HealVision: Enhancing SUD Recovery through Mobile Technology and Aspect-Based Emotion Analysis

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HEALVISION: ENHANCING SUD RECOVERY THROUGH MOBILE TECHNOLOGY AND ASPECT-BASED EMOTION ANALYSIS

A thesis submitted to the
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Computer Science

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APPROVAL BY THE BOARD OF EXAMINERS

Supervisor

AUTHORS DECLARATION

We take full responsibility for the research work conducted during the Thesis titled" **HealVision: Enhancing SUD Recovery through Mobile Technology and Aspect-Based Emotion Analysis"**.

We solemnly declare that the research and development work presented in the Thesis is done solemnly by me with no significant help from any other person; however, small help, wherever taken, is duly acknowledged. We have also written the Thesis by ourselves. Moreover, we have not previously presented this thesis or any part to any other degree-awarding institution in Pakistan or abroad.

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Tayyaba Arshad

DEDICATION

This research work is dedicated to our beloved people out there who are struggling with substance use disorders and mental health issues.

ABSTRACT

Substance Use Disorders (SUD) pose a high risk to both individuals and organizations, as excessive consumption leads to a drop in productivity, health issues, injuries, mental health concerns, unemployment risk, and death. This disorder falls under Sustainable Development Goal 3 - Good Health and Well-Being, Goal 10 – Reduced Inequalities, and Goal 16 – Peace, Justice, and Strong Institutions. To combat this, we introduced an Artificial Intelligence(AI) driven mobile application to precisely predict the emotions of individuals with SUD based on the textual messages, addiction determination through an interactive quiz, appointment system, health tracker, patient monitoring, and emotion detection-based chat module using our BERT-ANN model and a chatbot. To ensure the effectiveness of our strategy, We leverage models such as Artificial Neural Networks, BERT, feed-forward NN, Naïve Bayes, and Random forest. We worked on a flutter framework for the development of our mobile application. We created our dataset ensuring balanced classes (6003 dialogues) as well as correctly labeled data (6 classes) called the "Emotions-6000." we trained our AI models on that dataset, and with extensive testing and validation, our BERT-ANN model acquired a training and testing accuracy of 99.9% and 79.33% respectively. Although the testing accuracy of BERT-ANN trained on Emotions-6000 is less than that of our FNN trained on the "Emotions" Dataset (Balanced Version), testing by our custom input data proved that the BERT-ANN model with Emotions-6000 performed best.

These results confirm healthcare professionals can analyze textual data to perform emotion classification that can gather information about the patients' moods—introducing solutions using aspect-based analysis of textual data for emotion detection to aid the therapist in achieving meaningful results. The application aims to mitigate the gap in accessibility to those in need.

TABLE OF CONTENTS

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LIST OF ABBREVIATIONS AND SYMBOLS

GPS	Global Positioning Sensor
SD cards	Secure Digital Memory Card
PCB	Printed Circuit Board
App	Application
USB	Universal Serial Bus
Hz	Hertz
GND	Ground

1. INTRODUCTION

Drug addiction is a complex and profound issue that affects millions of people worldwide. It can involve substances such as tobacco, alcohol, and illicit drugs and has a significant impact on individuals' mental, physical, and emotional well-being, as well as their relationships, work, and overall quality of life. Access to high-quality treatment for drug addiction is often limited and expensive. According to data from the World Health Organization (WHO), an estimated 284 million people aged 15-64 used illicit drugs in 2020, with 60\% being male and 40\% female. Additionally, 265 million people used alcohol at harmful levels. These numbers are increasing at a concerning rate of 2.1\% per year. Pakistan is mainly affected by drug addiction due to the widespread use of opium and cannabis. A UN report in 2020 indicates that there are 7.6 million drug addicts in Pakistan, with 78\% being male and 22\% female, and this number is increasing at a rate of 1.8\% per year.

1.1. Current Work

Within addiction management and assistance, several notable initiatives are making significant headway. The "I Am Sober" application and the "BetterHelp" platform are critical players.

"I Am Sober" stands out as a widely acknowledged mobile app designed to be a companion for individuals navigating their recovery journey. The app offers a variety of features, such as daily commitment pledges to maintain sobriety, monitoring progress, and fostering a supportive community of users who share their experiences. Through functions like commemorating milestones and providing personalized motivations, "I Am Sober" aims to instill a sense of accomplishment and encouragement for users dedicated to sustaining sobriety. Similarly, the "BetterHelp" application provides online counseling services, connecting users with licensed therapists to offer professional support. While not exclusively tailored to addiction management, "BetterHelp" addresses the mental health aspect often intertwined with substance use disorders. The app allows users to conveniently access therapy from their devices, overcoming geographical barriers and making mental health support more readily available.

In tandem with these efforts, Heal Vision recognizes the significance of adopting a holistic approach to addiction management. The app incorporates features such as addiction assessment tools, intensity quizzes, and health tracking to provide users with a comprehensive understanding of their addiction and its impact on their well-being. Additionally, Heal Vision streamlines the scheduling of therapy appointments, establishing a seamless connection between users and therapists to enhance the overall support system.

2. BACKGROUND INFORMATION

Mental health is a critical issue often overlooked in our society, especially in our country. Addressing this problem, HealVision aims to bridge the accessibility gap caused by traditional therapy, which can be costly and difficult to access. Many people with substance use disorder (SUD) go untreated due to the stigma surrounding mental health and the reluctance to seek help. HealVision aims to address these issues by offering a wide-ranging mobile application that facilitates addiction determination through an interactive quiz, scheduling and managing appointments between patients and therapists, and, most importantly, includes an emotion detection-based chat module. The quiz assists in identifying the addict's condition, while the appointment system provides timely access to therapy. Moreover, the AI-powered chat module provides real-time emotional analysis through a chatbot during conversations, allowing therapists to present tailored interventions based on the patient's emotional condition. This holistic method aims to make mental health care more accessible and helpful for individuals struggling with substance use disorders.

Our research is dedicated to advancing HealVision's capabilities by incorporating aspect-based sentiment analysis to predict the emotional states of individuals grappling with drug addiction. This integration allows our Flutter app's chatbot to assess emotional states based on patients' messages, making it easier for therapists to understand and address their patient's moods. Our approach involved utilizing a dataset of 20,000 tweets named "Emotions", our balanced version of "Emotions" of 39,000 tweets, and a dataset we created, "Emotions-6000," with 6003 correctly classified sentences. Working with various AI models to predict the user's emotional state. We selected BERT, Artificial and Feed-forward Neural Networks, Naive Bayes, and Random Forest algorithms through extensive testing and validation to achieve enhanced accuracy.

Moreover, we balanced the Emotions dataset by adding more sentences to increase the count of other emotions and created our dataset. It is extensively discussed in the dataset section below. Continuing our research, we consulted with healthcare professionals, including a clinical psychologist, a consultant trainer, and a psychotherapist, to get valuable insights and make our application look more practical. They have highlighted the emotional challenges being faced by individuals with Substance Use Disorders (SUDs) and emphasized the impact of empathy, identifying textual emotional indicators, and implementing a holistic therapeutic approach. These insights have influenced refining our chatbot to support therapists in delivering empathetic and tailored interventions. The incorporation of professional expertise has substantially bolstered HealVision's capacity to bridge the gap in accessible mental health care for those impacted by drug addiction.

3. RELATED WORK

In the dynamic landscape of artificial intelligence and natural language processing, the ability to comprehend and interpret human emotions through textual data has become crucial for developing emotionally intelligent applications. This research journey extensively explores recent progress in emotion detection and sentiment analysis across diverse domains. The literature review encompasses nine papers, each providing valuable insights into methodologies, challenges, and innovations within emotion detection and sentiment analysis. From interdisciplinary surveys on emotion detection in text to inventive approaches employing deep learning techniques, these papers collectively offer a nuanced comprehension of the intricacies of extracting emotions from textual data.

Table 1: Literature Review

The summary of various research on aspect-based sentiment analysis

No.	Name, reference	Publisher	Year	Methodology	Dataset's Used	Description
1.	Emotion Detection of Textual Data: An Interdisciplinary Survey	Samira Zad, Maryam Heidari, James H Jr Jones, Ozlem Uzuner	2021	Supervised learning (SVM, Naive Bayes, and LSTMs.) Unsupervised learning (K-means.)	ISEAR, PAN, and MPQA. Challenge-specific datasets like SemEval.	Each dataset provides text samples labeled with emotions. Datasets vary in size, domain (e.g., Twitter, news), and annotation complexity. Challenges:
2.	Aspect-Based Sentiment Analysis of Drug Reviews Applying Cross-Domain and Cross-Data Learning	Felix Gräßer, Surya Kallumadi, Hagen Malberg, Sebastian Zaunseder	2018	Predict sentiment for overall satisfaction, side effects, and effectiveness of drugs in user reviews.	Drugs.com & Druglib.com Content: User reviews Size: Large Structure: Unlabeled text reviews	Each review expresses opinions on multiple aspects (satisfaction, side effects, effectiveness) without explicit labeling.

3.	Aspect-Based Sentiment Analysis and Emotion Detection for Code-Mixed Review	Andi Suciati, Indra Budi	2020	(ML): BR, LP, CC problem transformation methods (DL): BiLSTM & GRU deep learning models	14,103 restaurant reviews Sentiment & emotion labels (multi-label)	Classify multi-label sentiment & emotion in reviews using both ML & DL techniques.
4.	Aspect-based sentiment & emotion analysis with ROBERTa, LSTM	Uddagiri Sirisha, Bolem Sai Chandana	2022	Novel deep learning model: ABSA-based Roberta-LSTM	Significant, geographically tagged tweets related to Ukraine-Russia war Collected using hashtags like #ukraine, #russia, etc.	Analyzes tweet sentiment and emotion using the proposed hybrid model. Data pre-processed to remove noise and symbols. The model achieves state-of-the-art accuracy (94.7%)
5.	Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey	Ambreen Nazir, Yuan Rao, Lianwei Wu, Ling Sun	2020	Challenges and Solutions for AE, ASA, and SE Comparison with existing AbSA and SA surveys	SemEval, TripAdvisor, Amazon reviews)	This survey establishes a solid foundation for understanding AbSA advancements and developing universal strategies across different scenarios.
6.	A review of sentiment analysis and emotion detection from text	Pansy Nandwani, Rupali Verma	2021	Comparison with existing AbSA and SA surveys	SemEval, EmoBank, EmoTex	This survey establishes a solid foundation for understanding AbSA advancements and developing universal

						strategies across different scenarios.
7.	The Biases of Pre-Trained Language Models: An Empirical Study on Prompt-Based Sentiment Analysis and Emotion Detection	Rui Mao, Qian Liu, Kai He, Wei Li, Erik Cambria	2023	Applying different PLMs (RoBERTa, BERT, etc.) to annotated emotion/sentiment data	Extensive, annotated data for emotion and sentiment classification	Study assesses biases and effectiveness of PLMs in affective computing (emotion & sentiment)
8.	Knowledge-enabled BERT for aspect-based sentiment analysis	Anping Zhao , YuYu	2021	Knowledge-enabled BERT: Integrates a sentiment knowledge graph (SKG) into BERT for ABSA.	Online learner reviews Preprocessing: Size: 13167 sentences, 1692 unique terms.	Explores using SKG to improve BERT for ABSA and enhance result explanations.
9.	Deep learning for Aspect-based Sentiment Analysis	Jie Wang, Bingxin Xu, Yujie Zu	2021	Models like H-LSTM, PhraseRNN, and Coattention-LSTM is used	SemEval 2014 Task 4, Twitter.	Deep learning advancements in ABSA, highlighted models and their focuses, outlined challenges, and mentioned datasets and evaluation metrics for a concise overview.

2.1 Emotion Detection of Textual Data: An Interdisciplinary Survey

This paper is a survey and overview of recent text-based emotion detection (TBED) progress. It discusses various methodologies, datasets, limitations, and proposed improvements in the field. The document highlights using machine learning techniques for TBED and the importance of labeled datasets for training models. It mentions that the shortage of labeled datasets with multiple emotion labels is a challenge in constructing efficient TBED mechanisms. The annotation process for creating labeled datasets is time-consuming and costly. Another challenge mentioned is the lack of appropriate emotion lexicons. Existing lexicons are not domain-specific and do not consider the context-dependent nature of emotion labels. The paper suggests the construction of domain-specific lexicons for better TBED performance. The document compares TBED mechanisms based on their performance ratios, such as F1 score and accuracy. It also discusses the applications of TBED in various domains. In terms of proposed improvements, the document suggests finding the best combination of machine learning techniques and dimension reduction methods for TBED. It emphasizes the need for adequate labeled datasets to conduct such experiments. Additionally, the document mentions the need for domain-specific emotion lexicons and addresses open issues in the field.

2.2 Aspect-Based Sentiment Analysis of Drug Reviews Applying Cross-Domain and Cross-Data Learning

The paper presents a study on aspect-based sentiment analysis of drug reviews using machine learning techniques. The study focuses on predicting sentiments related to overall satisfaction, side effects, and effectiveness of drugs based on user reviews. The dataset used in the study is obtained from two independent web pages, Drugs.com and Druglib.com, which comprise many user reviews on specific drugs. The study investigates the transferability of trained models among medical domains and across data sources. The study's main limitation is the lack of annotated data, especially for distinct aspects, and the difficulty in transferring models across different domains and data sources. The study suggests that more sophisticated features and powerful machine learning models, such as deep learning approaches, could improve the results and facilitate aspect-based sentiment analysis of patient drug reviews.

2.3 Aspect-Based Sentiment Analysis and Emotion Detection for Code-Mixed Review

This study uses machine learning and deep learning techniques to focus on the multi-label classification of restaurant reviews. The researchers conducted experiments using two scenarios. In the first scenario, they applied problem transformation methods such as Binary Relevance (BR), Label Powerset (LP), and Classifier Chain (CC) with features extracted from unigram, bigram, and a combination of unigram-bigram. In the second scenario, they used deep learning algorithms, specifically Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU), with self-developed word embedding. The dataset used in the study consisted of 14,103 reviews with sentiment and emotion labels. The results showed that LP and CC performed better than BR in most aspects, and ET achieved the highest score for the "service" aspect. The study also highlighted the dataset's imbalanced label distribution and suggested using data augmentation or sampling methods to address this issue. Additionally, the researchers recommended incorporating other features, such as POS tagging, to enhance the performance of both machine learning and deep learning models.

Limitations of the study include the limited number of annotators and the small number of data samples for specific emotion labels. The researchers also noted that the combination of unigram and bigram features may not be effective if bigram words are infrequently mentioned in the reviews. The study suggests considering additional features and addressing the imbalanced label distribution to improve the classification results.

2.4 Aspect-based sentiment & emotion analysis with ROBERTa, LSTM

The paper focuses on sentiment and emotion analysis of tweets related to the Ukraine-Russia war using machine learning and deep learning techniques. The authors propose a novel deep-learning approach that combines the Roberta model with Aspect Sentiment Analysis (ABSA) and Long Short-Term Memory (LSTM) for sentiment analysis. They collected a large dataset of geographically tagged tweets related to the war from Twitter and analyzed it using the proposed model. The experimental results show that the suggested hybrid model outperforms state-of-the-art techniques with an accuracy of 94.7%.

The method involves data pre-processing to remove redundant tokens and symbols, followed by training and classification using the proposed ABSA-based Roberta-LSTM model. The model efficiently maps tokens into meaningful embedding space using pre-trained Roberta weights and captures long-distance temporal dependencies in the word embeddings using LSTM. The dataset was obtained from Twitter and contains tweets about the Ukraine-Russia war, collected using hashtags such as #ukraine, #russia, #Putin, #standwithUkraine, and others.

However, potential limitations could include the reliance on Twitter data, which may not represent the entire spectrum of public opinion, and the challenges associated with sentiment analysis of informal and noisy text data. The improvements include the development of a more accurate and effective sentiment analysis model using the proposed hybrid approach, which outperforms existing techniques. Additionally, the authors highlight the potential for future research to explore other social media platforms and incorporate more advanced natural language processing techniques for sentiment analysis.

2.5 Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey

This paper is a comprehensive survey on Aspect-Based Sentiment Analysis (AbSA), focusing on the challenges and solutions related to Aspect Extraction (AE), Aspect Sentiment Analysis (ASA), and Sentiment Evolution (SE). The methodology involves organizing the survey into sections that define sentiment concerning aspects, list significant issues and challenges, discuss recent solutions, and highlight future research directions. The survey also includes comparing existing surveys related to ABSA and SA.

Datasets and performance metrics are mentioned, with a reported performance of presented solutions for ASA, such as weakly supervised opinion summarization, supervised aspect rating, and unsupervised word negation. The paper also discusses using various datasets, including SemEval 2014 and 2015, TripAdvisor, and oposum dataset (amazon reviews), along with performance metrics like precision, recall, and F1 score. The limitations include improved personalized summarization for aspect summarization and the challenge of predicting sentiment dynamicity. The paper also highlights the limitations of existing surveys, such as being outdated due to exponential achievements and innovations in recent years.

Improvements include the need for future research directions to improve present solutions, achieve good classification accuracy at the aspect level, predict SE dynamicity, and measure the change of sentiment value with time. The document also proposes the consideration of sub-issues and sub-challenges for resolving significant challenges in

AbSA, as well as adopting cognitive techniques for studying human behaviors through machine intelligence imitation. Overall, the survey provides a foundation for researchers to understand the recent progress in the field of Absa and formulate general strategies applicable to various scenarios.

2.6 A review of sentiment analysis and emotion detection from text

Sentiment analysis is a technique used to analyze the sentiments of users or authors based on their opinions. It involves extracting features from text, applying machine learning algorithms, and evaluating the model's performance using metrics like accuracy, precision, and recall. The process faces challenges such as informal text, spelling mistakes, and slang, which make it difficult for machines to analyze sentiment and emotion accurately. Researchers have worked on various datasets, including Hindi-English code mixed with emotions, and have used techniques like word vectorization and the Bag of Words approach. Improvements have been made by updating lexicons and incorporating word embeddings to enhance sentiment classification performance.

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2.7 The Biases of Pre-Trained Language Models: An Empirical Study on Prompt-Based Sentiment Analysis and Emotion Detection

This paper discusses a study's methods, datasets, improvements, and limitations on prompt-based sentiment analysis and emotion detection. The study aims to analyze the biases of pre-trained language models (PLMs) and evaluate the utility of prompts in affective computing tasks.

The study uses enormous annotated emotion and sentiment classification data to evaluate the performance of different PLMs, including RoBERTa, BERT, ALBERT, and Bart. Fine-grained emotion taxonomies are more effective than coarse-grained ones in affective computing tasks. Using multiple-word forms of label-words improves performance, with adjective emotion words being more effective than nominal counterparts. PLMs show biases towards certain label classes in fine-grained classification tasks, resulting in weak performance. The variables of label-word selections, Part-of-Speech (PoS) variations, prompt templates, and positions influence the classification results of PLMs. Better label-word selection, prompt engineering methods, and ensemble learning are suggested as potential ways to mitigate biases and improve results.

