# Is a Picture Worth a Thousand Words? Adaptive Multimodal Fact-Checking with Visual Evidence Necessity

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## Abstract

Automated fact-checking is a crucial task that supports a responsible information ecosystem. While recent research has progressed from text-only to multimodal fact-checking, a prevailing assumption is that incorporating visual evidence universally improves verification accuracy. In this work, we challenge this assumption and show that the indiscriminate use of visual evidence can reduce accuracy. Building on this finding, we propose AMUFC, a modular fact-checking framework that employs two collaborative vision-language models with distinct roles to enable the adaptive use of visual evidence. Experimental results on three datasets, including WebFC, introduced in this study, demonstrate the effectiveness of adaptive visual evidence use in fact-checking.

## 1 Introduction

Fact-checking—the process of determining the veracity of claims—is a cornerstone of responsible journalism and an essential mechanism for mitigating the harms of misinformation in broader web environments (Hassan et al., 2015; Adair et al., 2017). Building on early work focused on text-only verification, recent research has increasingly shifted toward multimodal fact-checking, which addresses scenarios in which evidence is conveyed through multiple modalities, primarily text and images (Hameleers et al., 2020; Alam et al., 2022; Biamby et al., 2022). Various approaches have been proposed to integrate these modalities for fact verification. For example, multimodal fusion-based classifiers combine retrieved image–text evidence (Yao et al., 2023), while more recent work leverages reinforcement learning to summarize multimodal inputs (Chen et al., 2024). A common finding across these studies is that leveraging visual evidence can improve fact-checking accuracy (Tahmasebi et al., 2024; Cekinel et al., 2025), echoing the adage that *a picture is worth a thousand words*.

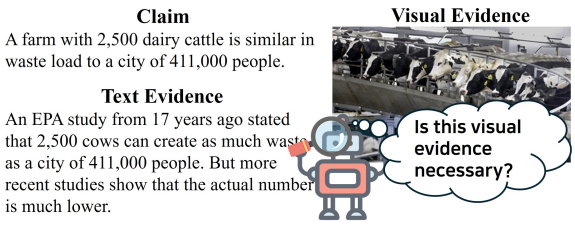



Figure 1: An example illustrating that visual evidence is not always necessary for multimodal fact-checking, motivating the research direction of this study.

In this study, we challenge a prevailing assumption in prior work—the presumed necessity of visual evidence—as illustrated in Figure 1. Using MOCHEG (Yao et al., 2023) as our primary testbed, we analyze the effects of visual evidence on verification accuracy. While prior work has shown that some claims cannot be reliably verified without visual evidence (Cekinel et al., 2025), we show that a naïve strategy of indiscriminately incorporating visual evidence can lead models to underperform text-only baselines. We further show that verification performance improves when the evidence modality is selected adaptively, as demonstrated in an oracle setting in which visual evidence is incorporated only when it is beneficial for verification.

Motivated by these findings, we propose AMUFC, a modular framework that adaptively incorporates visual evidence through the collaboration of two vision-language models (VLMs) with distinct roles. To examine whether the benefits of adaptive visual evidence use persist in practical settings, we adopt a simple Analyzer–Verifier design. An *Analyzer* determines whether visual evidence is necessary for verification, while a *Verifier* predicts claim veracity based on the Analyzer's natural-language assessment. Experimental results on MOCHEG demonstrate that AMUFC outperforms existing methods. We further conduct test-only evaluations on FIN-FACT (Ranga-



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| Dataset | Primary Inputs | Evidence | Task | Label Source | Claim Source | External Knowledge Source | Access |
|---|---|---|---|---|---|---|---|
| Fakeddit (Nakamura et al., 2020) | Img/Txt | - | Mixed | Synthetic | Reddit | ✗ | ✓ |
| NeuralNews (Tan et al., 2020) | Img/Txt | - | OOC | Mixed | Grover/GoodNews | ✗ | ✓ |
| NewsCLIPings (Luo et al., 2021) | Img/Txt | - | OOC | Mixed | CLIP/VisualNews | ✗ | ✓ |
| Factify (Suryavardan et al., 2023) | Img/Txt | Img/Txt | OOC | Mixed | Twitter | ✗ | ✓ |
| VERITE (Papadopoulos et al., 2024) | Img/Txt | - | Mixed | Mixed | Snopes/Reuters | ✗ | ✓ |
| Fauxtography (Zlatkova et al., 2019) | Img/Txt | Meta | FV | Expert | Snopes/Reuters | ✗ | ✓ |
| MMM (Gupta et al., 2022) | Img/Txt | Txt | FV | Mixed | FC webs | ✗ | ✗ |
| FactDrill (Singhal et al., 2022) | Txt | Vid/Aud/Img/Txt/Meta | FV | Expert | FC webs | ✗ | ✗ |
| ChartFC (Akhtar et al., 2023a) | Txt | Img | FV | Crowd | TabFact | ✗ | ✓ |
| ChartCheck (Akhtar et al., 2024) | Txt | Img/Txt | FV | Crowd | Wikimedia | ✗ | ✓ |
| MOCHEG (Yao et al., 2023) | Txt | Img/Txt | FV | Expert | FC webs | ✓ | ✓ |
| FIN-FACT (Rangapur et al., 2025) | Txt | Img/Txt | FV | Expert | FC webs | ✗ | ✓ |
| AVerImaTeC (Cao et al., 2025) | Img/Txt | Img/Txt | FV | Expert | FC webs | ✓ | ✓ |
| VeriTaS (Rothermel et al., 2026) | Vid/Img/Txt | - | FV | Mixed | FC webs | ✗ | ✓ |

Table 1: Datasets for multimodal fact-checking (OOC: out-of-context misinformation; FV: fact verification).

pur et al., 2025), a financial-domain dataset, and WebFC, a newly constructed dataset of recent claims paired with web-retrieved evidence, and observe that the performance gains from incorporating the Analyzer's assessment persist. These results suggest that the adaptive use of visual evidence, as operationalized by AMUFC, can be effective across diverse fact-checking scenarios, including cross-domain verification and verification of recent claims using noisy web evidence.

The key contributions of this study are summarized below.

- We show that visual evidence is not always beneficial for multimodal fact-checking, challenging a prevailing assumption in prior research that incorporating visual evidence inherently improves verification performance.
- We propose AMUFC, a modular framework that adaptively uses visual evidence. Despite its simplicity, AMUFC demonstrates the effectiveness of adaptive visual evidence use across diverse fact-checking scenarios.

## 2 Related Work

### 2.1 Multimodal Fact-checking

Previous research on multimodal fact-checking, or multimodal misinformation detection, can be broadly categorized into three tasks based on their verdict prediction settings: *manipulation classification*, *out-of-context detection*, and *fact verification* (Akhtar et al., 2023b). Manipulation classification focuses on detecting manipulated misinformation within a single modality (Gupta et al., 2013; Boididou et al., 2014; Huh et al., 2018; Heller et al., 2018; Shao et al., 2023). Out-of-context detection aims to determine whether a given image-text pair conveys consistent contextual information (Nakamura et al., 2020; Tan et al., 2020; Luo et al., 2021; Suryavardan et al., 2023; Papadopoulos et al., 2024). Fact verification, which is the focus of this paper, seeks to predict the truthfulness of a claim, typically in textual form (Singhal et al., 2022; Akhtar et al., 2023a, 2024; Yao et al., 2023). Table 1 summarizes widely used multimodal fact-checking datasets.

Following early attempts at zero-shot fact verification (Lee et al., 2020), most subsequent work has adopted retrieval-augmented generation (RAG) frameworks (Lewis et al., 2020), which retrieve both visual and textual evidence and leverage the retrieved content to support verification. Because evidence quality is critical for RAG-based verification, several studies have focused on mitigating noisy or irrelevant context. For example, MetaSumPerceiver was proposed to summarize multimodal document evidence (Chen et al., 2024). Other work introduced re-ranking methods based on predicted token probabilities (Tahmasebi et al., 2024), while additional approaches proposed tool-based RAG pipelines for fact verification. Most recently, Pang et al. (2025) proposed a hypergraph transformer-based fact-checking framework to capture higher-order relationships between claims and evidence. Our study explicitly examines the necessity of visual evidence for fact verification.

### 2.2 Adaptive Retrieval

We review previous research on adaptive retrieval for fact verification and, more broadly, for RAG. Although RAG improves performance on knowledge-

intensive tasks (Lewis et al., 2020), inaccurate or irrelevant retrieval can introduce noisy context that degrades performance (Yoran et al., 2024; Shi et al., 2023). Adaptive retrieval strategies mitigate this issue by retrieving on demand or filtering out unhelpful context (Tang et al., 2025; Parekh et al., 2025). For example, Self-RAG (Asai et al., 2023) enables dynamic retrieval via reflection tokens, while other approaches select RAG strategies based on query complexity (Jeong et al., 2024) or use trained relevance estimators to assess context utility (Kim and Lee, 2024). More recent work leverages hidden-state representations to decide whether retrieval is necessary (Baek et al., 2025) or dynamically incorporates retrieved passages based on their quality (In et al., 2025).

