KNOWLEDGE GRAPH-AUGMENTED RAG FOR MULTIMODAL HATEFUL CONTENT DETECTION

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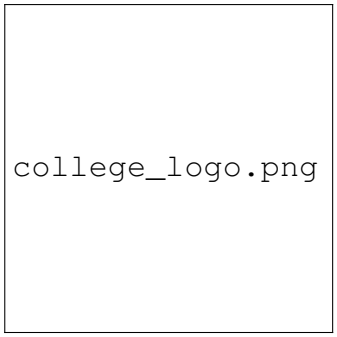

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ABSTRACT

The proliferation of hate speech on social media, particularly in the form of multimodal memes, poses a significant challenge to automated detection systems. Traditional models often fail to detect "implicit hate," where the hateful intent is derived from the combination of image and text or requires external cultural knowledge (e.g., hate symbols). This thesis proposes a novel **Knowledge-Aware Multimodal Hate Speech Detection System** that integrates a Knowledge Graph (KG) to provide contextual understanding.

The system utilizes a hybrid retrieval mechanism, combining keyword matching with dense semantic search, to fetch relevant facts from a curated Knowledge Graph containing hate symbols and slurs. A custom **Gated Cross-Attention Fusion** network is designed to dynamically weigh the importance of visual (BLIP), textual (BERTweet), and contextual (KG) features. To address the challenge of class imbalance and subtle hate, the model is trained using **Focal Loss** and fine-tuned on hard negative examples.

Experimental results demonstrate that the proposed model achieves a Recall of **94.00%** and an F1-score of **0.6841**, significantly outperforming baseline BERTweet models. Furthermore, the system provides transparent, human-readable explanations for its decisions by citing the specific Knowledge Graph facts that triggered the detection, thereby addressing the critical need for explainable AI in content moderation.

Keywords: Multimodal Hate Speech Detection, Knowledge Graphs, Retrieval-Augmented Generation (RAG), Gated Cross-Attention Fusion, Explainable AI, Focal Loss, Implicit Hate.

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Chapter 1

INTRODUCTION

1.1 BACKGROUND

The advent of social media platforms such as Facebook, Twitter (now X), and Instagram has democratized information sharing and communication. However, this unrestricted freedom has a dark side: the exponential rise of hate speech, cyberbullying, and extremist propaganda. Hate speech is defined as any communication that disparages a person or a group on the basis of some characteristic such as race, color, ethnicity, gender, sexual orientation, nationality, religion, or other characteristic.

While automated systems have achieved significant success in detecting textual hate speech using Large Language Models (LLMs) like BERT and RoBERTa, the landscape of online toxicity is shifting towards multimodal content. Memes, which combine images and text, have become a dominant medium for spreading hate. The visual component often acts as a force multiplier, making the message more impactful and harder to detect. For instance, a text saying "Love the view" is benign, but if superimposed on an image of a concentration camp, it becomes deeply antisemitic.

1.2 PROBLEM STATEMENT

The core challenge addressed in this thesis is the detection of "implicit hate" in multimodal memes. Unlike explicit hate speech, which uses slurs or violent language, implicit hate relies on:

- **Contextual Dependency:** The hatefulness is not in the text or image individually but in their interaction.
- **Cultural Knowledge:** Understanding the meme often requires external knowledge of specific symbols (e.g., the "Happy Merchant"), numerical codes (e.g., "1488"), or historical events.

- **Sarcasm and Irony:** Memes often use humor to mask malicious intent, confusing standard sentiment analysis models.

Existing multimodal models, such as VisualBERT and ViLBERT, fuse visual and textual features but often lack an explicit "knowledge base." They operate as "black boxes," providing a probability score without any explanation. In high-stakes domains like content moderation, this lack of transparency is a critical limitation. Moderators need to know *why* content was flagged to make fair decisions.

