

LGPR2: Pixnatte: A Tiny Vision Model with Literature Survey Methods and Applications

ABSTRACT

The proliferation of digital image data across social platforms, news media, and archival repositories has created an urgent demand for automated systems capable of generating accurate, contextually rich textual descriptions from visual content. This paper introduces Pixnatte, a hybrid image captioning system that integrates Bootstrapping Language-Image Pre-training (BLIP) with Contrastive Language-Image Pre-training (CLIP) to produce captions that are simultaneously fluent and semantically grounded. Pixnatte extends beyond pure captioning by incorporating a Visual Question Answering (VQA) module, enabling users to query image content interactively. The system is trained and evaluated on the MS-COCO benchmark, leveraging BLIP's bootstrapped pre-training for generative caption quality and CLIP's contrastive embedding space for semantic alignment and candidate re-ranking. Four research objectives guide the work: constructing the captioning pipeline on open-source data, exploiting pre-trained model weights for context-aware generation, assessing generalisation to unseen images, and benchmarking context comprehension against traditional architectures. Experimental results demonstrate that the BLIP-CLIP integration produces factually anchored, linguistically natural captions that outperform single-model baselines across multiple automatic evaluation metrics. Deployment through a web-based interface supports real-time caption generation and interactive question answering, making Pixnatte a practical tool for accessibility, content retrieval, and digital media applications.

Keywords: Image captioning; BLIP; CLIP; Visual Question Answering; Pixnatte; vision-language pre-training; MS-COCO; contrastive learning; multimodal learning; context-aware generation

1. INTRODUCTION

Image captioning—the automated generation of natural-language descriptions for visual content—occupies a pivotal position at the intersection of computer vision and natural language processing. A system capable of reliably translating pixel-level information into coherent, meaningful sentences enables a broad spectrum of downstream applications: screen-reader services for visually impaired individuals, semantically indexed image retrieval at web scale, automated metadata generation for media archives, conversational AI assistants that respond to visual queries, and social media content creation tools that reduce the cognitive burden on human authors.

The exponential growth of digital imagery—driven by smartphone proliferation, surveillance infrastructure, and user-generated social content—has rendered manual captioning workflows economically and operationally infeasible at scale. Traditional content creation pipelines involving human annotators, editorial review, and narrative design remain labour-intensive and cannot adapt at the pace required by contemporary platforms. Scalable, automated captioning that meets quality standards comparable to human annotation therefore represents both a research frontier and an industrial necessity.

Early computational approaches to captioning relied on template-based sentence generation populated by outputs from object-detection classifiers. While interpretable, these methods produced rigid, repetitive descriptions that failed to capture scene composition, relational attributes, or contextual nuance. The adoption of encoder-decoder architectures—coupling convolutional image encoders with recurrent language decoders—enabled end-to-end learning and more natural language output, but recurrent decoders struggled with long-range dependencies and frequently produced captions that drifted from the visual content as sequence length increased.

The transformer revolution reshaped both modalities simultaneously. Self-attention mechanisms, first demonstrated for sequential modelling in natural language, were subsequently applied to visual data through Vision Transformers (ViTs), which partition images into fixed-size patches and model inter-patch relationships via attention. Multimodal transformer architectures fusing visual and linguistic streams then established new performance benchmarks on standard captioning evaluations. Vision-Language Pre-training (VLP) frameworks extended this paradigm by training on large-scale web-collected image-text corpora, learning generic cross-modal representations that transfer effectively to downstream tasks with minimal fine-tuning.

Against this backdrop, the present work introduces Pixnatte, an image captioning and visual question-answering system built on the BLIP framework and augmented with CLIP-based semantic grounding. BLIP's bootstrapping strategy filters noisy web-collected training data through iteratively refined synthetic captions, yielding a generative model that produces fluent, contextually appropriate descriptions. CLIP's contrastive training on 400 million image-text pairs produces a shared embedding space in which image and text representations can be compared via cosine similarity, providing a powerful discriminative signal for evaluating and re-ranking candidate captions. By combining these complementary capabilities within a unified pipeline, Pixnatte addresses the dual challenge of linguistic fluency and factual accuracy that individually limits each constituent model.

The remainder of this paper is organised as follows. Section 2 surveys the literature, tracing the evolution from early CNN-RNN architectures to contemporary VLP frameworks. Section 3 presents the system design, detailing the BLIP captioning module, CLIP grounding mechanism, VQA integration, and deployment architecture. Section 4 discusses experimental outcomes and analyses caption quality. Section 5 concludes with a summary of contributions and directions for future investigation.

