A Survey on Knowledge Distillation of Vision-Language Models

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Abstract

Vision-language models (VLMs) achieve strong multimodal performance but remain expensive to deploy. Knowledge distillation (KD) is an effective approach for compressing these models and transferring their capabilities to more efficient student models. While KD for large language models (LLMs) is already well surveyed, no existing work provides systematic coverage of KD for VLMs, where the addition of a visual modality introduces challenges that text-only distillation does not face. This paper presents the first dedicated survey of knowledge distillation for vision-language models. We propose a unified taxonomy that organizes methods along three orthogonal views: knowledge type, teacher accessibility, and structural compatibility, use it to organize methods across major VLM distillation settings. We also survey the associated datasets and evaluation protocols, identify open challenges and outline directions for future research.

1 Introduction

Vision-language models (VLMs) integrate visual encoders with language model backbones to enable tasks requiring joint visual-linguistic understanding. Recent models such as LLaVA (Liu et al., 2023a), InternVL (Chen et al., 2024d), Qwen-VL (Bai et al., 2025), and DeepSeek-VL (Wu et al., 2024c) achieve strong results on multimodal benchmarks, but their computational cost, combining billion-parameter visual encoders with large language backbones, limits deployment on resource-constrained devices, motivating efficient alternatives. Knowledge distillation (KD) (Hinton et al., 2015) has become the principal technique for addressing these limitations: a compact student model is trained to approximate a stronger teacher's behavior through available knowledge signals, producing a model that is substantially smaller while retaining much of the teacher's capability. While KD for text-only large language models (LLMs) is now well surveyed (Xu et al., 2024b; Yang et al., 2025a; Moslemi et al., 2024; Fang et al., 2026), no existing survey provides systematic coverage of KD for VLMs, where the addition of a visual modality introduces challenges that text-only distillation does not face. KD for VLMs has consequently grown into an active research area, driven by demands across several fronts. The direct objective is compressing large multimodal models into compact students that retain multimodal reasoning capabilities at a fraction of the original cost while preserving conversational quality and visual grounding (Wang et al., 2023b; Shu et al., 2024; Cai et al., 2025; Feng et al., 2025b; Lee et al., 2025a). Beyond compression, KD transfers VLM representations into task-specific architectures: open-vocabulary detection (Wang et al., 2023a; Li et al., 2023b), zero-shot segmentation (Xiao et al., 2024), embodied navigation (Sumers et al., 2023a), and vision-based reinforcement learning (Xu et al., 2025). A parallel line of work compresses contrastive VLMs for mobile deployment through affinity mimicking (Wu et al., 2023b), cluster-instance discrimination (Yang et al., 2025b), or embedding-level transfer (Nair, 2024; Yang et al., 2024). Furthermore, self-distillation operates during VLM pretraining to strengthen cross-modal alignment without an external teacher (Dong et al., 2023; Jing et al., 2024; Kim et al., 2025b). The broad range of these settings, each with distinct objectives, knowledge signals, and evaluation criteria, motivates a systematic survey.

Despite this growth, no existing survey provides dedicated and in-depth coverage of KD for VLMs. On the VLM side, existing surveys treat distillation only peripherally: (Zhang et al., 2024a) devote one section to distilling VLM knowledge into downstream tasks, without covering generative VLM compression, CLIP distillation, or cross-modal feature alignment methods. (Shinde et al., 2025) survey efficient VLM techniques and include KD as

one subsection beside quantization, pruning, and fine-tuning, but do not provide a taxonomy or systematic method-level analysis of distillation approaches.Broader multimodal surveys (Yin et al., 2024; Liang et al., 2024) cover VLM architectures, training strategies, and evaluation, not treat distillation as a focus area. On the other hand, KD surveys do not address the multimodal setting: LLM-specific surveys (Xu et al., 2024b; Yang et al., 2025a; Fang et al., 2026) cover text-only distillation, and general KD surveys (Gou et al., 2021; Mansourian et al., 2025) mention VLMs only briefly. The result is that a researcher entering VLM distillation still lacks a single reference that systematically organizes the field: which methods exist, how they relate to each other, what knowledge signals they transfer, what teacher-access assumptions they require, how structural mismatches are handled, which evaluation settings are comparable across applications, and what problems remain open. This paper addresses this gap by providing the **first dedicated survey** of knowledge distillation for vision-language models. We observe that every VLM distillation method must answer three independent questions: **(1)** what knowledge is transferred from teacher to student, **(2)** what level of access to the teacher is available, and **(3)** what structural mismatch must be bridged before transfer can occur. These questions define a taxonomy that enables systematic cross-method comparison. We also survey datasets, evaluation protocols (as shown in Appendix B) across taxonomy categories, synthesize open challenges and future directions in this field. Our main contributions are: **(i)** We present the first comprehensive survey on knowledge distillation for vision-language models, providing a structured overview of methods, training objectives, and datasets. **(ii)** We propose a multi-view taxonomy that organizes VLM distillation along orthogonal axes, enabling practitioners to systematically locate, compare, and select approaches suited to their specific settings. **(iii)** We identify open challenges and future directions that we hope will guide subsequent research in KD for VLMs. Our anonymous repository is available at: Link.

2 Background

2.1 Vision-Language Models

A vision-language model (VLM) integrates a visual encoder with an autoregressive language model to enable tasks that require joint visual-linguistic understanding. The dominant architecture follows an encoder-projector-LLM pipeline: a visual encoder f_v extracts patch-level representations from an input image x_v, a learned projection W_{proj} maps these representations into the language model's embedding space as visual tokens z_v:

$$z_v = W_{\text{proj}} \cdot f_v(x_v) \in \mathbb{R}^{N_v \times d} \tag{1}$$

where N_v is the number of visual tokens and d is the language embedding dimension. The projected tokens z_v are concatenated with the text embeddings to form a mixed-modality input sequence. Given a text instruction x_t, a VLM generates a response $y = (y_1, \ldots, y_L)$ autoregressively:

$$p(y \mid x_v, x_t) = \prod_{l=1}^{L} p(y_l \mid y_{<l}, z_v, x_t) \tag{2}$$

This architecture is shared across the majority of current VLMs, despite differences in encoder scale, projection design, and language backbone. It also underlies both full-scale models and and distilled compressed variants (Wang et al., 2020, 2023b; Zhu et al., 2023a; Shu et al., 2024).

2.2 Knowledge Distillation for VLMs

When knowledge distillation is applied to VLMs, distillation objective operates over the multimodally conditioned distributions defined in Eq. 2. Given a teacher VLM π_T and a student VLM π_S, each with their own visual encoder and projection, the token-level distillation objective minimizes:

$$\mathscr{L}_{\text{distill}} = \sum_{l=1}^{L} D\Big(\pi_T(\cdot \mid y_{<l}, z_v^T, x_t) \,\|\, \pi_S(\cdot \mid y_{<l}, z_v^S, x_t)\Big) \tag{3}$$

where D is a divergence measure and z_v^T, z_v^S are the teacher's and student's projected visual representations (Eq. 1). A critical property of Eq. 3 is that teacher and student condition on *different* visual evidence ($z_v^T \neq z_v^S$ in general), even for the same input image. This asymmetry, absent in text-only distillation, is the source of difficulties specific to the multimodal setting. We formalize this distinction by comparing Eq. 3 to its LLM counterpart and derive the resulting challenges in Appendix A.

