MediLocker

Vansh Jain
Department of Electronics and Telecommunications
Sardar Patel Institute of Technology
Mumbai-58, India
vansh.jain@spit.ac.in

Kshitij Parab
Department of Electronics and Telecommunications
Sardar Patel Institute of Technology
Mumbai-58, India
kshitij.parab@spit.ac.in

Sharvari Kalgutkar
Department of Electronics and Telecommunications
Sardar Patel Institute of Technology
Mumbai-58, India
sharvari.kalgutkar@spit.ac.in

Dayanand Ambavde
Department of Electronics and Telecommunications
Sardar Patel Institute of Technology
Mumbai-58, India
dd_@spit.ac.in

***Abstract*—Healthcare has undergone significant advancements due to the use of computing technology in modern medicine. However, in India, there is a lack of a healthcare database management system that can be accessible to every citizen. This paper offers a solution to the problem by proposing complete digitization of medical records, prescription and clinical summarization through an application. This application will ensure proper organization of medical records.**

Keywords: Natural Language Processing, Named Entity Recognition, Spacey, Nodejs, React Native, Speech-to-Text, Clinical Summarization, Healthcare Database Management System.

I. Introduction

Organization of medical records play a vital role in determining the future treatments, tracking medical condition improvement and effectiveness of drugs administered in the past.When suffering from an acute medical condition, effectively organizing medical records becomes a arduous task.Patients often end up losing important reports, medical prescriptions which affects the tracking and planning of their treatment. Organized medical records, bills can also ease the process of claiming medical insurance and managing finances.For patients suffering from acute medical conditions, inaccessibility of patients medical records is a matter of constant concern. In case of an emergency, if such a patient meets with an accident, past medical records helps doctors to take informed decisions.Ongoing medications, medical condition, medical treatments play a huge role when taking decisions regarding surgeries to be performed, drugs to be administered etc.As a result, Electronic Health Records (EMR) can provide adequate tracking as well as improved treatment options to people suffering from medical ailments.

It is an advisable practice for doctors to take down soap notes during any clinical session. These notes can be quite helpful during emergency situations for doctors to get a clear idea about the patient's medical history. Subjective, objective, assessment and plan helps doctor to take informed decisions regarding the medical treatment plan that the patient should undergo. Along with this, these notes can always be referred by patients in case they forget seminal details. Till now, these notes are handwritten notes, thus making the entire task onerous. The use of Natural Language Processing to automate the summarization of clinical conversations will offer health care providers with a synopsis of the patient-doctor conversation, allowing them to track patients' progress and previous medical assessments.

The requirement for a voice automated prescription tool will aid in the reduction of prescription flaws and errors, allowing prescriptions to be readable and digital. Prescription errors account for 70% of medication errors that could result in serious adverse effects. Majority of patient find doctors prescription illegible and often seek the help of pharmacist to procure the correct medications and understand the dosage.This has proven to become a downside, especially in the pandemic period. The lack of readability of prescriptions discourage patients to order their medications online through various applications. Thus exposing them to the possibility of engaging with more people, in the period of Covid-19.

II. Related Work

In order to avoid medication errors due to paper prescriptions , the study [1] proposes a Natural Language interface to Prescription Management Systems, allowing clinicians to record prescriptions orally using mobile devices at the point of treatment. The study uses the dataset from the "Le Guide des Premieres Ordon- ' nances" textbook. The methodology used by the study is first the speech would be recorded. This recording will be sent to the NLU system which would analyze the speech and send structured data to the PMS system .Due to paucity of data the study uses an artificial method to generate prescriptions . The study uses four state of the art natural language understanding systems: Rasa NLU, Tri-CRF, Att-RNN, and seq2seq NLU. TRi-CRF outperforms all the models in F-score where as seq2seq and rasa show the lowest recall.

