PANACEA

A Final Report

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CERTIFICATE

This is to certify that the project entitled "**Panacea**" is the bonafide work carried out by **Deep Shah, Samit Shah, Dev Dhawan and Pannag Shah** of B.Tech Integrated (Computer Engineering), MPSTME (NMIMS), Mumbai, during the IXth semester of the academic year **2021-2022** , in partial fulfillment of the requirements for the award of the Degree of Bachelors of Engineering, Integrated as per the norms prescribed by NMIMS. The project work has been assessed and found to be satisfactory.

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Internal Mentor

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Chapter 1

Introduction

Electronic healthcare technology is widespread worldwide and offers enormous potential for improving clinical outcomes and transforming care delivery. At the national level, EHR data is a good indicator of the overall health of the population; at the institutional level, EHR data sharing can help doctors effectively assess patients' conditions and make correct assessments; and at the individual level, having complete EHR data, it is beneficial to improve the quality of EHR service. As healthcare progresses, so does operability, and communication between individual health sectors rises. The digitalization of health and health information increases and breaks some clinical, business, and health information models. Many medical institutions and hospitals communicate through existing electronic health records (EHRs) to obtain observations, diagnosis, and treatment information. Today, observing the rise of big data and IoT, the EHR and its value increase exponentially. Despite advances in technology, most health facilities in some countries rely on out-of-date systems in various healthcare areas. Electronic Health Record (EHR) not only contains great value, but also implies a large amount of personal privacy.

Additionally, most health-sensitive data is stored and sent via centralized architectures. Due to its centralized nature, interoperability across different health systems presents an additional challenge and a security issue. As a result of following security concerns and issues, a new technology called blockchain has emerged in the research fields of distributed systems. Blockchain technology has a trend and potential purpose in various fields of application. Because of its distributed nature and data invariability, Blockchain technology withstands potential failures and security vulnerabilities of centralized systems. In addition to security, Blockchain technology provides a digital way to verify ownership and credibility of user data. Using cryptographic methods like PKI (Public key infrastructure) also ensures user anonymity and authentication within the insecure network. Therefore, the adoption of blockchain can provide promising solutions to facilitate healthcare delivery and thus revolutionize the healthcare industry. As an inevitable application of network technology in medical field, Electronic Health Record (EHR) carries a lot of personal information. However, current EHR Systems are not fully trusted by the patients due to the lack of transparency about the data held and controlled by the health organizations. Blockchain provides many system qualities that can contribute to alleviating trust issues in healthcare systems such as tamper proof data storage and auditability. There has been much recent work around the core idea of adoption blockchain and EHR data storage systems.

Medical diagnosis and treatment methods are usually based on clinicians’ interpretation of the patient’s medical data, which can often be subjective. It is not uncommon for a patient to receive different opinions from several clinicians for a diagnosed medical problem. Using artificial intelligence (AI) combined with blockchain technology opens up new research opportunities in the healthcare sector. Since machine and deep learning use large amounts of data in their work, there is an opportunity to develop better models by leveraging the decentralized nature of blockchains, which encourage transparency, integrity, and data sharing.

Chapter 2

Literature Survey

Amit With the rise and popularity of cloud storage technology, the common method of EHR data sharing is that the data owner stores the encrypted EHR data on the cloud.

Cheng H [1] proposes a method to divide large data into several ordered data columns and store them on multiple cloud storage servers, which ensures the security of data. But it cannot validate the data effectively.

Based on it, Shen M [2] proposes a data storage scheme that can verify the integrity and security of data, which can detect whether the data has been tampered before downloading. However, the environment of cloud storage service is beyond the user's control and vulnerable to external attacks, which poses a threat to the security of user's personal data. Therefore, cloud storage technology faces many challenges and some problems that need to be solved urgently. The security and privacy protection of EHR data in EHR field can be solved by the decentralization of blockchain.

Zyskind et al. [3] proposed a EHR data privacy protection system based on the third-party mobile phone client, which collects and encrypts data from the user's mobile phone.

In order to improve the efficiency of collection and storage, Azaria et al. [4] proposed a decentralized environment to achieve the management of electronic EHR records.

On this basis, Xia et al. [5] combined cloud storage technology to build a tamper-proof framework and realize the sharing of EHR data records.

In order to make more flexible use of blockchain system, Kevin Peterson et al. [6] realized the sharing of EHR data by using blockchain technology, and proposed a novel consensus mechanism.

Using blockchain technology, Ekbla et al. [7] proposed a distributed information management system to realize the authentication, encryption, accountability, sharing and lightweight distributed storage of sensitive EHR information.

Fu et al. [8] built on the work of Ekbla et al. [7] using a better encryption algorithm to implement distributed privacy and replacing proof-of work system with a creditability verification mechanism to improve the performance of healthcare systems.

Liu et al. [9] proposed a cloud-based electronic patient record sharing system that supports keyword search, enabling users to retrieve EHR symptom-containing keywords quickly. But how to realize efficient storage, secure sharing and fast access of EHR data is an urgent problem to be solved.

Zhang et al. [10] proposed a project called" FHIRChain" to securely share EHR data using the blockchain. The main difference to the other approaches is the focus that FHIRChain places on being compliant with existing standards for EHR data sharing. The proposed approach is compatibile with HL7 FHIR interoperability standard [11].

Similarly, Tang et al. [12] also propose an EHR sharing platform which mainly focuses on sharing of medical images. However, compared to other solutions presented above which propose their own blockchain networks, this approach is based on Ethereum smart contracts of Credit Scores to intelligently supervise the sharing process.

Le Nguyen et al. [13] propose a conceptual deep learning model integrated with a medical app running on a blockchain network as a communication assistant for both patients and doctors during pre and post-surgery. Deep learning concepts are used to analyze patients' healthcare records and recommend medical recovery and treatments for patients under the supervision of a doctor. Furthermore, in their model, patient data is interconnected with insurance companies via blockchain if the patient must pay for surgery and following medical procedures. While the approach proposes some conceptually novel ideas, it is unclear how they solve particular issues such as data privacy and security, interoperability between insurance companies and healthcare institutions, which deep learning method they use in their models, and others.

Bhattacharya et al. [14] propose BinDaaS, a framework for securing patient EHR records in the Healthcare 4.0 environment that integrates quantum-resistant blockchain and deep learning as a service. Authors employ Quantum Bayesian networks, which leverage deep learning prediction models to reduce feature extraction time and enhance scalability over transactions by automating health suggestions. Suggestions are based on previous diagnoses to reflect current situations. It ensures rapid healing and medication for the patient by avoiding severe illnesses.

Kumar et al. [15] proposed a framework that collects a small amount of data from different sources to train the deep learning model collaboratively across the public unsecured network utilizing the concept of federal learning. Federated learning aggregates all the separately trained models throughout the blockchain, which represents the global model. The authors show that the usage of collaborative learning empowered with blockchain technology provides better and more accurate predictions compared to other proposed solutions. To maintain anonymity, hospitals only share gradients with the blockchain network. The blockchain-based federated learning network collects the gradients from different nodes and distributes updated models to verified clinics.