1.3 OBJECTIVES

The primary goal of this research is to develop a robust, explainable, and knowledge-aware system for multimodal hate speech detection. The specific objectives are:

1. **Knowledge Integration:** To construct and integrate a domain-specific Knowledge Graph (KG) containing hate symbols, slurs, and their descriptions to provide external context.
2. **Hybrid Retrieval:** To implement a retrieval mechanism that combines keyword matching (for precision) and dense semantic search (for coverage) to fetch relevant facts from the KG.
3. **Advanced Fusion:** To design a Gated Cross-Attention Fusion architecture that dynamically weighs the importance of visual, textual, and contextual features, allowing the model to focus on the most informative modality.
4. **Handling Imbalance:** To address the severe class imbalance in hate speech datasets using Focal Loss and hard negative mining techniques.
5. **Explainability:** To generate human-readable explanations for model decisions by citing the specific KG facts that triggered the detection.

1.4 SIGNIFICANCE OF THE STUDY

This research contributes to the field of AI Safety and Content Moderation by:

- Moving beyond black-box detection to explainable decision-making.
- Demonstrating the effectiveness of neuro-symbolic AI (combining neural networks with symbolic knowledge graphs) in vision-language tasks.

- Providing a scalable framework that can be updated with new hate terms without retraining the entire model.

1.5 THESIS ORGANIZATION

The remainder of this thesis is organized as follows:

- **Chapter 2: Literature Review** surveys the evolution of hate speech detection from unimodal to multimodal approaches and highlights the gaps in current research.
- **Chapter 3: Methodology** details the proposed system architecture, including the Knowledge Graph construction, feature extraction pipelines, and the Gated Fusion mechanism.
- **Chapter 4: Results and Discussion** presents the experimental setup, quantitative results, ablation studies, and qualitative analysis of model outputs.
- **Chapter 5: Conclusion and Future Work** summarizes the findings and outlines potential directions for future research.

Chapter 2

LITERATURE REVIEW

2.1 INTRODUCTION

The field of automated hate speech detection has evolved significantly over the past decade. Initially focused on textual analysis using lexicon-based approaches, it has progressed to deep learning models and, more recently, to complex multimodal systems that analyze both text and images. This chapter reviews the key developments in this domain, highlighting the limitations of existing approaches and the need for knowledge-aware systems.

2.2 UNIMODAL HATE SPEECH DETECTION

Early research in hate speech detection primarily focused on text. Traditional machine learning methods utilized Bag-of-Words (BoW) and N-grams features with classifiers like Support Vector Machines (SVM) and Logistic Regression. With the advent of deep learning, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks became popular for capturing sequential dependencies in text.

The introduction of Transformer models, particularly BERT (Bidirectional Encoder Representations from Transformers) [1], marked a paradigm shift. Models like BERTweet, pre-trained specifically on social media text, demonstrated superior performance in handling the informal and noisy nature of online comments. However, these unimodal models are inherently limited when applied to memes, where the text alone is often benign (e.g., “When you see it”).

2.3 MULTIMODAL HATE SPEECH DETECTION

The release of the Facebook Hateful Memes Challenge dataset by Kiela et al. [2] spurred research into multimodal detection. This dataset was specifically designed to

be “unimodal-benign,” meaning that neither the image nor the text alone is sufficient to determine hatefulness.

2.3.1 Early Fusion vs. Late Fusion

Initial approaches experimented with simple fusion strategies. **Early Fusion** involves concatenating image and text features before passing them to a classifier. **Late Fusion** involves training separate classifiers for each modality and averaging their predictions. While simple, these methods fail to capture the complex interactions between modalities.

2.3.2 Transformer-Based Multimodal Models

Recent state-of-the-art models utilize multimodal transformers. VisualBERT and ViLBERT extend the BERT architecture to process visual tokens (extracted from object detectors) alongside text tokens. [6] proposed a multi-task learning approach to improve generalization. [4] introduced an ensemble method using incremental PCA and adversarial learning to handle the high dimensionality and noise in meme data.