In fact verification, agent-based iterative frameworks integrate retrieval and verification across multiple rounds (Xie et al., 2025), while PASS-FC augments claims with temporal and entity grounding for progressive search (Zhuang, 2025). Related work also explores dynamically adjusting search depth to extract multimodal evidence (Braun et al., 2025). In contrast to prior work that primarily focuses on textual relevance or filters out irrelevant evidence before verification, this study focuses on the necessity of visual evidence and introduces a modular framework that enables the adaptive use of visual information.

## 3 Task and Dataset

Given a textual claim $c$ and an external knowledge source $K$, the task of *multimodal fact verification* aims to determine the veracity of $c$ by retrieving and reasoning over both textual and visual evidence. Specifically, a fact-checking system retrieves a set of textual evidence $E_t \subset K$ and visual evidence $E_v \subset K$, and then predicts a verdict label $y \in \{$*supported*, *refuted*, *not enough information (NEI)*$\}$ based on $(c, E_t, E_v)$.

Among existing multimodal fact-checking datasets (Table 1), we select MOCHEG (Yao et al., 2023) as the primary testbed for our study based on three criteria aligned with our research objectives. First, the dataset must explicitly target *fact verification*, thereby excluding datasets designed for related but distinct tasks, such as out-of-context detection in Factify (Suryavardan et al., 2023). Second, it must take a textual claim $c$ as input, excluding datasets such as AVerImaTeC (Cao et al., 2025) that assume text–image input pairs. Third, it must provide a knowledge source $K$ from which textual and visual evidence can be retrieved. MOCHEG (Yao et al., 2023) satisfies all three criteria and is therefore selected as our primary testbed. To assess generalizability beyond a single dataset, we use two additional datasets exclusively for testing: FIN-FACT and WebFC. These datasets represent diverse fact-checking scenarios, including generalization to claims from other domains and to recent claims, without in-domain training.

The datasets used in this study are described below.

- **MOCHEG** comprises claims with corresponding verdicts, supported by evidence curated by professional fact-checkers. The claims are collected from two fact-checking websites: PolitiFact[1] and Snopes[2]. The dataset includes 11,669 claims for training, 1,490 for validation, and 2,442 for testing. The knowledge source $K$ consists of 3,070,563 sentences and 137,621 images. Each claim is paired with gold textual evidence and, when available, gold visual evidence.

- **FIN-FACT** (Rangapur et al., 2025) is a financial fact-checking dataset containing claims and verdicts produced by human experts. We applied a sanitization process to the original dataset by removing claims without publicly accessible image evidence and refining the remaining claims, yielding 2,581 claims with associated multimodal evidence. As the dataset does not provide an external knowledge source, we treat the entire set of textual evidence and images as $K$.

- **WebFC** is a newly constructed corpus developed in this study, consisting of 621 recently published claims and their corresponding verdicts from PolitiFact, spanning January 2024 to September 2025. Treating web documents as the knowledge source $K$, we retrieved both textual and visual evidence using the Google Custom Search API. To prevent the retrieval of documents published after the corresponding fact-checking articles, which would create an unrealistic verification setting, we restricted retrieval to sources published before the fact-checking articles, following recent practice (Cao et al., 2025). We

[1] https://www.politifact.com/
[2] https://www.snopes.com/

also excluded evidence from fact-checking organizations to reduce the risk of directly retrieving previously published verdicts. Accordingly, WebFC better reflects a temporally realistic fact-checking scenario in which recent claims are verified using web-retrieved evidence, while also reducing the risk of temporal leakage from evidence published after the corresponding fact-checking decisions.

Details of dataset preprocessing and construction are provided in Appendix B.

## 4 Is Visual Evidence Always Needed?

We challenge a common assumption in prior research on multimodal fact-checking—that visual evidence is necessary for effective verification. Using MOCHEG, we examine how incorporating visual evidence affects fact-checking performance and then conduct qualitative analyses to identify when visual evidence contributes to verification and when it is unnecessary.

### 4.1 Effect of Visual Evidence on Performance

We compared the verification accuracy of VLMs across four input configurations: (1) textual evidence only, (2) textual evidence with *gold* image evidence, (3) textual evidence with retrieved image evidence, and (4) an oracle setting in which an input configuration yielding the correct verdict was selected for each instance, whenever one existed.

In all configurations, we assumed that the *gold* textual evidence was provided, as our focus was to assess the impact of visual evidence. Following prior work (Cekinel et al., 2025), configuration (2) used the first image as evidence when multiple images were available. In configuration (3), we used the fine-tuned CLIP model provided with the MOCHEG baseline to retrieve the top-1 image from $K$ as visual evidence. In configuration (4), the input combination that yielded the correct verdict—when such a configuration existed—was always selected, thereby representing an upper bound on achievable performance under perfect modality selection. This controlled comparison enabled us to isolate the impact of visual evidence on fact verification performance.

Table 2 presents the evaluation results. The first column lists the target VLMs, the second specifies the input configuration, and the third and fourth report verification performance on the MOCHEG test split, measured by accuracy (ACC) and macro F1. We evaluated two open-weight and two API-based VLMs. The open-weight models are Qwen2-VL-7B (Wang et al., 2024) and Llama-3.2-11B-Vision (Grattafiori et al., 2024), denoted throughout the paper as Qwen2-VL and Llama-3.2-V, respectively, while the API-based models are GPT-4o (Hurst et al., 2024) and Gemini-2.5-Pro (Comanici et al., 2025). Model checkpoints are provided in Appendix A.

| Model | Configuration | ACC | F1 |
|---|---|---|---|
| Qwen2-VL | (1) Text | 0.509 | 0.419 |
| | (2) + Image (G) | 0.506 | 0.410 |
| | (3) + Image (R) | 0.490 | 0.395 |
| | (4) Oracle | **0.547** | **0.451** |
| Llama-3.2-V | (1) Text | 0.496 | 0.495 |
| | (2) + Image (G) | 0.462 | 0.445 |
| | (3) + Image (R) | 0.412 | 0.393 |
| | (4) Oracle | **0.590** | **0.582** |
| GPT-4o | (1) Text | 0.642(.001) | 0.612(.000) |
| | (2) + Image (G) | 0.635(.003) | 0.596(.003) |
| | (3) + Image (R) | 0.630(.001) | 0.597(.001) |
| | (4) Oracle | **0.680**(.002) | **0.649**(.001) |
| Gemini-2.5-Pro | (1) Text | 0.627(.001) | 0.599(.001) |
| | (2) + Image (G) | 0.620(.001) | 0.570(.001) |
| | (3) + Image (R) | 0.596(.001) | 0.557(.001) |
| | (4) Oracle | **0.692**(.001) | **0.660**(.001) |

Table 2: Fact-verification performance across different evidence configuration strategies, indicating that visual evidence is not always necessary. Values in parentheses denote standard errors, which are omitted for open-weight models due to deterministic results (G: Gold, R: Retrieved).

We derived three key observations regarding the effects of visual evidence on verification performance. First, when comparing the text-only setting (configuration 1) with the multimodal setting using gold images (configuration 2), incorporating visual evidence consistently degraded performance across all evaluated models. Second, in configuration (3), which uses retrieved image evidence, performance decreased relative to both configurations (1) and (2) across all models. The largest drop was observed for Llama-3.2-V, with decreases of 0.084 in accuracy and 0.102 in macro F1. This result suggests that imperfect retrieval can introduce noisy or misleading context. Third, the oracle setup (configuration 4) consistently outperformed all other settings through optimal modality selection. According to the Mann–Whitney U test, the improvement over the non-oracle settings was statistically significant ($p<0.01$) for GPT-4o and Gemini-2.5-Pro.[3] Taken

[3]The results for the open-weight models are deterministic and therefore were not included in the statistical test.

| Type | Unnecessary | Necessary |
|---|---|---|
| **Claim** | Marquette University threatened to rescind student's admission over pro-Trump TikTok video. | In an episode of 'The Simpsons,' Mayor Quimby says he is canceling a trip to the Bahamas while he's in the Bahamas, because of an ongoing epidemic. |
| **Visual Evidence** |  |   |
| **Textual Evidence** | • The pro-Trump post was not at issue. Marquette and the people complaining to the university were examining comments on topics like sexuality and immigration in other social media posts.<br>• The student clearly felt her status was in doubt, but she has stopped short of calling it a threat. The school says no threat was made.<br>• The "threat" element is tricky to pin down, since that claim stems from a private conversation between the student and Marquette admissions staffers. | After initially saying he didn't do anything wrong, Steve Adler, the mayor of Austin, Texas, says he now realizes he 'set a bad example' by traveling to Cabo San Lucas, Mexico, for vacation last month. An Austin American-Statesman story revealed Wednesday that Adler attended an in-person wedding for his daughter in early November and then flew with others to Cabo for a weeklong vacation. At the same time, Adler was encouraging people to stay home to avoid contracting or spreading COVID-19. |

Table 3: Examples for visual evidence types according to their necessity for claim verification.

together, these findings support our hypothesis that visual evidence is not always necessary for claim verification. Moreover, the substantial performance gains observed in the oracle setting motivate the adaptive use of visual evidence.

