FactDebug at SemEval-2025 Task 7: Hybrid Retrieval Pipeline for Identifying Previously Fact-Checked Claims Across Multiple Languages

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Abstract

The proliferation of multilingual misinformation demands robust systems for crosslingual fact-checked claim retrieval. This paper addresses SemEval-2025 Shared Task 7, which challenges participants to retrieve fact-checks for social media posts across 14 languages, even when posts and fact-checks are in different languages. We propose a hybrid retrieval pipeline that integrates both sparse lexical matching techniques (utilizing BM25 and BGE-m3) and dense semantic retrieval methods (leveraging both pretrained and fine-tuned BGE-m3 embeddings). Our approach implements dynamic fusion of these complementary retrieval strategies and employs curriculum-trained rerankers to optimize retrieval performance. Our system achieves 67.2% crosslingual and 86.01% monolingual accuracy on the Shared Task MultiClaim dataset.

1 Introduction

Nowadays, fact-checking has become crucially important because it helps maintain accuracy and credibility, prevents the spread of misinformation, and ensures informed decision-making by verifying information before dissemination.

SemEval-2025 Task 7 is focused on *Previously Fact-Checked Claim Retrieval* (PFCR) (Shaar et al., 2020). The task involves ranking a set of fact-checked claims according to their relevance to an input claim such as a social media post, with the highest-ranking ones being most pertinent and beneficial for fact-checking.

So far only monolingual PFCR has been tackled, when the input claim and the fact-checked claims are in the same language. To address these shortcomings, the SemEval-2025 Task 7 (Peng et al., 2025) has been organized with MultiClaim dataset (Pikuliak et al., 2023) to encourage the community to develop a multilingual fact-checking system. The task is divided into two main subtasks: (1) monolingual fact-checking – given a social post, participants must develop systems to identify and retrieve the most relevant fact-checked claim written in the same language as the post; (2) crosslingual fact-checking – the task is essentially the same as the first one, but now posts and their relevant fact-checks can be written in a different language. This subtask requires participants to build a multilingual retrieval system.

This paper is structured as follows. Section 2 discusses existing work on fact-checking. Section 3 describes the modified version of MultiClaim dataset that was used in the SemEval-2025 Task 7. Section 4 introduces the evaluation metrics. Section 5 describes the proposed hybrid retrieval pipeline. Section 6 reports the results of the applied approaches.

Our contribution can be summarized as follows:

- We introduce a lightweight yet effective fact-checking hybrid retrieval system, that incorporates multistage fine-tuning components. This technique efficiently aligns multilingual social media posts with a multilingual fact-check corpus.

2 Related Work

The integration of information retrieval techniques and associated technologies hold potential for enhancing fact-checking. PFCR task is time-consuming for professionals fact-checkers and information retrieval methods can speed up the process. Multilingual PFCR is an even more complicated version for humans because it requires a deep understanding of multiple languages. Multilingual information search can facilitate the fact-checking between different languages.

For PFCR, traditional methods of information retrieval can be utilized. Vo and Lee (2018) effectively employed the BM25 method to identify fake news. Various text embedding techniques have

been used to improve the retrieval process, allowing for more nuanced comparisons between claims and also techniques like reranking are used to combine multiple methods, enhancing the efficiency and accuracy of claim retrieval (Pikuliak et al., 2023). In addition, some approaches enhance the results by incorporating visual data from images, using abstractive summarization, or identifying key sentences.

Research emphasizes the importance of context in detecting previously fact-checked claims, especially in political debates or documents (Shaar et al., 2022). Some studies focus on detecting claims within entire documents, aiming to rank sentences based on their verifiability using previously fact-checked claims (Shaar et al., 2020)

Zhang et al. (2023) presented a dataset for monolingual information search for 18 different languages and demonstrated the work of some baseline approaches for information retrieval.

Future research will likely focus on improving the efficiency and accuracy of these systems, particulary in low-resource languges and complex contextual scenarios.

3 Dataset

The competition organizers represented a modified version of the MultiClaim dataset. The original MultiClaim dataset consists of 28k posts in 27 languages on social media, 206k fact checks in 39 languages performed by professional fact checkers, and 31k connections between the two groups. Each connection consists of a post and a fact-check reviewing the claim made in the post. The main difference between the modified version presented in the competition and the original one is that the modified version contains fewer languages (14), but contains more fact checks (272k) and few more posts. In the competition a modified MultiClaim dataset was used. The entire dataset is split into three sections: training (comprising 153k fact-checks in 8 languages, 4,972 cross-lingual and 1,7016 monolingual posts), testing (featuring 272,447 fact-checks in 12 languages, 4,000 crosslingual and 4,276 monolingual posts) and development (consisting of the same fact-checks as training, 552 cross-lingual, and 1,891 monolingual posts). There are also 25,743 connections between posts and fact-checks for training and development parts.