3 A Taxonomy for Knowledge Distillation in Vision-Language Models

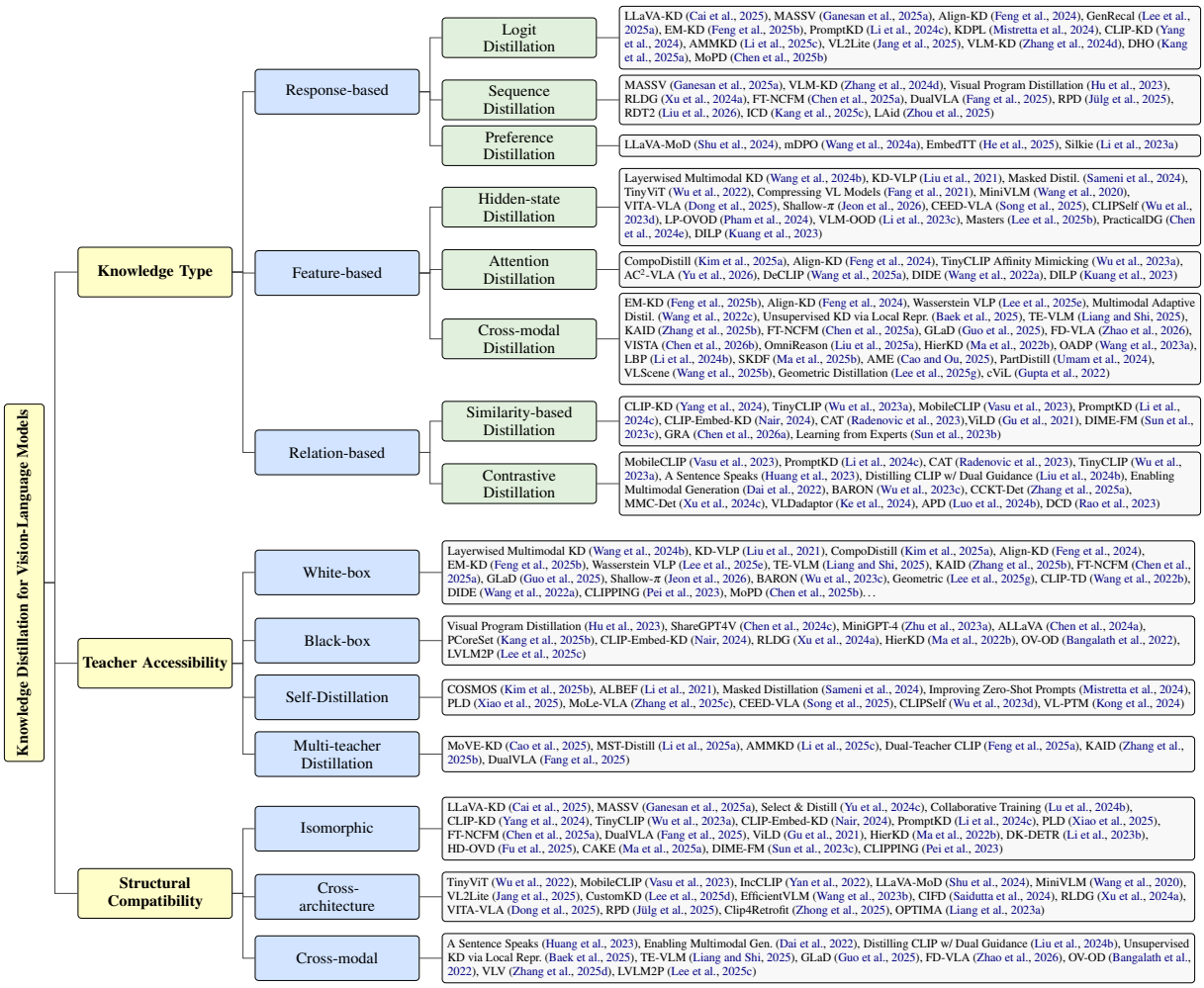

Figure 1: Taxonomy of VLM distillation methods.

We organize VLM distillation methods along four orthogonal views, each addressing a distinct design question a practitioner faces when designing or selecting a distillation approach:

- **Knowledge Type**: *What does the student learn from the teacher?*
- **Teacher Accessibility**: *What can be observed about the teacher?*
- **Structural Compatibility**: *What must be bridged before distillation can proceed?*.

The three views reflect genuinely independent design decisions with a natural ordering in practice. The practitioner first assesses *structural compatibility*: do teacher and student share a vocabulary, architecture, and modality pipeline? If not, a bridging mechanism must be designed before any distillation objective can be defined. Next, *teacher accessibility* determines what knowledge signals are

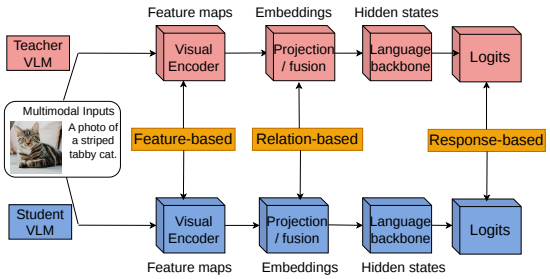

Figure 2: Knowledge type view of VLM distillation.

available, ranging from internal access to output-only observation, self-generated supervision, or aggregation across multiple teachers. This constrains which *knowledge types* are feasible. The complete taxonomy is shown in Figure 1. We now describe each view in detail.

3.1 Knowledge Type

Knowledge type axis categorizes *what* student learns from teacher. In VLMs, all teacher out-

puts are multimodally conditioned: the teacher's response to any text prefix depends on its visual representation. As illustrated in Figure 2, VLM distillation objective (Eq. 3) can be instantiated in several ways depending on which aspect of teacher's behavior is transferred.

Response-based Distillation. Response-based methods distill the teacher's output-level behavior, varying in the granularity and form of the supervision signal. *Logit distillation* directly minimizes the per-step divergence between teacher and student next-token distributions, both conditioned on the visual embedding v and text prefix q:

$$\mathscr{L}_{\text{logit}} = \frac{1}{|y|}\sum_{t=1}^{|y|} \text{KL}\big(p^T(y_t \mid y_{<t}, v, q) \parallel p^S(y_t \mid y_{<t}, v, q)\big) \tag{4}$$

This preserve the teacher's full output distribution including uncertainty and ranked alternatives at each decoding step. *Sequence distillation* replaces the soft distribution in Eq. 4 with discrete teacher-generated sequences $\hat{y} \sim p^T(\cdot \mid v, q)$, and trains the student with standard cross-entropy:

$$\mathscr{L}_{\text{seq}} = -\frac{1}{|\hat{y}|}\sum_{t=1}^{|\hat{y}|} \log p^S\big(\hat{y}_t \mid \hat{y}_{<t}, v, q\big). \tag{5}$$

By materializing the teacher's knowledge as text, this objective discards distributional information but enables black-box distillation where only generated outputs are available. *Preference distillation* cast teacher as a reference policy and training the student to distinguish preferred from dis-preferred responses via DPO objective (Rafailov et al., 2023):

$$\mathscr{L}_{\text{DPO}} = -\log\sigma\Big(\beta\log\tfrac{\pi_S(y_w|v,q)}{\pi_T(y_w|v,q)} - \beta\log\tfrac{\pi_S(y_l|v,q)}{\pi_T(y_l|v,q)}\Big) \tag{6}$$

where y_w and y_l are teacher-scored preferred and dis-preferred responses for the same (v, q) pair. This transfers the teacher's relative quality judgments rather than its token-level distributions.

Feature-based Distillation. Feature-based methods require white-box access and supervise the student's internal representations rather than its outputs. The cross-modal interface is the most important and uniquely VLM-specific target within this category. Three sub-types target different internal components: *hidden-state distillation* enforces layer-to-layer alignment of representations across the visual encoder, projection, and language backbone; *attention distillation* transfers the teacher's attention patterns, particularly cross-modal attention maps that encode which visual regions ground each text token; and *cross-modal feature distillation* operates directly on the projection-layer representations where visual and linguistic information are fused, targeting the modality interface. Methods of this type have also been applied to segmentation tasks, where segmentation networks are trained to align their internal representations with pretrained VLM features (Ma et al., 2022a; Liang et al., 2023b; Zhou et al., 2023; Ding et al., 2022).

Relation-based Distillation. Relation-based methods transfer the structural relationships among the teacher's embeddings rather than its individual predictions. *Similarity-based distillation* penalizes discrepancies in the teacher's $b \times b$ pairwise similarity matrix across a mini-batch of embeddings $\{h_i\}$:

$$\mathscr{L}_{\text{sim}} = \big\|S^T - S^S\big\|_F^2, \quad S_{ij} = \frac{h_i^\top h_j}{\|h_i\|\|h_j\|}. \tag{7}$$

This captures inter-sample relationships—which images are semantically close, which image-text pairs are well-aligned—that logit matching cannot express. *Contrastive distillation* goes further by training the student to reproduce the teacher's complete batch similarity distribution, capturing positive alignments and the near-miss structure among hard negatives rather than only the scalar similarity values. Objectives of both types have been applied beyond compression to transfer the relational structure of vision-language embedding spaces into segmentation networks (Xu et al., 2022; Ma et al., 2022a; Zhou et al., 2023).

