SMART INDIA HACKATHON 2023

Basic Details of the Team & Problem Statement

Ministry : DEPARTMENT OF NATIONAL COMMISSION FOR INDIAN SYSTEM OF MEDICINE , MINISTRY OF AYUSH .

PS Code : SIH1344

Problem Statement Title : AI-BASED TOOL FOR PRELIMINARY DIAGNOSIS OF DERMATOLOGICAL MANIFESTATIONS .

Team Name : MedTech Explorers

Team Leader Name : SUMIT RANJAN SATAPATHY

Institute Code (AISHE) : C-30068

Institute Name : PARALA MAHARAJA ENGINEERING COLLEGE , SITALAPALLI , BERHAMPUR , ODISHA , INDIA , 761003

Theme Name : MEDTECH / BIOTECH / HEALTHTECH

Idea/Approach Details

Objective : AI based Chatbot assistant termed AI Dermatology Diagnostic Assistant (ADDA) with image processing capability for preliminary diagnosis of Dermatological Manifestations basing on **severity stage analysis** .

General Idea :

- Using **Transfer learning ,** Models are pre-trained on big data , customized for our medical tasks .
- Aims to **Automate patient query resolution** by training on question-answer pairs to provide informative responses .
- Enhanced with skin image processing capabilities for **versatile functionality** & **increased accuracy** of the overall model .

Approch to the Problem :

- **Answer Search :**
  - **Problem :** Generate answers to patient queries .
  - **Approach :** We frame it as a **supervised seq2seq task** , generating answers from past question-answer pairs in response to the patient's query .
- **Semantic Search :**
  - **Problem :** Retrieve similar questions with answers from historical data .
  - **Approach :** When unsatisfied with the responses , we perform **unsupervised semantic search** to display similar previously answered doctor's questions & answers to the patient .
- **Image Processing :**
  - **Problem :** Enhance the **ChatBot's** capabilities by processing medical images .
  - **Approach :** Integrate a separate image-processing based model to interpret skin disease image dataset .

Model Components :

- **BioBERT :**
  Specialized **BERT model** termed with **BioBERT** for **biomedical** & **clinical** text .
  Pretrained on medical & biological data for **healthcare-related tasks** .
- **ResNet50 :**
  Deep neural network for image classification.
  Pretrained on large **image datasets** like **ImageNet** for **computer vision tasks** .
- **GPT-2 (Generative Pre-trained Transformer 2) :**
  Language model for **Natural Language** understanding & generation .
  Pretrained on a broad range of **internet text data** , ideal for question-answering systems & virtual assistants .

References

1 . Tschandl, P., Rosendahl, C., & Kittler, H. (2018). The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific data, 5(1), 1-9.

2 . **Medical-Q&A :** https://github.com/LasseRegin/medical-question-answer-data

3 . Hestiningsih, I., Thohari, A. N. A., & Kamarudin, N. D. (2023). Mobile Skin Disease Classification using MobileNetV2 and NASNetMobile. International Journal on Advanced Science, Engineering & Information Technology, 13(4).

4 . **Dermnet :** https://www.kaggle.com/datasets/shubhamgoel27/dermnet

Novel Integrations

1 . Integration of OCR technology can able to scan medical test reports .

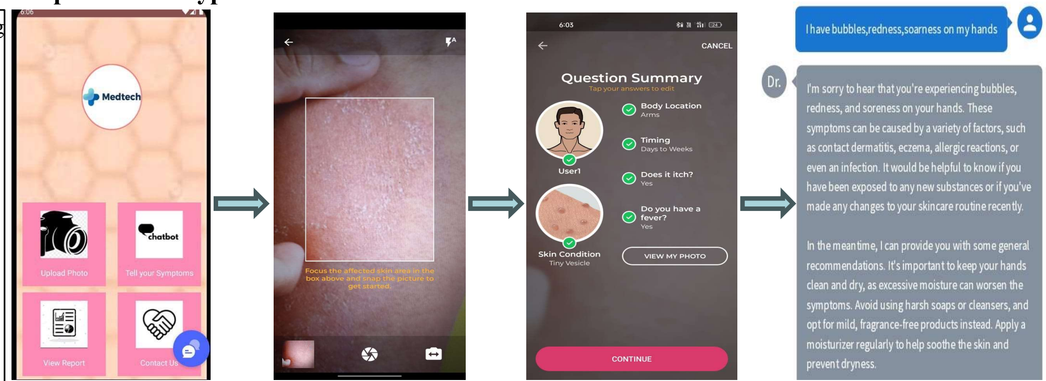
2 . For regional language translation , google translator API will be integrated .