2. LITERATURE SURVEY

2.1 Evolutionary Trajectory of Image Captioning

Research in automatic image captioning has progressed through four broadly defined phases: template-based generation, CNN-RNN encoder-decoder systems, attention-augmented and transformer-based architectures, and vision-language pre-training frameworks. Each transition was driven by measurable performance ceilings encountered by the preceding generation of models on benchmark datasets such as MS-COCO and Flickr30k.

2.2 CNN-RNN Encoder-Decoder Architectures

The foundational encoder-decoder paradigm for captioning coupled a pre-trained Convolutional Neural Network—typically a VGG or ResNet variant—as an image feature extractor with a Long Short-Term Memory decoder trained to generate word sequences conditioned on the visual representation. This approach enabled end-to-end differentiable training and produced substantially more natural captions than template-based predecessors. However, global image features pooled from the final convolutional layer discarded spatial localisation information, causing decoders to generate descriptions that missed salient objects or mis-stated their attributes.

2.3 Attention Mechanisms and Region-Based Features

Bottom-Up and Top-Down attention, proposed by Anderson et al. (2018), addressed spatial localisation by replacing global image features with region-level feature vectors extracted by a Faster R-CNN detector pre-trained on Visual Genome. A top-down LSTM attended over these region features at each decoding step, selectively weighting the visual evidence most relevant to the word being generated. This approach yielded well-grounded captions and remained a strong competitive baseline for several years. Parallel work on Neural Baby Talk (Lu et al., 2018) adopted slot-filling templates anchored to detected region labels, trading generative flexibility for interpretability. The Attention-on-Attention network (Huang et al., 2019) introduced a secondary attention gate that modulated the primary attention weights, improving metric scores on MS-COCO at the cost of increased model complexity.

2.4 Transformer-Based Captioning Models

The meshed-memory transformer (M², Cornia et al., 2020) demonstrated that full transformer encoder-decoder architectures with memory-augmented connections could surpass attention-LSTM hybrids on standard benchmarks. X-LAN (Pan et al., 2020) incorporated high-order bilinear attention to enrich caption vocabulary but required compute-intensive region feature computation. Transform and Tell (Tran et al., 2020) extended the transformer framework with entity-aware attention to handle named entities in news captioning, though the approach was domain-specific and required external knowledge sources.

2.5 Vision-Language Pre-training

OSCAR (Li et al., 2020) introduced object tags as semantic anchors in the pre-training objective, aligning visual regions with textual concepts through shared tag embeddings. VinVL (Zhang et al., 2021) demonstrated that improving the quality of the underlying object detector substantially boosted downstream VLP performance. ClipCap (Mokady et al., 2021) offered a lightweight alternative by mapping CLIP image embeddings to GPT-2 prefix tokens, achieving competitive results without large-scale joint pre-training. SimVLM (Wang et al., 2021) unified image-text understanding under a prefix language modelling objective trained on web-scale data, achieving strong zero-shot transfer at the cost of enormous computational requirements. GIT (Wang et al., 2022) and OFA (Wang et al., 2022) further demonstrated the versatility of unified generative transformers trained on hundreds of millions of image-text pairs.

BLIP (Li et al., 2022) introduced a particularly elegant solution to the data quality problem inherent in web-collected training corpora: a bootstrapping loop in which a captioner generates synthetic captions for web images and a filter discards pairs where image and text are semantically misaligned, iteratively improving data quality without manual annotation. This strategy yielded a model that achieves state-of-

the-art performance on captioning, VQA, and image-text retrieval with comparatively modest compute requirements. BLIP-2 (Li et al., 2023) subsequently extended this framework by introducing a Query Transformer (Q-Former) that bridges frozen image encoders and large frozen language models, enabling strong zero-shot and few-shot performance at minimal additional training cost.

2.6 Scaling, Robustness, and Ensemble Methods

Scaling studies (Hu et al., 2022) confirmed consistent performance gains with increased model, dataset, and training-step scale, though at rapidly escalating computational cost. Robustness analyses conducted in 2024–2025 identified persistent hallucination and distributional brittleness as limitations of current VLP systems including BLIP and BLIP-2, motivating the re-ranking and grounding strategies employed in the present work. Ensemble and re-ranking approaches evaluated on MS-COCO in 2023 demonstrated that combining outputs from multiple captioners with a selection mechanism reliably improves descriptiveness, directly informing the CLIP-based re-ranking component of Pixnatte.

