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Research Paper

AI-Based Healthcare Chatbot for Pregnancy Assistance Using NLP and LSTM

K. Krupa Sagari[1],K.Pavani[2], K. Navya Swetha[3]

#1 Assistant Professor of MCA, SRK Institute of Technology, Vijayawada.

#2 Assistant Professor &head of the Department of MCA, SRK Institute of Technology, Vijayawada.

#3 Student in the Department of MCA, SRK Institute of Technology, Vijayawada.

Abstract: This paper presents MAMABOT, an AI-based healthcare chatbot designed to assist pregnant women using Natural Language Processing (NLP) and Long Short-Term Memory (LSTM). The system processes user queries and provides accurate, real-time responses based on trained datasets. It reduces dependency on healthcare professionals for basic guidance and improves accessibility to medical information. Experimental results demonstrate effective response prediction and reliable conversational performance.

Index terms - *Artificial Intelligence, Natural Language Processing (NLP), Long Short-Term Memory (LSTM), Healthcare Chatbot, Machine Learning, Pregnancy Assistance, Conversational AI*

1. INTRODUCTION

Artificial Intelligence (AI) has significantly transformed the healthcare sector by enabling intelligent systems that assist in diagnosis, monitoring, and patient support. Among these advancements, chatbot technology has emerged as an effective tool for providing instant and automated responses to user queries. Chatbots reduce the workload on healthcare professionals and improve accessibility to medical information, especially for routine and repetitive queries.

With the increasing use of smartphones and digital platforms, there is a growing demand for reliable healthcare assistance systems that are available anytime and anywhere. Pregnant women often require continuous guidance regarding health, nutrition, symptoms, and precautions. However, immediate access to medical professionals is not always possible, making chatbot-based solutions highly beneficial in such scenarios.

This paper introduces MAMABOT, an AI-based healthcare chatbot designed specifically to support pregnant women and their families. The system uses Natural Language Processing (NLP) to understand user queries and Long Short-Term Memory (LSTM), a deep learning technique, to generate accurate responses. The chatbot is trained on a dataset of pregnancy-related questions and answers, enabling it to provide relevant and context-aware information.

The main objective of this work is to develop an efficient, user-friendly, and intelligent conversational system that can deliver real-time assistance. By leveraging machine learning techniques, the proposed system enhances user experience, improves accessibility to healthcare knowledge, and demonstrates the potential of AI-driven solutions in maternal healthcare support.

2. LITERATURE SURVEY

a) **Four trends that will transform healthcare in Europe in 2016*:***

The Kaiser Associates European Healthcare team anticipates another year of significant upheavals, changes, and innovations as the healthcare sector continues to revamp antiquated business structures, with 2015 providing some indications of what is to come.

b) **A Systematic Review of Healthcare Applications for Smartphones**

Background

Smartphones, which can run third-party software, combine advanced mobile communications with portable processing. Smartphone use is rising significantly, even among healthcare workers. This study categorized smartphone-based healthcare technologies in academic literature by function and summarized papers in each category.

Methods

In April 2011, MEDLINE was searched for papers on smartphone-based software design, development, assessment, or usage for healthcare professionals, medical or nursing students, and patients. From 2,894 MEDLINE publications, 55 papers on 83 applications were chosen for this investigation.

Results

The 83 applications included 57 for healthcare professionals focusing on disease diagnosis (21), drug reference (6), medical calculators (8), literature search (6), clinical communication (3), Hospital Information System (HIS) client applications (4), medical training (2), and general healthcare applications (7); 11 for medical or nursing students focusing on medical education; and 15 for patients focusing on disease. Healthcare professionals and nursing students preferred illness diagnostic, medication reference, and medical calculator apps.

Conclusions

Health professionals and patients utilize several smartphone medical apps. Smartphones are gaining popularity in healthcare. Smartphones may be used for mobile clinical communication and evidence-based medicine at the point of treatment thanks to medical apps. Smartphones can also aid patient education, illness self-management, and remote monitoring.

c) **Mobile cell-phones (M-phones) in telemicroscopy: increasing connectivity of isolated laboratories*:***

Background

Modern information telecommunication (ITC) technologies and telemedicine are helping remote populations obtain some diagnostic treatments. However, technical and budgetary obstacles in accessing broad band data-transmission networks still hinder tele-pathology picture transmission.

Methods

Indifferently using m-phones of different brands and a variety of microscopic preparations, images were taken without an adaptor by simply approaching the mobile cell phone camera lens to the ocular of common optical microscopes. The images were then sent via MMS to distant reference centers for tele-diagnosis. MMS service access was examined in the African ICT market.