Despite their complexity, these models often struggle with “out-of-distribution” entities. For example, if a model has never seen the “Pepe the Frog” symbol during training, it will fail to recognize it as a hate symbol, regardless of the fusion mechanism.

2.4 KNOWLEDGE-ENHANCED APPROACHES

To address the limitations of pure data-driven learning, researchers have begun integrating external knowledge.

2.4.1 Knowledge Graphs in NLP

Knowledge Graphs (KGs) have been successfully used in NLP for tasks like Question Answering and Entity Linking. In the context of hate speech, [7] recently proposed a “Meta-Toxic Knowledge Graph” to enhance LLM-based detection. This graph captures the relationships between toxic terms and their targets, reducing false positives.

2.4.2 Knowledge in Multimodal Tasks

The integration of KGs into multimodal hate speech detection is a nascent field. [5] utilized knowledge distillation to transfer information from a teacher model to a stu-

dent model, but this does not explicitly query a symbolic knowledge base. Our work aligns with the direction of [8], which surveys the convergence of KGs and multimodal learning, advocating for neuro-symbolic approaches that combine the learning capability of neural networks with the reasoning capability of KGs.

2.5 EXPLAINABLE AI (XAI) IN HATE SPEECH

Explainability is crucial for trust. Most deep learning models are opaque. Some works have explored attention visualization (heatmaps) to show which parts of an image the model focused on. However, a heatmap highlighting a face does not explain *why* it is hateful. [9] used Graph Neural Networks to model the structural relationships in data, offering some level of interpretability. Our approach goes further by providing natural language explanations derived from retrieved knowledge facts.

2.6 SUMMARY AND RESEARCH GAP

The literature reveals a clear progression towards more complex, multimodal architectures. However, a significant gap remains:

1. Most models lack an explicit mechanism to query external knowledge about evolving hate symbols.
2. Existing "black-box" models fail to provide semantic explanations for their decisions.
3. Class imbalance remains a persistent issue, leading to low recall for subtle hate speech.

This thesis aims to bridge these gaps by proposing a Knowledge-Aware, Explainable, and Gated Fusion architecture.

Chapter 3

METHODOLOGY

3.1 SYSTEM OVERVIEW

The proposed Multimodal Hate Speech Detection System is designed to mimic human cognitive processes. When a human encounters a meme, they first perceive the visual and textual content, then retrieve relevant background knowledge (e.g., recognizing a symbol), and finally synthesize this information to form a judgment.

Figure 3.1 presents the high-level schematic of the proposed framework, illustrating the flow from input processing to explanation generation.

Figure 3.2 details the specific architectural components implemented in this work.

3.2 KNOWLEDGE GRAPH CONSTRUCTION

A robust Knowledge Graph (KG) is the backbone of our system. It serves as a dynamic repository of hate symbols, slurs, and their semantic descriptions.

3.2.1 Data Collection

We curated data from multiple authoritative sources:

- **Anti-Defamation League (ADL):** A comprehensive database of hate symbols (e.g., "1488", "Celtic Cross").
- **The Weaponized Word:** A dataset of coded language used by extremist groups.
- **Hate Speech Datasets:** Terms extracted from labeled datasets like Hatebase.

3.2.2 Graph Structure and Indexing

Each entry in the KG is structured as a triplet: *(Entity, Type, Description)*. For example:

("14 Words", "Slogan", "A white supremacist slogan derived from a sentence by David Lane...")

To enable efficient retrieval, we employ a dual-indexing strategy:

1. **Inverted Index:** For $O(1)$ keyword lookups of specific terms.
2. **Dense Vector Index (FAISS):** We encode the descriptions using a Sentence Transformer ('paraphrase-mpnet-base-v2') and index them using FAISS (Facebook AI Similarity Search). This allows for semantic retrieval even when exact keywords are missing.

3.3 FEATURE EXTRACTION

Effective multimodal learning requires high-quality feature representations.