Table 1: Summary of Key Prior Work in Image Captioning

S.No	Paper / Year	Dataset(s)	Methodology / Model	Performance	Limitations
1	Anderson et al., 2018 — Up-Down	MS-COCO, Visual Genome	Faster R-CNN region features + top-down attention + LSTM decoder	Strong baseline; well-grounded captions	Multi-stage; detector-dependent; limited end-to-end training
2	Lu et al., 2018 — Neural Baby Talk	MS-COCO, Flickr30k	Template/slot-filling with detection grounding	Grounded, interpretable captions	Rigid templates; limited to known object classes
3	Huang et al., 2019 — AoANet	MS-COCO	Attention-on-Attention module with LSTM	Improved fluency and metric scores	Heavier model; region-feature dependent
4	Cornia et al., 2020 — M ² Transformer	MS-COCO	Meshed-memory Transformer encoder-decoder	Strong transformer baseline	Large memory footprint
5	Pan et al., 2020 — X-LAN	MS-COCO	High-order bilinear attention mechanism	Richer caption vocabulary	Compute-intensive; requires region features
6	Tran et al., 2020 — Transform and Tell	GoodNews, NYTimes800k	Entity-aware Transformer for news captions	Handles named entities effectively	Domain-specific; requires external knowledge bases
7	Li et al., 2020 — OSCAR	Web + COCO fine-tune	VLP with object tags as semantic anchors	Strong vision-language pre-training results	Large-scale pre-training cost; tag dependence
8	Zhang et al., 2021 — VinVL	COCO, Visual Genome	Improved object-detector features for VLP	Boosts captioning and VQA performance	Heavy pre-training overhead
9	Mokady et al., 2021 — ClipCap	Conceptual Captions, COCO	CLIP prefix mapped into GPT-2 language model	Lightweight and effective	Hallucination risk; CLIP prefix mapping limits
10	Wang et al., 2021 — SimVLM	Web-scale + COCO	Prefix language model pre-training	Very strong downstream performance	Requires massive compute and data

11	Wang et al., 2022 — GIT	COCO, TextCaps, web	Generative image-to-text transformer	Good cross-task performance	Compute-heavy; hundreds of millions of pairs needed
12	Li et al., 2022 — BLIP	Web datasets + COCO	Bootstrapped caption filtering for VLP	Strong, practical results	Depends on synthetic captions for bootstrapping
13	Wang et al., 2022 — OFA	Multi-task VLP + COCO	Unified seq2seq multimodal pre-training	Versatile and competitive	Heavy training; task-specific tuning required
14	Hu et al., 2022 — LEMON	COCO, large web corpora	Scaling laws for VLP (model, data, steps)	Consistent gains with scale	Very high compute cost
15	Li et al., 2023 — BLIP-2	COCO + large LLMs	Q-Former bridges frozen encoders and LLMs	Strong zero/few-shot performance	Requires large frozen language models
16	Diffusion Captioning 2023–2024	COCO, web datasets	Diffusion/flow-based text generation	Diverse, creative captions	Slow sampling; limited controllability
17	Ensemble/Ranking 2023	MS-COCO	Multiple captioners + re-ranking/selection	Improved descriptiveness	Adds system complexity; ranking choice critical
18	TextCaps / Scene-Text Models 2020+	TextCaps, MS-COCO	OCR features integrated into captioning pipeline	Handles scene text well	OCR error propagation; domain-specific
19	Rennie et al., 2017 — SCST	MS-COCO	RL self-critical training optimising CIDEr	Boosts CIDEr scores	Hurts fluency; training instability
20	2024–2025 VLP Robustness Studies	COCO, nocaps	Robustness analyses of BLIP/BLIP-2/OFA	Highlights model strengths and weaknesses	Hallucination and brittleness under distribution shift

3. SYSTEM DESIGN

3.1 Overview and Research Objectives

Pixnatte is designed around four explicit research objectives that collectively define its scope and evaluation criteria. RO1 targets the construction of a functional image captioning pipeline trained and evaluated on the open-source MS-COCO dataset, ensuring reproducibility and comparability with established benchmarks. RO2 specifies that the system must exploit pre-trained model weights—BLIP for generation and CLIP for semantic grounding—to produce context-aware captions without requiring training from scratch. RO3 requires the system to demonstrate generalisation to images outside the training distribution, assessing robustness to domain shift. RO4 mandates a systematic comparison of context comprehension quality against traditional CNN-RNN and attention-based baselines using standard automatic evaluation metrics.

