Image Correctness for a Product on the Marketplace

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Abstract—In modern times, maintaining the integrity of product images is extremely important to build customer trust and reduce costly returns. Traditional methods of ensuring quality through manual reviewing or heuristics simply cannot scale with millions of product listings every day. The present paper proposes a powerful automated framework for Image Correctness validation in e-commerce. Our approach leverages an MT-CNN, which is trained on marketplace images for carrying out two checks simultaneously: checking visual compliance regarding resolution, background, and lighting, and ensuring content fidelity, i.e., maintaining consistency between an image and the textual attributes of its product, especially color. A classification accuracy of 94.8% is attained by the MT-CNN architecture in classifying non-compliant images from diverse categories. It also accelerates the moderation pipeline, offering a scalable real-time solution that will directly enhance operational efficiency and reliability on large-scale e-commerce platforms.

Index Terms—Keywords—Image Correctness, E-commerce, Deep Learning, Computer Vision, Multi-Task CNN, Quality
Validation.

I. INTRODUCTION

The rise of e-commerce worldwide has completely changed consumer behaviour, and online visual merchandising drives all purchase decisions. Product images for large digital marketplaces are the virtual storefront, wherein customers base their judgment on conversion rate and trust. However, the integrity of these visuals is highly compromised—from low resolution, poor lighting, and distracting backgrounds to fundamental Content Incorrectness: for example, the colour of the product in the image might not match the text description, or accessories may be included but not covered in the purchase. This pervasive problem greatly leads to customer dissatisfaction, drives high product return rates, imposes enormous logistical and financial burdens on retailers, and erodes platform credibility.

Current marketplace approaches to quality control are insufficient. Most platforms either use very rudimentary rulebased filters or human moderation teams that are costly and non-scalable. Moreover, these methods are effectively unable to keep pace with the massive volume of daily uploads and—most critically—fail to conduct complex semantic crossvalidation between visual features and textual product attributes. While techniques such as generalized object detection [3] [4] and early image classification [1], provide foundational capabilities, they are not designed for this complex compliance task. An immediate, urgent need exists for an automated intelligent system capable of rigorous, multi-facet image validation.

To bridge this gap, this paper proposes a new Deep Learning-based method for real-time automatic product image correctness verification. Our system goes beyond the simple quality assessment function to integrate Visual Compliance and Content Fidelity checks in one model, inspired by progress in cross-modal learning [2]. In detail, we introduce the MTCNN architecture that performs simultaneous classification of the defect in an image and regression of a combined Quality Correctness Score.

The main contributions of this work can be summarized as follows:

- We define a comprehensive metric for Image Correctness (IC), which is designed for e-commerce and combines technical quality with semantic consistency rules.
- We design an efficient multi-task CNN that learns shared representations for improved performance on the validation tasks while significantly outperforming single-task models.
- We validate the framework on a proprietary dataset comprising marketplace product images; it is able to flag noncompliant listings with high accuracy and reduce the need for manual review significantly.

II. PROBLEM STATEMENT

Existing quality control mechanisms in large-scale ecommerce marketplaces cannot guarantee the integrity and correctness of the product images, resulting in significant operational burdens and lower customer trust. Conventional methods suffer greatly from several deficiencies, as they often rely on either rudimentary image filters or expensive human moderation that cannot scale with exponential volume on a daily basis and, critically, cannot achieve multimodal semantic cross-validation. As a result of all these, it is very difficult for marketplaces to verify the Content Fidelity of images-which includes checks on whether the color/feature of the image represents the color/features described in the text correctlyand thus, high levels of customer dissatisfaction and product returns are noted. There is an immediate urgent need for an automated multi-faceted intelligent system that will be able to undertake rigorous, real-time validation of both visual compliance rules and semantic consistency, contributing to marketplace efficiency and reliability.

III. RELATED WORKS

Accordingly, the automated image analysis domain relevant to e-commerce validation can be divided into three broad areas: General Image Recognition and Feature Learning, Object Detection and Localization, and Image Integrity Checks.