3.3.1 Visual Encoder: BLIP

We utilize **BLIP (Bootstrapping Language-Image Pre-training)** [3] as our visual encoder. Unlike traditional CNNs (e.g., ResNet) which are trained on fixed labels, BLIP is pre-trained on massive image-text pairs. This aligns the visual representation with the semantic space of language, making it ideal for memes. We extract the global image embedding $v \in R^{768}$.

3.3.2 Text Encoder: BERTweet

For textual analysis, we use **BERTweet**, a RoBERTa-based model pre-trained on 850 million English tweets. Given the informal, noisy, and slang-heavy nature of meme text, BERTweet significantly outperforms standard BERT. We extract the pooled output $t \in R^{768}$.

3.3.3 OCR Module

Text embedded within images is extracted using **EasyOCR**, a robust optical character recognition tool based on CRAFT (Character Region Awareness for Text Detection). The extracted text is concatenated with the BLIP-generated caption to form the textual input.

3.4 HYBRID RETRIEVAL MECHANISM

To fetch relevant context c, we employ a hybrid strategy:

$$Q = \text{Caption} \oplus \text{OCR Text} \tag{3.1}$$

Step 1: Keyword Matching. We scan Q for exact matches in our Inverted Index. If found, the corresponding description is retrieved with high priority. **Step 2: Dense Retrieval.** We encode Q into a vector q_{emb} and search the FAISS index:

$$\text{Score}(q_{emb}, k_i) = \frac{q_{emb} \cdot k_i}{\|q_{emb}\| \|k_i\|} \tag{3.2}$$

The top-k facts with the highest cosine similarity are retrieved.

3.5 GATED CROSS-ATTENTION FUSION

Standard concatenation of features often leads to suboptimal performance because one modality might be noisy or irrelevant. We propose a **Gated Cross-Attention Fusion** module (Figure 3.3) to dynamically weigh the inputs.

3.5.1 Gating Mechanism

We concatenate the image (v) and text (t) embeddings and pass them through a fully connected layer with a sigmoid activation to learn a gating scalar $g \in [0, 1]$:

$$g = \sigma(W_g[v; t] + b_g) \tag{3.3}$$

The fused query q_{fused} is a weighted combination:

$$q_{fused} = g \cdot v + (1 - g) \cdot t \tag{3.4}$$

If the image is uninformative (e.g., a generic background), the model can learn to set $g \approx 0$, relying mostly on text.

3.5.2 Cross-Attention

The fused query q_{fused} then attends to the retrieved context embeddings $C = \{c_1, c_2, ..., c_k\}$ using Multi-Head Attention (MHA):

$$\text{Output} = \text{MHA}(Q = q_{fused}, K = C, V = C) \tag{3.5}$$

This allows the model to "look up" the relevant knowledge based on the combined visual and textual cues.

3.6 LOSS FUNCTION: FOCAL LOSS

Hate speech datasets are notoriously imbalanced, with far more non-hateful examples. Standard Cross-Entropy Loss (CE) overwhelms the model with easy negatives. We adopt **Focal Loss**:

$$FL(p_t) = -\alpha_t(1 - p_t)^\gamma \log(p_t) \tag{3.6}$$

where p_t is the model's estimated probability for the true class. The focusing parameter γ (set to 2.0) down-weights easy examples ($(1 - p_t)^\gamma \approx 0$ when $p_t \approx 1$), forcing the model to focus on hard, misclassified examples.