In this study [2], a web based approach is used , to solve the prescription problem. The study uses a web based API to convert speech to text. The text result is searched in the database which outputs the relevant messages based on the keyword and from this list the doctor can select the appropriate medicines for the patient, which finally generates the prescription. Along with the medicines the doctor can add the dosage and time .The study used Mysql as their database and JavaScript Web Speech API to convert speech to text.further work include making the web application mobile responsive and to add few more features to the application.The study achieves 0.91 F1-Score on slots and 0.1 Intent accuracy was achieved. Future scope includes exploring ASR modules where emerging technologies such as transformers can be applied and identifiers for each patient can be added.

This paper[3] proposes a mobile based application for prescription which works on NLP. Instead of writing prescriptions by hand, doctors can use a mobile device-based speech recognition technology to let them utter prescriptions and get them in tabularized format.To address the simultaneous problem of intent detection and slot filling, a stack-propagation strategy was used.1000 prescriptions were taken and given ”prescriptive” intent before combining them with 1000 ”non-prescriptive” intent stat. Self-Attentive Bi-LSTM Encoding which is used to create a context-sensitive hidden state, it reads the input sentence forward and backward.Unidirectional LSTM was used for intent detection and Stack-Propagation for slot filling. The models are joint trained, thus it predicts the intent and fills the slot.

The use of an e-prescription system allows for real-time EHR management while ensuring patient privacy. The planned and realised system [4] cuts the time it takes to create and access patient records in half. It is a web based solution which takes voice input through the microphone and the voice will be recorded until a 10 sec silence is there or manual stop. After this the using the speech to text library in python the text is produced which is processed in python and then sent to the server as an array.Finally the prescription is displayed in an editable manner on the site.

The following paper[5] proposed an app based solution where the app takes the input from the user which is then converted to text and finally this text is filled into the form which is reviewed by the doctor and finally this prescription is sent to the user via email or sms. Firstly for the speech to text the study uses the Google API (more than 80 languages) along with UML which helps to visualize , construct and document the artifacts of the system. For the application, android studio is used.To convert the form to pdf the ITEXT Dependency is used which generates the pdf files and these files are stored in the Firebase . In the near future, the Authors are planning to integrate and use the system in the real hospital ecosystem to test and validate the implementation and to analyze the impact it will create in the healthcare domain.

This course [6] deals with app development using react native with node.js backend. React is a frontend tool developed by facebook used for building sites and apps. In today’s time it is used by major companies like airbnb, facebook, uber etc .It simplifies app building along with it manages the state of every component. Using the expo client we don’t have to develop separate apps for android and iphone. Expo client converts the code into their respective software languages.The course provides a comprehensive knowledge regarding react native and its components. The course provides information regarding :

1. Installation and setup of react native and basics of react. Along with it , it also shows how to run it on android as well as iphone.
2. Styling components to make them look much better according to our needs
3. Navigation: Navigation helps in moving through pages in the app. The course talks about 3 types of navigation. Bottom tab navigation which appears at the bottom.
Stack navigation which is the main navigation controlling the flow of the app. Drawer navigation which provides a side drawer navigation.
4. State management using Redux . State management is one of the most important features in react.It manages the state of the app so that if any changes take place the app automatically changes its current state.
5. Node.js setup and its basic.React serves as the frontend whereas node js handles the backend. It works on working with databases, fetching api and serving information from api and database to the frontend.
6. Mongodb as our database: Mongodb is a non-relational database storing data as objects.
7. Validation and authentication: Finally the app needs the user to login and register. Therefore we need to validate and authenticate our users
8. Deployment: Finally we deploy the app on heroku and play store.

This paper [7] presents a design of a voice-based mobile prescription application. System architecture is 3 tire consisting of client device, server and mysql database. The system is developed using VoiceXML, PHP(Hypertext Preprocessor) was used for server side application and mysql for database. The detailed steps involved in using the application have been mentioned in the paper. The application can be accessed by dialing a number using your mobile phone. By avoiding time-consuming call-backs, the application enhances the efficiency of health-care services that may be linked to the therapy process. Future studies may take into account Paradigm algorithm for enhanced results.