2.8 Knowledge-enabled BERT for aspect-based sentiment analysis

The paper discusses the use of a sentiment knowledge graph (SKG) to improve aspect-based sentiment analysis (ABSA) using the BERT language representation model. The goal is to incorporate external domain knowledge into the model and explain ABSA results. The paper presents the methodology, experimental setup, and evaluation metrics used to assess the performance of the knowledge-enabled BERT model. A dataset of online learner reviews is used for evaluation. The limitations of the model are also discussed.

The proposed method involves integrating a sentiment knowledge graph (SKG) into the BERT model for ABSA. The SKG captures the sentiment relations between aspect terms and sentiment words. The model uses the BERT architecture with parameter settings similar to the basic version of BERT. The SKG is added during the fine-tuning phases of the model. The performance of the knowledge-enabled BERT model is evaluated using accuracy, Macro-F1, and F1-score metrics.

Using the sentiment knowledge graph (SKG) in the BERT model improves the performance of aspect-based sentiment analysis. By incorporating external domain knowledge, the model can explain the ABSA results. The experimental results demonstrate that the knowledge-enabled BERT model produces better token embedding representations and improves ABSA performance.

The model is evaluated using a dataset of online learner reviews collected from MOOC offerings on two Chinese university MOOC platforms. The dataset consists of posts by online learners in different advanced language programming courses. The dataset is preprocessed by separating sentences, segmenting words, and removing stop words. The final dataset includes 13167 sentences with 1692 unique terms. The sentence's aspect terms and sentiment terms are labeled by term type into nouns and adjectives. One limitation of the model is the requirement for a consistent vector space to learn the embeddings of words with knowledge from the sentiment knowledge graph (SKG). This can be challenging as words in the text and SKG entities are acquired separately. Another limitation is the assumption that the sentiment knowledge graph provides comprehensive domain knowledge. However, there may be limitations in the coverage and accuracy of the knowledge graph.

2.9 Deep learning for Aspect-based Sentiment Analysis

The paper discusses the development and advancements in Aspect-Based Sentiment Analysis (ABSA) using deep learning methods. It mentions that traditional methods for ABSA rely on emotional dictionaries and have limitations such as low precision and the need for continuous updates. Deep learning approaches based on CNN/RNN have been proposed to address these challenges. Several methods and models are mentioned in the paper, including H-LSTM (Hierarchy bidirectional LSTM), PhraseRNN, and Coattention-LSTM network. These models aim to improve sentiment analysis at the sentence and review levels, enhance the representation of target aspects, and address the issue of unfair attention scoring for context.

The paper also highlights the challenges in ABSA, such as domain adaptation, multilingual environments, and imbalanced data. Domain adaptation refers to the transferability of parameters trained in one domain to another. Multilingual environments pose challenges due to word sense ambiguity, language-specific structures, and translation errors. The lack of resources for constructing NLP models in many languages also contributes to imbalanced data. Datasets mentioned in the paper include SemEval 2014 Task 4 and Twitter for evaluating the performance of different models. The limitations of current DL methods in ABSA are acknowledged, and the need for further research and improvement is emphasized.

Overall, the paper analyzes the recent developments, challenges, and suggestions for future research in ABSA using deep learning methods.

4. Application Design Architecture

4.1. Class Diagram

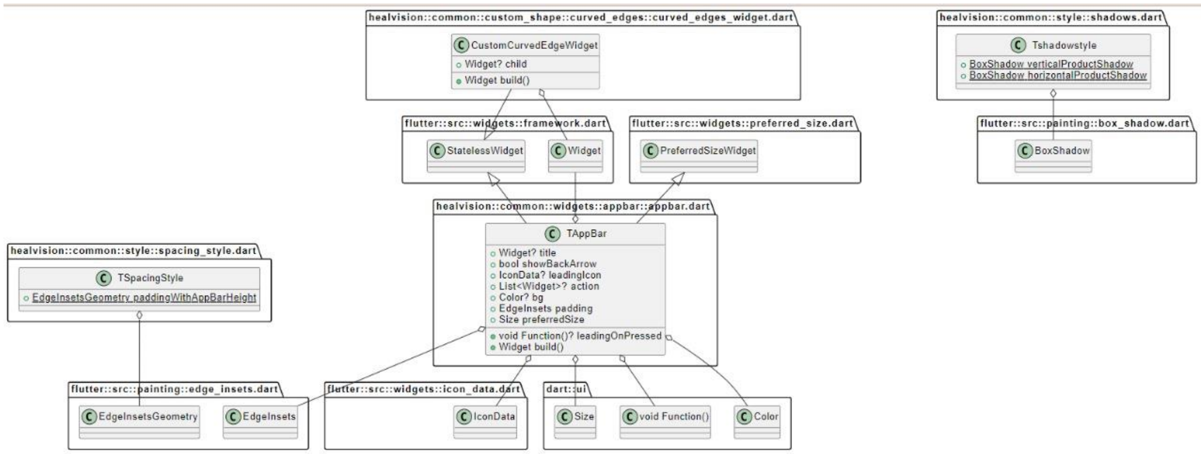


Figure 1.0: Class Diagram

Part 1

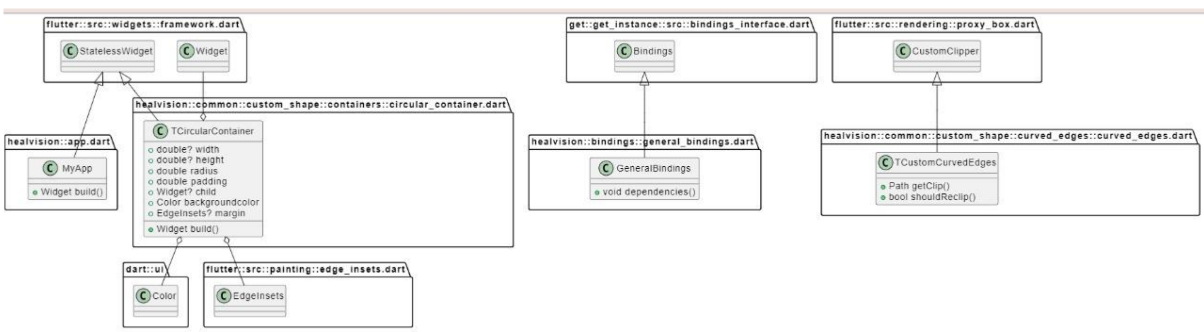


Figure 1.1: Class Diagram

Part 2

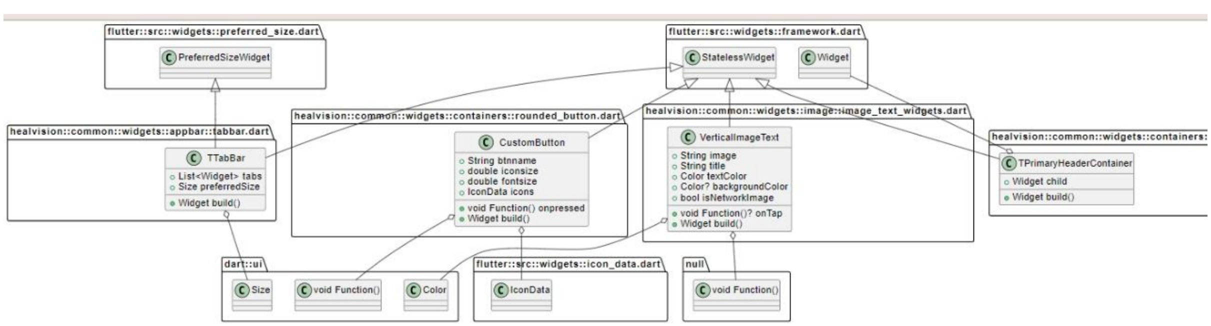


Figure 1.2: Class Diagram

Part 3

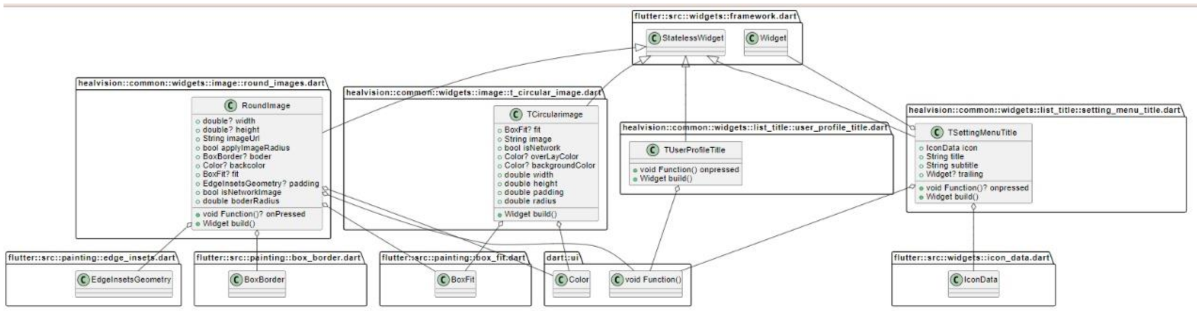


Figure 1.3: Class Diagram

Part 4

The class diagram is split into four diagrams due to many classes, and it showcases the inheritance and composition relationships among different widgets and utilities used in our app.

At the top, the MyApp class extends StatelessWidget, representing the main application widget. The GeneralBindings class, extending Bindings, defines dependencies for the app. Custom widgets like TCircularContainer, TCustomCurvedEdges, and CustomCurvedEdgeWidget extend or compose standard Flutter widgets, adding specific functionalities and styles unique to the HealVision application.

The TAppBar and TTabBar classes, inherited from StatelessWidget and implemented PreferredSizeWidget, customize the app's app and tab bar. The diagram also includes custom containers and buttons, such as TPrimaryHeaderContainer and CustomButton, which encapsulate specific UI elements and their behaviors.

Custom image widgets like VerticalImageText, RoundImage, and TCircularimage handle image display with additional attributes for customization. List title widgets like TSettingMenuTitle and TUserProfileTitle provide formatted list items with icons and action callbacks.

Login and signup-related widgets, such as TFormDivider and TSocialButtons, enhance user authentication interfaces. The SuccessScreen widget displays success messages, while text widgets like ProductTitleText and SectionHeading manage text styling and layout.

Overall, the diagram captures the comprehensive architecture of the HealVision Flutter application, highlighting the modularity and reusability of custom widgets and the integration of Flutter's core functionalities. We facilitated a well-organized and maintainable codebase, ensuring a cohesive and scalable application design.

4.2. Entity - Relationship Diagram

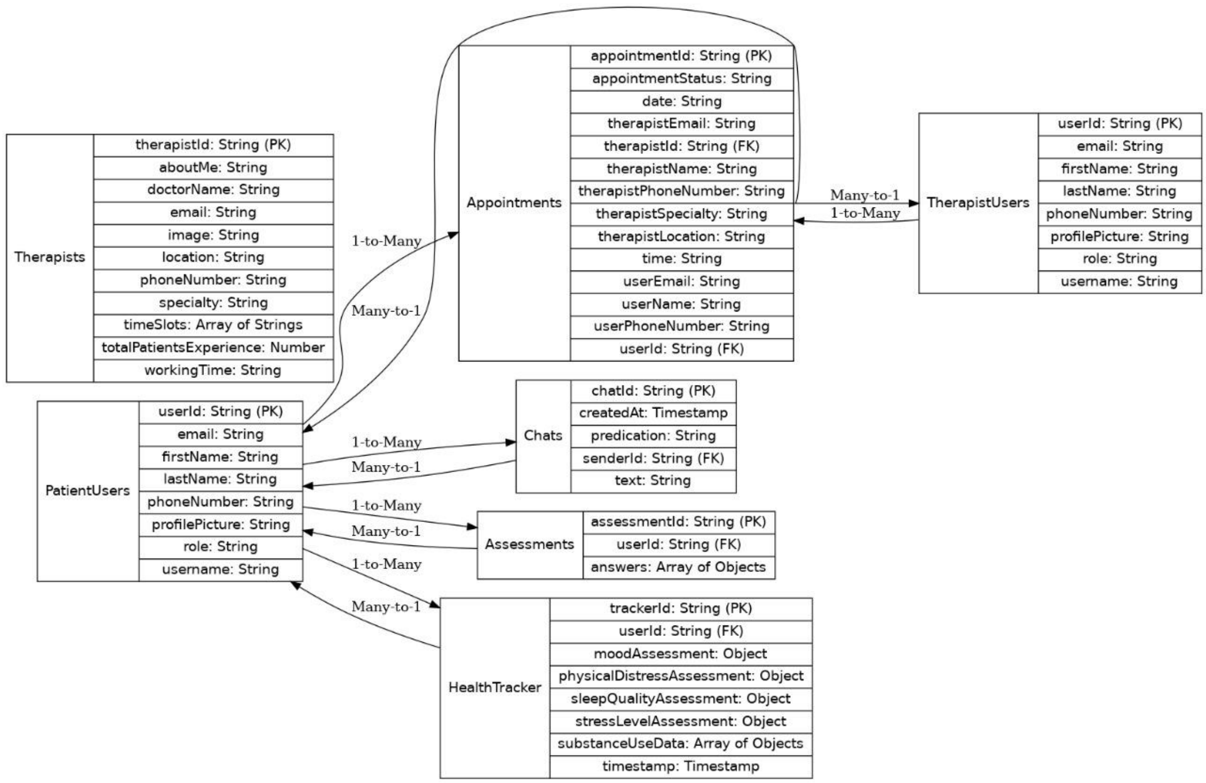


Figure 1.4: ERD

Abstraction of relationships

4.3. Data Flow Diagram

4.3.1. Level 0

Level 0, as shown in Fig 1.5, shows the inflow and outflow of data among Healvision users.

Level 0

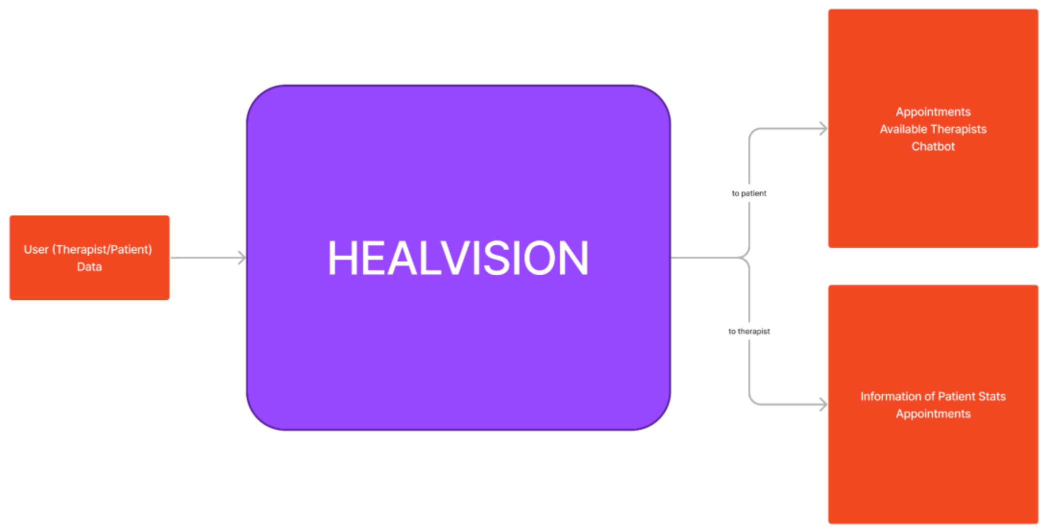


Figure 1.5: DFD

Level 0

4.3.2. Level 1

Level 1 is an in-depth abstraction of data usage from patients and therapists, how it is connected with Firebase, and the results shown.

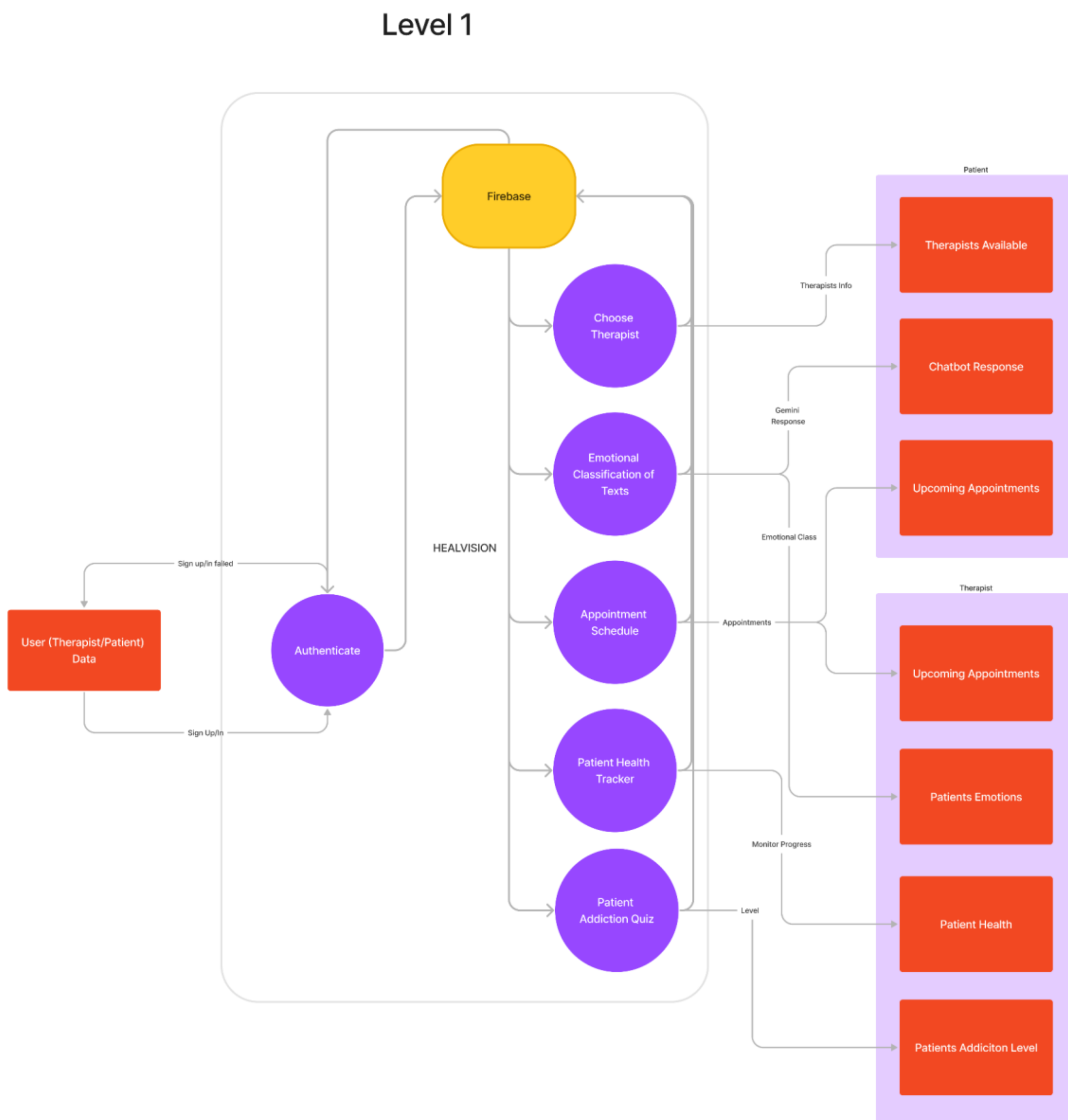


Figure 1.6: DFD

Level 1

4.4. Use Case Diagram

The use case diagram accurately represents the User's (patient/therapist) interaction with the system and the system's interaction with the database hosted on Firebase.