In the blockchain system, recovering lost keys is practically hard, and security issues occur due to the requirement to recover private keys. Zheng et al. [16] present a key secret sharing strategy based on generative adversarial networks (GANs) to address the challenges of hard key recovery, security concerns due to the demand for recovering the private key, and low communication efficiency. Because of the high-performance goals, DNA coding was included to encode/decode secret. The fundamental idea of the proposed approach is to visualize the secret as an image during the secret-sharing procedure. If the user's private key is text, the text key is converted to the original image. First step of the approach consists of image segmentation, followed by splitting the original image into several original sub-images. DNA coding is used to encode each original sub-image. After DNA coding, the generative adversarial secret key sharing network is trained. In the proposed network, secret sharing can be considered as the classification of secure sub-images.

Witowski et al. [17] presented the" MarkIt" project, a blockchain based platform for collaborative annotation of medical datasets. The platform is built on Panacea blockchain using the Cosmos SDK. The web-based platform enables multiple expert radiologists to collaboratively annotate medical images in order to create machine learning datasets. The platform also implements several classification tools which automatically check the experts' annotations. This tools can also provide training sessions for annotators based on already created annotations. The platform also provides a review mode, where experts can resolve disagreements between different annotations, in order to maintain consistency of the datatset. The platform is still in the proof-of-concept stage and focuses primarily on the chest X-ray images. Other types of images, especially volumetric data, are not yet supported.

Patel et al. [18] proposed a blockchain-based framework for cross-domain medical image sharing and access control. The framework would use the blockchain to create a distributed ledger of radiological studies and allow another medical institution and patients to access the patient's radiological study directly. The permission system is based on public-private cryptography, where each participant in the network is identified with their public key and where each medical institution runs its node on the network. Thus, the network would use its blockchain, with institutions acting as validators using a PoS consensus. To protect patient's privacy, the institution that created the study would not publish the image data directly on the ledger.

In the domain of image segmentation, Li et al. [19] propose an improved consensus algorithm called Proof-of- Deep-Learning (PoDL). PoDL proposes replacing hash calculation with segmentation model training. Each block in the blockchain is separated into two phases. The first phase involves distributing the training dataset and the deep learning model's hyperparameters to miners and full nodes. Miners train and commit the hash of their deep learning model during phase 1. After phase 2 begins, they receive a test dataset, after which they submit a block header with their ID and transaction list, trained model, and trained model accuracy. Full nodes validate the provided models to ensure that the claimed accuracy is correct. Full nodes discard any block whose model was not committed during Phase 1. Full nodes will accept the block with the highest accuracy if the provided model is valid. The proposed blockchain technique can manage many tasks submitted by different task publishers, and it also provides a mechanism for dealing with substantial deep neural network models and training datasets

While most of the presented papers propose either storing the images encrypted inside the blockchain, or hosted on the medical institustion's own digital infrastructure, the approach by Kumar et al. [20] proposed to host the images on an IPFS decentralized storage network.

Chapter 3

Design Diagrams

The overall Architecture Diagram is shown below:

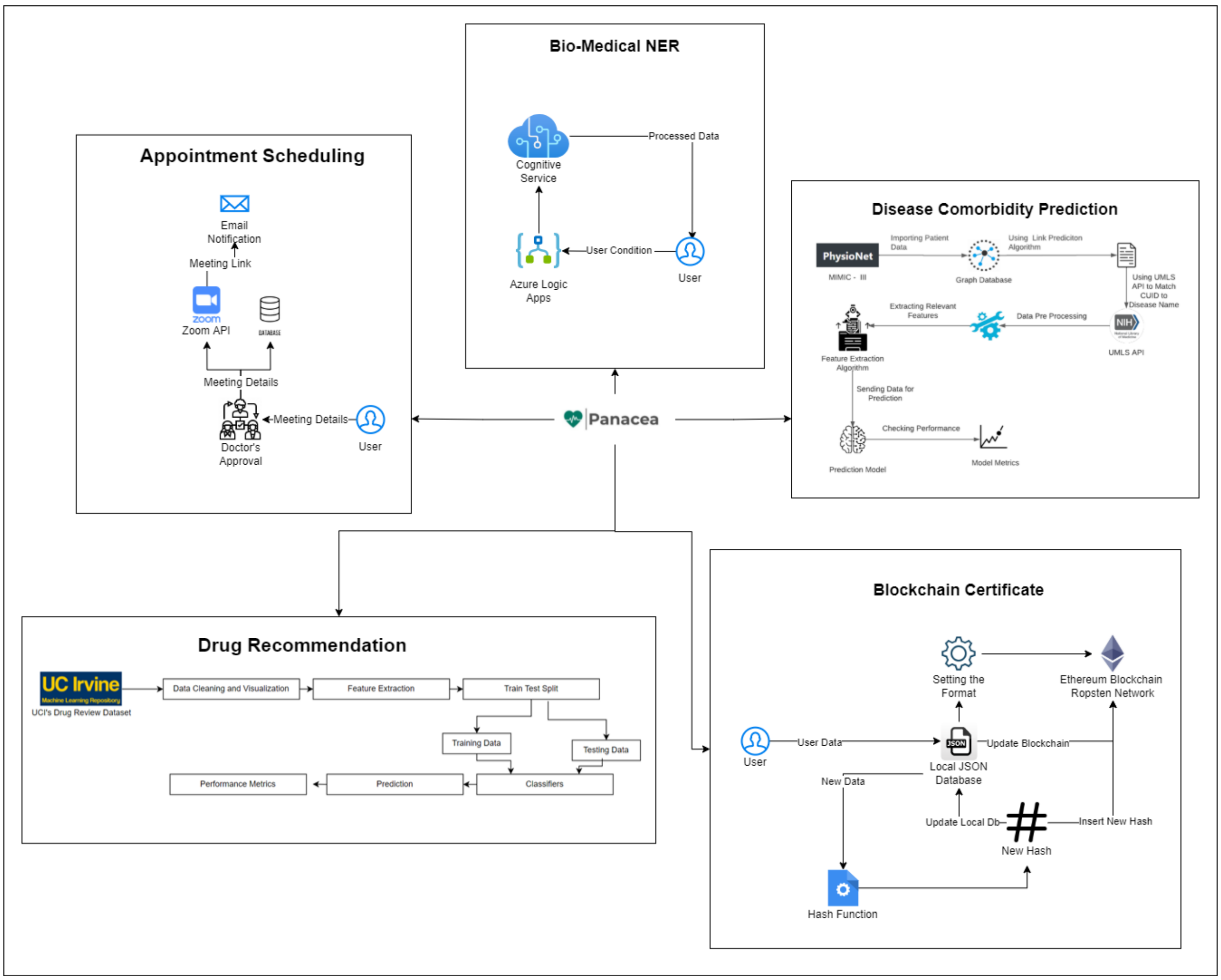

Figure 1 – Architecture Diagram

Blockchain Certificate:
The process flow of the blockchain EHR system:

- Create a json file that acts as a local database.
- Use Ethereum blockchain which is deployed on ropsten test network.

- Use the local json database to set the format for the Ethereum database.
- Each time iterate the hash function to generate a new has file and insert into the json files as a dictionary which has details of the previous hash to link.
- This is the updated in the local database as well has the Ethereum blockchain network.
- To verify the integrity of the data, we compare the last data's previous hash along with the second last data's hash.
- If the value matches, the data is not tampered, else the data is tampered.