Results

The cell phone's MMS could record and send images of any pathologic preparation without requiring broadband internet connection. The brand and type of the cell phone did not affect image quality, but solely digital resolution, with photographs over 0.8 megapixel being diagnostic.

Access to MMS is expanding to distant, poor communities. The service is offered in practically every African country, with penetration ranging from 1.5% to 92.2%.

Conclusion

Utilising widely available technologies without adaptors or additional technology could increase opportunities, quality diagnostics, cost savings, and connectivity between most isolated laboratories and distant reference centres.

d) **Smartphone medication adherence apps: Potential benefits to patients and providers**

Objectives

To provide an overview of medication adherence, discuss the potential for smartphone medication adherence applications (adherence apps) to improve nonadherence, evaluate adherence app features across OSs, and identify future opportunities and barriers.

Describe practice

Nonadherence to medication is prevalent, difficult, and costly, resulting in poor treatment results and health care resource waste. Nonadherence is hard to assess, and therapies have failed.

Be inventive

Smartphone adherence applications are an innovative way to improve adherence. Many elements of this easily available technology can assist patients and health care professionals improve medication-taking behavior.

Main results measures

Apps from Apple, Android, and Blackberry were detected. Desirable qualities for adherence applications were also found and evaluated by perceived user desirability: 1, modest; 2, moderate; or 3, high. The top 10 applications were installed and tested using a regular pharmaceutical routine.

Results

160 applications were graded for adherence. Android has the most of these apps. Advanced adherence applications were more common on iPhone. MyMedSchedule, MyMeds, and RxmindMe were the most popular applications due to their basic medication reminder capabilities and expanded functionality.

Conclusion

Despite being unproven, pharmacists may prescribe medication apps to nonadherent patients and use them in their practise.

e) **An emerging model of maternity care: Smartphone, midwife, doctor?*:***

Background

Smartphones are increasingly utilized, especially during pregnancy, and are a powerful source of information.

Aim

To discuss the variety of smartphone pregnancy apps and warn that they may alter maternity care and should be addressed in future planning.

Methods

Apple and Android smartphones were searched for pregnant applications and assessed for purpose and popularity.

Findings

Apple and Google Play found 1059 and 497 pregnancy applications. Informational applications made up 40%, interactive apps 13%, medical tools 19%, and social media apps 11%. The most popular applications, based on reviews and average rating, were interactive.

Discussion

The popularity of pregnant apps may signify a move toward patient empowerment in maternity care. Electronic equipment must be included into the 'shared maternity care' approach. Smartphone-delivered interactive and personalized information may lessen healthcare professional reliance. This plus the fact that many women of reproductive age use cellphones might change maternity care and pregnancy experiences. Thus, healthcare professionals and policymakers must be aware of these new changes, which may affect healthcare and health-seeking behavior. Additionally, healthcare professionals must decide whether to address app usage during pregnant with patients.

3. METHODOLOGY

i) Proposed Work:

The proposed work focuses on developing MAMABOT, an AI-based healthcare chatbot designed to assist pregnant women by providing instant and accurate responses to their queries. The system utilizes Natural Language Processing (NLP) to understand user input and Long Short-Term Memory (LSTM), a deep learning algorithm, to predict relevant answers based on trained data.

The chatbot is trained using a dataset of pregnancy-related questions and answers stored in JSON format. The process includes data collection, preprocessing (tokenization and stemming), feature extraction using Bag-of-Words, and model training using LSTM. When a user submits a query, the system processes the input, converts it into numerical form, and feeds it to the trained model to generate the most appropriate response.

The proposed system aims to provide real-time assistance, improve accessibility to healthcare information, and reduce dependency on medical professionals for basic guidance. It offers a user-friendly interface and ensures efficient communication between users and the chatbot, making it a reliable digital healthcare support system.

ii) System Architecture:

The system architecture of MAMABOT is designed as a multi-layered framework that enables smooth interaction between the user and the chatbot system.

The user interacts with the chatbot through a web-based interface, where queries are entered in natural language. These inputs are sent to the backend system through a web server, which acts as an intermediary between the user interface and the processing modules.

Once the input is received, the preprocessing module applies Natural Language Processing (NLP) techniques such as tokenization and stemming to clean and structure the data. The processed input is then converted into a numerical format using the Bag-of-Words approach. This data is passed to the trained Long Short-Term Memory (LSTM) model, which predicts the most relevant response based on learned patterns. The response is retrieved from the dataset and sent back through the server to the user interface, ensuring real-time interaction. The architecture also supports database integration for storing user data and chatbot responses, making the system efficient, scalable, and user-friendly.

patient location.