### 4.2 When Does Visual Evidence Not Help?

Building on the mixed effects of visual evidence on verification performance, we conducted a qualitative analysis to examine when visual evidence does not aid verification. We first defined *claim categories* based on whether visual evidence changed GPT-4o's verification outcome on the validation set, as GPT-4o achieved the best overall performance among the four VLMs in Table 2. Specifically, we labeled claims as **Visual-successful** (51 claims) when the model predicted the correct verdict only after visual evidence was added to the textual evidence, and as **Visual-unsuccessful** (61 claims) when the model predicted the correct verdict using textual evidence alone but changed to an incorrect prediction after visual evidence was incorporated. Since our goal is to understand the influence of visual evidence on verification, we excluded claims for which adding images did not affect the text-only model's prediction.

Next, we manually assessed whether visual evidence was necessary for claim verification.

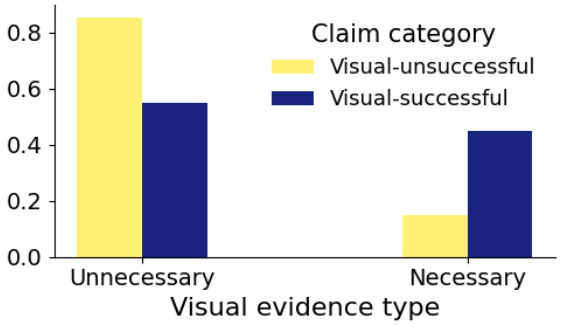



Figure 2: Distribution of visual evidence types across claim categories, illustrating the association between visual evidence necessity and verification outcomes.

Through an iterative process, we developed an annotation scheme that distinguished two *visual evidence types* according to their necessity for verification. We annotated visual evidence as **Unnecessary** (80 pieces) when it was redundant (i.e., it merely repeated information already conveyed by the text) or irrelevant (e.g., it omitted the key entity or event mentioned in the claim, or merely showed a portrait of a person without adding contextual value), and as **Necessary** (32 pieces) when it provided unique information required to evaluate the claim's truthfulness. Two annotators from Soongsil University applied this scheme to all 112

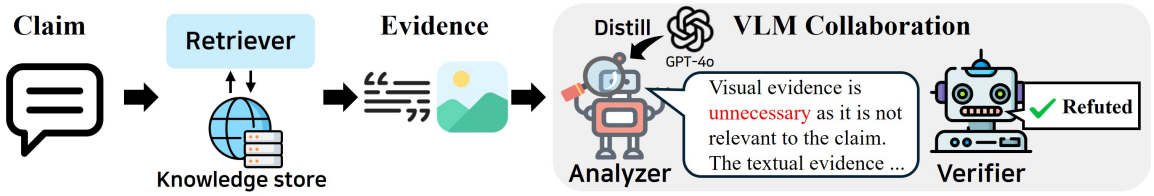



Figure 3: Overall pipeline of AMUFC. Given the retrieved evidence, the two VLMs—Analyzer and Verifier—are responsible for assessing the necessity of visual evidence and predicting the claim's veracity, respectively.

samples, whose claim categories had already been determined based on GPT-4o's predictions, following the annotation guidelines in Figure A4. This process achieved high agreement (Krippendorff's $\alpha = 0.809$), indicating substantial inter-annotator agreement. Examples are shown in Table 3.

Figure 2 shows how the manually annotated visual evidence types (Unnecessary or Necessary) varied across the automatically determined claim categories (Visual-successful or Visual-unsuccessful). We observed a significant association between claim categories and evidence types ($p<0.001$, chi-square test), indicating that the effect of visual evidence on verification performance is closely related to whether the visual evidence is actually necessary for verification. In particular, redundant or irrelevant visual evidence may degrade verification performance rather than improve it. Consistent with the results in Table 2, these findings motivate the adaptive use of visual evidence.

## 5 Proposed Method: AMUFC

We propose a modular fact-checking framework that adaptively incorporates visual evidence, termed **A**daptive **Mu**ltimodal **F**act-**C**hecking with Visual Evidence Necessity (AMUFC). Building on the mixed effects of visual evidence on verification performance observed in Section 4, we examine whether the benefits of adaptive visual evidence use persist in practical settings through AMUFC. As illustrated in Figure 3, AMUFC comprises two collaborating VLMs with distinct roles that operate on evidence retrieved from the knowledge source.

- *Analyzer*: Assesses whether visual evidence is necessary for verifying a claim. Given a claim and the retrieved textual and visual evidence, it generates a natural-language assessment of visual evidence necessity together with its reasoning traces. Building on the findings in Section 4, the Analyzer is instructed to reason about whether visual evidence is required for verification.
- *Verifier*: Predicts the veracity of the claim. In addition to the claim and retrieved evidence, the Verifier incorporates the Analyzer's natural-language assessment to adaptively decide how visual evidence should be used during verification.

```
Your task is to determine whether the provided image evidence is necessary for verifying the given claim or clarifying the accompanying text evidence. Follow these steps:
1. Analyze the claim and the text evidence to understand the context.
2. Assess whether the image provides important information that is not already conveyed by the text.
3. Decide whether the image is necessary for verification and justify your reasoning.
Respond only with your analysis.

Claim: {claim}
Image Evidence: {image evidence}
Text Evidence: {text evidence}
```

(a) Analyzer

```
Given a claim, your task is to determine the correct verdict based on the provided image evidence and text evidence. Provide a justification for your answer, then choose one of the following verdicts: 'Supported', 'Refuted', or 'NEI' (Not Enough Information).
Claim: {claim}
Image Evidence: {image evidence}
Image Analysis: {analysis generated by Analyzer}
Text Evidence: {text evidence}
```

(b) Verifier

Figure 4: Prompts used in AMUFC.

This modular design is inspired by the fact-checking practices of human experts (Borel, 2023; Graves and Amazeen, 2019), who assess the relevance and quality of candidate evidence before reaching a verdict. We hypothesize that incorporating the Analyzer's natural-language assessment can improve overall fact-checking accuracy. This

hypothesis is evaluated empirically in Section 6.

Focusing on open-weight models, our best-performing configuration employs Llama-3.2-V as the Analyzer and Qwen2-VL as the Verifier. The prompts used in this framework are shown in Figure 4. Both the Analyzer and the Verifier were fine-tuned on the MOCHEG training split via QLoRA (Dettmers et al., 2023). The Analyzer was fine-tuned using outputs distilled from GPT-4o, generated by prompting GPT-4o with the corresponding claims and gold evidence. Further details are provided in Appendix A.

## 6 Evaluation Results

This section presents experimental results evaluating whether the adaptive use of visual evidence operationalized by AMUFC is effective for multimodal fact verification.

### 6.1 Experimental Setting

We evaluated fact verification performance using accuracy (ACC) and macro F1, which are standard metrics for multi-class classification. We adopted the retriever provided with MOCHEG and employed by the baseline methods to ensure a fair comparison. Specifically, a fine-tuned CLIP (Radford et al., 2021) was used for image retrieval, while SBERT (Reimers and Gurevych, 2019) was used for text retrieval. The top-ranked textual and visual evidence items based on cosine similarity were passed to subsequent verification stages. Additional experimental details are provided in Appendix A.

### 6.2 Comparison with Baseline Methods

On MOCHEG, we compared AMUFC with four existing multimodal fact-verification approaches. Our focus was on methods that (1) assume a fixed knowledge source $K$ and (2) employ open-weight models. For a fair comparison, all methods were trained on the MOCHEG training split.

- MOCHEG (Yao et al., 2023): This method encodes the concatenated claim, textual evidence, and visual evidence using CLIP. It then applies stance detection to derive claim–text and claim–image stance features, which are averaged and fed into a multimodal fusion classifier to predict the final verdict.

- LVLM4FV (Tahmasebi et al., 2024): This method re-ranks initially retrieved evidence using Mistral-7B (Jiang et al., 2023) for textual evidence and InstructBLIP (Dai et al., 2023) for visual evidence. The re-ranked evidence is then fed into a LLaVa-based verifier (Liu et al., 2023).

- HGTMFC (Pang et al., 2025): This method retrieves textual evidence using SBERT and visual evidence using CLIP. It encodes the claim and textual evidence as text tokens and the visual evidence as image patches using CLIP. A Hypergraph Transformer with group attention and line-graph propagation performs higher-order reasoning across evidence from different modalities, and an MLP classifier predicts the final verdict.

- MetaSumPerceiver (Chen et al., 2024): This method encodes textual evidence in chunks using BART and visual evidence using CLIP. These modalities are fused through a dynamic Perceiver module to generate a claim-conditioned evidence summary. A fine-tuned Llama 2 (Touvron et al., 2023) then acts as a surrogate fact-checker, predicting the final veracity verdict by evaluating whether the summary is entailed by the claim.

Table 4 shows the fact-verification performance of AMUFC and the baseline methods on the MOCHEG test set. In the *Gold* setting, we provided gold evidence without retrieval, simulating perfect retrieval, whereas the *Retrieved* setting relied on retrieved evidence. We reported baseline scores from their original papers and omitted the macro F1 score for the retrieved setting of MetaSumPerceiver, as its implementation was not publicly available and the reported results could not be reproduced.