4 Evaluation

To evaluate retrieval in Shared Task 7, we use **Success-at-10** (**S@10**) as a quality measure for both monolingual and cross-lingual subtasks. This is because we depend on the retrieval module to capture as much relevant information as possible.

5 Proposed Approach

Our retrieval pipeline combines sparse and dense retrieval paradigms with fusion and reranking to address cross-lingual and monolingual fact-checking tasks. The architecture consists of four stages: (1) sparse vector encoding for lexical matching, (2) dense vector encoding for semantic alignment, (3) fusion to merge multi-perspective results, and (4) reranking to refine relevance ordering.

5.1 Sparse Retrieval

Sparse vector representations are generated using the following methods:

(1) BM25: Traditional sparse retrieval using TF-IDF weighting. (2) BGE-m3 Lexical Weights (Chen et al., 2024): Enhanced sparse vectors from the sparse component of `BAAI/bge-m3`[1], which captures the importance of the term through learned token-level scores.

Preprocessing Pipeline: converting emoji to a text name.

5.2 Dense Retrieval

Dense vector representations are generated using several transformer-based models: (1) BGE-m3 Dense Encoder: The `BAAI/bge-m3` model is also employed to produce dense vectors, taking advantage of its large-scale pretraining on diverse data sources; (2) Task-Specific Adaptation: A fine-tuning process using contrastive loss is applied to the `BAAI/bge-m3` model to optimize its ability to discriminate between relevant and irrelevant results.

5.3 Fusion

To unify sparse and dense signals, we employ Reciprocal Rank Fusion (RRF) (Cormack et al., 2009) with tunable weights, ensuring a balanced combination of both approaches:

$$\text{RRF}(d) = \sum_{i=1}^{n} \frac{w_i}{k + \text{rank}_i(d)} \quad (1)$$

[1] https://hf.co/BAAI/bge-m3

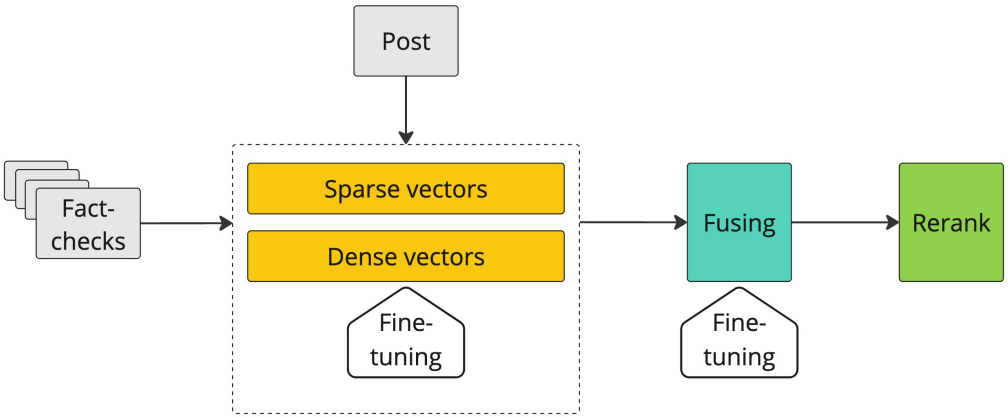

Figure 1: Hybrid Fact-Check Retrieval Pipeline

where k is a smoothing constant, $rank_i(d)$ denotes the rank of document d in the i-th retrieval system, and w_i represents the retriever-specific weight coefficient.

5.4 Rerank

The reranking phase refines the top retrieved documents based on additional features, improving relevance and quality: (1) BGE-m3 Reranker: `BAAI/bge-reranker-v2-m3` cross-encoder model, based on the `BAAI/bge-m3` architecture, it computes query-document relevance scores by jointly encoding pairs, resolving ambiguities in lexical matches; (2) Curriculum-Learned Reranker: `BAAI/bge-reranker-base` fine-tuned in two stages: First, adaptation to fact-checking using focal loss (with parameters `alpha=0.95` and `gamma=0.4`) to handle class imbalance; second, optimisation on hard negations derived from sparse search errors to refine decision boundaries.

