Research Letter

Evaluating the Diagnostic Accuracy of ChatGPT-4 Omni and ChatGPT-4 Turbo in Identifying Melanoma: Comparative Study

Samantha S. Sattler¹, MD; Nitin Chetla², BS; Matthew Chen³, BS; Tamer Rajai Hage⁴, BS; Joseph Chang⁵, BS; William Young Guo¹, MD; Jeremy Hugh¹, MD

¹Department of Dermatology, Stony Brook University Hospital, Stony Brook, NY, United States

²School of Medicine, University of Virginia, Charlottesville, VA, United States

³Renaissance School of Medicine, Stony Brook University, Stony Brook, NY, United States

⁴Virginia Tech, Blacksburg, VA, United States

⁵University of Passau, Passau, Germany

Corresponding Author:

Tamer Rajai Hage, BS Virginia Tech Blacksburg, VA, 24061 United States Phone: 1 7038948362 Email: tamerwh@gmail.com

Abstract

ChatGPT is increasingly used in healthcare. Fields like dermatology and radiology could benefit from ChatGPT's ability to help clinicians diagnose skin lesions. This study evaluates the accuracy of ChatGPT in diagnosing melanoma. Our analysis indicates that ChatGPT cannot be used reliably to diagnose melanoma, and further improvements are needed to reach this capability.

JMIR Dermatol 2025;8:e67551; doi: 10.2196/67551

Keywords: melanoma; skin cancer; chatGPT; chat-GPT; chatbot; dermatology; cancer; oncology; metastases; diagnostic; diagnosis; lesion; efficacy; machine learning; ML; artificial intelligence; AI; algorithm; model; analytics

Introduction

Artificial Intelligence (AI) is being increasingly integrated into health care [1]. Multiple AI systems exist in medicine, including large language models (LLMs), neural networks, and predictive models. While studies have demonstrated AI's mixed precision and accuracy, the technology is poised to assist with data-driven diagnostics in dermatology [2].

There has a been rapid popularization of the LLM, ChatGPT for home-based medical inquiries [3]. Minimal research exists on ChatGPT's accuracy in detecting melanoma. Given that patients are increasingly presenting internet-derived diagnostics during cancer consultations, it is imperative to understand the capabilities of commonly used AI engines, such as ChatGPT [4]. In this study, we compare the capabilities of two models—ChatGPT-4 Omni (GPT-40) and ChatGPT-4 Turbo (GPT-4 Turbo)—in identifying melanoma versus "not melanoma" skin lesions. These LLMs were chosen due to their accessibility and ability to answer image-based dermatology board-style questions correctly [5].

Methods

OpenAI was used to query GPT-4o and GPT-4 Turbo for classifying dermatoscopic images of melanoma versus "not melanoma" (ie, melanocytic nevi, basal cell carcinoma, actinic keratoses, dermatofibromas, and vascular lesions) selected from the HAM10K database, which contains >10,000 dermatoscopic images collected over 20 years from multiple populations, and verified by histopathology or confocal microscopy [6].

Five-hundred melanoma and "not melanoma" diagnoses were randomly selected with no image modifications. A standardized prompt was used: "This is an image of the step 1 examination. The multiple-choice question is as follows: Based on the image, does the patient have (A) melanoma

JMIR DERMATOLOGY

(B) no melanoma? Only output the answer as A or B." Incomplete responses were categorized as "not a number" and excluded.

To assess the effect of binary versus nonbinary prompting, an additional 1000 randomly selected "not melanoma" dermatoscopic images were classified by GPT-40, given its higher sensitivity compared to GPT-4 Turbo. Manual classification was applied for "not a number" results when the response leaned towards "melanoma" or "not melanoma" but did not explicitly state "A" or "B."

Results

The diagnostic accuracies of GPT-4 Turbo and GPT-40 were 0.546 (95% CI 0.515-0.577) and 0.577 (95% CI 0.547-0.608), respectively. There was no significant

difference in accuracy between the two models (P=.10). GPT-4 Turbo demonstrated a sensitivity of 76.3%, specificity of 32.9%, and false-positive rate of 67.1% (Table 1). GPT-40 yielded a higher sensitivity of 96.8% (P<.001), lower specificity of 18.4% (P=.09), and higher false-positive rate of 81.6% (P<.001).

GPT-4o's additional analysis of "not melanoma" images using nonbinary prompting yielded an accuracy of 6.56% (95% CI 4.94%-8.18%), correctly classifying 59 of 899 images (Table 2). Binary prompting increased GPT-4o accuracy to 25.25% (95% CI 22.55%-27.95%), with 252 of 998 images correctly identified as "not melanoma." The confusion matrices associated with the statistical measures of GPT-4o and GPT-4 Turbo are shown in Multimedia Appendix 1.

Table 1. GPT-4 Omni and GPT-4 Turbo demonstrate low accuracy	and low specif	icity for melanoma	diagnosis.
--	----------------	--------------------	------------

	5 1 5	e
Statistical measure	Chat-GPT 4 Turbo	Chat-GPT 4 Omni
Accuracy, (95% CI)	0.546 (0.515-0.577)	0.577 (0.547-0.608)
Precision	0.532	0.544
Specificity, % (95% CI)	32.9 (0.288-0.370)	18.4 (0.150-0.218)
Sensitivity, % (95% CI)	76.3 (0.726-0.801)	96.8 (0.952-0.983)
F1-score	0.627	0.697
False-positive rate (%)	67.1	81.6

Table 2. Accuracy of ChatGPT-40 in diagnosing melanoma and "not melanoma" with binary versus nonbinary prompting.

