

10th International Skin Imaging Collaboration (ISIC) Workshop
on Skin Image Analysis @ MICCAI 2025

Retrieval-Augmented VLMs for Multimodal Melanoma Diagnosis

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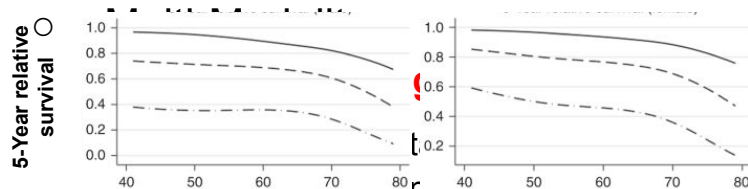
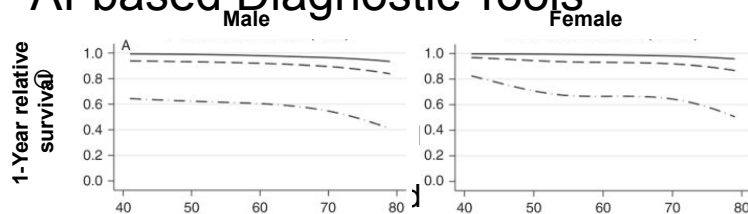
Handong Global University

Background

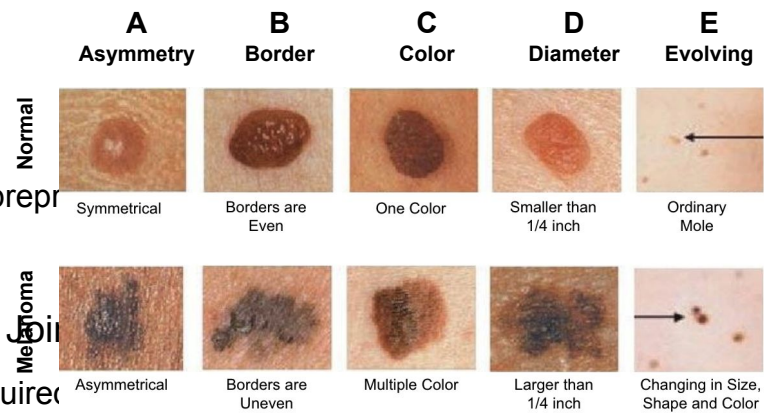
- **Malignant Melanoma**

- Early Detection Critical
 - 99% vs < 35% survival rate
- Traditional Approach: ABCDE rule
 - Clinical **expertise**: **Pattern recognition** based on experience

- **AI-based Diagnostic Tools**



1- and 5-year relative survival curves as a function of age at diagnosis [Aiden et al., 2020]



The ABCDEs of Detection Melanoma [Alfghani, 2018]

Challenges



- **VLMs** for Medical Domain
 - General-purpose training: Lack medical domain specificity
 - Fine-tuning limitation: Resource intensive, privacy constraints, data variability
- **Example-based explainability** - Find similar cases to justify decision
 - More effective at decisions if they mimicked a dermatologist's experience
 - **AI**: Classification based on **content-based image retrieval**
 - **Human**: Compare with similar cases with structured analysis

- **Retrieval-Augmented Generation (RAG)** for Medical Reasoning
 - Clinical insight: Physicians compare new cases with similar historical cases
 - External knowledge: Incorporates relevant examples without fine-tuning
 - Medical application: Retrieve similar patient cases

