RESEARCH PAPER

A Multimodal Deep Learning-based Conversational AI for Disease Prediction through Gujarati Textual and Visual Inputs

Dr. Falguni M. Patel[1]*, Prof. Sneha A Gaywala[2]

[1]Assistant Professor, Department of Information Technology, Sardar Vallabhbhai Patel Institute of Technology, Vasad, Gujarat, India-388306
[2]Assistant Professor, Department of Information Technology, Sardar Vallabhbhai Patel Institute of Technology, Vasad, Gujarat, India-388306.
[1]Orchid Id: 0000-0003-3560-3453
*Corresponding author- Dr. Falguni M. Patel: falgunimanish19@gmail.com

ABSTRACT
Healthcare and primary medical care accessibility remains a significant challenge for specific regions in India. This paper includes a Gujarat region user who have a medical reachability issue for general diseases as well as people who have no computer typing knowledge. This type of users can click the photo and upload to system to predict the skin disease is cancerous or not. It means this system is working with symptoms based general disease prediction using Gujarati textual data and image data-based skin cancer prediction as multimodal using deep learning model. This paper demonstrated and experimented with both type inputs. Textual content-based symptoms prediction experiments performed and around 95% accuracy for NB, RF, DT and around 92% accuracy for k-NN achieved. For image-based skin disease prediction GPT-5 model, 94% training accuracy and 69% test accuracy achieved. This system can be easily deployed on existing healthcare system for easy access to users.
Keywords: Computerized Diagnosis, Healthcare Chatbot, Disease Prediction, Natural Language Processing, AI and ML.
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INTRODUCTION

In the health care sector, AI and ML are used for medical image analysis, disease prediction, virtual healthcare assistance, personalized treatment recommendation system, voice-based health assistance, predict disease outbreaks or spread, wearable health device for health parameters tracking, mental health prediction, medicine recommendation system and many more [1]. Every year, millions of deaths occur worldwide annually. Among these, according to the report, approximately 25% of deaths occurred before age 60 years. Also, approximately 52 million deaths occur around the world each year, with significant variations observed from region to region. During COVID-19[2,13,14,15] WHO focused more on this situation [2,3,5,6]. In this situation, automatic symptoms -based virtual AI health assistance helped many people at home. In this digital era, technological advancement, health related data increase on online platforms. This data is helpful for research study, disease prediction, all stages of treatment etc. In some cases, diagnosing a disease only based on patient symptoms and report by a doctor, is a challenging task. In such cases, AI will be helpful to assist or provide additional knowledge to predict disease with greater efficiency and accuracy [1,4].

In recent years, symptoms-based ML applications are gaining importance. Researchers are trying to enhance the features of applications as well as effectiveness, ease of use, higher accuracy, voice-based features, multi-linguistics content for communication etc. in all directions [7,8]. In the existing systems, natural language processing and machine learning models as a combination are used to analyze users' textual content and symptoms and based on that predict disease [8,9,10]. In this system, image-based disease prediction is not available in the same system. It is a limited task for researchers to combine till now. In this paper, skin image-based disease prediction is added in AI based automatic health chatbot systems which work with gujarati language. For textual content-based analysis and disease prediction, ML based models like k-NN (k-Nearest Neighbor), NB(Naive Bayes), RF(Random Forest) and DT(Decision Tree) are used. In addition to this, Deep learning-based CNN model is used for image-based skin disease prediction. As in any emergency or regular case, users just have to take a photo and just upload or give it to AI assistance. It is an easy method for users to get image-based skin disease-based predictions with the same or combined system.

