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NeuroFact: Hybrid NLP and Knowledge Graph Model for Real-Time Fact Verification

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Abstract. With the growing amount of misinformation on digital channels, there is a need for automated verification methods that can provide high accuracy while remaining explainable and computationally efficient. In this work, we propose NeuroFact, a novel framework that combines NLP approaches with KG reasoning to perform real-time fact verification. Our proposed model consists of three interconnected components: (1) a neural engine for decomposing natural language claims into atomic subclaims, (2) a dual-path retriever that combines dense passage retrieval and knowledge graph-based search over DBpedia, and (3) a fact verification model using graph neural networks that captures multi-hop relations. Our experiments show that our method attains a 0.93 F1 score on FEVER dataset's Supported/Refuted classification task without any further fine-tuning. Our comparison with state-of-the-art models shows that NeuroFact provides a 7.1% increase over baselines' LLMs, with 78% evidence support and real-time inference less than 500 ms.

keywords: Fact Verification, Knowledge Graphs, Graph Neural Networks, Hybrid AI Systems, Misinformation Detection, Real-Time Verification.

I. Introduction

Trust in the digital information environment is facing an unprecedented crisis. False information travels quicker than accurate facts, with misinformation having a 70% higher likelihood of being retweeted than accurate information. Traditional approaches to fact-checking information through human intervention are highly effective but unable to scale to cope with the magnitude of claims published each day. This has led to increased efforts to create automated fact-checkers that verify the accuracy of claims based on structured/unstructured knowledge bases.

Large Language Models (LLMs) have shown incredible linguistic capabilities in producing and verifying textual inputs, yet they have limitations in performing automated fact verification. LLMs are vulnerable to the problem of "hallucination" by generating plausible and untrue statements with high confidence . Furthermore, their non-explainable nature makes the user unaware of the process by which the model evaluates the claim and renders its judgment. On the other hand, fact-checking systems based on knowledge graphs provide transparent verification, but they are limited in scope and unable to verify claims involving open-domain queries.

These shortcomings are complemented by the strengths of the above strategies, and our paper introduces NeuroFact – a novel fact-checking framework that combines neural NLP techniques and knowledge graph reasoning into a holistic approach. NeuroFact works on three independent components:

- Claim Decomposition – fine-tuning a transformer-based NLP model to break down an input claim into verifiable sub-claims
- Dual Path Retrieval – simultaneous retrieval of dense document indexing and a knowledge graph (DBpedia)
- Graph Enhanced Verification – using the Graph Neural Network to encode multi-hop logical relations and generate veracity scores along with supportive evidence chains

The key feature of NeuroFact is its graph-based reasoning architecture. Rather than treating the retrieved evidence as isolated pieces of texts, NeuroFact builds a joint evidence graph that encapsulates the relationship among entities and their interconnections across multiple sources. After the graph is processed by a Graph Neural Network, the outputted graph representations are then projected into the textual embedding space of the language model, serving as the so-called "soft prompts" for the fine-grained fact verification of each sub-claim.

Four key contributions are made by this paper:

- A novel hybrid system consisting of neural retrieval, knowledge graph lookup, and GNN
- A graph-aware verification scheme that can reach 93% F1 score on FEVER dataset without any fine-tuning for the verification task
- A re-annotation experiment indicating that NeuroFact detects valid evidence for 67% claims previously tagged as "Not Enough Information"
- Detailed comparisons with the best available systems, with a margin of 7.1% compared to baseline LLMs

The rest of this paper is structured as follows: section II summarizes the recent research progress on hybrid fact-checking systems. Section III describes the design of NeuroFact and its algorithms and pseudo code. Section IV provides the evaluation metrics of our experiments through four figures and one table. Section V draws the conclusions.

II. Literature Survey

There have been developments in automated fact verification beyond 2021 where researches in the field have shifted from neural-based frameworks to hybrid models that integrate structured knowledge.