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Drug Recommendation system:
The process flow of the drug recommendation system:

- UCI Drug Review Dataset is used to train the model
- Data cleaning and visualization is done.
- Features are extracted and the data is split into training and testing data.
- Classification and prediction are done next.
- Performance metrics are created.
- The output of the system is a safety prediction based on disease.

Disease Comorbidity Prediction:
The process flow of the disease comorbidity system:

- Data from MIMIC-III is imported to graph database.
- CUID is matched to the disease name using the UMLS 5 API.
- Data is pre-processed and the relevant features are extracted.
- The prediction model is applied to develop the model metrics.

Bio-Medical NER (Named Entity Recognition):
In biomedical text mining, named entity recognition (NER) is an important task used to extract information from biomedical articles. Azure cognitive services is used for the NER and the process is managed using the azure logic apps.

Chapter - 4

Implementation

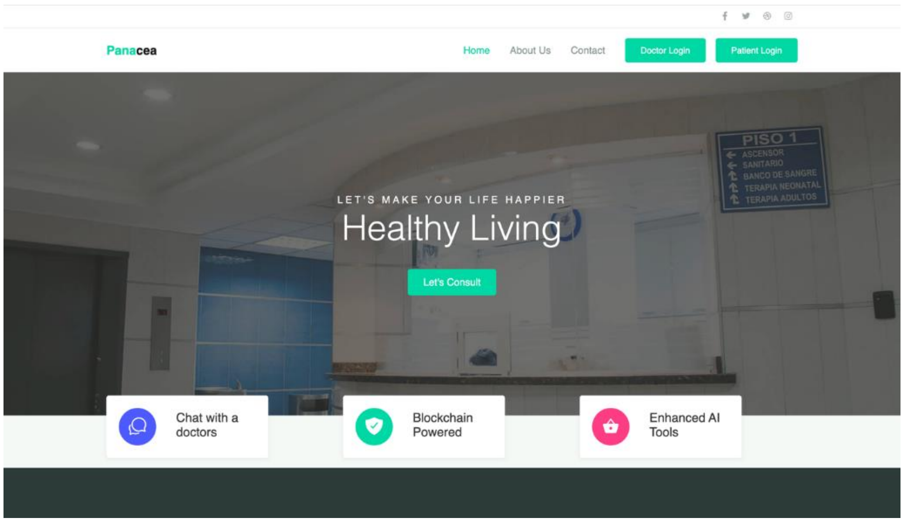


Figure 2 – Application Landing Page

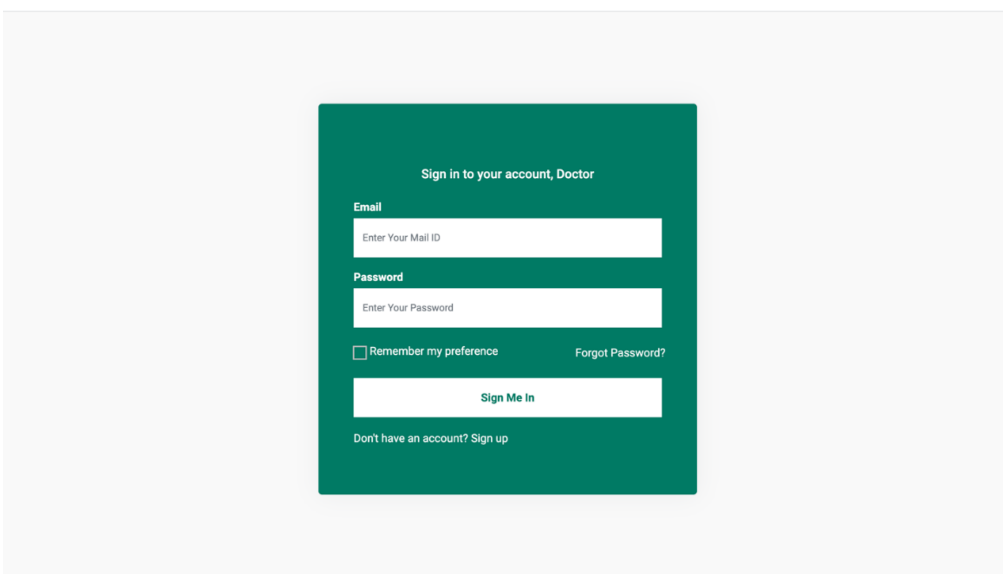


Figure 3 – Doctor Login

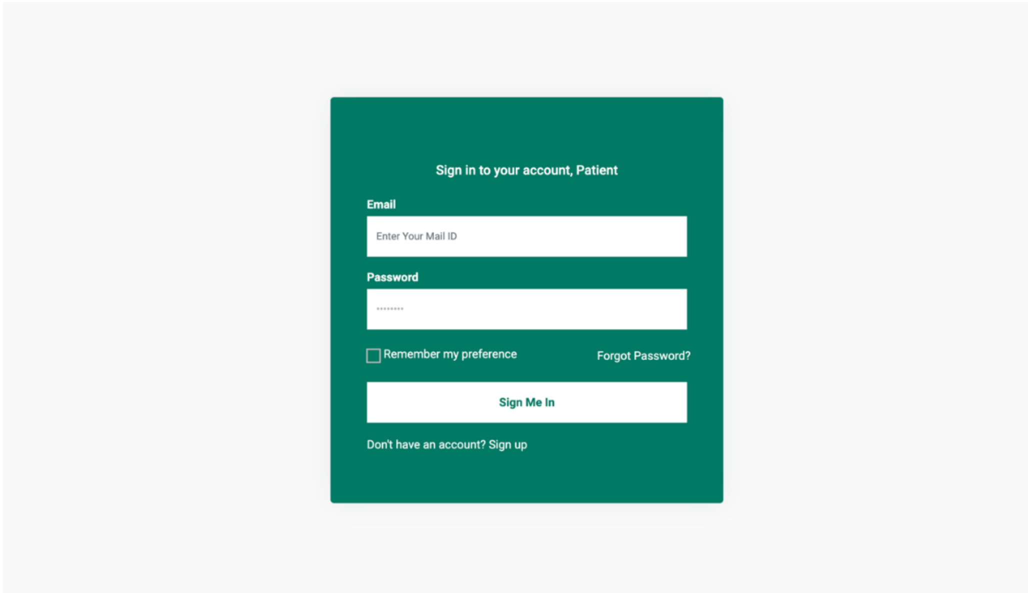


Figure 4 – Patient Login

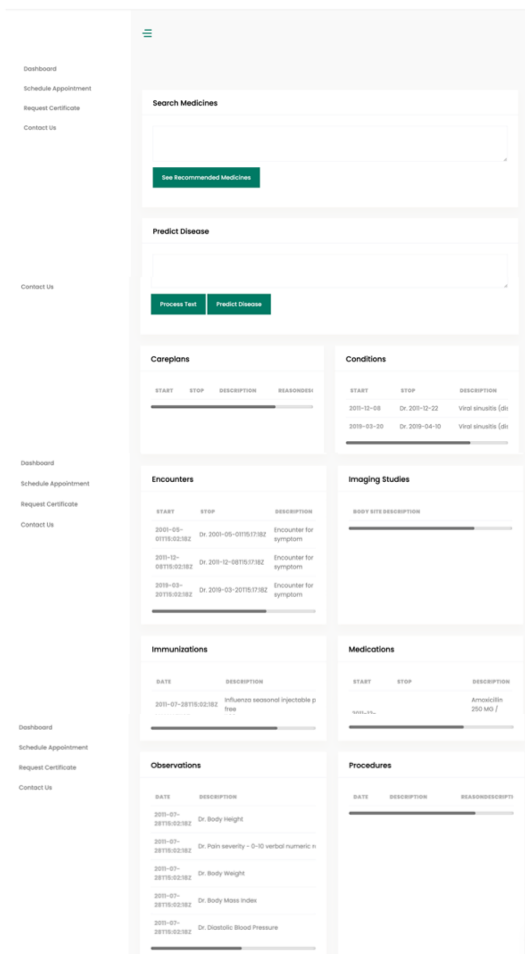


Figure 5 – Patient Dashboard

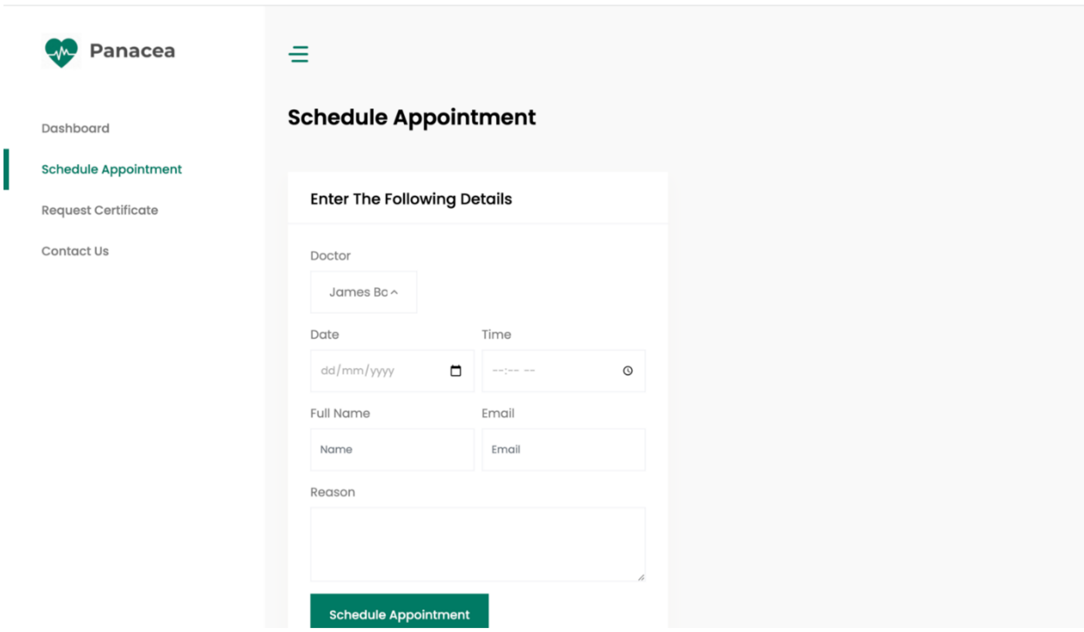


Figure 6 – Doctor’s Appointment Scheduling (Patient’s End)

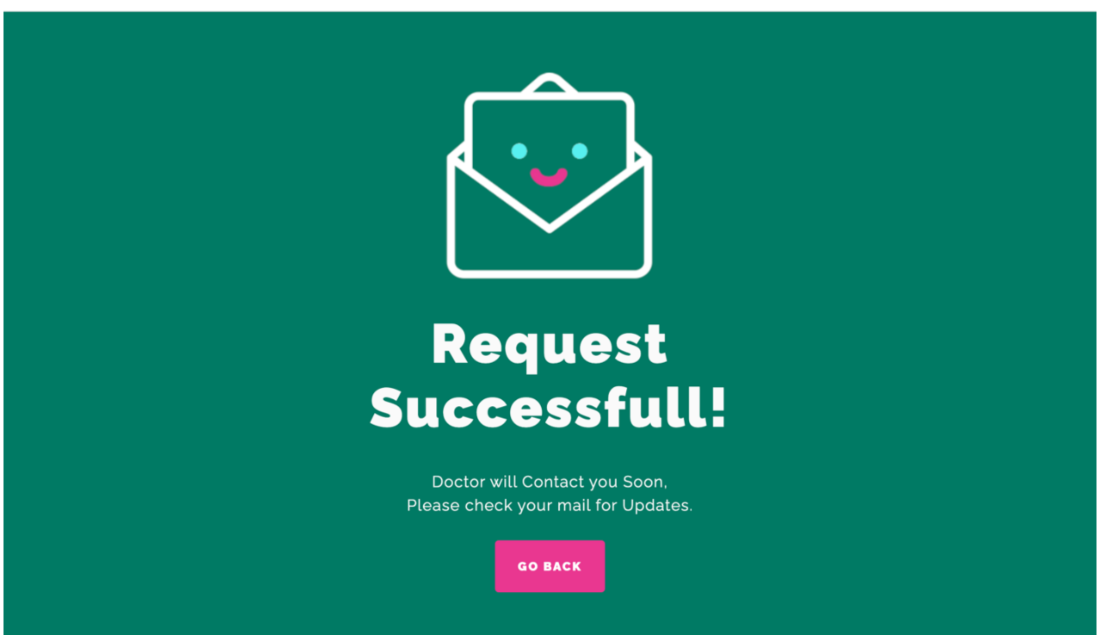


Figure 7 – Appointment Confirmation (Patient End)

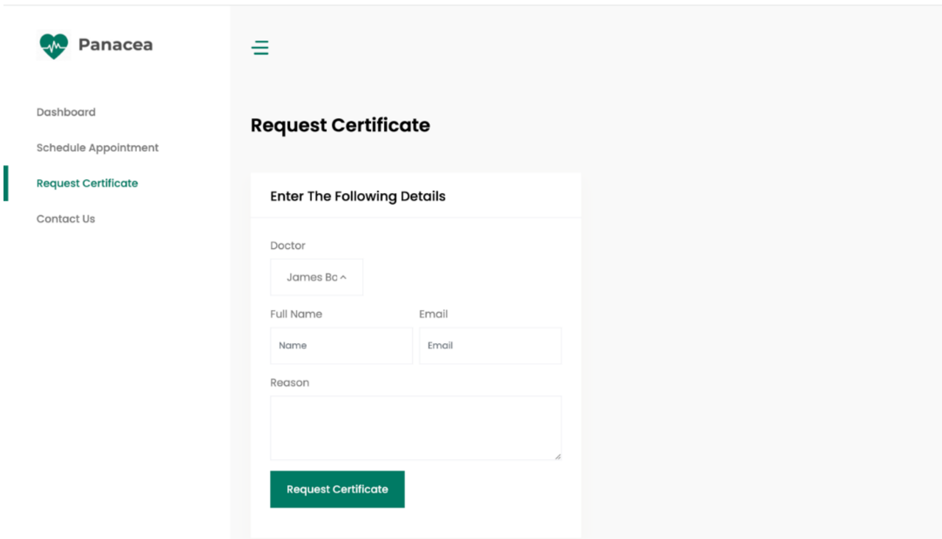


Figure 8 – Request Certification (Patient End)

