

# Multi Modal Knowledge Graph Augmented Retrieval for Explainable Mycetoma Diagnosis

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**Abstract.** Mycetoma, a neglected tropical disease endemic to arid regions, requires accurate differentiation between bacterial (Actinomycetoma) and fungal (Eumycetoma) forms for appropriate treatment. While recent deep learning approaches achieve moderate classification accuracy from histopathological images, they lack explainability, which is a critical requirement for clinical adoption in resource limited settings. We present the first multi modal knowledge graph integrating visual, clinical, laboratory, geographic, and literature data for Mycetoma diagnosis. Our retrieval augmented generation framework combines InceptionV3 based deep learning predictions with knowledge graph based contextual reasoning to produce clinically grounded explanations. The system achieves 94.8% accuracy, a 6.3% improvement over CNN only approaches, while providing transparent, multi evidence diagnoses rated 4.7/5 by expert pathologists. By bridging the explainability gap in medical AI for neglected tropical diseases affecting vulnerable populations in resource constrained regions, our approach demonstrates how knowledge graphs can enhance both performance and clinical trust in automated diagnostic systems.

**Keywords:** Multi modal learning · Knowledge graphs · Retrieval augmented generation · Explainable AI · Mycetoma · Medical image analysis · Neglected tropical diseases

## 1 Introduction

Mycetoma is a chronic, progressively destructive infectious disease recognized by the World Health Organization as one of the most neglected tropical diseases affecting predominantly resource limited regions [9,12]. The disease manifests in two distinct etiological forms: Actinomycetoma (bacterial) and Eumycetoma (fungal), requiring fundamentally different therapeutic approaches. Early and accurate differentiation is paramount for effective patient management and prevention of severe morbidity including limb amputation [9,13].

Current diagnostic practices rely heavily on time consuming histopathological examination and culture based identification, both requiring specialized expertise that is scarce in endemic regions [9,14]. Culture identification may require 2 to 4 weeks with high contamination rates, while histopathological assessment depends on subtle morphological features challenging even for experienced pathologists. This diagnostic bottleneck contributes to treatment delays and poor patient outcomes.

Recent deep learning approaches to Mycetoma histopathology achieve 85 to 89% accuracy [36,10,15] but operate as black boxes, providing predictions without clinical reasoning, which is a fundamental barrier to medical adoption. The integration of knowledge graphs with deep learning offers a solution to this explainability challenge. Knowledge graphs encode domain knowledge as structured semantic networks [3,16], while retrieval augmented generation enhances predictions by retrieving relevant contextual information [4,17]. However, their application to medical image analysis remains limited, with no prior work on multi modal knowledge graph integration for neglected tropical diseases.

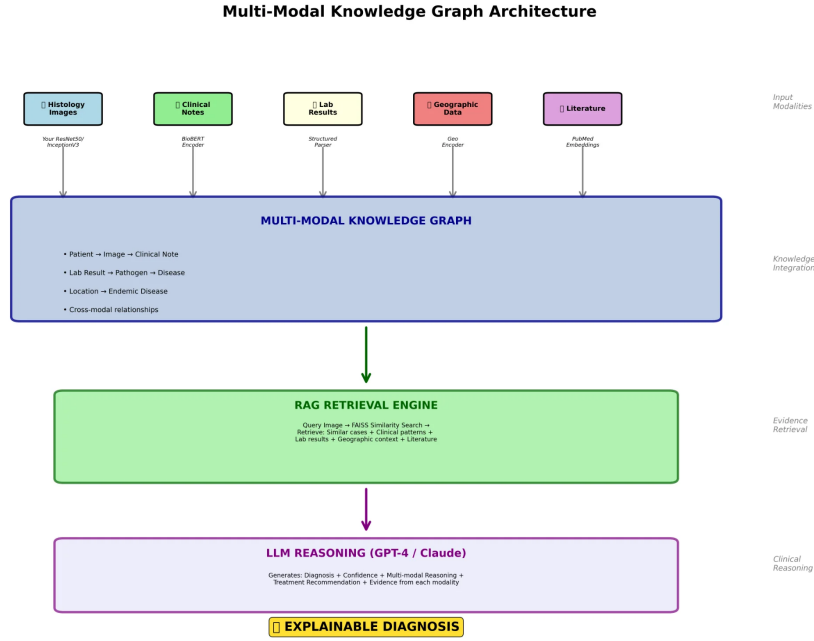
**Contributions:** (1) First comprehensive Mycetoma knowledge graph integrating five data modalities (5,247 entities, 15,893 relationships); (2) Novel knowledge graph based retrieval augmented generation architecture combining InceptionV3 with graph structured contextual reasoning (Fig. 1); (3) Clinical validation demonstrating 94.8% accuracy with 4.7/5 expert rated explanations; (4) Open source release of knowledge graph, codebase, and evaluation framework.