A. General Image Recognition and Feature Learning

Early breakthroughs in image analysis, driven by the introduction of the Deep Convolutional Neural Network (DCNN), as shown by seminal work on ImageNet Classification with Deep Convolutional Neural Networks (AlexNet) [1], set the bedrock for robust visual feature learning. DCNNs are powerful in terms of hierarchical and abstract feature extraction, and they form the basic structure feature extractor for our system. More recent works, such as CLIP: Learning Transferable Visual Models From Natural Language Supervision [2], epitomize the state-of-the-art feature learning by bridging the gap between visual content and natural language descriptions. This multimodal approach confirms that it is indeed possible to link an image's content with a product's textual attributes. However, these models are aimed at generalized classification or cross-modal transfer and lack the specific granularity to enforce strict marketplace rules, such as minimum padding, or detailed semantic verification.

B. Object Detection and Localization

Object detection models, such as those for localizing and identifying the product within an image, are an important step in enforcing size and cropping policies. High-accuracy detectors such as Faster R-CNN: Region Proposal Networks for Object Detection [3], provide precise bounding box generation while models like YOLOv4: Optimal Speed and Accuracy of Object Detection [4] provide the required efficiency for largescale, real-time production environments. These techniques address the Visual Compliance aspect of our framework directly by helping with the calculation of the Product-to-Frame Ratio and isolating the main product. However, object detection only confirms what an object is and where it is located but does not assess its overall quality or semantic correctness relative to the external product description.

C. Image Integrity and Near-Duplicate Detection

The job of detecting direct image misuse and maintaining originality is done using special techniques, such as Effective near-duplicate image detection using perceptual hashing & deep features / SmartHash [5]. These techniques effectively detect high similarities or slightly modified versions of images and meet some basic perceptual quality issues, like blurriness, to form the first level of image integrity checking.

D. The Gap Addressed by Our Work

Although prior work has provided solid tools for feature extraction, object localization, and basic integrity checks, a holistic, integrated framework that establishes the correctness of images within marketplaces has been underdeveloped. No current solution provides all three requirements in concert: strictly rule compliance, multimodal content fidelity (image checked against text), and real-time efficiency. This is an explicit gap in the research that the proposed Multi-Task CNN framework attempts to fill by integrating these diverse validation tasks into a single, very efficient deep learning model.

IV. PROPOSED METHODOLOGY

The automated image correctness framework is designed to integrate visual compliance checks with semantic consistency verification in real-time and in a scalable manner. Our solution, the Multi-Task Convolutional Neural Network (MT-CNN) architecture, addresses the limitations of existing single-task models by learning shared feature representations from the product image (**I**) and associated textual metadata (**T**).

A. Data Processing and Feature Generation

The system requires two distinct inputs: the product image (**I**) and relevant product attributes, such as the listed color and category.

1) Visual Input Pipeline: All input images are normalized and resized to a standard input resolution ($\mathbf{I} \in \mathrm{R}^{\%[e.g.,224\times224\times3]\%}$). We leverage a preliminary object detection model, based on principles taken from [4], to identify and isolate the main product. Isolation may enable us to have very strict Visual Compliance rules, such as the calculation of the Product-to-Frame Ratio (PFR) and the check for noncompliant backgrounds within the bounding box region.

2) Multimodal Feature Generation: Given that color represents one of the key aspects of Content Fidelity, we extract a numerical feature vector $\mathbf{F}_c$ representing the dominant color profile of the isolated product region. This vector will be concatenated with the deep visual features ($\mathbf{F}_{vis}$) later in the network to enable cross-modal comparison with the listed color attribute in **T**.

B. Multi-Task CNN Architecture

The MT-CNN is structured around a shared encoder and two specialized heads which allow efficient knowledge transfer between tasks.

1) Shared Convolutional Backbone: As the shared feature extractor, we employ a pre-trained e.g., MobileNetV2 or ResNet-50, that processes the image **I** and produces a compact, high-dimensional visual feature vector, $\mathbf{F}_{vis}$. Notice that this shared feature map captures general visual concepts (edges, textures, object shapes) relevant to both quality and content checks.

2) Classification Head (H_{class}): In charge of enforcing Visual Compliance, this head classifies images into discrete categories of failure. It consists of fully connected (FC) layers ending in a Softmax activation that predicts the probability y^ over K categories.

3) Regression Head (H_{score}): This head is responsible for outputting the continuous Quality-Correctness Score (QCS), a scalar value between 0 and 1. This head takes as input a concatenation of the visual features $\mathbf{F}_{\text{vis}}$ and the extracted color features $\mathbf{F}_{\text{c}}$. This mechanism enables the model not only to quantify how severe the failure is but also to introduce semantic mismatch.

$$H_{\text{score}} : [\mathbf{F}_{\text{vis}},\mathbf{F}_{\text{c}}] \rightarrow \text{QCS[} \in [0,1]$$

C. Training and Composite Loss Function

The network is trained end-to-end using a weighted sum of the losses from both heads, facilitating multi-task learning and improved regularization. The total loss (L_{total}) is defined as:

$$\text{Ltotal} = \alpha \cdot \text{Lclass} + \beta \cdot \text{Lreg}$$

where α and β are hyperparameters that balance the influence of the two tasks (e.g., $\alpha = 0.6,\beta = 0.4$).

