FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY

COMPUTER SCIENCE DEPARTMENT

Title of the Project

Personalized Diagnosis and Treatment Recommendation System

By

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Eswatini Medical Christian University

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This is to certify that this project report entitled

Personalised Diagnosis and Treatment Recommendation System

Submitted to ESwatini Medical Christian University, Computer Science Department, is a bonafide record of work done by

Samkelo Oneal Shambali

under my supervision from ………………………… to ………………………….

______________________ , ________________

Supervisor Name Signature

______________________, ________________

Head of Department Signature

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<<Name of Author>>

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<<Signature of author>>

ABSTRACT:

The fourth industrial revolution is upon us, and the traditional methods of doing things are slowly becoming obsolete, which makes the adaptation into the new world era more of a necessity. The healthcare department is no exception to this, as it also seeks faster, accurate and convenient methods to take care of its patients, and as such, this paper seeks to provide a solution in the form of a diagnosis and treatment recommendation system.

Other than the obvious reasons of convenience and being cost effective, this system looks to ease the workload on the already strained medical facilities in our country, by taking care of the rather basic illnesses. The main idea behind the functionality of the system is that a user inputs a range of the symptoms they are exhibiting, and it runs it against its own database, and produces results on what the patient might be suffering from, and what medication they should take, and where they can find it.

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Chapter 1: Introduction

1.1 Introduction

The healthcare industry is constantly seeking more efficient and effective methods for diagnosing and treating illnesses. One promising solution is the development of an artificial intelligence based system that can provide accurate diagnoses and treatment recommendations based on patient symptoms and medical history.

1.2 Definition

An expert system is a computer program that utilizes a knowledge base and a set of rules to provide expert-level decision-making capabilities (Shortliffe et al., 2005). Such systems have been successfully used in various fields, including medicine, to assist healthcare professionals in making accurate diagnoses and treatment recommendations. Expert systems have been developed for a wide range of medical conditions, such as urinary tract infections (Shortliffe et al., 2005), acute chest pain (Miller et al., 1991), skin diseases (Gao et al., 2019), and diabetes (Zhang et al., 2020). These systems have demonstrated high accuracy in identifying various medical conditions and providing appropriate treatment recommendations.

1.3 Background Information

Several studies have explored the use of expert systems in healthcare. For example, a study by Shortliffe et al. (2005) developed an expert system for the diagnosis and treatment of urinary tract infections, achieving high accuracy in diagnosing and treating patients. Similarly, a study by Miller et al. (1991) developed an expert system for the diagnosis and treatment of acute chest pain, resulting in improved diagnostic accuracy and reduced hospitalization rates.

More recently, a study by Gao et al. (2019) developed an expert system for the diagnosis of skin diseases, achieving high accuracy in identifying various skin conditions. Another study by Zhang et al. (2020) developed an expert system for the diagnosis and treatment of diabetes, resulting in improved glycemic control and reduced healthcare costs.

1.4 Objectives

1. To conduct an extensive literature review of the current state of the healthcare sector and the fourth industrial revolution, focusing on the potential benefits and challenges of implementing a diagnosis and treatment recommendation system.

2. To design and develop a diagnosis and treatment recommendation system that leverages advanced technologies, such as artificial intelligence, to provide faster and more accurate diagnoses and treatment recommendations for patients.

3. To validate the system's accuracy and effectiveness using real-world patient data, and to address any potential biases in the system's algorithms.

4. To assess the potential impact of the system on healthcare providers and facilities, including its ability to reduce their workload and improve overall patient outcomes.

5. To provide recommendations for the implementation of a diagnosis and treatment recommendation system in clinical practice, based on the findings of the study and insights gained from the research.

Chapter 2: Literature Review

Personalized diagnosis and treatment recommendation systems have gained significant attention in recent years due to their potential to revolutionize healthcare by providing tailored medical advice and treatment plans for individual patients based on their unique characteristics and medical history. This chapter presents a comprehensive review of the existing literature on personalized diagnosis and treatment recommendation systems, including the different approaches and techniques that have been proposed using expert systems, their effectiveness and limitations, and the challenges and opportunities associated with their development.

Personalized medicine is an emerging field that aims to provide personalized healthcare based on an individual's unique genetic, environmental, and lifestyle factors. The goal of personalized medicine is to enable more precise diagnosis, treatment, and prevention of diseases, and ultimately improve patient outcomes. However, the implementation of personalized medicine in clinical practice faces several challenges, such as the need for more precise diagnostic tools and the integration of patient preferences and values into treatment recommendations.

Artificial intelligence programs are one approach to personalized diagnosis and treatment recommendation systems using mobile devices. Artificial intelligence systems in healthcare use a combination of clinical data, patient characteristics, and medical knowledge to provide clinicians or patients with recommendations on diagnosis, treatment, and monitoring. For example, an expert system developed by Shah et al. (2019) for the diagnosis of breast cancer achieved a sensitivity of 96.0% and a specificity of 92.0%, demonstrating the potential of expert systems to improve the accuracy and efficiency of clinical decision-making.

Several studies have evaluated the effectiveness of personalized diagnosis and treatment recommendation systems using expert systems and artificial intelligence in improving patient outcomes. For example, a study by Liu et al. (2020) found that an expert system for the diagnosis and treatment of diabetes in primary care was associated with significant improvements in glycemic control and patient satisfaction. Similarly, a study by Chen et al. (2016) found that an expert system for the management of chronic obstructive pulmonary disease was associated with a significant reduction in hospitalization rates and improved quality of life for patients.

This chapter has provided a comprehensive review of the existing literature on expert systems for personalized diagnosis and treatment recommendation, including the different approaches and techniques that have been proposed and their effectiveness and the challenges and opportunities associated with their development. The information presented in this chapter demonstrate the feasibility and effectiveness of these systems in clinical practice, and highlight the potential for personalized medicine to improve patient outcomes and revolutionize healthcare for smartphone users. Further research and development are needed to address the remaining challenges and limitations and realize the full potential of personalized medicine.

Chapter 3: Methodology

Various programming and scripting languages will be used in the development of this study's system, but at the heart of them will be the python programming language and bootstrap will be used solely for the user interface. This study intends to build a flask application which will be used as the application's web server. Several machine learning algorithms in the development of the system. On top of that, the system is made to be in the form of a chat bot to provide an enhanced user experience and to provide an interface that will be more user friendly, allowing patients to input their data with ease.

