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Development of Natural Language Based Medical Consultancy Information Flow for Hospital Out-Patients Using Machine Learning Techniques

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ABSTRACT
Medical consultancy today is characterized by numerous demanding tasks which are prone to ill-vices and needs to be efficiently managed by medical practitioners using emerging techniques and solutions. Although there are concerted efforts by both the doctors and other medical stakeholders aimed at improving thecondition, however, human errors abound. Sequel to this,the level of management bottlenecks recorded in the hospitals on daily basis abound, such as unordered information flow in the out-patients department (OPD), thus, effective health service delivery is being stifled. In this regard, the application of natural language based medical consultancy information flow can't be undermined. This work is sought to develop a natural language based medical consultancy information flow for hospital out-patients using machine learning techniques. The architecture of the system was modeled using universal modeling language (UML) tools. The medical information flow is processed using machine learning techniques (MLT) which is named Word-Rank. The word rankpositions and sorts all sentences accordingly in an input corpus of a patient case report and presented in a summarized versionof the word. So the Word-Rank algorithm generates summary of the patient's record based on the input corpus. The implemented system can be deployed to the Nigerian Electronic Health Records (NEHR) used in hospitals to make for efficient information flow of patients in the outpatient department of every hospital. The system would therefore reduce the effort expended by the medical practitioners in comprehending a case report and offering various medical services since it would be very easy toview the salient parts promptly, therefore resulting to a reasonablysmooth information flow, easier consultation process and reduction of the waiting time by patients. Cosine similarity is used as the metric to evaluate the accuracy of the output from the algorithm when weighted againstthe tradition information flow in the outpatient department.

Key: Natural Language, Medical Consultancy, Information Flow system, Hospital Out-Patients Department, Machine Learning Techniques

I. BACKGROUND

The flow of services in the hospitalsis incredibly important in ensuring efficient development, gathering and management of information. The flow of information in the service delivery of hospitals is paramount for thediagnosis and treatment of patients, as well as the conduct of research and implementation of insurance systems [1].Information flow improves the strength of service delivery and enhances the standard of attention given to patients, thereby improving patients' satisfaction.The flow of information

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among the health workers should be of utmost interest to every stakeholder in the healthcare industry as better health is a prerequisite to the happiness and well-being of human. It is also pertinent to economic development as healthy populations report a longer life-span, higher productivity and higher savings rate [1]. Medical practice and human health are so intertwined that one cannot make mention of one without the other. Thus, information flow in the hospitals should be purposeful, reliable, accurate, timely, complete and valid in order to assist healthcare providers in elongating the lifespan of the populace [1]. In ensuring a smooth information flow in the healthcare industry, attention should be given to the development and maintenance of an efficient technology enabled information flow system, rather than paper and pen based information gathering, such as the taking notes during consultation, as well as admission/discharge and so on.A patient's information flow is made up of many different pieces of data that tells the complete story about that patient's current and past health status. A patient's information flow is very vital as it helps the physician to know what medications he or she is placed on, nature of allergies, and diagnoses to treat the person in an optimal way. A well comprehended medical consultation information systemensures an effective medical consultation and serves as motivation to healthcare workers.

Medical consultation information system is progressively a knowledge intensive domain for hospitals. Hence, the information created and employed in this domain should be correct, comprehensive, accessible, consistent, up-to-date, relevant, timely and it ought to be outlined in order that it can be reworked into purposeful data [4]. Hence, poor knowledge quality in medical consultation information systemwill increase attention prices, hinders health data exchange and threatens patient safety [5]. Thus, medical consultation information systemis considered the inspiration for higher health, the glue holding the health system along and also the oil keeping the health system running [6]. Hence health practitioners (such as nurses, community medical experts, medical doctors, pharmacists) and hospital policy makers utilize information to enhance the health and well being of people [7]. Hence, in a medical consultation information system,knowledge needs to be analyzed and evaluated to ensure that the data stored in the system allows for smooth running of the hospital and aid threatment, as well as decision-making [8].