3 . Voice assistant feature .

4 . Generation of comprehensive medical report .

5 . Introduce Gamification elements to motivate User .

Proposed Prototype User Interface



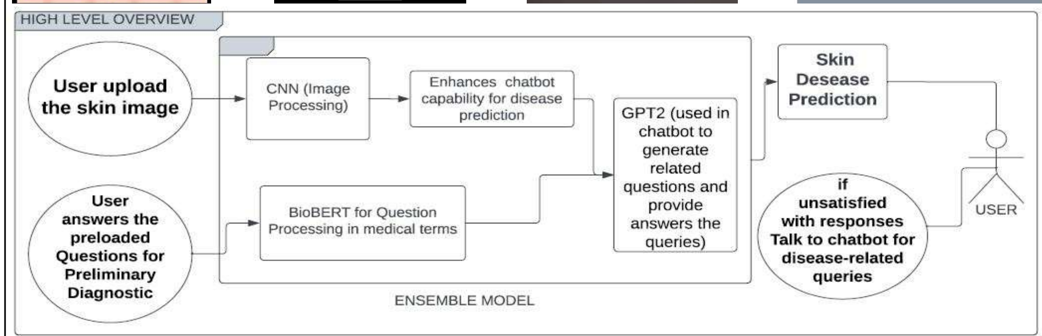
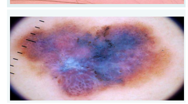


Image Metadata with labeled Stages for ChatBot Prediction Analysis

Image	Descriptive Symptoms	Conditions	Outcomes	Potential Dermatological Medications	Appointment Status
	Persistent inflammatory lesions , Skin thickening , Scaly patches .	Severe psoriasis , Lichen planus .	Complex or Chronic conditions .	Topical corticosteroids , calcineurin inhibitors , phototherapy or systemic medications . Biologic agents for severe cases .	Virtual Doctor consultation is essential .
	Presence of unusual skin growths , Changes in moles , Ulcerations .	Melanoma (Skin cancer) , Squamous cell carcinoma .	Potentially dangerous or Non curable conditions .	Medications may not be effective for these severe conditions . Treatment typically involves surgery , radiation therapy or chemotherapy .	Immediate in person consultation with a dermatologist is crucial for diagnosis & treatment planning .

Stages Of Impetigo

Vesicle Pustule Crusted lesion-facial area Crusted lesion-groin area

Proposed Algorithm

Keyframe Selection & Skin Image Processing :

Input : Video frames of a skin condition in case of video input along with image input .

Output : Skin disease detection report & recommendations .

- Initialize an empty list to store selected keyframes .
- Initialize an empty graph **G** for frame similarity .
- Initialize a variable to keep track of the number of clusters .
- FOR each frame in the video DO :
  - a . Extract image features using **Multi-feature Fusion** Algorithm .
  - b . Calculate frame similarity with other frames using a **cosine similarity metric** :

Cosine Similarity(Frame1 , Frame2) = (Frame1 * Frame2) / (||Frame1|| * ||Frame2||)

  - c . Add the frame to graph **G** as a node .
- Apply **Graph Modularity Clustering** Algorithm to **G** to identify clusters based on modularity scores .
- Calculate **modularity (Q)** of the graph :

$$Q = \Sigma\ [e(ij) - (a(i) * a(j) / (2m))] * \delta(c(i) , c(j))$$

where **e(ij)** is the fraction of edges that connect nodes in communities **c(i)** & **c(j)** , **a(i)** is the fraction of edges connected to nodes in community **c(i)** , **m** is the total number of edges & **δ(c(i), c(j))** is the **Kronecker delta function** .