Statistical measure	Nonbinary prompting (n=899)	Binary prompting (n=998)
Accuracy, n (%)	59 (6.56)	252 (25.25)
95% CI (%)	4.94-8.18	22.55-27.95
False-positive rate (%)	81.6	67.1

Discussion

Currently, GPT engines demonstrate low accuracy for diagnosing melanoma. Higher diagnostic accuracies have been achieved using neural networks such as Moleanalyzer pro (87.7%) and ChatGPT Vision (85%); however, these studies included much smaller sample sizes of 100 and 60 images, respectively [7,8]. Our findings exhibit a higher-powered analysis of ChatGPT performance.

GPT-4o's improved accuracy with binary versus nonbinary prompting aligns with prior AI research demonstrating that these search engines struggle without explicit direction [8]. When more intricate prompts are provided, results improve [7,8]. However, such a methodology is not generalizable to the average user. Patients using these engines to self-diagnose suspicious lesions at home are more likely to use nonbinary prompts without detailed instructions for the AI engine. Thus, our nonbinary prompting results reflect that ChatGPT would provide inaccurate outputs when used by the average patient. The high false-positive rates of GPT-40 and GPT-4 Turbo in evaluating "not melanoma" suggest a conservative bias. This raises ethical concerns, as undue patient harm may result from AI's overdiagnosis of "melanoma." Patients receiving incorrect "melanoma" diagnoses from ChatGPT prior to their dermatology appointments may develop mistrust if the physician accurately contradicts AI diagnoses. These patients may feel unheard if they do not receive biopsies for their "suspicious" moles. Increased in-office counseling may be warranted to disentangle the biases AI imparts to patients.

Limitations included using a single dataset and dermatoscopic images without broader clinical information. The models were not specifically trained before querying. ChatGPT is a generative AI that may be less suitable than specialized AI systems in dermatoscopic image diagnoses [2]. Nevertheless, inherent flaws in the GPT4-0 and GPT-4 Turbo systems are still evident. Therefore, patients should avoid ChatGPT diagnoses before evaluation of their suspected pigemented lesions by trained dermatologists.

https://derma.jmir.org/2025/1/e67551

Multimedia Appendix 1

Confusion matrix of ChatGPT-4 Omni performance (top) and confusion matrix of ChatGPT-4 Turbo performance (bottom). [PNG File (Portable Network Graphics File), 56 KB-Multimedia Appendix 1]

References

- 1. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature New Biol. Feb 2, 2017;542(7639):115-118. [doi: 10.1038/nature21056] [Medline: 28117445]
- 2. Tejeda H, Kumar A, Smyth P, Steyvers M. AI-assisted decision-making: a cognitive modeling approach to infer latent reliance strategies. Comput Brain Behav. Dec 2022;5(4):491-508. [doi: 10.1007/s42113-022-00157-y]
- Chow JCL, Wong V, Li K. Generative pre-trained transformer-empowered healthcare conversations: current trends, challenges, and future directions in large language model-enabled medical chatbots. BioMedInformatics. 2024;4(1):837-852. [doi: 10.3390/biomedinformatics4010047]
- Xu L, Sanders L, Li K, Chow JCL. Chatbot for health care and oncology applications using artificial intelligence and machine learning: systematic review. JMIR Cancer. Nov 29, 2021;7(4):e27850. [doi: <u>10.2196/27850</u>] [Medline: <u>34847056</u>]
- 5. Smith L, Hanna R, Hatch L, Hanna K. Computer vision meets large language models: performance of ChatGPT 4.0 on dermatology boards-style practice questions. SKIN J Cutan Med. 2024;8(5):1815-1821. [doi: 10.25251/skin.8.5.5]
- 6. Alexander Scarlat. Melanoma: augmented dermoscopic pigmented skin lesions from HAM10k. Kaggle. URL: <u>https://www.kaggle.com/datasets/drscarlat/melanoma</u> [Accessed 2024-11-29]
- Winkler JK, Blum A, Kommoss K, et al. Assessment of diagnostic performance of dermatologists cooperating with a convolutional neural network in a prospective clinical study: Human With Machine. JAMA Dermatol. Jun 1, 2023;159(6):621-627. [doi: 10.1001/jamadermatol.2023.0905] [Medline: 37133847]
- Cirone K, Akrout M, Abid L, Oakley A. Assessing the utility of multimodal large language models (GPT-4 Vision and Large Language and Vision Assistant) in identifying melanoma across different skin tones. JMIR Dermatol. Mar 13, 2024;7:e55508. [doi: 10.2196/55508] [Medline: <u>38477960</u>]

Abbreviations

AI: artificial intelligence GPT-4 Turbo: ChatGPT-4 Turbo GPT-4o: ChatGPT-4 Omni LLM: large language model

Edited by John Meisenheimer; peer-reviewed by James C L Chow, Lucia Mosca; submitted 14.10.2024; final revised version received 05.02.2025; accepted 17.02.2025; published 21.03.2025

<u>Please cite as:</u> Sattler SS, Chetla N, Chen M, Hage TR, Chang J, Guo WY, Hugh J Evaluating the Diagnostic Accuracy of ChatGPT-4 Omni and ChatGPT-4 Turbo in Identifying Melanoma: Comparative Study JMIR Dermatol 2025;8:e67551 URL: <u>https://derma.jmir.org/2025/1/e67551</u> doi: 10.2196/67551

© Samantha S. Sattler, Nitin Chetla, Matthew Chen, Tamer Rajai Hage, Joseph Chang, William Young Guo, Jeremy Hugh. Originally published in JMIR Dermatology (<u>http://derma.jmir.org</u>), 21.03.2025. This is an open-access article distributed under the terms of the Creative Commons Attribution License (<u>https://creativecommons.org/licenses/by/4.0/</u>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in JMIR Dermatology, is properly cited. The complete bibliographic information, a link to the original publication on <u>http://derma.jmir.org</u>, as well as this copyright and license information must be included.