. Since consumers cannot physically examine products, they rely heavily on the images provided, making these visuals a crucial factor in the decision-making process. However, image quality issues, such as the use of logos instead of product images or product images placed against inappropriate backgrounds, can severely undermine customer satisfaction and trust, leading to lost sales and tarnished reputations (Di et al., 2014; Qalati et al., 2021). Poor image management can also increase operational costs (Appelbaum et al., 2017; Biryukov, 2020), while the lack of automated solutions to manage this process has become increasingly problematic (Russom, 2011).

The advent of vision language models (VLMs), such as Moondream2 and LLaVA, offers promising new tools to address these issues by automating the detection of inappropriate product images in e-Commerce platforms. These models are capable of interpreting both visual and textual prompts, enabling them to identify instances where product images do not meet predefined standards. For example, VLMs can be trained to detect whether an image contains a company logo instead of the actual product, or if

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the product is depicted against a background that deviates from the commonly accepted white or neutral backdrop.

This paper explores the potential of using VLMs to enhance the quality of product data by ensuring visual consistency across e-commerce platforms. Specifically, it investigates the capabilities of Moondream2[1] and LLaVA (Liu et al., 2023) to detect and classify non-compliant images, addressing challenges related to manual data entry and the maintenance of image quality across various online marketplaces. Using AI-driven solutions, this research aims to propose a scalable approach to improving product data quality, contributing to the broader goal of optimizing e-commerce platforms for both businesses and consumers.

We begin by presenting an overview of the current landscape of e-commerce and the critical role of data quality in product imagery validation. In the Methodology section, we outline our approach to evaluating two specific VLMs, detailing the model setup, prompt design, and evaluation metrics used to measure performance. The Experiments and Results section discusses the practical tests conducted with each model on various prompts, providing a detailed comparison based on accuracy, precision, and processing efficiency. Finally, in the Conclusion, we summarize our findings, discuss the implications of VLMs in e-Commerce validation, and propose directions for future research aimed at enhancing image compliance accuracy in large-scale online catalogs.

2 RELATED WORK

Recent research emphasizes the critical role of high-quality product images in e-Commerce, especially as visual consistency and precision become essential to foster consumer trust and engagement. Niemir and Mrugalska (2022) observe that, unlike physical stores, e-commerce relies on images to convey product attributes, necessitating standards for clarity, resolution, and object visibility across all product categories. Muszyński et al. (2022) highlight the importance of data quality in high-safety industries such as food and cosmetics, advocating for the use of artificial intelligence in validating both visual and textual attributes. Their work underscores the need for automated solutions that not only categorize images but also ensure visual compliance with established e-commerce standards, suggesting that automated validation and AI support can significantly enhance industry standards, such as the Global Data Model, while also facilitating large-scale data management.

Michalski (2020) examines consumer perception, demonstrating how the shapes of digital packaging influence purchase intent. The study indicates that ergonomic, standard packaging shapes increase customer preference, underscoring the need for visually appealing and consistent presentations to foster positive shopping experiences. These findings align with the need for automated quality checks to effectively manage visual presentation in extensive product catalogs.

Ouni et al. (2022) introduced a method of semantic image quality assessment based on Convolutional Neural Networks (CNN) to analyze product images within the e-commerce context. Their approach, based on perceptual models, detects common visual issues, such as poor lighting, color distortions, and low sharpness, without the need for a reference image. This method, known as Semantic Image Quality Assessment (SIQA), enables a detailed analysis of features such as naturalness, readability, and color consistency—critical to the visual quality of online products. SIQA focuses primarily on perceptual image quality rather than on verifying conformity with product-specific category data.

Szymkowski and Niemir (2024) investigated the use of CNNs and Visual Transformers (VTs) in automatic classification of products according to GS1 GPC codes, indirectly assessing the degree to which an image's depicted object aligns with the expected category.