LITERATURE SURVEY

Over the past several decades, AI and ML have been used to modernize the medical era. ML is used to enhance diagnostic precision, customize patient care etc. [11,12]. AI-ML models are now working with text, tabular data and images of large datasets. The advanced deep-learning based systems are now demonstrating the ability to work like humans in the medical radiology and pathology domain. In this recent era, Generative AI is helpful to health care, education, diagnostic reporting etc. They provide interactive simulation like real life problem solutions. OpenAI developed a LLM that generates and communicates text like humans [12,13,14,15]. There are different types and versions of GPT (Generative Pre-trained Transformer) for understanding language. Very first model GPT-1 strong natural language understanding model but has limited size of parameters, unable to understand long conversion and weak at complex tasks. GPT-2 is very good at story, paragraph writing but less accurate and produces repetitive biased content sometimes. GPT-3 has the ability to write good contents, learn from examples and given prompts by users. This model has some understanding, logic problem and give wrong answers so confidently. The advanced GPT-3.5 version is fast and cheaper, better conversational capacity but limited deep learning or reasoning ability. Advanced GPT4, turbo, 4.o versions are fast response, good ar text as well as image, voice but still less accurate at reasoning. Latest version GPT-5 has better memory, fast, more reliable for coding, studies, problem-solving but still need accuracy at some level, required high computational cost. This technology enhancement can be helpful to health care as it is the most important and sensitive field. This paper mainly focuses on health-related symptoms text and skin image-based disease prediction for gujarati users. In this survey, health related specific disease checker or predictors applications, websites studies are done. All applications, software and websites include NLP (Natural Language Processing) components (like ChatGPTs), Medical knowledge Base (for example Ada health's chatbot dynamic knowledge base, Babylon's system, Infermedica and Symptoma), Machine learning models (i.e. LLMs, Hybrid bots, Babylon's triage bot) and reasonings, user interface (i.e. Avatars, voices, Sensely's 3D nurse "Molly" etc.), clouds and storage spaces etc [14,15,16,17].

Web-based symptoms checkers are available with measurable accuracy like COVID-19 symptoms checker [15,16,26]. Here is a list some chatbots examples available in public in form of application or website - Ada [13] Apple [14] Babylon [15] CDCa website (not chatbot)[16] Cleveland Clinic website (not chatbot) [17] Docyet-german website (not chatbot) [18] Infermedica [19] Providence [20] Symptoma [21] Your.MD[22] etc.

ADA Health app for iPhone is worked-based on probabilistics graphics model (PGM). It uses reasoning based on medical-expert-knowledge base for symptoms assessment. To refine the result, in addition it uses the LLM model. This app is paid and works on specific languages [13,23,24]. Infermedica (Symptomate) is an AI-powered medical guidance tool. It uses a probability Bayesian networks model with NLP and clinical logic with LLM, Proprietary database curated over 140,000+ hours by medical professionals, covering 800+ diseases and 1,500+ symptoms. This model has around 84.4% accuracy but is little costly and biased for some content. Authors compared the ADA model and real-time view of Orthopedic Pathologies doctors [25,26,27,28,29]. Chat Ella uses a GPT-2 transformer with around 97% accuracy [28,30]. Providence is a patient message assistant chatbot to handle patients' symptoms and diagnosis. It has a limit to work and 62% on average patients' issues are diverted to nurses even if they need doctors' treatment in special cases [20,28,30]. DISCERN-AI uses LLMs to handle questions related to tuberculosis. ChatGPT, Gemini, and Copilot are used for diagnosis, treatment, prevention and control, and disease management. These models' outcomes were compared and got a score 4 for ChatGPT, 4.4 for Gemini, 3.6 for Copilot overall performance [31,32,59]. Babylon Health (eMed chatbot by UK) uses symptoms-based analysis and telephonic communication/virtual consultation. LLM combines Bayesian Inference and Probabilistic Models, Knowledge Graph/Medical Ontology, Rule based logic. This app has security and accuracy concerns at some level [33,34]. HealthTap for general questions and routine users. In addition, it also provides virtual consultation but limited to text-based interaction [35]. Buoy Health is symptoms analysis tool, not a treatment provider and accuracy is lower. It uses a probabilistic model (like Bayesian Network Approach), Rule-Based Logic/algorithm [36,37,38].

