



# Seeing is believing! Towards Knowledge-Infused Multi-modal Medical Dialogue Generation

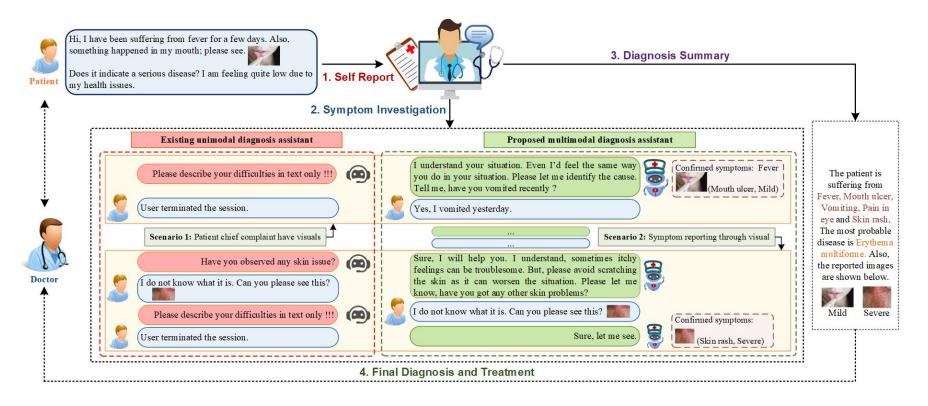
**LREC-COLING 2024** 

May 20 - May 25, 2024 Torino, Italia

> Abhisek Tiwari Research Scholar, PMRF Dept. of Computer Science and Engineering Indian Institute of Technology, Patna (IIT Patna)

#### Introduction

**Problem Statement:** We often describe our chief medical complaints using visuals; however, the traditional diagnosis assistants perform symptom/sign extraction through text only.



#### **Research Questions**

- **Importance of Visual expressions:** Does a diagnosis assistant diagnose patients more accurately and satisfactorily if it considers visual signs and their severity in addition to symptoms conveyed through text?
- Role of Dialogue Context in Identifying an Image: Can dialogue context help in identifying a sign image and its severity, which appears during the conversation?
- **Impact of External Knowledge:** What impact might global knowledge, such as knowledge of symptom-disease associations, have on the diagnosis ability of diagnosis assistants? Does the mechanism of knowledge infusion influence its efficacy?

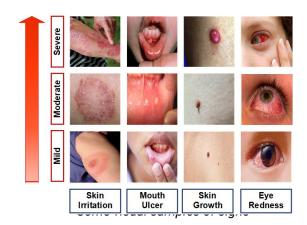
## **Key Contributions**

- Empathy and severity-aware Multi-Modal Medical Dialogue (ES-MMD): We curate an Empathy and severity-aware Multi-Modal Medical Dialogue (ES-MMD) corpus in English, where each utterance is annotated with its corresponding intent, sign, symptom, and severity level.
- Knowledge-Infused, Multi-modal Medical Dialogue Generation (KI-MMDG): We propose a transformer-based Knowledge-Infused, Multi-modal Medical Dialogue Generation (KI-MMDG) framework, which leverages a discourse-aware selective filtering strategy for knowledge distillation and a natural language understanding (NLU) module for semantic understanding of textual-visual utterances.
- State-of-the-art Performance: Our proposed, KI-MMDG, exhibits a substantial performance improvement over several non-knowledge infused uni-modal medical dialogue generation models across a variety of evaluation metrics, including human evaluation. Additionally, the DII model surpasses existing pre-trained image models in both symptom identification (by 7.84%) and severity recognition (by 2.63%).