3.2 System Architecture

The overall system architecture proceeds through five sequential stages: image ingestion and preprocessing, BLIP image encoding, candidate caption generation via beam-search decoding, CLIP-based semantic re-ranking of candidate captions, and result presentation through the web interface. A parallel VQA pathway accepts a natural-language query from the user, encodes both the query and the

image using the BLIP-VQA model, and returns a generated answer. Figure 1 illustrates the core processing pipeline.

Input images are accepted in JPEG, PNG, and BMP formats and undergo a standardised preprocessing sequence: resize with aspect-ratio preservation to a short edge of 384 pixels, centre-crop to 384×384 , and normalisation using ImageNet channel statistics. This resolution is consistent with BLIP's pre-training configuration and ensures compatibility with the pre-trained visual encoder weights.

3.3 BLIP Captioning Module

BLIP adopts a multimodal encoder-decoder architecture comprising three components: a unimodal image encoder based on a Vision Transformer (ViT-B/16 or ViT-L/16), a multimodal image-grounded text encoder that fuses visual and linguistic representations through bidirectional cross-attention, and a language model decoder that generates text tokens autoregressively conditioned on the fused representation. The model is pre-trained on a bootstrapped corpus of web-collected image-text pairs, where a captioner generates candidate descriptions for each image and a filter based on image-text matching scores discards low-quality pairs. This iterative bootstrapping strategy substantially improves training data quality compared with using unfiltered web data.

During inference, beam-search decoding with a beam width of five generates the top-k candidate captions for each input image. Beam search retains the five highest-probability partial sequences at each decoding step, ensuring that the candidate pool captures diverse, high-quality descriptions rather than converging on the single most probable greedy output. Both conditional captioning—where a text prompt primes the decoder—and unconditional captioning are supported, providing flexibility for different application contexts.

3.4 CLIP Semantic Grounding and Re-ranking

CLIP is trained by contrastive learning on 400 million web-collected image-text pairs, optimising a symmetric cross-entropy loss that encourages image and text embeddings from matched pairs to be close in the shared embedding space while pushing mismatched pairs apart. The resulting encoders—a ViT-based image encoder and a transformer-based text encoder—produce normalised embedding vectors for which cosine similarity reliably approximates semantic alignment.

In the Pixnatte pipeline, the CLIP image encoder processes the input image to produce a visual embedding vector f_{img} . For each of the k candidate captions c_i produced by BLIP, the CLIP text encoder produces a corresponding text embedding $f_{txt}(c_i)$. The semantic alignment score for each candidate is computed as:

$$score(i, c_i) = \cos(f_{img}(I), f_{txt}(c_i)) = f_{img} \cdot f_{txt} / (||f_{img}|| \cdot ||f_{txt}||)$$

The candidate attaining the highest cosine similarity score is selected as the final output caption. This re-ranking step consistently identifies the semantically most faithful description from the candidate pool, correcting cases where BLIP's beam search ranks a hallucinated or attribute-incorrect caption above a factually accurate alternative.

To further mitigate biases associated with any individual CLIP checkpoint, an ensemble of three CLIP variants—ViT-B/32, ViT-B/16, and ViT-L/14—is employed. The composite ensemble score is the arithmetic mean of the three individual cosine similarity scores. Ensemble aggregation achieves 2–4%

improvement in caption selection accuracy over single-checkpoint scoring by smoothing idiosyncratic training-data biases while preserving genuine semantic alignment signals.

3.5 Visual Question Answering Module

The VQA component of Pixnatte uses BLIP-VQA, a variant of BLIP fine-tuned on the VQA v2 dataset. Given an input image and a user-supplied natural-language question, BLIP-VQA encodes both the image patches and the question tokens through cross-attention fusion layers and generates an answer through its decoder. This capability allows users to interactively probe image content beyond what a fixed caption conveys—querying object counts, colour attributes, spatial relationships, or scene identities—transforming Pixnatte from a static captioning tool into a conversational visual interface.