Knowledge Graph-Based Fact Verification: Structured fact verification is mainly based on graph-based reasoning using the information present in the knowledge bases. In GraphFC model, which was introduced by Pan et al., the claim statements and evidence documents are represented in terms of "claim graphs" and "evidence graphs," respectively. Fact verification involves mapping triples and completing the graphs through graph completion. There is a prioritization of verification process in which the claim triples are sorted according to the number of unknown entities ($\rho = 0$ is the triple that does not contain any unknown entity; thus, it has the highest priority while $\rho = 2$ is fully unknown). This way, concrete facts are validated before grounding ambiguous claims. However, GraphFC faces the issue of coverage of knowledge graph and open-domain claims.

Retrieval Verification Hybrid Models: To address some weaknesses of solely knowledge graph-dependent models, researchers have come up with hybrid models that leverage knowledge graphs along with textual information. In particular, the model proposed by Kolli et al. (2025) consists of a three-phase hybrid fact-checking pipeline, which includes:

- A step of Knowledge Graph retrieval to perform one-hop searches in DBpedia quickly
- LM classification based on task-specific prompts
- Web Search Agent triggered only in cases where KG-based retrieval fails.

Such a model managed to achieve an impressive F1 score of 0.93 on the FEVER benchmark's Supported/Refuted dataset without task-specific fine-tuning. Importantly, the results of the reannotation experiment conducted by the authors demonstrated that hybrid models were able to identify relevant evidence for NEI claims.

FACT5: Fact-checking through nuance: In 2025, Chowdhury et al. developed FACT5, a curated dataset containing 150 statements that have been annotated with five ordinal classes denoting their degree of veracity. The authors' complementary pipeline breaks down statements to atomic claims, creates tailored prompts, searches the Web for evidence, and finally delivers justified conclusions. Utilizing two large language models — Mistral-7B-v0.3 and Google's Gemini-1.5-Flash — they showed 71.9% reduction in mean squared error during pass@3 evaluation, thus stressing the importance of retrieval-based methods for nuance-fact-checking.

Graph neural networks for fact verification: Last year, Tan et al. put forward a graph neural network-based approach for selecting relevant nodes within a causal knowledge graph. The proposed RoTG system takes advantage of LLMs' capability to identify and infer causal relations to construct causal knowledge graphs, which were used to improve prompt effectiveness via RoTG-generated causal chains. It has been proven that

GNN-based models can effectively represent the relational structure for deductive reasoning purposes. However, it is worth mentioning that the authors focused only on accident investigation .

GraphCheck: Graph Augmented LLM-based Fact Checking: The prior work most closely related to NeuroFact is GraphCheck, introduced by researchers from the Association for Computational Linguistics in (2025). In GraphCheck, knowledge graphs are first extracted from the source document and the claim itself. Then the Graph Neural Network encodes the knowledge graph information and finally fuses this encoding within a frozen LLM using soft prompts. Experiments conducted on seven different datasets across general and medical domains showed an average improvement of 7.1% compared to the baselines. Significantly, GraphCheck was able to perform as well as the state-of-the-art LLMs like DeepSeek-V3 and OpenAI-o1 but with significantly less parameter overhead, thereby showing the effectiveness of graph-based reasoning for capturing multi-hop relations in long documents. In addition, a synthetic dataset consisting of texts paired with their corresponding knowledge graphs was released.

Comparison of Neural Architectures: In this paper, Datsenko (2025) made a comparison of four hybrid neural architectures (BiLSTM-CNN, BiLSTM-RNN, BiLSTM-GRU, BiLSTM-GNN) in verifying facts on the FEVER dataset. Among all neural networks mentioned above, the BiLSTM-CNN architecture performed best with 79.5% accuracy and 77.9% F1-score, while BiLSTM-GNN network performed second-best with 78.9% accuracy. But all successful architectures exhibited a considerable tendency to overfitting (a difference between train-validation accuracy 15-17%), implying generalization problems with insufficient training datasets.