While these studies provide valuable insights, a universal and comprehensive solution for image quality assessment in e-commerce—encompassing various quality issues and offering guidance on the types of errors encountered—remains lacking. Vision language models (VLM), such as those described by Zhang et al. (2024), have significant potential to fill this gap. These models employ contrastive learning to pair images with textual descriptions, enabling precise categorization even in novel product contexts. Although current VLM implementations are primarily focused on categorization rather than on detailed quality control tailored to specific e-commerce standards, our research demonstrates their potential application as image validators.

[1] https://www.moondream.ai/

3 METHODOLOGY

3.1 Our Approach

In response to the limitations of existing Vision-Language Models (VLMs) that are primarily optimized for categorization rather than comprehensive quality control, our research takes a more generalized approach. Rather than relying on highly specific criteria tied to e-commerce standards, we explore the utility of Moondream2 and LLaVA in a flexible validation framework, focusing on whether an image could reasonably represent a product suitable for an online marketplace.

Moondream2 and LLaVA each contribute unique strengths to this general approach. Moondream2 excels in object recognition and classification, making it well-suited for straightforward validation tasks where accurate identification of a product in the image is essential. LLaVA, meanwhile, provides contextual descriptions and interpretative feedback, supporting scenarios where qualitative judgment is needed to determine if an image's composition aligns with typical e-commerce product photos.

In our experiments, we focused on broad prompts that ask each model to identify whether the content in a given image could plausibly be used as a product image. It is important to emphasize that the input to the models consisted solely of product images and predefined textual prompts. No additional metadata, such as product names or attributes, were utilized during the evaluation. This approach emphasizes generalizability and flexibility, enabling us to evaluate whether an image depicts a product in a way that aligns with the expectations for online retail without strictly adhering to platform-specific quality standards.

For our evaluation, we developed and tested several dozen prompts for both models. From this set, we selected six prompts—three for Moondream2 and three for LLaVA—designed to assess the models' ability to provide basic yet meaningful information about image suitability. This approach allowed us to analyze their effectiveness in general product image validation. A detailed description of these prompts and the corresponding results is presented in Section 5, where we evaluate each model's potential to facilitate a generalized, adaptive approach to image validation in e-Commerce. We acknowledge that the selected prompts are not identical for both models; however, they were chosen to best reflect the objective function. The aim was not to compare the models based on identical prompts but to evaluate their effectiveness in the process of image validation. This approach allowed us to focus on the practical utility of each model in addressing validation tasks.

3.2 Setup

To simulate the computing power available to a medium-sized company that does not necessarily specialize in providing AI solutions, we assumed that the maximum computing power we could use in our experiments was two NVIDIA GeForce RTX 3090 graphics cards.

The Moondream2 and LLaVA:34b-v1.6 models were inferenced directly after downloading from the HuggingFace[2] server. Furthermore, it is important to note that the LLaVA model was used in the quantized Q4 version, balancing performance with precision (Gholami et al., 2022).

3.3 Evaluation Method

To evaluate our models, we used standard metrics such as accuracy, precision, recall, and F1 (Powers, 2011). Accuracy allowed us to measure the overall correctness of classification, indicating the percentage of cases where the model correctly identified both suitable and unsuitable images. Precision referred to the proportion of images classified by the model as suitable that genuinely met quality requirements—the higher the precision, the fewer cases where the model incorrectly identified low-quality images as suitable. Recall expressed the model's ability to correctly identify all images that were indeed suitable—a higher recall indicated that the model rarely missed images meeting quality criteria. The F1 score combined precision and recall, enabling us to assess the models in a more balanced manner, particularly when these two metrics varied.

To further assess the models' performance in detecting unsuitable images, we incorporated specificity and Negative Predictive Value (NVP). Specificity (Altman and Bland, 1994a) measured the model's ability to correctly reject images that were indeed unsuitable - the higher the specificity, the more effectively the model identified low-quality images. Negative Predictive Value (NVP) (Altman and Bland, 1994b) indicated the percentage of images classified as unsuitable that truly did not meet quality standards; a higher NVP denoted greater confidence that images labeled as unsuitable indeed failed to meet the criteria.