K-Health is an AI-powered telemedicine platform for virtual primary care, urgent care and mental health. It uses LLM models with copilot [39]. Youper is a mental health chatbot used to handle anxiety, depression and emotional well-being. It uses LLM for engaging in conversions. In addition, decision trees are used for evidence-based interventions like Cognitive Behavioral Therapy (CBT) methods to help users manage anxiety, depression, and stress as well as track mood daily [40]. Exotel chatbot developed for faster response delivery, more personalized patient support. It handles patient appointment booking, prescription management and patient communication. It uses GPT-4 LLMs models to handle text, voice-based IVR data for analysis [41,]. Florence is an AI-Powered virtual nurse using the RASA Model (RASA word comes from sanskrit meaning as feeling). RASA has two components- RASA NLU(Natural Language Understanding) and RASA core for dialogue management. It sometimes lacks empathy, technical limitations like security, risks, bias, fairness and transparency [42,43]. Healthily/ YourMD is a symptom checker and self-care for users. Models are not disclosed but by study, know that it uses deep learning models as it is black box nature [44,45,46]. Alpaca Chatbot developed by Stanford University using the LLaMA model (Lighter version of ChatGPT) of Meta. It is not only for medical, general purposes like education, coding etc. [47] The Sensely and Multi-model uses text, image or video data with GPT-4 model for assistance, telemedicine, wearable devices. It has no ability to handle complex, rare medical conditions, time-consuming and an expensive model [48,49].

In recent years, some chatbots are introduced in gujarati language as trial based. SSG hospital oncology chatbot (2025) providing cancer care guidance of OPD details, surgery, chemotherapy). It is related to oncology queries not full evaluation analysis [50]. BHASHINI (Health Module, 2024) provide prescriptions translation and describing medical instruction given by doctor in prescription only. Accuracy is depend on translation module [51]. Edesy Hospital Voicebot (2026) provides OPD booking and lab report notification automatically to patients[52]. Just ask (Khulke Puchho, 2023) provides a education on reproduction and sexual issues of youth[53]. Krushna153 chatbot(2022) is probability based symptomatic disease prediction, has approx. 25% error rate [54]. Soniox AI (2025) provides information for AI-driven therapy sessions for patients [55]. Many other chatbots are assistance chatbot like DISHA, Aarogya NCD Follow-up etc [56,57].

Through the survey, lots of methods, models, specific and general disease-oriented and application-oriented problem solutions were found and, in their place, they are working well. AI-ML overall plays an important role in developing these systems. In this paper, general symptoms based and skin cancer disease prediction performed using text and image data.

PROBLEM STATEMENT

The existing AI-powered chatbot systems have some disadvantages in different models like lower accuracy, patient or data privacy and security, language understanding, not all language covering means specific users' consideration etc. Early detection of disease based on symptoms can mitigate the risk of developing serious illness. Due to busy life, language barrier, unreachable areas, unhealthy nutrition etc., people must have a system that identifies symptoms in their local language as well as those people who have skin related issues can click the photo and give to the system for disease prediction. The system will be helpful to make life easy for middle and normal people.

METHODOLOGY

In this proposed system, combine two papers in one system. first part is text-based prediction and natural language processing are used for symptoms to predict disease using traditional classifiers. Another part is image-based skin cancer detection combined as a regular basis any user can click the photo and upload the image to classify as cancerous or not at home. For text-based prediction k-NN, NB, DT and RF are used and google translators are used. In some cases, Google translator is not properly converting specific typical Gujarati words that are converted manually in the knowledge base. Interactive environment asks the question in gujarati and takes input based on options list as symptoms [58,59]. The system will provide disease names and its description in gujarati which is understandable by local people. For image-based skin disease cancer prediction, GPT-5 model is used [58,59,60,61].

RESULT

For text-based symptoms and disease prediction description looks as shown in figure-1. For image-based skin cancer prediction, dermatoscopic (magnified skin) image datasets are used from kaggle [63,64,65,66]. The dataset has 10015 numbers of skin images, among these 70% images used for training and 30% for testing the model. Datasets has a list of images with its related class label for different skin cancer/disease categories. Some skin sample images shown in Figure 1. Class labels are Nv, Mel, Bkl, Bcc, Akiec, Vasc, Df. Nv means Melanocytic Nevi is a common mole. Mel means Melanoma, is a serious form of skin cancer. It appears as a dark, irregular, changing spot. Bkl means Benign Keratosis-like Lesions, which are non-cancerous, aging-related spots. Bcc means Basal Cell Carcinoma, is the most common form of skin cancer. It appears as a pearly, pink, or reddish bump, sometimes with a small ulceration. Akiec means Actinic Keratoses/Bowen's Disease, is pre-cancerous skin lesions. Rough, scaly patches caused by years of sun exposure. Vasc means Vascular Lesions, is Lesions caused by abnormal blood vessel growth. They typically look reddish, purple, or blue. Df means Dermatofibroma, is a common benign skin tumor. It looks like small, firm, red-brown bumps that are often found on the legs. They are made of fibrous tissue. Figure 2 shows the different skin diseases images, While Figure 3 shows