3.2 Teacher Accessibility

The accessibility axis determines which knowledge signals are observable and thus constrains which knowledge types from Section 3.1 are feasible (Figure 3). *White-box distillation* grants access to teacher's internal representations, including weights, hidden states, attention maps, and intermediate activations. Such access is required for feature-based and attention-based knowledge types. *Black-box distillation* restricts student to the teacher's observable outputs, typically generated text. *Self-distillation* uses no external teacher and instead derives supervision from the model's own

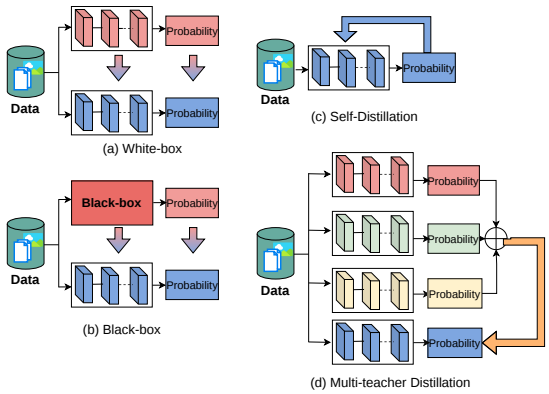

Figure 3: Teacher accessibility view of VLM distillation.

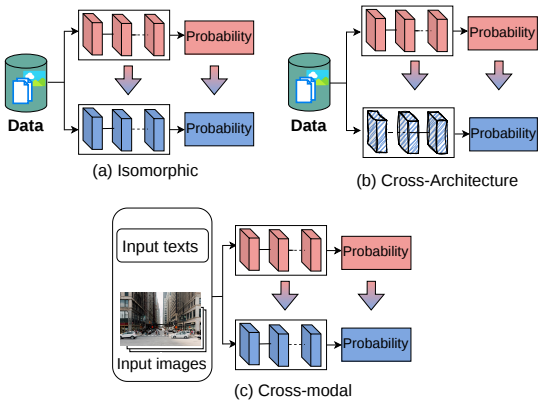

Figure 4: Structural compatibility view of VLM distillation.

alternative forward passes or cross-modal consistency constraints. *Multi-teacher distillation* combines signals from multiple specialized teachers, each capturing a complementary aspect of visual or linguistic information. This regime requires coordinating heterogeneous supervision signals and managing capacity allocation across teachers.

3.3 Structural Compatibility

The structural compatibility axis characterizes what must be bridged before any distillation objective can be applied (Figure 4). *Isomorphic* pairs share the same vocabulary, architecture, and modality configuration, differing only in scale. No bridging is required: all knowledge types are directly applicable. *Cross-architecture* pairs share the same input-output modality structure but differ in internal architecture of the visual encoder, the language backbone, or both. Feature-level alignment requires intermediate projection layers to bridge representational differences. *Cross-modal* pairs involve a VLM teacher that jointly processes vision and language, and a student that operates in a fundamentally different paradigm. This is the most extreme structural mismatch, where student lacks the architectural components needed to replicate teacher's cross-modal processing. Cross-modal knowledge transfer from VLMs to segmentation models has also been explored in both 2D and 3D settings (Ma et al., 2022a; Zhou et al., 2023; Xu et al., 2022; Umam et al., 2024).

4 Distillation for Vision-Language Models

Having defined the taxonomy in Section 3, we now review how specific methods instantiate each knowledge type, accessibility regime, and structural setting.

4.1 Knowledge Types

4.1.1 Response-based Distillation.

Logit distillation. LLaVA-KD (Cai et al., 2025) extends Eq. (4) with modality-separated KL terms over visual and language tokens (MDist) and a cosine similarity regulariser over the visual token self-correlation matrix (RDist). MASSV (Ganesan et al., 2025b) applies Eq. (4) for speculative decoding by distilling VLM-generated continuations into a small draft model. Align-KD (Feng et al., 2024) replaces the forward KL with its reverse form $\mathrm{KL}(p^S \| p^T)$ to encourage mean-seeking optimisation, combined with an attention-map distillation term on the first decoder layer. VLsI (Lee et al., 2024) generalises to every intermediate layer by projecting hidden states into vocabulary space via lightweight verbaliser heads, applying KLD at each matched layer pair as well as final output layer.

Sequence distillation. MASSV (Ganesan et al., 2025a) uses sequence distillation to build a self-distilled fine-tuning set by sampling target-VLM continuations at multiple temperatures and training the draft model on the resulting outputs. Distilling Internet-Scale VLMs into Embodied Agents (Sumers et al., 2023b) applies the same idea to action learning, using hindsight relabelling in which the teacher retroactively describes agent trajectories in natural language for behavioural cloning. VPD (Hu et al., 2023) extends sequence distillation to programmatic reasoning: the teacher samples multiple candidate programs, filters them by execution correctness, and the student is trained on the valid sequences. VLM-KD (Zhang et al., 2024d) uses teacher-generated image descriptions

as textual supervision, distilling sequence-level semantic information into the student vision encoder.

Preference distillation. LLaVA-MoD (Shu et al., 2024) applies Eq. (6) in a two-stage protocol: mimic distillation via KL logit matching is followed by preference distillation where the large MLLM serves as π_T. mDPO (Wang et al., 2024a) addresses the unconditional preference problem in multimodal DPO - where the model ignores the image - by introducing an image-conditioned DPO term and a reward anchor that prevents the likelihood of the chosen response from decreasing during training.

4.1.2 Feature-based Distillation.

Hidden-state distillation. LMD (Wang et al., 2024c) enforces layer-by-layer alignment across the visual encoder, projection layer, and language backbone, showing that each stream provides complementary supervision signals. KD-VLP (Liu et al., 2021) adds an object-detection teacher to provide region-level hidden-state supervision, grounding language tokens to image patches for spatially aware VQA. SF-CLIP (Sameni et al., 2024) replaces pixel reconstruction in masked image modeling with the teacher's hidden-state representations of masked regions. TinyViT (Wu et al., 2022) supervises small ViT pre-training with teacher soft-label distributions, transferring semantic structure learned from internet-scale data.

Attention distillation. CompoDistill (Kim et al., 2025a) identifies cross-modal visual attention misalignment as the root cause of compositional reasoning failures in small VLMs, and transfers the teacher's visual attention maps to the student via a cosine similarity loss. Align-KD (Feng et al., 2024) distills the teacher's first-layer text-query-vision attention scores to dynamically select the top-K most informative visual tokens for injection into the student, combining this with a reverse KL logit loss to produce one of the most complete cross-modal interface distillation implementations targeting mobile-scale deployment.

Cross-modal feature distillation. EM-KD (Feng et al., 2025b), MAD (Wang et al., 2022c), and TE-VLM (Liang and Shi, 2025) reweight cross-modal supervision to emphasise more informative signals. MKD (Lee et al., 2025e) instead matches teacher and student joint visual–language distributions through optimal transport, capturing global alignment geometry under strong compression. UKD (Baek et al., 2025) extends this idea to the local level by using patch-level visual representations as alignment anchors without requiring labeled image–text pairs.

4.1.3 Relation-based Distillation.

Similarity-based distillation. CLIP-KD (Yang et al., 2024) proposes a Relation Distillation (RD) component that aligns pairwise image-text similarity distributions via KL divergence, and further combines it with Contrastive Representation Distillation (CRD) to treat instance pairs as positives and negatives for relational matching. COSMOS (Kim et al., 2025b) applies cross-modal self-distillation by aligning similarity distributions between global and local multi-modal crops through an EMA teacher, preserving cross-modal relational structure without external supervision.

Contrastive distillation. Preserving the teacher's cross-modal similarity geometry is a common approach, where the student matches the teacher's batchwise image–text relational structure rather than individual predictions (Vasu et al., 2023; Wu et al., 2023b). Another line of work enforces relational consistency across different prompting or prediction contexts to transfer the teacher's internal alignment behaviour without labeled data (Li et al., 2024c). Improving the quality of relational supervision through data curation and hard-negative mining has also been shown to significantly affect CLIP distillation performance (Radenovic et al., 2023). Finally, several works extend relational distillation to specialised settings such as domain generalisation, structured human-body representations, or transferring generative capability into contrastive models (Huang et al., 2023; Liu et al., 2024b; Dai et al., 2022).

4.2 Accessibility

4.2.1 White-box Distillation

Access to intermediate hidden states is the most common form, supporting layerwise feature matching and compression via internal alignment. LMD (Wang et al., 2024b), KD-VLP (Liu et al., 2021), SF-CLIP (Sameni et al., 2024), TinyViT (Wu et al., 2023b), Compressing VLMs via KD (Fang et al., 2021), and MiniVLM (Wang et al., 2020) all supervise student with teacher activations from intermediate encoder or transformer layers, enabling component-level alignment, masked-feature reconstruction, attention-head supervision, or stage-wise layer-reduction distillation that cannot be recovered from outputs alone.

Access to attention weight matrices enables explicit transfer of the teacher's internal reasoning patterns. CompoDistill (Kim et al., 2025a) and Align-KD (Feng et al., 2024) match teacher cross-attention or self-attention maps to preserve compositional grounding and spatial focus, while TinyCLIP (Wu et al., 2023b) transfers the teacher's cross-modal affinity structure through similarity-matrix matching.