Our primary objective was to achieve the highest possible precision, with acceptable levels of NVP and

[2]https://huggingface.co/

specificity. This approach minimized the number of false positive classifications of low-quality images as suitable, while simultaneously reducing the risk of incorrectly rejecting suitable images.

4 DATASETS

The test dataset was sourced from a product catalog created by the producers of these items (over 60,000 companies). The catalog covers a wide range of product categories available online. The data entry process in the catalog is not centrally supervised, leading to various types of errors stemming from lack of knowledge or random mistakes, making it an ideal source for testing data improvement capabilities. Among the analyzed categories were food products, clothing, automotive items, consumer electronics, DIY equipment, household chemicals, medical supplies, stationery, handicrafts, and furniture. From the available 1.2 million images, a preliminary filtering process was applied to ensure they met essential technical standards, including appropriate size, background brightness, and background uniformity. Additional criteria involved assessing the proportion of background coverage in the image. This was determined by analyzing the ratio of the product object to the overall image area. Images where the background occupied more than 80% of the total area were excluded. These measures aimed to eliminate images with excessive background dominance or insufficient focus on the product, resulting in a more consistent set of images that better aligned with the visual standards in e-commerce. Subsequently, using a perceptual hash algorithm, images significantly different from each other were randomly selected.

Manual annotation of image accuracy was conducted by a trained annotator with experience in e-commerce product data validation. The annotator followed standardized guidelines, including detailed examples of correct and incorrect product images, to ensure consistency and reliability across evaluations. Ambiguous cases were evaluated through consultation to minimize potential biases. The criteria used for annotation included factors such as readability of information, visibility of the main product object, appropriate presentation form, and background neutrality (Niemir and Mrugalska, 2022).

A total of 1,663 unique images were annotated and assigned to random product categories. Among them, 174 images were assessed as incorrect and 1,489 as correct. The assessment process focused on eliminating images that deviated significantly from online product presentation standards, such as missing images, substitute packaging (e.g., box graphics), company logos instead of actual product images, outdoor photos, product presentation suggestions, or labels. Notably, the analysis excluded verifying the consistency of the product name and category with its visualization in the image, as the objective was to conduct a general evaluation of image quality.

During the analysis, certain product categories whose specific presentation style hindered effective verification based on the packaging form were necessary to be excluded. In particular, this applied to categories where the image depicted the product with a dominant pattern or texture element, which often led to incorrect interpretation by the model. Problematic categories included:

- **Books, magazines, CDs, DVDs, vinyl records** - images are usually only accompanied by covers or labels, making it difficult to assess the full presentation of the product.
- **Wall coverings, carpets** – images focused on textures or patterns, preventing the identification of the entire product.
- **Decorative magnets, stickers, paintings, posters** – products were often presented on surfaces or in contexts that could confuse the models.
- **Live plants** – photos often taken outdoors did not meet the standard requirements for presentation on a neutral background.
- **Services** – images related to services, such as logos or graphic elements, did not meet the typical criteria for physical products.

These categories required different visual analysis strategies to avoid classification errors and improve the accuracy of evaluating image suitability in the e-commerce context; therefore, they were excluded from the study. For apparel products, several presentation methods are commonly accepted in online retail. Clothing can be displayed against a white background, as is typical for other products, hung on a hanger, or shown on a person, similar to images in advertising brochures of marketplaces. This practice is generally permitted as long as the image focuses on the product, ensuring that the presentation emphasizes the clothing item without distracting elements. However, some e-commerce platforms enforce additional restrictions on specific clothing categories, particularly children's apparel. These restrictions may include limitations on the use of human models or stricter requirements for presentation neutrality. As a result, including apparel products in the validation pipeline necessitates additional verification steps to ensure compliance with platform-specific standards. This becomes especially relevant when contextually validating the chosen form of presentation. Nevertheless, this study employed a simplified validation approach, prioritizing general usability criteria without addressing these more detailed considerations.