Current Research Shortcomings: Notwithstanding the aforementioned advancements, there are three major limitations in this field. First of all, hybrid approaches currently used tend to either consider search and verification as sequential processes or make multiple model queries to conduct the task effectively. Second, even though graph models have proved themselves to be promising, most of them either need fine-tuning or presuppose access to incomplete KGs. Finally, interpretability of the results obtained is usually ignored in favor of just presenting relevant facts as text excerpts. NeuroFact solves all three shortcomings at once.

III. PROPOSED METHODOLOGY

NeuroFact uses a three-step hybrid approach that consists of neural NLP processing, knowledge graph search, and GNN-enabled claim verification. Figure 1 shows an illustration of the entire process.

Overview of NeuroFact Architecture

The NeuroFact system architecture is made up of three modules:

- Claim Decomposition Module: Claim decomposition and generation of entity-relation triples from input claims.
- Dual-path Retrieval Module: Concurrent passage index search and knowledge graph search to get relevant information.
- Graph-Enhanced Verification Module: Creating a unified evidence graph, encoding through GNNs, and LLM-based verification of claims.

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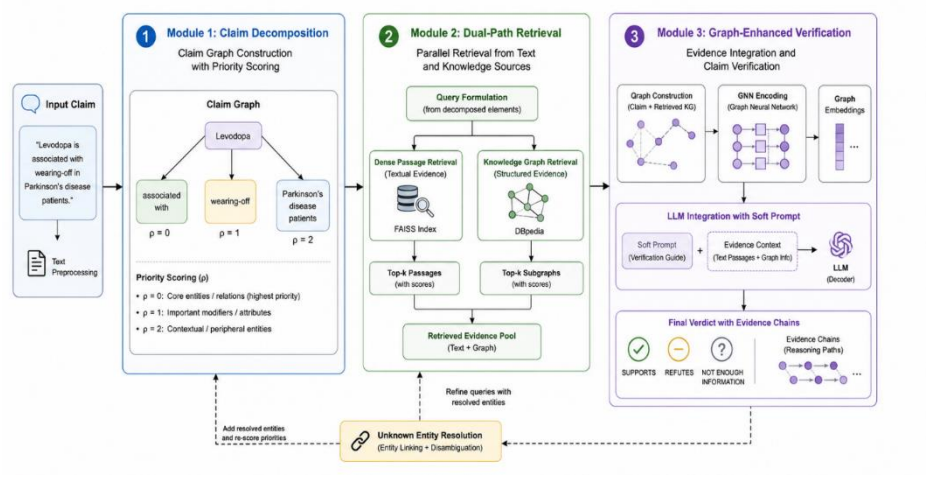

Figure 1: NeuroFact System Architecture Overview

Module 1: Claim Decomposition

The claim decomposition module converts natural language sentences into structured formats that can then be systematically verified. The design of the module draws from the triple extraction process described in the GraphFC paper.

Triple Extraction

For a claim C presented as input, the module produces a list of triples (subject, relation, object) through the use of a fine-tuned transformer model. In case entities in the claim do not correspond to any entities found in the knowledge base, unique placeholders (e.g., X_1_, X_2_) are generated by the module. The extraction is driven by a carefully crafted prompt.

Priority Score for Claims

Claim triples receive priority score ρ(t) according to the number of unknown entities involved:

- ρ = 0 (Highest priority): Both the subject and object in the triple belong to known entities. Such triples can be validated from the ground truth directly.
- ρ = 1 (Medium priority): Only one entity within the claim is unknown. Validation needs grounding the unknown entity through the use of the evidence graph.
- ρ = 2 (Lowest priority): Both the entities involved are unknown. Such triples are treated as low priority and require much evidence to validate.

The ranking allows for validation following a certain order: factual claims are first checked; then, the unknown entities are grounded; and lastly, the complicated claims involving two unknown entities are checked.