Access to cross-modal projection outputs supports direct supervision of image–text alignment at the representation boundary. EM-KD (Feng et al., 2025b), MKD (Lee et al., 2025e), and MAD (Wang et al., 2022c) match teacher projection-layer embeddings; UKD (Baek et al., 2025) extends this to patch-level correspondences; and TE-VLM (Liang and Shi, 2025) and KAID (Zhang et al., 2025b) exploit richer internal signals such as hidden-state trajectories, transfer entropy, gating decisions, and encoder-specific representations to determine what cross-modal knowledge should be transferred.

Access to output logit distributions remains the least structural but still richer than hard labels. LLaVA-KD (Cai et al., 2025) and GenRecal (Lee et al., 2025a) distill next-token teacher distributions through token-level KL alignment, preserving uncertainty and ranked alternatives, though this requires the teacher to remain loaded during training for joint forward passes.

4.2.2 Black-box Distillation

VPD (Hu et al., 2023) generates teacher's structured visual programs over a question corpus, and only these sequences serve as student supervision. ShareGPT4V (Chen et al., 2024c) constructs a large-scale caption dataset by prompting GPT-4V for high-quality image descriptions, then uses these captions as sequence-level supervision targets for open-source VLM students. MiniGPT-4 (Zhu et al., 2023a) and ALLaVA (Chen et al., 2024a) adopt the same approach, using GPT-3.5/GPT-4 generated instruction-response pairs as black-box supervision for instruction-following distillation.

4.2.3 Self-Distillation

COSMOS (Kim et al., 2025b) generates cross-modal supervision entirely from the model itself via bidirectional image-text consistency, and remarkably matches external-teacher distillation on VLP benchmarks at substantially lower training cost. Before this, ALBEF (Li et al., 2021) uses a momentum encoder as a self-distillation target to stabilise VLP contrastive learning, validating that alignment before cross-attention fusion prevents spurious correlations. In a related but prompt-centric direction, KDPL (Mistretta et al., 2024) regularizes learned prompts against domain-specific overfit by distilling consistency between teacher's prompted and unprompted predictions on a diverse unlabeled set.

4.2.4 Multi-teacher Distillation

MoVE-KD (Cao et al., 2025) proposes a Mixture-of-LoRA-Experts student with a gating network that dynamically routes inputs to the expert specialised for each teacher encoder (CLIP, SAM, DINOv2). Extending the multi-teacher paradigm from visual encoders to task-specialised VLMs, MST-Distill (Li et al., 2025a) employs multiple task-specialised VLM teachers with dynamic confidence-based weighting to capture complementary capabilities across reasoning, counting, spatial comprehension, and open-domain VQA. To avoid capacity fragmentation under multiple teachers, AMMKD (Li et al., 2025c) applies curriculum-style adaptive weighting that down-weights teachers the student has already approached, directing limited capacity toward the most productive signal. In a more targeted dual-teacher setup, LongD-CLIP (Feng et al., 2025a) uses specialised short-text and long-text CLIP teachers to address CLIP's short-text training bias while extending context length.

4.3 Structural Compatibility

4.3.1 Isomorphic

LLaVA-KD (Cai et al., 2025) and MASSV (Ganesan et al., 2025a) all compress within LLaVA family, where the same CLIP visual encoder and LLaMA-family language backbone are shared. Similarly, Select and Distill (Yu et al., 2024c) and Collaborative Training of Tiny-Large VLMs (Lu et al., 2024b) operate within a fixed VLM family at different scales. In the CLIP sub-domain, scale-matched compression: CLIP-KD (Yang et al., 2024), TinyCLIP (Wu et al., 2023b), CLIP-Embed-KD (Nair, 2024), PromptKD (Li et al., 2024c), Filtering, Distillation and Hard Negative (Radenovic et al., 2023), and Improving CLIP Fine-tuning Performance (Wei et al., 2023), also falls here, since both teacher and student are standard CLIP ViTs with the same BPE text vocabulary. MobileCLIP's (Vasu et al., 2023) contrastive distillation objective and Distilling CLIP with Dual Guidance (Liu et al., 2024b) likewise operate in this regime from the distillation objective standpoint.

4.3.2 Cross-Architecture

TinyViT (Wu et al., 2022) distills large deep ViTs into small shallow ViTs, establishing a pre-training recipe for cross-scale transfer. MobileCLIP (Vasu et al., 2023) extends this to mobile deployment by distilling a ViT teacher into a lightweight CNN-based visual encoder. IncCLIP (Yan et al., 2022) addresses continual learning using generative negative text replay to reduce representational drift. LLaVA-MoD (Shu et al., 2024) distills a dense language backbone into a sparse Mixture-of-Experts student. MiniVLM (Wang et al., 2020) instead designs a compact student VLM with substantially smaller visual and language components. VL2Lite (Jang et al., 2025) and CustomKD (Lee et al., 2025d) target task-specific lightweight deployment through importance-based distillation into custom compact architectures. DistillVLM (Fang et al., 2021) studies transformer layer-reduction distillation, while CIFD (Saidutta et al., 2024) enables architectural mismatch using rate–distortion modules that preserve key information through an information bottleneck.

4.3.3 Cross-Modal

RISE (Huang et al., 2023) transfers CLIP text encoder representations into a visual-only encoder, crossing from the multimodal teacher to a unimodal visual student. VLKD (Dai et al., 2022) transfers generative capability from a VLM into a CLIP model that was not designed for generation, crossing the discriminative-to-generative architectural boundary. CLIP3DReID (Liu et al., 2024b) distills into a domain-specific visual encoder specialised for body understanding. Theoretical foundation for why cross-modal transfer is effective is provided by MFH (Xue et al., 2022): teacher cross-modal alignment predictions implicitly select for linguistically relevant visual features, enabling the student to inherit semantic grounding even without a shared cross-modal structure. Beyond general VLM compression, it has been adapted to several specialized settings: open-vocabulary object detection (Appendix F), segmentation (Appendix E), vision-language-action models (Appendix C), and embedding models (Appendix D) - each of which introduces distinct structural and supervision challenges that we survey in the appendices.

5 Open Challenges and Future Directions

▷ ***Unified Cross-Modal Distillation Objectives.*** Challenges identified in Appendix A.2 are currently handled by separate loss terms. Whether these components reinforce or interfere with each other when composed remains unknown. Framing VLM distillation as a structured alignment problem over joint visual-linguistic token space could replace ad hoc objective design with a more principled framework.

▷ ***Tokenization Heterogeneity Across Modalities.*** Cross-tokenizer distillation is well studied in LLMs, but GenRecal (Lee et al., 2025a) remains the only VLM method addressing mismatched text vocabularies. VLM setting compounds this: teacher and student may simultaneously differ in text vocabulary, visual patch size, and visual token count.

▷ ***Cross-Modal Transfer Under Black-Box Access.*** Feature-based methods that most effectively transfer visual grounding require white-box access. Under black-box access, VLM distillation remains limited to sequence-level transfer through teacher-generated text, where grounding is only implicit. Recovering cross-modal structure from output sequences alone would enable distillation from proprietary multimodal models, but requires fundamentally new objective designs.

▷ ***Adaptation to Evolving Architectures.*** Most surveyed methods target encoder-projector-LLM pipeline, where projection layer serves as a natural cross-modal distillation target. This assumption breaks down for native multimodal architectures, mixture-of-experts VLMs, and models for video or 3D inputs. Distillation objectives must therefore extend to architectures in which the cross-modal interface is distributed rather than localized.

6 Conclusion

This paper has presented the first dedicated survey of knowledge distillation for vision-language models. The multi-view taxonomy proposed in this work organizes VLM distillation methods along knowledge type, teacher accessibility, and structural compatibility perspectives, accompanied by a systematic compilation of training and evaluation datasets across VLM distillation settings. Our survey reveals that addressing VLM distillation goes beyond adapting text-only objectives: it requires unified cross-modal alignment, structural bridging across heterogeneous tokenizers, and evaluation protocols that measure grounding fidelity rather than aggregate accuracy. We hope this survey provides a structured reference and a solid foundation for future research on KD for VLMs.

Limitations

While this survey provides the first dedicated taxonomy for knowledge distillation in vision-language models, it has limitations. Distillation methods for video-language and 3D vision-language models may not be fully represented. Due to the rapid development of the field, the proposed taxonomy will require timely updates to incorporate new methods and paradigms. We hope that this survey serves as a foundation for both methodological and empirical advances in VLM distillation.