The paper[8] underscores that summarising the dialogue, particularly for the problem description and therapy recommendations, is a critical duty in assisting new patients in finding relevant information to address their medical problems. A Chinese medical conversation dataset acquired from a famous online healthcare service provider in China is used. It has over 40,000 cases which enclose around 2000 types of diseases under a section called “Frequently Inquired Health Problems. The dataset consists of two summaries one is regarding patients symptoms, problems; other is regarding doctor’s diagnosis and recommendation. The paper proposes a hierarchical encoder-tagger (HET) model which tags the utterances in the conversation.The overlap between utterances and summary are then scored using rouge. The utterances having score greater than threshold value are labeled.The input to the model are the utterances which then enter a hierarchical model which consist of encoders .These encoded utterances are then tagged by taggers which are further concatenated to generate summary. LSTM and BiLSTM are used to encode the utterance sequence for each conversation, where the dimension of hidden states is set to 300 for LSTM and 150 for BiLSTM encoder.This is further enhanced by addition of memory modules. Further studies include collecting disease specific data to enhance identification of similar cases easily.

This qualitative research[9] provides an overview of all recent Conversational Analysis research on the medical interview and treatment recommendations from the beginning to the completion of the interview. More studies of specialty clinics can be done to highlight doctor–patient communication aiming to address clinical medical and educational difficulties.

The paper[10] presents a novel deep learning approach for medical conversation summary.In sectors like medicine, where source integrity is crucial, encouraging copying in the learning process gives the best model (2M-PGEN) on human evaluation, using a deep learning approach called pointer generator networks. Experts estimate that 2M-PGEN summaries contain up to 80% of the relevant information, making this method a viable alternative to human summarization.Further works aims at generalizing using vast specialized data.

The paper[11] presents a review of research in medical conversational summary. It discusses methods for summarization, NLP for dialogue analysis and medical conversation systems. The frequently used models, techniques for dialogue summary, shortcomings. Future work relates to See et al. (2017). Model using PubMed data and working on Mccowan et al. produced the AMI corpus (2005).The goal is to create a system that can extract abstractive summaries from medical discussions.

This blog [12] talks about the types of summarization. There are two types of summarization : Extractive Summarization and Abstractive Summarization. Extractive summarization identifies important phrases , words etc. and then it forms a summary. In Abstractive summarization Nlp techniques are used to form a completely different summary.Page and Text ranking summarization are further elaborate. Page ranking ranks a page by giving page score based on the probability of a user visiting the page.In text ranking similarity between the sentences is used to rank the sentences.The sentences with highest similarity are then included in the summary.An example of text summarization along with code and dataset has been provided in the article. Future work possibilities may include details regarding Multi-domain text summarization.

This paper [13] is regarding medical dialogue dataset; the largest dataset currently available. They have created a large-scale medical dialogue datasets – MedDialog, for example – to aid research and development of medical dialogue systems.A dataset in English comprising 0.26 million dialogues, 0.51 million utterances, and 44.53 million tokens encompassing 96 illness specialties. Medical dialogue systems have the potential to help telemedicine improve access to healthcare services, improve patient care quality, and lower medical expenditures.

The paper [14] proposes a four component pipeline structure that included speech transcription, Triple Extraction, Triple matching and Report Generation. It implements triple analyzers namelyu Frog, Ollie and FRED that were tested on eight real-world consultations with a precision of 63.5%.

This study [15] is a theoretical research paper that advocates for the use of electronic medical records (EMR). It emphasises the need of having easy access to medical records in the event of an emergency. Once medical records are in electronic form, the basic functions of a healthcare information management system (HIMS) can be built. With the migration to a paperless environment, HIMS professionals will need to concentrate on efficient systems that offer accurate data in a timely manner, save space, and assist in the inventive management of records. Having a successful Electronic Medical record System (EMRS) will not only capture, store and manage data effectively but also allow all authorised personnel to access simultaneously so that everyone will get maximum benefits from the system.