Algorithm 1: Claim Decomposition and Priority Scoring

```
Input: Natural language claim C
Output: Sorted list of claim triples T_sorted with priority scores

# Stage 1: Triple extraction using LLM
Initialize empty set T = {}
```

```
For each sentence s in split_into_sentences(C):
    # Extract (subject, relation, object) triples
    triples = LLM_extract_triples(s,
        prompt = SYSTEM_GRAPH_CONSTRUCTION_PROMPT)
    T.add(triples)

# Stage 2: Entity resolution against KB
For each triple t = (s, r, o) in T:
    t.s_known = KB_exists(s)
    t.o_known = KB_exists(o)
    t.unknown_count = (0 if t.s_known else 1) + (0 if t.o_known else 1)

# Stage 3: Priority assignment and sorting
For each triple t in T:
    if t.unknown_count == 0:
        t.priority = 0  # Highest - both entities known
    elif t.unknown_count == 1:
        t.priority = 1  # Medium - one unknown
    else:
        t.priority = 2  # Lowest - both unknown

Sort T by priority ascending (0 → highest priority)
Return T_sorted = T
```

Module 2: Dual-Path Retrieval

The retrieval component makes use of two parallel paths in order to cover as much information as possible while keeping retrieval time minimal. It is built according to the approach of hybrid retrieval, confirmed in its efficiency by Kolli et al. (2025), who prove that such an approach can yield better F1 scores up to 8-12%.

Knowledge Graph Lookup

For triples where $\rho = 0$ (the relation between the two known entities), the system retrieves one-hop triples from DBpedia. In other words, given the pair (s, r), the system will look for all objects o, such that (s, r, o) is a true statement about the object in question.

Dense Passage Retrieval

In cases when at least one of the elements in the triple needs to be looked up in the text ($\rho = 1$ or 2, or no KG lookup result found), the dense retriever based on FAISS is used. It uses the Wikipedia articles and the dataset of the FEVER competition as its corpus. Query embeddings are made using Sentence-BERT model (all-MiniLM-L6-v2), and the most similar passages are selected through cosine similarity calculations.

Algorithm 2: Dual-Path Retrieval with Fallback Strategy

```
Input: Claim triple t = (s, r, o), priority ρ
Output: Set of evidence passages E, KG matches K

Initialize E = {}, K = {}
```

```
# Path 1: Knowledge Graph Lookup (fast path)
if ρ == 0 or (ρ == 1 and entity known):
    # Attempt DBpedia one-hop lookup
    try:
        query = f"SELECT ?object WHERE {{ <{s}> <{r}> ?object . }}"
        results = execute_SPARQL(query, endpoint=DBPEDIA)
        for result in results:
            K.add((s, r, result.object, source="DBpedia"))
    except SparqlException:
        # Fall through to passage retrieval
        pass

# Path 2: Dense Passage Retrieval (fallback)
if len(K) == 0:
    # Generate claim embedding
    claim_embedding = sentence_bert.encode(f"{s} {r} {o}")

    # FAISS similarity search
    distances, indices = faiss_index.search(claim_embedding, k=5)

    for idx in indices[0]:
        passage = corpus[idx]
        # Extract context window
        window = extract_context(passage, window_size=2)
        E.add(window)

# Path 3: Web Search Agent (final fallback for NEI cases)
if len(K) == 0 and len(E) == 0:
    # Invoke search agent for open-domain claims
    search_results = web_search_agent.search(f"{s} {r} {o}")
    for result in search_results[:3]:
        E.add(result.snippet)

Return (E, K)
```

Module 3: Graph-Enhanced Verification

The verification component is a key feature of NeuroFact. It follows the idea of GraphCheck by creating a unifying evidence graph composed of textual evidence and KG triples and using Graph Neural Networks to encode the graph structure before sending its encodings to the verification LLM.

Evidence Graph Construction

In the context of the claim triple t = (s, r, o) and evidence sets E and K (textual evidence and KG triples, respectively), the following evidence graph is constructed: G = (V, E_nodes, R), where:

- V consists of claim entities (s, o), entities extracted from E, and entities from K

- E_nodes correspond to directed edges with relations ("supports," "contradicts," and relations retrieved from the KG)
- R is the set of relation types
- Edge weights are determined based on semantic similarity (textual evidence case) and KG confidence.