The results show that AMUFC consistently outperformed existing methods by a substantial margin across both evidence settings and evaluation metrics. Specifically, AMUFC achieved an accuracy of 0.612 and a macro F1 of 0.6 in the gold setting. When retrieved evidence was used, overall performance decreased, but the performance advantage of AMUFC persisted. These results demonstrate the effectiveness of the proposed framework and suggest that the adaptive use of visual evidence is beneficial for multimodal fact verification.

| Method | Gold | | Retrieved | |
|---|---|---|---|---|
| | ACC | F1 | ACC | F1 |
| AMUFC | **0.612** | **0.600** | **0.546** | **0.540** |
| MOCHEG | 0.520 | 0.500 | 0.456 | 0.438 |
| LVLM4FV | 0.534 | 0.535 | 0.451 | 0.450 |
| HGTMFC | 0.541 | 0.520 | 0.486 | 0.468 |
| MetaSumPerceiver | 0.556 | 0.482 | 0.486 | - |

Table 4: Verification performance of AMUFC and baseline methods on the MOCHEG test set, indicating the effectiveness of the proposed framework.

| Method | Gold | | Retrieved | |
|---|---|---|---|---|
| | ACC | F1 | ACC | F1 |
| AMUFC | **0.612** | **0.600** | **0.546** | **0.540** |
| Label-only | 0.599 | 0.581 | 0.517 | 0.492 |
| Pre-filtering (Analyzer) | 0.574 | 0.551 | 0.492 | 0.460 |
| Pre-filtering (CLIP) | 0.569 | 0.546 | 0.495 | 0.463 |
| w/o Analyzer | 0.563 | 0.537 | 0.477 | 0.435 |

Table 5: Ablation results for different Analyzer–Verifier integration strategies, demonstrating the effectiveness of incorporating the Analyzer's natural-language assessment used in AMUFC.

| Method | Gold | | Retrieved | |
|---|---|---|---|---|
| | ACC | F1 | ACC | F1 |
| AMUFC | **0.612** | **0.600** | **0.546** | **0.540** |
| Unified Verifier | 0.577 | 0.555 | 0.531 | 0.513 |
| Verifier with CoT | 0.553 | 0.511 | 0.493 | 0.459 |

Table 6: Comparison with alternative verifiers, demonstrating the benefit of separating evidence assessment from verdict prediction.

### 6.3 Ablation Analysis

**Analyzer-Verifier Integration** We evaluated whether incorporating the Analyzer's natural-language assessment into the Verifier's prompt is critical to the performance gains of AMUFC. To this end, we implemented four alternative strategies that incorporate visual evidence necessity into their designs. The first, *Label-only*, treats the Analyzer as a classifier that generates a visual evidence necessity label without an accompanying explanation. Only the predicted label is incorporated into the Verifier's prompt. The second, *Pre-filtering (Analyzer)*, excludes images predicted as *unnecessary* by the Analyzer from the Verifier's input. The third, *Pre-filtering (CLIP)*, replaces the fine-tuned Analyzer with CLIP and considers visual evidence necessary when the text–image cosine similarity exceeds a predefined threshold of 0.42, optimized on the validation set. The fourth, *w/o Analyzer*, removes the Analyzer entirely.

Table 5 reports the verification performance of these strategies, all of which employ the fine-tuned Qwen2-VL as the Verifier. The results indicate that all alternative integration strategies performed worse than AMUFC, supporting the conclusion that the Analyzer's natural-language assessment contributes substantially to its performance gains. In particular, given that both Label-only and Pre-filtering (Analyzer) retain a separate call to the Analyzer, the results suggest that relying on the Analyzer's assessment of visual evidence necessity alone does not explain the observed performance gain of AMUFC. The results further suggest that the Verifier does not treat the Analyzer's assessment as a binding decision for reasoning during verification.

**Alternative Verifiers** We compared AMUFC with two fine-tuning alternatives that use different Verifier configurations. The first, *Unified Verifier*, combines the roles of the Analyzer and Verifier into a single model that jointly determines the necessity of visual evidence and predicts the veracity label. The second, *Verifier with CoT*, generates a justification before predicting the verdict, unlike the Verifier in AMUFC, which predicts only the verdict. Both models are based on Qwen2-VL and were fine-tuned on the MOCHEG training split using GPT-4o-generated explanations; *Unified Verifier* used the same supervision as the Analyzer in AMUFC. Table 6 reports the experimental results. *Unified Verifier* underperformed relative to AMUFC, highlighting the benefit of separating evidence assessment from verdict prediction. *Verifier with CoT* also underperformed, indicating that the Analyzer's assessment of visual evidence necessity provides a distinct signal beyond the benefits of eliciting explicit reasoning within the Verifier itself.

Details of the methods are described in Appendix A.2, and additional ablation results on the choice of VLM backbones and retriever models are presented in Appendix C.

### 6.4 Error Analysis

To assess the strengths and weaknesses of AMUFC, we compared its error distribution with that of a baseline method that excludes the Analyzer. Fig-

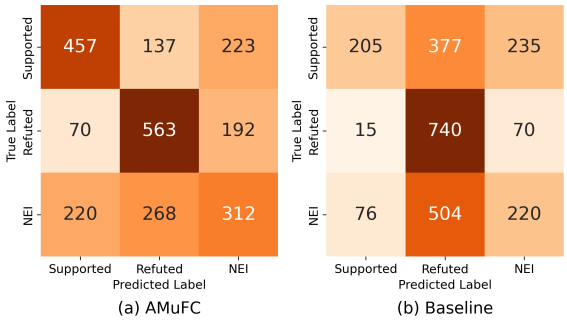



Figure 5: Distribution of confusion patterns for AMUFC compared with the Verifier-only baseline.

ure 5 shows the corresponding confusion matrices. Overall, the baseline method tended to overpredict the *Refuted* label across the three ground-truth classes, whereas AMUFC produced more correct predictions across all classes. The largest gap was observed for the *Supported* class (457 vs. 205). As illustrated by the left example in Table A9, the Analyzer's natural-language assessment of visual evidence necessity helped the Verifier produce the correct *Supported* verdict. Another notable trend is that AMUFC predicted *NEI* more frequently than the baseline, resulting in more correct *NEI* predictions (312 vs. 220). Although this conservative tendency can sometimes lead to incorrect predictions (e.g., the right example in Table A9), such behavior may be desirable in practical fact-checking settings, where withholding a verdict in the absence of sufficient evidence can help avoid premature conclusions.

### 6.5 Test-only Evaluation

We conducted test-only evaluations on FIN-FACT and WebFC to assess the generalizability of the proposed framework across diverse fact-checking scenarios. We evaluated how AMUFC, trained on the MOCHEG training split, performed on these two datasets. Thus, these datasets represent practical fact-checking scenarios involving cross-domain verification and verification of recent claims using noisy web evidence, respectively. Using the same retriever for each method, we compared AMUFC with a Verifier-only baseline. Table 7 shows that AMUFC outperformed the baseline on both datasets. While the absolute performance decreased compared with performance on MOCHEG, the performance advantage of the proposed method over the baseline persisted in both test-only evaluations without in-domain training. These results suggest that the adaptive use of visual evidence, as operationalized by AMUFC, can be effective across diverse fact-checking scenarios, including cross-domain verification and verification of recent claims using noisy web evidence.

| Method | FIN-FACT | | WebFC | |
|---|---|---|---|---|
| | ACC | F1 | ACC | F1 |
| AMUFC | **0.491** | **0.461** | **0.316** | **0.241** |
| Verifier-only | 0.469 | 0.384 | 0.309 | 0.179 |

Table 7: Test-only evaluation on two datasets, demonstrating the effectiveness of AMUFC across diverse fact-checking scenarios.

## 7 Conclusion

This study examines a common assumption in multimodal fact-checking (Tahmasebi et al., 2024; Cekinel et al., 2025): that incorporating visual evidence leads to more accurate verdict prediction. Performance analyses across different modality settings show that indiscriminate use of visual evidence can reduce fact-checking accuracy, while our manual annotation further shows that visual evidence can be particularly harmful when it is redundant or irrelevant. This observation aligns with findings from psychology research showing that some images are ineffective for misinformation correction (Whitehead et al., 2025).

Building on this finding, we present AMUFC, a modular framework that adaptively uses visual evidence through collaboration between two vision-language models with distinct roles. We conduct experiments on three datasets, including WebFC, introduced in this study. The results demonstrate the effectiveness of adaptive visual evidence use across diverse fact-checking scenarios, including cross-domain verification and verification of recent claims using noisy web evidence. Future work could extend AMUFC to agentic fact-checking systems, building on recent work demonstrating the potential of this direction (Braun et al., 2025; Lin et al., 2025; Jung et al., 2026).

## Limitations

This work has several limitations, which open directions for future research. First, to ensure a fair comparison with existing methods, we used the same retrievers, CLIP and SBERT, for the main experiments on MOCHEG. To address the limitation, we conducted additional experiments with

different retrievers, the results of which are reported in Table A3. Second, the Analyzer-Verifier collaboration introduces additional computational costs compared to the single-model baseline (Table A4). Employing smaller models represents a promising direction for improving the practicality of real-world fact-checking systems (Belcak et al., 2025). Third, the primary evaluation was conducted on a single English-language dataset, MOCHEG. We conducted test-only evaluations using FIN-FACT and the proposed WebFC, further demonstrating the effectiveness of the proposed framework across diverse fact-checking scenarios. Future studies could incorporate recently released benchmarks that meet our data selection criteria, including VeriTaS (Rothermel et al., 2026).