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A Connection Between KD for LLMs and VLMs

This appendix reviews the LLM distillation framework that VLM distillation inherits, then identifies the challenges that arise when the visual modality is introduced.

A.1 LLM Distillation Objective

Knowledge distillation (Hinton et al., 2015) trains a compact student to approximate a stronger teacher using supervision signals richer than hard labels: output distributions, generated sequences, intermediate hidden states, attention patterns, or preference rankings. These knowledge types, together with the level of access to the teacher (white-box vs. black-box (Yang et al., 2025a)) and structural constraints such as cross-tokenizer alignment (Zhang et al., 2024c; Cui et al., 2025), define the main design axes of distillation methods. For autoregressive LLMs, the standard objective (Hinton et al., 2015; Kim and Rush, 2016) minimizes a per-token divergence over a sequence x:

$$\mathcal{L}_{\text{distill}}^{\text{LLM}} = \sum_{t=1}^{|x|} D(\pi_T(\cdot \mid x_{<t}) \,\|\, \pi_S(\cdot \mid x_{<t})) \tag{8}$$

The divergence D has been instantiated as forward KL (Hinton et al., 2015; Kim and Rush, 2016), reverse KL (Gu et al., 2023; Wu et al., 2025), Jensen-Shannon divergence (Wen et al., 2023; Agarwal et al., 2024), skewed variants (Ko et al., 2024), and Wasserstein distances (Cui et al., 2024b; Lee et al., 2025f). The context $x_{<t}$ may be drawn from teacher generations (off-policy) or the student's own outputs (on-policy) (Agarwal et al., 2024). These text-only methods are now well surveyed (Xu et al., 2024b; Yang et al., 2025a; Fang et al., 2026). A key property of Eq. 8 is that both teacher and student condition on exactly the same input: the text prefix $x_{<t}$.

A.2 VLM-Specific Distillation Challenges

Comparing the VLM distillation objective (Eq. 3, Section 2.2) to its LLM counterpart (Eq. 8) reveals a fundamental difference: the conditioning no longer matches. In the LLM case, both models see the same text prefix $x_{<t}$. In the VLM case, each model produces its own visual representation through a separate encoder f_v and projection W_{proj}, so $z_v^T \neq z_v^S$ in general. Teacher and student therefore see different visual evidence even for the same input image. This asymmetry is the source of three challenges absent in text-only distillation.

Visual grounding dependency. Because the teacher's token distribution depends on z_v^T, a student whose z_v^S is weaker or differently structured cannot match the teacher's outputs regardless of the language backbone's capacity. Minimizing Eq. 3 directly does not correct a poor z_v^S; the visual encoder and projection must be explicitly supervised to reduce the gap between z_v^T and z_v^S.

Unsupervised modality interface. The projection W_{proj} and the self-attention layers where visual and text tokens interact are the most VLM-specific components, yet Eq. 3 supervises only the final output distribution and provides no gradient signal targeted at these components. Hidden-state matching treats all layers uniformly without distinguishing cross-modal coupling from unimodal processing. This gap motivates cross-modal feature distillation as a distinct knowledge type.

Cross-modal credit assignment. Eq. 3 sums over L language tokens, but the visual evidence supporting each token is spread across N_v visual tokens, where typically $N_v \gg L$. Uniform matching over visual positions is therefore dominated by low-information tokens (background, redundant patches) rather than the sparse regions that actually determine generation quality.

B Datasets and Evaluations

This section summarises the datasets commonly used for training and evaluating VLM distillation methods.

B.1 Datasets

B.1.1 Datasets for Training

As summarized in Table 1, the data landscape for vision–language model (VLM) training has evolved from relatively small, curated English-caption datasets toward web-scale and increasingly multilingual corpora. Early public resources such as SBU Caption (Ordonez et al., 2011), COCO Caption (Lin et al., 2014), Visual Genome (Krishna et al., 2017), and Conceptual Captions (Sharma et al., 2018) established the basic image–text supervision paradigm, whereas later datasets such as WIT, LAION400M, and LAION5B substantially expanded both scale and linguistic coverage. At the same time, several influential pretrained VLMs were built on large non-public corpora, such as CLIP, ALIGN, FILIP, and WebLI, indicating that proprietary data remains a major factor in scaling high-capacity models. Another clear trend is the growing separation between *pre-training* data and *post-training* data: while representation learning typically relies on massive web-scale corpora, knowledge distillation and instruction tuning increasingly depend on smaller but more curated datasets, including LLaVA-style instruction data, preference-learning resources, and edit-oriented or feedback-based supervision. Domain-specific adaptation follows a similar pattern. In remote sensing, for example, recent works combine large-scale alignment corpora with comparatively smaller instruction-tuning datasets, reflecting a broader shift from generic cross-modal alignment toward task-aware and domain-specialized supervision (Table 1).

Table 1: Summary of datasets used for VLM training and distillation. † Num. of samples refers to instruction/preference pairs rather than raw image-text pairs. ‡ Auxiliary dataset; may not consist solely of image-text pairs. § Num. of samples refers to region descriptions rather than images.

Dataset	Year	Num. of Image-Text Pairs	Language	Public
General VLM Pre-training (Public)				
SBU Caption (Ordonez et al., 2011)	2011	1M	English	✓
COCO Caption (Lin et al., 2014)	2015	1.5M	English	✓
YFCC100M (Thomee et al., 2016)	2015	100M	English	✓
Visual Genome (VG) (Krishna et al., 2017)	2017	5.4M§	English	✓
Conceptual Captions (CC3M) (Sharma et al., 2018)	2018	3.3M	English	✓
Localized Narratives (LN) (Pont-Tuset et al., 2020)	2020	0.87M	English	✓
Conceptual 12M (CC12M) (Changpinyo et al., 2021)	2021	12M	English	✓
Wikipedia-based Image Text (WIT) (Srinivasan et al., 2021)	2021	37.6M	108 Languages	✓
Red Caps (RC) (Desai et al., 2021)	2021	12M	English	✓
LAION400M (Schuhmann et al., 2021)	2021	400M	English	✓
LAION5B (Schuhmann et al., 2022)	2022	5B	Over 100 Languages	✓
WuKong (Gu et al., 2022)	2022	100M	Chinese	✓
General VLM Pre-training (Non-public)				
CLIP (Radford et al., 2021)	2021	400M	English	×
ALIGN (Jia et al., 2021)	2021	1.8B	English	×
FILIP (Yao et al., 2021)	2021	300M	English	×
WebLI (Chen et al., 2023b)	2022	10B	109 Languages	×
Auxiliary / Supplementary Pre-training				
JFT3B‡ (Sun et al., 2017)	—	∼3B images	English	×
C4‡ (Raffel et al., 2020)	2020	∼750 GB text	English	✓
Object365‡ (Shao et al., 2019)	2019	638K images	English	✓
Gold-G‡ (Kamath et al., 2021)	2021	0.8M	English	✓
VLM Knowledge Distillation & Instruction Tuning				
RLAIF-V-Dataset† (Yu et al., 2024b)	2024	83K	English	✓
Mantis-Instruct† (Jiang et al., 2024)	2024	721K	English	✓
LLaVA-558K† (Liu et al., 2023b)	2023	558K	English	✓
LLaVA-mix-665K† (Liu et al., 2024c)	2023	665K	English	✓
LLaVA-OneVision† (Li et al., 2024a)	2024	∼4M	English	✓
JourneyDB (Sun et al., 2023a)	2023	4M+	English	✓
SEED-Data-Edit (Part-2&3) (Ge et al., 2024)	2024	147K	English	✓
UltraFeedback† (Cui et al., 2024a)	2023	64K	English	✓
RLHF-V† (Yu et al., 2024a)	2024	1.4K (paper)/5.7K (HF)	English	✓
Remote Sensing Domain				
LHRS-Align (Muhtar et al., 2024)	2024	1.15M	English	✓
GeoChat-Instruct† (Kuckreja et al., 2024)	2024	306K	English	✓
LHRS-Instruct† (Muhtar et al., 2024)	2024	39.8K	English	✓
SkySenseGPT† (Luo et al., 2024a)	2024	381K	English	✓
SkyScript (Wang et al., 2024d)	2024	2.6M (paper)/ 5.2M (GitHub)	English	✓
RemoteCLIP (Liu et al., 2024a)	2024	—	English	✓
VHM (Pang et al., 2024)	2024	—	English	✓

Table 2: Summary of datasets used for VLM evaluation. "—" denotes not applicable or not reported. HF denotes HuggingFace.