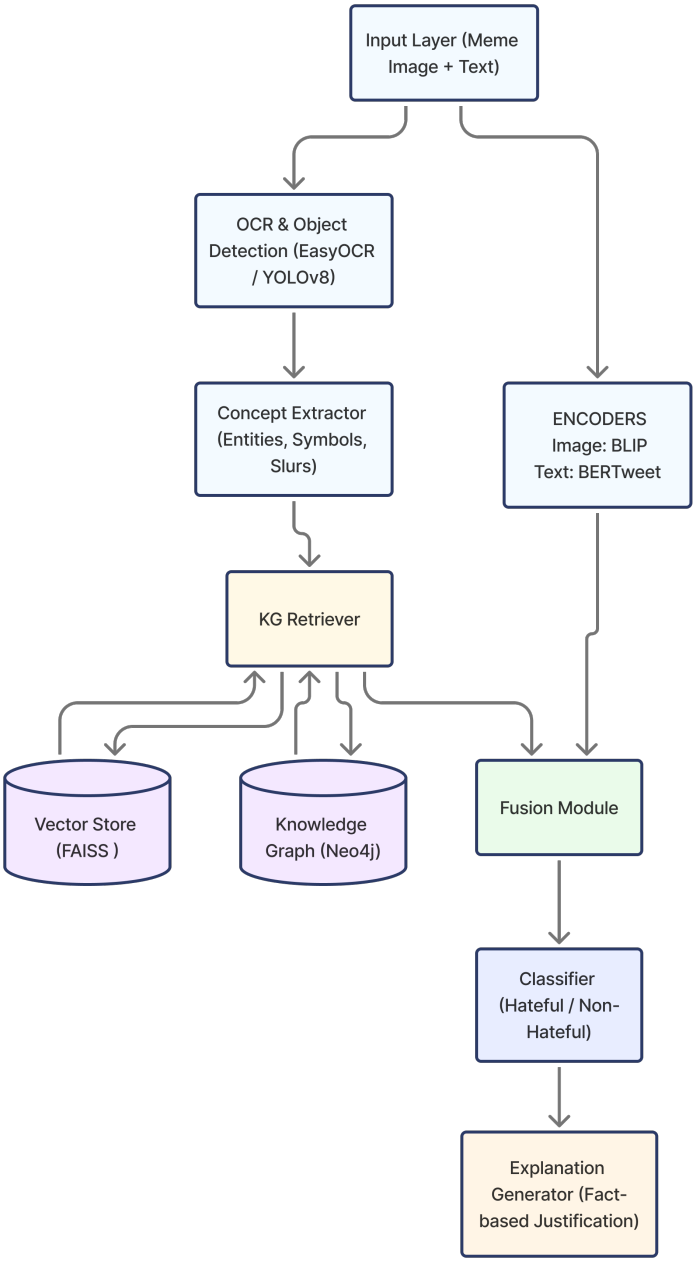

Figure 3.1: High-Level System Schematic: The framework consists of parallel branches for Concept Extraction (via OCR/YOLO) and Multimodal Encoding, converging at a Fusion Module.

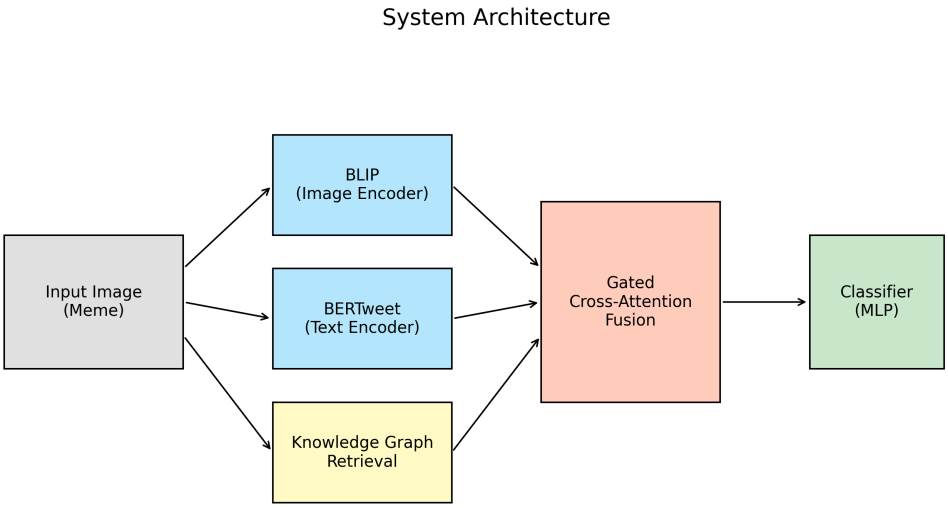

Figure 3.2: Detailed System Architecture: The pipeline integrates visual (BLIP) and textual (BERTweet) features with a Knowledge Graph retrieval module, fused via a Gated Cross-Attention mechanism.