## Ethical Considerations

**Annotator Information** Two annotators—one graduate and one undergraduate student (both male) from the authors' institution—were recruited for manual data annotation (Section 4). As fact verification is an objective task, we expect that the annotators' gender had minimal impact on the outcomes. In compliance with local wage regulations, the annotators were compensated at a rate of approximately USD 7 per hour.

**Copyright and Privacy Issues** WebFC is released to support the evaluation of multimodal fact-checking methods. Its intended use is to evaluate methods without additional training, including zero-shot evaluation of LLM/VLMs. The dataset is released exclusively for academic purposes through `https://github.com/ssu-humane/AMuFC` under CC BY-NC 4.0. This dataset contains references to fact-checking articles published by PolitiFact, a service of The Poynter Institute. The CC BY-NC 4.0 license applied to WebFC does not apply to any PolitiFact content. Since the dataset is derived from publicly available fact-checking verdicts, its use poses minimal privacy concerns.

**AI Assistant Usage** We used AI-assisted language editing tools (e.g., Grammarly and ChatGPT) exclusively to improve grammar and readability.

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## References

Bill Adair, Chengkai Li, Jun Yang, and Cong Yu. 2017. Progress toward "the holy grail": The continued quest to automate fact-checking. In *Computation+ Journalism Symposium,(September)*.

Mubashara Akhtar, Oana Cocarascu, and Elena Simperl. 2023a. Reading and reasoning over chart images for evidence-based automated fact-checking. In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 399–414, Dubrovnik, Croatia. Association for Computational Linguistics.

Mubashara Akhtar, Michael Schlichtkrull, Zhijiang Guo, Oana Cocarascu, Elena Simperl, and Andreas Vlachos. 2023b. Multimodal automated fact-checking: A survey. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5430–5448, Singapore. Association for Computational Linguistics.

Mubashara Akhtar, Nikesh Subedi, Vivek Gupta, Sahar Tahmasebi, Oana Cocarascu, and Elena Simperl. 2024. ChartCheck: Explainable fact-checking over real-world chart images. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 13921–13937, Bangkok, Thailand. Association for Computational Linguistics.

Firoj Alam, Stefano Cresci, Tanmoy Chakraborty, Fabrizio Silvestri, Dimiter Dimitrov, Giovanni Da San Martino, Shaden Shaar, Hamed Firooz, and Preslav Nakov. 2022. A survey on multimodal disinformation detection. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 6625–6643, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.

Akari Asai, Zeqiu Wu, Yizhong Wang, Avirup Sil, and Hannaneh Hajishirzi. 2023. Self-rag: Learning to retrieve, generate, and critique through self-reflection. In *The Twelfth International Conference on Learning Representations*.

Ingeol Baek, Hwan Chang, ByeongJeong Kim, Jimin Lee, and Hwanhee Lee. 2025. Probing-RAG: Self-probing to guide language models in selective document retrieval. In *Findings of the Association for Computational Linguistics: NAACL 2025*, pages 3287–3304, Albuquerque, New Mexico. Association for Computational Linguistics.

Peter Belcak, Greg Heinrich, Shizhe Diao, Yonggan Fu, Xin Dong, Saurav Muralidharan, Yingyan Celine Lin, and Pavlo Molchanov. 2025. Small language models are the future of agentic ai. *arXiv preprint arXiv:2506.02153*.

Giscard Biamby, Grace Luo, Trevor Darrell, and Anna Rohrbach. 2022. Twitter-COMMs: Detecting climate, COVID, and military multimodal misinformation. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1530–1549, Seattle, United States. Association for Computational Linguistics.

Christina Boididou, Symeon Papadopoulos, Yiannis Kompatsiaris, Steve Schifferes, and Nic Newman. 2014. Challenges of computational verification in social multimedia. In *Proceedings of the 23rd international conference on world wide web*, pages 743–748.

Brooke Borel. 2023. *The Chicago guide to fact-checking*. University of Chicago Press.

Tobias Braun, Mark Rothermel, Marcus Rohrbach, and Anna Rohrbach. 2025. DEFAME: Dynamic Evidence-based FAct-checking with Multimodal Experts. In *Proceedings of the 42nd International Conference on Machine Learning*.

Rui Cao, Zifeng Ding, Zhijiang Guo, Michael Schlichtkrull, and Andreas Vlachos. 2025. Averimatec: A dataset for automatic verification of image-text claims with evidence from the web. *arXiv preprint arXiv:2505.17978*.

Recep Firat Cekinel, Pinar Karagoz, and Çağrı Çöltekin. 2025. Multimodal fact-checking with vision language models: A probing classifier based solution with embedding strategies. In *Proceedings of the 31st International Conference on Computational Linguistics*, pages 4622–4633, Abu Dhabi, UAE. Association for Computational Linguistics.

Ting-Chih Chen, Chia-Wei Tang, and Chris Thomas. 2024. MetaSumPerceiver: Multimodal multi-document evidence summarization for fact-checking. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8742–8757, Bangkok, Thailand. Association for Computational Linguistics.

Gheorghe Comanici, Eric Bieber, Mike Schaekermann, Ice Pasupat, Noveen Sachdeva, Inderjit Dhillon, Marcel Blistein, Ori Ram, Dan Zhang, Evan Rosen, and 1 others. 2025. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities. *arXiv preprint arXiv:2507.06261*.

Wenliang Dai, Junnan Li, Dongxu Li, Anthony Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale N Fung, and Steven Hoi. 2023. Instructblip: Towards general-purpose vision-language models with instruction tuning. volume 36, pages 49250–49267.

Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. 2023. Qlora: Efficient finetuning of quantized llms. *Advances in neural information processing systems*, 36:10088–10115.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, and 1 others. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.

Lucas Graves and Michelle Amazeen. 2019. Fact-checking as idea and practice in journalism.

Aditi Gupta, Hemank Lamba, Ponnurangam Kumaraguru, and Anupam Joshi. 2013. Faking sandy: characterizing and identifying fake images on twitter during hurricane sandy. In *Proceedings of the 22nd international conference on World Wide Web*, pages 729–736.

Vipin Gupta, Rina Kumari, Nischal Ashok, Tirthankar Ghosal, and Asif Ekbal. 2022. Mmm: an emotion and novelty-aware approach for multilingual multimodal misinformation detection. In *Findings of the Association for Computational Linguistics: AACL-IJCNLP 2022*, pages 464–477.

Michael Hameleers, Thomas E Powell, Toni GLA Van Der Meer, and Lieke Bos. 2020. A picture paints a thousand lies? the effects and mechanisms of multimodal disinformation and rebuttals disseminated via social media. *Political communication*, 37(2):281–301.

Naeemul Hassan, Chengkai Li, and Mark Tremayne. 2015. Detecting check-worthy factual claims in presidential debates. In *Proceedings of the 24th acm international on conference on information and knowledge management*, pages 1835–1838.

Silvan Heller, Luca Rossetto, and Heiko Schuldt. 2018. The ps-battles dataset-an image collection for image manipulation detection. *arXiv preprint arXiv:1804.04866*.

Minyoung Huh, Andrew Liu, Andrew Owens, and Alexei A Efros. 2018. Fighting fake news: Image splice detection via learned self-consistency. In *Proceedings of the European conference on computer vision (ECCV)*, pages 101–117.

Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, and 1 others. 2024. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*.

Yeonjun In, Sungchul Kim, Ryan A. Rossi, Mehrab Tanjim, Tong Yu, Ritwik Sinha, and Chanyoung Park. 2025. Diversify-verify-adapt: Efficient and robust retrieval-augmented ambiguous question answering. In *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 1212–1233, Albuquerque, New Mexico. Association for Computational Linguistics.

Soyeong Jeong, Jinheon Baek, Sukmin Cho, Sung Ju Hwang, and Jong Park. 2024. Adaptive-RAG: Learning to adapt retrieval-augmented large language models through question complexity. In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 7036–7050, Mexico City, Mexico. Association for Computational Linguistics.

Albert Qiaochu Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de Las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. 2023. Mistral 7b. *arXiv preprint arXiv:2310.06825*.

Jaeyoon Jung, Yejun Yoon, Seunghyun Yoon, and Kunwoo Park. 2026. VILLAIN at AVerImaTeC: Verifying image–text claims via multi-agent collaboration. In *Proceedings of the Ninth Fact Extraction and VERification Workshop (FEVER)*, pages 114–126, Rabat, Morocco. Association for Computational Linguistics.

Kiseung Kim and Jay-Yoon Lee. 2024. RE-RAG: Improving open-domain QA performance and interpretability with relevance estimator in retrieval-augmented generation. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 22149–22161, Miami, Florida, USA. Association for Computational Linguistics.

Jaeyoung Lee, Ximing Lu, Jack Hessel, Faeze Brahman, Youngjae Yu, Yonatan Bisk, Yejin Choi, and Saadia Gabriel. 2024a. How to train your fact verifier: Knowledge transfer with multimodal open models. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 13060–13077, Miami, Florida, USA. Association for Computational Linguistics.

Nayeon Lee, Belinda Z. Li, Sinong Wang, Wen-tau Yih, Hao Ma, and Madian Khabsa. 2020. Language models as fact checkers? In *Proceedings of the Third Workshop on Fact Extraction and VERification (FEVER)*, pages 36–41, Online. Association for Computational Linguistics.