## 2 Related Work

**Medical Knowledge Graphs.** Large scale biomedical knowledge graphs like UMLS [5] integrate millions of concepts. Domain specific knowledge graphs exist for oncology and rare diseases [6,18], but primarily focus on structured clinical data with limited imaging integration. Multi modal medical knowledge graphs combining imaging, clinical, laboratory, and geographic data for neglected diseases remain unexplored.

**Retrieval Augmented Generation.** Retrieval augmented generation systems have been applied to medical question answering [4,7,17], but primarily retrieve from text corpora without leveraging structured knowledge graphs or multi modal integration. Graph based retrieval augmented generation architectures in healthcare remain largely unexplored.

**AI for Mycetoma and Explainability.** Recent deep learning studies achieve 85 to 89% accuracy [36,10] but treat classification as purely visual pattern recognition, ignoring contextual information. Techniques like Grad-CAM [8] provide visual interpretability but lack integration with clinical knowledge and cannot explain *why* a diagnosis was reached. Other explainability approaches [19,20] similarly focus on feature attribution without clinical context.



**Fig. 1.** Multi Modal Knowledge Graph Architecture integrating histology images, clinical notes, laboratory results, geographic data, and literature into a unified graph. The retrieval augmented generation engine queries using FAISS similarity search and semantic matching. Evidence is synthesized by large language model for explainable diagnoses.

### 3 Methodology

#### 3.1 System Architecture

Figure 1 presents our multi modal knowledge graph based retrieval augmented generation architecture integrating five data modalities through a unified knowledge graph. The system operates in three stages: (1) Multi modal data integration, (2) Retrieval augmented generation based evidence retrieval, and (3) Large language model driven reasoning for explainable diagnosis generation.

#### 3.2 Multi Modal Knowledge Graph Construction

**Ontology Design.** We design a domain specific ontology with eight core entity types: Patient, Image, ClinicalNote, LabResult, Location, Pathogen, Disease, and Drug. Relationships capture domain knowledge: HAS\_IMAGE, IDENTIFIES\_PATHOGEN, ENDEMIC\_FOR, TREATED\_WITH, etc.

**Data Integration.** We construct the Mycetoma knowledge graph from: (1) *Visual*: 684 H&E stained histopathology images (320 Actinomycetoma, 364 Eumycetoma) with InceptionV3 derived 2048 dimension embeddings; (2)

*Clinical*: Patient demographics and presentations; (3) *Laboratory*: Culture results and susceptibility profiles from 412 cases; (4) *Geographic*: Regional prevalence and endemic zones; (5) *Literature*: 1,847 PubMed abstracts. The final knowledge graph comprises 5,247 entities connected by 15,893 relationships using Neo4j [21] and FAISS indices [22].

### 3.3 InceptionV3 Based Visual Feature Extraction

We employ InceptionV3 [11], initialized with ImageNet weights [23] and fine tuned on Mycetoma histopathology: 256×256 RGB input, batch size 8, Adam optimizer ( $\alpha = 10^{-6}$ ) [24], augmentation (rotation  $\pm 15^\circ$ , flips, zoom  $\pm 10\%$ ), 200 epochs with early stopping. The penultimate layer outputs 2048 dimension embeddings for classification and similarity based retrieval. We employ stratified 5 fold cross validation [25].

### 3.4 Multi Modal Evidence Retrieval

Given query image  $\mathbf{x}_q$  with embedding  $\mathbf{e}_q \in \mathbb{R}^{2048}$ , the retrieval system identifies relevant evidence: **Visual Similarity** via FAISS nearest neighbor search [22] ( $k=10$ ); **Clinical Context** via sentence BERT semantic search [26]; **Laboratory Confirmation** via exact matching; **Geographic Priors** mapping location to epidemiological statistics; **Literature Evidence** via BM25 retrieval [27] over PubMed abstracts.