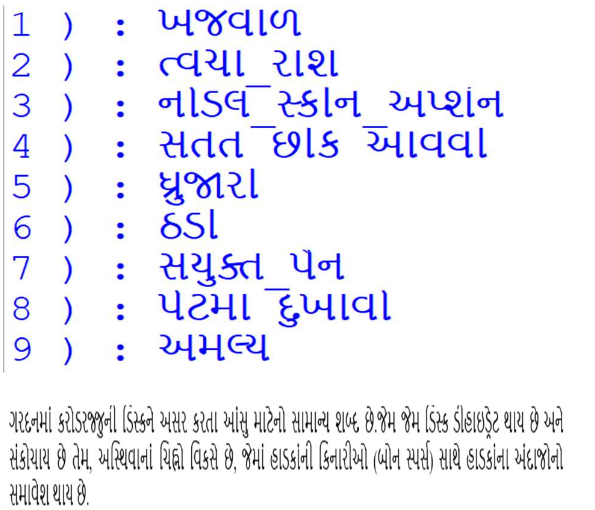

Fig. 1. Sample symptoms list and disease description.

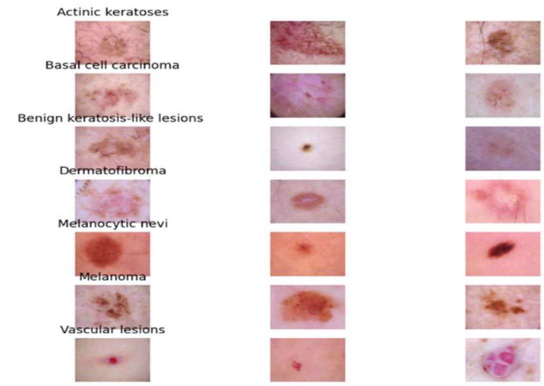

Fig. 2 Skin Images with different diseases name as class labels

data analysis like - how skin problems/issues faced by male and female gender-wise analysis. For skin related image-based prediction the model gives around 94% training accuracy and 69% test accuracy with learning rate learning rate = 0.00075, epochs=50, batch size=10, SwisGLU activation function instead of ReLU and GELU, category cross-entropy loss function, AdamW optimizer and transfer learning fine tuning procedure used. Figure4 shows training accuracy and loss effect for a trained model on training data. Text based question answering chatbot is shown in figure-1 for symptoms listing and disease description. . This system achieved around 95% accuracy for NB, RF, DT and around 92% accuracy for kNN for symptoms-based disease prediction.

CONCLUSION

After this whole study, an innovative question-answering Gujarati chatbot is created for symptom-based disease prediction using textual symptoms. In