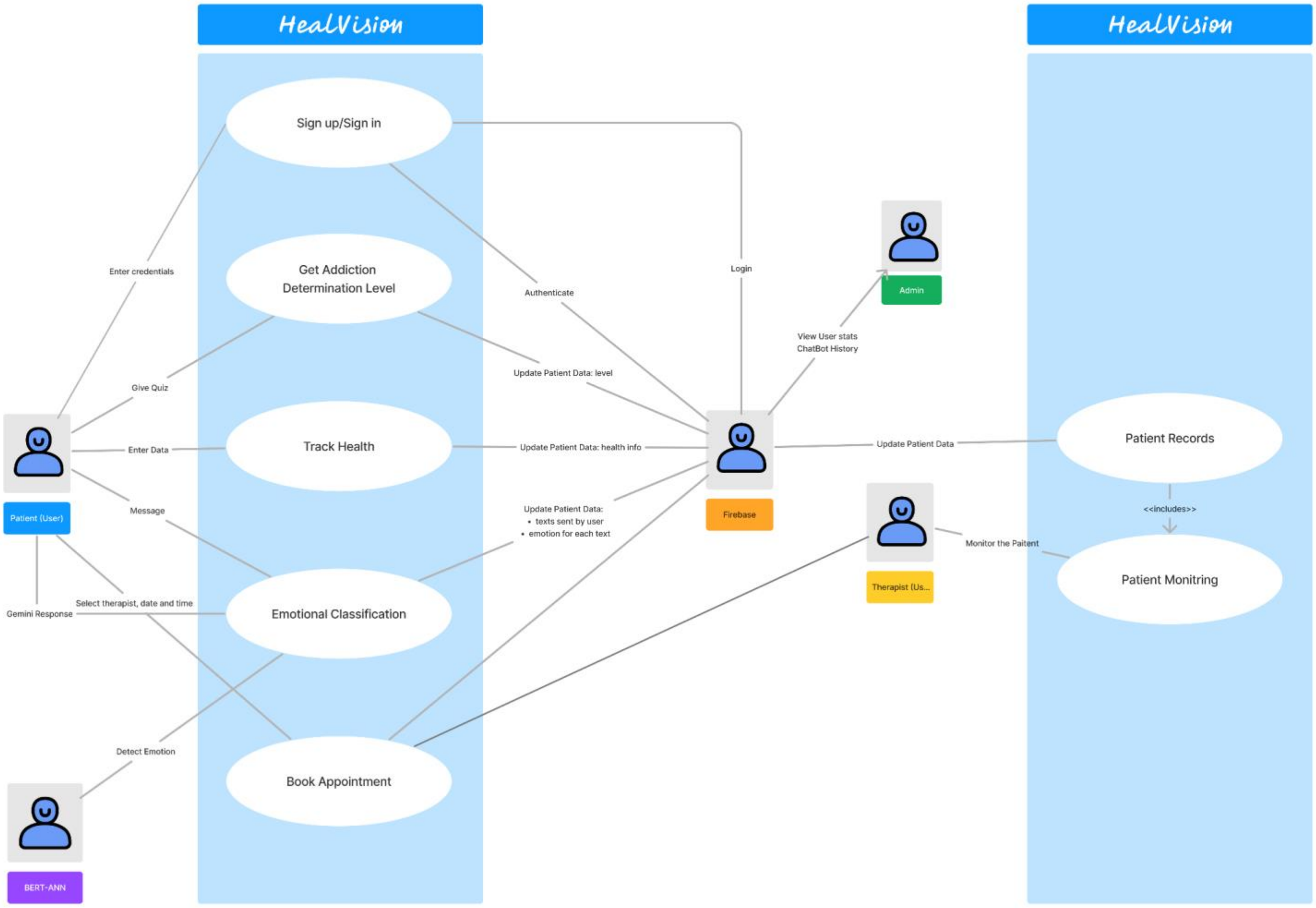


Figure 1.7: DFD

Shows in-depth actors and use case relations

4.5. Sequence Diagrams

This section further breaks down each use case, explaining how the user interacts through the system using UML diagrams.

4.5.1. Sign up/in

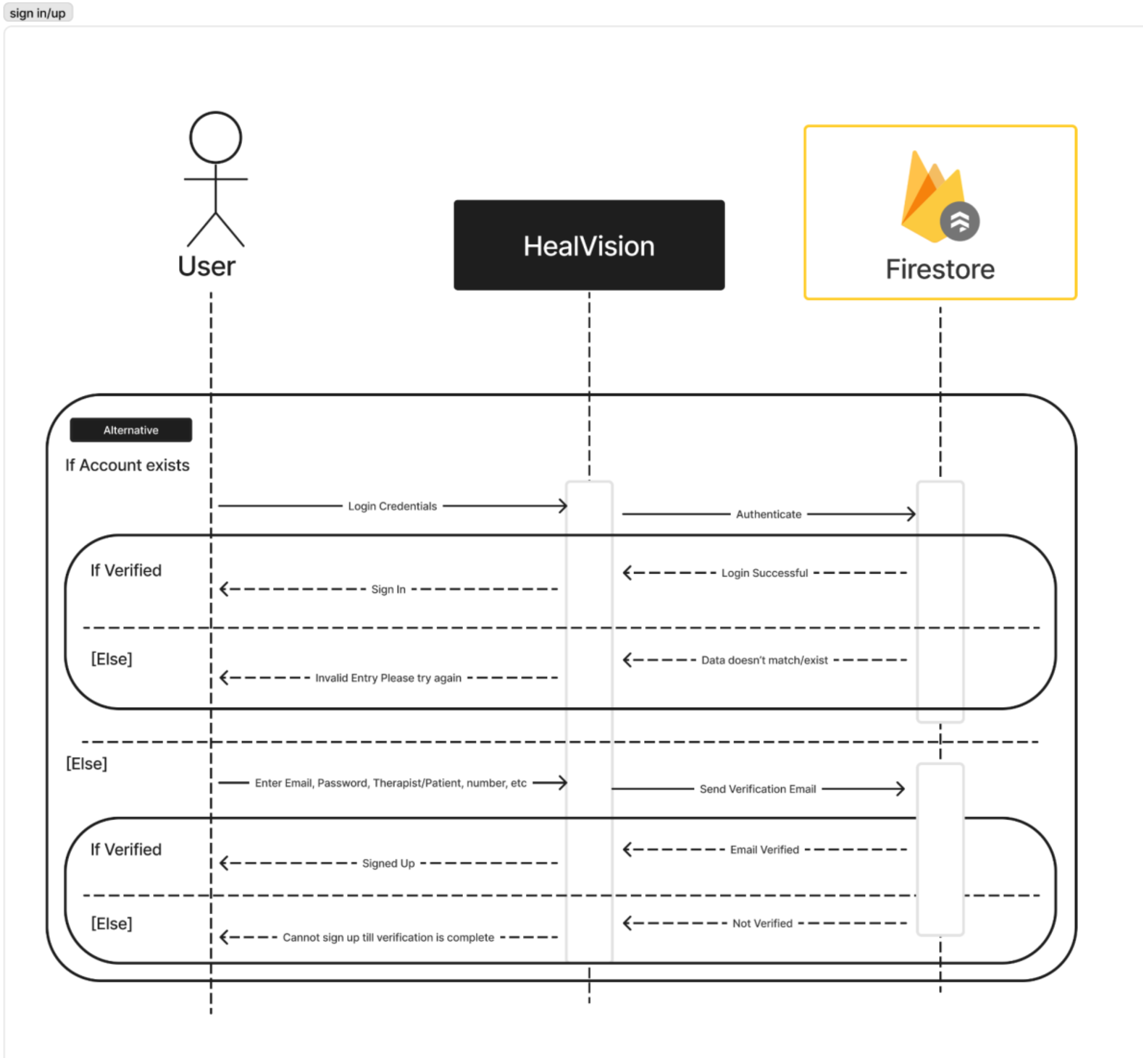


Figure 1.8: Sequence Diagram: Sign in/up
How to sign in or register to Healvision

4.5.2. Addiction Determination

Figure 1.9: Sequence Diagram: Addiction Determination
The quiz determines the level of severity of the patient

4.5.3. Book Appointment

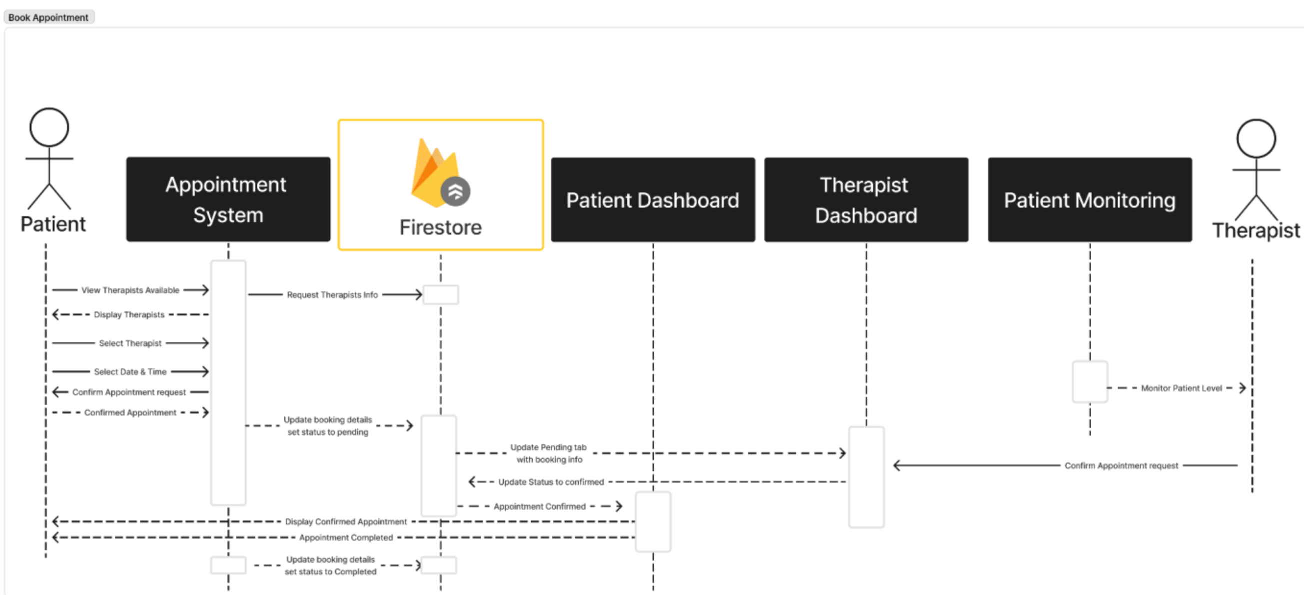


Figure 2.0: Sequence Diagram: Book Appointment
Scheduling a session

4.5.4. Emotion Classification

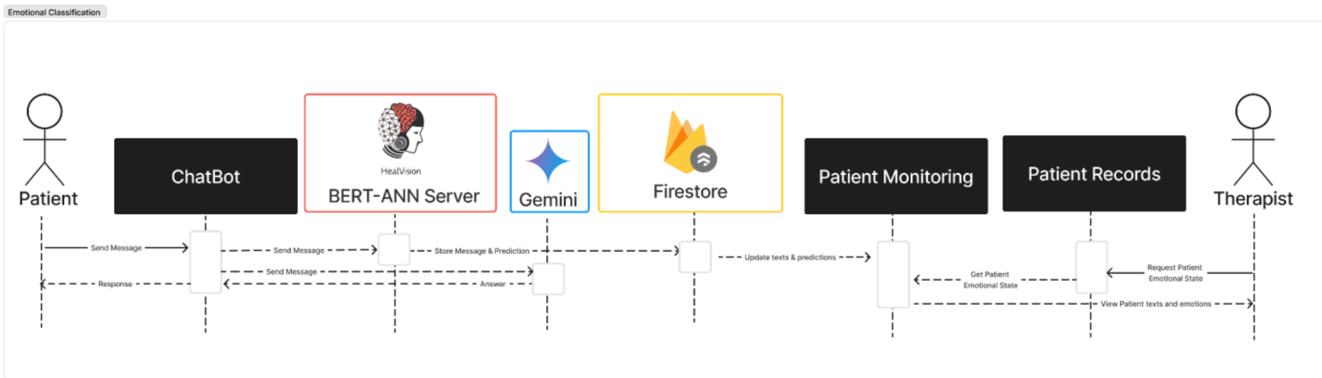


Figure 2.0: Sequence Diagram: Emotional Classification
Making predictions and giving a response

4.5.5. Track Health

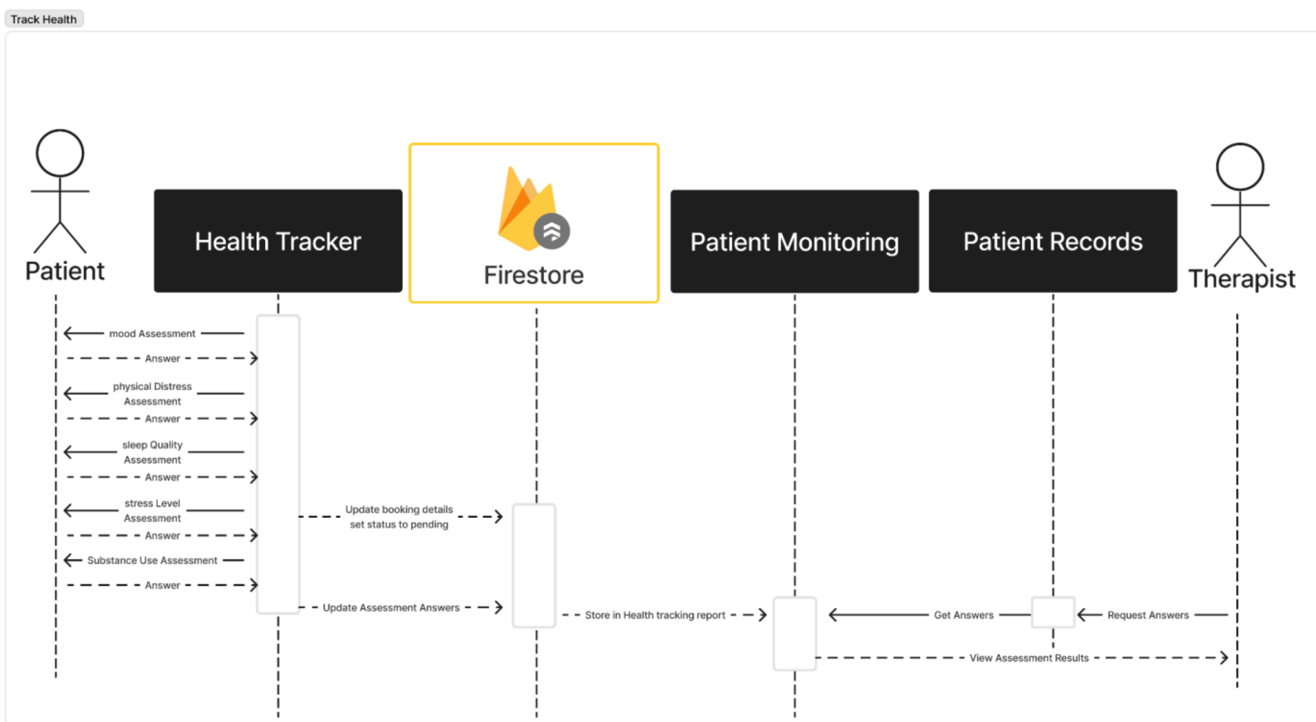


Figure 2.1: Sequence Diagram: Track Health
Data sequence of access and entry for health tracker

5. EXPERIMENTS

5.1. Survey of Healthcare Professionals

5.1.1. Summary of Insights:

Areeba Aamir, a Student of Masters in Clinical Psychology, highlighted the significance of certain textual features such as emojis and exclamation marks as indicators of different emotions. She emphasized the challenges individuals with Substance Use Disorders (SUDs) face in expressing feelings and the importance of empathy, acceptance, and patience in therapy outcomes.

Zarak Ahmad Jan Khan, a Consultant Trainer, identified specific words indicative of emotions in the text and discussed emotional challenges faced by individuals with SUDs, including feelings of guilt and embarrassment. He emphasized the importance of accepting acknowledging mistakes, and the drive to continue despite challenges for successful therapy outcomes.

5.1.2. Key Outcomes:

During a meeting with Ali Ilyas, a Psychotherapist, and other healthcare professionals, several key outcomes were gathered:

1. Patients with SUDs often experience heightened levels of shame, stress, low tolerance, and lack of social support, leading to feelings of isolation.
2. Prioritizing rapport building and establishing comfort with patients at the outset of therapy sessions was unanimously agreed upon.
3. Comprehensive assessments were deemed essential, including exploration of patients' developmental history, childhood experiences, and relevant contextual factors.

4. Identifying specific traumas, losses, and sensitivities and assessing distress tolerance levels within patients were emphasized.
5. Effectively recognizing and addressing the emotional underpinnings of patients' experiences during therapy sessions was highlighted.
6. Utilization of the psychosocial model in therapy sessions, emphasizing a holistic approach to treatment, was deemed essential.
7. Tracking progress effectively through weekly reports containing comprehensive data such as trigger logs, physiological arousal levels, and patterns was proposed.
8. Integration of feedback mechanisms into therapy sessions to enhance patients' self-awareness and regulation skills was suggested.
9. Establishing policies regarding handling sensitive patient data to ensure confidentiality and compliance with regulations was recommended.
10. Continued iterative development and refinement of chatbots and health trackers to augment patient care was proposed.
11. Implementing action items discussed during the meeting into therapy sessions, ensuring a comprehensive and tailored approach to patient care was agreed upon.
12. Maintenance of regular communication and collaboration with relevant stakeholders to monitor progress and address any emerging challenges promptly was emphasized.
13. Scheduling follow-up meetings to review progress, discuss any outstanding issues, and plan further initiatives was recommended.

5.1.3. Takeaways:

The meeting concluded with a consensus to prioritize the development of a chatbot health tracker and augment patient care, reflecting the collective commitment to enhancing the treatment and support provided to individuals with Substance Use Disorders.