Furthermore, other artificial intelligence concepts like natural language processing will be used to try and breach language disputes between user and the system, and also the jquery google API will be used for reading and processing user input.

3.1 System Architecture

This system in essence will resemble a typical expert system, in the sense that there is a user interacting with the user interface of the system, where he inputs his data and awaits a response, and then the user interface interacts with the inference engine which processes, selects and retrieves information from the knowledge base that has been added by a field expert. Experts in an expert system are just humans with vast knowledge in that particular domain. Below is the architecture of an expert system.

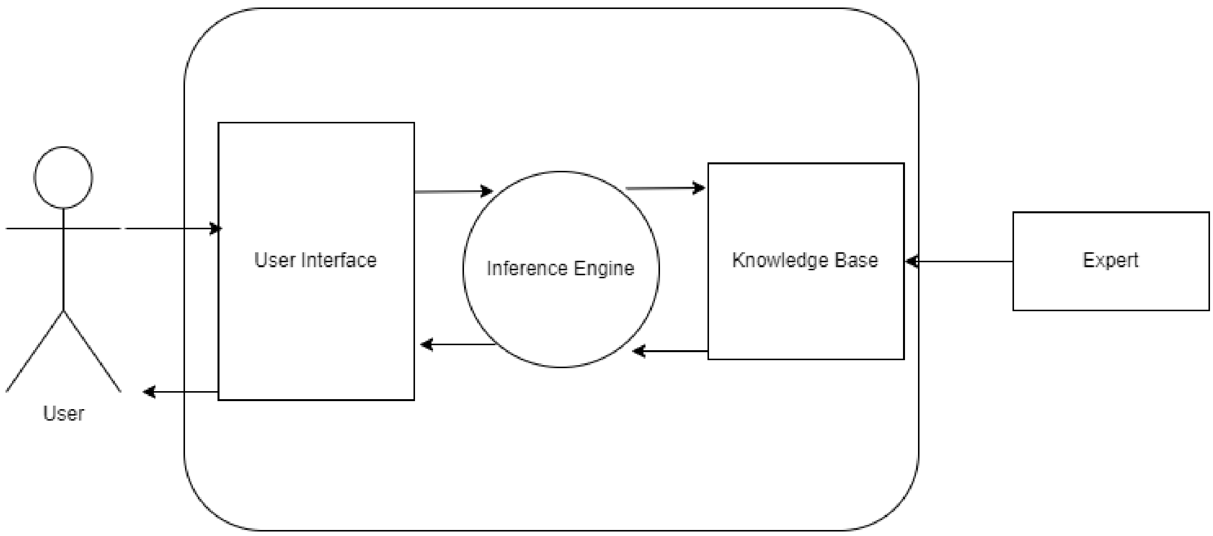

Fig 3.1 System Architecture

3.2 System Development Stages

- **Requirement Analysis:** In this stage all the necessary requirements will be specified, and acquired. This phase will also include the data acquisition from the expert into a readable format.
- **Design:** The software system is designed, and the rules are added into the knowledge base using multiple programming languages
- **Code:** Development and integration of the different modules of the software.
- **Testing:** the system will be tested for accuracy and bugs within the code
- **Implementation:** System will be deployed

3.3 How It Works

The system upon completion will be a locally hosted application that has the interface of a chatbots which will not be too dissimilar to popular chat apps like Facebook Messenger and Whatsapp Messenger.