Sean Lee, Aamir Shakir, Darius Koenig, and Julius Lipp. 2024b. Open source strikes bread - new fluffy embeddings model.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, and 1 others. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in neural information processing systems*, 33:9459–9474.

Hongzhan Lin, Yang Deng, Yuxuan Gu, Wenxuan Zhang, Jing Ma, See-Kiong Ng, and Tat-Seng Chua. 2025. FACT-AUDIT: An adaptive multi-agent framework for dynamic fact-checking evaluation of large language models. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 360–381, Vienna, Austria. Association for Computational Linguistics.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. 2023. Visual instruction tuning. volume 36, pages 34892–34916.

Grace Luo, Trevor Darrell, and Anna Rohrbach. 2021. NewsCLIPpings: Automatic Generation of Out-of-Context Multimodal Media. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6801–6817, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Kai Nakamura, Sharon Levy, and William Yang Wang. 2020. Fakeddit: A new multimodal benchmark dataset for fine-grained fake news detection. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 6149–6157, Marseille, France. European Language Resources Association.

Hui Pang, Chaozhuo Li, Litian Zhang, Senzhang Wang, and Xi Zhang. 2025. Beyond text: Fine-grained multi-modal fact verification with hypergraph transformers. *Proceedings of the AAAI Conference on Artificial Intelligence*, 39(6):6389–6397.

Stefanos-Iordanis Papadopoulos, Christos Koutlis, Symeon Papadopoulos, and Panagiotis C Petrantonakis. 2024. Verite: a robust benchmark for multimodal misinformation detection accounting for unimodal bias. *International Journal of Multimedia Information Retrieval*, 13(1):4.

Tanmay Parekh, Pradyot Prakash, Alexander Radovic, Akshay Shekher, and Denis Savenkov. 2025. Dynamic strategy planning for efficient question answering with large language models. In *Findings of the Association for Computational Linguistics: NAACL 2025*, pages 6038–6059, Albuquerque, New Mexico. Association for Computational Linguistics.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, and 1 others. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PmLR.

Aman Rangapur, Haoran Wang, Ling Jian, and Kai Shu. 2025. Fin-fact: A benchmark dataset for multimodal financial fact-checking and explanation generation. In *Companion Proceedings of the ACM on Web Conference 2025*, pages 785–788.

Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*

*and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.

Mark Rothermel, Marcus Kornmann, Marcus Rohrbach, and Anna Rohrbach. 2026. VeriTaS: The first dynamic benchmark for multimodal automated fact-checking. In *Proceedings of the 64th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 42066–42100, San Diego, California, United States. Association for Computational Linguistics.

Rui Shao, Tianxing Wu, and Ziwei Liu. 2023. Detecting and grounding multi-modal media manipulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6904–6913.

Freda Shi, Xinyun Chen, Kanishka Misra, Nathan Scales, David Dohan, Ed H Chi, Nathanael Schärli, and Denny Zhou. 2023. Large language models can be easily distracted by irrelevant context. In *International Conference on Machine Learning*, pages 31210–31227. PMLR.

Shivangi Singhal, Rajiv Ratn Shah, and Ponnurangam Kumaraguru. 2022. Factdrill: A data repository of fact-checked social media content to study fake news incidents in india. In *Proceedings of the international AAAI conference on web and social media*, volume 16, pages 1322–1331.

S Suryavardan, Shreyash Mishra, Parth Patwa, Megha Chakraborty, Anku Rani, Aishwarya Reganti, Aman Chadha, Amitava Das, Amit Sheth, Manoj Chinnakotla, and 1 others. 2023. Factify 2: A multimodal fake news and satire news dataset. *arXiv preprint arXiv:2304.03897*.

Sahar Tahmasebi, Eric Müller-Budack, and Ralph Ewerth. 2024. Multimodal misinformation detection using large vision-language models. In *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, CIKM '24, page 2189–2199, New York, NY, USA. Association for Computing Machinery.

Reuben Tan, Bryan Plummer, and Kate Saenko. 2020. Detecting cross-modal inconsistency to defend against neural fake news. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2081–2106, Online. Association for Computational Linguistics.

Xiaqiang Tang, Qiang Gao, Jian Li, Nan Du, Qi Li, and Sihong Xie. 2025. MBA-RAG: a bandit approach for adaptive retrieval-augmented generation through question complexity. In *Proceedings of the 31st International Conference on Computational Linguistics*, pages 3248–3254, Abu Dhabi, UAE. Association for Computational Linguistics.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, and 1 others. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Michael Tschannen, Alexey Gritsenko, Xiao Wang, Muhammad Ferjad Naeem, Ibrahim Alabdulmohsin, Nikhil Parthasarathy, Talfan Evans, Lucas Beyer, Ye Xia, Basil Mustafa, and 1 others. 2025. Siglip 2: Multilingual vision-language encoders with improved semantic understanding, localization, and dense features. *arXiv preprint arXiv:2502.14786*.

Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, and 1 others. 2024. Qwen2-vl: Enhancing vision-language model's perception of the world at any resolution. *arXiv preprint arXiv:2409.12191*.

Peter S Whitehead, Charles P Davis, Joyce S Park, and Elizabeth J Marsh. 2025. Pictures are not always worth a thousand words: Nonprobative pictures did not increase the effectiveness of misinformation corrections. *Journal of Applied Research in Memory and Cognition*.

Zhuohan Xie, Rui Xing, Yuxia Wang, Jiahui Geng, Hasan Iqbal, Dhruv Sahnan, Iryna Gurevych, and Preslav Nakov. 2025. FIRE: Fact-checking with iterative retrieval and verification. In *Findings of the Association for Computational Linguistics: NAACL 2025*, pages 2901–2914, Albuquerque, New Mexico. Association for Computational Linguistics.

Barry Menglong Yao, Aditya Shah, Lichao Sun, Jin-Hee Cho, and Lifu Huang. 2023. End-to-end multimodal fact-checking and explanation generation: A challenging dataset and models. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '23, page 2733–2743, New York, NY, USA. Association for Computing Machinery.

Yejun Yoon, Jaeyoon Jung, Seunghyun Yoon, and Kunwoo Park. 2025. Team HUMANE at AVeriTeC 2025: HerO 2 for efficient fact verification. In *Proceedings of the Eighth Fact Extraction and VERification Workshop (FEVER)*, pages 224–228, Vienna, Austria. Association for Computational Linguistics.

Ori Yoran, Tomer Wolfson, Ori Ram, and Jonathan Berant. 2024. Making retrieval-augmented language models robust to irrelevant context. In *The Twelfth International Conference on Learning Representations*.

Ziyu Zhuang. 2025. Pass-fc: Progressive and adaptive search scheme for fact checking of comprehensive claims. *arXiv preprint arXiv:2504.09866*.

Dimitrina Zlatkova, Preslav Nakov, and Ivan Koychev. 2019. Fact-checking meets fauxtography: Verifying claims about images. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing*

*(EMNLP-IJCNLP)*, pages 2099–2108, Hong Kong, China. Association for Computational Linguistics.

# Appendix

## A Experimental Details

### A.1 Training and Inference

For experiments on MOCHEG, we used the fine-tuned CLIP and SBERT retrievers provided with the baseline to ensure a fair comparison by controlling for the effects of the retrieval components. We accessed GPT-4o and Gemini-2.5-Pro via API, while Qwen2-VL-7B and Llama-3.2-11B-Vision were used through pretrained checkpoints. Fine-tuning was performed with QLoRA (Dettmers et al., 2023), using a rank of 128, an alpha value of 256, and a dropout rate of 0.05. We employed the AdamW optimizer with a cosine learning rate scheduler, a base learning rate of $2 \times 10^{-5}$, a warmup ratio of 0.03, and a batch size of 32. Training was conducted for two epochs. All experiments were run on a single node equipped with eight NVIDIA H100 80GB GPUs, which were used for both training and inference. Training the Analyzer (Llama-3.2-11B-Vision) and Verifier (Qwen2-VL-7B) required approximately 6 and 2 H100 GPU-hours, respectively. Per-sample inference times are reported in Table A4.

The Verifier was fine-tuned on the MOCHEG training split using the claim, gold textual evidence, and gold image evidence when available. The training target consisted solely of the verdict label; Analyzer outputs were not used during Verifier training. The Analyzer's natural-language assessment was incorporated only at inference time through the *Image Analysis* field. The same fine-tuned Verifier was used for both gold-evidence and retrieved-evidence evaluations. This decoupling also allowed different Analyzers to be paired with the same Verifier without retraining, as shown in Table A2.

We fixed the inference hyperparameters to ensure reproducibility. Specifically, we used greedy decoding for both Qwen2-VL-7B and Llama-3.2-11B-Vision; accordingly, all results from the open-weight models are deterministic. GPT-4o and Gemini-2.5-Pro were evaluated with a temperature of 0.0, with a thinking budget of 128 for Gemini-2.5-Pro. For API-based results, we reported the mean and standard error of performance across three runs. Variability due to fine-tuning seeds is evaluated separately in Appendix C.4.

```
Your task is to determine if the provided image evidence is essential to verify the given claim or clarify the provided text evidence. To do this, follow these steps:
1. Analyze the claim and the text evidence to understand the context.
2. Assess whether the image evidence provides critical information not conveyed by the text alone.
3. Decide if the image evidence is necessary for verification or clarification.
Respond only with 'Yes' if the image evidence is necessary or 'No' if it is not.
```

Figure A1: Prompt used for Pre-filtering (Analyzer).