5 EXPERIMENTS AND RESULTS

The evaluation focused on the capabilities of two AI vision-language models (VLMs), LLaVA and Moondream2, in classifying product images for their suitability in e-commerce applications. Each model was tested with three distinct text prompts to examine how variations in query phrasing influence model predictions. The list of prompts is as follows:

- LLaVA - prompt 1 (llava_1): Can it be a photo for online sales? The product packaging picture does not have to be detailed. It is important that the product or its packaging is visible. The composition of the product does not have to be visible, the photo does not have to be sharp. Return answer in JSON format: {'answer': [YES/NO], 'explanation': string}
- LLaVA - prompt 2 (llava_2): Is it a product on a photo? Return answer in JSON format: {'answer': [YES/NO], 'explanation': string}
- LLaVA - prompt 3 (llava_3): Verify whether a buyer will understand what they are purchasing based on the provided product name, considering the following assumptions: 1. The buyer is a native Polish speaker. 2. During the shopping process, the buyer only sees the product name. 3. The buyer shops at a store within a specific industry, so they are familiar with industry-specific terms and phrases. 4. The product name may include brand names and manufacturer codes. 5. The product does not necessarily need to have description on it. Return answer in JSON format: {'answer': [YES/NO], 'explanation': string}
- Moondream2 - prompt 1 (moondream_1): Does the photo show the product? Answer yes or no.
- Moondream2 - prompt 2 (moondream_2): Is it a photo that shows a product for online sales? Answer yes or no.
- Moondream2 - prompt 3 (moondream_3):Can provided image be a an image for an online auction? Answer yes or no.

For both models, the input consisted exclusively of a product image and a corresponding predefined textual query. No metadata, such as product names or descriptive attributes, were included in the experiments. This approach ensured that the evaluation focused solely on the models' ability to process visual and prompt-based inputs without additional contextual information. The Moondream2 model required a two-step query process: first, to obtain a "yes" or "no" answer, and second, to provide an explanation if the initial response was "no", due to limitations in handling both response types within a single prompt. A comprehensive comparison of key metrics such as accuracy, precision, and recall is presented in Table 1.

Table 1: Performance metrics for different prompts. Own work.

Model	Accuracy	Precision	Recall	F-1
llava_1	0.90	0.90	0.99	0.94
llava_2	0.54	0.91	0.53	0.67
llava_3	0.23	0.93	0.15	0.26
moon_1	0.92	0.95	0.97	0.96
moon_2	0.75	0.92	0.79	0.85
moon_3	0.50	0.92	0.49	0.64

The best prompt for each model was selected based on a combination of accuracy and F1 score, as these metrics provide a balanced view of the model's capability to correctly classify suitable images while minimizing both false positives and false negatives.

In this table, the results indicate that Moondream2 achieved consistently higher accuracy and F1 scores compared to LLaVA, particularly with prompt "moon_1," which yielded an accuracy of 0.92 and an F1 score of 0.96. This prompt demonstrated Moondream2's strength in maintaining a high level of precision (0.95) and recall (0.97), making it the most effective prompt for this model. For LLaVA, "llava_1" was identified as the best prompt, with an accuracy of 0.90 and an F1 score of 0.94, showing strong recall (0.99) and balanced precision (0.90).

By selecting the prompt with the highest combined accuracy and F1 score for each model, we established a basis for more in-depth analysis. The subsequent evaluation, which included NPV and specificity metrics, further refined our understanding of each model's ability to correctly reject non-compliant images, as detailed in Table 2. and represented in the confusion matrices in Figures 1 and 2.

The confusion matrices presented above illustrate the performance of the LLaVA and Moondream2 models in classifying product images for e-commerce suitability, with the best-performing prompt for each model. In these matrices, the "True" labels represent the actual classifications (1 for suitable and 0 for unsuitable images), while the "Predicted" labels show the model's classification outcomes.

Table 2: Performance metrics for different models. Own work.