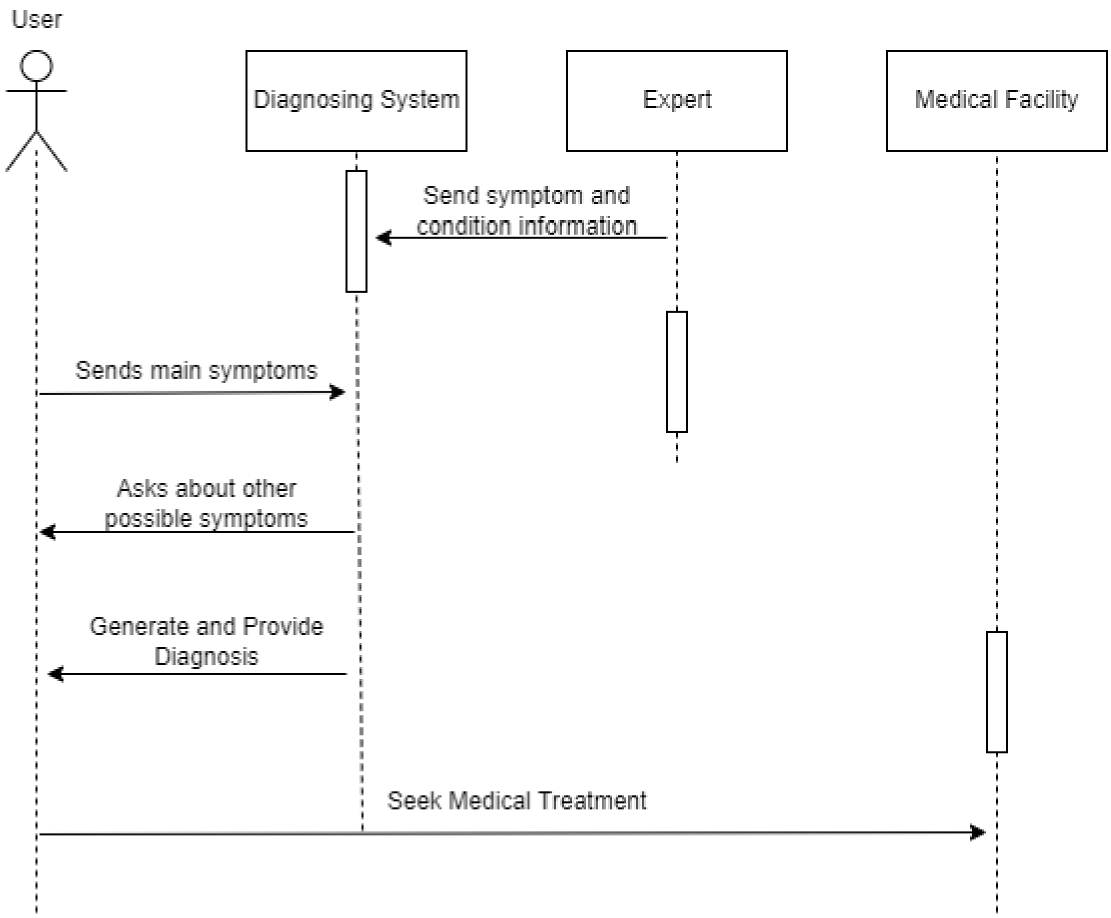

Fig 3.3.1 System Layout

When the user opens the system, he or she will be greeted by a message from the system, asking him or her if she is feeling good or not, to which she can either reply good, or not good, and then the system will ask the user if he would like a diagnosis, and following the instructions the diagnosis process will begin. He or she will then be asked to list the symptoms he or she may be exhibiting, to which the system will then run against its knowledge base to try and match it with the correct diagnosis. Diagnosis will be returned with a certain percentage of accuracy, and then a treatment will be recommended. Fig 3.3.2 below illustrates the process.

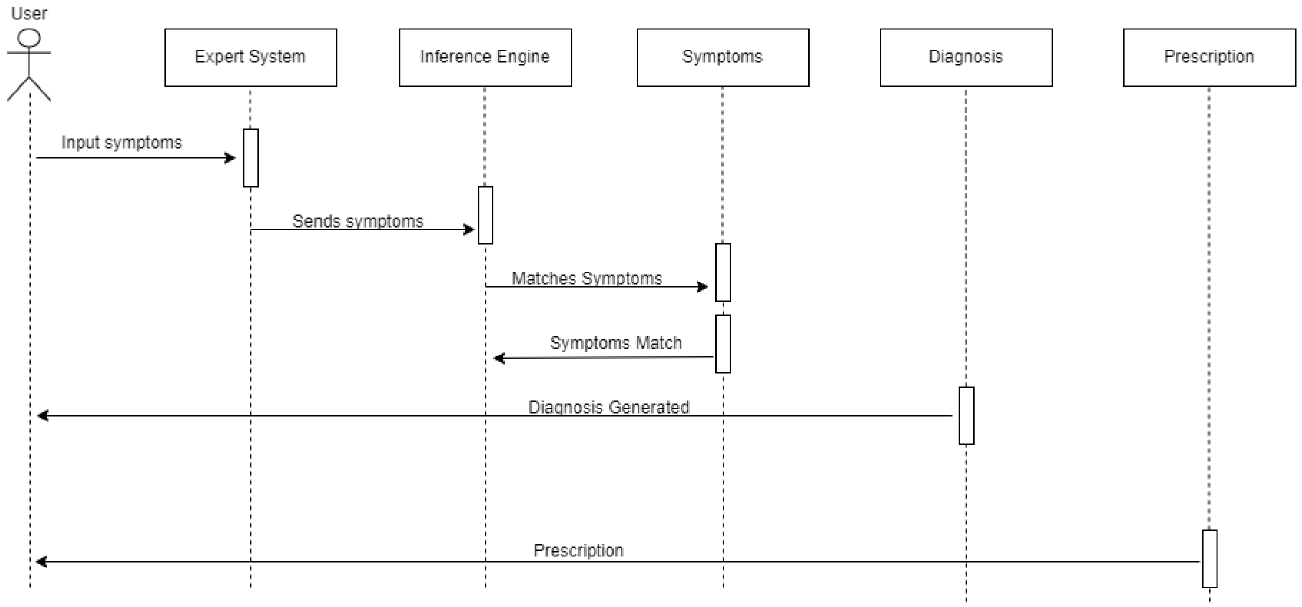

Fig 3.3.2 Diagnosis Process

3.4 How to improve system accuracy.

Should the system not meet the specified benchmark in terms of accuracy, these are the measures to be deployed to improve system accuracy

- ❖ Change source of knowledge base to a more reputable one
- ❖ Add certainty factors
- ❖ Handle uncertainties
- ❖ Add more rules
- ❖ Collect data from patients
- ❖ Evaluate performance
- ❖ Get feedback from users

3.5 Evaluation Matrices

The system will use four matrices to evaluate the performance of the system; sensitivity, specificity, positive predictive value, negative predictive value. This will ensure that the system produces accurate diagnosis and treatment recommendations.

3.6 Error analysis

Error analysis will also be conducted to see where the system has made errors, and subsequently make changes in those areas that need correction, to ensure the best performance by the system.

Chapter 4: Results

4.1 Data Preprocessing

For this project, a dataset retrieved from kaggle was used,and it had a list of conditions, and all the symptoms associated with each condition. It uses binary labelling to highlight which symptom matches with which condition. Fig 4.1.1 shows a snippet of the dataset.

```
In [4]: df_tr.head()
```

Out[4]:

	itching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	joint_pain	stomach_pain	acidity	ulcers_on_tongue	...	blackheads	scurrin
0	1	1	1	0	0	0	0	0	0	0	...	0	
1	0	1	1	0	0	0	0	0	0	0	...	0	
2	1	0	1	0	0	0	0	0	0	0	...	0	
3	1	1	0	0	0	0	0	0	0	0	...	0	
4	1	1	1	0	0	0	0	0	0	0	...	0	

5 rows × 133 columns

Fig 4.1.1 Training data

Out[6]:

...	blackheads	scurring	skin_peeling	silver_like_dusting	small_dents_in_nails	inflammatory_nails	blister	red_sore_around_nose	yellow_crust_ooze	prognosis
...	0	0	0	0	0	0	0	0	0	Fungal infection
...	0	0	0	0	0	0	0	0	0	Allergy
...	0	0	0	0	0	0	0	0	0	GERD
...	0	0	0	0	0	0	0	0	0	Chronic cholestasis
...	0	0	0	0	0	0	0	0	0	Drug Reaction

Fig 4.1.2 Training data with response variable

As seen on Fig 4.1.1 and Fig 4.1.2, the dataset contains 132 columns of different symptoms, and then the final column is the prognosis column. The Figs above also illustrate the binary marking of the symptoms, ‘1’meaning that this symptom is in the list of symptoms associated with that particular condition. From Fig 4.1.2 we can conclude that none of the symptoms are associated with either fungal infection, allergy, gerd, chronic cholestasis or drug reaction.