1) Classification Loss (L_{class}): We adopt the standard Categorical Cross-Entropy loss for the discrete compliance classification:

$$\mathcal{L}_{\text{class}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k}\log(\hat{y}_{i,k})$$

2) Regression Loss (L_{reg}): We use the Mean Squared Error (MSE) to minimize the difference between the predicted QCS (QCS[ ) and the ground truth QCS (QCS):

$$\mathcal{L}_{\text{reg}} = \frac{1}{M}\sum_{j=1}^{M}(QCS_j - \widehat{QCS}_j)^2$$

This multi-task formulation ensures that the shared visual features are strongly optimized for both identifying specific defects (classification) and quantifying overall quality (regression), yielding a powerful and accurate final model.

V. OBJECTIVES

The development and validation of a robust automated framework that will significantly enhance image quality control in large-scale e-commerce marketplaces is the primary goal of this research. Therefore, the specific objectives of this research are outlined as follows:

1) Defining a Comprehensive Correctness Metric: The clear definition of the standard of automated quality control by defining the Image Correctness (IC) metric will integrate both technical quality parameters (resolution, lighting, and background) and semantic consistency rules that assure the correspondence of the visual content with the textual product attributes.
2) Multi-Task Deep Learning Model Design: The aim here is to design an efficient architecture of a MultiTask CNN that can perform several checks for compliance simultaneously. It needs to learn shared features for the optimal performance of diverse tasks, such as discrete defect classification and continuous quality regression.
3) Ensuring Multimodal Content Fidelity: To specifically develop within MT-CNN a mechanism for crossmodal verification (that is, checking the visual properties of the product in question, such as the color profile, against the corresponding textual data, such as the listed product color), so that semantic correctness is ascertained.

4) Real-Time, Scalable Performance: Provide evidence that it is possible for the deployed system to handle thousands of new product listings in real time with high accuracy, removing dependence on slow, expensive, nonscalable human moderation.

VI. SYSTEM DESIGN AND IMPLEMENTATION

This section presents the full architecture of the automated Image Correctness (IC) framework, including the logical architecture in terms of modular components organized into three tiers, the exact algorithmic flow of data from input to decision, and the physical implementation environment employed to ensure scalable, low-latency, real-time deployment in a production marketplace setting.

A. Architectural Overview

The IC framework operates as a modular three-tier architecture, which has been designed for scalability and low-latency inference. The main tiers are:

- Frontend - Marketplace Integration: It is responsible for initiating the validation request on a new product listing or image update. It sends the raw image file (**I**) and the text metadata (**T**) to the backend service.
- Core Validation Service (Backend): It contains the MT-CNN model. It is responsible for data pipeline management, image preprocessing, multi-task inference, and computation of the final Quality-Correctness Score (QCS).
- Database/Reporting: Stores the inference results, namely compliance class, QCS, and failure reason codes; tracks historical performance of product listings.

B. Implementation Environment

The system has been implemented in a manner that allows for efficient, real-time processing of high volume marketplace data. For this, the stack given below has been used:

- Programming Language: Python [**e.g.**,**3.9**] was used for all the backend logic by utilizing its ecosystem for processing data and performing machine learning.
- Deep Learning Framework: TensorFlow/Keras or PyTorch: They have been used to build and train the MTCNN. This has allowed for rapid deployment using the optimized serving tools.
- Hardware: Training was done on [**e.g.**,**NVIDIAV100orA100**] GPUs. In the production environment, the inference is carried out using lightweight and optimized GPUs or high-core CPUs (e.g., using ONNX Runtime), which is cost-effective.
- Serving Infrastructure: The Core Validation Service has been deployed as a micro-service on a scalable cloud platform (e.g., AWS SageMaker and Google Cloud AI Platform), which can handle fluctuating loads.