	LLaVA	MoonDream2
Accuracy	89.84%	93.87%
Precision	90.34%	95.06%
Recall	99.26%	98.25%
NPV	59.26%	79.03%
Specificity	9.20%	56.32%

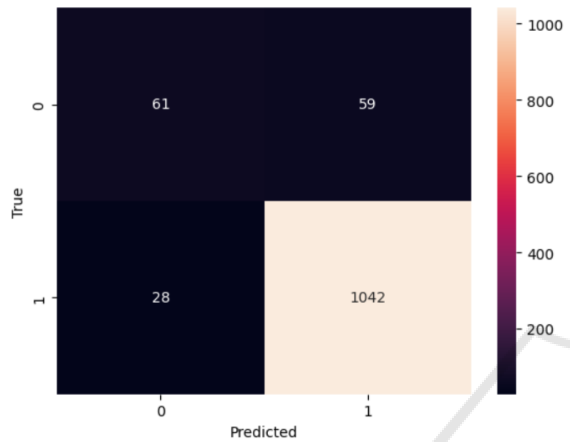


Figure 1: Confusion matrix for the MoonDream2 model and the best-performing prompt (Prompt 1). Own work.

In the confusion matrix of the LLaVA model, we observe relatively high false positives, where unsuitable images are classified as suitable. Meanwhile, Moondream2 demonstrates a better balance, with fewer false positives and a higher true negative count, reflecting better specificity and Negative Predictive Value (NPV).

A critical aspect of data validation is the ability to provide a clear explanation of why an image has been flagged as non-compliant. Both models evaluated in this study — Moondream2 and LLaVA — are capable of generating comprehensive assessments of the images, explaining the reasons for their suitability or unsuitability for e-commerce use. Table 3 presents examples of such responses generated by the Moondream2 model. Due to space limitations in this publication, we have included only the responses from Moondream2. LLaVA's evaluations were substantively similar in content but tended to be more detailed and linguistically refined.

Each entry in the Table 3 includes an image and a brief explanation generated by the model, clarifying why the image may not meet e-commerce standards. For example, the first image shows a symbolic graphic rather than an actual product, which Moondream2 notes as lacking the necessary detail to represent a sellable item. Similarly, other examples highlight issues such as inadequate color representation, absence of the product itself, or an overly distracting background. These explanations demonstrate Moondream2's ability to provide nuanced assessments, focusing on factors such as visibility, color accuracy, and background relevance, which are essential for high-quality product representation in online catalogs.

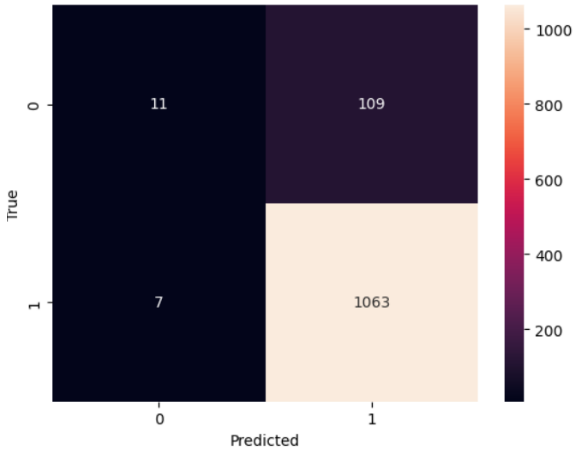


Figure 2: Confusion matrix for the LLaVa model and the best-performing prompt (Prompt 1). Own work.

In addition to examining the models' capabilities for data validation, we evaluated the response time of each model by calculating the average processing time for 1,000 samples. For scalable solutions managing large product catalogs, processing speed is critical, especially in a dynamic e-commerce environment.

Table 4 presents the average response times for both models, with Moondream2 achieving a significantly faster processing time of 0.34 seconds per image compared to LLaVA's 3.37 seconds. This disparity in response times highlights Moondream2's efficiency, making it better suited for large-scale e-commerce applications where rapid processing of extensive product catalogs is necessary to maintain operational effectiveness and user experience.