4.2 Machine Learning Prediction Model

Once the dataset was imported, preprocessing methods were applied to the dataset, and that led to three conditions being dropped because they had strings of zeros for all symptoms, which is impossible and thus was treated as data input error.

After preprocessing, a machine learning prediction model was developed, initially two models were created, the decision tree model and the K Nearest Neighbour model, the Fig below shows the classification report of the two models.

	precision	recall	f1-score	support
(vertigo) Paroymsal Positional Vertigo	1.00	1.00	1.00	1
AIDS	1.00	1.00	1.00	1
Acne	1.00	1.00	1.00	1
Alcoholic hepatitis	1.00	1.00	1.00	1
Allergy	1.00	1.00	1.00	1
Arthritis	1.00	1.00	1.00	1
Bronchial Asthma	1.00	1.00	1.00	1
Cervical spondylosis	1.00	1.00	1.00	1
Chicken pox	1.00	1.00	1.00	1
Chronic cholestasis	1.00	1.00	1.00	1
Common Cold	1.00	1.00	1.00	1
Dengue	1.00	1.00	1.00	1
Diabetes	1.00	1.00	1.00	1
Dimorphic hemmorhoids(piles)	1.00	1.00	1.00	1
Drug Reaction	1.00	1.00	1.00	1
Fungal infection	1.00	1.00	1.00	1
GERD	1.00	1.00	1.00	1
Gastroenteritis	1.00	1.00	1.00	1
Heart attack	1.00	1.00	1.00	1
Hepatitis B	1.00	1.00	1.00	1
Hepatitis C	1.00	1.00	1.00	1
Hepatitis D	1.00	1.00	1.00	1
Hepatitis E	1.00	1.00	1.00	1
Hypertension	1.00	1.00	1.00	1
Hyperthyroidism	1.00	1.00	1.00	1
Hypoglycemia	1.00	1.00	1.00	1
Hypothyroidism	1.00	1.00	1.00	1
Impetigo	1.00	1.00	1.00	1

Fig 4.2.1 KNN Classification Report

	precision	recall	f1-score	support
(vertigo) Paroymsal Positional Vertigo	1.00	1.00	1.00	1
AIDS	1.00	1.00	1.00	1
Acne	1.00	1.00	1.00	1
Alcoholic hepatitis	1.00	1.00	1.00	1
Allergy	1.00	1.00	1.00	1
Arthritis	1.00	1.00	1.00	1
Bronchial Asthma	1.00	1.00	1.00	1
Cervical spondylosis	1.00	1.00	1.00	1
Chicken pox	1.00	1.00	1.00	1
Chronic cholestasis	1.00	1.00	1.00	1
Common Cold	1.00	1.00	1.00	1
Dengue	1.00	1.00	1.00	1
Diabetes	1.00	1.00	1.00	1
Dimorphic hemmorhoids(piles)	1.00	1.00	1.00	1
Drug Reaction	1.00	1.00	1.00	1
Fungal infection	1.00	1.00	1.00	1
GERD	1.00	1.00	1.00	1
Gastroenteritis	1.00	1.00	1.00	1
Heart attack	1.00	1.00	1.00	1
Hepatitis B	1.00	1.00	1.00	1
Hepatitis C	1.00	1.00	1.00	1
Hepatitis D	1.00	1.00	1.00	1
Hepatitis E	1.00	1.00	1.00	1
Hypertension	1.00	1.00	1.00	1
Hyperthyroidism	1.00	1.00	1.00	1
Hypoglycemia	1.00	1.00	1.00	1
Hypothyroidism	1.00	1.00	1.00	1
Impetigo	1.00	1.00	1.00	1
Jaundice	1.00	1.00	1.00	1

Fig 4.2.2 DT Classification Report

As seen from Fig 4.2.1 and Fig 4.2.2 above there is not much to separate the two models, as they all have the same precision score, recall score, fl-score, and support score, which is a 100% for all the conditions, and they also had the same micro average and weighted average for all the conditions in the testa data, which was 41. At the end, the KNN model was chosen.

4.3 Natural Language Processing

After the creation of the prediction model, a natural language processing model was created to analyze and interpret user input. For the creation of the NLP, a JSON file was imported, Fig 4.3 shows the contents of the JSON file.

```
 'tag': 'abdominal_pain'},
{'patterns': ['abnormal menstruation',
  'heavy period',
  'Heavy flow',
  'Period lasts longer',
  'period painful',
  'strong menstrual pain',
  'Menstrual cramps strong'],
 'tag': 'abnormal_menstruation'},
{'patterns': ['acid reflux', 'acidity problems', 'heartburn'],
 'tag': 'acidity'},
{'patterns': ['acute liver failure',
  'liver hurts',
  'pain around liver',
  'Upper right abdomen hurts'],
 'tag': 'acute_liver_failure'},
{'patterns': ['altered sensorium',
  "can't think clearly",
  'hard to think',
  'unable to concentrate'],
```

Fig 4.3.1 Unprocessed json data

Tokenisation and lemmatisation was perfomed on the data in the json file, and this is the final processed output of the json file.

```
(['rusty', 'brown', 'sputum'], 'rusty_sputum'),
(['brown', 'sputum'], 'rusty_sputum'),
(['runny', 'nose'], 'runny_nose'),
(['watery', 'runny', 'nose'], 'runny_nose'),
(['watery', 'secretion', 'from', 'nose'], 'runny_nose'),
(['Fluid', 'from', 'nose'], 'runny_nose'),
(['restlessness'], 'restlessness'),
(['need', 'to', 'move', 'around'], 'restlessness'),
(['inner', 'tension'], 'restlessness'),
(['ca', "n't", 'calm', 'mind'], 'restlessness'),
(['cramps', 'in', 'extremities'], 'restlessness'),
(['urge', 'to', 'move'], 'restlessness'),
(['redness', 'of', 'eyes'], 'redness_of_eyes'),
(['red', 'eyes'], 'redness_of_eyes'),
(['eyes', 'are', 'red'], 'redness_of_eyes'),
(['eyes', 'are', 'dry'], 'redness_of_eyes'),
(['red', 'spots', 'over', 'body'], 'red_spots_over_body'),
(['red', 'spots', 'on', 'body'], 'red_spots_over_body'),
(['small', 'patches', 'on', 'body'], 'red_spots_over_body')]
```