II. INFORMATION FLOW IN NIGERIAHOSPITALS

Information flow in hospitals [16] refers to the manner that patients record are gathered and transferred from one health worker to the other in Nigeria hospitals. When a patient visits ahospital in Nigeria, the primary purpose of contact is typically with a secretary or associate body that directs the patient to buy a hospital card. Once the payment is created, a case history Officer (MRO) will attend to the patient by providinghim/herwith a hospital card, and thereafter distribute the patient's Hospital file to the appropriate officer for diagnosis and treatment. The MRO gets the patient's demographic data like name, address, sex and records it within the card;the nursetakes the patient's important signs and records it within the card. The nurse then directs the patient to a medical doctor. The doctor diagnoses the patients by playacting Physical Examination (PE) and recording his findings within the patients file. The doctor could request for a laboratory examination or/and associate imaging procedure to support his finding and ensure accurate treatment. The laboratory workers take blood of patientsor alternative sample and perform check on that, whereas a radiotherapist takes the image of the patient. The medical doctor interprets the laboratory or radiologist's results; and either admits, treats or refers the patient supported these results. Throughout the method of treatment, the doctor prescribes medicine to the patient that the patient gets from a health care provider. Patients on admission can eventually be discharged if well. Activity diagram that depicts this method is illustrated in figure 1 below.

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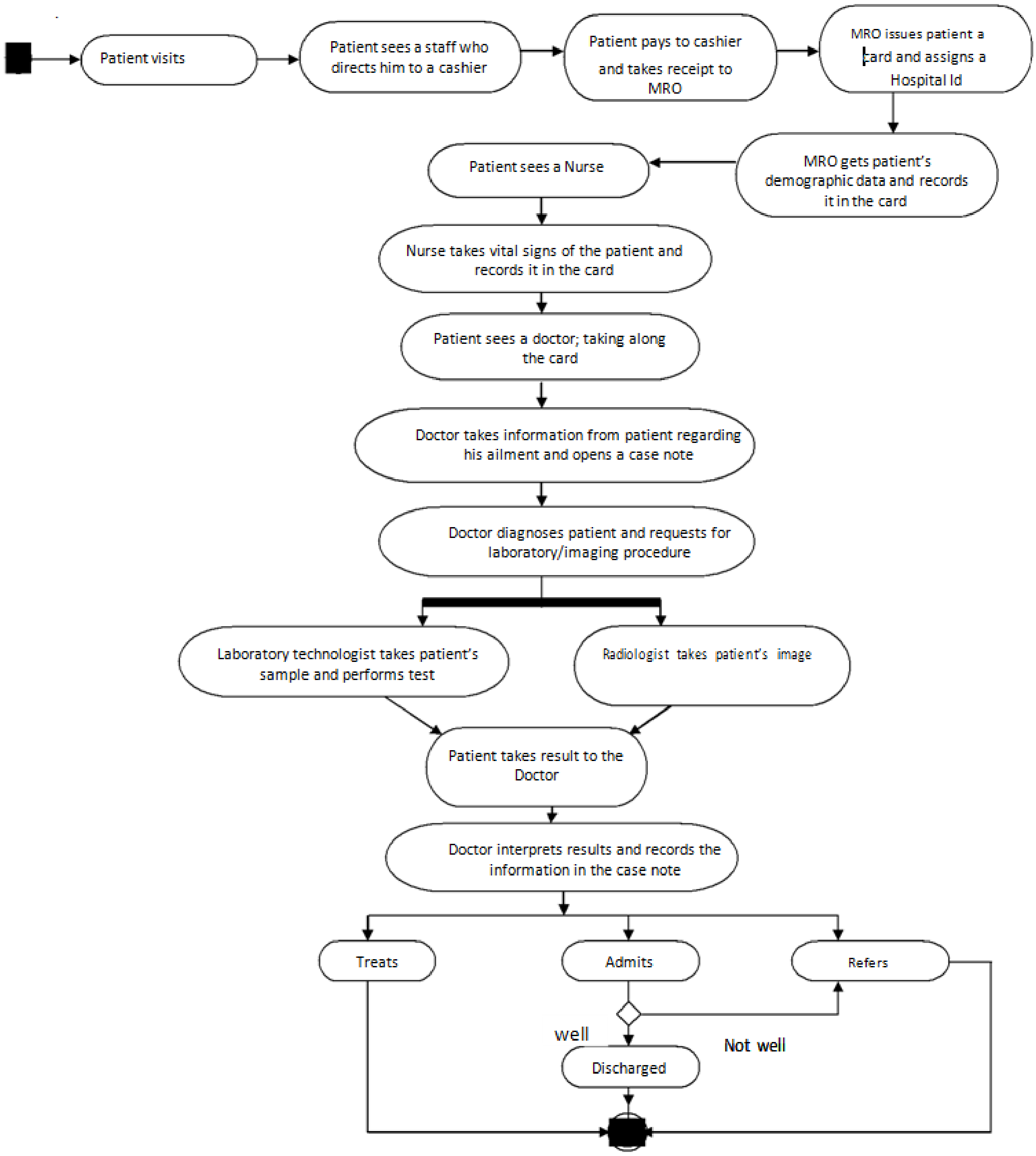

