

Reference in the second for Ocular Surface Disease Diagnosis MICCAI202Chun-Hsiao Yeh^{1,5}, Jiayun Wang^{1,2}, Andrew D. Graham¹, Andrea J. Liu¹, Bo Tan¹, Yubei Chen³, Yi Ma^{4,5}, and Meng C. Lin^{1,5} ¹CRC, UC Berkeley ²Caltech ³UC Davis ⁴HKU ⁵UC Berkeley Introduction Our Multi-Modal Diagnostic Pipeline (MDPipe) **Current Challenges & Our Contributions Motivation:** Given clinical data and imaging, can we build a diagnostic pipeline using LLMs for Multi-Modal Diagnostic Pipeline Clinician ocular surface disease (e.g., DE, MGD, ...) diagnosis with clinically relevant rationales? I have a first visit patient

Challenge 1: Can a model process meibography images with the same level of attention and detail as a human clinician?





LLM-based Clinical

Report Summarizer

Challenge 2: Can the model make a precise and accurate diagnosis and provide clinically sound rationales for diagnoses.

→ LLM-based Clinical Report Summarizer



→ Clinical Data from real-life clinician diagnoses

Methodology

Shortcomings in MLLMs? Apply Visual Translator!



Multi-Modal

Clinical Data

: Please confirm whether Dry Eye and MGD is present or not, and why?

LLaVA-1.5: The presence of a black spot in the eye suggests that the person might have dry eye. Additionally, the black spot might be a result of MGD ...

(a)

MiniGPT-4: There is no sign of dry eye, I made this prediction because the image shows a close up view of a person's eye, with the iris and pupil visible ... hatGPT-4-Vision: I am unable to provide medical diagnoses or confirm medical conditions such as dry eye ...

() → (⇒) Visual Translator V Segmented MG Visual Data I Instance Segmentation (UNet arch.) gland length and width (mm) Automated \succ contrast, tortuosity (%) MG Morphology > percent of atrophy (%) Analysis gland density (%) MG Morphology V(I)**(b)**

He is a 35 years old Asian man,

morphology is... Can you tell me

his NIKBUT is 3.2 sec, and his

if he has any ocular surface

diseases? and why?

(F) **Clinical Raw data** "Subject 266 2 R" "Gender": "Male", Clinical "Age": "33" Measurements C "Race": "Hispanic" "TMH": 0.22, "NIKBUT": 16.81 "MG Morph" MG Morphology V(I)"PA": 0.2599686374777542, "mg density": 0.291128820870333, "avg length": 7.4117925645275875, "avg width": 0.3014360053679746, "avg_contrast": 17.543419386080856 "avg tortuosity": 0.481618317420705 "Dry Eye": "Yes" "Meibomian Gland Dysfunction": "No" "Aqueous Deficiency": "No", "Blepharitis": "Yes" Disease Diagnosis D

LLM-based Clinical Report Summarizer

LLM-Based Clinical Report Summarizer

Task Description

S(.) Your task is to generate a clinical report summary for the raw clinical metadata mentioned in the caption Please generate a human readable Q&A format by setting subject's demography, ... and morphology as the Question, while the ocular surface disease as the Answer...

Supporting Examples

"###Human: Subject 159 and left eye. The person is Female with an age of 25, and the race is Asian. The Non-Invasive Keratograph Tear Breakup Time (NIKBUT) registers at 5.4 sec...determine any ocular surface diseases in the subject? ###Assistant: The Dry Eye (DE) status for this individual is No. The Meibomian Gland Dysfunction (MGD) diagnosis is Yes..."

Prompting the Clinical Metadata

Please generate a clinical report summary for the clinical metadata I attach below..

$|\overline{\bullet}|$ Clinical Report Summary (**Q**, **A**) ###Human:

MOROCCO

Subject 266 and it's right eye. The individual is identified as Male, with an age of 33, and belongs to the Hispanic race. The Non-Invasive Keratograph Tear Breakup Time (NIKBUT) measures 16.81 sec ... The MG morphological features exhibit the average length of 7.4mm ... Could you measure if the subject has any ocular surface diseases?

###Assistant:

The Meibomian Gland Dysfunction (MGD) diagnosis for this individual is No ...

We employed an LLM-based summarizer to generate Q&A clinical reports (via GPT-4)

(a) Limitations of current MLLMs (LLaVA, GPT..) in processing visual data, (b) Our visual

translator V is designed to interpret visual data I by converting them into quantifiable MG morphology data.

to contextualize insights from both the non-narrative clinical metadata and MG morphology to enhance LLMs' learning capability.

Quantitative and Qualitative Evaluations

Comparison (General & Medical Domain LLMs)

Method /	DE				MGD			Blepharitis				
Disease	Acc.	SN	SP	F1	Acc.	SN	SP	F1	Acc.	SN	SP	F1
General LLMs without fine-tuning												
Llama	49.8	93.2	14.7	60.5	40.6	88.7	17.1	55.9	44.7	28.5	55.3	30.8
GPT-3.5	57.7	86.7	32.7	64.9	48.6	95.5	25.6	60.6	46.2	31.3	61.9	33.8
Llama2-7B	63.9	88.2	38.6	66.6	52.7	83.2	23.3	62.3	47.4	31.8	59.3	34.4
GPT-4	70.7	77.1	66.3	67.7	65.2	65.7	76.8	65.5	58.2	39.3	72.9	48.8
LLMs fine-tuned on medical domain data												
Med-Alpaca	62.5	87.3	33.5	70.3	53.4	84.7	28.2	61.9	54.9	53.8	55.8	49.7
PMC-LLaMA	73.3	73.1	77.7	75.8	63.6	70.7	61.5	64.7	60.5	50.3	74.4	56.8
MDpipe-7B (ours)	86.9	89.3	84.3	87.8	76.1	67.2	81.7	69.2	71.2	56.3	79.7	63.8
Mdpipe-13B (ours)	89.5	88.2	91.0	89.9	74.4	61.4	82.9	65.7	73.1	58.7	80.1	65.1

Clinician Preference Study - MDPipe vs GPT-4



Comparison between general and medical domain-tuned LLMs for diagnosing ocular diseases: Dry Eye (DE), Meibomian Gland Dysfunction (MGD), and Blepharitis. Evaluation criteria include accuracy, sensitivity (SN), specificity (SP), and F1 score.

Dataset (3513 entries): (Train / Test) set has (1903 / 198) metadata-only & (1257 / 155) image+metadata instances. There are a total of 878 subjects.

Comparison (Training Variables within MDPipe)

Pretrain		+ Training Va	Diagnosis Acc. (%)				
	Metadata	Morphology	MG-Express.	Real Diag.	DE	MGD	Bleph.
LLaMA2		×	×	×	83.5	65.5	69.4
			×	×	84.1	74.4	68.8
				×	85.8	75.6	70.1
					86.9	76.1	71.2

The impact of various training variables within our MDPipe on ocular disease diagnosis. It is observed that MG morphology is essential in MGD diagnosis.

score, alongside moderate Meibomian gland atrophy, may indicate mild dry eye syndrome.

Accuracy Completeness Rationale Robustness

Comparative evaluation and clinician study between MDPipe and GPT-4. Five clinicians were masked as to which model produced each output, and then asked to read and rate the two models' output on a scale from 1 (poor) to 5 (best) regarding 1) clinical accuracy, 2) diagnostic completeness, 3) diagnostic rationale, and 4) the model's robustness to handle ambiguous or incomplete patient data.

GPT-4



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