Fig 4.3.2 Processed json data

As part of the NLP development, certain steps were employed in creation of the model,and certain python libraries like spacy, wordnet and stopwords were installed. Below are the steps undertaken in developing the NLP model

- Segmentation (Tokenisation)
- Cleaning
- Stemming
- Lemitisation
- POS-Tagging
- Name-Entity Recognition
- en-core-web-sm importation

Through these steps, the NLP model was now fully functional. Tokenisation was important in training the model into breaking sentence strings into individual words, and the cleaning process trained the model to read and remove basic english words that do not carry essential meaning to the sentence. Fig 4.3.3 illustares that. Fig 4.3.4 illustrates the part about Name-Entity Recognition, and the python module ‘en-core-web-sm’ was imported to find similarity in words, or rather different words that mean the same thing. This was all done to simplify the user experience as one person may refer to one particular symptom as one thing and another person refer to the same thing in a different way, or using different words, so the NLP model was created to try and breach that language barrier.

```
In [4]: from nltk.corpus import stopwords
        from nltk.tokenize import word_tokenize
        data="Hello, i am very happy to meet you. I created this course for you. Good by!"
        word_tokens = [word.lower() for word in word_tokenize(data)]
        data_clean = [word for word in word_tokens if (not word in set(stopwords.words('english')) and  word.isalpha())]
        print(data_clean)

        ['hello', 'happy', 'meet', 'created', 'course', 'good']
```

Fig 4.3.3 Tokenisation

```
In [15]: import nltk
         from nltk.tokenize import word_tokenize
         data="William Henry Gates III (born October 28, 1955) is an American business magnate," \
              " software developer, and philanthropist. He is best known as the co-founder of Microsoft Corporation." \
              "During his career at Microsoft, Gates held the positions of chairman, " \
              "chief executive officer (CEO), president and chief software architect, " \
              "while also being the largest individual shareholder until May 2014. " \
              "He is one of the best-known entrepreneurs and pioneers of the microcomputer " \
              "revolution of the 1970s and 1980s."
         words=word_tokenize(data)
         print(nltk.ne_chunk(nltk.pos_tag(words)))
```

```
(S
  (PERSON William/NNP)
  (PERSON Henry/NNP Gates/NNP III/NNP)
  (/(
  born/JJ
  October/NNP
  28/CD
  ,/,
  1955/CD
  )/)
  is/VBZ
  an/DT
  (GPE American/JJ)
  business/NN
  magnate/NN
  ,/,
  software/NN
  developer/NN
  ,/,
```

Fig 4.3.4 Name Entity Recognition

4.4 Severity Dictionary

A severity dictionary in the form of a csv file was imported, it contained all the conditions in the training and test set, and it contained days in which user has been experiencing symptoms. This allowed for the system after diagnosis has been made to enter the number of days in which user has been experiencing symptoms, and usually the longer the number of days presumably the more severe the condition, this also worked hand in hand with the precaution dictionary, which will be explained below.

4.5 Precaution Dictionary

This imported csv file works hand in hand with the severity dictionary as stated above. The fewer the number of days stated by the user the less severe the condition, and thus the precaution is one that that is subtle in terms of course of action, but the higher the severity the more serious the precaution which is often the need to consult the doctor with immediate effect!

4.6 Symptom Description

The last csv to be imported is the symptom description csv file, which contains a short and straight-forward description of each and every condition in the system, which is given to the user after the diagnosis has been produced.

4.7 User Interface

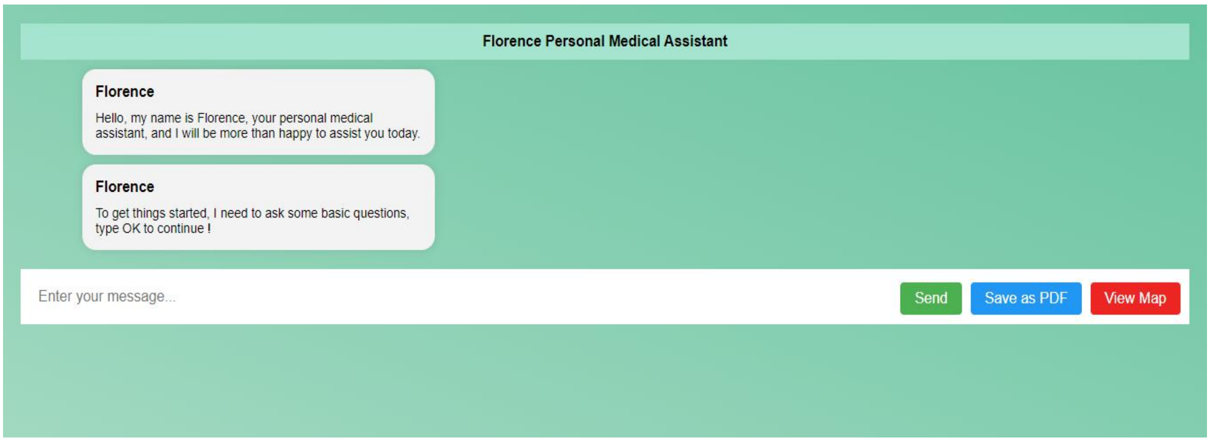

Fig 4.7 Home Screen

Fig 4.7 shows the systems home screen, or landing screen, this page shows is basically the introductory part of the system, in which the system introduces itself, by stating its name, and states that it will be more than happy to assist you. On top of that, it then prompts the user to tap ok, to start the diagnosis process.

Below that is a text entry field, and three buttons namely 'Send', 'Save as PDF', and View Map. The send button sends the user input back to the system, for processing and giving a proper response. The two buttons are for saving the whole conversation as a pdf, and open the map, to view user location, and pharmacies in close vicinity, respectively, as will be further explained later on.