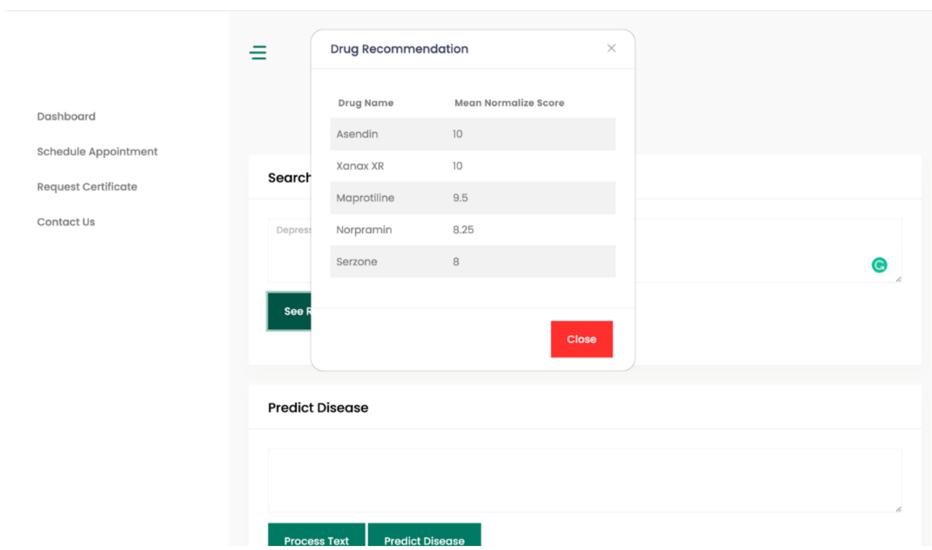


Figure 9 – Drug Recommendation Module (Patient End)

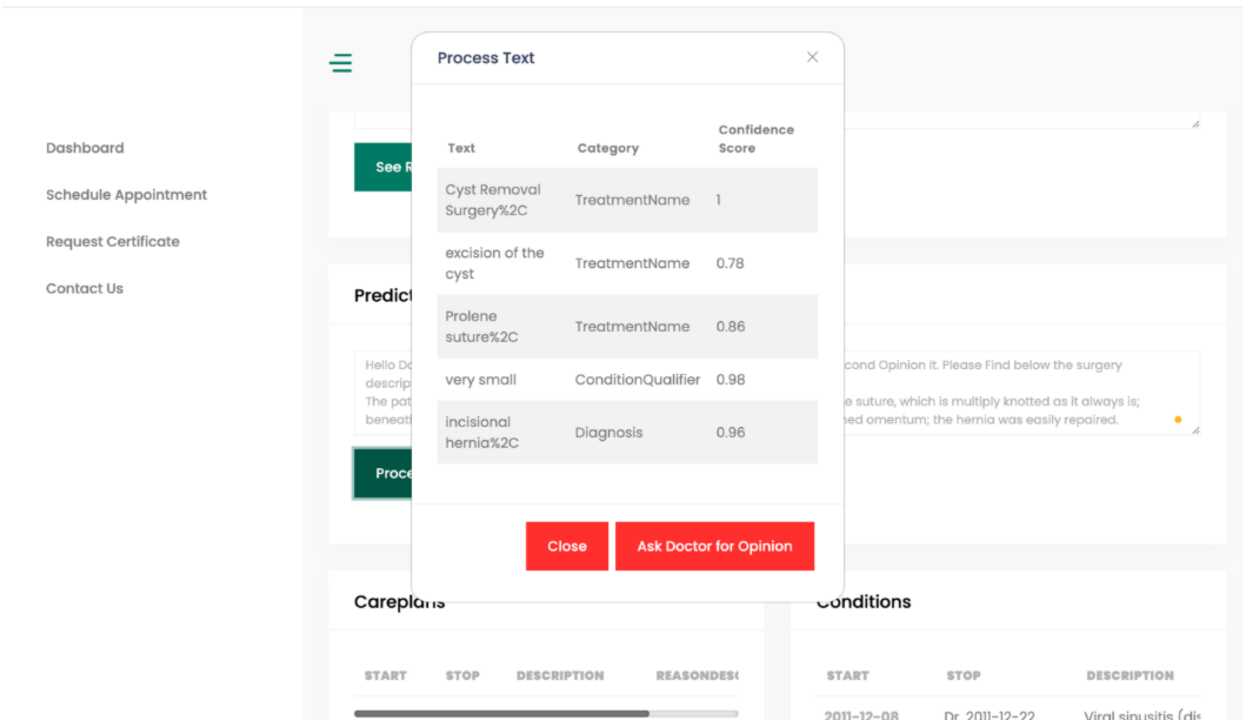


Figure 10 – Medical Named Entity Recognition (Patient End)

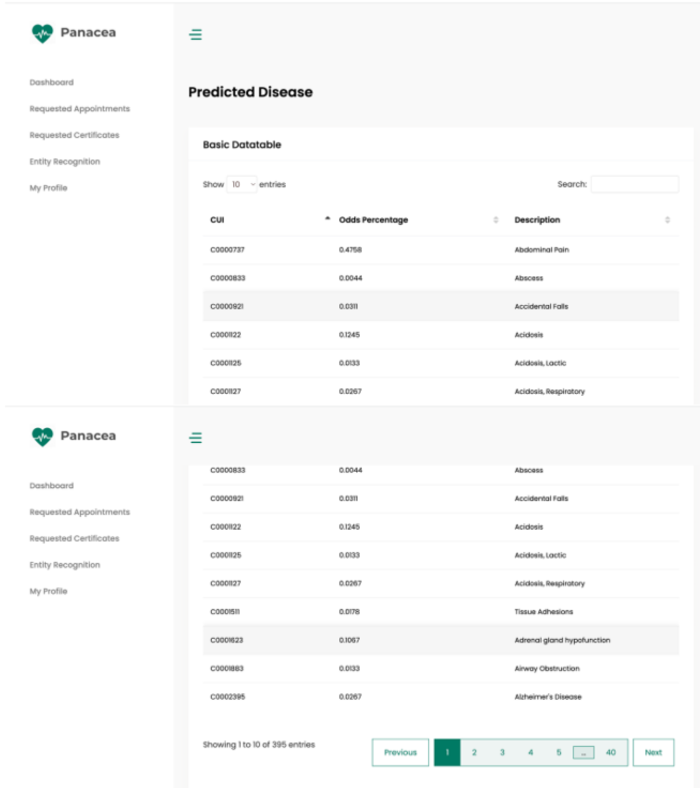


Figure 11 –Post Recovery Comorbidity Prediction (Patient End)