5.2. Mobile Application Development

5.2.1. Overview

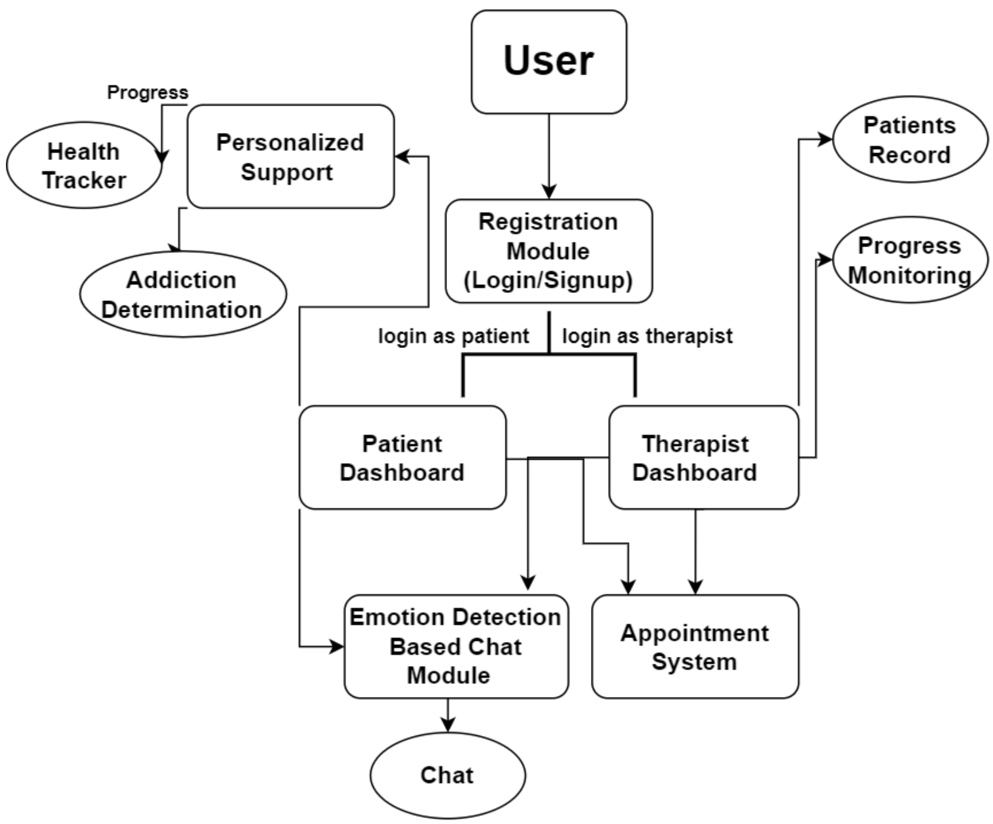


Figure 2.2: Block Diagram

As shown in Figure 2.2, this architecture maintains a consistent yet refined application flow to ensure ease of communication and usage of the AI emotion detection module and the exchange between patient and therapist. As the user will be able to first identify themselves as either patient or therapist, each will be able to address their domain of need.

For Instance, once a patient logs into the application for the first time, they may be able to take a short quiz to assess the severity of their Substance Use Disorder by taking an Addiction Level Determination quiz. This will ask a series of questions explicitly designed to identify the extremity. Furthermore, the user can book appointments with a designated therapist and communicate with them as they feel the need.

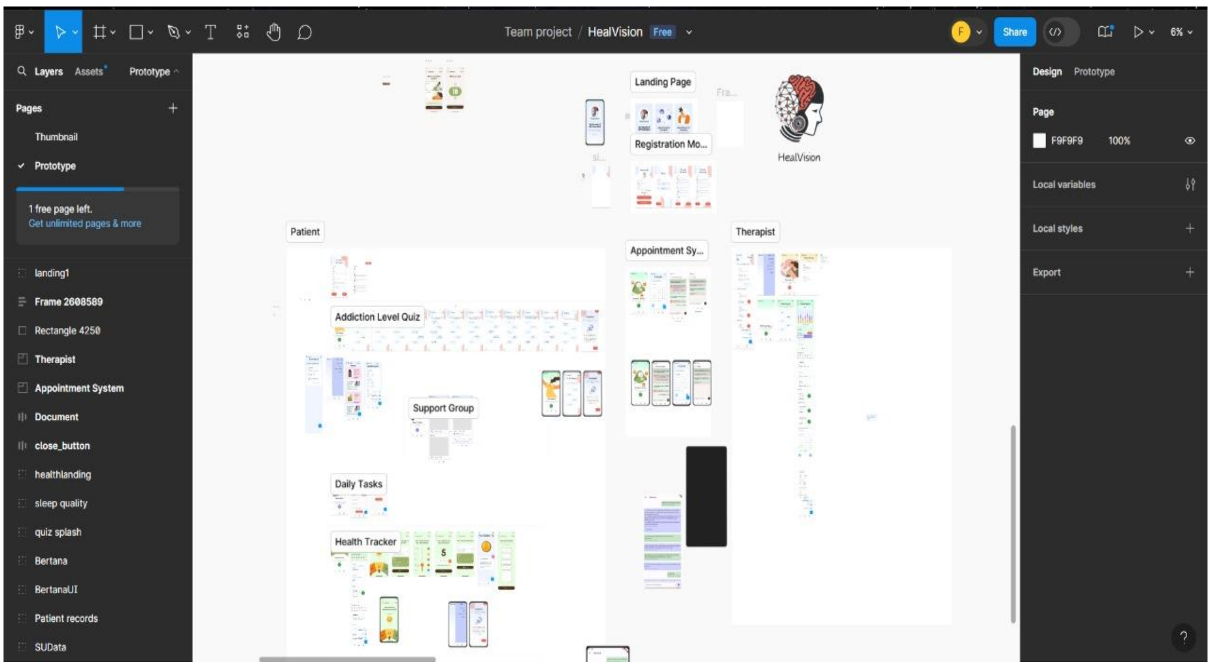
On the other hand, an AI chat module heavily focused on identifying emotional labels through text will be ready and available at all times to interact with the patient. This can not only ensure that the patient has a safety net, but the data stored on the patient's emotional states can also significantly aid the therapist and close the gap of lack of information on the patient. Figures (2.3) display the seamless user interface addressing each block diagram section.

5.2.2. User Interface Design

To create a seamless experience for the patient and therapist, a carefully crafted UI/UX experience is defined using Figma tools to cater to each application module.

Figure 2.3: Figma Designer

View of Figma designer of Healvision



This helps the development process of HealVision and identifies each feature requirement and implementation use cases.

5.2.3. Flutter Development

5.2.3.1. Project Structure

The "HealVision" project is meticulously structured to ensure efficient management and scalability of different features and functionalities. The project is divided into several main directories, each serving a specific purpose. These include directories for authentication, home, patient features, therapist features, and personalization. Within these directories, subdirectories are organized to handle controllers, models, screens, and utilities. This modular approach enhances code readability and makes it easier to maintain and expand the application as new features are introduced.

5.2.3.2. Main File (main. dart)

The main. The dart file is the entry point of the Flutter application. This file initializes essential services and configurations required for the app to run.

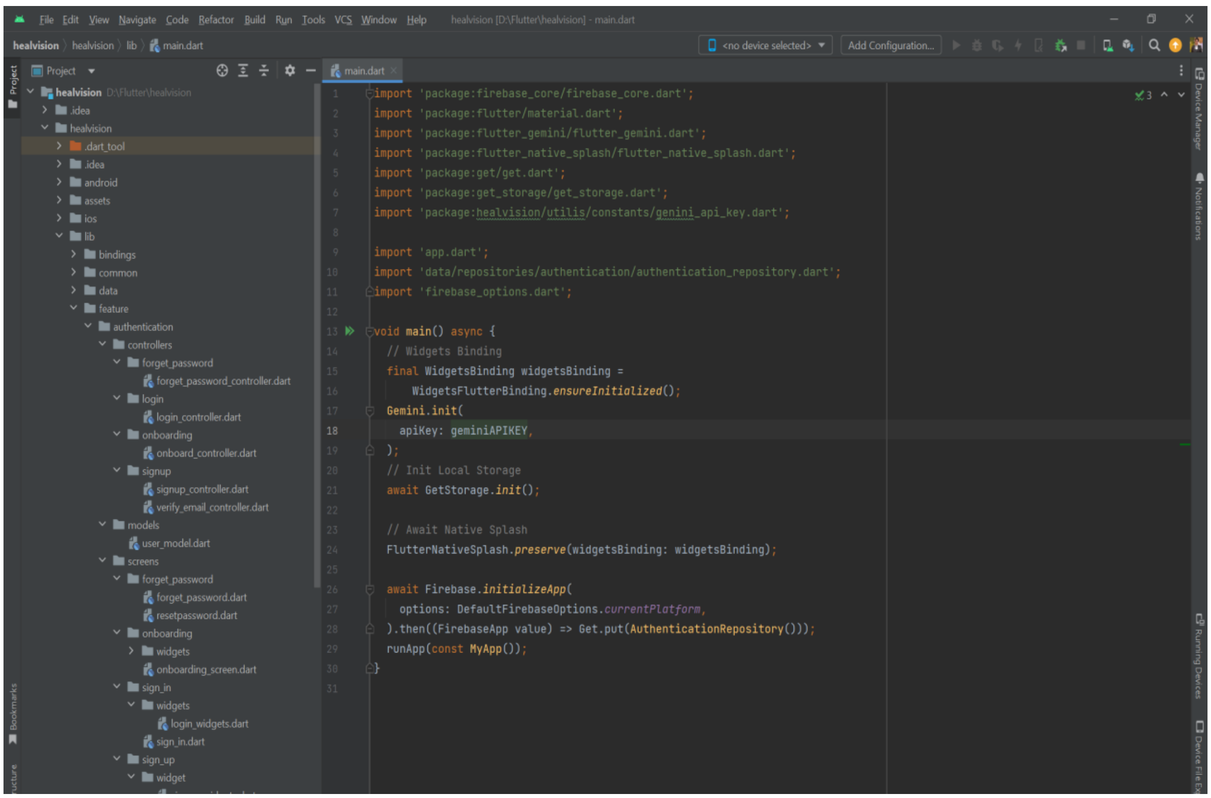


Figure 2.4: Main. dart

- Widgets Binding Initialization: Ensures the Flutter framework is initialized correctly before running the app.
- Gemini API Initialization: Sets the Gemini API with the provided API key.
- Local Storage Initialization: Prepares the local storage using the get_storage package.
- Firebase Initialization: Configures the Firebase options and initializes Firebase for the app.

- Native Splash Screen: Preserves the native splash screen until the Flutter framework is fully initialized.
- RunApp: Launches the app's central widget.

5.2.3.3. Authentication

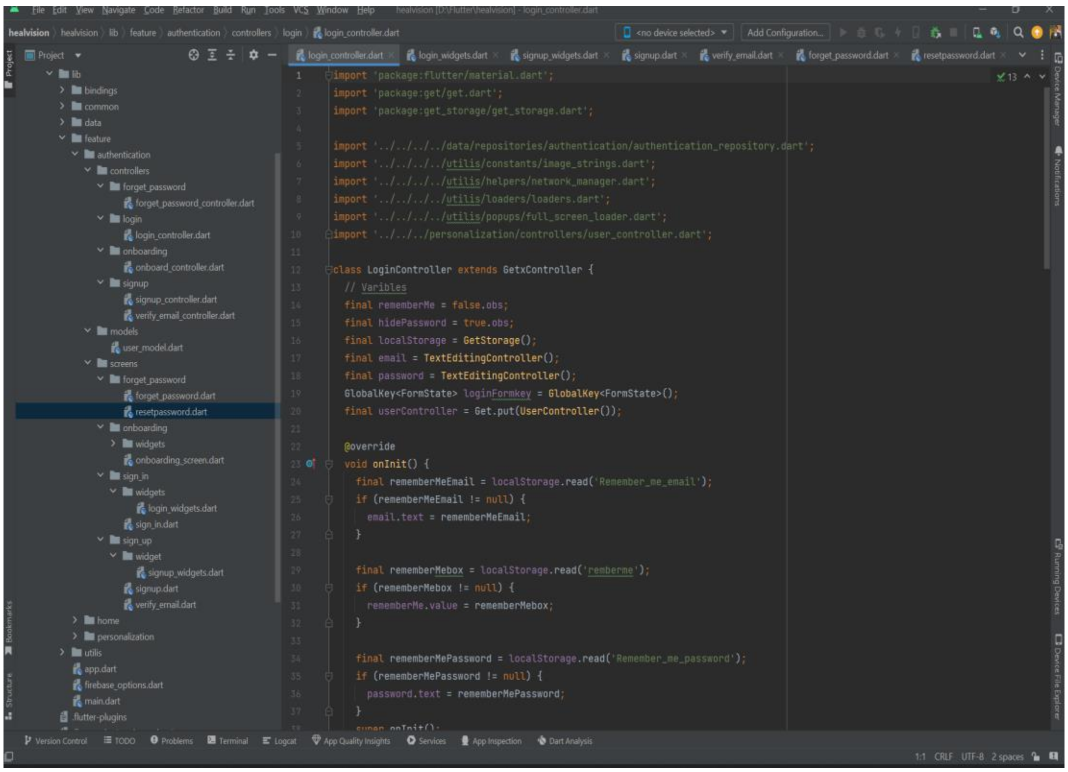


Figure 2.4: Main. dart

The authentication feature of "HealVision" is designed to manage user login, signup, and password-related functionalities. The authentication directory houses several controllers and screens that streamline these processes. The forget_password_controller.dart handles the logic for password recovery, while the login_controller.dart and signup_controller.dart manages user login and signup processes, respectively. The verify_email_controller.dart also ensures that users verify their email addresses to enhance security. The corresponding screens, such as sign_in.dart, forget_password.dart, and signup. Dart provides user-friendly interfaces for these actions. The user_model.dart defines the user data model, encapsulating essential user information and supporting authentication operations.

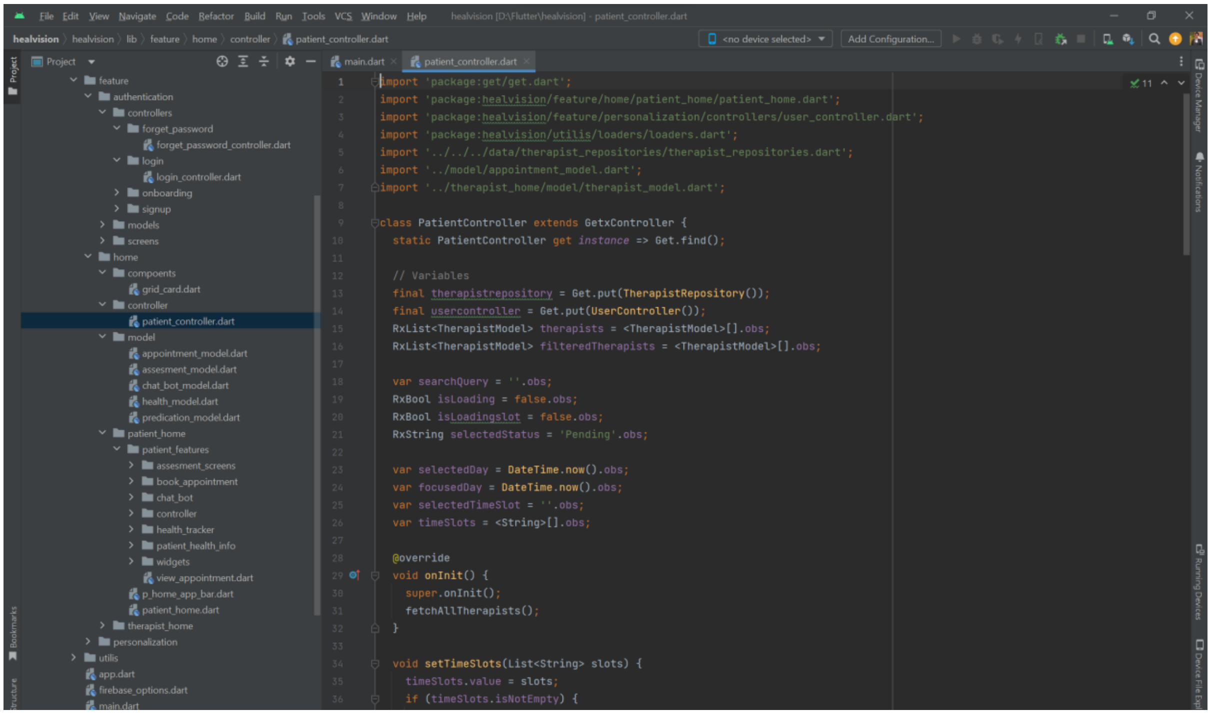


Figure 2.5: Authentication

5.2.3.4. Home

The home feature serves as the primary interface for the application, presenting users with various components and functionalities. Central to this feature is the patient_controller.dart, which manages logic and data related to patients. The home screen includes components like grid_card.dart, which displays information in a visually appealing grid format. This organization helps users navigate through the app's features effortlessly. Additionally, various models, such as appointment_model.dart and assessment_model.dart, define the data structures for appointments and assessments, ensuring that all home-related data is handled consistently and efficiently.

5.2.3.5. Patient Features

Patient features encompass a range of functionalities explicitly tailored for patients, including assessments, appointments, and chatbot interactions. The assessment_intro_screen.dart provides an introduction to evaluations, while the assessment_result_page.dart displays the outcomes. The question_screen.dart facilitates the presentation of assessment questions. Booking appointments is streamlined with screens such as all_doctors_screen.dart and appointment_book_screen.dart, allowing patients to view available doctors and book appointments seamlessly.

Additionally, the chat_bot_screen.dart offers an interactive interface for chatbot communications. Controllers like assessment_controller.dart and chat_bot_controller.dart manages the underlying logic for these features, ensuring a smooth user experience. Multiple health tracker screens support health tracking, and detailed patient information is displayed through UIs like chats_bot_info.dart and health_assessment_details.dart.

5.2.3.6. Therapist Features

Therapist features are designed to assist therapists in managing appointments and monitoring patient progress. Controllers such as monitoring_process_controller.dart and view_appointments_controller.dart handle the logic for these tasks, while therapist_model.dart defines the data model for therapists. Features like monitoring_progress.dart and patient_appointment.dart provide interfaces for monitoring patient progress and managing appointments. The therapist_details.dart screen allows therapists to view and update their details, while the home_app_bar.dart and navigation_menu.dart screens offer navigation tools to enhance usability. These features collectively ensure that therapists can efficiently manage their responsibilities within the application.