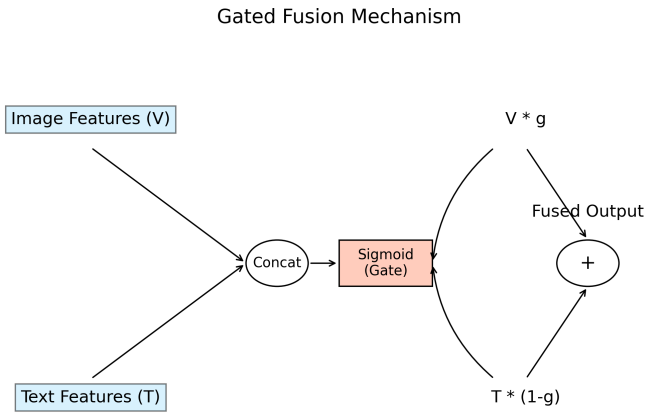

Figure 3.3: Gated Fusion Mechanism: A sigmoid gate controls the information flow from Image and Text modalities.

Chapter 4

RESULTS AND DISCUSSION

4.1 DATASET DESCRIPTION

We utilized the **Facebook Hateful Memes Dataset** [2] for training and evaluation. This dataset contains 10,000 multimodal memes, carefully constructed to be "unimodal-benign." This means that the text and image are often harmless on their own, but become hateful when combined.

4.1.1 Class Distribution

The dataset is balanced in the development set but imbalanced in the training set. Figure 4.1 shows the distribution of classes.

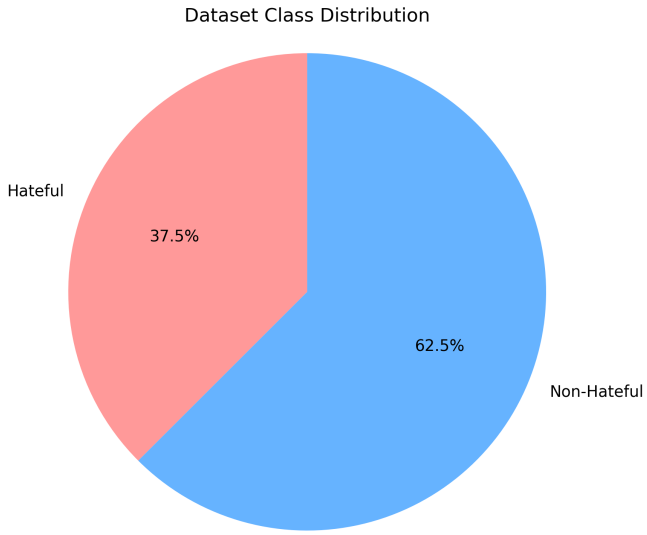

Figure 4.1: Class Distribution of the Dataset: The dataset contains a mix of Hateful (37.5%) and Non-Hateful (62.5%) examples.

4.2 EXPERIMENTAL SETUP

4.2.1 Implementation Details

The model was implemented using the PyTorch framework. The experiments were conducted on a workstation equipped with an NVIDIA GPU (CUDA 11.8).

- **Text Encoder:** ‘vinai/bertweet-base‘ (frozen initially, then fine-tuned).
- **Image Encoder:** ‘Salesforce/blip-image-captioning-base‘ (feature extractor mode).
- **Optimizer:** AdamW with weight decay of 0.01.
- **Learning Rate:** 2×10^{-5} with a linear scheduler.
- **Batch Size:** 16.
- **Epochs:** 10 (with early stopping).