4.8 User name and age collection

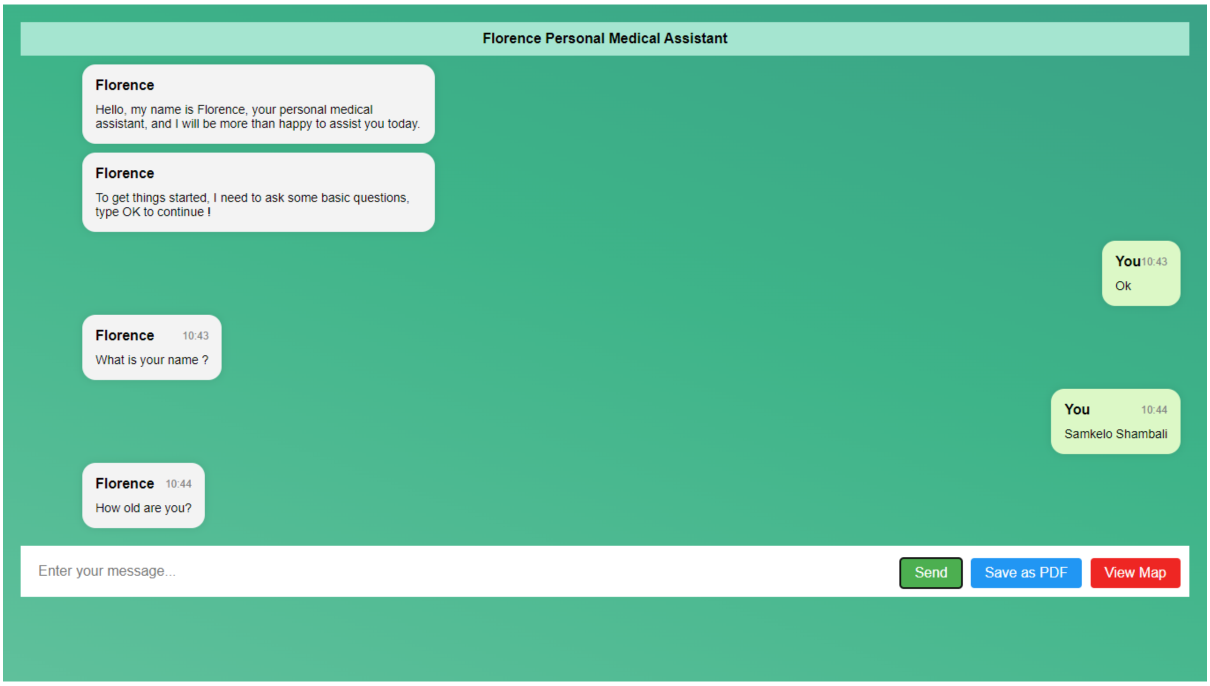

Fig 4.8 User Credentials

Fig 4.8 The system prompts the user to enter his name and age, the purpose of this section of the system, is mostly there just to add a sense of friendliness between user and system, so that the user feels somewhat at ease before the diagnosis process begins.

4.9 More User Credentials

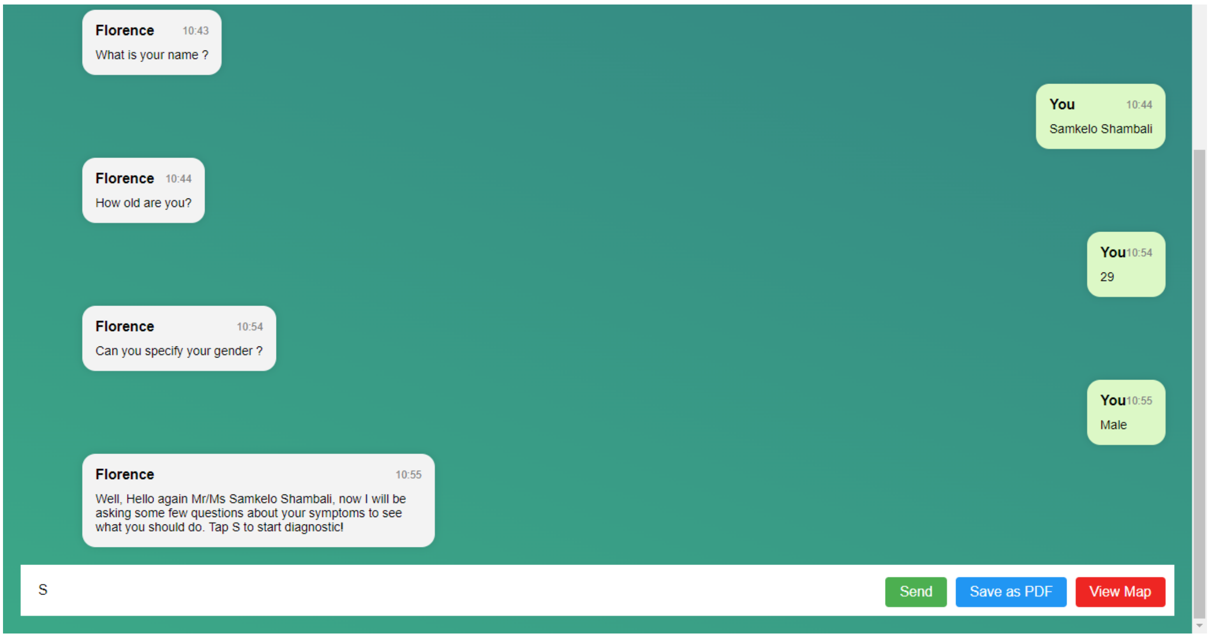

Fig 4.9 Gender and starting process.

Fig 4.9 The system prompts the user to his or her gender now, all as part of the introductory process. In the use case of Samkelo Shambali, who is a male of 29 years, it then greets him, and then alerts him that it is going to ask him a few questions on how he is feeling and the symptoms he is exhibiting, to decipher the next method of action, it then prompts him to type 'S' to start the diagnostic process, which is an assumption that he is giving consent to start the process.