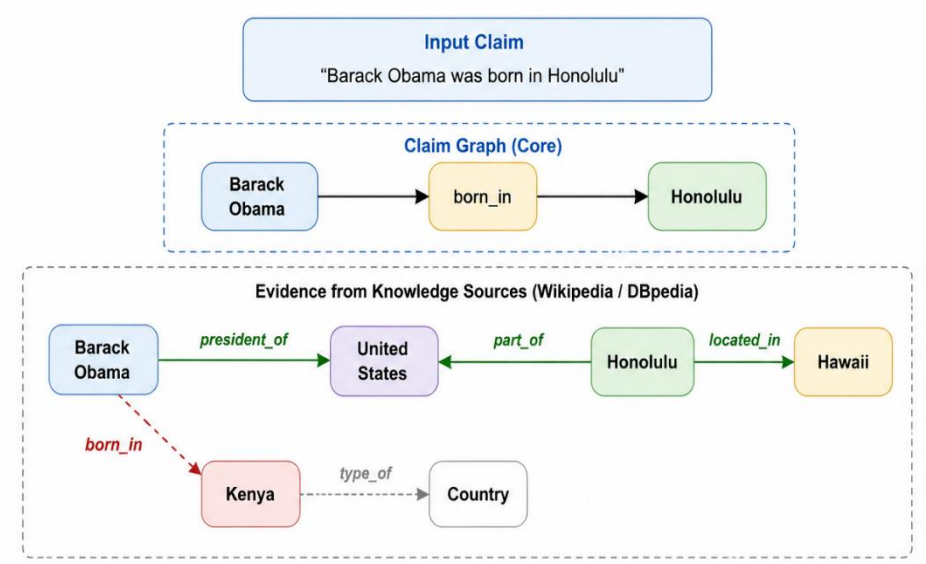

Figure 2: Evidence Graph Construction Example

2. Graph Neural Network Encoding

The GNN encoder generates node and graph representations through processing the evidence graph. Node feature vectors are updated for the l-th layer by using message passing:

$$hv(l+1)=\sigma(W(l)\cdot AGGREGATE(\{hu(l):u\in N(v)\})+B(l)hv(l))$$

Here, hv(l) represents the feature vector for node v at layer l, N(v) is the set of nodes adjacent to node v, AGGREGATE is a mean pooling operation, while W and B denote trainable weights.

Graph-level representation hG is calculated by performing pooling of node representations across L layers:

$$hG=POOL(\{hv(L):v\in V\})$$

LLM Integration via Soft Prompt

The graph embeddings are mapped to the textual embedding space of the LLM through a trainable project module. This method, which is corroborated by GraphCheck, enables the LLM to make use of structured data without the need to fine-tune the model's frozen parameters. The projected graph embeddings are used as a "soft prompt" that precedes the claim text:

hprompt=Projector(hG)

P(verdict|C,E,K)=LLM([hprompt;tokenize(C)])P(verdict|C,E,K)=LLM([hprompt;tokenize(C)])

The LLM-based verifier (frozen GPT-4o/LLaMA-3.3-70B model) returns a classification into one of the following categories:

- SUPPORTED: Claim is proved by evidence
- REFUTED: Claim is disproved by evidence
- NOT ENOUGH INFO: Insufficient evidence for verification