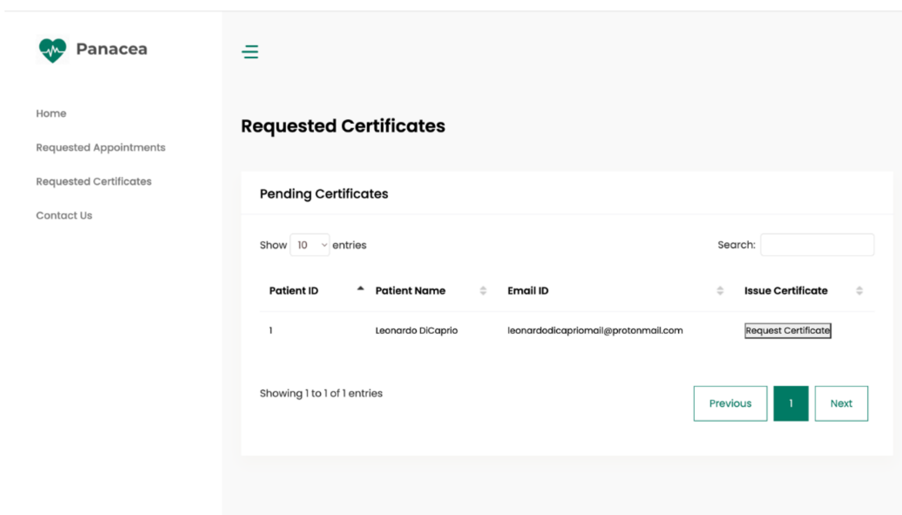


Figure 12 –Doctor Request Certificate (Doctor’s End)

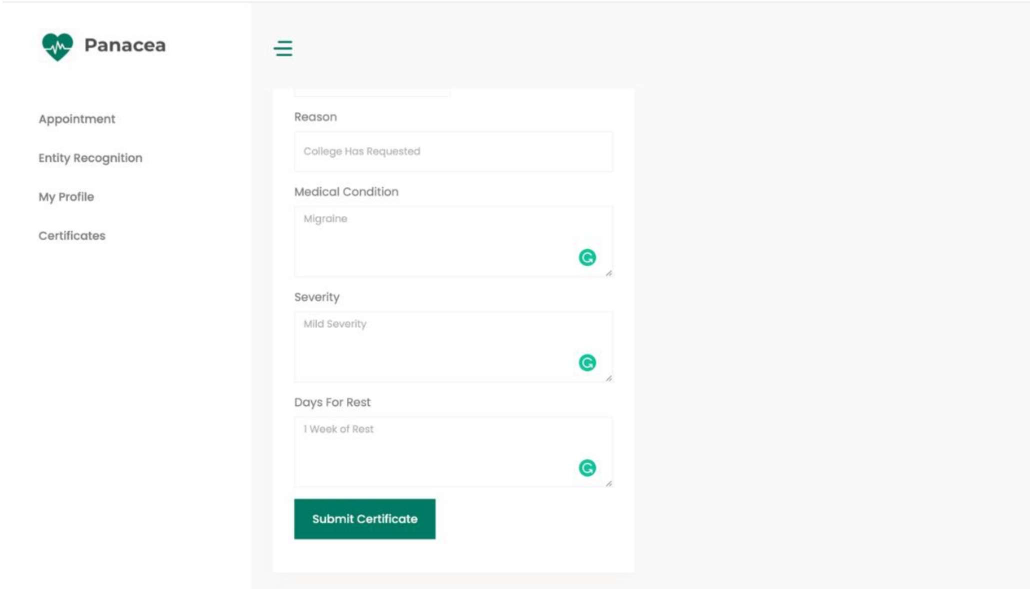
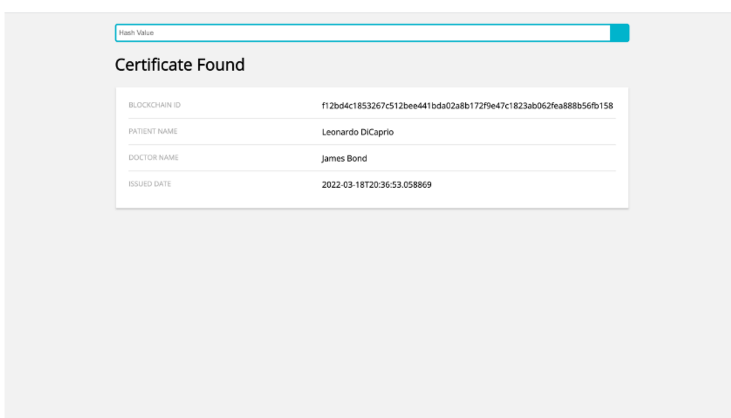


Figure 13 –Certificate Issue Form (Doctor's End)

Figure 14 – Blockchain Generated Certificate



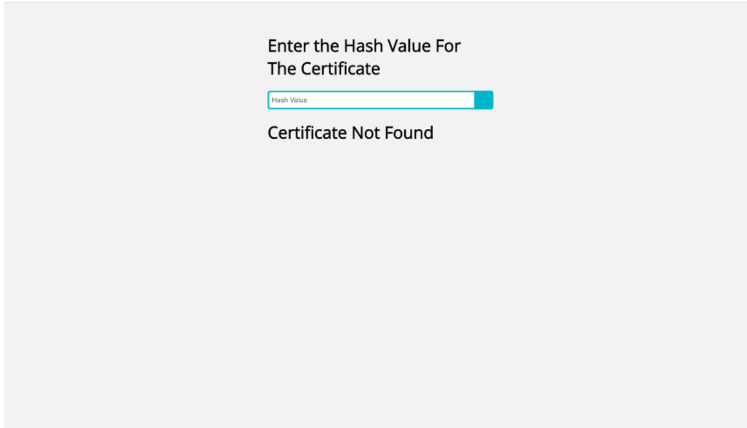


Figure 15 – Certificate Validator

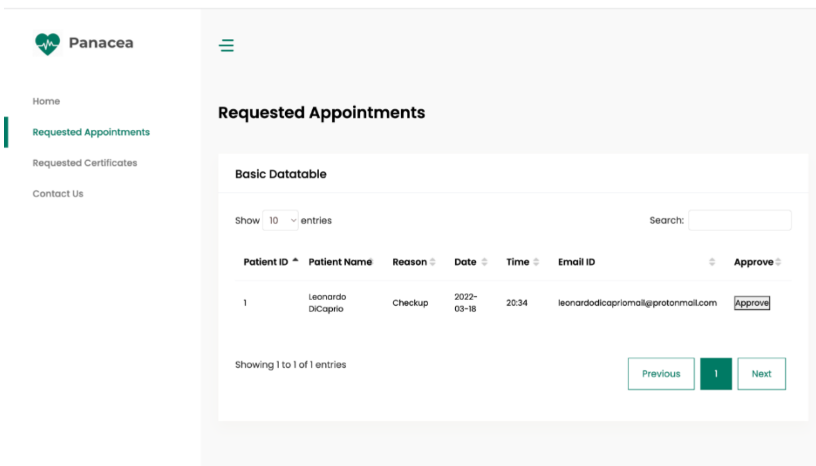


Figure 16 – Requested Appointments (Doctor's End)