Figure.1: Activity diagram of information flow in Nigeria hospitals

2.1 Challenges of information flow in Nigeria hospitals

The challenges of information flow encountered in the hospitals in Nigeria are as follows:

i. Information exchange is mostly Paper based

In the hospitals in Nigeria, knowledge is typically collected, processed, and hold on in paper-based systems, inheritance systems and proprietary systems that are heterogeneously developed. Hence, effective communication/ info exchange amongst medical practitioners at intervals and across attention organizations is poor. This but adversely affects patients care because the timely access to patient's info is hindered. Hence, evitable deaths and injuries sometimes occur as a results of poor communication amongst medical practitioners [17]. What is more, as patients' info grows exponentially over the years, they're sometimes destroyed by medical practitionersthanks to lack of physical area.

ii. Untimely Delivery of Patients' info

Patients' information is not sometimes delivered promptly to medical practitioners at the purpose of care. Hence, medical practitioners don't have immediate and timely access to patients' information. Moreover, information is typically delivered manually to the care suppliers by the patients. Forexample, a patient is typically expected to require the results of a laboratory check to the attention professional that requests for it. This method is typically manual and time overwhelming. For example, the high price of transportation in areas just like the core riverine areas within the Niger Delta could hinder the movement of the patients. Consequently, selections regarding patients' attention are delayed. This in turns affects the patient's care adversely.

iii. **Lack of ability**

The attention system is incredibly advanced because it needs the cooperative efforts of numerous health providers throughout care. What is more, patients receive care from quite one health establishment. However, patients' information is basically held on in numerous silos of paper based systems across different medical organizations within Nigerian context. Moreover, medical organizations do not seem to be conjointly integrated. Consequently, this has led to important fragmentation and duplication of patients' informations and therefore impedes the flexibility of numerous medical practitioners to share knowledge. Thus, a professional could repeat a procedure since he doesn't have previous information regarding the patient. Hence, it's troublesome to determine a relationship amongst all entities of care within the Health care system in Nigeria. Consequently, medical suppliers are sometimes bestowed with incomplete and inconsistent information throughout the care given in the hospitals.

iv. Poor or no Feedback Mechanism

There is sometimes poor or no feedback amongst health providers once patients are referred from one health establishment to different ones. The care of a patient sometimes ends in a very specific health establishment as before long because the patient needs another kind of care that may not be gotten in a particular hospital. Moreover, there's poor integration of personal health facilities within the Nigeria's health care delivery system [18]. Hence, there's sometimes no continuity within the flow of knowledge amongst numerous points of care, sometimes from personal health establishments and government closely-held health establishments.

v. Medical Errors

Patients sometimes receive care from quite one attention supplier UN agency will be situated in numerous geographical locations. Hence, patients' informationis sometimes scattered in numerous health establishments. This method is related to medical errors as a results of inadequacy of patients information and unorganized medical processes.

vi. Rising price of attention

One of the key challenges of Health care system in Nigeria is that the rising price of attention is significantly high. The ineffective communication of information amongst the stakeholders within the circle of care could be a major issue that results in the augmented price of attention in Nigeria.

2.1.1 A way out of the problem of Information flow in Nigeria hospitals

Information flow in Nigeria hospitals, especially in the outpatients department are usually as a result of the use of paper and pen in the management of patient's record. Hence, hospitals are fragmented and healthcare activities are significantly duplicated. Consequently, there is poorcoordination of information between patients and the health workers, both in the primary, secondary and tertiary levels of healthcare. However, if a healthcare information system such as natural language based medical consultancy information flow is provided at all levels of Nigeria healthcare system, especially at the outpatient departments, interoperability will be facilitated. Thus, the efficient and faultless flow of information in the Nigerian hospitals amongst health care workers enhanced.

III. METHODOLOGY

This research was sought to develop a system for hospital information flow using natural language based medical consultancy information flowin order to reduce the shortcomings of the manual consultation process. The system architecture and model was based on Unified Modeling Language (UML) tools.The logic design of the Machine Learning Techniques isis discussed in-depth in the subsequent sections.