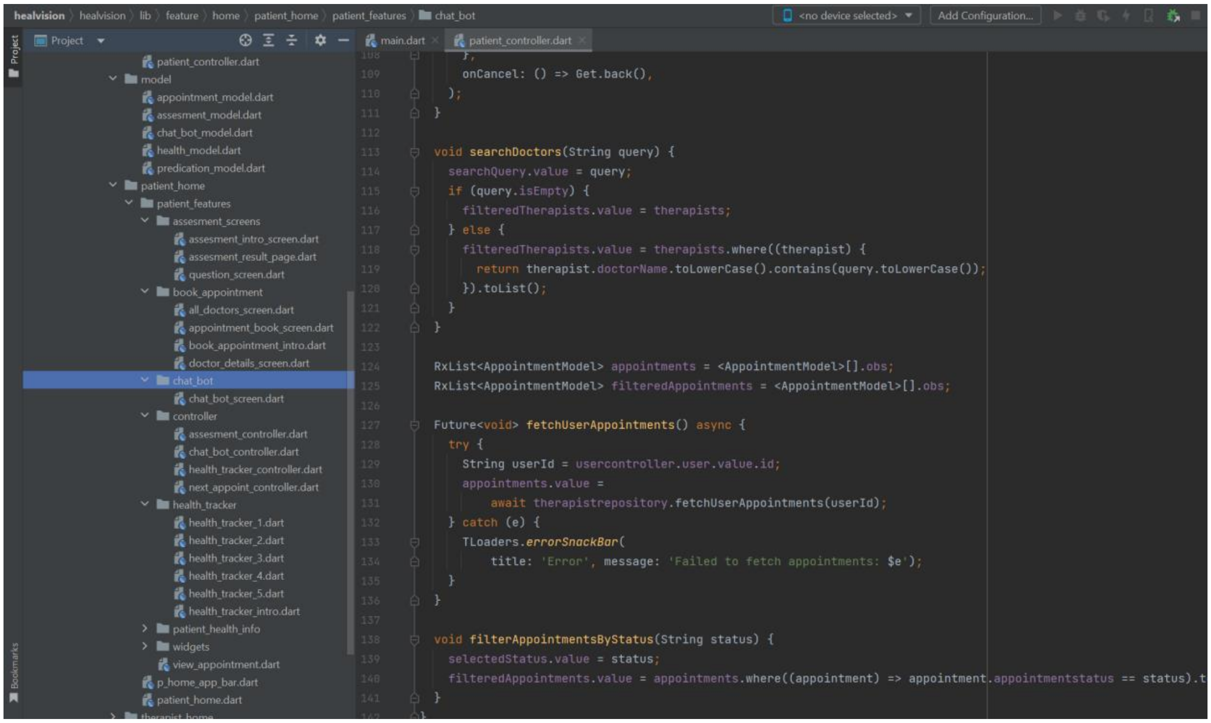


Figure 2.6: Therapist Features

5.2.3.7. Personalization

Personalization features in "HealVision" enable users to customize their profiles and settings to suit their preferences. Controllers like update_name_controller.dart and user_controller.dart manages the logic for updating user names and handling user-related operations. Screens such as change_name.dart and profile_menu.dart provide interfaces for these personalization actions. The re_authenticate_user_login_form.dart screen ensures secure re-authentication when necessary while the profile is on. Dart and setting. Dart screens allow users to view and adjust their profile and app settings. These personalization options enhance the user experience by providing flexibility and control over personal information and preferences.

5.2.3.8. Utilities

Utility files provide essential functionalities that support various aspects of the application. The app. dart file contains the main app configuration, ensuring all components are correctly initialized and managed. The firebase_options.dart file holds the configuration options for Firebase, facilitating seamless integration with Firebase services. The gemini_api_key.dart file securely stores the API key for the Gemini platform, ensuring that sensitive information is protected. Additionally, the authentication_repository.dart serves as a repository for managing authentication data, centralizing authentication-related operations, and enhancing the security and efficiency of user authentication processes.

5.2.4. Firebase Integration

Firebase Authentication is a powerful service that simplifies the process of user authentication in web and mobile applications. It supports various authentication methods, including email/password, phone authentication, and federated identity providers like Google, Facebook, and Twitter.

User Management

In the below figure, the Firebase Authentication dashboard shows a list of users who have signed up or logged into the application. Each user entry includes:

- Identifier: The email address used by the user to sign up.
- Providers: The method used for signing in (email/password).
- Created: The date the user account was created.
- Signed in: The last date the user signed in.
- User UID: A unique identifier assigned to each user by Firebase.

This setup helps track user activity, manage authentication states, and handle user-related operations such as resetting passwords or verifying emails.

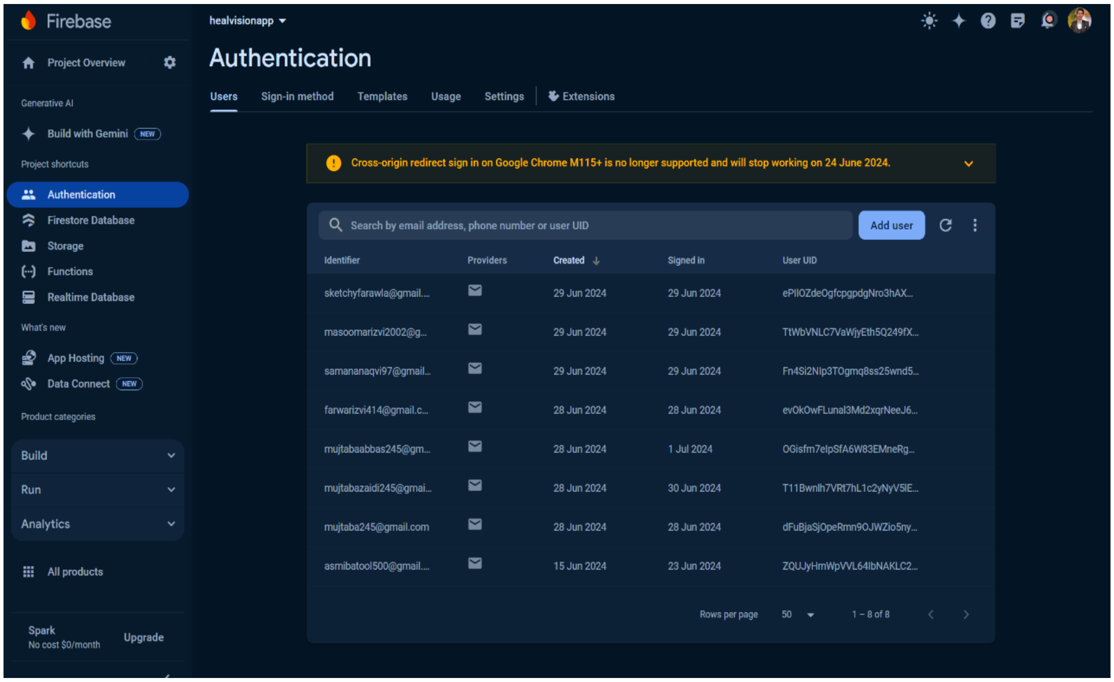


Figure 2.7: Firebase Authentication

Firebase Firestore Database

Firebase Firestore is a flexible, scalable mobile, web, and server development database. It allows you to store and sync data in real-time across all clients. The structure is based on collections and documents, which are organized hierarchically.

Assessments Collection

The "Assessments" collection stores user assessment data. Each document represents an individual user's assessment with various fields:

- answers: An array field containing the user's responses to assessment questions. Each response includes:

- question: The assessment question.
- score: A numerical score assigned to the response.
- selectedOption: The user's chosen option for the question.

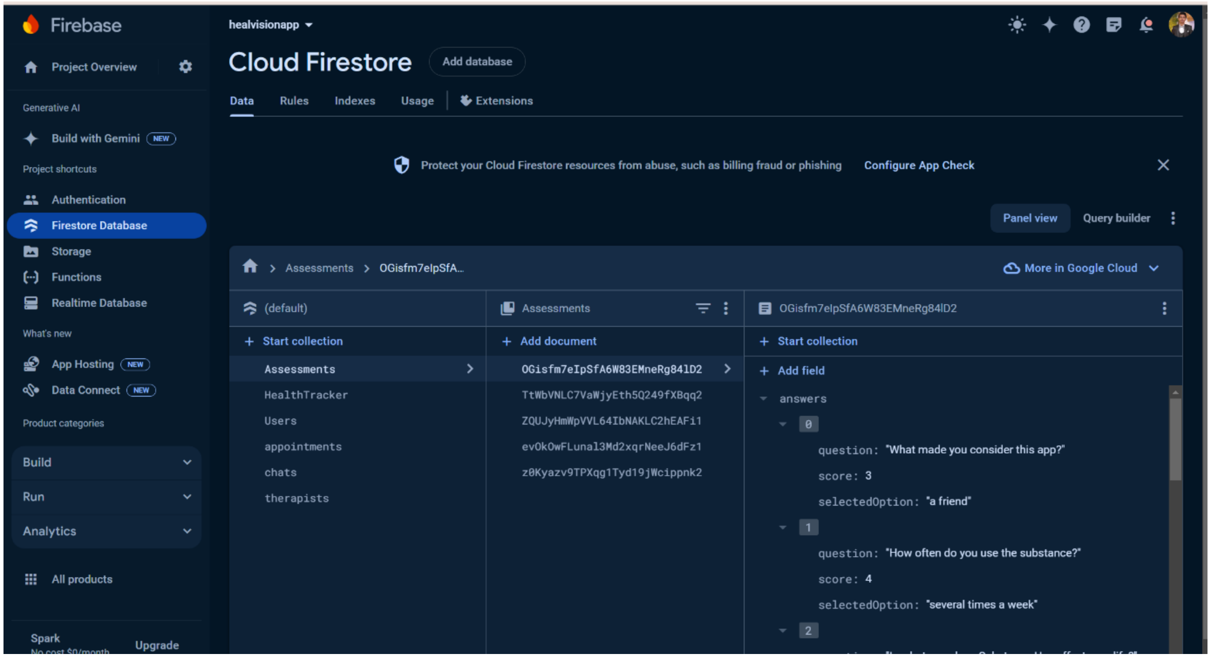


Figure 2.8: Cloud Firestore Database: Assessments

Health Tracker Collection

The Health Tracker collection contains documents that record various health-related assessments for users. Each document includes:

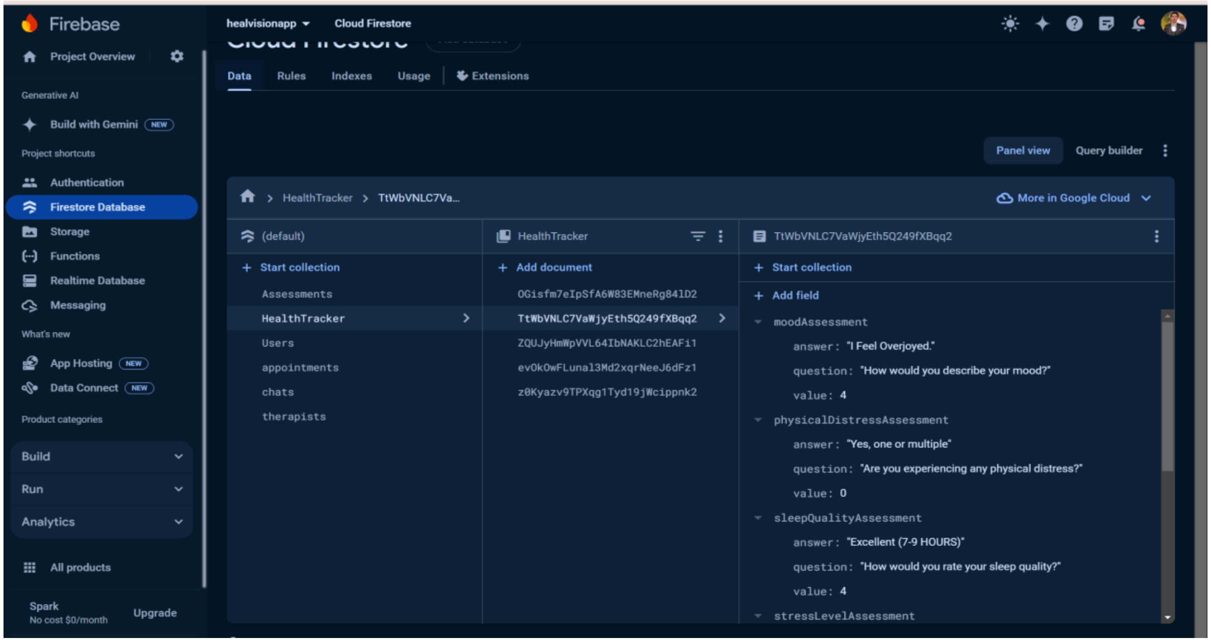


Figure 2.9: Cloud Firestore Database: Health Tracker

moodAssessment:

- answer: Five options: "I Feel Depressed." "I Feel Sad.", "I Feel Neutral." "I Feel Happy." "I Feel Overjoyed." (string)
- question: "How would you describe your mood?" (string)
- value: Number from 1 to 5 based on the answer

physicalDistressAssessment:

- answer: "Yes, one or multiple" or "No Physical Pain At All" (string)
- question: "Are you experiencing any physical distress?" (string)
- value: 0 and 1 (number)

sleepQualityAssessment:

- answer: "Worst (<3 HOURS)", "Poor (3-4 HOURS)", "Fair (5 HOURS)", "Good (6-7 HOURS)", "Excellent (7-9 HOURS)", (string)

- question: "How would you rate your sleep quality?" (string)
- value: Number from 1 to 5 based on the answer

stressLevelAssessment:

- answer: "You are Completely Relaxed." "You are Slightly Stressed.", "You are Moderately Stressed." "You are Very Stressed." "You are Extremely Stressed Out." (string)
- question: "How would you rate your stress level?" (string)
- value: Number from 1 to 5 based on the answer

substanceUseData:

- substances: An array containing maps of substance use instances.
- amount: (string)
- date: (string)
- name: (string)
- reason: (string)
- time: (string)
- timestamp

Users Collection

The "Users" collection contains documents for each user, storing personal and contact information:

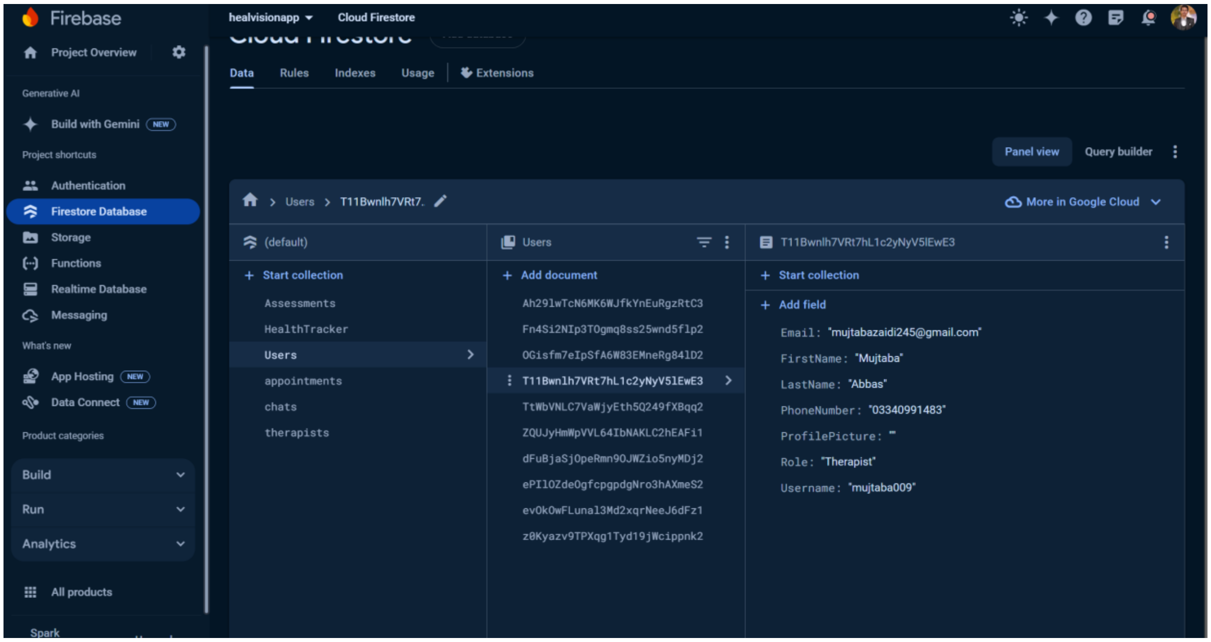


Figure 3.0: Cloud Firestore Database: Users

- Email: (string)
- FirstName: (string)
- LastName: (string)
- PhoneNumber: (string)
- ProfilePicture: "" (string)
- Role: "Patient" or "Therapist" (string)
- Username: (string)

Appointments Collection

The "appointments" collection stores data related to user appointments with therapists:

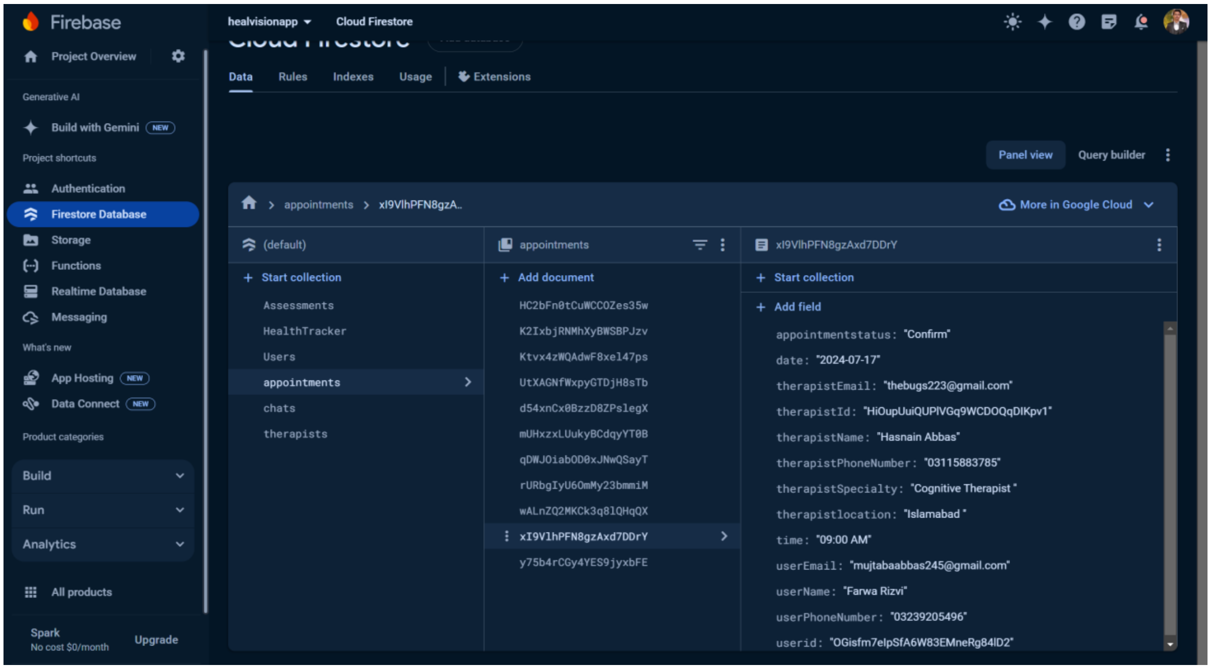


Figure 3.1: Cloud Firestore Database: Appointments

- appointmentstatus: "Pending", "Confirm", "Completed", "Cancel" (string)
- date: (string)

Therapist

- therapistEmail: (string)
- therapistId: "T11Bwnlh7VRt7hL1c2yNyV5lEwE3" randomly generated (string)
- therapistName: (string)
- therapistPhoneNumber: (string)
- therapistSpecialty: (string)
- therapistlocation: (string)
- time: (string)

Patient

- userEmail: (string)
- username: (string)
- userPhoneNumber: (string)
- userid: "Ogisfm7eIpSfA6W83EmneRg84lD2" randomly generated (string)

Therapists Collection

The "therapists" collection contains data about therapists available in the application:

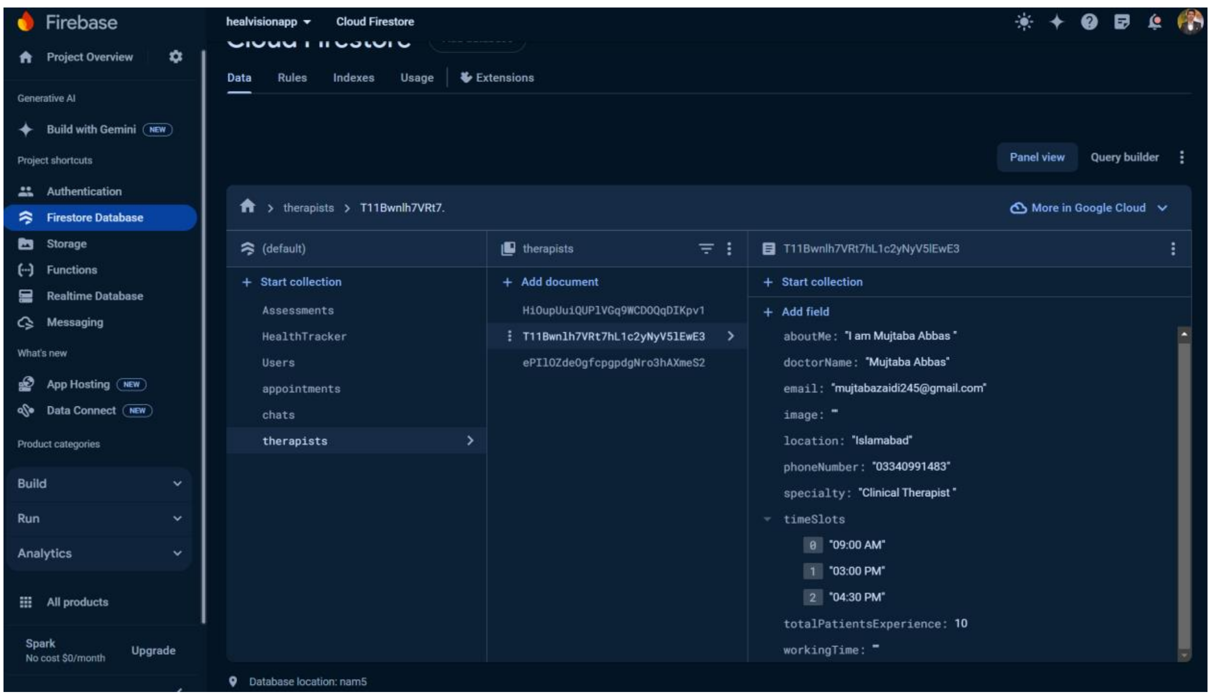


Figure 3.2: Cloud Firestore Database: Therapists

- aboutMe: "experienced psychiatrist of 8 years with 20 successful cases" (string)
- doctorName: (string)
- email: (string)
- image: "" (string)

- location: (string)
- phonenumber: (string)
- specialty: (string)
- timeSlots: An array of available time slots. "09:00 AM", 10:00 AM", "11:00 AM", "11:30 AM", "03:00 PM", "04:00 PM", "04:30 PM", "05:30 PM" (string)
- totalPatientsExperience: (number)
- working-time: (string)

5.3. Machine Learning

5.3.1. Overview

This section highlights the methods used to create the emotion detection on the text model. The datasets were balanced and made, followed by training on numerous models, testing the model and the app, and finally, the deployment methods used.

5.3.2. Dataset

5.3.2.1. Emotions Dataset

The aspect-based emotional analysis uses the Emotions dataset, consisting of dialogues extracted from tweets and labeled accordingly. Emotions are unique as they emphasize emotion detection and accessibility within dialogues. Containing 16000 dialogues of training, 2000 for testing, and 2000 for validation, spanning six emotions labeled as sadness, joy, love, anger, fear, and surprise. This distribution supplies a diverse landscape for training and evaluating models to analyze the emotional labels in textual data.

Upon further data analysis of the Emotions dataset, it was discovered that, although unique, it needed to be balanced. This unequal distribution of classes would lead to issues further discussed in model training and testing accuracy. Figure 3.3 represents a graphical illustration of the distribution.

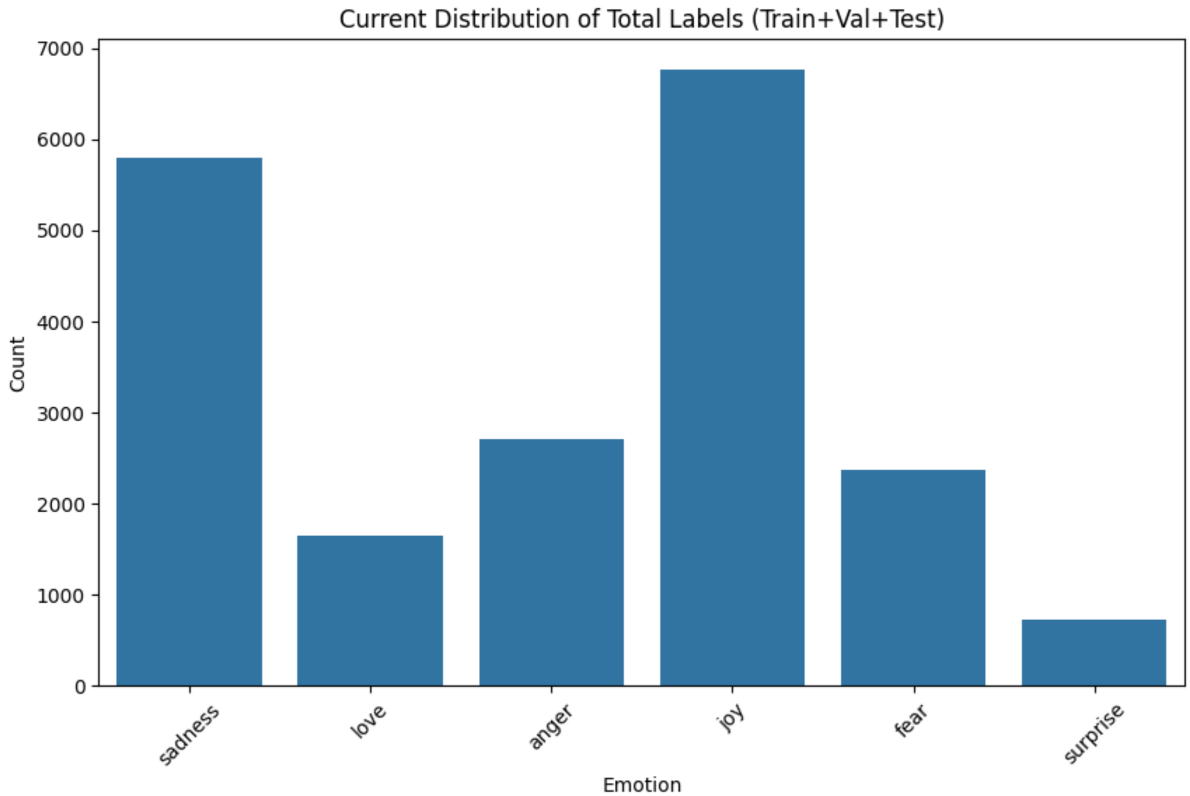


Figure 3.3: Emotions Dataset Distribution

The classes appear to be imbalanced. The highest count of joy (6761) was followed somewhat closely by sadness (5797). There was a significant drop in anger (2709), fear (2373), love (1641), and surprise (719).

The Emotions dataset imbalance was mitigated by increasing the counts of other emotions to reach approximately the exact count as class joy. Data augmentation methods, such as replacement with synonyms, were used. An addition of sadness (+965), anger (+4021), fear (+4325), love (+4768), and surprise (+5652) was made.

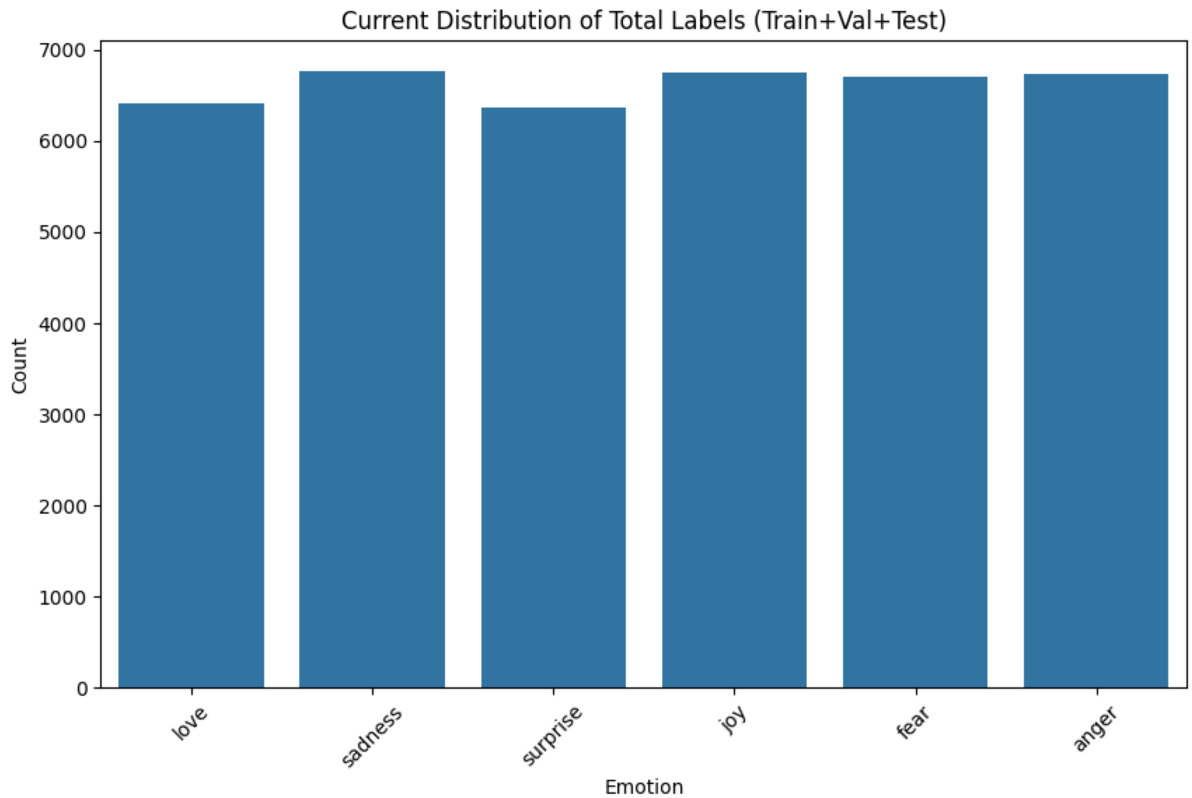


Figure 3.4: Balanced Emotions Dataset Distribution

As shown in Figure 3.4, the counts across all labels were made approximately equal. Leading with sadness (6762), followed closely by joy (6752), anger (6730), fear (6698), surprise (6371), and Love (6049).

Although balancing the dataset improved usage significantly, the original 20,000 tweets were still found to be mislabeled, which tampered with the results.

5.3.2.2. Emotions-6000 Dataset (custom-made)

To mitigate the misclassification drawback that existed in "Emotions", the "Emotions-6000" Dataset was created with 6003 statements, all classified into six classes, namely joy, sadness, neutral, anger, fear, and love.

While creating this new dataset, we decided to ensure the dataset catered to our needs. We altered the surprise class to neutral, which can accurately classify patients' emotional states. Each class had the distribution as represented by Figure 3.5.

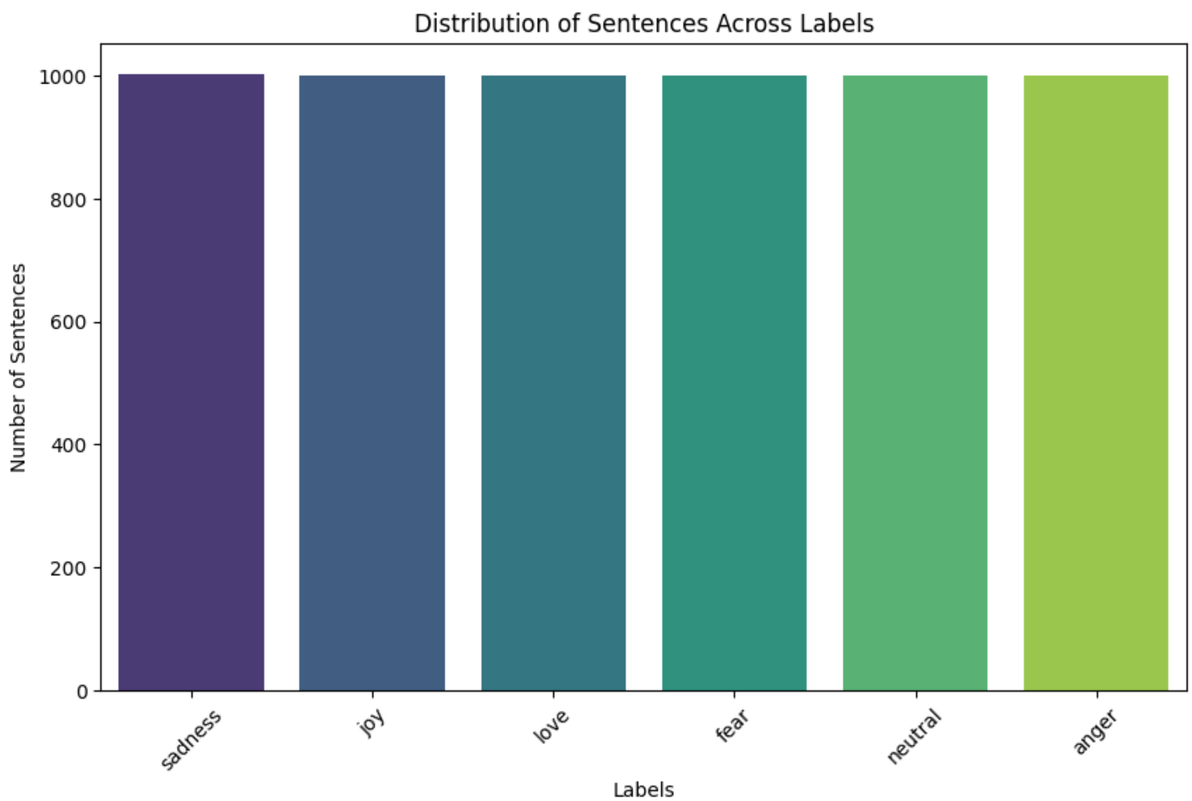


Figure 3.5: Balanced Emotions-6000 Custom Dataset Distribution

Every statement is flagged, offering a straightforward, concise framework streamlining the preprocessing phase. Ultimately simplifying the data manipulation and integration into development pipelines. The data is split into train, test, and validation data as 700, 200, and 100, respectively, as shown in Fig 3.5.

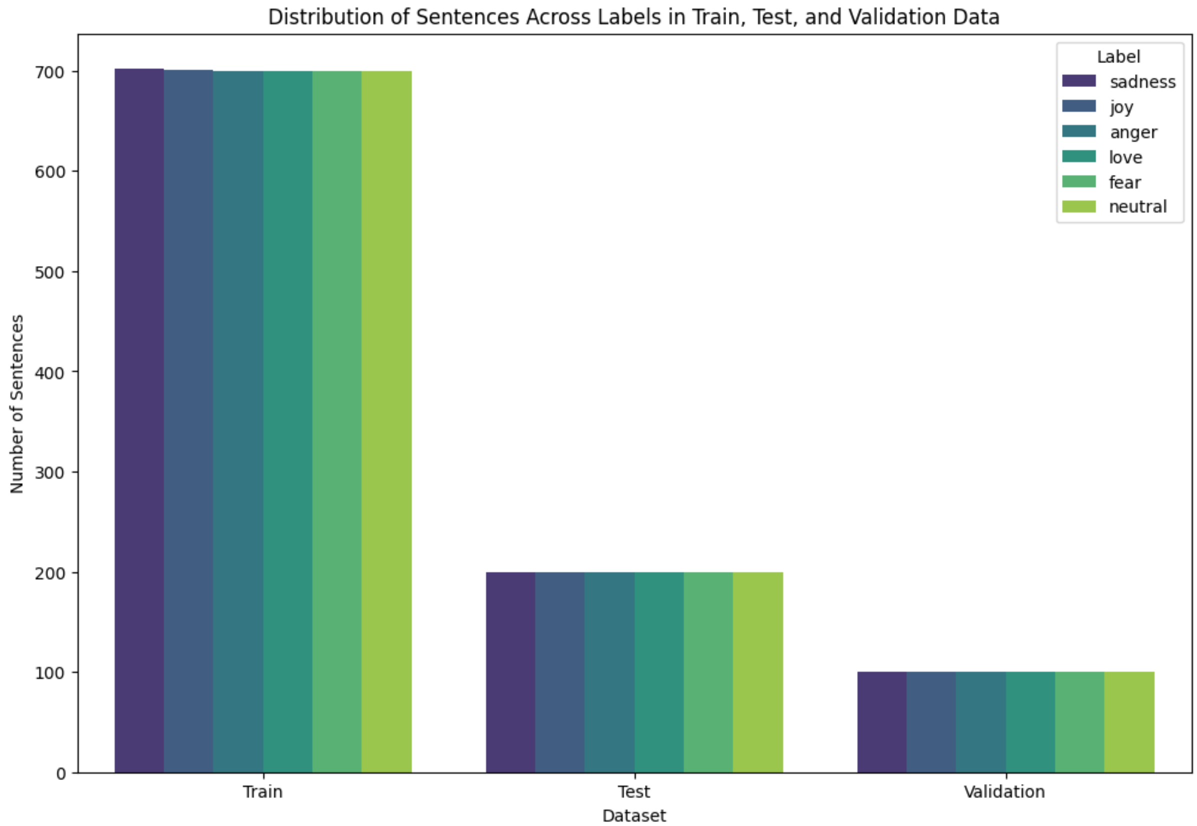


Figure 3.6: Emotions-6000 Distribution of Test-train-validation

The word cloud in Fig 3.6 represents the datasets' textual similarities across each emotion.