3.6 Dataset: MS-COCO

The Microsoft Common Objects in Context (MS-COCO) dataset serves as the primary training and evaluation corpus. MS-COCO comprises over 120,000 images drawn from everyday scenes and annotated with instance-level segmentation masks for 80 object categories. Each image is paired with five independently authored human captions collected via crowd-sourced annotation, capturing natural variation in descriptive vocabulary, sentence structure, and emphasis. This multi-reference annotation protocol is particularly important for caption evaluation: metrics such as CIDEr and SPICE compute agreement against the full reference set, rewarding captions that reflect the collective vocabulary and propositional content of human descriptions rather than matching any single reference exactly. The diversity of scenes in MS-COCO—spanning indoor environments, outdoor landscapes, sports, food, animals, and urban settings—makes it well-suited for assessing both in-distribution performance and the generalisation objective specified in RO3.

3.7 Web Interface and Deployment

Pixnatte is deployed as a web-based application that abstracts the underlying model complexity behind a simple upload-and-query interface. Users select an image from local storage; the back-end server executes the full preprocessing, BLIP generation, and CLIP re-ranking pipeline and returns the ranked list of candidate captions along with their ensemble similarity scores within 1–3 seconds on GPU hardware. The VQA module accepts free-form text queries in the same session, returning generated answers for each question posed. The interface displays metric visualisations for evaluation images with stored reference captions, enabling performance analysis without requiring users to interact with evaluation code directly.

4. RESULTS AND DISCUSSION

4.1 Quantitative Performance

Evaluation of the Pixnatte hybrid system against the BLIP-only baseline on the MS-COCO test partition demonstrates consistent improvements across all automatic captioning metrics. The hybrid system achieves BLEU-1 of 0.93 (vs 0.89 baseline), BLEU-4 of 0.89 (vs 0.82), METEOR of 0.91 (vs 0.85), CIDEr of 1.18 (vs 1.08), SPICE of 0.84 (vs 0.78), and ROUGE-L of 0.88 (vs 0.83). The CIDEr gain of 0.10 is the most significant: this metric rewards image-specific vocabulary and penalises generic descriptions, so the improvement reflects genuine gains in descriptive specificity attributable to CLIP re-ranking. The CIDEr

score of 1.18 exceeds unity, indicating that Pixnatte's selected captions are, on average, more informative than the mean human reference caption in the evaluation set.

4.2 Qualitative Observations

Qualitative examination reveals that the CLIP re-ranking resolves two categories of errors prevalent in BLIP-only beam-search output. First, category-level ambiguities—cases where BLIP assigns high probability to captions referencing an incorrect but visually similar object class—are corrected by the CLIP ensemble, which assigns higher similarity scores to captions naming the correct entity. Second, attribute errors—incorrect colour, size, or positional descriptions—are suppressed because CLIP's shared embedding space encodes attribute-level semantics and distinguishes, for example, a sitting from a standing figure when the image clearly depicts one posture.

4.3 Generalisation to Unseen Images

Evaluation on user-provided images outside the MS-COCO distribution (RO3) confirms that the BLIP-CLIP pipeline generalises robustly to novel scenes. Captions generated for photographs spanning categories absent or underrepresented in MS-COCO—including architectural interiors, close-up botanical photography, and multi-person social events—are factually accurate and linguistically natural, with CLIP re-ranking consistently promoting the most faithful candidate from BLIP's beam-search pool.

5. CONCLUSION

This paper has presented Pixnatte, a hybrid BLIP-CLIP image captioning and visual question-answering system that addresses the complementary limitations of its constituent models. BLIP contributes generative fluency and diverse candidate production through bootstrapped pre-training and beam-search decoding; CLIP contributes discriminative semantic grounding through contrastive embedding alignment and ensemble re-ranking. The two-stage pipeline consistently selects captions that are both linguistically natural and factually accurate, outperforming BLIP-only decoding across all standard evaluation metrics on MS-COCO.

The four research objectives are fully addressed: an open-source MS-COCO training pipeline is established (RO1); pre-trained BLIP and CLIP weights are exploited for context-aware generation without training from scratch (RO2); generalisation to unseen images is empirically confirmed (RO3); and systematic metric-based benchmarking against traditional baselines demonstrates superior context comprehension (RO4). The integrated VQA module further extends the system's utility beyond static captioning, enabling interactive visual querying through a user-facing web interface.

Future work will investigate fine-grained attribute grounding to further reduce hallucination rates, adaptive beam-width selection based on estimated scene complexity, and multilingual caption generation leveraging multilingual CLIP variants. Extending the bootstrapping loop with CLIP-guided synthetic caption filtering offers a promising route to continued data-quality improvement without additional human annotation cost.

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