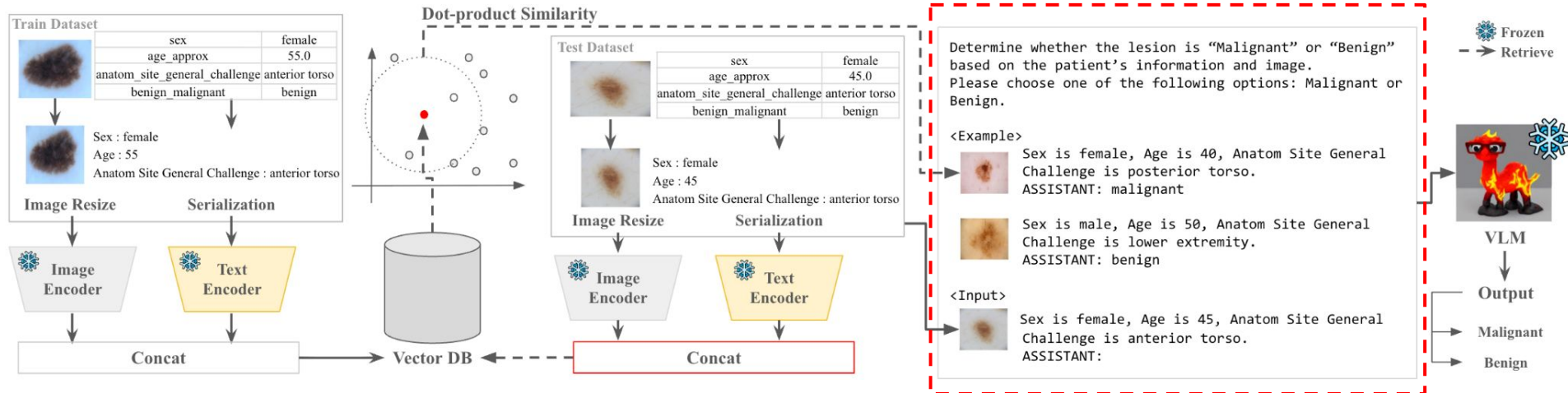
- ➡ Retrieval-augmented VLM-based diagnostic framework
- Can **VLM** be **effectively** used for dermoscopic image **classification**?
 - Does RAG **improve** performance through **example-based reasoning** without fine-tuning?

Proposed Approach

Multimodal Embedding and Case Indexing (Indexing)

Semantically-Guided Retrieval (Retrieval)

Prompt Construction and VLM Inference (Generation)



Proposed Approach

- **Prompt** Construction

- **Task Definition**

- Clear instruction to classify

- **Constrained Output**

- **Contextual Examples**

- Infer the label
- Top- K (K -shot) similar cases

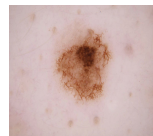
- **Target query**

- Zero-shot cases

Determine whether the lesion is “Malignant” or “Benign” based on the patient’s information and image.

Please choose one of the following options: Malignant or Benign.

<Example>

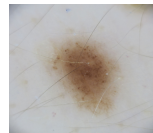


Sex is female, Age is 40, Anatomical Site General Challenge is posterior torso.
ASSISTANT: malignant



Sex is male, Age is 50, Anatomical Site General Challenge is lower extremity.
ASSISTANT: benign

<Input>



Sex is female, Age is 45, Anatomical Site General Challenge is anterior torso.
ASSISTANT:

Proposed Approach



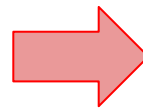
- **Template**-Based Sentence Transformation

- **3 serialization** strategies:

1. **HTML**: Preserve tabular structure
2. **Attribute-Value pair**: Reduce prompt length and improve parsing
3. **Sentence**: VLMs training style

Attribute	Value
sex	female
age_approx	55.0
anatomic_site_general_challenge	anterior torso
benign_malignant	benign

Raw Clinical Metadata

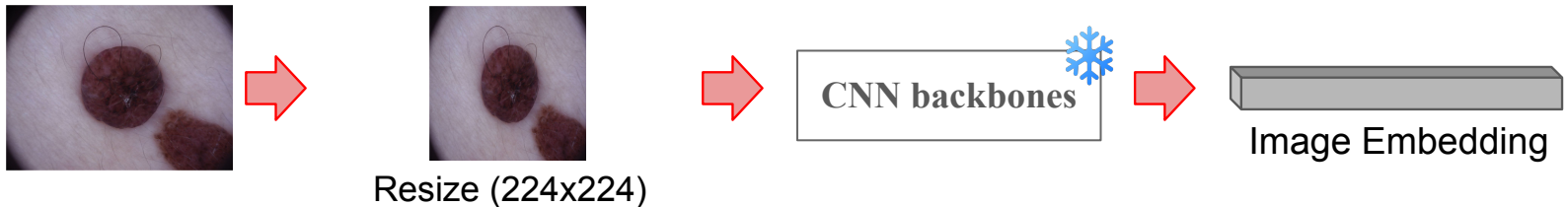


```
<table>
<tr>
<th>Sex</th>
<th>Age</th>
<th>Anatomic Site General Challenge</th>
<td>female</td>
<td>55</td>
<td>anterior torso</td>
</tr>
</table>
```