- FOR each cluster in identified clusters DO :
  - a . Calculate the average frame quality score for frames in the cluster .
  - b . Select the frame with the highest quality based on quality metrics .
  - c . Add the keyframe to the list of selected keyframes .
- FOR each selected keyframe DO :
  - a . Apply skin image processing using ResNet-50 .
  - b . Classify the skin condition type & severity stage .
- Generate a diagnostic report based on classification results .
- Integrate the report with the AI Dermatology Diagnostic Assistant (ADDA) .
- In ADDA , use the severity stage for user recommendations .

Fine-Tuning the ResNet-50 Model :

Input : Skin infection images .

Output : Pre-trained ResNet-50 model with custom layers removed & feature embeddings .

- Load the dataset containing skin infection images .
- Load the pre-trained ResNet-50 model .
- Create a sequential model " model " & add layers :

  model.add(layers.Dense(units , activation = 'relu'))
  model.add(layers.Flatten())
- Train the model with the dataset . The loss function can include classification loss that is **Categorical Cross - Entropy** & regularization terms that is **L2 regularization** :

Loss = ClassificationLoss + λ * L2RegularizationTerm

- Compile the model with a suitable loss function & optimizer.
- Remove the custom classification layers , leaving the ResNet-50 base .
- Pass each image through the base model to obtain feature embeddings .
- Save the extracted feature embeddings for later use .

Fine-Tuning the BioBERT Model :

Input : Medical question-answer dataset .

Output : Fine-tuned BioBERT model for question-answer embeddings .

- Load the BioBERT model .
- Feed your medical question-answer dataset to the model & fine-tune it . The loss function can include mean squared error (MSE) for similarity prediction :

  Loss = MSE(PredictedSimilarity , ActualSimilarity)
- Extract the question & answer embeddings using the q_ffn & a_ffn layers of the FFN (Feed Forward Neural Network) transformer layers .
- Train the model to predict similarity scores .
- Calculate cosine similarity between the question & answer embeddings :

CosineSimilarity(QuestionEmbedding , AnswerEmbedding) = (Q * A) / (|| Q || * || A ||)

Amalgamation of Embeddings & GPT-2 :

Input : Text & Image embeddings , User Questions , Pre-computed question-answer embeddings .

Output : GPT-2 model with **Context-Aware Learning** & **Weighted Loss Mask** (WLS) .

- Generate embeddings separately for text **(E_T)** & images **(E_I)** & concatenate them :

$$\text{Concatenated Embeddings (CE)} = [E_T, E_I]$$

- Obtain embeddings for original user questions using BioBERT :

  Question Embeddings (QE) = BioBERT(User Questions)
- Employ **FAISS** for **Cosine Similarity-based search** to compare the **Current Question (CQ)** with pre-computed question-answer embeddings :

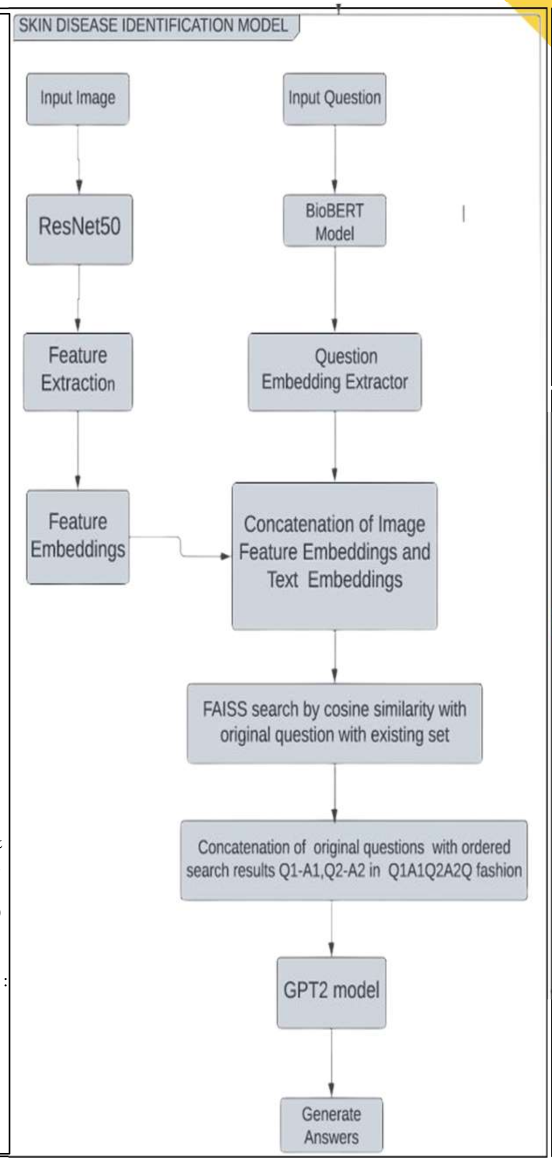
Similar Pairs = FAISS(CQ , Pre-computed Question-Answer Embeddings)