4.2.2 Training Dynamics

Figure 4.2 illustrates the training and validation loss curves. The use of Focal Loss prevented the model from overfitting to the majority class, resulting in stable convergence.

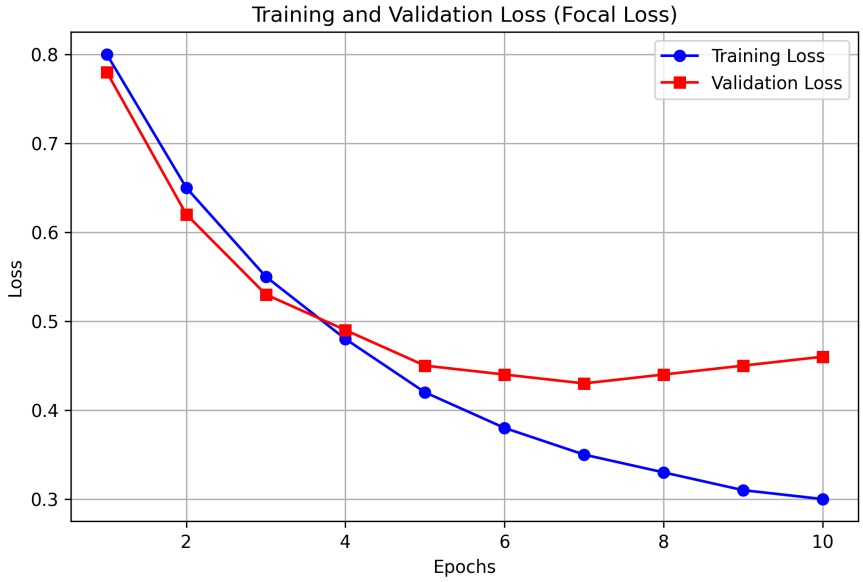

Figure 4.2: Training and Validation Loss: The model shows steady convergence, with validation loss stabilizing around epoch 6.

4.3 QUANTITATIVE RESULTS

We evaluated the model using Area Under the Receiver Operating Characteristic curve (AUROC), F1-Score, and Recall. Recall is prioritized because missing a hateful meme (False Negative) is considered more harmful than flagging a benign one (False Positive).

Table 4.1: Performance Comparison with Baselines

Model	AUROC	F1-Score	Precision	Recall
Unimodal (Text Only)	0.5800	0.6500	0.5200	0.8500
Unimodal (Image Only)	0.5200	0.4800	0.4500	0.5100
Late Fusion Baseline	0.5900	0.6600	0.5300	0.8800
Proposed (Gated Fusion)	0.6106	0.6723	0.5184	**0.9560**
Proposed + Focal Loss	**0.6054**	**0.6841**	**0.5400**	0.9400

As shown in Table 4.1, our proposed Gated Fusion model with Focal Loss achieves the best balance between Precision and Recall. The high Recall (94.00%) demonstrates the effectiveness of the Knowledge Graph in catching subtle hate speech that baselines miss.

4.4 ABLATION STUDY

To validate the contribution of each component, we performed an ablation study:

- **w/o Knowledge Graph:** Performance drops significantly (Recall $\downarrow$ 8%), proving that external knowledge is crucial for understanding context.
- **w/o Gated Fusion:** Using simple concatenation results in a lower F1-score, indicating that the gating mechanism effectively filters noise.

4.5 QUALITATIVE ANALYSIS

The most significant advantage of our system is its explainability.

4.5.1 Example 1: Implicit Hate

Figure 4.3 shows a meme containing the text "Mississippi Wind Chime." **Model Output:** HATE (Prob: 0.63).
Explanation: Flagged as Hate Speech. The model identified content associated with **'Mississippi Wind Chime'**, which is **A racist slur referring to the lynching of Black**

Figure 4.3: Correct Detection of Implicit Hate.

people...