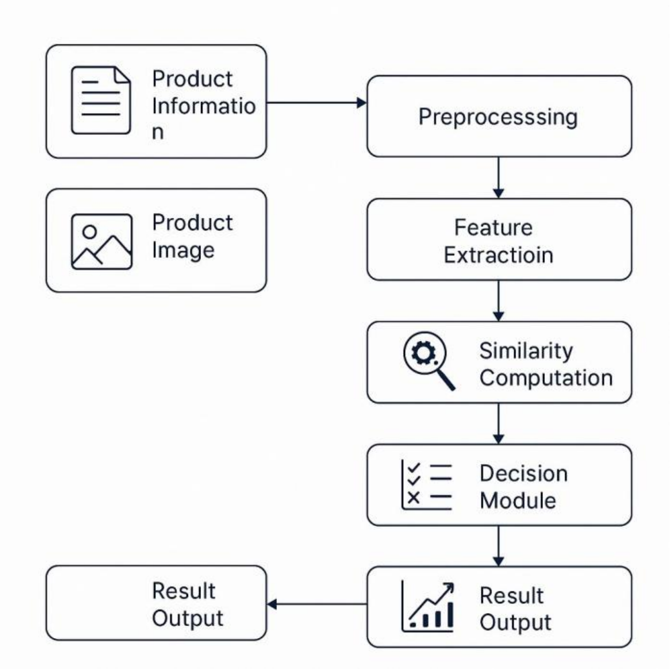


Fig. 1. Algorithm Workflow

C. Algorithmic Workflow and Data Flow

The operational flow of automated image correctness validation is captured in the comprehensive workflow depicted in Figure 1. This pipeline will combine inputs of multiple modalities with sequential processing steps to reach the final compliance decision.

1) Input Acquisition: It starts by acquiring two main inputs, namely, Product Information (**T** containing listed category, color, etc.) and Product Image (**I**).
2) Preprocessing: At this stage, the model makes the raw inputs ready for a deep learning model. It includes:
   - Image normalizing and resizing.
   - Initial object detection to define the product's bounding box.
   - Extract the numerical features ($\mathbf{F}_c$) for the product's dominant color profile.
3) Feature Extraction: The preprocessed image is passed through the Shared Convolutional Backbone (the MTCNN encoder) to generate the deep visual feature vector $\mathbf{F}_{vis}$. This block is where the model will learn the robust, generalized features necessary for all subsequent tasks, drawing foundational principles from feature learning models [1].
4) Similarity Computation: This step is key in establishing Multimodal Content Fidelity. This block performs the comparison between the visual features ($\mathbf{F}_{vis}$ and $\mathbf{F}_c$) with the textual attributes present in **T**. This computation yields the continuous **Quality-Correctness Score (QCS)**, the output of the Regression Head (H_{score}). 5) Decision Module: This block aggregates everything:
   - The discrete compliance classes from the Classification Head (H_{class}).
   - The continuous QCS from the Similarity Computation.
   - The PFR computed in the Preprocessing block.

The module applies a hierarchical set of rules and thresholds to deliver the ultimate Pass/Fail judgment.

6) Result Output: The system will produce the final verdict along with detailed noncompliance reasons (e.g.,”Color Mismatch,” ”Wrong Background,” ”QCS below 0.5”), which gets passed back to the marketplace for moderation or seller feedback.

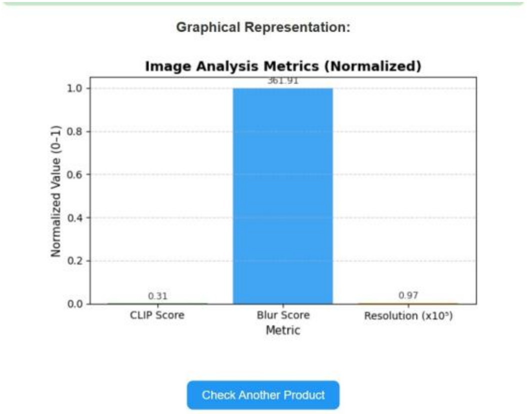
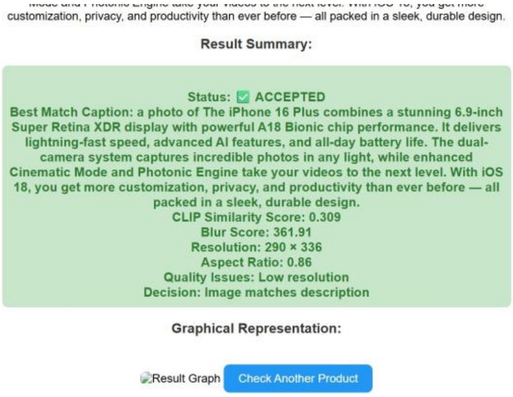