This paper[16] proposes a web-based database management system that is personalised for one single hospital. However, it incorporates all the departments in the hospital thereby minimizing the need for any on-paper administration. The system presents an effective way of handling electronic medical record systems via having a personal login for every doctor and patient.

This paper[17] proposes a system that uses Ethereum blockchain technology to create a healthcare ecosystem that is iterative, scalable, secure, accessible and decentralized. This would allow patients to exchange their medical records freely and safely with doctors, hospitals, research organizations and other stakeholders-all while maintaining full control over the privacy of their medical data.

This book[18] reviews current developments in automatic speech recognition, with a focus on discriminative and hierarchical models.This will be the first automatic voice recognition book to cover recent advances such as conditional random fields and deep learning approaches in depth.It gives theoretical foundations and insights into a variety of recent sequential learning models, including conditional random fields, semi-Markov and hidden conditional random fields, deep neural networks, deep belief networks, and deep stacking models.It also explores the practical implications of employing these models for continuous speech recognition in both acoustic and linguistic modelling.

This blog [19] shows us the building of speech to text model in python using Natural language Processing and Deep Neural Networks(Convolutional Networks).

Thousands of audio utterances for common medical complaints like ”knee pain” or ”headache” make up this data, which totals more than 8 hours. Individual human contributors produced each speech based on a certain symptom. In the medical industry, these audio clips can be used to train conversational agents.A multi-job workflow was used to construct the Figure Eight dataset. The first task required participants to write text sentences to describe the symptoms they were given. For example, a contributor might put ”I need help with my migraines” under ”headache.” Following jobs recorded audio utterances for text strings that were accepted.This dataset contains both the audio utterances and corresponding transcriptions.[20]

In this paper[21] the fundamentals are discussed and its recent progress is investigated. The various approaches available for developing a Voice Recognition System based on adapted feature extraction techniques and the speech recognition approach for the particular language are compared in this paper. The authors developed a system that will allow the computer to translate voice request and dictation into text using MFCC and VQ techniques. Feature extraction and feature matching were done using Mel Frequency Cepstral Coefficients and Vector Quantization technique.

This paper[22] talks about speech recognition systems in general, which essentially are a kind of pattern recognition system having three basic units such as feature extraction, pattern matching, and reference model library. The unknown speeches are converted into electrical signals through microphones attached to the input of the identification system which is preprocessed first. The model is then established according to the characteristics of human speech sounds and the input voice signal is analyzed, and the desired characteristics are extracted. It also states the various detailed applications of speech recognition.

Meeting minutes are a record of the details discussed in the meeting, its agenda, important decisions taken, future plans etc. In today’s time of Covid-19 virtual meetings play a very important role in businesses. This paper aims to summarize conversations of a virtual meeting using text rank approach.An extraction approach along with a new model is proposed which extends the text rank approach of summarization.Preprocessor, summariser, and post-processor are the three stages of the VRoom summarisation process. A pre-processor reads the transcript and corrects spelling, grammar, and enhances term consistency. The summariser then extracts the most relevant sentences using a method and policy chosen from a list of options.The post-processor puts meta-data in the meeting minutes, including a summary of each item. The paper achieves a TRIT score of .Future work includes adding weightage to the summary words according to the role of the person in the organization. [23]

Delivery of excellent primary care that is central to overall medical care demands that providers have the necessary information when they give care. This paper, developed by the National Alliance for Primary Care Informatics, is a collaborative group sponsored by a number of primary care societies, argues that providers’ and patients’ information and decision support needs can be satisfied only if primary care providers use electronic medical records (EMRs). Substantial benefits realizable through routine use of electronic medical records include improved quality, safety, and efficiency, along with increased ability to conduct education and research. It also talks about research and financial barriers that come with this new adoption. But it remains firm on implementing specific policies that can accelerate utilization of EMRs in the U.S.[24]