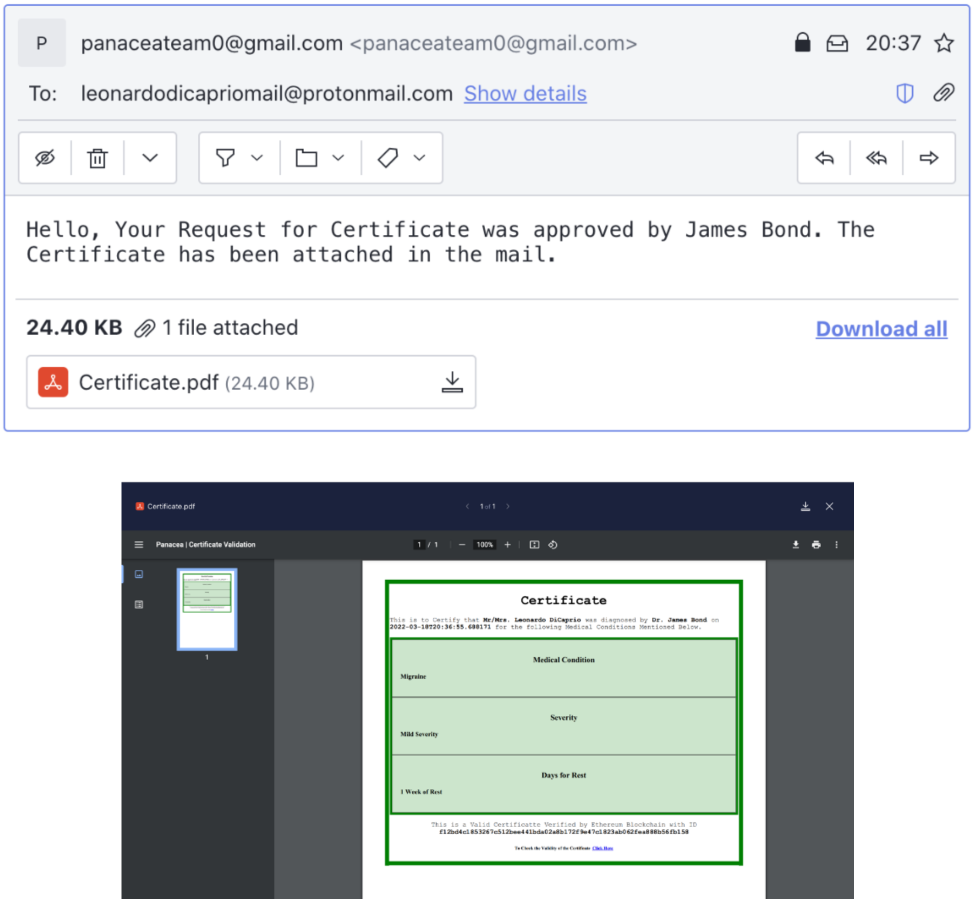


Figure 17 – Patient Certificate Email Update

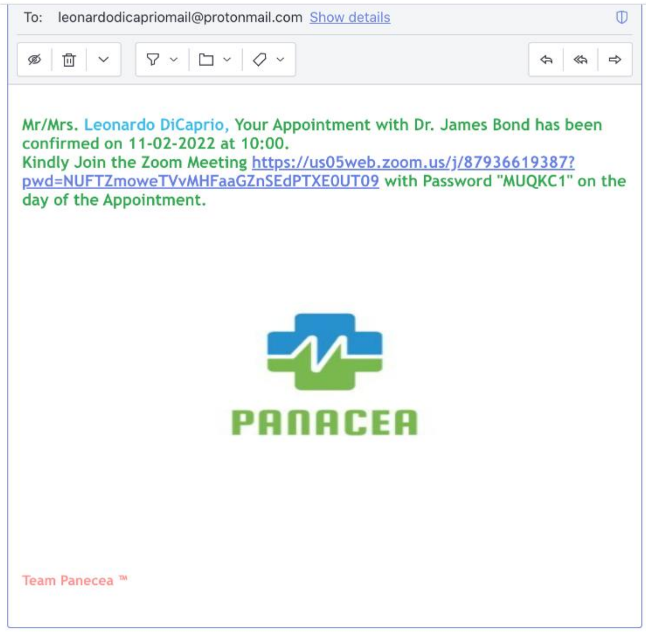


Figure 18 – Appointment Confirmation Email Update

Result Discussion

Post Recovery Comorbidity Prediction

We are using Spearman's rank correlation coefficient to predict the disease comorbidity.

Spearman's rank correlation coefficient between two variables X and Y can be calculated using the following formula:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where,

ρ = Spearman's Rank Correlation Coefficient

d_i = Difference between the two ranks of each observation

n = Number of Observations

A Spearman's rank correlation coefficient of Steatohepatitis with other comorbidities is mentioned in the table below:

Table 1 – Sample with Steatohepatitis and its comorbidities.

Sample (Steatohepatitis)	Spearman's rank correlation coefficient
Rheumatoid Arthritis	0.26394337
Acid-base disorders	0.0406176
Seronegative arthritis	0.03845534
Punctate inner choroidopathy	0.04989318
Cellulitis of leg	0.07321594
Bacterial dysentery	0.07321594
Shigella Infections	0.07026581
Glossalgia	0.88024735
Trimalleolar Fractures	0.88024735
Epilepsy, Partial, Motor	0.07651529
Chronic arthritis'	0.07651529
Stasis	0.01879325
Steatohepatitis	1
Upper Respiratory Infections	0.01267449
Primary bacterial peritonitis	0.78681908

Here, all the correlation values between 0 and 1 so we can conclude, that there is a positive correlation among the comorbidities and condition mentioned.