### **ES-MMD Corpus**

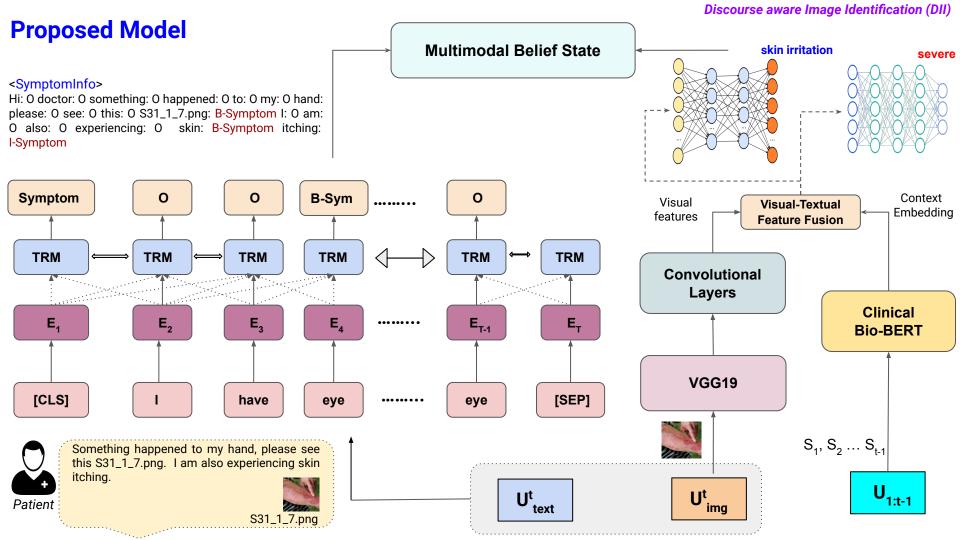
Dataset	Language	Conversation	Intent	Symptom	Multimodality	Severity
RD (Wei et al., 2018)	Chinese	×	×	×	×	×
DX (Xu et al., 2019)	Chinese	✓	×	✓	✓	×
M <sup>2</sup> - MedDialogue (Yan et al., 2021)	Chinese	✓	×	1	×	×
MedDialog-EN (Zeng et al., 2020)	English	×	×	×	×	×
MedDG (Liu et al., 2020)	Chinese	✓	×	✓	×	×
SD (Zhong et al., 2022)	English	×	×	×	×	×
ES-MMD (ours)	English	✓	1	✓	✓	1

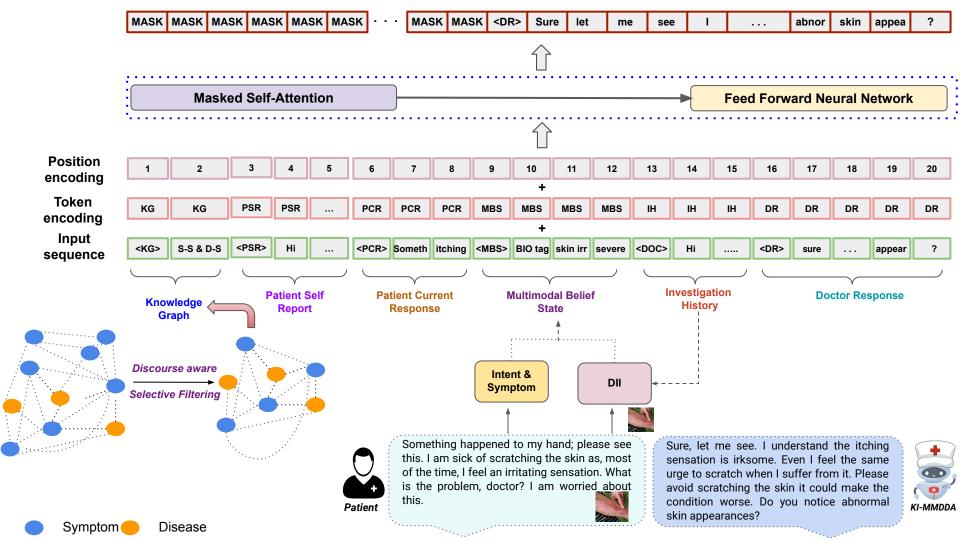
Attribute	Value
# of Dialogues	1742
# of Utterances	12466
Avg. dialogue length	7.16
# of intents	3
# of diseases	90
# of symptoms	266
# of signs	17
# of symptom images	1805





A conversation from the curated ES-MMD corpus





#### **Experimental Setup**

# Algorithm 1 Discourse-aware Selective Filtering (DSF)

```
Initialization: KG = {(s_i, s_j, a_{ij})} where s_i, s_j are nodes, a_{ij} is the edge weight.
```

**Input**: Current Knowledge Graph (KG $_t$ ), PSR: Patient Self Report, and Current Discourse (C $_t$ )

```
Output: Filtered Knowledge Graph (KG_{t+1})
```

```
1: C_t = \{(s_0), (s_1), (DII(i_2), s_2)...(s_t)\}
2: KG_{t+1} = KG_t
```