The Aadhar number of a patient should be used to link his/her medical records to the system.All health records generated by the healthcare provider are held in trust on behalf of the patient; all protected health information contained in the EHR is owned by the patient; and the healthcare provider owns the medium used to store or transmit such electronic medical records.Patients will have the ability to: • Inspect and access their medical records at any time without restriction.Limit who has access to and who can disclose personally identifiable health information.To approve access and/or use, you must offer express consent that will be audited.disclosures.All recorded data will be made available to caregivers on a as needed basis.To withhold, temporarily or permanently, particular information that he or she does not want released to other organisations or individuals (within 30 days of request).When the patient dies (and there are no pending procedures or court cases), records should be rendered inactive. It is preferable to follow the “three (3) year rule,” which states that all records of a deceased person should be made inactive three (3) years after death.[25]

Text summarization using spacy was performed. It accepts three kinds of inputs. One is direct text input; the second way is web URL and the third way is Files in text format.It processes the input by spacy summarizer algorithmic means and produces the summarized text as output. The output is of two forms. One is direct text and the other is the result stored in the files in the text format. Remove stop words using spacy stop word identifier followed by word Frequency Determination, Sentence Tokenization, Sentence Score Determination, Spacy summarized ResultA book of length 1032 words is considered for rundown was summarized is 280 words.[26]

The work’s main contribution is the proposed Named Entity Recognition model which identifies prescription entities like medicine name, dosage, frequency, time period by processing the entire voice command. Previous methodologies required the doctor to separately enter voice commands for each entities making the interface less user friendly.

Further, for clinical summarisation, a stop word dictionary targeted towards reducing redundant occurrences is created thus aiming towards creating a more concise medical conversation summary. In previous studies, sentences appear out of order in final summary. Since sequence of sentences in a medical conversation can alter logic. The study arranges the sentences in summary according to their sequence of appearance in the conversation.

III. Named Entity Recognition

Named Entity Recognition is used for entity detection in NLP. In this process, the model automatically scans the entire text. It classifies the key entities in the text into previously defined categories. A NER model recognises noun phrases in the text and categorises them. To prevent entity misclassification, a validation layer at the top ensures entity disambiguation.

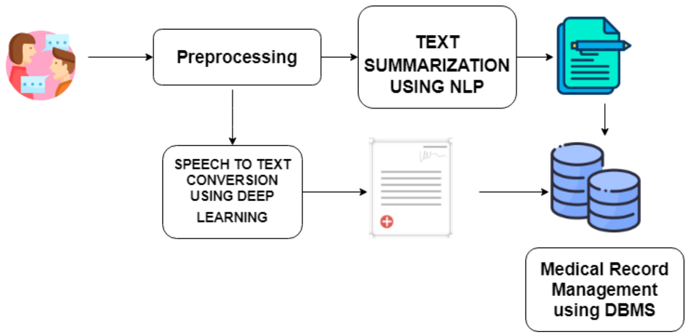

Fig. 1: Flow Diagram

IV. Experimental Setup

A. Technologies

1. Voice Prescription: NER Model
2. Summary: Spacy
3. Backend: Nodejs
4. Frontend: React native
5. Expo client
6. Database: MongoDB
7. Speech-to-Text API: Google Cloud Platform

B. Software

1. Google Colab
2. Jupyter Notebook
3. Visual Studio Code

C. Hardware

1. 2-core Xeon 2.2GHz - 13GB RAM - 33GB HDD
2. Intel(R) Core(TM) i5-9300H CPU @ 2.40GHz 2.40 GHz - 8GB RAM - 1 TB HDD

V. Implementation

Fig 1. shows the flow diagram of the study. The conversation between the patient and the doctor is recorded through an android application. This data is processed and passed through a speech to text converter.