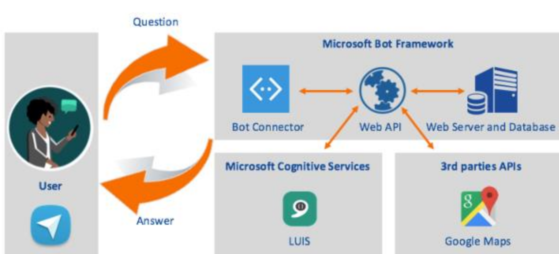

Fig1 Proposed system

iii) Modules:

1. Data Collection Module

Collects pregnancy-related questions and answers from online sources and medical references. The data is stored in JSON format for training the chatbot.

2. Data Preprocessing Module

Processes raw text using NLP techniques like tokenization and stemming. It removes unnecessary words and prepares clean input data for the model.

3. Feature Extraction Module

Converts processed text into numerical form using the Bag-of-Words technique. This helps the machine learning model understand input data.

4. Model Training Module

Trains the chatbot using the LSTM algorithm on the prepared dataset. The model learns patterns between questions and corresponding answers.

5. Prediction Module

Takes user input, processes it, and predicts the most relevant response using the trained model. It ensures accurate and fast responses.

6. Response Generation Module

Selects the appropriate answer from the dataset based on prediction results. It also checks the relevance of the response before displaying.

7. User Interface Module

Provides a web-based interface for user interaction. It allows users to enter queries and view chatbot responses in real-time.

iv) Algorithms:

1. Natural Language Processing (NLP)

NLP is used to understand and process user input in natural language. It performs operations such as tokenization (splitting sentences into words), stemming (reducing words to root form), and removal of unnecessary characters. This converts human language into a structured format that the machine learning model can interpret effectively.

2. Bag-of-Words (BoW)

Bag-of-Words is a feature extraction technique used to convert text into numerical vectors. It creates a vocabulary of all words in the dataset and represents each input sentence as a vector indicating the presence or absence of words. This enables the model to process textual data mathematically.

3. Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) designed to handle sequential data and long-term dependencies. It uses memory cells and gates to retain important information over time. In this system, LSTM learns patterns from training data and predicts the most appropriate response for a given user query.

4. Softmax Classification

The Softmax function is used in the output layer of the model to convert predicted values into probabilities. It selects the most likely response category (intent) based on the highest probability, ensuring accurate response generation.

4. EXPERIMENTAL RESULTS

The proposed MAMABOT system was implemented using Python, TensorFlow, and NLP libraries, and trained on a dataset of pregnancy-related questions and answers . The dataset was preprocessed using tokenization and stemming, and features were extracted using the Bag-of-Words technique. The LSTM model was trained over multiple epochs to achieve optimal performance.

During testing, the chatbot was evaluated with both trained and unseen user queries. For known queries, the system produced accurate and contextually relevant responses. For unknown inputs, the chatbot successfully handled them by providing fallback messages such as “Sorry, I am not trained to answer this question,” ensuring robustness. The system demonstrated fast response time and smooth real-time interaction.

The performance analysis indicates that the model achieves high accuracy in intent classification and response prediction. The results confirm that the proposed chatbot effectively assists users by providing reliable healthcare information, making it suitable for practical deployment in pregnancy support systems.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \textit{the AP of class } k$$

$$n = \textit{the number of classes}$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