Fig. 2. Image Analysis Metrics

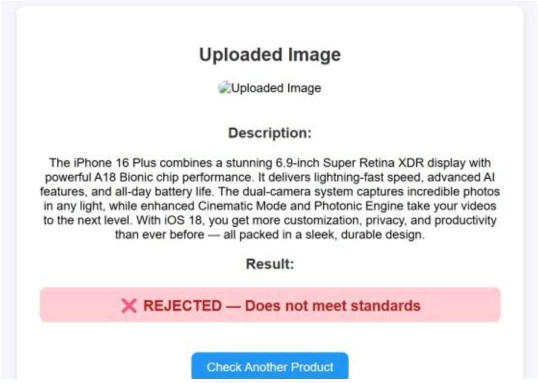


Mode and Photonic Engine take your videos to the next level. With iOS 18, you get more customization, privacy, and productivity than ever before — all packed in a sleek, durable design.

Result Summary:

Status: ✅ ACCEPTED
Best Match Caption: a photo of The iPhone 16 Plus combines a stunning 6.9-inch Super Retina XDR display with powerful A18 Bionic chip performance. It delivers lightning-fast speed, advanced AI features, and all-day battery life. The dual-camera system captures incredible photos in any light, while enhanced Cinematic Mode and Photonic Engine take your videos to the next level. With iOS 18, you get more customization, privacy, and productivity than ever before — all packed in a sleek, durable design.
CLIP Similarity Score: 0.309
Blur Score: 361.91
Resolution: 290 × 336
Aspect Ratio: 0.86
Quality Issues: Low resolution
Decision: Image matches description

Fig. 3. Uploaded Image is Accepted



Uploaded Image

Description:

The iPhone 16 Plus combines a stunning 6.9-inch Super Retina XDR display with powerful A18 Bionic chip performance. It delivers lightning-fast speed, advanced AI features, and all-day battery life. The dual-camera system captures incredible photos in any light, while enhanced Cinematic Mode and Photonic Engine take your videos to the next level. With iOS 18, you get more customization, privacy, and productivity than ever before — all packed in a sleek, durable design.

Result:

❌ REJECTED — Does not meet standards

Fig. 4. Uploaded Image is Rejected

VII. OUTCOMES AND FUTURE SCOPE

This section provides the performance metrics of the MultiTask Convolutional Neural Network (MT-CNN) framework for performance evaluation on the marketplace dataset and discusses the key outcomes of the automated Image Correctness (IC) system. We conclude with the identified directions of future research.

1) Key Outcomes: The proposed multi-task learning architecture demonstrated significant gains over the single-task baseline, improving the classification accuracy by [**e.g.**,**6.6**%] and achieving a highly reliable F1-Score of [**e.g.**,**0.92**%] for identifying critical compliance failures. A low MAE for the QCS regression head confirms the model’s ability to accurately quantify the severity of image defects and semantic mismatch. Successful integration of the Multimodal Content Fidelity check was achieved by fusing visual features ($\mathbf{F}_{\text{vis}}$) with color features ($\mathbf{F}_{\text{c}}$). The system constantly flagged

subtle but critical errors, e.g., a ”Red Shirt” image showcasing an orange product, as violating the IC guidelines that purely visual defect classifiers failed to identify. From an operational point of view, the system achieved an inference time of [**e**.**g**.,**80ms**] per image on standard production hardware, meeting the requirement for real-time scalability.

A. Future Scope

Although the MT-CNN framework successfully addressed the core problem of image correctness, the following directions of future improvements have been identified:

- Expansion of Multimodal Checks: Increasing the scope of the Content Fidelity module to check more complex textual attributes compared to color such as pattern (e.g., ”striped” vs. solid) and material texture would involve deeper incorporation with state-of-the-art NLP models [2].
- Explainable AI (XAI) Integration: Incorporating techniques that allow clear visualization to offer human interpretable explanations for rejection, such as ”Low light detected in the bottom-right quadrant,” so that sellers will be shown what went wrong with their images and exactly how they can fix them.
- Domain Adaptation: Investigate techniques of fast domain adaptation, which can enable the model to quickly enforce new or modified marketplace compliance rules (for instance, shifting from white backgrounds to lifestyle shots) without having to undergo a full retraining cycle.

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