The model IDs of the VLMs used in our experiments are provided below.

- **GPT-4o (Hurst et al., 2024)**: gpt-4o-2024-11-20
- **Gemini-2.5-Pro (Comanici et al., 2025)**: gemini-2.5-pro
- **Qwen2-VL-7B (Wang et al., 2024)**: https://huggingface.co/Qwen/Qwen2-VL-7B-Instruct
- **Llama-3.2-11B-Vision (Grattafiori et al., 2024)**: https://huggingface.co/meta-llama/Llama-3.2-11B-Vision-Instruct

The model IDs of the retrievers used in our experiments are provided below.

- **CLIP (Radford et al., 2021)**: https://huggingface.co/sentence-transformers/clip-ViT-B-32
- **SigLIP (Tschannen et al., 2025)**: https://huggingface.co/google/siglip-so400m-patch14-384
- **SBERT (Reimers and Gurevych, 2019)**: https://huggingface.co/sentence-transformers/multi-qa-MiniLM-L6-cos-v1
- **mxbai (Lee et al., 2024b)**: https://huggingface.co/mixedbread-ai/mxbai-embed-large-v1

### A.2 Methods in Ablation Studies

**Label-only** A VLM Analyzer (Llama-3.2-11B-Vision) was fine-tuned to predict a binary label indicating whether visual evidence is necessary,

| Type | Claim ID 28 | Claim ID 35 |
|---|---|---|
| **Claim** | Google PhoneBook | Barack Obama's Net Worth |
| **Refined Claim** | Entering a phone number into the Google search engine can produce a home address and a map with directions to that address. | Barack Obama's net worth increased over $10 million from 2008 to 2012. |

Table A1: Examples of refinement results for incomplete claims from FIN-FACT.

using labels generated by GPT-4o. The predicted label was then passed to the Verifier through the *Image Analysis* field. The prompt is shown in Figure A1.

**Pre-filtering (Analyzer)** The VLM Analyzer used for *Label-only* was also used to exclude images predicted to be unnecessary from the Verifier's input.

**Pre-filtering (CLIP)** The fine-tuned CLIP model provided by Yao et al. (2023) was used to compute the cosine similarity between the claim text and the image. Images with similarity scores below 0.42, a threshold optimized on the validation set, were excluded from the Verifier's input.

**Unified Verifier** A VLM (Qwen2-VL-7B) was fine-tuned to perform both visual evidence necessity assessment and verdict prediction in a single pass, using a concatenated Analyzer and Verifier prompt. The model was trained to generate a natural-language analysis followed by the verdict. The analysis was distilled from GPT-4o and was identical to the supervision used to train the Analyzer in AMUFC.

**Verifier with CoT** A single Qwen2-VL-7B Verifier used the same prompt as the Verifier in AMUFC but was trained to generate a justification before the verdict, rather than outputting only the verdict label. The justification data were obtained from the GPT-4o-generated justifications provided by Lee et al. (2024a).

### A.3 Licenses and Software

**Artifact Licenses** All datasets and open-weight models used in this study are publicly available under licenses permitting academic research use. MOCHEG (Yao et al., 2023) is released under CC BY 4.0, and FIN-FACT (Rangapur et al., 2025) is released under the MIT License. Qwen2-VL-7B is distributed under the Apache 2.0 License, whereas Llama-3.2-11B-Vision is governed by the Llama 3.2 Community License. CLIP is released under the MIT License; SBERT, SigLIP, and mxbai-embed-large are distributed under the Apache 2.0 License. The proposed WebFC dataset will be publicly released through a software repository under the CC BY-NC 4.0 for the authors' original annotations, labels, and metadata. To avoid redistributing third-party content, the release will exclude raw web documents, images, and generated document summaries, and will instead provide retrieval queries, evidence URLs, metadata, and scripts to recollect evidence from the original sources.

**Software and Packages** All experiments were conducted using Python 3.11.13 with CUDA 12.6, using PyTorch 2.7.0, HuggingFace Transformers 4.57.3, PEFT 0.17.1, TRL 0.16.1, BitsAndBytes 0.47.0, Accelerate 1.6.0, DeepSpeed 0.17.5, SentenceTransformers 5.1.2, FAISS 1.12.0, `bm25s` 0.2.14, scikit-learn 1.7.1, and SciPy 1.16.1. Classification metrics, including accuracy and macro F1, were computed with `sklearn.metrics`, where macro F1 used `average="macro"`. Statistical tests used `scipy.stats.mannwhitneyu` with a two-sided alternative and `scipy.stats.chi2_contingency`. Krippendorff's $\alpha$ was computed manually using the nominal-metric formulation on the 112 doubly annotated samples.

## B Dataset Details

This section describes the dataset sanitization and construction processes.

### B.1 FIN-FACT

The original FIN-FACT (Rangapur et al., 2025) dataset contains 3,369 claims, comprising 840 text-only claims and 2,529 claims with multimodal evidence. Among 4,285 referenced image URLs, we successfully downloaded 3,027 images. We then retained 1,741 multimodal claims for which more than one referenced image was successfully retrieved. Combined with the text-only portion, the

```
You are a fact-checking assistant. Your task
is to determine whether the given claim is
complete in intention and clearly stated. If
the claim is vague or incomplete (e.g., a
keyword like "Google PhoneBook"), refine it
into a clear and complete sentence using the
provided evidence, justification, and label.
If the claim is already clear and complete,
return "not needed".


Claim: {claim}
Evidence: {evidence}
Justification: {justification}
Label: {label}


Return ONLY the refined claim or "not needed".
```

Figure A2: Prompt used for claim refinement.

resulting dataset contains 2,581 claims.

We observed that a substantial portion of FIN-FACT claims are incomplete phrases or keywords rather than self-contained, verifiable statements, such as "*Google PhoneBook*" or "*Barack Obama's Net Worth*." To address this issue, we refined vague and incomplete claims using Gemini-2.5-Pro by providing the original claim along with its evidence, justification, and label. Examples of refined claims are presented in Table A1, and the claim-refinement prompt is shown in Figure A2.

Because FIN-FACT does not provide an external knowledge source, we constructed a knowledge source $K$ consisting of 39,850 sentences extracted from all textual evidence passages in the original dataset, together with the 3,027 downloaded images. We also transformed labels from *True* and *False* to *Supported* and *Refuted*, respectively, to align with the MOCHEG label space. We used the refined FIN-FACT dataset for retrieval-based evaluation in the experiments.

### B.2 WebFC

Using a web-based retriever (Google Custom Search API), we queried the web for each claim to retrieve the top 10 documents and the top 1 image as textual and visual evidence. We excluded claims for which more than eight of the top 10 document URLs could not be parsed. As the retrieved documents varied widely in length and were often long, we summarized each of the documents using GPT-4o-mini (gpt-4o-mini-2024-07-18) with the prompt in Figure A3, which is adapted from Yoon et al. (2025). After temporal and source filtering, 2,365 evidence remained for 621 claims.

```
Your task is to read the following document
carefully and summarize it into a single,
coherent paragraph. Focus on capturing the main
ideas and essential details without adding new
information or personal opinions.
Document:
{document}
```

Figure A3: Prompt used for document summarization.

| Verifier | Analyzer | Gold | | Retrieved | |
|---|---|---|---|---|---|
| | | ACC | F1 | ACC | F1 |
| Qwen2-VL | None | 0.563 | 0.537 | 0.477 | 0.435 |
| | Qwen2-VL | 0.610 | 0.598 | **0.547** | **0.543** |
| | Llama-3.2-V | 0.612 | 0.600 | 0.546 | 0.540 |
| | GPT-4o | **0.631** | **0.620** | 0.538 | 0.537 |
| | Gemini-2.5-Pro | 0.612 | 0.606 | 0.478 | 0.470 |
| Llama-3.2-V | None | 0.491 | 0.398 | 0.423 | 0.314 |
| | Qwen2-VL | 0.555 | 0.455 | 0.513 | 0.408 |
| | Llama-3.2-V | 0.562 | 0.461 | 0.514 | 0.409 |
| | GPT-4o | 0.575 | 0.473 | 0.515 | 0.412 |
| | Gemini-2.5-Pro | 0.525 | 0.445 | 0.415 | 0.329 |

Table A2: Comparison of verification performance across different VLM choices for the Analyzer and Verifier.

## C Supplementary Results

### C.1 VLM Comparison

Table A2 reports verification accuracies under different VLM configurations. For the Verifier, we compared two open-weight VLMs: Qwen2-VL and Llama-3.2-V. For the Analyzer, we additionally evaluated two closed-weight VLMs accessed via API: GPT-4o and Gemini-2.5-Pro. Although our primary focus is on open-weight VLMs, this comparison allows us to assess how effectively the fine-tuned Analyzer in AMUFC performs relative to high-performing closed-weight models.

### C.2 Effects of Varying Retrievers

We conducted an ablation study to assess the effectiveness of AMUFC across varying retrievers. For text retrievers, we considered the pretrained SBERT, the fine-tuned SBERT, and mxbai. For image retrievers, we compared pretrained CLIP, fined-tuned CLIP, and SigLIP. As shown in Table A3, the effectiveness of AMUFC persisted across different retriever configurations.