3.1 Architecture of the Medical Consultancy Information Flow System (MCIFS)

Figure 1 presents the architecture of MCIFS. The flow begins with the consultation between a doctor and a patient. The notes taken by

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the doctor are saved in a consultation repository. The notes are fed into the MCIFS in which the bulk of the work takes place. The MCIFS system converts the unstructured text sent by the doctor into tokens and then filters the tokens for the keywords, which are analysed and classified to give an accurate summary. The summary is then viewed by the doctor. Based on the summary, further insight is provided for the doctor by the use of charts and graphs. This is also stored in the repository which stores the consultation notes (input) and results of the MCIFS process, and feeds the requested summary (output) to the doctor.

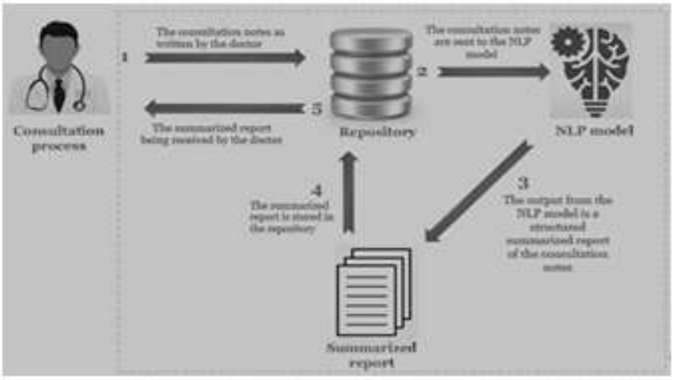

Fig. 2 General Architecture of MCIFS

3.2 **Context Diagram of MCIFS**

Context models are used to show system boundaries. Context models normally show that the environment includes several other automated systems. However, they do not show the types of relationships between the systems in the environment and the system that is being specified. Figure 2 depicts the context diagram of MCIFS. MCIFS interacts with the patient's records, which contains the bio-data of the patient. The summary generated from MCIFS further becomes an element of the patient records, which is stored in the patient record system. The consultation system handles the exchange between the doctor and the patient, wherein the doctor sends the details of the consultation and also receives the summary of the patient's record.

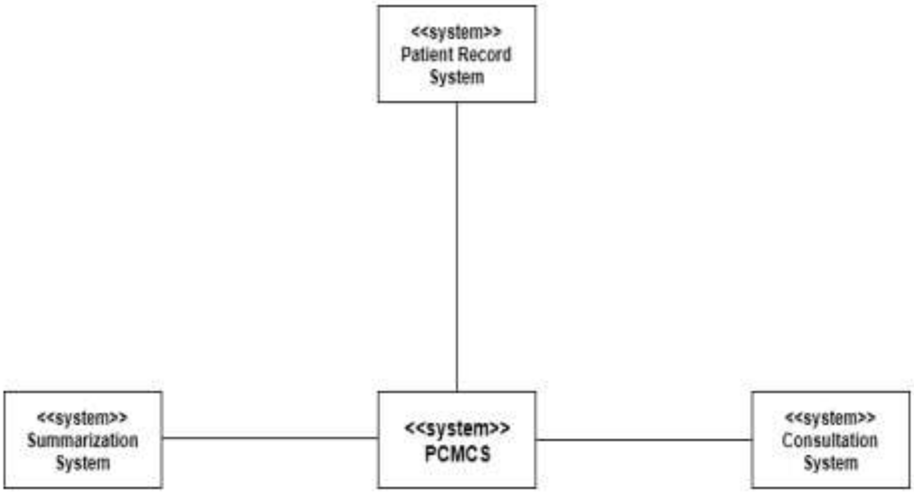

Fig. 3 Context Diagram of MCIFS

3.3 Use Case Diagram of MCIFS

Use-case modeling is applied to analyse the functional requirements of a system without worrying about how those requirements will be implemented. Use case diagram models the interactions between the system and external actors (users or other systems). Figure 3 shows the principal actor in the system (the doctor) and the

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different functionalities that can be carried out by the actor.