Dataset	Year	Classes	Training	Testing	Eval. Metric
Image Classification					
MNIST (LeCun et al., 1998)	1998	10	60,000	10,000	Accuracy
Caltech-101 (Fei-Fei et al., 2004)	2004	102	3,060	6,085	Mean Per Class
PASCAL VOC 2007 Classif. (Everingham et al., 2010)	2007	20	5,011	4,952	11-point mAP
Oxford 102 Flowers (Nilsback and Zisserman, 2008)	2008	102	2,040	6,149	Mean Per Class
CIFAR-10 (Krizhevsky, 2009)	2009	10	50,000	10,000	Accuracy
CIFAR-100 (Krizhevsky, 2009)	2009	100	50,000	10,000	Accuracy
ImageNet-1K (Deng et al., 2009)	2009	1,000	1,281,167	50,000	Accuracy
SUN397 (Xiao et al., 2010)	2010	397	19,850	19,850	Accuracy
SVHN (Netzer et al., 2011)	2011	10	73,257	26,032	Accuracy
STL-10 (Coates et al., 2011)	2011	10	1,000	8,000	Accuracy
GTSRB (Stallkamp et al., 2011)	2011	43	26,640	12,630	Accuracy
KITTI Distance (Geiger et al., 2012; Zhai et al., 2019)	2012	4	6,770	711	Accuracy
IIIT5k (Mishra et al., 2012)	2012	36	2,000	3,000	Accuracy
Oxford-IIIT PETS (Parkhi et al., 2012)	2012	37	3,680	3,669	Mean Per Class
Stanford Cars (Krause et al., 2013)	2013	196	8,144	8,041	Accuracy
FGVC Aircraft (Maji et al., 2013)	2013	100	6,667	3,333	Mean Per Class
FER 2013 (Goodfellow et al., 2015)	2013	8	32,140	3,574	Accuracy
Rendered SST2 (Zhai et al., 2019)	2013	2	7,792	1,821	Accuracy
Describable Textures (DTD) (Cimpoi et al., 2014)	2014	47	3,760	1,880	Accuracy
Food-101 (Bossard et al., 2014)	2014	102	75,750	25,250	Accuracy
Birdsnap (Berg et al., 2014)	2014	500	42,283	2,149	Accuracy
RESISC45 (Cheng et al., 2017)	2017	45	3,150	25,200	Accuracy
CLEVR Counts (Johnson et al., 2017)	2017	8	2,000	500	Accuracy
PatchCamelyon (Veeling et al., 2018)	2018	2	294,912	32,768	Accuracy

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Table 2 *(continued)*

Dataset	Year	Classes	Training	Testing	Eval. Metric
EuroSAT (Helber et al., 2019)	2019	10	10,000	5,000	Accuracy
Hateful Memes (Kiela et al., 2020)	2020	2	8,500	500	ROC AUC
Country211 (Radford et al., 2021)	2021	211	43,200	21,100	Accuracy
Image-Text Retrieval					
Flickr30K (Young et al., 2014)	2014	—	31,783	—	Recall
COCO Caption (Lin et al., 2014)	2015	—	82,783	5,000	Recall
Action Recognition					
UCF101 (Soomro et al., 2012)	2012	101	9,537	1,794	Accuracy
Kinetics700 (Carreira et al., 2019)	2019	700	494,801	31,669	Mean(Top-1,Top-5)
RareAct (Miech et al., 2020)	2020	122	7,607	—	mWAP, mSAP
Object Detection					
COCO 2014 Detection (Lin et al., 2014)	2014	80	83,000	41,000	box mAP
COCO 2017 Detection (Lin et al., 2014)	2017	80	118,000	5,000	box mAP
LVIS (Gupta et al., 2019)	2019	1,203	118,000	5,000	box mAP
ODinW (Li et al., 2022b)	2022	314	132,413	20,070	box mAP
Semantic Segmentation					
PASCAL VOC 2012 Seg. (Everingham et al., 2010)	2012	20	1,464	1,449	mIoU
PASCAL Context (Mottaghi et al., 2014)	2014	459	4,998	5,105	mIoU
Cityscapes (Cordts et al., 2016)	2016	19	2,975	500	mIoU
ADE20K (Zhou et al., 2017)	2017	150	25,574	2,000	mIoU
Multimodal Visual Question Answering					
VQAv2 (Goyal et al., 2017)	2017	—	443,757	81,434	VQA Score
OK-VQA (Marino et al., 2019)	2019	—	9,009	5,046	Accuracy
TextVQA (Singh et al., 2019)	2019	—	34,602	5,734	Accuracy
GQA (Hudson and Manning, 2019)	2019	—	943,000	12,578	Accuracy
VizWiz (Gurari et al., 2018)	2020	—	20,523	8,000	Accuracy
ScienceQA (image) (Lu et al., 2022)	2022	—	12,726	4,241	Accuracy

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Table 2 *(continued)*

Dataset	Year	Classes	Training	Testing	Eval. Metric
Multimodal Capability Benchmarks					
MME (Fu et al., 2023)	2023	14	—	2,194	Score
MMBench (Liu et al., 2024d)	2023	—	—	4,329	Accuracy
MMBench-CN (Liu et al., 2024d)	2023	—	—	4,329	Accuracy
POPE (Li et al., 2023d)	2023	—	—	9,000	Accuracy / F1
MMMU (Yue et al., 2024)	2024	30	—	11,500	Accuracy
MMStar (Chen et al., 2024b)	2024	6	—	1,500	Accuracy
HallusionBench (Guan et al., 2024)	2024	—	—	1,129	Accuracy
MathVista (mini) (Lu et al., 2024a)	2024	—	—	1,000	Accuracy
OCRBench (Liu et al., 2023c)	2024	—	—	1,000	Score
AI2D (Kembhavi et al., 2016)	2022	—	12,413	3,088	Accuracy
MMVet (Yu et al., 2023)	2023	6	—	218	Score
Hallucination Assessment					
Object HalBench (Rohrbach et al., 2018)	2023	—	—	300	Accuracy
MMHal-Bench (Sun et al., 2023d)	2023	—	—	96	Score
LLaVA-Bench (In-the-Wild) (Liu et al., 2023b)	2023	—	—	60	Score
Image Captioning					
COCO Test 2017 (Lin et al., 2014)	2017	—	118,000	5,000	CIDEr / BLEU
Image Generation					
GenEval (Ghosh et al., 2023)	2023	6	—	533	Overall Score
Image Editing					
GEdit-Bench EN (Liu et al., 2025b)	2025	—	—	—	G_SC, G_PQ, G_O
GEdit-Bench CN (Liu et al., 2025b)	2025	—	—	—	G_SC, G_PQ, G_O
RS Image Classification					
NWPU-RESISC45 (Cheng et al., 2017)	2017	45	—	31,500	Top-1 Acc
AID (Xia et al., 2017)	2017	30	—	10,000	Top-1 Acc
SIRI-WHU (Zhao et al., 2016)	2016	12	—	2,400	Top-1 Acc
WHU-RS19 (Xia et al., 2010; Dai and Yang, 2011)	—	19	—	950	Top-1 Acc

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Table 2 *(continued)*

Dataset	Year	Classes	Training	Testing	Eval. Metric
fMoW (Christie et al., 2018)	2018	63	—	16,948	Top-1 Acc
EuroSAT (RS) (Helber et al., 2019)	2019	10	—	27,000	Top-1 Acc
METERML (Zhu et al., 2022)	—	—	—	—	Top-1 Acc
RS Image-Text Retrieval					
UCM-Caption (Qu et al., 2016)	2011	—	—	2,100	R@1, R@5
RSICD (Lu et al., 2018)	2017	—	8,734	10,921	R@1, R@5
SkyScript (Wang et al., 2024d)	2024	—	—	—	Top-1 / R@1
RS Visual Question Answering					
RSVQA-HR (Lobry et al., 2020)	2020	—	—	—	Accuracy
RSVQA-LR (Lobry et al., 2020)	2020	—	—	—	Accuracy
RS Visual Grounding					
VG-DIOR (Zhan et al., 2023)	2023	—	—	—	Acc@IoU>0.5
RS General Knowledge					
LHRS-Bench (Muhtar et al., 2024)	2024	11	—	—	Accuracy

B.1.2 Datasets for Evaluation

Table 2 shows that VLM evaluation has become increasingly broad and multi-dimensional, extending well beyond conventional image classification or retrieval. Classical vision benchmarks such as ImageNet, CIFAR, COCO, and VOC remain important anchors for measuring core perceptual performance, but recent evaluation practice places much greater emphasis on multimodal reasoning, visual question answering, hallucination robustness, OCR capability, and instruction-following behavior. This trend is reflected in the growing use of specialized benchmarks such as MME, MMBench, MMMU, MMStar, HallusionBench, MathVista, OCRBench, and MMVet, which probe more fine-grained capabilities than traditional recognition datasets alone. At the same time, evaluation is becoming increasingly domain-aware: remote-sensing VLMs are now assessed not only on classification and retrieval, but also on visual question answering, grounding, and broader knowledge-oriented benchmarks. Overall, the benchmark distribution in Table 2 suggests that modern VLM evaluation is no longer centered on a single task family; instead, it requires a diverse suite of datasets that jointly capture perception, reasoning, robustness, and domain generalization.