- 3: Potential\_diseases (PD) =  $\Pi_{i=1}^{i=3}$  i $^{th}$  most\_associated\_disease (PSR)
- 4: for d in PD do
- 5: triplet = (PSR, d,  $a_{PSR-d}$ )  $\Rightarrow a_{PSR-d}$ : edge (PSR, d) weight (Equation 3)
- 6:  $KG_{t+1} = append(KG_{t+1}, triplet)$
- 7: end for
- 8: for s in  $C_t[-1]$  do

```
9: ps = \prod_{i=1}^{j=3} j^{th}-most_associated_symptom(s)
```

- 10: for k in ps do
- 11:  $triplet = (s, k, a_{s-k})$
- 12:  $KG_{t+1} = append(KG_{t+1}, triplet)$
- 13: end for
- 14: end for
- 15: return  $KG_{t+1}$

- Training: (i) NLU and (ii) Dialogue Generation Module
- Train and Test split: 80% and 20%
- Total no. of epoch: 10, RTX 2080 Ti GPU, time: 2-3 hrs
- Loss func : Cross entropy
- Batch size: 4, optimizer: Adam, learning rate (6.25e-05)



### **Results**

Model	Accuracy (%)	F1-Score
CNN (Li et al., 2014)	40.99	0.4247
Inception v3 (Xia et al., 2017)	66.14	0.6475
Inception v3 + Conv Layers	72.29	0.7163
DenseNet121 (Huang et al., 2017)	68.17	0.6712
DenseNet121 + Conv Layers	75.58	0.7412
DenseNet169 (Serte et al., 2022)	72.27	0.7157
DenseNet169 + Conv Layers	78.51	0.7734
VGG19 + Conv Layers (Gupta et al., 2022)	81.11	0.7924
DII with CW=1	82.82	0.8271
DII with CW=2	85.27	0.8505
DII with CW=3	88.95 (7.84 ↑)	0.8703 (0.0779 ↑)
DII with CW=4	81.59	0.8171

Performance of different models for visual signs identification

Model	Accuracy (%)	F1-Score
VGG19+ Conv Layers (Gupta et al., 2022)	50.65	0.5086
DII with CW=1	49.34	0.4907
DII with CW=2	52.63	0.5233
DII with CW=3	<b>53.28</b> ( <b>2.63</b> ↑)	0.5117 (0.0091 †)
DII with CW=4	50.01	0.4771

DII with varying dialogue context window for severity recognition

#### **Results**

Model	BLEU 1	BLEU 2	BLEU 3	BLEU 4	BLEU	ROUGE 1	ROUGE L	METEOR
DLGNet (Oluwatobi and Mueller, 2020)	21.84	9.66	4.21	2.10	9.45	26.86	25.05	21.98
DLGNet with VSI-KG	25.48 (3.641)	12.26 (2.601)	6.86 (2.65 <sup>↑</sup> )	3.51 (1.411)	12.02 (2.571)	29.45(2.591)	28.82(2.571)	25.79(3.771)
BART (Lewis et al., 2020)	23.19	12.34	7.32	4.37	11.80	27.77	27.37	29.66
BART with VSI-KG	25.69(2.50↑)	<b>15.07(2.73</b> ↑)	9.41(2.091)	5.62(1.251)	<b>13.95(2.15</b> ↑)	29.93(2.231)	29.58(2.211)	32.41(2.751)
DialoGPT (Zhang et al., 2020)	26.59	16.16	10.52	6.92	15.05	30.63	30.22	34.07
KI-MMDG	<b>28.53(1.94</b> ↑)	<b>18.41(2.25</b> ↑)	<b>12.28</b> ( <b>1.76</b> ↑)	<b>8.34(1.42</b> ↑)	<b>16.89(1.84</b> †)	<b>32.69(2.06</b> ↑)	<b>32.25</b> ( <b>2.03</b> ↑)	<b>36.52(2.45</b> ↑)

Performance of different baselines and proposed models incorporated with the visual sign and knowledge (VS-KG) guided disease diagnosis component