6 Results and Discussion

6.1 NLI Analysis

Fact-check retrieval requires identifying claims that entail (support) or contradict a social media post. To quantify this relationship, we analyze post-fact-check pairs using `FacebookAI/roberta-large-mnli` (Liu et al., 2019), pretrained on large web-text corpora (Appendix A).

Entailment Distribution Scores exhibit a bimodal distribution: 68% of pairs cluster near 0 (no entailment) and 24% near 1 (strong entailment), with only 8% in the ambiguous middle range (0.2–0.8). This polarization likely reflects the NLI model's overconfidence rather than true task-specific relationships, as social media claims often involve nuanced or implicit connections.

Contradiction Rarity 92% of pairs score below 0.1 for contradiction. The scarcity of high-contradiction pairs may stem from the NLI model's limited exposure to adversarial social media claims during pretraining, rather than genuine absence of contradictions.

Neutrality as Noise Neutral scores follow a U-shaped distribution: 54% near 0 (non-neutral) and 32% near 1 (strongly neutral). The high-neutrality cluster may include false negatives where the NLI model fails to recognize subtle entailment/contradiction signals, particularly in code-switched or informally phrased text.

Despite the bias of the out-of-the-box NLI model, these results reveal that the task can be noise-aware retrieval: prioritize lexical overlap for high-recall candidate generation, mitigating reliance on noisy semantic signals.

6.2 Retrieval Analysis

Table 1 compares the performance of sparse, dense, and hybrid retrieval systems on cross-lingual and monolingual fact-checking tasks.

Component Analysis The standalone BGE-m3-lexical sparse retriever achieved strong monolingual performance (80.44%), outperforming the dense-only BGE-m3-dense-finetuned system (67.02%). This lexical advantage persisted in cross-lingual settings (61.17% vs. 65.4%), though dense retrieval showed greater cross-lingual robustness.

Sparse Retrieval	Dense Retrieval	Fusion	Rerank	Mono	Cross
BGE-m3-lexical	–	–	✗	80.44	61.17
–	BGE-m3-dense	–	✗	78.91	65.9
–	BGE-m3-dense-finetuned	–	✗	67.02	65.4
BGE-m3-lexical	BGE-m3-dense-finetuned	1:1	✓	85.90	**67.2**
		8:2	✗	85.43	66.95
		8:2	✓	**86.01**	66.57
BM25	–	–	✗	62.96	56.15

Table 1: Performance of retrieval systems on cross-lingual (Cross) and monolingual (Mono) tasks. Measured in Success@10, %. Fusion $k : n$ indicates that the sparse weight is k and the dense weight is n in Reciprocal Rank Fusion.

The BM25 baseline (62.96% Mono, 56.15% Cross) underperformed modern neural methods, highlighting the need for learned lexical representations.

Fusion Strategies Combining sparse and dense components via RRF yielded substantial gains. A 1:1 sparse-dense ratio with reranking produced the best cross-lingual performance (67.2% Cross), surpassing individual components. Monolingual performance peaked at 86.01% with an 8:2 sparse-dense ratio and reranking, demonstrating lexical dominance in single-language contexts. Notably, reranking consistently improved monolingual results (improvements of 0.58-1.27 points across metrics) but showed mixed cross-lingual effects, suggesting language-specific optimization potential.

Lexical Primacy The sparse component's predominance aligns with our NLI analysis, which revealed polarized entailment scores (68% near 0, 24% near 1) and rare contradictions (92% <0.1). This semantic noise profile favors lexical overlap as a stable signal for candidate generation. While dense retrieval aids cross-lingual alignment through latent semantic spaces, the lexical backbone ensures robustness against NLI model overconfidence—particularly critical for social media text with implicit claims and code-switching.

Crosslingual Performance Optimal cross-lingual performance required balanced sparse-dense fusion (1:1 ratio), contrasting with the lexical-heavy 8:2 ratio preferred for monolingual tasks. This suggests that while lexical matching anchors retrieval quality, cross-language generalization benefits from controlled semantic integration, but this may be due to the nature of crosslingual translation utilisation.

In addition to the results in Table 1 we evaluated configurations for `stella_en_1.5B_v5`[2] (Zhang and FulongWang, 2024) and `multilingual-e5-large-instruct`[3] (Wang et al., 2024) with the prompt *"Given a post on a social network, retrieve the claims it contains"*, but it did not give any increase in quality. Replacing the dense retriever in hybrid pipeline with `stella_en_1.5B_v5` performs 84.45% Mono and 65.47% Cross, `multilingual-e5-large-instruct` performs 84.86% Mono and 66.37% Cross.