4.10 Main Symptom

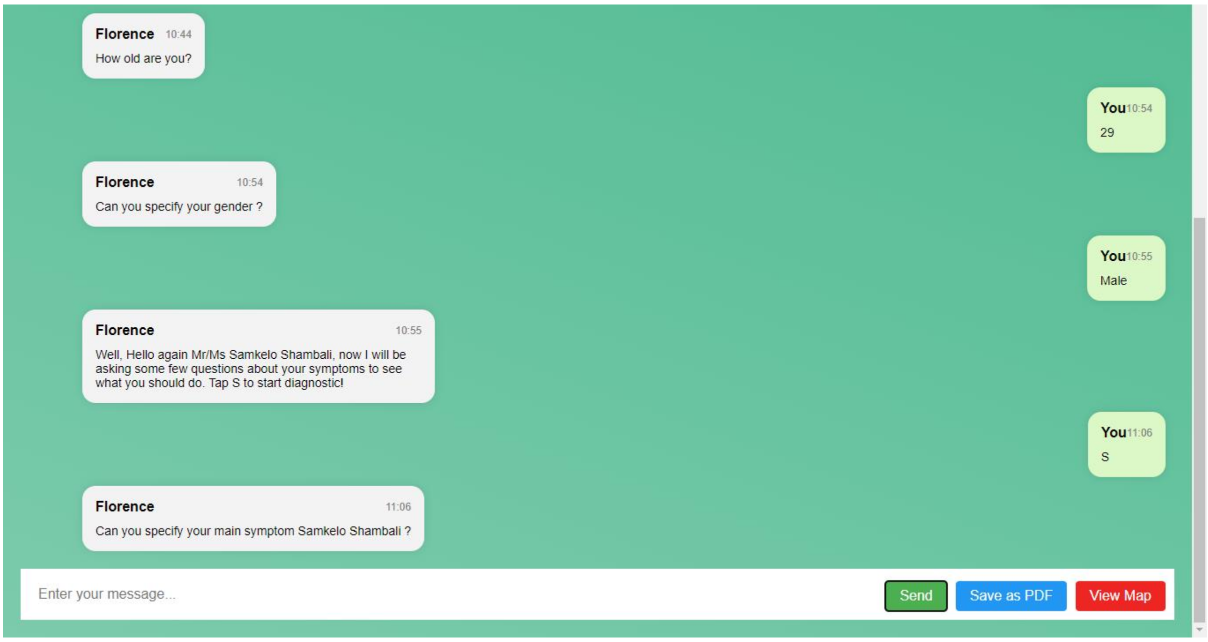

Fig 4.10 User's Main Symptom

Fig 4.10 Shows the system now prompting the user to enter his main symptom. A condition can have multiple symptoms associated with it, but there are often key ones, or major ones that help identify that symptom. The system then prompts the user to enter the main symptom, or perhaps the most severe of the symptoms he is exhibiting, and this will allow for a faster and accurate diagnosis.

4.11 Alternative Symptom

The system takes two symptoms from the user, the main symptom, and the alternative symptom. The alternative symptom is a secondary which is also very important, because when the two symptoms are combined it creates a pattern of possibilities, this then allows the system with its own symptoms, in which he or she will have to answer with yes or no answers, until the system can arrive to one final definitive condition.

4.12 The Diagnosis

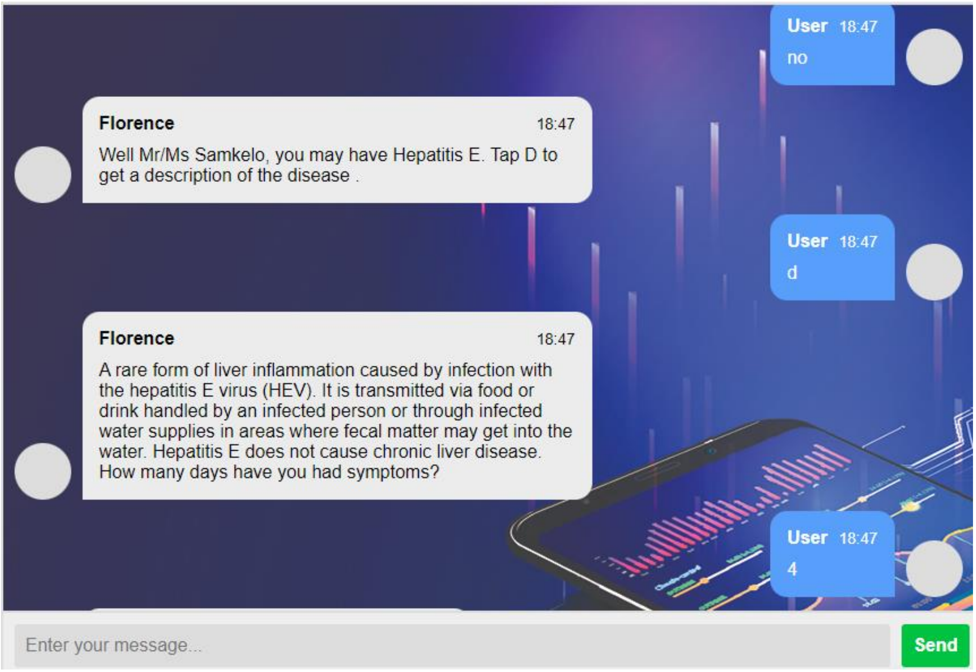

Fig 4.12 The Diagnosis

After the system has asked you asked you the questions and it feels confident enough that it has reached a conclusive verdict, it then provides a diagnosis as illustrated in Fig 4.12. After the diagnosis is produced, it then provides the user with the diagnosis description, just so the user has a clear indication of what he has been diagnosed with, and then it asks the user how long he has been feeling the symptoms.