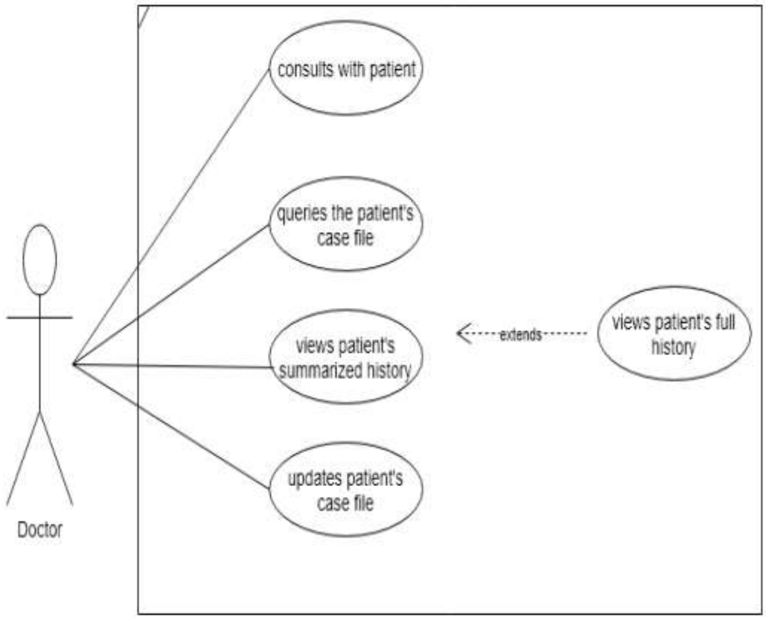

Fig. 4 Use Case Diagram of MCIFS

Table 1 elucidates each of the system functionalities depicted by the use cases in figure

Table 1 Description of the Use Cases

USE CASE	DESCRIPTION
Consults with patient	The doctor inputs the details from the consultation process into the system. Data: Patient's complaints, treatment summary Response: Confirmation that the data has been saved
Queriespatient's case file	The doctor can query the patient's case file if he wants to view the history of the patient.
Views case history	This shows the full history of the patient for a more in-depth analysis
View'spatient'ssummary	This shows the summarized history of the patient for a quick overview.
Updatespatient's case file	The doctor is able to update the patient's case file by saving the details of the most recent consultation

3.4 Activity Diagram of MCIFS

Activity diagrams are intended to show the activities that make up a system process and the flow of control from one activity to another. It gives a high level view of a system's functionalities. It is therefore required to model the requirements of the system. Figure 4 shows the flow of the different activities within MCIFS. From the initiation of the consultation process, a doctor requests to view a patient's history. S/he may decide to view the summary if he wants the high-level history or if he wants to see the full history, he has the option of seeing that too. Then, s/he is able to input a new consultation note base on his conversation with the patient. Once s/he is done with the patient, he saves his new note and thus, that particular patient's history is updated. For subsequent consultations, the saved case note becomes a part of the summarized report to be presented to the doctor.

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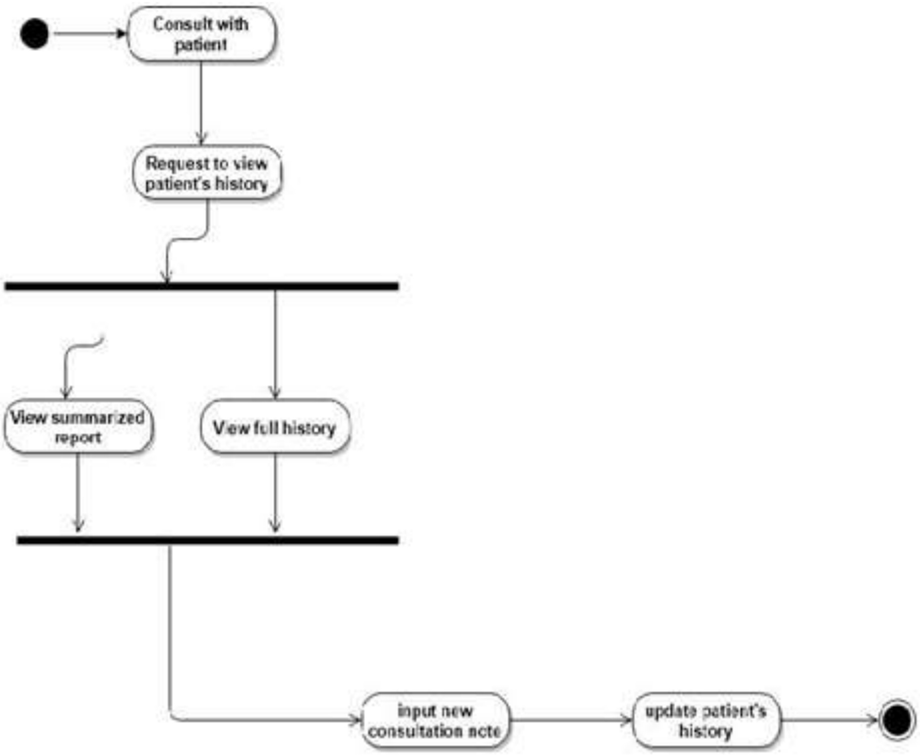