6 CONCLUSIONS

The results of the conducted study demonstrated that Vision-Language Models (VLMs) can serve as effective tools for supporting additional validation of product images in terms of their suitability. This represents an innovative approach that has not been achievable with traditional validation methods. Notably, these models do not require fine-tuning to achieve satisfactory results, which significantly reduces costs and implementation time. Another advantage lies in the universality of image validation, meaning that

Table 3: Descriptions generated by the Moondream2 model. Own work.

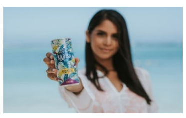
	The photo does not showcase the product, but rather a minimalist symbol – a green circle with a white heart in the center, symbolizing love, care, and affection. The absence of additional details allows the focus to be on the symbolic meaning of the heart, often used in marketing materials and visual communication.
	The image does not effectively depict the product as it is in black and white, making it difficult to convey colors and details accurately. In this case, the tortilla and wheat tortilla are key elements, and a color photograph would better represent their appearance.
	The photo does not depict the product, as it only shows its label, focusing on information about ingredients, nutritional values, and key characteristics. The lack of an actual image of the product means it is not visible in the photo.
	The product is not visible in the image because the woman is holding it in front of her face, making her and her actions the main focus of the picture. The background, which shows the ocean, adds an aesthetic value to the image, but it is not essential for showcasing the product, which is the KABISA tea.

Table 4: Performance time for different models. Own work.

Model	Avg time
LLaVA	3,37 s
MoonDream2	0,34 s

building a validator does not necessitate referencing specific products within particular categories.

Although the primary goal of this study was not to benchmark the models, the results further indicated that the smaller Moondream2 model outperformed LLaVA in both validation accuracy and operational efficiency. Moondream2 achieved higher scores in key metrics, such as NPV and specificity, highlighting its greater effectiveness in identifying non-compliant product images for this task. Despite LLaVA's advanced language capabilities and ability to generate detailed descriptions, it proved less efficient in tasks focused on visual validation in the e-commerce context. The findings thus indicate that employing large multimodal models is not necessary to achieve satisfactory results. Moreover, the analysis conducted on a dedicated infrastructure showed that Moondream2 processes queries more than ten times faster than its larger counterpart, making it a more efficient solution for large product catalogs.

6.1 Future Work

This study did not incorporate metadata, such as product names, unit counts, packaging types, and other attributes, which could enable significantly more detailed validation of image content. In future research, we plan to integrate such data, allowing for the validation of consistency between attributes and more precise visual assessment of image compliance with requirements.

Further efforts will also focus on expanding the variety of prompts tailored to specific product categories. A comprehensive query system is planned, where appropriate prompts will be assigned to individual nodes or branches of a product category graph. This approach could significantly enhance validation effectiveness, particularly for product categories with specific graphical presentation requirements (e.g., clothing, media with covers, wall coverings, magnets, stickers, posters, graphics, photographs, services, live plants).

Another direction of development involves dividing image validation into separate problem categories. Individual validation stages could include analyzing background quality (uniformity, brightness, and the ratio of the background to the area occupied by the product), detecting the presence of company logos only, verifying the number of products in an image, and assessing proper product presentation, especially in the clothing category.

Additionally, we consider incorporating alternative models such as BLIP, CLIP, and GPT to compare their effectiveness through benchmarking. We also plan to develop a dedicated multimodal model specialized in product data validation, including evaluating the accuracy of product images. This solution could leverage methods and mechanisms used in training the LLaVA model, allowing for a tailored approach to the specific requirements of e-commerce.

6.2 Limitations

The conducted research highlights the promising potential of Vision-Language Models (VLMs) for automating image validation in e-commerce. However, certain limitations of this approach should be acknowledged.

One limitation is the accuracy of the validation itself, which is not error-free. Consequently, the validator may work well as a module for suggesting quality improvements and flagging image defects for catalog administrators, but its use for definitively rejecting defective images requires detailed testing before implementation in a specific catalog. Similarly, any update to the model version in a production environment should also be preceded by prior research, as results may vary.

Additionally, VLMs have significant computational requirements, which may pose a barrier for smaller enterprises. Further extensions of these models to accommodate industry-specific requirements could negatively affect their performance unless they are optimized for computational load and infrastructure accessibility.

