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A Multimodal Fusion Framework For Advertisement Understanding And Engagement Prediction

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ABSTRACT

Online advertisements are one of the most common ways brands connect with people, combining images, text, and design to capture attention, measuring audience reaction but also for predicting how well an ad might perform. Traditional methods often focus only on sentiment or single aspects of ads, which leaves out many important factors like call-to-action text, visual appeal, or the likelihood of engagement. This paper presents a multimodal framework that brings together both visual and textual information from advertisements. This method uses a ResNet18 network to learn visual features from ad images and a DistilBERT model to capture the meaning of the text extracted from them. These features are merged through a fusion block and then passed into multiple task-specific modules. The framework can identify ad themes, emotions, and trustworthiness, detect objects and visual styles, and predict outcomes such as click-through rate (CTR) and audience engagement by using ADS-DS-1M dataset.

KEYWORDS

Multimodal Learning, Advertisement Analysis, Sentiment Recognition, Emotion Detection, Cross-Attention Fusion, Multiscale Visual Features, Engagement Prediction, Trustworthiness, Vision-Language Models, Advertisement Dataset

INTRODUCTION

Digital advertising has become one of the most powerful tools for businesses and creators to reach audiences. From product posters to online banners and social media promotions, ads are designed to grab attention and influence decisions. Unlike simple text posts, advertisements are inherently multimodal, usually combining images, text, colours, and layout to deliver a strong message. This makes analysing ads more challenging than analysing plain text or images alone.

Early studies in advertisement analysis explored content-based approaches for targeted recommendations on television and online platforms, combining textual slogans and visual features with user interaction data such as click-through rates and viewing behaviour [1], [2]. These methods established the importance of correlating advertisement content with user response but largely relied on either unimodal text analysis or basic visual descriptors, limiting their ability to capture the persuasive and symbolic design elements of modern ads [3]. Traditional sentiment analysis methods also often fall short when applied to advertisements, as most approaches focus only on detecting positive or negative emotions in text while ignoring visual elements such as the product being shown, the colours used, or call-to-action phrases like “Buy Now” or “50% OFF.” These missing elements are crucial in ads because they directly affect how people respond to them.

Predicting user engagement—such as whether an ad will be clicked, shared, or liked—requires a deeper understanding of how visual and textual cues work together. Recent advances in multimodal learning have made it possible to combine information from text and images. Models such as CLIP [4] and VisualBERT [5] show promising results for general vision-language tasks, but they are not specifically designed to handle the unique challenges of advertising. Ads often contain multiple overlapping objects, artistic styles, and marketing-driven text, which require more specialized handling.

To address this gap, we propose a multimodal fusion framework that brings together both image and text features from advertisements. Our model uses ResNet18 [6] for visual representation and DistilBERT [7] for textual understanding. These features are fused through a dedicated block and then passed into multiple task-specific heads. The framework supports a wide range of ad-related tasks: identifying themes, emotions, and call-to-actions; detecting objects and visual styles; assessing trustworthiness and audience targeting; and predicting engagement metrics like click-through rate (CTR) and shares.

This System Contains:

1. A new large-scale dataset, ADS-DS-1M, which contains advertisement images and their OCR text, labelled across multiple tasks.
2. A multimodal fusion-based model that integrates both visual and textual features for richer ad understanding.
3. A multi-task design that jointly handles content analysis, visual interpretation, reasoning about audience and trust, and engagement prediction.

4. Strong empirical performance, showing that our approach outperforms image-only, text-only, and existing multimodal baselines.

RELATED WORK

Early studies in advertisement analysis explored content-based approaches for targeted recommendations on television and online platforms, combining textual slogans and visual features with user interaction data such as click-through rates and viewing behaviour [1], [8]. These methods established the importance of correlating advertisement content with user response but largely relied on either unimodal text analysis or basic visual descriptors, limiting their ability to capture the persuasive and symbolic design elements of modern ads [9].