Fig. 5: Activity Diagram of MCIFS

3.5 System Design of MCIFS

This section describes the processes involved in the design of MCIFS, to convert the input to the required output, which is the summary of a patient's record. Figure 5 shows the system design using Word-Rank Algorithm. Word-Rank is an unsupervised text summarization technique. The algorithm calculates sentence vectors, calculates the similarities between sentence vectors and stores it in a matrix. The similarity matrix is converted to a graph, with sentences as vertices and similarities as edges, for sentence rank calculation. A certain number of top ranked sentences form the final summary. Figure 6 shows an alternative approach using a neural network. The word embeddings are calculated using a pretrained word embedding and the vectors are fed into the neural network. The neural network then summarizes the data based on the labeled input fed into it (a form of supervised learning).

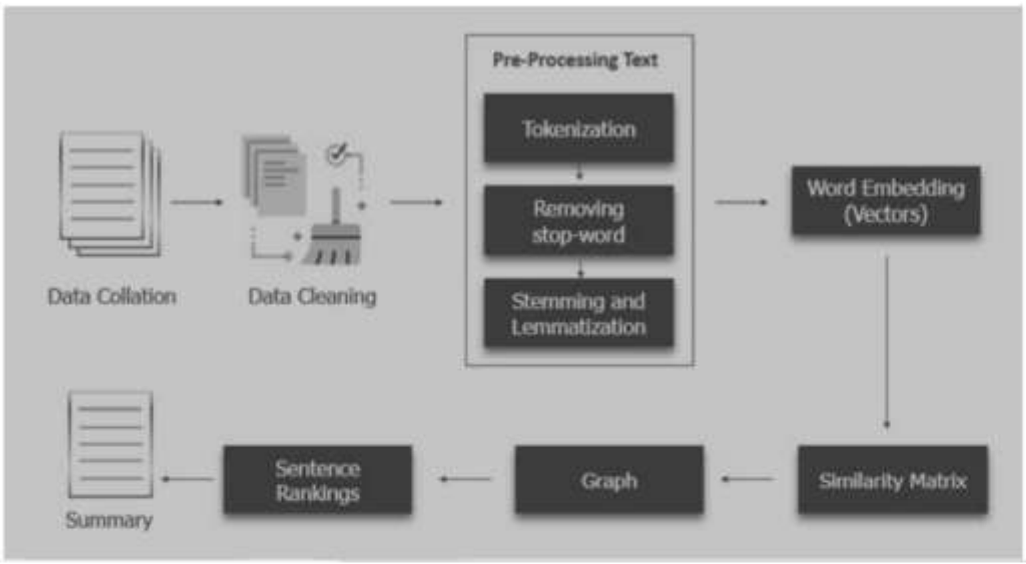

Fig. 6Word-Rank algorithm process

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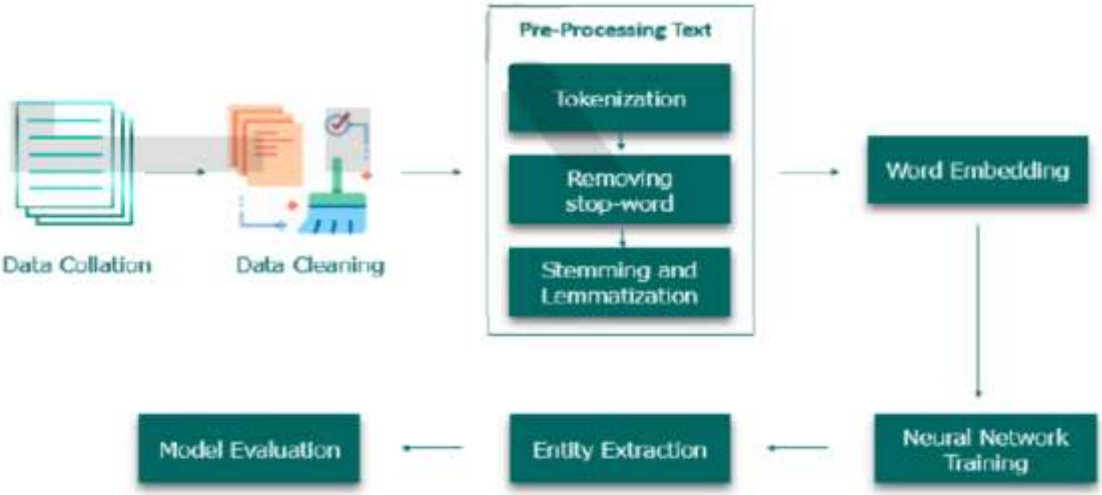