Attribute-Value Pair

Proposed Approach

- **Multimodal Embedding** and Case Indexing
 - Use **modality-specific** encoders
 - **Image**: Resized to 224x224 and encoded using CNN backbones
 - ResNeXt-50, EfficientNet-V2-M
 - **Text**: Serialized into text and embedding using a pre-trained language model

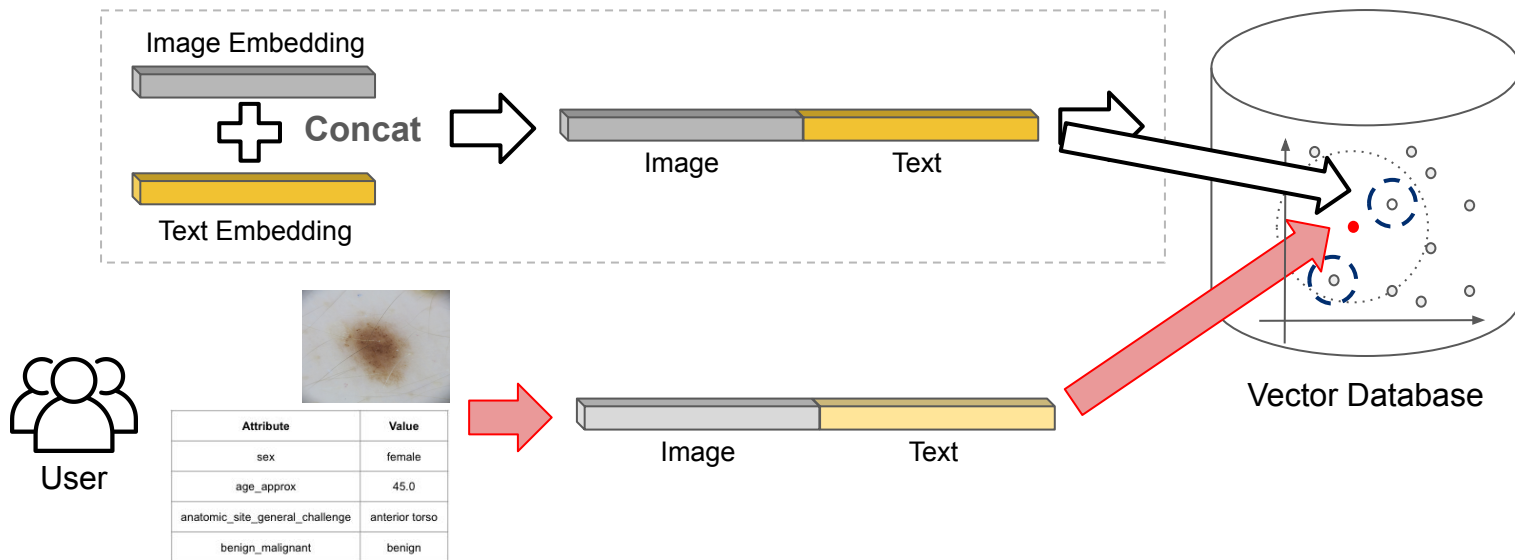


Attribute	Value
sex	female
age_approx	55.0
anatomic_site_general_challenge	anterior torso
benign_malignant	benign



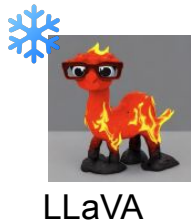
Proposed Approach

- Case **Indexing** and **Retrieval**
 - Stored in **FAISS-based** database
 - Similarity is computed using **dot-product**
- ➔ **Top-K (K-shot)** most similar patient cases retrieved as contextual examples



Proposed Approach

- **Classification** using VLMs
 - **Generate** diagnosis results in natural language text form
 - **Parse** to extract sentence containing the keywords “malignant” or “benign”



Determine whether the lesion is “Malignant” or “Benign” based on the patient’s information and image.
Please choose one of the following options: Malignant or Benign.