B.2 Evaluation Metrics in Vision-Language Model Distillation

Evaluation in vision-language model (VLM) distillation is typically performed using standard downstream task metrics rather than distillation-specific criteria. In practice, the most commonly reported metrics are accuracy-based measures for classification and question answering, ranking-based measures for retrieval, and overlap-based measures for generation.

For classification-style tasks, the most common metric is *Accuracy*, defined as

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\{\hat{y}_i = y_i\},$$

where $\hat{y}_i$ and y_i denote the predicted and ground-truth labels for the i-th example. In some settings, especially when class imbalance is relevant, *F1-score* is also reported:

$$\mathrm{F1} = 2 \cdot \frac{\mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}.$$

These metrics are widely used when evaluating whether the distilled student preserves the teacher's decision quality on classification, VQA, or multiple-choice multimodal reasoning tasks.

For retrieval-oriented VLMs, especially CLIP-style dual-encoder models, the dominant metrics are *Recall@K* and sometimes *Mean Reciprocal Rank (MRR)*. Recall@K measures whether the correct target appears in the top-K retrieved results:

$$\mathrm{Recall@}K = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}\{\mathrm{rank}_i \leq K\},$$

where rank_i is the rank of the correct match for query i. MRR is defined as

$$\mathrm{MRR} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\mathrm{rank}_i}.$$

Among these, R@1, R@5, and R@10 are the most frequently reported, with R@1 usually serving as the headline retrieval metric.

For generative VLMs, such as captioning or instruction-following models, the most common automatic metrics are *BLEU*, *ROUGE-L*, and *CIDEr*. BLEU evaluates n-gram precision with a brevity penalty:

$$\mathrm{BLEU} = \mathrm{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n \right),$$

where p_n is the modified n-gram precision, w_n is the corresponding weight, and BP denotes the brevity penalty. ROUGE-L is based on the longest common subsequence (LCS) between a candidate sequence Y and a reference sequence X:

$$R_{\mathrm{LCS}} = \frac{\mathrm{LCS}(X,Y)}{|X|}, \qquad P_{\mathrm{LCS}} = \frac{\mathrm{LCS}(X,Y)}{|Y|},$$

with the corresponding F-score

$$\text{ROUGE-L} = \frac{(1+\beta^2) R_{\mathrm{LCS}} P_{\mathrm{LCS}}}{R_{\mathrm{LCS}} + \beta^2 P_{\mathrm{LCS}}}.$$

CIDEr measures consensus between the generated caption and reference captions using TF-IDF weighted n-gram similarity:

$$\mathrm{CIDEr} \approx \frac{1}{M} \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{\mathbf{g}_n^{\mathrm{cand}} \cdot \mathbf{g}_n^{\mathrm{ref}(m)}}{\|\mathbf{g}_n^{\mathrm{cand}}\| \, \|\mathbf{g}_n^{\mathrm{ref}(m)}\|},$$

where $\mathbf{g}_n$ denotes the TF-IDF representation of n-grams. In practice, CIDEr is often treated as one of the most informative single metrics for captioning-style evaluation.

Some works additionally report calibration quality using *Expected Calibration Error (ECE)*, which measures the discrepancy between model confidence and empirical correctness:

$$\mathrm{ECE} = \sum_{m=1}^{M} \frac{|B_m|}{N} \left| \mathrm{acc}(B_m) - \mathrm{conf}(B_m) \right|,$$

where B_m is the m-th confidence bin. Although less universal than task accuracy or retrieval metrics, ECE is useful when the goal is to assess whether distillation improves the reliability of the student's confidence estimates.

Overall, the most commonly used metrics in VLM distillation are therefore *Accuracy/F1* for classification-style tasks, *Recall@K* (especially R@1, R@5, and R@10) and *MRR* for retrieval, and *BLEU*, *ROUGE-L*, and *CIDEr* for generation. Their choice is mainly determined by the downstream task on which the distilled student is evaluated.

C Knowledge Distillation for Vision-Language-Action Models

Knowledge distillation in Vision-Language-Action (VLA) models has become a general mechanism for improving data quality, representation richness, reasoning-action transfer, and deployment efficiency. Viewed from this perspective, recent VLA distillation methods can be organized by where knowledge is injected into the pipeline: the training distribution, the perceptual and action representation, the policy backbone, or the inference process itself.

At the data level, distillation is increasingly used to replace or refine expensive human demonstrations. RLDG (Xu et al., 2024a) shows that trajectories generated by converged RL specialists can serve as stronger supervision than teleoperated data while preserving the generalization benefits of the VLA backbone. PLD (Xiao et al., 2025) further addresses the mismatch between offline training data and rollout-time failure states by training residual recovery policies and distilling their corrective behaviors back into the generalist. In a more explicitly data-centric formulation, FT-NCFM (Chen et al., 2025a) compresses large training corpora into compact, high-value coresets through fact tracing and adversarial synthesis, reducing training cost without substantial performance loss. Together, these works suggest that in VLA, distillation often acts first as a tool for curating better supervision.

A second line of work leverages distillation to enrich representations beyond what standard RGB-conditioned VLAs can capture. LatBot (Li et al., 2025d) learns transferable latent actions from large-scale manipulation videos and distills them into downstream VLAs, thereby injecting motion- and physics-aware priors before task-specific adaptation. GLaD (Guo et al., 2025) and FD-VLA (Zhao et al., 2026) extend the same principle to geometry and force, respectively, distilling privileged 3D or tactile information into latent tokens so that the deployed policy remains sensor-light at test time. VISTA (Chen et al., 2026b) addresses a related issue from the alignment side, first improving visual grounding in a surrogate task and then distilling that improved alignment into the instruction-following policy. In all cases, distillation serves as a bridge from auxiliary signals to a compact control policy that can operate under realistic sensing constraints.

Distillation is also increasingly used to manage the tension between high-level reasoning and low-level action execution. VITA-VLA (Dong et al., 2025) transfers action competence from a smaller action-specialized model into a large VLM through hidden-state alignment and selective fine-tuning. DualVLA (Fang et al., 2025) makes this trade-off explicit, arguing that naïve joint tuning can harm manipulation ability, and therefore uses dual-teacher supervision to preserve both reasoning and actuation performance. In the reverse direction, RPD (Jülg et al., 2025) distills a generalist VLA policy into a compact RL student, which can then continue improving through online interaction. These methods collectively frame distillation as a way to allocate competence across heterogeneous policies, rather than assuming a single model should learn reasoning and control equally well from scratch.

Finally, a growing body of work treats distillation as a practical enabler of real-time deployment. Shallow-π (Jeon et al., 2026), MoLe-VLA (Zhang et al., 2025c), CEED-VLA (Song et al., 2025), and AC^2-VLA (Yu et al., 2026) all use distilled supervision to preserve policy quality while reducing latency, either through backbone compression, dynamic layer execution, consistency-based decoding, or structured sparsification. Beyond tabletop manipulation, the same principle extends to broader embodied settings: OmniReason (Liu et al., 2025a) distills spatiotemporal reasoning for interpretable autonomous driving, while RDT2 (Liu et al., 2026) uses multi-stage distillation to support real-time, cross-embodiment generalization. In conclusion, the recent literature suggests that knowledge distillation in VLA should be understood less as a narrow compression recipe and more as a unifying strategy for transferring privileged data, sensing, structure, and policy competence into deployable embodied agents.

D Knowledge Distillation for Vision–Language Embedding Models

Recent advances in vision–language (VL) embedding models increasingly leverage knowledge distillation from large multimodal models (LVLMs or MLLMs) to transfer richer semantic and ranking signals into efficient embedding architectures. Instead of relying solely on contrastive training, these approaches exploit stronger teachers such as cross-encoder rerankers or multimodal LLMs to provide fine-grained supervision. For instance, Qwen3-VL-Embedding and Qwen3-VL-Reranker employ a two-stage retrieval

framework in which a powerful cross-encoder reranker produces soft relevance scores for query–candidate pairs; these scores are then distilled into the embedding model via distribution alignment over positive and hard-negative samples, enabling the bi-encoder to approximate reranking-level semantic discrimination while maintaining efficient retrieval (Li et al., 2026). Similarly, UniME-V2 treats an MLLM as a semantic judge that assigns soft matching scores to query–candidate pairs drawn from a global candidate pool. The student embedding model is trained to align its similarity matrix with these soft judgments, effectively distilling high-level multimodal reasoning into a lightweight embedding representation (Gu et al., 2025b).