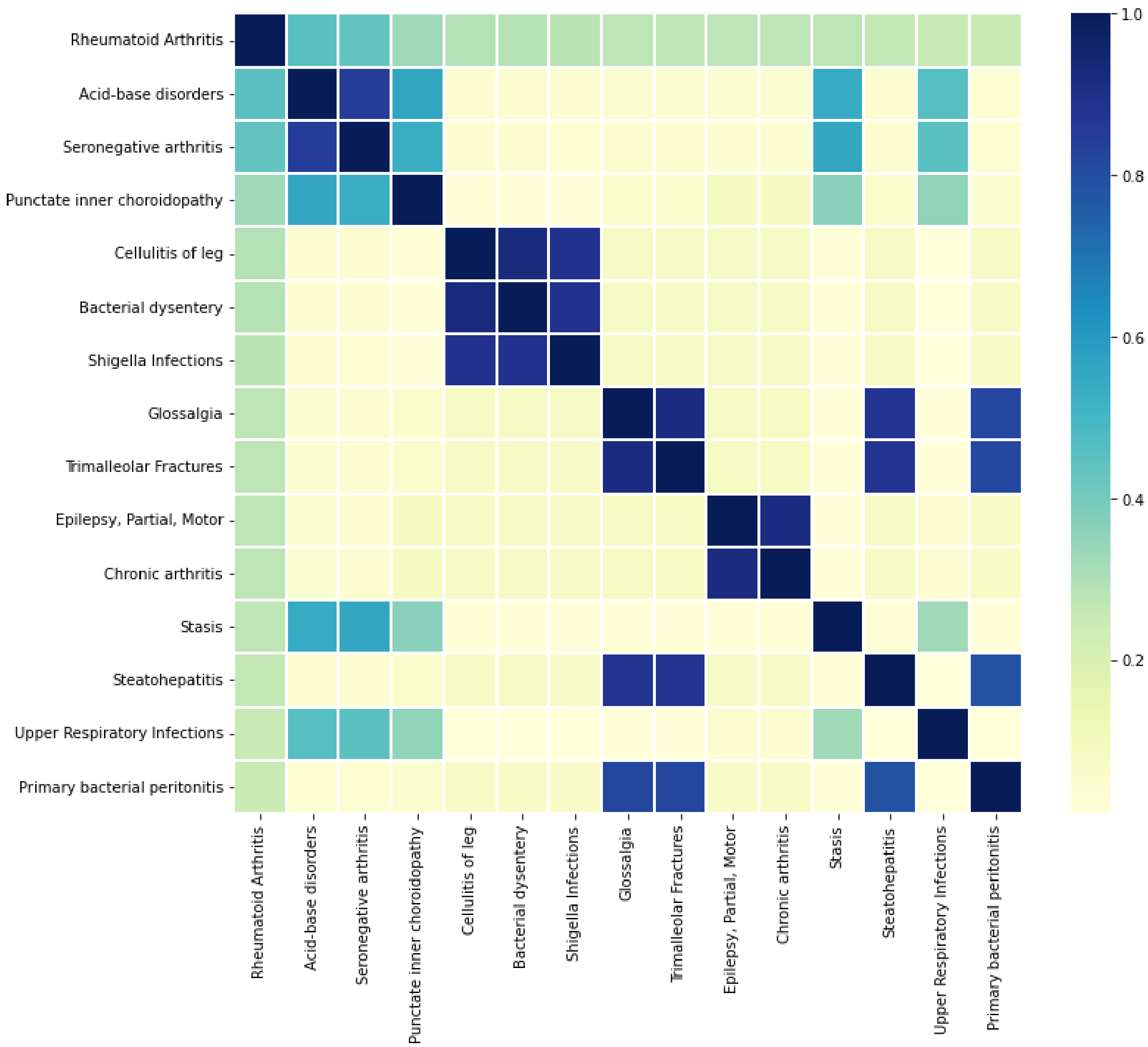


Figure 19 – Correlation Matrix for Rheumatoid Arthritis with K = 15

Drug Recommender

The training and testing data is split into 80:20 ratio. We are using a logistic regression model to obtain an accuracy of 91.33%, precision of 0.96, an F1 score of 0.94, and an AUC of 0.903

Table 2 – Model Metrics Comparison

Our Model	Class	Precision	F1	Accuracy	AUC
Logistic Regression	Class 1 Class 2	0.81 0.93	0.82 0.96	0.9133	0.903

Multinomial Naïve Bayes	Class 1 Class 2	0.87 0.88	0.71 0.92	0.8778	0.908

Author's Paper [22]	Class	Precision	F1	Accuracy	AUC
Logistic Regression	Class 1 Class 2	0.79 0.89	0.76 0.90	0.86	0.826
Multinomial Naïve Bayes	Class 1 Class 2	0.85 0.93	0.65 0.88	0.90	0.883

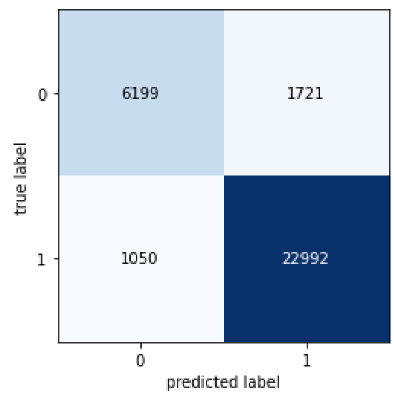


Figure 20 – Logistic Regression Confusion Matrix

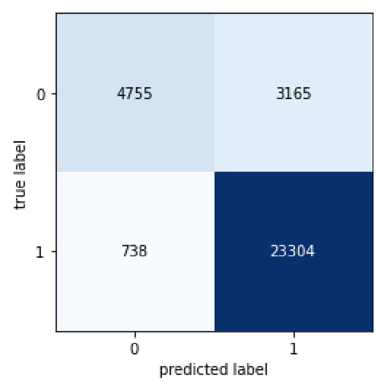


Figure 21 – Multinomial Naïve Bayes Confusion Matrix

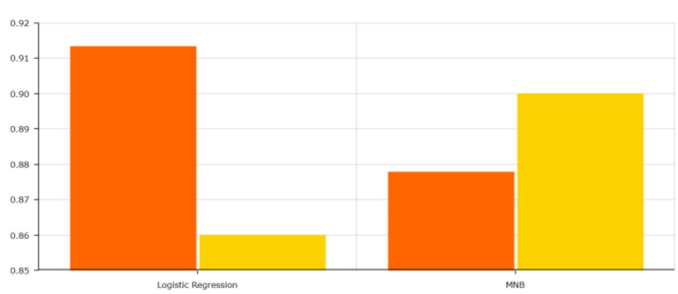


Figure 22 – Comparison of Accuracy between our model (orange) and author's model (yellow)

Blockchain EHR

Comparison between our model and the existing model has been presented below:

Table 3 – Comparison between our proposed architecture and existing architecture.

Paper	Ledger Technology	Data Generation / Storage	EHR	AI
Our Architecture	**Private Ethereum Blockchain**	**EHR stored locally and Blockchain IDs stored in JSON**	**Yes**	**Yes**
Zhang et al. [10]	Dedicated blockchain	EHRs stored locally, blockchain for managing the access to the data, HL7 FHIR standard [40] compliant storage	Yes	No
Tang et al.[12]	Ethereum smart contracts of Credit Scores	EHRs stored locally, Ethereum smart contracts manage access to the data	Yes	No
Le Nguyen et al. [13]	Ethereum, PoW	Geth IPC, IPFS, Enigma	No	Yes
Bhattacharya et al. [14]	Dedicated quantum resistant blockchain, PoA, Lattice cryptography for signature generation verification for data exchange	EHR servers for data processing, EHR encrypted in the ledger	Yes	Yes
Kumar et al. [15]	Dedicated permissioned blockchain with blockchain-based federated learning framework, PoW combined with the voting process	local model weights and encrypted EHR in the ledger	Yes	Yes
Witowski et al.[17]	Panacea blockchain on top of Cosmos SDK	Images and labels stored locally, blockchain for distribution of rewards	No	Yes
Patel et al. [18]	Dedicated blockchain, permissioned PoS	URI stored in the ledger; images hosted on the	Yes	No

		existing institution's infrastructure		
Li et al. [19]	Dedicated blockchain, improved PoDL consensus mechanism	URL to trained model or dataset stored in the ledger	No	Yes
Kumar et al. [20]	Dedicated blockchain	IPFS-based medical image storage	Yes	No

Conclusion And Future Work

Conclusion:

In this project, we present a machine learning and a blockchain-based stage for managing patient electronic records. Albeit a few changes are important to tweak the answer for production scale, key objectives and targets are accomplished. A further turn of events and upgrades can make the proposed arrangements a proficient and successful stage for both the community and the medical care industry. Even though all execution has effectively done according to the momentum client assumptions by utilizing the previously mentioned innovations and techniques, from the prerequisite social event to the consequences of the examination can be changed according to the future client necessities. Specialists will address the important pre-requisites and will do the form administrations accordingly. Furthermore, block-chain and computerized reasoning fueled arrangement which is coordinated through a web application give an easy-to-understand road to draw in with the model administration. It is additionally vital to take note that this large number of highlights are accomplished while regarding and sticking to administrative limitations, for example, HIPAA and GDPR making it appropriate for the business to take on without a second thought.

Future Work:

- Since we have applied for and received the UMLS (Unified Medical Language System) license, the use of the knowledge-rich data from the UMLS dataset as backend would enhance the accuracy as well as increase the potential for additional medical functionalities in our application.
- Learning graph database using neo4j during the development of the project, the project can be further improved by using the graph database for creating and storing relationships between entities.

References

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