<Example>



Sex is female, Age is 40, Anatom Site General Challenge is posterior torso.
ASSISTANT: malignant

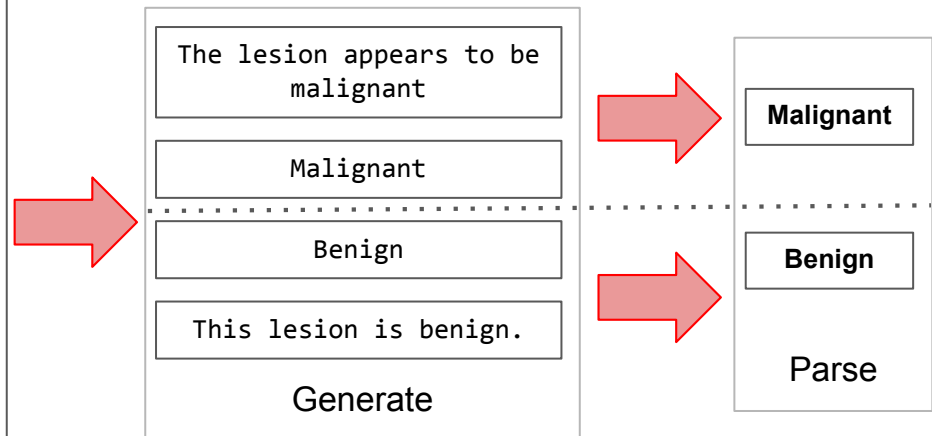


Sex is male, Age is 50, Anatom Site General Challenge is lower extremity.
ASSISTANT: benign

<Input>



Sex is female, Age is 45, Anatom Site General Challenge is anterior torso.
ASSISTANT:



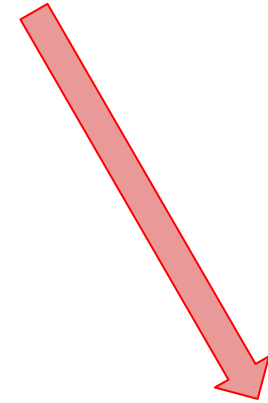
- ISIC 2019 dataset
 - **Binary** classification task: Malignant vs. Benign
 - Dermoscopic images with corresponding patient metadata (age, sex, anatomical site)
 - 70/30 split for train / test
- Evaluation metrics
 - Accuracy, Balanced accuracy, **F1 score**
- **Baselines**
 - **Image-based**: ResNeXt-50, EfficientNet-V2-M
 - **Text-based**: Random Forest, Vicuna-7B v1.5
 - **Multimodal early-fusion**: Classified via Random Forest, ReLU-activated FNN
 - **Zero-shot VLM**: LLaVA v1.5
- **Ours**
 - **Training data** (16,756 image–text pairs) indexed with FAISS
 - Retrieve **Top-2** neighbors ($K = 1, 2, 3, 4$)

Results



- Can **VLM** be **effectively** used for dermoscopic image **classification**?

- Single-Modality Limitations: Image-based and text-based achieve **< 30%** F1 score
 - Multimodal advantage: **42.7%** improvement
- VLM advantage: **74.9%** improvement
- RAG effectiveness:
 - Achieve **44%** improvement over best baseline
 - 1.8x** better than zero-shot VLM



Baselines

	Modality			Serialization	Accuracy	Balanced	
	Image	Metadata	Model			Accuracy	F1 score
Image-based	✓	-	EfficientNet-V2-M	-	0.6954	0.5061	0.2001
Text-based	-	✓	Vicuna 7B v1.5	Sentence	0.6063	0.5152	0.2613
Multimodal Early-Fusion	✓	✓	BERT + ResNeXT-50 + FNN	HTML	0.6819	0.5079	0.2132
Zero-Shot VLM	✓	✓	LLaVA 7B v1.5 hf	Attribute-Value pair	0.7126	0.6128	0.3729
Ours ($K = 2$)	✓	✓	BERT + ResNeXT-50 + LLaVA 7B v 1.5 hf	Attribute-Value pair	0.8876	0.797	0.6864

+ 42.7%

+ 74.9%

+ 44%

Results

- Does RAG **improve** performance through **example-based reasoning** without fine-tuning?
 - Similar **lesions** with corresponding patient's **metadata**