Fig. 7 System Design of MCIFS using Machine Learning Techniques

3.6 Pseudocode for Text Summarizer

Figure 7 shows the pseudocode for the text summarization algorithm. The input text corpus is first loaded into the system. Next, each paragraph is tokenized into its respective sentences. Stopwords are then taken out of the sentences. The Word-Rank Algorithm works based on the ratio of frequency of occurrence of words in a particular sentence, to the frequency of occurrence within the entire text. Each sentence is then attributed a weight based on this ratio. Sentences which contain the most frequent words within the text were assigned the highest weight. For the remaining words, the frequency of occurrence of each is calculated, so is the weighted frequency. The weighted frequency is obtained by dividing the frequency of each word with the highest frequency. Each word in the sentence is replaced by its weighted frequency in the original sentence and each sentence is added up. The sentences arethen sorted in decreasing order of sum to get the summarized version of the input text of patients' report.

```
#Sorting the sentences in decreasing order of sum
summary_sentences = largest(7, sentence_scores, key=sentence_scores.get)
automated_summary = ' '.join(summary_sentences)
print(automated_summary)

# Using cosine similarity to evaluate the summary
Human_summary = read('human_summary.csv')
Similarity_ratio = []
For i in range(0, len(automated_summary))
        Similarity_ratio.append(Get_cosine_similarity(human_summary[i],
automated_summary[i]))

# Compute the average similarity ratio
Sum(similarity_ratio) / len(similarity_ratio)
```

```
#Load data into program
File = read("project.csv")

#Convert Paragraphs to sentences
Sentence_list = sententence_tokenize(file)

#Text Preprocessing
No_punctuation = re.sub(/[^\w\s]/gi , '', sentence_list)
Stopwords = nltk.stopwords('english')

#Finding the frequency of occurrence of each word
For word in word_tokenize(no_punctuation)
        If word not in stopwords
                Word_frequency[word] = 1
        Else
                Word_frequency[word] +=1
Finding the weighted frequency
for word in word_frequencies.keys():
word_frequencies[word] = (word_frequencies[word]/maximum_frequency)

#Replacing words by their weighted frequency in the original sentence and
summing
For sent in sentence_list
        sentence_scores[sent] += word_frequencies[word]
```

Fig. 8: Pseudocode for the Text Summarization algorithm

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IV. RESULTS AND DISCUSSION

This section documents the results of the implementation of MCIFS based on the MCIFS technique. Anonymized patients case reports from online source were collated into the corpus as input dataset. An instance of a case report is depicted by Figure 8. The data is collated into a CSV file. Subsequently, preprocessing of the corpus using the preprocessing tools available in the NLTK library follows. Thereafter, Word-Rank algorithm is used to summarize the corpus. The autogenerated summary extracts the relevant sentences from the bulk of text.

A 72 years old male presented to an emergency department in America with complaints of nausea and vomiting for 72 hours. The patient had been overseas on business where he travelled throughout Nigeria,Eriteria, and the Ethiopia region. He stated that his vaccines were up to date but that he was not taking anti-malarial medication as he was only briefly travelling through these Nigeria countries. He also noted that he had many “bug bites”. The patient further stated that he also had a questionable meal before he started feeling nauseous. There was no evidence of blood in the vomit and no diarrhea. Patient appears diaphoretic and flush in the face. No signs of respiratory distress. GI exam in normal with no abdominal tenderness or evidence of organomegaly; however, the patient complained of extreme nausea during examination. Laboratory Results showed increased PT and INR, elevated ALT and positive Rapid Diagnostic Test for falciparum. The patient was diagnosed with uncomplicated falciparum malaria. The patient was admitted to internal medicine and Infectious Disease was notified. The patient was started on Atovaquone-proguanil 4 tabs qd for three days. Patient was discharged 5 days later.