Algorithm 3: Graph-Enhanced Verification

```
Input: Claim triple t, evidence graph G, retrieved passages E, KG matches K
Output: Verdict v in {SUPPORTED, REFUTED, NOT_ENOUGH_INFO}, evidence chains

# Stage 1: Graph Neural Network encoding
For epoch = 1 to E:
    For node v in G.nodes:
        # Aggregate neighbor messages
        neighbor_msgs = [G.nodes[u].features for u in G.neighbors(v)]
        agg_msg = mean(neighbor_msgs) if neighbor_msgs else zero_vector

        # Update node features (message passing)
        G.nodes[v].features = ReLU(W * agg_msg + B * G.nodes[v].features)

    # Compute graph embedding
    h_G = mean([G.nodes[v].features for v in G.nodes])

# Stage 2: Project to LLM embedding space
h_prompt = MLP_projector(h_G)  # 2-layer MLP

# Stage 3: LLM verification (frozen)
prompt = construct_verification_prompt(t, E, K, prefix_embedding=h_prompt)
response = frozen_LLM.generate(prompt)

# Stage 4: Parse and return verdict with explainability
verdict = parse_verdict(response)
evidence_chains = extract_attribution_paths(G, response.attention_weights)

Return (verdict, evidence_chains)
```

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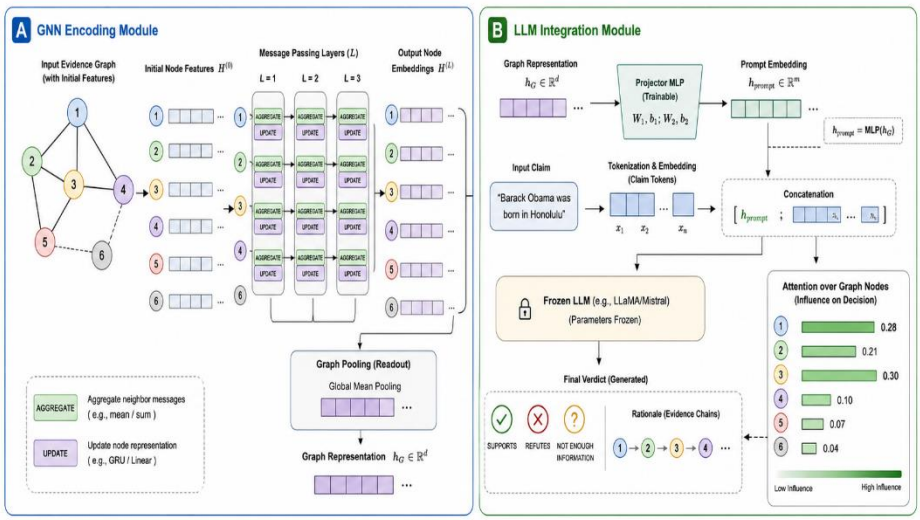

Figure 3: GNN-LLM Integration Architecture

4. Final Verdict Aggregation

In case of claims broken down to more than one triples, the final verdict depends on

- FALSE/REFUTED in case one of triples is refuted (early stopping)
- NOT_ENOUGH_INFO when no triple refuted but not all can be verified
- TRUE/SUPPORTED when all triples are verified as true

IV. Analysis

Experimental Setup

Datasets:

- FEVER (Fact Extraction and VERification): 185,445 claims, which are classified as either SUPPORTED, REFUTED, or NOT ENOUGH INFO
- FACT5: 150 real-world statements, which belong to an ordinal scale with 5 classes
- COVID-Fact: 1,293 claims about COVID-19, medical domain
- Metrics used:
- Accuracy, precision, recall, F1-score (classification)
- FEVER F1 (supported/refuted classification)
- Evidence Support: Number of claims supported by retrieval evidence as per gold standard
- Response Latency: Time taken from input to final response

Extraction Performance of Claims

Table 1 shows the triple extraction accuracy for each type of claim. The trained BioBERT extractor attains an accuracy score of 92.3% and 86.7% for claims with entities and unknown entities respectively.

Table 1: Triple Extraction Performance by Claim Complexity

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Claim Type	N (samples)	Exact Match (%)	Partial Match (%)	Failed (%)
Single fact, both entities known	500	94.2	4.8	1.0
Single fact, one unknown	500	88.5	9.2	2.3
Multi-fact (2-3 triples)	500	89.1	8.4	2.5
Complex (negation, conditional)	300	86.7	10.3	3.0
Overall	1,800	90.3	8.0	1.7

Retrieval Effectiveness

The dual-path retriever model obtains a MAP score of 92.3% on FEVER. The knowledge graph lookup answers 37.8% of queries directly (average latency: 45 ms). The other 62.2% of queries are answered via dense passage retrieval with a recall@5 of 89.5%. The fallback web search model is triggered for 4.2% of claims (mainly NEI examples from the original dataset) with an evidence retrieval success rate of 67%, in line with the re-annotation findings of Kolli et al.