### C.3 Accuracy–Efficiency Trade-offs

While the proposed framework focuses on improving verification accuracy, the Analyzer-Verifier collaboration introduces additional computational overhead. Specifically, compared to a standard

| Method | | Verifier-only | | AMUFC | |
|---|---|---|---|---|---|
| Text | Image | Acc. | F1 | Acc. | F1 |
| SBERT | CLIP | 0.475 | 0.434 | **0.530** | **0.527** |
| Mxbai | SigLIP | 0.502 | 0.476 | **0.521** | **0.523** |
| SBERT(FT) | CLIP(FT) | 0.477 | 0.435 | **0.546** | **0.540** |

Table A3: Verification performance across different text and image retriever configurations. FT denotes fine-tuned models.

| Method | Accuracy | F1 | Inference time |
|---|---|---|---|
| AMUFC | **0.612** | **0.600** | 1.531 |
| Analyzer | - | - | 1.420 |
| Verifier | - | - | 0.111 |
| Baseline | 0.563 | 0.537 | **0.112** |

Table A4: Accuracy-efficiency trade-offs, with inference time averaged per sample (seconds).

retrieval-based fact-verification pipeline, it incurs extra inference costs due to the Analyzer's assessment of the necessity of visual evidence. We provide a detailed analysis of these trade-offs in Table A4. We measured inference time on the test dataset with gold evidence using single-instance inference and a basic inference pipeline implemented with Hugging Face Transformers, evaluated on a single NVIDIA H100 GPU.

### C.4 Fine-tuning Seed Variability

To assess variability across fine-tuning runs, we retrained both the Analyzer and the Verifier with two additional seeds (43 and 44), alongside the original seed (42). All three runs were evaluated using the same prompt configuration as the main experiments. Table A5 reports the mean and standard error across the three seeds on MOCHEG. AMUFC consistently outperformed the Verifier-only baseline, with mean improvements of approximately 6.0–11.0 percentage points across the four metrics. Two-sided paired t-tests across seeds indicated statistically significant improvements for all four metrics ($p < 0.01$).

### C.5 More Comparisons on WebFC

We additionally compared AMUFC with a recent method, DEFAME (Braun et al., 2025), on WebFC. Both systems used the same WebFC-retrieved evidence to control for differences in web search and evidence retrieval. We used Llama-4-Scout as the Verifier backbone for both systems, following the original DEFAME configuration. For AMUFC, we

```
Given a claim and its associated textual and
visual evidence, determine whether the visual
evidence is necessary for evaluating the claim.

Inputs:
Claim: {claim}
Textual Evidence: {textual evidence}
Visual Evidence: {visual evidence}

Necessary visual evidence refers to visual
content that provides novel, complementary, or
clarifying information beyond what is conveyed
in the textual evidence, and that meaningfully
contributes to interpreting or supporting the
claim.

Unnecessary visual evidence refers to visual
content that is irrelevant, only depicts
entities, is loosely related, or is redundant
with the textual evidence.

Select one:
☐ Necessary
☐ Unnecessary
```

Figure A4: Annotation guidelines for determining whether visual evidence is necessary.

| Method | Gold | | Retrieved | |
|---|---|---|---|---|
| | ACC | F1 | ACC | F1 |
| AMUFC | $0.613 \pm 0.005$ | $0.600 \pm 0.007$ | $0.541 \pm 0.006$ | $0.536 \pm 0.003$ |
| Verifier-only | $0.553 \pm 0.006$ | $0.523 \pm 0.008$ | $0.476 \pm 0.002$ | $0.426 \pm 0.006$ |

Table A5: MOCHEG verification performance across three fine-tuning seeds (mean $\pm$ standard error).

replaced only the Verifier backbone with Llama-4-Scout while keeping the Analyzer unchanged. Table A6 shows that AMUFC achieved higher accuracy and macro F1 than DEFAME under this setting. These results provide support for the effectiveness of adaptive visual evidence use.

### C.6 Standalone Evaluation of the Analyzer

We evaluated the Analyzer's visual-necessity classification performance on the 112 manually annotated validation examples described in Section 4.2. We compared the fine-tuned Analyzer used in AMUFC with its GPT-4o teacher and a majority-class baseline that always predicts *Unnecessary*, which accounts for 80 of the 112 examples. Table A7 shows that the fine-tuned Analyzer performed comparably to its GPT-4o teacher while substantially outperforming the majority-class baseline in macro F1. These results suggest that the distilled Analyzer captures meaningful visual-necessity judgments on these annotated ex-

| Method | ACC | F1 |
|---|---|---|
| AMUFC | **0.662** | **0.338** |
| DEFAME | 0.478 | 0.307 |

Table A6: Comparison with DEFAME on WebFC using Llama-4-Scout as the Verifier backbone.

| Model | ACC | Macro F1 |
|---|---|---|
| Fine-tuned Analyzer | 0.768 | 0.721 |
| GPT-4o | 0.777 | 0.738 |
| Majority class | 0.714 | 0.417 |

Table A7: Visual-necessity classification performance on 112 manually annotated validation examples.

amples. However, AMUFC does not use the Analyzer as a binding binary classifier. As shown in Table 5, the Label-only variant performs worse than the full natural-language assessment, suggesting that the verbalized reasoning provides additional benefits beyond the binary necessity label.

### C.7 Effects of Generation Length

Table A8 summarizes the ablation configurations, average generated token counts, and verification performance in the MOCHEG gold-evidence setting. Tokens were counted using each model's tokenizer. Unified Verifier and Verifier with CoT generated 110.3 and 96.6 tokens on average, respectively, compared to approximately 90.5 tokens generated across the Analyzer and Verifier in AMUFC, yet their accuracy was lower by 3.5 and 5.9 percentage points. Despite generating only a short necessity label, Label-only improved over w/o Analyzer by 3.6 percentage points in accuracy and 4.4 points in macro F1. The full natural-language assessment yielded further improvements, indicating that the performance gains cannot be explained by generation length alone.

### C.8 Qualitative Examples

Table A9 shows successful and failed predictions of the proposed method, along with the corresponding Analyzer outputs. The successful case shows that the Analyzer's assessment can help the Verifier correct a baseline error when the analysis explains why visual evidence complements the text evidence in verifying the claim. However, the failed case also illustrates that the Verifier can produce an incorrect verdict despite a correct analysis, indicating that accurate evidence-necessity assessment alone does not guarantee correct verification.

| Method | Separate Analyzer | Necessity Information | Generated Tokens (Analyzer) | Generated Tokens (Verifier) | ACC | F1 |
|---|---|---|---|---|---|---|
| AMUFC | Yes | Assessment | 85.9 | 4.6 | **0.612** | **0.600** |
| Label-only | Yes | Label | 12.1 | 4.6 | 0.599 | 0.581 |
| Pre-filtering (Analyzer) | Yes | Filter | 12.1 | 4.6 | 0.574 | 0.551 |
| w/o Analyzer | No | None | – | 4.6 | 0.563 | 0.537 |
| Unified Verifier | No | Joint assessment | – | 110.3 | 0.577 | 0.555 |
| Verifier with CoT | No | None | – | 96.6 | 0.553 | 0.511 |

Table A8: Average generation length and verification performance across ablation configurations.

| Type | Successful | Failed |
|---|---|---|
| **Claim** | A Boeing B-17E bomber from World War II was found in the jungle with coffee still in thermoses. | Students no longer say the Pledge of Allegiance in schools. |
| **Visual Evidence** |  |  |
| **Textual Evidence** | • They found the rear door of the airplane, two aluminum receptacles and a third which contained coffee residue.<br>• Both the impactor and the condensate were stored and transported to the laboratory at 2-8 °C.<br>• Print LONG BEACH, Calif. - A B-17 bomber that lay in a New Guinea swamp for decades after being forced down during a World War II combat mission has been returned to the United States after years of salvage efforts.<br>• As food stores were running low at the airplane, Zerbino and Fito went searching for cadavers and although they found one, they were too tired to bring it back to the fuselage.<br>• Ignited by fire, ammunition was exploding inside the cabin. | • Students still say the Pledge of Allegiance in classrooms, though they don't have to.<br>• Virtual learning has presented new challenge for how schools say the Pledge of Allegiance. |
| **Analysis** | The image evidence is **necessary** for verifying the claim. While the text evidence provides detailed information about the discovery of the Boeing B-17E bomber in the jungle, including the presence of coffee residue and thermoses, the image directly shows the plane in its jungle location, confirming the physical context of the claim. The visual evidence complements the text by providing a tangible representation of the scene described, which is essential for verifying the authenticity of the claim. | The image evidence is **not necessary** for verifying the claim. The text evidence already provides sufficient information to address the claim that students no longer say the Pledge of Allegiance in schools. It clarifies that students still say the Pledge of Allegiance in classrooms, though it is not mandatory, and that it is recited at every school. The image of students raising their hands does not add any new or essential information to verify or refute the claim. |
| **Prediction** | Ground truth: *Supported*<br>Baseline: *Refuted* ✗<br>AMUFC: *Supported* ✓ | Ground truth: *Refuted*<br>Baseline: *Refuted* ✓<br>AMUFC: *NEI* ✗ |

Table A9: Examples for successful and failed predictions of AMUFC.