- Retrieve top-ranked **Similar Question-Answer pairs (SQ)** & integrate them with the original content to establish context .
- Calculate a **Loss Mask (LM)** for context-aware learning based on the similarity between the **Current Question (CQ)** & retrieved question-answer pairs . Here , We used a weighted combination of **Cosine Similarities (CS)** between the **Current Question (CQ)** & each similar pair :

$$LM = \sum_i CS_i \times \text{Weight}_i$$

- Train GPT-2 with context-aware learning , applying a weighted loss mask (WLM) during training to encourage context-aware learning & align with retrieved similar pairs :

Weighted Loss = LM × Loss



Predefined Algorithm used in our Proposed Algorithm

1 . FAISS (Facebook AI Similarity Search) : An efficient & versatile library developed by Facebook AI Research , tailored for conducting similarity searches & clustering large datasets whether it's image or text-based . In our proposed algorithms , FAISS finds application in two key areas . First , in Algorithm for Keyframe Selection & Skin Image Processing , it aids in identifying visually similar video frames which are vital for skin image processing . Second , in Algorithm for Amalgamation of Embeddings & GPT-2 , FAISS enables similarity-based searches for matching user questions with pre-computed embeddings , enhancing context integration for more context-aware responses with the GPT-2 model .

2 . Feed Forward Neural Network (FFN) : A foundational neural network architecture which is integral to our proposed algorithms . Within Algorithm for Fine-Tuning the BioBERT Model , it fine-tunes the BioBERT model by enhancing question-answer similarity prediction through suitable mapping of embeddings . Within Algorithm for Amalgamation of Embeddings & GPT-2 , it utilizes FFN to extract question & answer embeddings , creating a context-rich environment for effective user interactions . Overall , FFN's contributions significantly boost the system's ability to provide accurate responses & recommendations for skin disease-related queries , making it a central component in the solution .

Technology stack

Java, TensorFlow, Keras, PyTorch, HTML, CSS, JavaScript, M E R N, React JS, Flutter, vertex.ai, OpenAI, Transformers, Amazon SageMaker

Dependencies / Show stopper

- Regulatory Compliance
- Data Privacy
- Cybersecurity
- Patient Feedback
- Feedback Data Iteration

Team Member Details

Team Leader Name : SUMIT RANJAN SATAPATHY

Branch : B . Tech | Stream : CSE | Year : IV

Team Member 1 Name : ABHISEK TRIPATHY

Branch : B . Tech | Stream : CSE | Year : IV

Team Member 2 Name : AISWARIYA DASH

Branch : B . Tech | Stream : CSE | Year : IV

Team Member 3 Name : PRACHI PRAGNYA PADHI

Branch : B . Tech | Stream : CSE | Year : III

Team Member 4 Name : SHRIMAN ADITYA RANJAN NAYAK

Branch : B . Tech | Stream : CSE | Year : III

Team Member 5 Name : DEBASISH PADHY

Branch : B . Tech | Stream : CSE | Year : IV

Team Mentor 1 Name : DR. NIRANJAN PANIGRAHI

Category : Academic | Expertise : Wireless Sensor Network | Domain Experience (in years) : 16

,

Team Mentor 2 Name : DR. DEBASIS MAHAPATRA

Category : Academic | Expertise : Complex Networks | Domain Experience (in years) : 13