Conclusion

In this paper, we have described the system we submitted for the SemEval Task 7 challenge, specifically concentrating on developing a multilingual and crosslingual fact-checked claim retrieval. We proposed a simple yet effective hybrid retrieval pipeline with fine-tuned components.

Future directions include dynamic fusion mechanisms that weight sparse and dense contributions per language pair, and joint training of sparse and dense components to enhance overall performance.

Limitations

Our approach has two key constraints: (1) Partial fine-tuning - only dense and reranker components were optimized, leaving potential gains from end-to-end sparse-dense co-training unexplored due to optimization instability; (2) Translation and OCR inaccuracies propagate through the pipeline, particularly harming low-resource languages and slang-heavy social media text.

[2] https://hf.co/NovaSearch/stella_en_1.5B_v5

[3] https://hf.co/intfloat/multilingual-e5-large-instruct

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A NLI Scores Distribution

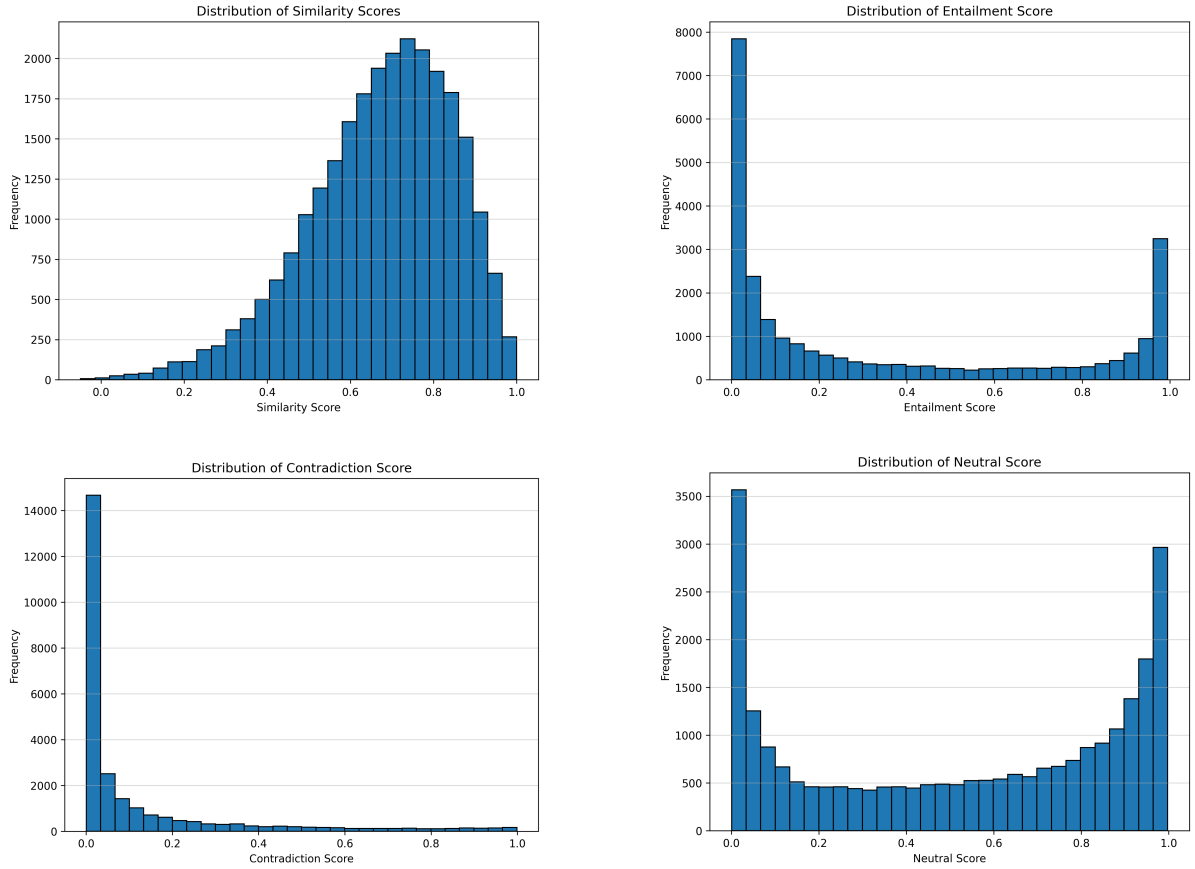

Figure 2: Distributions of NLI scores