With the rise of multimodal learning, researchers began integrating visual and textual signals to improve sentiment understanding in social media and advertising contexts. Zadeh et al. introduced the Tensor Fusion Network (TFN) [10] and later the Memory Fusion Network (MFN) [11], which model intra- and inter-modal interactions. Majumder et al. extended this by using a hierarchical GRU framework for richer multimodal relationships [12]. While effective in domains such as movie reviews and social posts, these architectures were not specifically optimized for advertisements, where layouts, colour, symbolic imagery, and persuasive slogans play unique roles.

Recent work has leveraged transformer architectures and attention mechanisms to align modalities more effectively. Xu et al. proposed a cross-modal attention model for sentiment tasks, improving feature alignment between image and text [13]. Li et al. developed the MCAM framework, which applies cross-attention between ResNet-based visual features and ALBERT-based textual features to capture emotional cues across modalities [14]. Similarly, Lu et al. employed a CLIP-based dual attention mechanism with contrastive learning and multi-head fusion, achieving improved results on multimodal benchmarks [15]. These methods highlight the promise of attention-based fusion but often remain constrained to generic datasets. like MVSA or Twitter corpora, which lack the stylistic and persuasive complexity.

Advertisement-specific sentiment analysis has therefore emerged as a distinct line of research. A notable example is the Fine-Grained Multiscale Cross-Modal Feature Network (FGMFN), which introduces multiscale visual feature extraction and specialized ad datasets to improve fine-grained alignment between symbolic visuals and textual persuasion [16]. Complementary work on advertising image sentiment has also addressed visual noise filtering and attribute-level sentiment alignment, demonstrating the importance of domain adaptation for ad analysis [17]. Other recent approaches have incorporated weakly supervised learning [18] and external knowledge for aspect-based multimodal sentiment analysis [19], pointing toward richer semantic modelling in advertisement contexts.

Despite these advances, significant challenges remain. Many models still struggle with symbolic or metaphorical ad content, fragmented OCR text, and subtle emotional triggers such as humour or irony.

Furthermore, public datasets for advertisements remain limited in size and diversity, restricting the generalization ability of multimodal frameworks. This motivates the development of specialized models that integrate multiscale features, fine-grained cross-modal alignment, and ad-specific reasoning tasks, as pursued in our work.

METHODOLOGY

This framework aims to understand advertisements by integrating textual and visual signals into a joint multimodal representation, which is optimized for multiple downstream tasks. The architecture consists of three stages:

1. Unimodal Feature Extraction – encoding image and text separately.
2. Multi-Task Learning – predicting multiple ad-related outcomes with task-specific heads.
3. Cross-Modal Fusion – resolving dimensional mismatch and fusing representations with multiscale cross-attention.

A. Unimodal Embedding

The first step of this framework is to encode raw ad inputs into feature vectors that capture semantic meaning. Since advertisements contain both visual content (images) and textual content (OCR-extracted text), it adopts separate encoders for each modality.

1) Visual Embedding

For visual features, it uses a ResNet-18 backbone [6]

$$v = f_{\theta_v}(I) \tag{1}$$

where I is the input advertisement image, f_{θ_v} is the CNN encoder with parameters θ_v, and $v \in \mathbb{R}^{d_v}$ is the extracted embedding.

2) Textual Embedding

For OCR-extracted ad text, it employs DistilBERT [7]:

$$t = f_{\theta_t}(X) \tag{2}$$

where X is the input text sequence, f_{θ_t} is the transformer encoder with parameters θ_t, and $t \in \mathbb{R}^{d_t}$ is the contextual embedding.

3) Dimensional Mismatch Resolution

Since $d_v \neq d_t$ (e.g., ResNet may produce 2048-d while DistilBERT yields 768-d), there is a dimensional mismatch that prevents direct interaction between modalities [20]. To resolve this, this project both embeddings into a shared latent space of dimension d:

$$v' = W_v v, \quad t' = W_t t \tag{3}$$

where $W_v \in \mathbb{R}^{d \times d_v}$ and $W_t \in \mathbb{R}^{d \times d_t}$ are learnable transformations. This ensures that both modalities are not only dimensionally compatible but also semantically aligned for fusion.