Model	BLEU 1	BLEU 2	BLEU 3	BLEU 4	BLEU	<b>ROUGE 1</b>	<b>ROUGE L</b>	METEOR
DLGNet with only KG	23.54	8.65	4.85	0.99	9.51	29.18	26.01	22.78
DLGNet with only VS	23.59	10.65	5.81	2.44	10.62	28.31	25.45	26.69
DLGNet with only VSI	24.25	10.77	5.91	3.40	11.08	29.37	27.72	25.42
BART with only KG	25.03	14.20	9.30	5.91	13.61	29.04	28.60	31.11
BART with only VS	25.37	14.85	9.39	5.63	13.81	29.58	29.12	32.35
BART with only VSI	25.69	14.98	9.65	5.93	14.06	29.92	29.43	31.88
DialoGPT with complete KG(w/o DSF)	1.58	0.73	0.48	0.28	0.77	1.99	1.95	2.20
DialoGPT with only KG	27.72	17.27	11.39	7.70	16.02	31.74	31.21	35.42
DialoGPT with only VS	27.53	17.08	11.47	7.82	15.98	31.54	31.13	35.29
DialoGPT with only VSI	27.11	16.94	11.45	7.74	15.81	31.23	30.91	35.07

Ablation study– performances of the proposed KI-MMDG model with different components. Here, KG, V S, V SI, and DSF refer to the knowledge graph, visual symptom, visual & severity information, and discourse-aware filtering

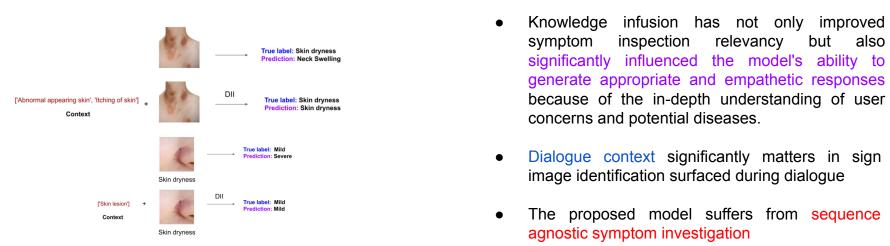
# **Key Findings**

- Dialogue context significantly matters in sign image identification surfaced during dialogue
- We observed that the infusion of the symptoms and diseases relation significantly narrows the exploration space for the agent, resulting in context-based symptom inspection and disease diagnosis.
- While knowledge is crucial, **focusing on relevant knowledge** is more significant while solving a task

#### **Analysis**

Context	Gold	DialoGPT	DialoGPT+VSI	DialoGPT+KG	KI-MMDG
Hello doctor, I am suffering from	I understand; it must be	Please be patient; it can	Please let me investigate.	I understand that the pain	I can understand how hard
Lower body pain. And because	hard. Do you also have	be treated. Do you feel	Do you feel headache?	would be hard. Do you	it is for you to sleep with this
of it, I cannot sleep properly	back pain?	headache?		also feel back pain?	pain. Let me check, do you have back pain?
I am having weight gain. I feel	You don't have to think	Weight gain is a common	Weight gain is a common	I can understand your con-	You are not alone. Weight
like I look ugly because of it	like that. You will be fine.	problem these days. You	problem these days and	cern. Weight gain can	gain is a common prob-
Do you feel fatigue? yes	You seem to have Cushing	will be fine if you take care	can be completely curable	be due to various reasons.	lem these days and can
	syndrome	of it. Do you have aches	as well. Are you suffering	Let me ask you a few	be completely curable as
		all over?	from Acne or pimples?	questions to get a better	well. Based on your symp-
			5. 25	idea of its cause. Do you have skin lesion?	toms, you have Cushing syndrome.
Hello doctor, can you please	Is there any neck	And do you have any skin	Do you have any skin	Do you have any skin	Do you have neck swelling?
check my eye? I am not sure what is wrong with it [moderate Swollen eye].	swelling?	swelling? Please show.	rash?	rash? Please show me	Please show your neck.

Some generated responses by different models for some common test cases



#### **Conclusion**

- In this paper, we proposed a knowledge-infused, multi-modal medical dialogue generation (KI-MMDG) framework
- We also introduced a discourse-aware image identification (DII) model that exploits dialogue context to identify an image and its severity effectively
- The obtained improvements and detailed ablation study firmly establish the efficacy of (a) visual signs, (b) discourse-aware selective filtering (DSF) for knowledge infusion, and (c) discourse information for identifying an image surface during the conversation



LREC-COLING 2024

LREC-COLING 2024

# Thank You!