REFERENCES

Altman, D. G. and Bland, J. M. (1994a). Statistics notes: Diagnostic tests 1: sensitivity and specificity. *BMJ*, 308(6943):1552.

Altman, D. G. and Bland, J. M. (1994b). Statistics notes: Diagnostic tests 2: predictive values. *BMJ*, 309:102.

Appelbaum, D., Kogan, A., Vasarhelyi, M., and Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems*, 25:29–44.

Ballou, D. P., Madnick, S. E., and Wang, R. Y. (2004). Special section: Assuring information quality. *J. Manag. Inf. Syst.*, 20:9–11.

Biryukov, A. (2020). Data quality as a service. *Journal Of Applied Informatics*, 15:120–132.

Cao, M. and Zhang, Q. (2011). Supply chain collaboration: Impact on collaborative advantage and firm performance. *Journal of operations management*, 29(3):163–180.

Di, W., Sundaresan, N., Piramuthu, R., and Bhardwaj, A. (2014). Is a picture really worth a thousand words? - on the role of images in e-commerce. In *Proceedings of the 7th ACM international conference on Web search and data mining*, WSDM '14, page 633–642, New York, NY, USA. Association for Computing Machinery.

Gholami, A., Kim, S., Dong, Z., Yao, Z., Mahoney, M. W., and Keutzer, K. (2022). *A Survey of Quantization Methods for Efficient Neural Network Inference*, pages 291–326. Chapman and Hall/CRC.

Haug, A., Zachariassen, F., and Van Liempd, D. (2011). The costs of poor data quality. *Journal of Industrial Engineering and Management*, page 168–193.

Hole, Y., Pawar, S., and Bhaskar, M. P. (2018). Service marketing and quality strategies. *Periodicals of Engineering and Natural Sciences (PEN)*, 6(1):182–196.

Liu, H., Li, C., Wu, Q., and Lee, Y. J. (2023). Visual instruction tuning. *ArXiv*, abs/2304.08485.

Michalski, R. (2020). The role of virtual package shapes in digital product presentation. In Rebelo, F. and Soares, M., editors, *Advances in Ergonomics in Design*, page 24–30, Cham. Springer International Publishing.

Muszyński, K., Niemir, M., and Skwarek, S. (2022). Searching for ai solutions to improve the quality of master data affecting consumer safety. In *Business Logistics in Modern Management*, page 121–140, Osijek, Croatia. Faculty of Economics in Osijek.

Niemir, M. and Mrugalska, B. (2022). Product data quality in e-commerce: Key success factors and challenges. In *Production Management and Process Control*.

Ouni, S., Kamoun, K., and AlAttas, M. (2022). *Semantic Image Quality Assessment Using Conventional Neural Network for E-Commerce Catalogue Management*, page 89–113. Springer International Publishing, Cham.

Powers, D. M. W. (2011). Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation. *ArXiv*, abs/2010.16061.

Qalati, S. A., Vela, E. G., Li, W., Dakhan, S. A., Hong Thuy, T. T., and Merani, S. H. (2021). Effects of perceived service quality, website quality, and reputation on purchase intention: The mediating and moderating roles of trust and perceived risk in online shopping. *Cogent Business & Management*, 8(1):1869363.

Russom, P. (2011). Big data analytics. *TDWI best practices report, fourth quarter*, 19(4):1–34.

Szymkowski, M. and Niemir, M. (2024). Convolutional neural networks and vision transformers in product gs1 gpc brick code recognition. In Sheng, B., Bi, L., Kim, J., Magnenat-Thalmann, N., and Thalmann, D., editors, *Advances in Computer Graphics*, Lecture Notes in Computer Science, page 440–450, Cham. Springer Nature Switzerland.

Wang, R. Y. and Strong, D. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, 12(4):5–33.

Zhang, J., Huang, J., Jin, S., and Lu, S. (2024). Vision-language models for vision tasks: A survey. arXiv:2304.00685.