Figure 3.7: Emotions-6000 Word Cloud of joy and love

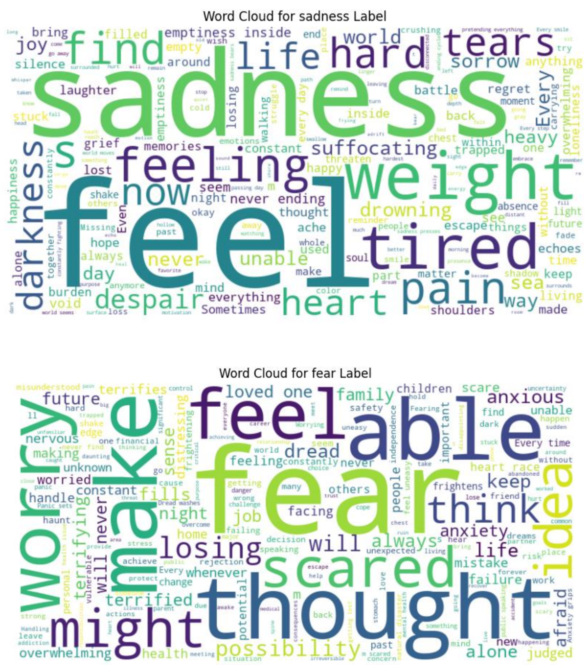


Figure 3.8: Emotions-6000 Word Cloud of sadness and fear

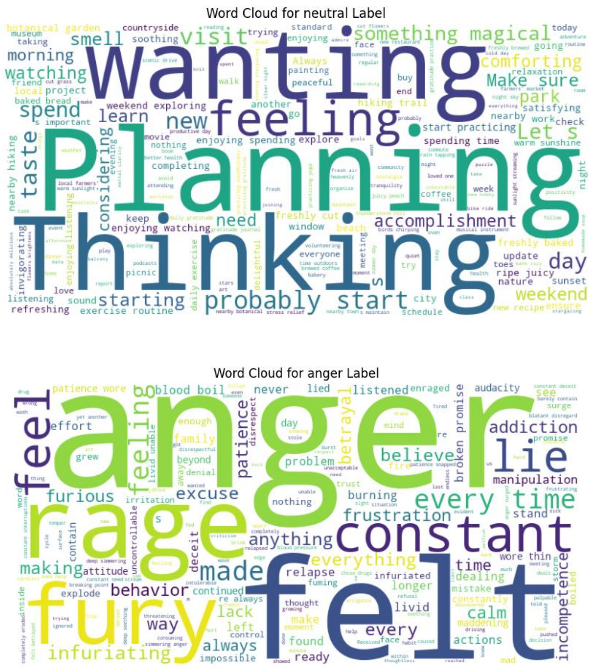


Figure 3.9: Emotions-6000 Word Cloud of neutral and anger

5.3.2.3. Preprocessing Dataset

The preprocessing of the datasets involves removing any non-alphabetic characters in the dialogue, converting it to lowercase, splitting the text into words, and applying stemming to each word. It then removes any stopwords and joins the words back into a single string. This string is transformed using the loaded count vectorizer.

5.3.3. Model Training

Various models were considered to approach this dataset, but BERT, Naive Bayes, Random Forest Classifier, GloVe, LSTM, CNN, and Neural Networks were the primary focus of this research. Each initially uses its default parameters. Furthermore, accuracy is chosen as the metric to measure the performance evaluation of each emotion on the original and balanced dataset.

5.3.3.1. Feed-forward NN

The simplest form of NN is a feed-forward Neural Network (FNN), where information flows in one direction. The optimizer was kept as Adam, with the loss function as sparse categorical loss entropy and the output layer consisting of 6 neurons mapping to emotional classes with the softmax activation function. This offers a more flexible design for the specified task.

The chosen Feed-Forward Neural Network Model encapsulates two hidden dense layers with a neuron sequence of 12, 8, and 6 with the activation functions ReLU, sigmoid, and softmax, respectively, with a batch size and epoch count of 20, and a learning rate of 0.09.

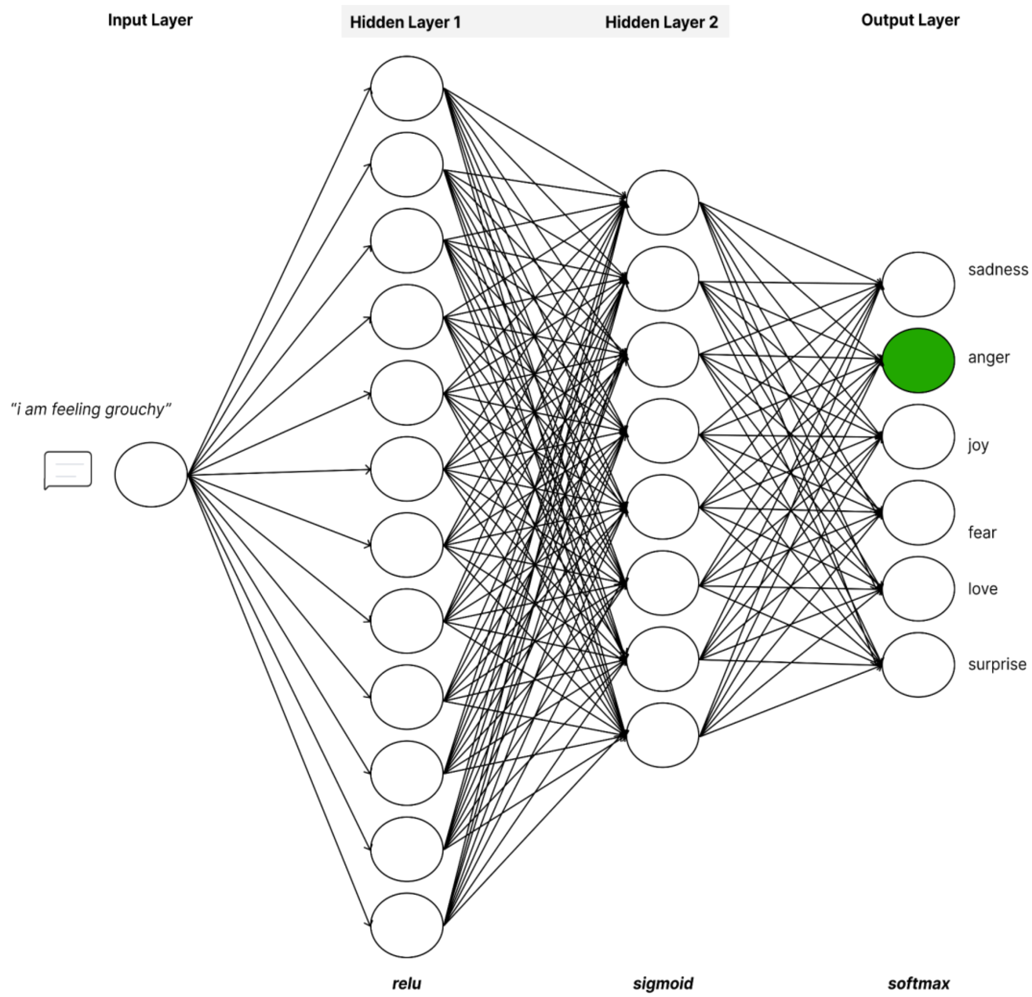


Figure 4.0: FNN Version 4

5.3.3.2. BERT-ANN

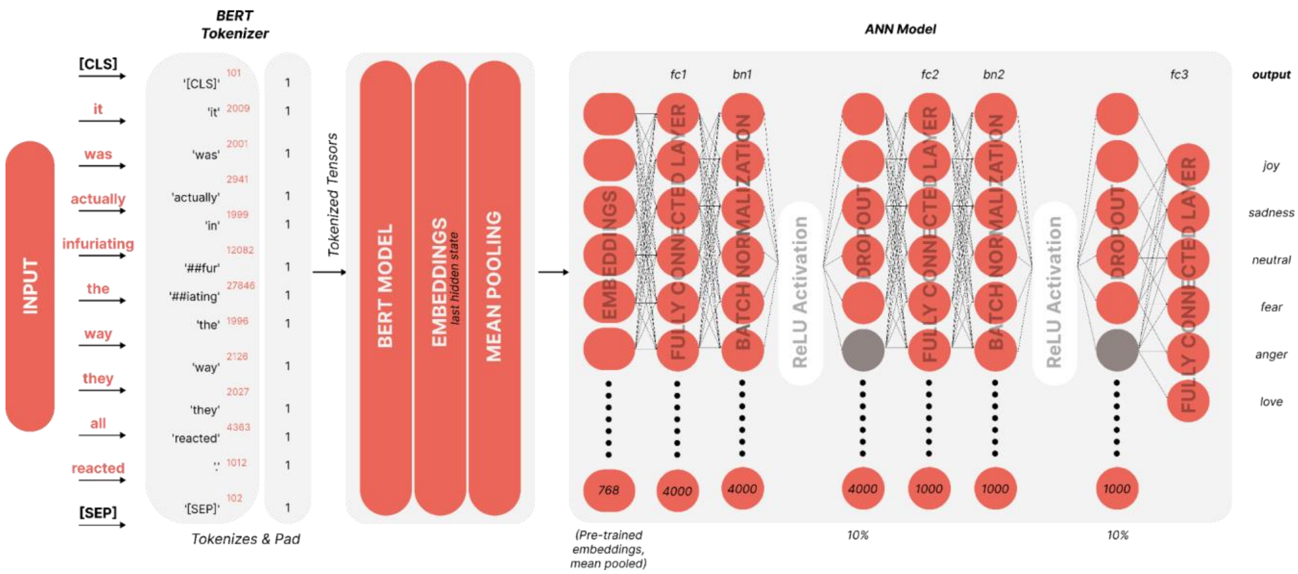


Figure 4.1: BERT-ANN Version 2

BERT-ANN Model starts by taking the sentence as the input, preprocessing the input message by tokenizing, and padding the words. Each message has a beginning and end identified by the [CLS] and [SEP] tokens, respectively. Furthermore, the BERT Uncased Embeddings are applied. After this, our own Artificial Neural Network is used with combinations of fully connected, batch normalization, and dropout layers ex, which will be Lastly, the initial message is classified into one of the six classes of emotions, namely joy, sadness, fear, neutral, anger, and love.

5.3.3.2.1. BERT Embeddings

Bidirectional Encoder Representations from Transformers uncased embeddings is a type of word representation generated by the BERT model.

1. Tokenization: The text is first tokenized to sub-words using the Word Piece tokenizer. This enables efficient treatment of rare words. For

instance, In Fig 4.1, the word 'infuriating' is broken down to 'in', '##fur', and '##iating'.

2. Embedding Layer: After tokenization, each token is represented with an initial vector, which gives us the position of each token present in the sequence. Every word has a defined token ID according to its vocabulary. The type ID identifies which sentence it belongs to. For instance, the tokens of the first sentence will be ID 0, and the second sentence will be ID 1.
3. Transformer Layers: The tokenized embeddings are passed through various layers of transformers, where each transformer uses a self-attention mechanism to create contextualized embeddings. Therefore, the meaning of each word depends on the context of the sentence it is used in.
4. Output Embeddings: Finally, BERT creates a final set of embeddings. These encapsulate solid contextual data depending on each token.

5.3.3.2.2. Artificial Neural Network

Architecture:

1. Mean Pooling: First, the ANN model applies a mean pooling layer such that the token embeddings from the last hidden state are averaged, producing one embedding vector for one sentence.
2. Mean-pooled Embeddings: Provides summarized data for the message.
3. Fully Connected Layer 1: The mean-pooled embeddings are transformed from 768 neurons to 4000.

4. Batch Normalization Layer 1: Applied to the 4000 neurons to maintain performance and stability.
5. ReLU Activation: Apply the rectified linear unit activation function to make the neurons nonlinear, reducing the vanishing gradient problem.
6. Dropout of 10%: Randomly selects 10% of neurons and sets their outputs as 0 to avoid overfitting.
7. Fully Connected Layer 2: transforms neurons from 4000 to 1000.
8. Batch Normalization 2: Once again, it normalizes the output of 1000 neurons.
9. ReLU Activation Function: Rectified to ensure non-linearity for the next set of neurons.
10. Dropout 10%: Ensuring decreased overfitting.
11. Fully Connected Layer 3: The last fully connected layer is applied, transforming the 1000 neurons to 6 targetted classes.
12. Output Classification: Finally, the input is classified into a singular emotional label.

5.3.4. Hyperparameter Tuning

Hyperparameter tuning was explored using k-fold cross-validation. Parameters such as batch size, epochs, activation function, and learning rate were tuned to optimize the models' performance and test different models. This procedure involved experimenting with other metrics and choosing the ones that yielded promising results.

5.3.4.1. Feed-forward NN

Version 1 of the model consisted of 2 hidden layers utilizing the reLU activation function and one output layer holding 12, 8, and 6 neurons, respectively. It was trained across ten epochs, with a batch size of 10 and a learning rate of 0.001 at default.

Version 2 of the Feed-Forward Neural Network Model encapsulates double the hidden layers with a 12, 24, 16, and 8-neuron sequence. It is followed by three dropout layers after the first three hidden layers to drop 20\% of the neurons during each iteration. The batch size and learning rate are kept the same, but the number of epochs is increased to 20.

Version 3 tracked back to *Version 1* by following the number of hidden layers, neurons, and learning rates in each; however, the activation function of the hidden layer was changed to sigmoid, and epochs and batch size were set at 20.

Version 4, the final version of the model, Figure 4.0, retained version 3, but the increase in learning rate from the default of 0.001 to 0.09 achieved a significantly good result.

5.3.4.2. GloVe Based

5.3.4.2.1. GloVe Embeddings

Creating an embedding matrix of pre-trained GloVe word embeddings of a 100-dimensional vector.

5.3.4.2.2. GloVe - LSTM

Retaining the GloVe embeddings, the authors of this paper further implemented the LSTM model like so:

1. LSTM Layer is applied of 128 units.
2. Dense Layer 1: Holding 64 neurons and activation function of sigmoid.
3. Dense Layer 2: 6 neurons are used to map onto six emotional classes, with a softmax activation function.

The performance of this model was deficient at training and testing accuracy of 16.6% and 16.16%, respectively.

5.3.4.2.3. GloVe - NN

Using epochs 10 and batch size:32, the architecture is as follows:

1. Flatten Layer to convert to a 1D vector with 10,000 elements.
2. Dropout of 50%
3. Dense Layer 1: With 128 neurons, ReLU activation, L2 regularization with lambda = 0.01.
4. Dropout of 50%
5. Dense Layer 2: With 64 neurons, ReLU activation, L2 regularization with lambda = 0.01.
6. Dropout of 50%
7. Output Layer with six neurons for the emotional classes using Softmax activation function.

A training and testing accuracy of 80.85% and 51.25% was acquired, respectively.

5.3.4.2.4. GloVe - CNN

After applying the pre-trained GloVe embeddings, the following sequence was chosen to implement CNN.

1. Two convolutional layers are applied, first with ReLU and the second wit Sigmoid, that extract features from sequences.
2. A max-pooling layer is applied to reduce the dimensions of the output, ensuring only the most essential features are captured.
3. A dense layer that acts as an output layer using softmax activation creates probabilities for each emotion.

A training and testing accuracy of 99.41% and 56.17% was acquired, respectively.

5.3.4.3. BERT

By applying only the BERT pre-trained embeddings, the model was unable to gain the required results (train accuracy: 58.66%)

5.3.4.3.1. BERT - ANN

Version 1, Applied Pre-trained BERT embeddings, followed by the custom-made ANN model with its' first fully connected layer, transforms neurons from 768 to 500. Additionally, batch normalization layer, ReLU activation, and a dropout rate of 20%. In the second fully connected layer, the neurons are transformed to 350, followed by the same order of batch normalization, ReLU activation, and dropout. The following fully connected layer is converted to 150 neurons, and the third batch normalization, ReLU activation, and dropout layer is applied. Finally, the last fully connected layer is used to classify six emotions by six neurons.

Version 2: The last version of this model retained most of the structure of Version 1. However, it reduced the number of fully connected layers from 4 to

3, dropped the dropout rate by 10%, and increased the neuron count significantly. The neuron distribution of the fully connected layers was 4000, 1000, and 6 for the last classification layer and for fully connected layers 1, 2, and 3, respectively.

5.3.5. Model Deployment

To deploy the chosen (BERT-ANN - Version 2 trained on Emotions-6000) model and make it ready to be successfully integrated within the application, the BERT-ANN was deployed on the Fast API server, using python to make the API post methods and to monitor the requests and app usage history, NGROK server was used. With ngroks' traffic inspector and tunnel manager, it displays all successful and false requests made to the server to use the emotion recognition through text model.

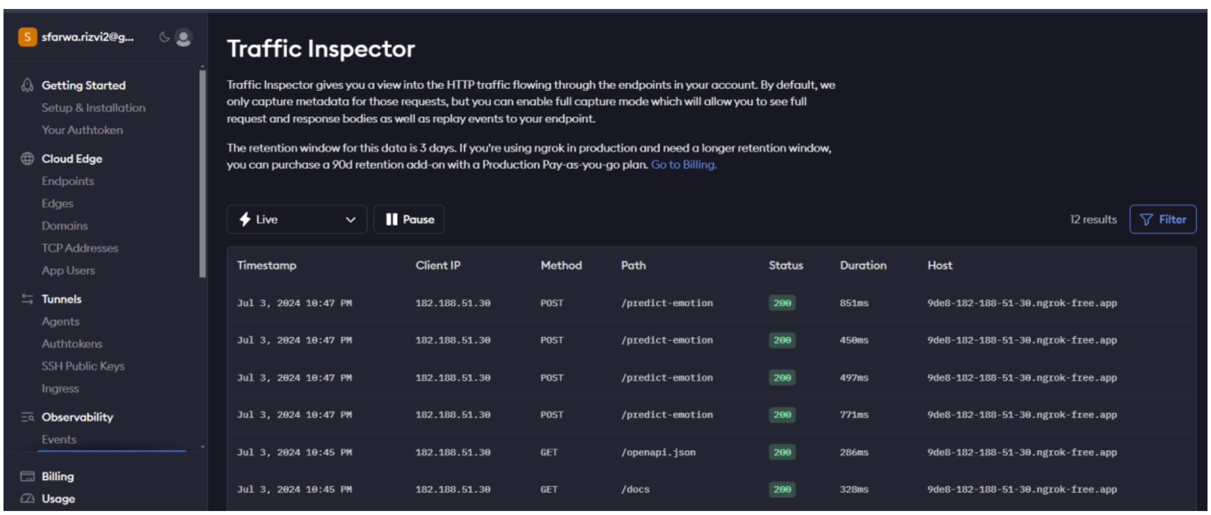


Figure 4.2: Ngrok Traffic Inspector

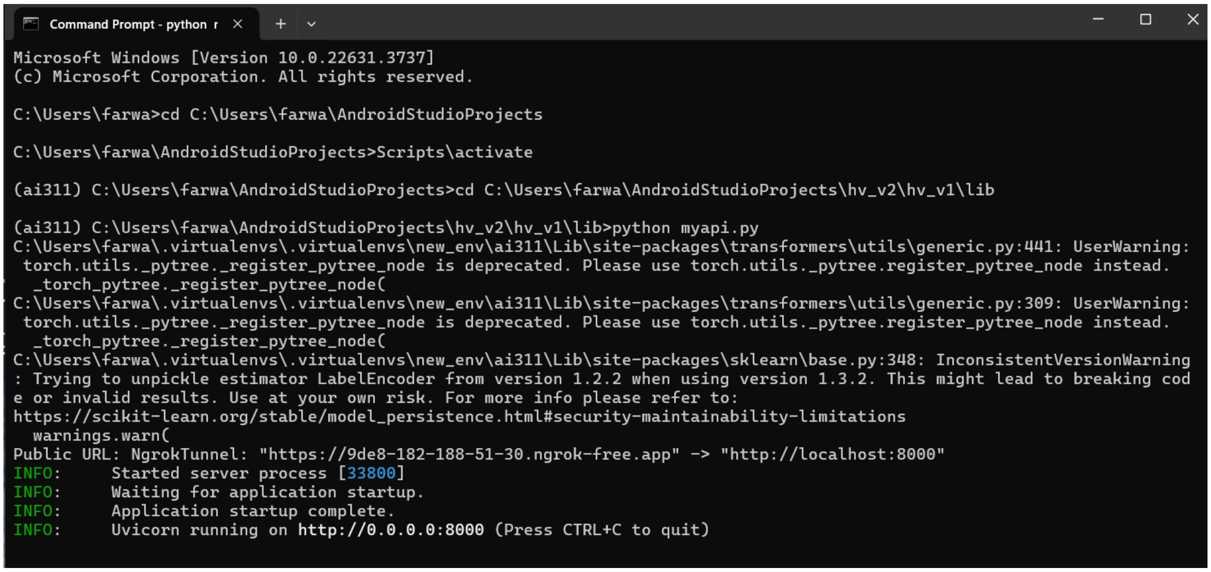


Figure 4.3: CMD Traffic logs

The server successfully lives on the Ngrok Tunnel's Public URL by running the API Python code. It can be checked as well through the web browser directly, as shown in fig 4.2