4.13 Symptom Severity

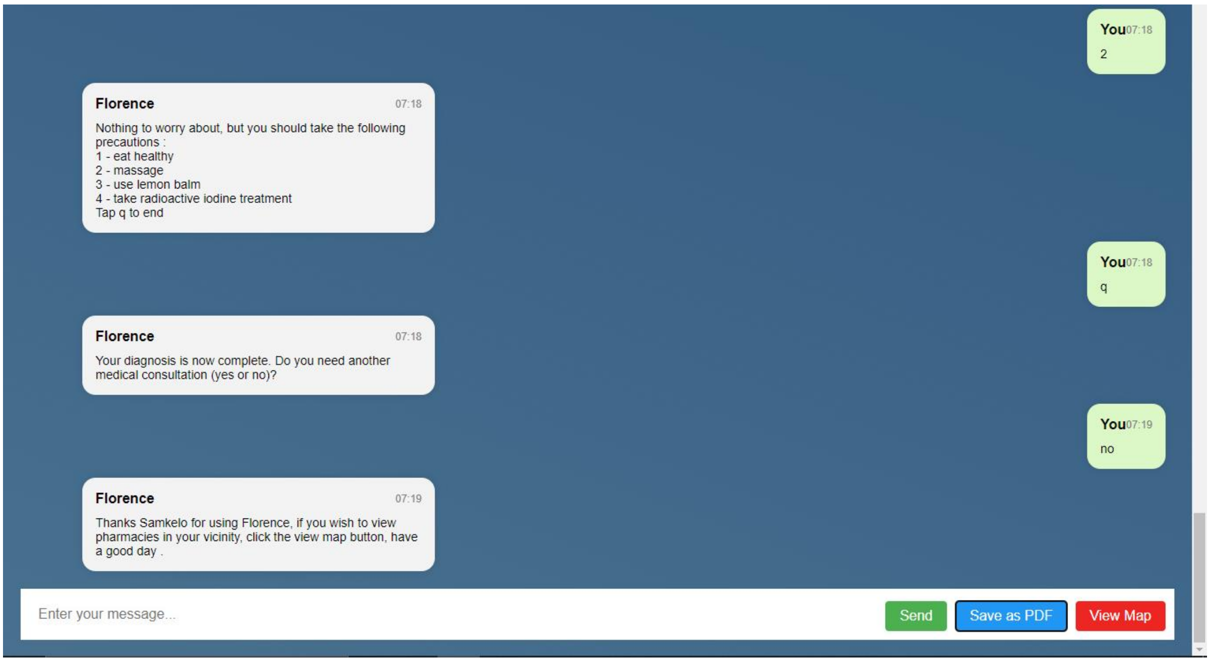

Fig 4.13.1 Low Severity

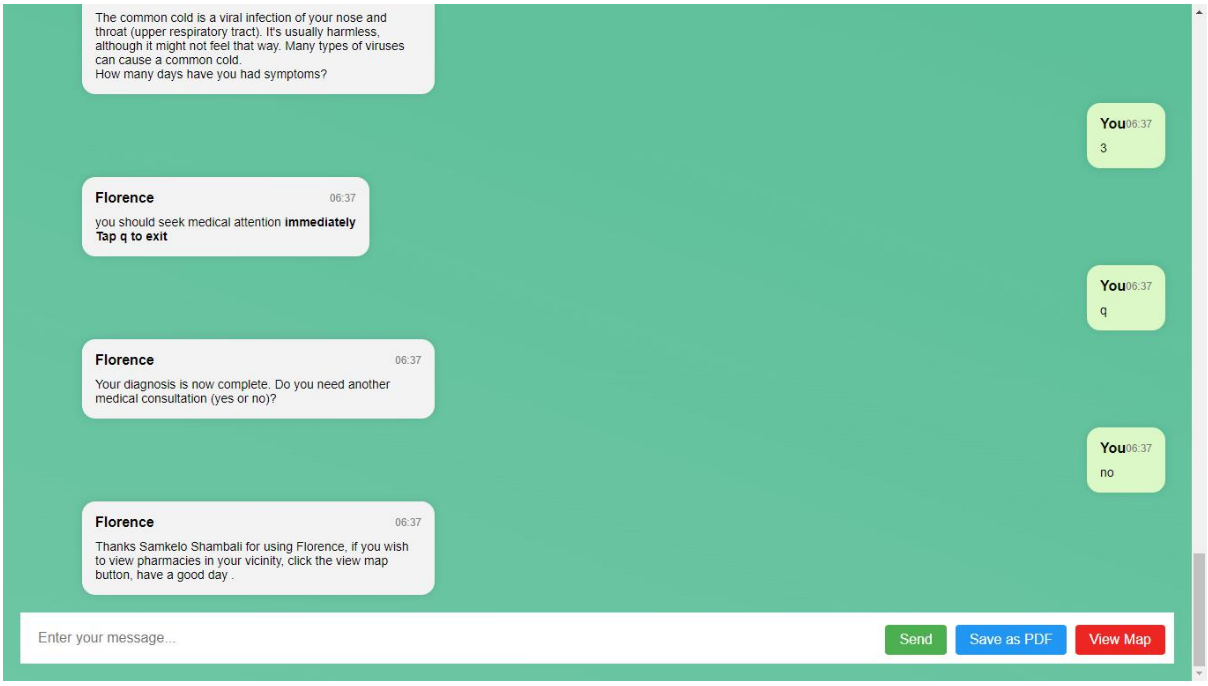

Fig 4.13.2 High Severity

Fig 4.13.1 and Fig 4.13.2 show some of the possible responses, depending on the number of days the user has had symptoms and also the condition that is being dealt with influences the overall recommendation. On Fig 4.13.1, user has been experiencing symptoms of the common cold for two days, and so it provides first hand treatment recommendations, but on Fig 4.13.2, in which the user has been diagnosed with common cold, it recommends that the user should seek medical attention immediately.

4.14 Save as PDF Button

The user has the option to save whole conversation as a pdf, which he can view later, reference later or provide to his medical practitioner in order to get treatment.

4.15 View Map Button

The View Map Button allows the user to view pharmacies or hospitals within his or her vicinity after the diagnosis has been made, to get the necessary medication or any appropriate treatment.

4.16 Flask Application

A flask application was developed to allow the application to run on a local server which would integrate both the user interface and the back end.

Chapter 5: Conclusion

5.1 Summary

This application seeks to alleviate the workload that is exerted on medical personnel working on medical facilities in the country, because currently the ratio of nurse and doctors to patients is staggeringly imbalanced. On top of that, this system will produce faster and accurate diagnoses to patients and also outline the first line of treatment for those diagnosed conditions if necessary, and also users will be able to view pharmacies and hospitals in close vicinity to them.

A couple of programming concepts have been deployed in the creation of this system, Machine Learning in the development of the prediction algorithm, Natural Language Processing in order to cater for language disputes, Google APIs were used for text entry and the location of user and medical facilities close to him or her, and lastly, bootstrap and a flask application were used for the development of the user interface and locally hosting it in a web server respectively.

5.2 Future Works

As part of further development of the system, since it is a medical system, and currently it has a 132 conditions in its knowledge base, the first step would be increasing the number of conditions it can provide diagnoses for, secondly, it should allow for screening and assessment and screening of chronic diseases like tuberculosis and diabetes, and lastly it needs to maintain the high levels of accuracy.

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