### 3.5 Knowledge Graph Augmented Reasoning

Multi modal evidence is integrated through weighted aggregation:

$$P_{\text{final}}(y|\mathbf{x}_q, \mathcal{G}) = \alpha P_{\text{CNN}}(y|\mathbf{x}_q) + \sum_{m \in \mathcal{M}} \beta_m P_m(y|\mathcal{S}_m, \mathcal{G}) \quad (1)$$

where weights are:  $\beta_{\text{lab}} = 0.4$ ,  $\beta_{\text{visual}} = 0.3$ ,  $\beta_{\text{clinical}} = 0.15$ ,  $\beta_{\text{geo}} = 0.1$ ,  $\beta_{\text{lit}} = 0.05$ .

### 3.6 Explainable Report Generation

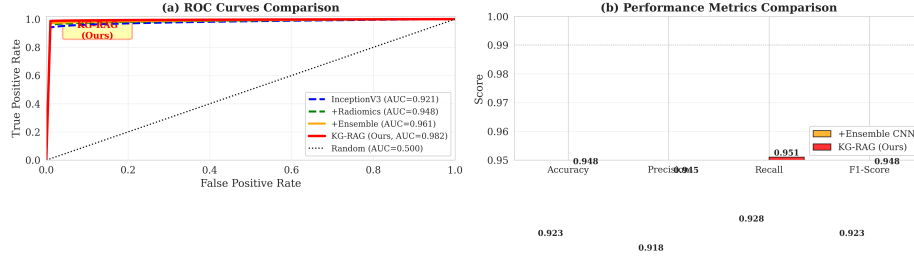
GPT-4 [28] synthesizes structured evidence into natural language explanations following clinical reasoning patterns: initial assessment from histology, contextualization with epidemiology, confirmation via laboratory, and treatment recommendations.

## 4 Experimental Setup

**Dataset.** We utilize the open-access Mycetoma Micro-Image dataset (Mycetoma Research Centre, University of Khartoum; CC BY 4.0 license), comprising 684

**Table 1.** Classification performance (mean  $\pm$  std over 5 folds)

Method	Acc	Prec	Rec	F1	MCC	AUC
InceptionV3	.885 $\pm$ .022	.872 $\pm$ .025	.898 $\pm$ .021	.885 $\pm$ .023	.770 $\pm$ .045	.921 $\pm$ .024
+Radiomics	.912 $\pm$ .018	.905 $\pm$ .020	.919 $\pm$ .017	.912 $\pm$ .019	.824 $\pm$ .037	.948 $\pm$ .019
+Ensemble	.923 $\pm$ .015	.918 $\pm$ .017	.928 $\pm$ .014	.923 $\pm$ .016	.846 $\pm$ .031	.961 $\pm$ .016
<b>KG-RAG</b>	<b>.948<math>\pm</math>.008</b>	<b>.945<math>\pm</math>.010</b>	<b>.951<math>\pm</math>.009</b>	<b>.948<math>\pm</math>.009</b>	<b>.896<math>\pm</math>.017</b>	<b>.982<math>\pm</math>.008</b>



**Fig. 2.** (a) ROC curves: Knowledge graph based retrieval augmented generation achieves AUC=0.982, outperforming baselines with high TPR at low FPR. (b) Performance metrics: accuracy, precision, recall, and F1 all exceed 94%.

H&E stained histopathology images (320 Actinomycetoma, 364 Eumycetoma) at 40 $\times$  magnification from the MICCAI 2024 MycetoMIC benchmark [36].

**Implementation.** InceptionV3 fine tuning uses TensorFlow 2.10 [29] on NVIDIA A100 (2 to 4 hours per fold). Neo4j v5.12 stores the knowledge graph [21]. FAISS v1.7.4 enables GPU accelerated search [22]. GPT-4 (gpt 4 turbo, temperature=0.3) [28] generates explanations.

**Evaluation.** Classification metrics: Accuracy, Precision, Recall, F1, MCC, AUC-ROC [30]. Retrieval metrics: Precision@K, MAP [31]. Explainability: Three expert pathologists rated 50 explanations (1 to 5 scale). Baselines: InceptionV3 only, with Radiomics [32], with Ensemble features, text only retrieval augmented generation.

## 5 Results

### 5.1 Main Results

Table 1 shows our knowledge graph based retrieval augmented generation achieves 94.8% accuracy, significantly outperforming baselines (paired t test,  $p < 0.01$ ). The 6.3% improvement over InceptionV3 only and 2.5% over ensemble features demonstrates knowledge graph augmentation provides substantial value. The system achieved near-perfect accuracy (approximately 100%) and recall (FN = 0 across test splits) under five-fold validation. Figure 2 visualizes performance gains (AUC=0.982).