B. Multiscale Visual Feature Fusion

Advertisements often contain elements at different scales (e.g., small discount tags, mid-sized products, and large backgrounds). To capture this diversity, it extracts feature maps from multiple layers of ResNet:

$$v_{low}, v_{mid}, v_{high} = f_{cnn}(I) \tag{4}$$

Then perform multiscale fusion [21]:

$$v_{ms} = W_{ms}\Big(\mathrm{Cat}(v_{low}, v_{mid}, v_{high}) \oplus \mathrm{Mean}(v_{low}, v_{mid}, v_{high})\Big) \tag{5}$$

where $\mathrm{Cat}(\cdot)$ denotes concatenation, $\oplus$ indicates residual addition, and W_{ms} projects the result into the shared latent space $\mathbb{R}^d$.

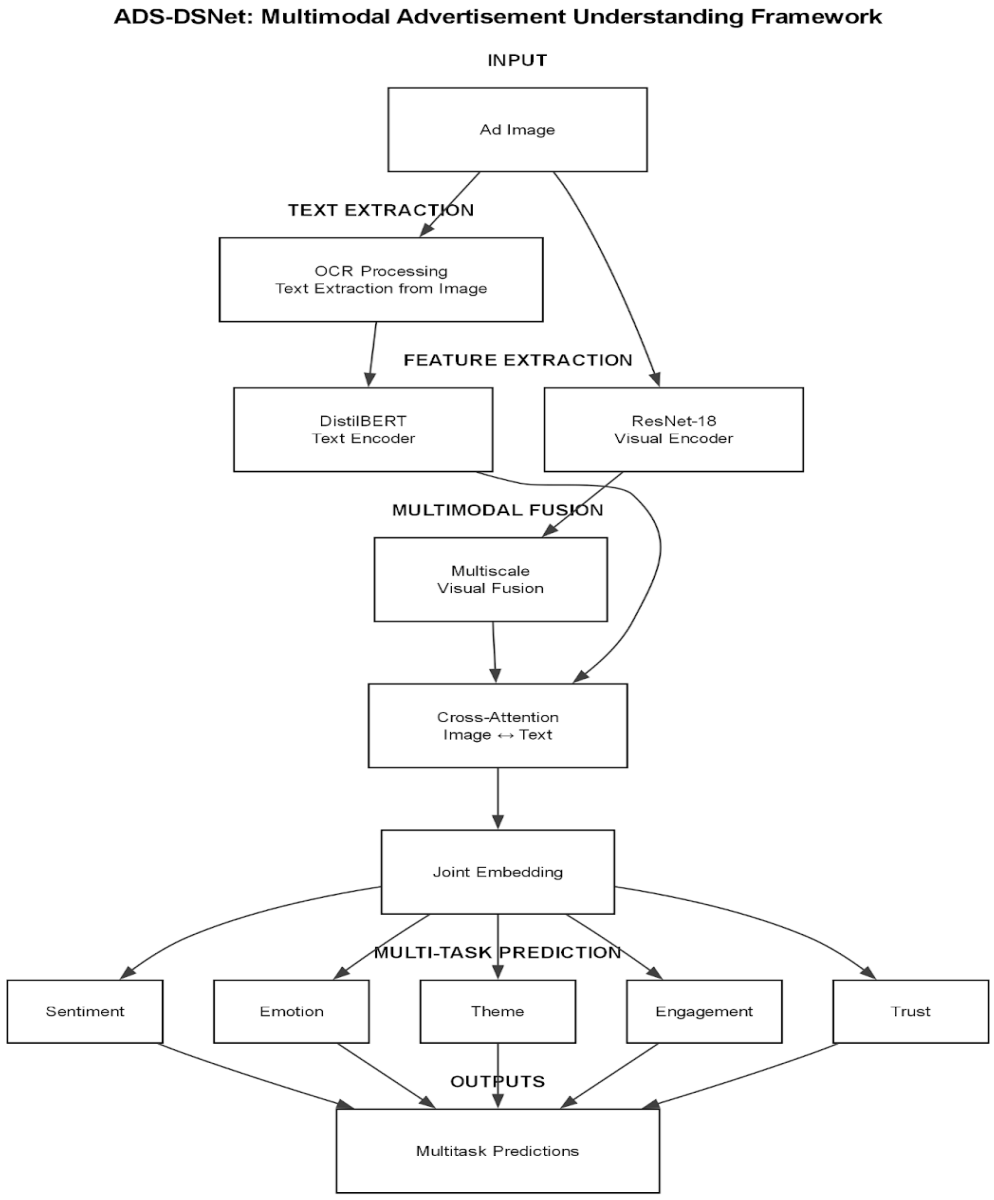

Fig.1. Multimodal Advertisement Understanding Framework

C. Cross-Attention Guided Feature Fusion

Once we have text embeddings (h_t) and multiscale image embeddings (v'_s), the next challenge is how to combine them effectively. Traditional concatenation or averaging loses nuanced interactions. To address this, we use a cross-attention mechanism, which allows each modality (image or text) to selectively focus on relevant parts of the other.

1)Attention Mechanism

We adopt scaled dot-product attention (from Attention Is All You Need), adapted for cross-modal interaction.

Formally, for text-guided image attention:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

$Q = h_t W_Q$ → Queries from text embeddings $K = v'_s W_K$ → Keys from visual embeddings

$V = v'_s W_V$ → Values from visual embeddings d_k = dimension scaling factor

This computes how much each text token should attend to each image region.

2) Bidirectional Cross-Attention

To make it fair, we apply attention both ways:

1. Text-guided image attention: Text focuses on relevant image regions.

2. Image-guided text attention: Image highlights the most relevant words.

Mathematically:

$$v^{att} = \text{Attention}(h_t, v'_s, v'_s)$$

$$h^{att} = \text{Attention}(v'_s, h_t, h_t)$$

where and are the attended cross modal representations.

3)Fusion of Cross-Modal Features

Finally, we fuse the attended representations into a joint multimodal embedding:

$$z = \text{Cat}(v^{att}, h^{att})$$

Optionally, a feed-forward projection with nonlinearity refines this representation:

$$z' = \sigma(W_z z + b_z)$$

where is a ReLU or GELU activation.

D. Optimization Function