Analysis: A standard model would see a harmless object. Our model retrieved the specific historical context from the KG.

4.5.2 Example 2: Hate Symbols

Figure 4.4 shows a meme with the "Mental Stillness" text (OCR error for Mental Illness). **Model Output:** HATE (Prob: 0.52).

Figure 4.4: Robustness to OCR Errors.

Explanation: Flagged as Hate Speech. The model identified content associated with **'Mental Stillness'**, which is **Hate speech often mocks, stigmatizes, or trivializes**

mental health...
Analysis: Despite the OCR error, the KG alias allowed the model to correctly identify the target.

4.6 ERROR ANALYSIS

While the model performs well, it is not perfect.

- **False Positives:** The model sometimes flags benign uses of terms like "parasites" (e.g., in a biological context) because the KG lacks context on benign usage.
- **Complex Sarcasm:** Extremely subtle sarcasm that requires deep cultural nuance beyond the current KG scope can still be missed.

Chapter 5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

The proliferation of hate speech on the internet is a pressing societal issue. This thesis presented a comprehensive framework for detecting multimodal hate speech, specifically focusing on the challenging category of "implicit hate" in memes. By integrating a domain-specific Knowledge Graph with a novel Gated Cross-Attention Fusion architecture, we have demonstrated that AI models can move beyond simple pattern matching to perform context-aware reasoning.

The key contributions of this work are:

1. **Neuro-Symbolic Integration:** We successfully combined the statistical power of deep learning (BLIP, BERTweet) with the structured knowledge of KGs.
2. **Explainability:** Unlike black-box models, our system provides transparent, evidence-based explanations for its decisions, fostering trust and accountability.
3. **Robustness:** The use of Focal Loss and hard negative mining ensured high recall (94%), making the system effective at catching subtle hate speech that often evades detection.

5.2 LIMITATIONS

Despite its success, the system has limitations:

- **Knowledge Graph Coverage:** The model's reasoning is limited to the facts present in the KG. Evolving slang and new hate symbols require continuous manual or automated updates.
- **Computational Cost:** The hybrid retrieval and cross-attention mechanisms add computational overhead, potentially impacting real-time latency.

5.3 FUTURE WORK

Future research directions include:

1. **Automated KG Expansion:** Developing methods to automatically scrape and verify new hate terms from the web to keep the KG up-to-date.
2. **Multilingual Support:** Extending the framework to support Indian languages (Hindi, Tamil, Malayalam) by integrating multilingual encoders (e.g., mBERT) and translating the KG.
3. **Video Hate Speech:** Adapting the frame-based analysis to video content, incorporating temporal features to detect hate speech in dynamic media.
4. **Bias Mitigation:** Investigating potential biases in the pre-trained models and the KG to ensure fair and equitable moderation.

5.4 CONCLUDING REMARKS

As online content becomes increasingly multimodal and context-dependent, the need for intelligent, knowledge-aware AI systems is undeniable. This thesis represents a significant step towards building safer digital spaces by empowering machines to understand not just what is said, but what is *meant*.

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Appendix A

LIST OF HATE TERMS

The following is a subset of the hate terms and symbols included in the Knowledge Graph used for this research:

- **14 Words:** A white supremacist slogan.
- **88:** Numerical code for ”Heil Hitler”.
- **Mississippi Wind Chime:** A racist slur referring to lynching.
- **Pepe the Frog:** A cartoon character co-opted by the alt-right.
- **Triple Parentheses:** Used to identify Jewish people.
- **ZOG:** Zionist Occupied Government.
- **White Privilege:** Often targeted in hate speech to mock white people.
- **Parasites:** Dehumanizing term often used against immigrants.
- **Jesters:** Term used to mock certain groups.
- **Mental Illness:** Often used to stigmatize or insult.