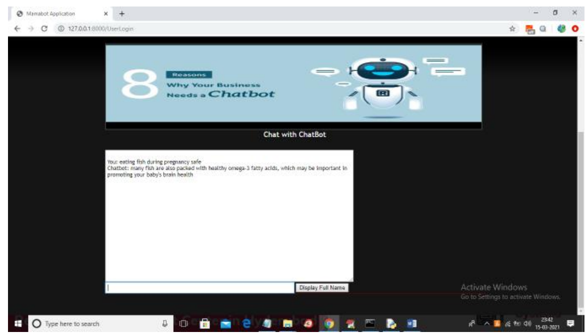

Fig: **Request to CHATBOT**

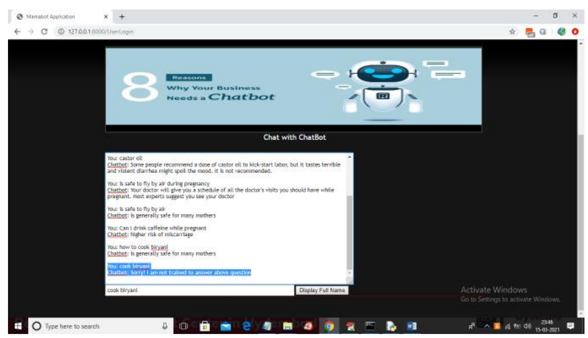

Fig: RESULTS

5. CONCLUSION

The proposed system, MAMABOT, successfully demonstrates the application of Artificial Intelligence in healthcare by providing an intelligent chatbot for pregnancy assistance. By integrating Natural Language Processing (NLP) and Long Short-Term Memory (LSTM), the system is capable of understanding user queries and delivering accurate, real-time responses.

The chatbot improves accessibility to healthcare information and reduces the burden on medical professionals for routine queries. It offers a user-friendly and efficient platform for pregnant women to receive guidance and support. Overall, the system proves to be a reliable and scalable solution, highlighting the potential of AI-driven technologies in enhancing maternal healthcare services.

6. FUTURE SCOPE

The proposed MAMABOT system can be further enhanced by integrating advanced features to improve accuracy and user experience. One major improvement is the inclusion of speech-based interaction, where users can ask questions through voice using speech-to-text and receive responses through text-to-speech. This will make the system more accessible and user-friendly.

Additionally, the chatbot can be expanded with larger and more diverse datasets to improve prediction accuracy and handle a wider range of queries. Integration with real-time healthcare systems and IoT devices (such as wearable health monitors) can enable personalized recommendations based on user health data.

Future enhancements may also include multilingual support, emotion-aware responses, and the use of advanced deep learning models like transformers for better conversational understanding. These improvements will make the system more intelligent, scalable, and suitable for real-world healthcare applications.

REFERENCES

1. PricewaterhouseCoopers LLP, 2016.
2. W. Hochfeld, J. Riffell, N. Levinson. Four trends that willtransform healthcarein Europe in 2016. European Pharmaceutical Review 21(1) 2016.
3. A.S. Mosa, I. Yoo, L. Sheets, A systematic review of healthcare applications for smartphone, BMC Med. Inform. Decis. Mak. 2012;12:67.
4. L. Bellina, E. Missoni, Mobile cell-phones (M-phones) in telemicroscopy: Increasing connectivity of isolated laboratories, Diagn. Pathol. 2009;4:19.
5. L. Dayer, S. Heldenbrand, P. Anderson, P.O. Gubbins, B.C. Martin, Smartphone medication adherence apps: Potential benefits to patients and providers, J. Am. Pharm. Assoc. 2013; 53:172.
6. N. Tripp, K. Harney, A. Liu, A. Poulton, M. Peek, J. Kim, R. Nanan, An emerging model of maternity care: Smartphone, midwife, doctor?, Women Birth. 2014;27:64--67.
7. A.P. Demidowich, K. Lu, R. Tamler, Z. Bloomgarden, An evaluation of diabetes self-management applications for Android smartphones, J. Telemed. Telecare. 2012;18:235--238.
8. A. Rao, P. Hou, T. Golnik, J. Flaherty, S. Vu, Evolution of data management tools for managing self-monitoring of blood glucose results: A

survey of iPhone applications, J. Diabetes Sci. Technol. 2010;4:949--957.

9. S. Wallace, M. Clark, J. White, "It's on my iPhone": Attitudes to the use of mobile computing devices in medical education, a mixed-methods study, BMJ Open. 2012;2:e001099.

Author Profiles

Ms. K. KrupaSagariis working as an Assistant Professor in the Department of MCA at SRK Institute of Technology, Vijayawada. She has completed her MCA and M.Sc. (Mathematics). She has 6 years of teaching experience at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. Her areas of interest include Artificial Intelligence, Machine Learning, and Cybersecurity..

Ms. K. Pavani Working as Assistant & Head of Department of MCA, in SRK Institute of technology in Vijayawada. She done with MCA, M. Tech in Computer Science. Her area of interest includes Machine Learning with Python and DBMS.

.**Ms.K. Navya Swetha** is MCA Student in the Department of Computer Applications at SRK Institute of Technology, Enikepadu, Vijayawada, NTR District. She has Completed Degree in B.Sc. (Chemistry,Computers) from SKSD Mahila Kalasala Tanuku. Her area of interest are Deep learning and Machine Learning with Python.