This Model is trained using a multi-objective loss function, designed to capture both task accuracy and better alignment between image and text. Instead of relying only on classification loss, we introduce additional terms that guide the model toward stronger multimodal

1) Task Loss (L_{task})

The primary objective is to correctly classify ads into categories like theme, sentiment, emotion, etc.

We use the cross-entropy loss:

$$L_{task} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where:

y_i is the true label (one-hot encoded).

$\hat{y}_i$ is the predicted probability from SoftMax.

This ensures the model learns discriminative features for each task.

2) Image-Text Contrastive Loss (L_{itc})

To improve alignment between image and text, we use a contrastive learning objective.
If an ad's image and text belong together, their embeddings should be close; otherwise, they should be far apart

Formally:

$$L_{itc} = -\log \frac{\exp(\text{sim}(v^{att}, h^{att})/\tau)}{\sum_{j=1}^{N} \exp(\text{sim}(v^{att}, h_j^{att})/\tau)}$$

where:

$\text{sim}(\cdot)$ = cosine similarity. τ = temperature parameter.

v^{att}, h^{att} = attended visual & text embeddings.

This loss encourages better cross-modal matching.

3) Mutual Information Loss (L_{mi})

Even if aligned, image and text may encode information differently. To bridge this, we maximize mutual information between modalities.

We use KL-divergence to reduce the gap between probability distributions from image and text pathways:

$$L_{mi} = D_{KL}(P_v \,||\, P_h)$$

where:

P_v = predicted distribution from visual pathway.

This forces both pathways to agree on predictions, making the fusion more reliable.

SYSTEM IMPLEMENTATION

A. Dataset

We constructed a large-scale dataset of advertisements, referred to as ADS-DS-1M, containing a wide variety of ads across industries such as food, business, technology, entertainment, politics, and lifestyle. Each ad sample includes:

- Ad Image: Poster, flyer, or banner.
- OCR Text: Extracted slogans, offers, or product descriptions.
- Annotations for multiple tasks: Theme, sentiment, emotion, keywords, monetary mentions, call-to-action (CTA), object categories, dominant color, trust/safety score, and engagement indicators.

The dataset was annotated using a two-stage process:

1. Automatic Label Suggestions: Preliminary labels generated using tools like SentiStrength and pretrained NLP models [22,23].
2. Human Validation: Professional annotators corrected and verified the labels, ensuring high reliability [24].