Other work explores complementary distillation strategies to enhance the capability and generality of VL embeddings. xVLM2Vec introduces a self-knowledge distillation framework in which an LVLM-based embedding model serves as both teacher and student, enabling multilingual adaptation by aligning embeddings across translated image–text pairs while preserving the original English semantic structure (Musacchio et al., 2025). More broadly, recent studies explore using multimodal LLMs as teachers for universal embedding learning. By combining textual discriminative distillation with multimodal instruction tuning, these approaches transfer high-level semantic knowledge from large multimodal models into compact embedding representations that generalize across tasks such as retrieval, classification, and compositional reasoning (Gu et al., 2025a). Together, these works highlight a growing paradigm in which large multimodal models supervise lightweight embedding systems, enabling them to inherit richer cross-modal semantics and stronger ranking capabilities.

In general, distillation for VL embedding models aims to align the embedding space produced by a student model $f_S(\cdot)$ with that of a stronger teacher model $f_T(\cdot)$. A common objective is feature-level alignment, which encourages the student embeddings to match teacher embeddings:

$$\mathscr{L}_{\text{feat}} = \mathbb{E}_x \, \| f_S(x) - f_T(x) \|_2^2 , \tag{9}$$

where x denotes an image–text input pair and f_T, f_S represent the teacher and student embedding functions respectively. When the teacher provides fine-grained ranking signals (e.g., from a reranker or MLLM judge), the student can also learn by matching the teacher's relevance distribution over a candidate set $\mathscr{D}$. Let $s_T(d_i|q)$ and $s_S(d_i|q)$ denote the teacher and student scores for document d_i given query q. The teacher distribution is defined using a temperature τ:

$$P_T(d_i|q) = \frac{\exp(s_T(d_i|q)/\tau)}{\sum_j \exp(s_T(d_j|q)/\tau)}, \tag{10}$$

and the student is trained to match this distribution via cross-entropy:

$$\mathscr{L}_{\text{rank}} = -\sum_i P_T(d_i|q) \log P_S(d_i|q). \tag{11}$$

These objectives allow lightweight embedding models to inherit semantic structure and ranking signals from stronger multimodal teachers, which has proven effective for improving retrieval-oriented VL representations.

E VLM Knowledge Distillation for Segmentation

Vision–language models (VLMs) trained on large-scale image–text corpora offer rich semantic knowledge that can be distilled into dense prediction models such as semantic segmentation networks. Models such as CLIP, trained on large-scale image–text corpora, encode rich open-vocabulary representations that can serve as powerful teachers for segmentation models. Instead of relying solely on pixel-level annotations, recent approaches leverage VLMs to provide supervision through feature distillation, pseudo-label generation, or language-guided alignment. These strategies allow segmentation systems to inherit the semantic knowledge learned from large-scale multimodal pretraining, enabling improved generalization and open-vocabulary recognition.

A common strategy is to extract dense supervision signals from VLM representations. For instance, MaskCLIP converts CLIP feature maps into pixel-wise pseudo-labels that can supervise segmentation networks without manual mask annotations (Zhou et al., 2022). Similarly, CLIP-based attention and

similarity maps can provide localization cues for weakly supervised segmentation models (Lin et al., 2023). Recent work further demonstrates that dense segmentation masks can be extracted directly from VLM representations using plug-and-play pipelines, allowing segmentation models to be trained without dense annotations (Luo et al., 2023). In addition, large foundation models can generate high-quality pseudo-labels that serve as effective supervision signals in weakly supervised segmentation settings (Jiang and Yang, 2023). These approaches can be viewed as forms of knowledge distillation, where semantic information embedded in pretrained VLMs is transferred to task-specific segmentation networks.

Another line of research focuses on adapting frozen VLM representations for open-vocabulary semantic segmentation. Methods such as ZegCLIP (Zhou et al., 2023), Open-Vocabulary Semantic Segmentation with Frozen Vision-Language Models (Ma et al., 2022a), and Mask-Adapted CLIP (Liang et al., 2023b) demonstrate that pretrained CLIP encoders can provide strong semantic supervision when integrated with segmentation architectures. Simple baselines further show that aligning pixel embeddings with textual category embeddings allows segmentation models to recognize unseen classes during inference (Xu et al., 2022). These ideas are extended to large-scale training setups that exploit image-level supervision to scale open-vocabulary segmentation models (Ghiasi et al., 2022). Unified frameworks such as FreeSeg also incorporate VLM supervision into more flexible segmentation pipelines supporting universal and open-vocabulary segmentation tasks (Qin et al., 2023).

Beyond feature transfer, language-guided and prompt-based approaches further exploit VLM knowledge for segmentation. Language-driven segmentation frameworks utilize textual descriptions to guide dense prediction models (Li et al., 2022a), while prompt-based methods combine text and image prompts to produce flexible segmentation outputs (Lüddecke and Ecker, 2022). Prompt-learning strategies have also been proposed to enhance open-world segmentation by learning category-level prompts that better align visual and textual representations (Zhu et al., 2023b). In addition, recent work demonstrates that VLM supervision can support segmentation without human-provided labels (Chen et al., 2023a) and even enable instance-level segmentation without manual mask annotations (VS et al., 2023). More explicitly, distillation-based approaches such as CLIPSelf show that vision transformers can distill knowledge from VLM representations to improve open-vocabulary dense prediction (Wu et al., 2024b). The distillation paradigm has also been extended beyond 2D images; for example, PartDistill transfers knowledge from vision–language models to perform 3D part segmentation (Umam et al., 2024). Overall, these studies highlight the potential of VLM knowledge distillation as a scalable and label-efficient strategy for building open-vocabulary segmentation systems.

F VLM Knowledge Distillation for Open-Vocabulary Object Detection

Knowledge distillation from pretrained vision-language models (VLMs), especially CLIP (Radford et al., 2021), has become one of the dominant paradigms for open-vocabulary object detection (OVD) (Zhang et al., 2024b; Wu et al., 2024a; Zhu and Chen, 2024; Li et al., 2025b). Early work established the basic transfer recipe: ViLD (Gu et al., 2021) distilled image- and text-level semantics from a pretrained VLM into a two-stage detector, while HierKD (Ma et al., 2022b) extended this idea to one-stage architectures through hierarchical global- and instance-level distillation. A central limitation of this paradigm, however, is the mismatch between image-level VLM supervision and region-level detection features. Much of the subsequent literature can be understood as attempts to narrow this gap. OV-OD (Bangalath et al., 2022) performs object-centric alignment and augments supervision with pseudo-labels; CLIPSelf (Wu et al., 2023d) aligns dense region features with crop-level CLIP representations through self-distillation; OADP (Wang et al., 2023a) and BARON (Wu et al., 2023c) enrich the transfer unit from isolated proposals to object-aware or bag-of-regions representations; and DeCLIP (Wang et al., 2025a) improves local discriminability and spatial consistency by decoupling content and context features.

Recent work has focused less on whether VLM knowledge should be transferred and more on how to make that transfer detector-friendly. DK-DETR (Li et al., 2023b) adapts distillation to DETR-style detectors with semantic and relational objectives, while HD-OVD (Fu et al., 2025) and CAKE (Ma et al., 2025a) emphasize multi-granularity or category-aware semantic transfer. Other methods refine the source of supervision itself: CCKT-Det (Zhang et al., 2025a) reduces reliance on extra supervision through

cyclic contrastive transfer, and LBP (Li et al., 2024b) shows that background regions can also carry useful semantic cues instead of being treated purely as noise while MMC-Det (Xu et al., 2024c) distilled multi-modal contextual knowledge via a teacher fusion transformer trained with diverse masked language modeling, supervising concept-region similarity through attention scores. Related extensions have carried the same distillation perspective into adjacent settings, including simplified transfer schemes such as LP-OVOD (Pham et al., 2024), open-world detection (Ma et al., 2025b), and domain adaptation (Ke et al., 2024). These works suggest that the main challenge in distillation-based OVD is not the availability of VLM knowledge, but how to convert image-level, context-rich semantics into detector-compatible region representations that preserve local detail, inter-object relations, and background cues.