A. Speech to Text preprocessor

The conversation between patient and doctor is passed as an input to Google-cloud speech-to-text API to convert the recorded medical conversation into textual data.The speech client requires a key that can be downloaded from Google Cloud in order to authenticate. The audio path is the only argument to the function. The API uses a sample rate of 48000 Hz for the conversion and produces the text and confidence value.

B. Clinical Summarization

Once the speech is converted to text, it is passed through a spacy based summarizer. The summarizer highlights the key points during the session.The text is first preproccessed by removing the basic stop words and punctuations and to keep focus on medical terms, a custom stop words list is passed. To find the importance of a sentence, we consider the page rank algorithm which determines the importance based on frequency. Similarly, if a sentence has a word with highest frequency, its importance increases. Firstly, word frequency is computed for every word in the document and these frequencies are normalized using maximum frequency.Finally, a sentence score is computed by adding the word frequency and based on these scores, the sentences are sorted. Once the sorting is completed, the top 50 percent sentences form the final summary.

C. Voice-Based Prescription

The prescription text is passed through Voice-based prescription system that generates a prescription by speech-to-text conversion to ensure reduction in prescription faults and errors.To train a machine learning model, a custom annotated dataset of 30 sentences was create using spacy annotation tool wich highlights five entities in a sentence: Medicine Name, Dosage, Period, Type of Medicine, and the Frequency. The dataset was trained on the Named Entity recognition model which matches the entities with word in a sentence. The model was trained for 200 epochs and to help the model generalize better a Stochastic Gradient Descent optimizer and a dropout of 0.5 was used. To keep the focus on medicine names, the sentence was preproccesed by removing custom stop words from the sentence and then passing through the model. Once the model outputs the entities, these entities were converted into a tabular format and pasted on a PDF file using the python FPDF library.

D. Mobile Application

The PDF file is stored on the Google Cloud Bucket Storage under the name of user ID. These file can be accessed through a mobile application. The application forms the platform where we deliever our services and. The application uses React Native for its frontend and Node.js for its backend. The application stores the user details and doctor detail after registration on the MongoDB database and all files of an user are stored on the Google Cloud Storage. An array of these files name is stored within an user object in MongoDB.

VI. Results

A. Google API Speech-text

Figure 2 shows the Google speech-text API output. The API converts the audio into a text with a confidence value of 0.9002 and total time of 45 seconds.

```
print(response.results[0].alternatives[0].transcript)
```

```
Thank you for choosing the Olympus dictation management syst
em free Olympus dictation management system gives you the po
wer to manage your dictations transcriptions and document se
amless and to improve the productivity of your daily work, f
or example, you can automatically sends extension files or t
ranscribed document your system to the author by email. If y
ou're using the speech recognition software the speech recog
nition engine works in the background to support your docume
nt creation. We hope you enjoy the simple flexible reliable
and Secure solutions from the lenders.
```

Fig. 2: Google API Speech-text Output

```
#Example : Take Avas tablet 10mg twice a day for five days
for i in output:
  print(i)
```

```
('avas', 'Medicine name')
('tablet', 'type')
('10mg', 'dosage')
('twice a day', 'frequency')
('five days', 'period')
```

Fig. 3: NER model output

B. Voice Prescription

Figure 3 shows the NER model output.The model outputs a list with a length of the number of entities and each item in the list is a tuple having two values:Entity name and the value in the sentence. Figure 4 represents the PDF formed by using the FPDF library.The pdf consists of the doctor details, patient details and a table with the list of medicines.