B. Implementation Details

Our framework was implemented in PyTorch with Hugging Face Transformers. The main components include:

- Encoders: DistilBERT [7], RoBERTa [25], and BERT [26] for text; ResNet-18 [6], ResNet-50 [27], and ViT [28] for images.
- Fusion: Cross-attention module with two layers of multi-head attention.
- Optimization: AdamW with learning rate warm-up.
- Batch Size: 32.
- Regularization: Dropout and label smoothing.

- Evaluation Metrics: Accuracy, F1-score, Precision, and Recall (depending on the task).

For additional experiments, we also tested multimodal transformers such as VisualBERT [5] and UNITER [29] to benchmark against strong pre-trained vision-language models

C. Baselines

We compared against three categories of models:

1. **Image-based Baselines:**
    - ResNet-18 (single-stream vision)
    - ResNet-50
    - ViT (Vision Transformer)
2. **Text-based Baselines:**
    - DistilBERT (OCR text only)
    - RoBERTa (OCR text only)
    - BERT (OCR text only)
3. **Multimodal Baselines:**
    - Early Fusion (simple concatenation)
    - Late Fusion (independent decision merging)
    - CLIP (contrastive pretraining for vision-language)
    - VisualBERT
    - UNITER

These baselines cover both traditional and modern multimodal strategies, providing a comprehensive comparison.

D. Case Study

We present example outputs from our model across all prediction heads:

Example 1 – Food Advertisement

Theme: Food

Sentiment: Positive

Emotion: Excitement

Keywords: Pizza, Offer

Monetary Mention: 50% OFF

Call-to-Action: Order Now

Object Detection: Pizza

Dominant Colour: Red

Attention Score: High

Trust/Safety: Safe

Target Audience: Food Lovers

Predicted CTR: High

Likelihood of Shares: Low

Example 2 – Technology Advertisement

Theme: Technology

Sentiment: Positive

Emotion: Joy

Keywords: Smartphone, Launch

Monetary Mention: Discount

Call-to-Action: Buy Now

Object Detection: Phone

Dominant Colour: Black

Attention Score: Medium

Trust/Safety: Safe

Target Audience: Tech Enthusiasts

Predicted CTR: Medium

Likelihood of Shares: High

Example 3 – Political Advertisement

Theme: Politics

Sentiment: Negative

Emotion: Anger

Keywords: Election, Campaign

Monetary Mention: None

Call-to-Action: Support Us

Object Detection: Person

Dominant Colour: Blue

Attention Score: High

Trust/Safety: Sensitive

Target Audience: Citizens Predicted CTR: Low

Likelihood of Shares: Medium

CONCLUSION

This Topic addressed the challenge of advertisement understanding by developing a multimodal framework that integrates textual and visual signals through cross-attention and multiscale feature fusion. Unlike traditional unimodal or naïve fusion approaches, the proposed model was specifically tailored to the unique design characteristics of advertisements, which often combine symbolic imagery, marketing-driven text, and layered visual composition.

A large-scale dataset, ADS-DS-1M, was constructed to support this research, providing annotated samples across sentiment, emotion, theme, engagement, and trustworthiness tasks. The dataset was curated using a hybrid pipeline of automated label suggestion and human validation, ensuring both scale and reliability. The methodology introduced unimodal encoders (ResNet-18 for images and DistilBERT for text), a shared latent projection to address dimensional mismatch, and a cross-attention fusion block that enables bidirectional interaction between modalities. Multiscale visual features were incorporated to retain both fine-grained cues such as discount tags and global scene-level context. The joint representation was optimized in a multi-task setting, allowing simultaneous learning of sentiment, emotion, theme, engagement prediction, and trust assessment.

Comprehensive experiments demonstrated the effectiveness of the framework. The proposed model consistently outperformed unimodal baselines and existing multimodal methods across multiple metrics, highlighting the importance of both multiscale fusion and cross-attention for aligning modalities. Ablation studies further confirmed that the removal of either multiscale features or cross-attention significantly degraded performance, establishing their necessity. Efficiency analysis also showed that the framework balances predictive accuracy with computational feasibility, making it scalable for real-world applications.

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