Fig. 9 Sample of Input data 4.1 Computer Generated Summary TheWord-Rank algorithm enables the ordering of the text summary in terms of the most frequently used words in the text. The sentence which contains most words with the highest frequency is assigned the highest weight, and as such, is ordered first. Figures 9 and 10 present the summary in 5 and 7 sentences

'The patient had been overseas on business where he travelled throughout Nigeria, Eriteria, and the Ethiopiaregion.The patient further stated that he also had a questionable meal before he started feeling nauseous.GI exam in normal with no abdominal tenderness or evidence of organomegaly examination; however, the patient complained of extreme nausea during.Respiratory exam is normal with no evidence of accessory muscle use to adventitious breath sounds.The patient was started on\xa0Atovaquone-proguanil\xa04 tabs qd for three days.'

Fig. 10: Summary in 5 sentences

'The patient had been overseas on business where he travelled throughoutNigeria,Eriteria, and the Ethiopiaregion.The patient further stated that he also had a questionable meal before he started feeling nauseous.GI exam in normal with no abdominal tenderness or evidence of organomegaly; however, the patient complained of extreme nausea during examination.Respiratory exam is normal with no evidence of accessory muscle use to adventitious breath sounds.Laboratory Results showed increased PT and INR, elevated ALT and positive\xa0Rapid Diagnostic Test for\xa0falciparum.The patient was admitted to internal medicine and Infectious Disease was notified.The patient was started on\xa0Atovaquone-proguanil\xa04 tabs qd for three days.'

Fig. 11: Summary in 7 sentences

In solving the problem of time consumption on the part of consultants, this system allows consultants view a condensed version of a patient’s medical history. The consultant still has the option of viewing the detailed history for further understanding, if need be. The system also allows consultants search for particular keywords in the course of the consultation process. This leads to a higher service quality received by patients as they do not have to spend additional time on the waiting queue. As only authorized personnel are able to log into the system, MCIFS ensures security of patients' record. Finally, the auto generated summary is compared with a human generated summary. 4.2 Human Summary of Corpus Text The manually generated summary for the sample patient case report is as shown in figure 11. This serves as a means of evaluating the accuracy of the computer generated version using the text processing technique.

A 72 years old male presented complaints of nausea and vomiting for 72 hours. He also noted that he had many bug bites. The patient further stated that he also had a questionable meal before he started feeling nauseous. Patient appears diaphoretic and with flushed-face. The patient complained of extreme nausea during examination. Laboratory results showed increased-PT, increased-INR and elevated-ALT and positive rapid-diagnostic-test for falciparum. The patient was diagnosed with uncomplicated falciparum-malaria. The patient was treated with Atovaquone-proguanil 4 tabs qd for three days.

Fig. 12: Human generated summary of Sample Case Report

4.1 System Evaluation of MCIFS

Both qualitative and quantitative evaluation methods are applied to the output of MCIFS. The former method entails the comparison between the human generated summary and the theMCIFS - based algorithm generated summary. The algorithm generated summary and the human generated summary both reduce the volume of the initial input text of patients' case report. For instance, evaluating the sample case of figure 8, the human summary highlighted the major aspects of the case note such as the symptoms, tests taken, results, and the prescribed treatment. The algorithm generated summary highlighted the complaints, the physical examination done and the treatment. With more input to the algorithm, it would be able to further understand which parts of the entire input are more relevant than the others.

Applying quantitative evaluation method, the Word-Rank algorithm is evaluated using cosine similarity between the summary generated by the algorithm and the initial corpus text of case report. The similarity metric is as depicted in (1).

Similarity(A, B) = A . B = (1)
* √ * √

Where A and B are representations of a system summary and its reference document (initial case report) based on the vector space mode respectively [16]. There is a 59% similarity rate when five sentences are used for the summary and a 61% similarity when seven sentences are used. Further increment of the number of sentences does not yield a significant increase in the similarity rate.

V. CONCLUSION

This study shows that although medical data/record is highly unstructured, inconsistent and somewhat ambiguous, there is a lot of insight that could be uncovered from it. The developed system, MCIFS is able to read through a doctor's consultation note, a patient's medical record, or a case report, and then extract the relevant keywords from the input data/text report. This work uses a Natural Language Processing-based technique to analyze medical history of a patient in order to extract the relevant keywords and then present to a doctor a concise summary of the previous consultation notes. Thus, this technique improves medical consultation process, thereby reducing the time spent in the consultation room and leading to better quality of treatment received by patients. Further work would consider more input data on a deep learning driven system for an improved accuracy of summary.

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