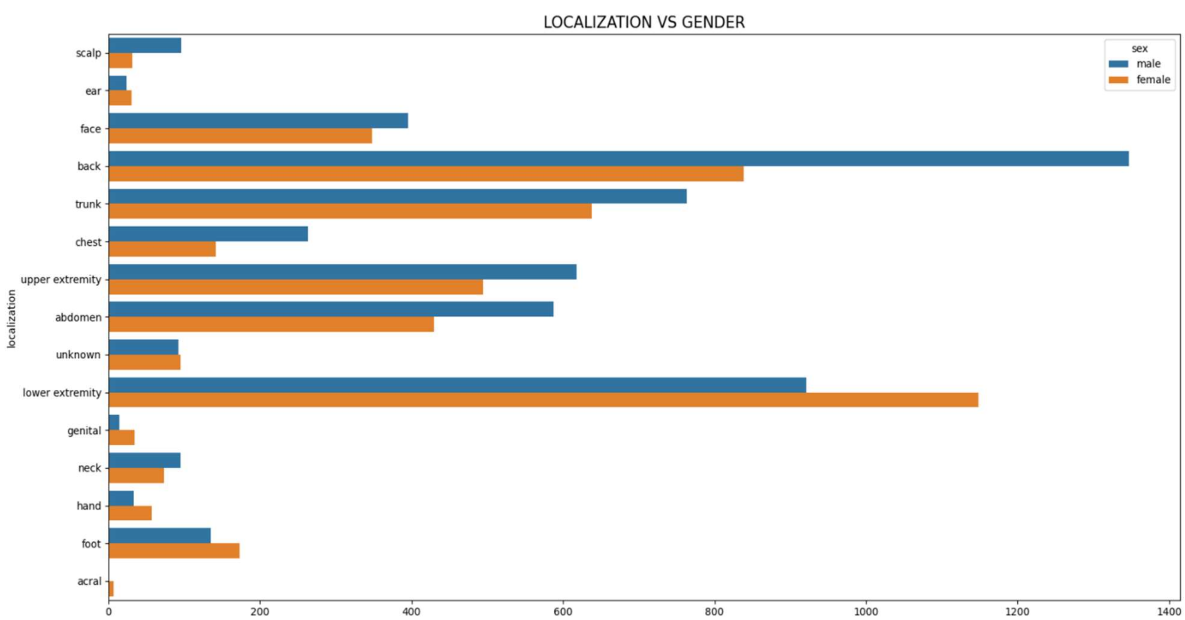

Fig. 3 Skin Disease Localization Effect Vs Genders

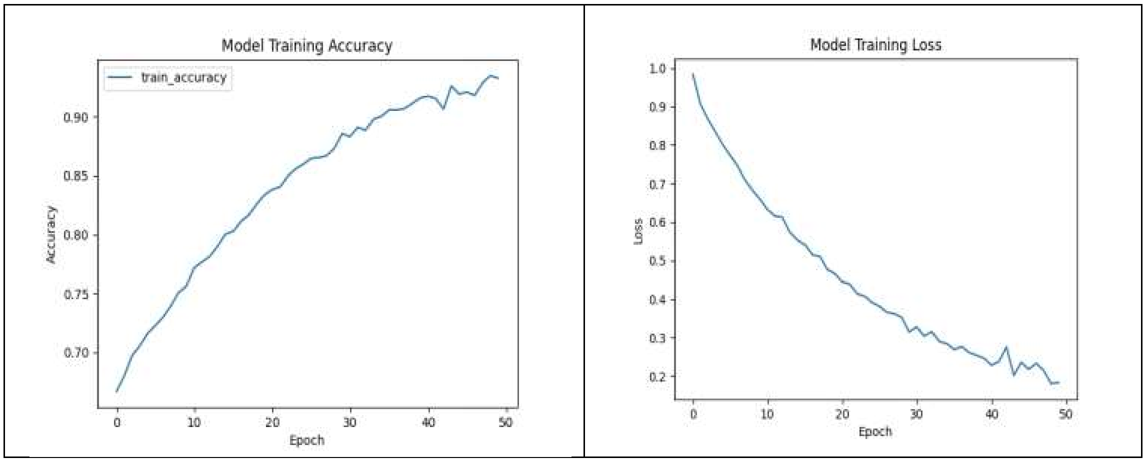

Fig. 4 Training Accuracy and Loss of the Model with Different Epoch

addition, image-based skin cancer disease prediction has also been performed in the same system. Users can easily communicate with the system using Gujarati text as well as image/photo uploading for disease prediction as primary knowledge. So, disease can't be severed as unknown and no primary knowledge. This system is helpful to users to give primary health assistance. In the future, the model can be extended with higher performance, add more different disease predictions based on image and proper GUI platform as combination of two parts-text and image-based.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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AUTHOR CONTRIBUTION

Dr. F. M. Patel- Conceptualization, Methodology, Investigation, and writing-original draft. Prof. S. A. Gaywala- review and editing manuscript. All authors have read and approved the final manuscript and agree to be accountable for all aspects of the work.

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