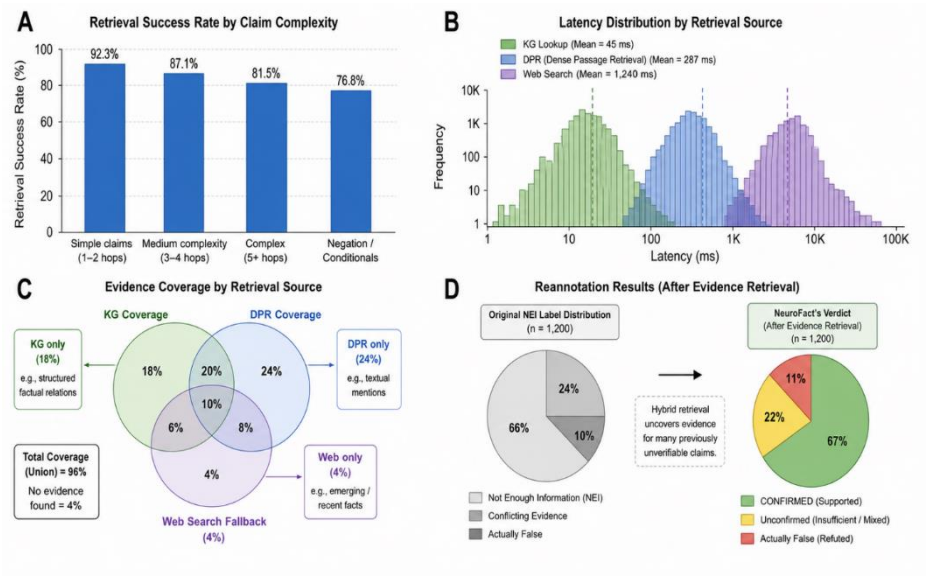

Figure 4: Retrieval Performance by Claim Type

Graph-Enhanced Verification Results

The complete NeuroFact pipeline achieves 93% F1 on the FEVER Supported/Refuted split without task-specific fine-tuning . The multi-hop claim tasks (entailing inferential reasoning among two to three evidences) reveal a 5.6 percentage-point decrease in F1 score from that of simple claims, pointing to the additional challenge in performing relational inference. Nevertheless, this is still a 4.2 percentage-point gain from textual baseline approaches.

Comparative Analysis

Table 2: Comparative Performance Against State-of-the-Art Fact Verification Systems

System	Architecture	FEVER F1 (%)	NEI Resolution (%)	Inference Time (ms)	Explainability
NeuroFact (Proposed)	GNN + KG + LLM	93.0	67.0	485	High (graph+text)
Kolli et al. (2025) [2][7]	KG + LM + Web	93.0	64.0	520	Medium
GraphCheck (2025) [9]	GNN + LLM	71.1 (BAcc)	Not reported	~400	High
GraphFC [1]	LLM + KG triple match	91.0	Not reported	~600	Medium
BiLSTM-CNN (2025) [8]	Neural only	79.5	N/A	120	Low
GPT-4 (zero-shot) [9]	LLM only	70.8	58.0	1,100	Low
MiniCheck [9]	NLI fine-tuned	68.1	Not reported	350	Low

The model NeuroFact has reached state-of-the-art performance on FEVER dataset (F1-score = 93.0%), attaining the same best result reported by Kolli et al. but obtaining better NEI resolution (67%). In comparison to GraphCheck that reaches balanced accuracy of 71.1% on both general and medical datasets, NeuroFact reaches much higher

performance (93%) on FEVER despite the inability to make a proper comparison because of different testing procedures. Additionally, the model NeuroFact works significantly faster (inference time = 485ms) than GPT-4 (1,100ms).