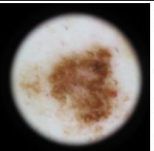
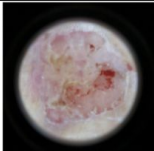
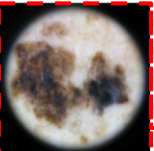

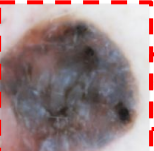
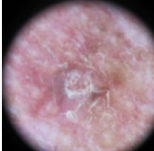



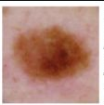
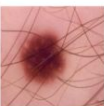


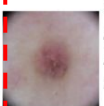
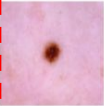
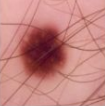

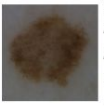
Ground Truth		Malignant	Benign
Input		Sex: male Age: 75.0 Anatom Site General Challenge: anterior torso	 Sex: female Age: 85.0 Anatom Site General Challenge: anterior torso
Retrieved Similar Cases	Ours at $K = 1$	 Sex: male Age: 75.0 Anatom Site General Challenge: anterior torso	 Sex: female Age: 85.0 Anatom Site General Challenge: anterior torso
		ASSISTANT: malignant	ASSISTANT: benign
	Ours at $K = 2$	 Sex: female Age: 65.0 Anatom Site General Challenge: anterior torso	 Sex: male Age: 70.0 Anatom Site General Challenge: anterior torso
		ASSISTANT: malignant	ASSISTANT: benign

Fig 2. (a) Misclassified case by all baselines (LLM, early-fusion, zero-shot VLM) correctly classified by our method ($K = 2$).

Results

- Effect of Input Serialization
 - **Structured** metadata encoding enhances VLM's clinical understanding

Ground Truth	Benign		Malignant	
Serialization	HTML	Attribute-value pair	Sentence	Attribute-value pair
Input	 <pre><table><tr><th>Sex</th><th>Age</th><th>Anatom Site General Challenge</th></tr> <tr><td>male</td><td>5.0</td><td>lower extremity</td></tr></table></pre>	 <pre>Sex: male Age: 5.0 Anatom Site General Challenge: lower extremity</pre>	 <pre>Sex is male, Age is 40.0, Anatom Site General Challenge is upper extremity.</pre>	 <pre>Sex: male Age: 40.0 Anatom Site General Challenge: upper extremity</pre>
Prediction	Malignant	Benign	Benign	Malignant
Ours at K =1	 <pre><table><tr><th>Sex</th><th>Age</th><th>Anatom Site General Challenge</th></tr> <tr><td>male</td><td>5.0</td><td>anterior torso</td></tr></table> ASSISTANT: benign</pre>	 <pre>Sex: male Age: 35.0 Anatom Site General Challenge: lower extremity ASSISTANT: benign</pre>	 <pre>Sex is male, Age is 45.0, Anatom Site General Challenge is head/neck. ASSISTANT: benign</pre>	 <pre>Sex: male Age: 55.0 Anatom Site General Challenge: anterior torso ASSISTANT: benign</pre>
Ours at K = 2	 <pre><table><tr><th>Sex</th><th>Age</th><th>Anatom Site General Challenge</th></tr> <tr><td>female</td><td>55.0</td><td>anterior torso</td></tr></table> ASSISTANT: benign</pre>	 <pre>Sex: male Age: 5.0 Anatom Site General Challenge: anterior torso ASSISTANT: benign</pre>	 <pre>Sex is male, Age is 55.0, Anatom Site General Challenge is anterior torso. ASSISTANT: benign</pre>	 <pre>Sex: male Age: 40.0 Anatom Site General Challenge: upper extremity ASSISTANT: malignant</pre>

- Proposed a **retrieval-augmented VLM framework** to improve melanoma classification using retrieved similar cases
- Provide **example-based explanations** via retrieved similar cases
- Achieve improved diagnostic performance without fine-tuning
- Future work
 - Extend to multi-class skin lesion classification and other multimodal clinical tasks
- Limitations
 - Depends on curated training data
 - Retrieval speed needs improvement for real-time use



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Thank you for your attention

Title **Retrieval-Augmented VLMs for Multimodal Melanoma Diagnosis**

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Advisor Charmgil Hong (charmgil@handong.ac.kr)