Dr. Dushyant

M.B.B.S |
Phone no: 8291395170
Bhavans Campus, Old D N Nagar, Munshi Nagar, Andheri West, Mumbai, Maharashtra 400058

Name: Vansh Jain
Age: 21

Problem: Fever
Phone no: 8291395170

Medicine name	type	dosage	frequency	period
avas	tablet	10mg	twice a day	five days

Fig. 4: NER model output

```
summary
```

```
'i want to get a pregnant .i got period March 14th. After 10 days my egg is not r
upturing. An egg (cyst) ruptured. From that day i have taken duphaston for 10 day
s 2 times which is given by doctor. she told me that after 10 days stop duphaston
and wait for one week then if you r not get periods come and see me . April 9th m
y 10th day over. from that day i stoped to take dupalaston. today i felt that i g
ot periods. i got period doctor told me to come 14th. i got period March 14. my e
gg rupured on March 31th. sometimes this does happen that when u expect periods u
see just drops esp. when u are taking menstuation regulating drugs its because ur
endometrium has not shed properly.u may need withdrawal bleeding with other drugs
before u start for this menstrual cycle infertility treatment.\n '
```

Fig. 5: Clinical Summarization Output

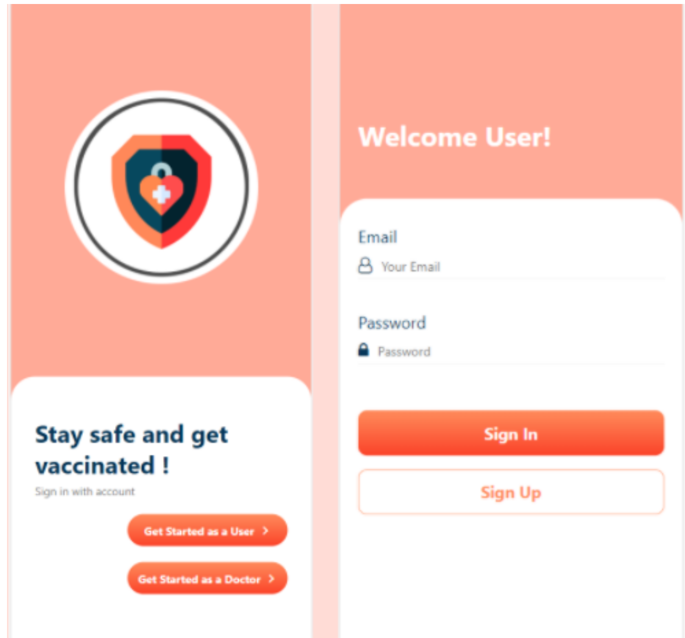

Fig. 6: Mobile Application Output

C. Clinical Summarization

Figure 5 shows the summary of the conversation between the doctor and patient. The Spacy model reduces the total words from 261 to 167.

D. Mobile Application

Figure 6 shows the screenshots of the mobile application build using react native and Nodejs.

VII. Conclusion

Digitisation of medical records is essential to ensure easy access to one's medical history in times of unforeseen accidents.Patients lack access to the medical history especially those suffering from chronic health issues. This can force doctors to take uninformed decisions during an emergency which can lead to medical complications.

Further, to ensure efficiency in the tracking of the medical history of patients minutia of the patient-doctor meets often play a vital role. Thus, clinical summarization can provide valuable information for a better treatment plan for the patient.

Moreover, voice-enabled user-friendly prescriptions can help avoid fatalities caused by prescription errors and provide more legible and easy to organise prescription records.This work focuses on integrating voice prescription, conversational summarization and personalised healthcare database management system.

The application generates a document in PDF format that contains a tabulated prescription along with the conversational summary.The prescription ensures reduction in prescription faults and errors. The clinical summary of the conversation between the doctor and the patient provides a gist of the crucial details which can be aid further treatment plans. The database stores all the records of the patient at one place thus making it feasible for the patient to access them anywhere and anytime. Both the patient and the doctor have their own login credentials from where they can access the reports, prescriptions, summary and other medical records. This application organizes and provides easy access, management and tracking of the progress of the medical treatment.

Future scope for this work can consider attaching every citizen's Aadhar Number (National Identification Number) to their respective accounts that will make this application a national venture for all of India's citizens to organize their medical records. Along with this endeavour, new features can be added to the application to give the customers as well as patients a wholesome experience.

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