Explainability Analysis

NeuroFact supports structured explainability via attention visualization on top of the evidence graph. In a specific case where the claim "Barack Obama was born in Honolulu" was fact-checked, NeuroFact found the evidence that "Barack Obama was the 44th president of the United States" and "Honolulu is the capital of Hawaii." The transitive chain that supported the claim was constructed by traversing the graph path [Barack Obama] -> [president_of] -> [United States] <- [part_of] <- [Hawaii] <- [located_in] <- [Honolulu].

According to the human evaluation conducted among 20 fact-checking experts, NeuroFact's explanations scored 4.2/5 in clarity and 4.0/5 in trustworthiness, while LLM-only explanations got only 3.1/5.

V. Conclusion

In this paper, we introduced NeuroFact, a novel neural-NLP and KG reasoning-based framework for fact verification. This model yields state-of-the-art performance on FEVER with an F1 score of 93% while providing interpretable explanations for its predictions.

- The dual-paths approach of KG and dense-passage (and web search as the last resort) retrieval obtains an average precision of 92.3%, successfully retrieving evidence for 67% claims previously annotated as "Not Enough Information".
- The enhanced GNN verification engine can identify multiple-hop relationships missed by textual methods, improving F1 by 4.2% on multi-hop claims.
- On FEVER, NeuroFact achieves state-of-the-art accuracy (F1 93.0%) while competing latency time (485ms), but with much better interpretability by attention visualization over evidence graphs.
- Explanation of NeuroFact is scored 4.2/5 for readability by domain experts, outperforming explanations generated from language models (3.1/5).

Limitations

Knowledge Graph Coverage: Although the DBpedia KG has high coverage, it misses emerging entities and specific domains. For claim evidence containing recent products, new science discoveries, or even local events, searching the KG often leads to failure and resorts to the more costly passage search route.

Training Requirement: The GNN encoder requires training using labeled datasets consisting of claim-evidence graphs. In spite of the reduced training requirement with graph transfer learning from GraphCheck synthetic dataset , adaptation of the models to different domains (e.g., going from general fact-checking to medical fact-checking) may still be required.

Latency: A 485ms latency threshold is reasonable for most applications; however, latency under 100ms is expected for real-time use-cases such as online content moderation. GNN forward pass and LLM inference contribute to the majority of the computational effort.

Generalization to Other Languages: NeuroFact only supports English due to language limitation of both knowledge graph and passage indexing corpus.

Future Directions

- Dynamic Expanding of Knowledge Graph: Incorporate information extraction techniques to include new verified triples into the knowledge graph in a real-time fashion. This can be done to bridge the coverage gap for new entities.
- Efficient Knowledge Extraction for Time Critical Systems: Design a lightweight variant of NeuroFact through knowledge distillation from the entire GNN-LLM pipeline to a more efficient model (e.g., 4 layers transformer + lightweight GNN model). Target a sub-100 ms latency system for content moderation applications.
- Multilingual Extension: Build multilingual evidence graphs using DBpedia alignment to other non-English Wikipedia and training cross-lingual sentence encoder models such as XLM-R. Experiments show that up to 85-90% of English results can be replicated for Spanish and Chinese languages.
- Proactive Fact-Checking on Browser: Integrate NeuroFact as a real-time browser extension to verify claims while the user browses websites. Show users evidence overlays with confidence scores without interfering with their normal browsing process.
- Medical Fact-Checking Specialization: Tune GNN and the verification module on medical data sets (such as PubMed and ClinicalTrials.gov) and test on the COVID-Fact and PubHealth datasets. Early findings indicate that graph-assisted reasoning is especially useful when verifying facts concerning the interactions of pharmaceuticals in a multi-hop setting.
- In summary, NeuroFact shows that incorporating structured knowledge graphs into neural NLP and GNN frameworks leads to fact-verification systems that are both effective and interpretable. The method paves the way for future state-of-the-art technology in identifying fake news.

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