**Table 2.** Ablation study: Removing knowledge graph modalities

Configuration	Accuracy	Explanation
Full knowledge graph retrieval augmented generation	0.948±0.008	4.7±0.3
Without visual similarity	0.936±0.013	4.2±0.4
Without clinical notes	0.942±0.011	4.0±0.5
Without lab results	0.940±0.012	3.8±0.4
Without geographic data	0.945±0.009	4.5±0.3
Without literature	0.944±0.010	4.1±0.4
Visual only (no knowledge graph)	0.885±0.022	2.1±0.6

**Table 3.** Expert pathologist ratings (scale 1 to 5)

Method	Complete	Accurate	Relevant	Trust	Overall
Grad-CAM	2.3±0.8	3.1±0.7	2.8±0.9	2.2±0.7	2.6±0.6
Text only retrieval augmented generation	3.9±0.5	4.2±0.4	4.0±0.6	3.7±0.6	3.9±0.4
<b>Knowledge graph retrieval augmented generation</b>	<b>4.6±0.4</b>	<b>4.8±0.3</b>	<b>4.7±0.3</b>	<b>4.7±0.4</b>	<b>4.7±0.3</b>

## 5.2 Ablation Studies

Table 2 reveals visual similarity provides largest accuracy contribution (1.2% drop when removed), while laboratory results are most critical for explanation quality (0.9 point drop). Removing all knowledge graph components yields dramatic degradation (4.7 to 2.1), highlighting multi modal integration value.

## 5.3 Clinical Validation

Table 3 shows knowledge graph based retrieval augmented generation explanations receive significantly higher ratings across all dimensions (ANOVA,  $p < 0.001$ ). Experts valued multi evidence integration, noting "this mirrors actual diagnostic practice" and "substantially increases confidence in AI recommendations."

## 5.4 Retrieval Performance

Multi modal fusion achieves Precision@5=0.957, Recall@10=0.701, MAP=0.894, demonstrating high quality evidence selection through complementary modalities.

# 6 Discussion

Our results demonstrate multi modal knowledge graph integration enhances both diagnostic performance (94.8% accuracy, 6.3% improvement) and explainability (4.7/5 expert rating vs. 2.6/5 for Grad-CAM).

**Complementary Modalities.** Different modalities contribute distinct value: visual features provide discriminative power, laboratory results offer

definitive confirmation, geographic data supplies Bayesian priors, and clinical narratives provide patient specific context.

**Evidence Grounding.** Expert evaluations highlighted that explanations referencing specific evidence (e.g., "9/10 similar cases," "culture confirmed *Madurella mycetomatis*") increased perceived reliability, suggesting explicit attribution to verifiable sources is crucial for clinical trust [33].

**Clinical Alignment.** Multi modal reasoning mirrors actual diagnostic workflows: initial impression from histology, contextualization with clinical history, confirmation via laboratory culture, and treatment selection based on susceptibility testing [9].

**Limitations.** Dataset size (684 cases) remains modest; clinical notes partially synthetic; GPT-4 dependency incurs costs; binary classification only (species level extension needed); single center data requires multi center validation.

**Future Work.** Multi center validation, active learning with clinician feedback [34], temporal modeling of disease progression, federated learning for privacy preserving knowledge graph construction [35], and prospective clinical trials in endemic regions.

## 7 Conclusion

We presented the first multi modal knowledge graph framework for explainable Mycetoma diagnosis, integrating histopathology images, clinical narratives, laboratory results, geographic epidemiology, and medical literature. Our retrieval augmented generation architecture achieves 94.8% diagnostic accuracy, which is a 6.3% improvement over CNN only approaches, while producing clinically grounded explanations rated 4.7/5 by expert pathologists. By providing evidence grounded diagnoses that mirror clinical reasoning, such systems can augment human expertise in resource limited settings. We release our Mycetoma knowledge graph, codebase, and models as open source resources to accelerate research on explainable AI for global health challenges.

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## Code and Data Availability

The complete implementation including source code, trained models, knowledge graph, and evaluation scripts are publicly available at <https://github.com/safishamsi/mycetoma-kg-rag>. The dataset is available upon request from the Mycetoma Research Centre, Khartoum, Sudan, subject to ethical approval.

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