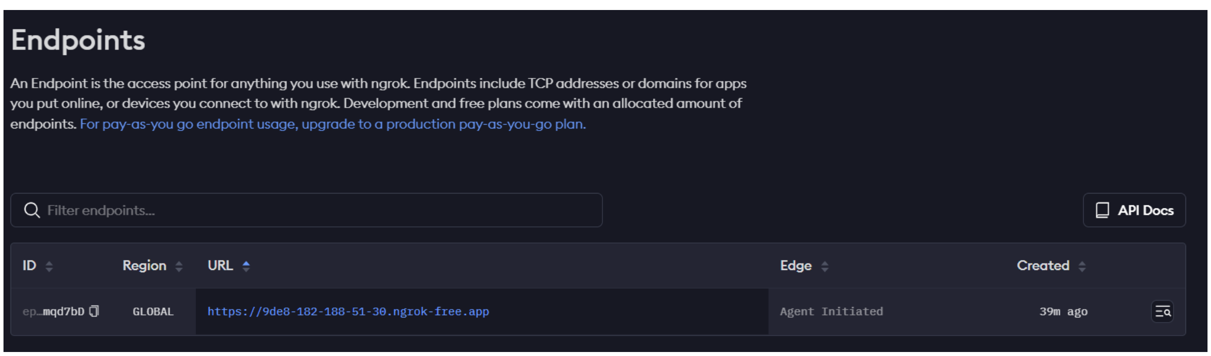


Figure 4.4: Ngrok Endpoints

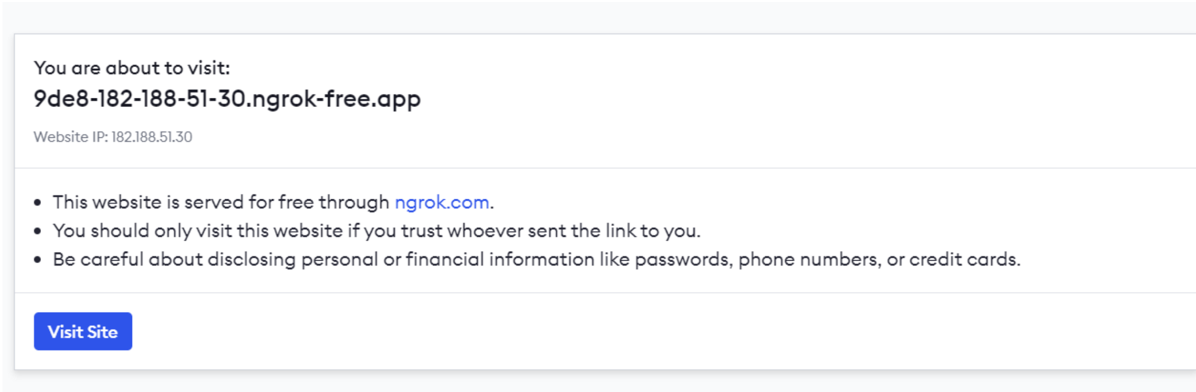


Figure 4.5: Public URL from Ngrok Leading to Fast API

This accesses the Fast API deployed methods, as shown in fig 4.6

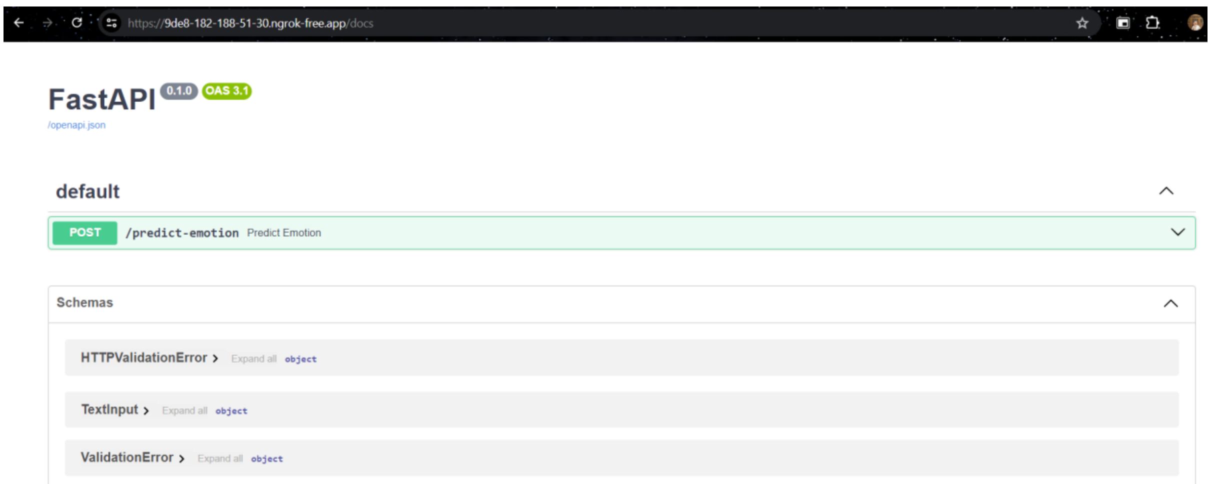


Figure 4.6: Model on Fast API deployed on Public URL

Once this URL is updated on the android studio code (fig 4.7), it is ready to use the chatbot module and make emotional predictions on textual data accordingly.

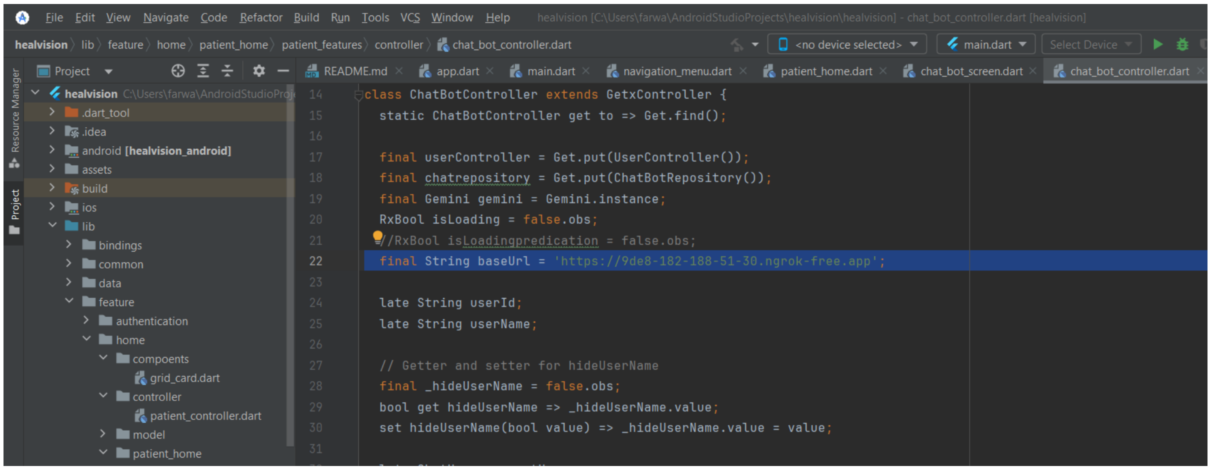


Figure 4.7: chat_bot_controller.dart consists of updating the base URL

On the Ngrok Traffic inspector and command line interface, any requests made will be shown through the authentication account used for Ngrok. As shown in fig 4.8.

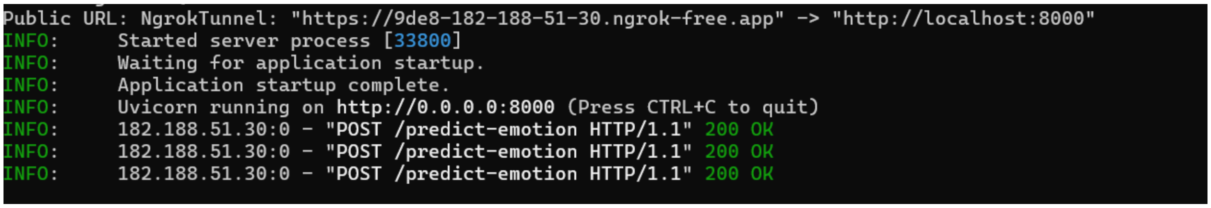


Figure 4.8: Live Model shows traffic updates on CMD

6. Results and Discussions

6.1. Application

We have developed HealVision efficiently using the Flutter framework and used Android Studio as the IDE. The application is designed in a properly structured way. All the UI files, controller files, model files, and universal files are organized in desired folders with a classification of a specified module.

6.1.1. Onboarding Screens

Our Application HealVision opens with a splash screen and proceeds with the three onboarding screens, as seen in the figures attached below. Users can skip by clicking the skip option at the top right bottom, and the user will be exposed to the sign-in page.

Onboarding1

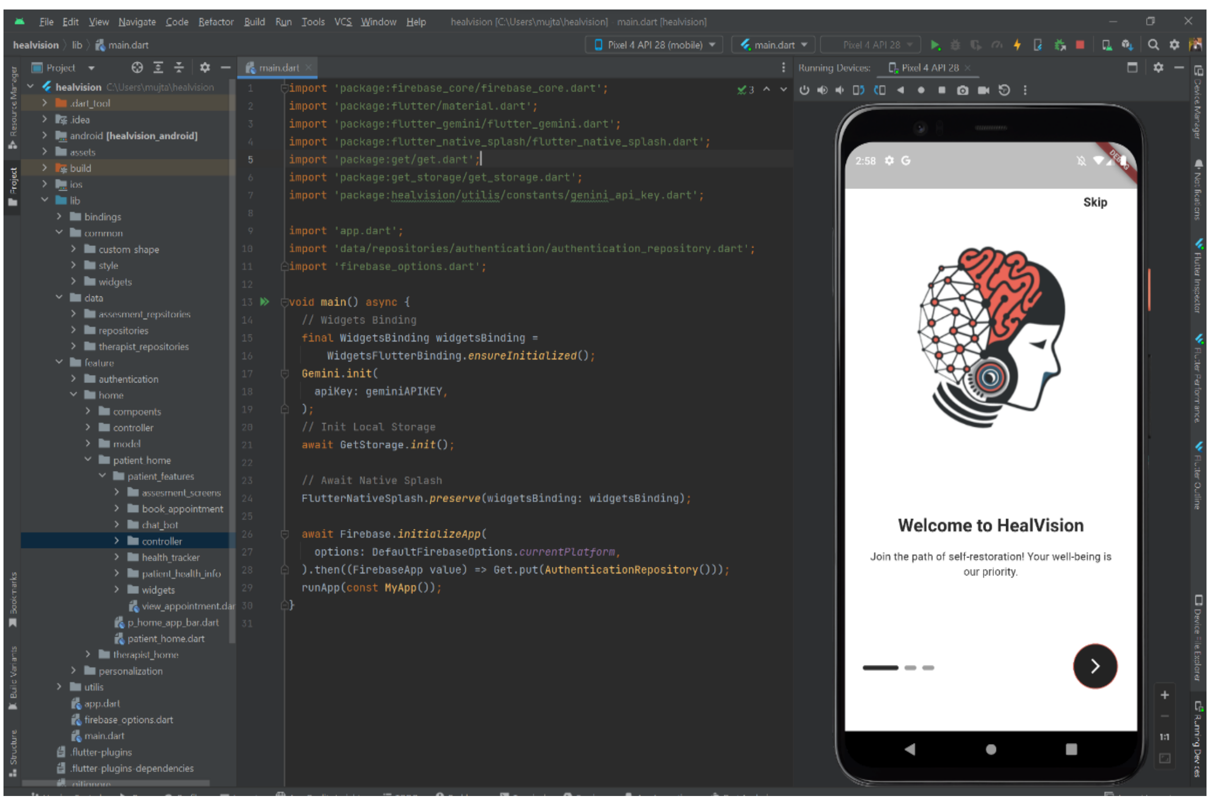


Figure 4.9: Onboarding screen 1

Onboarding2

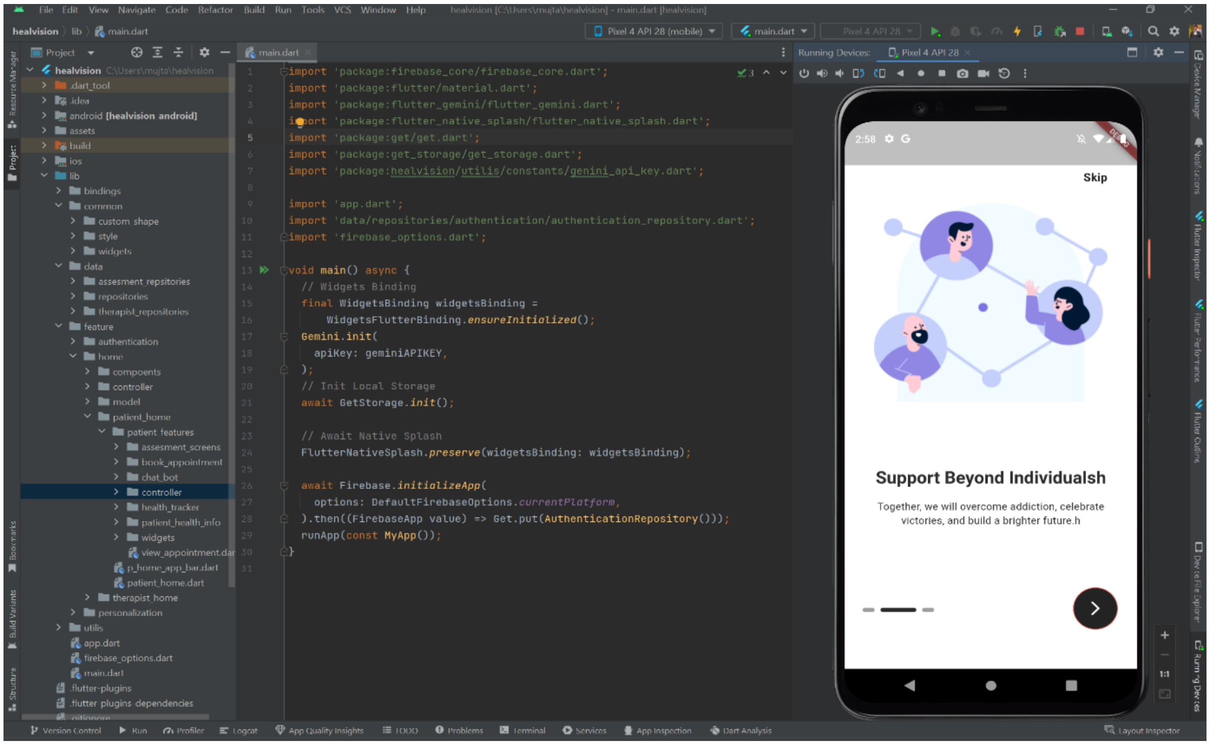


Figure 5.0: Onboarding screen 2

Onboarding3

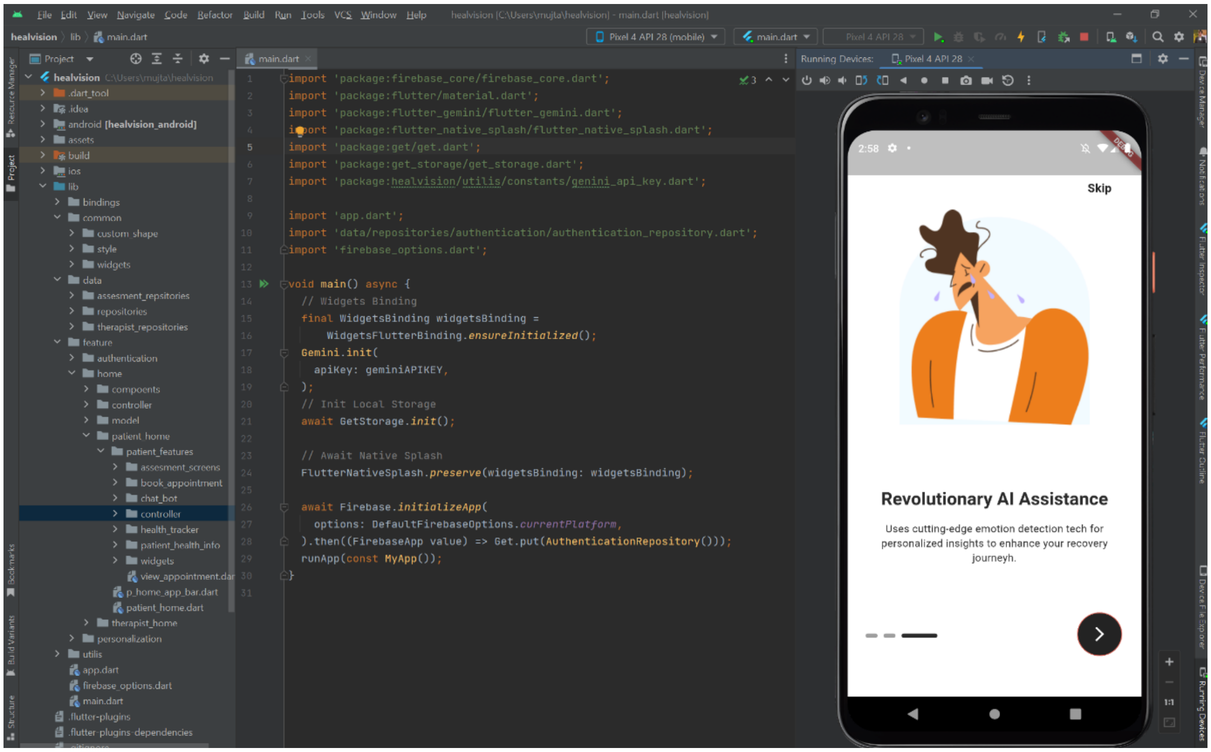


Figure 5.1: Onboarding screen 3

6.1.2 Login & Signup Screens

That is where our application got a kickstart.

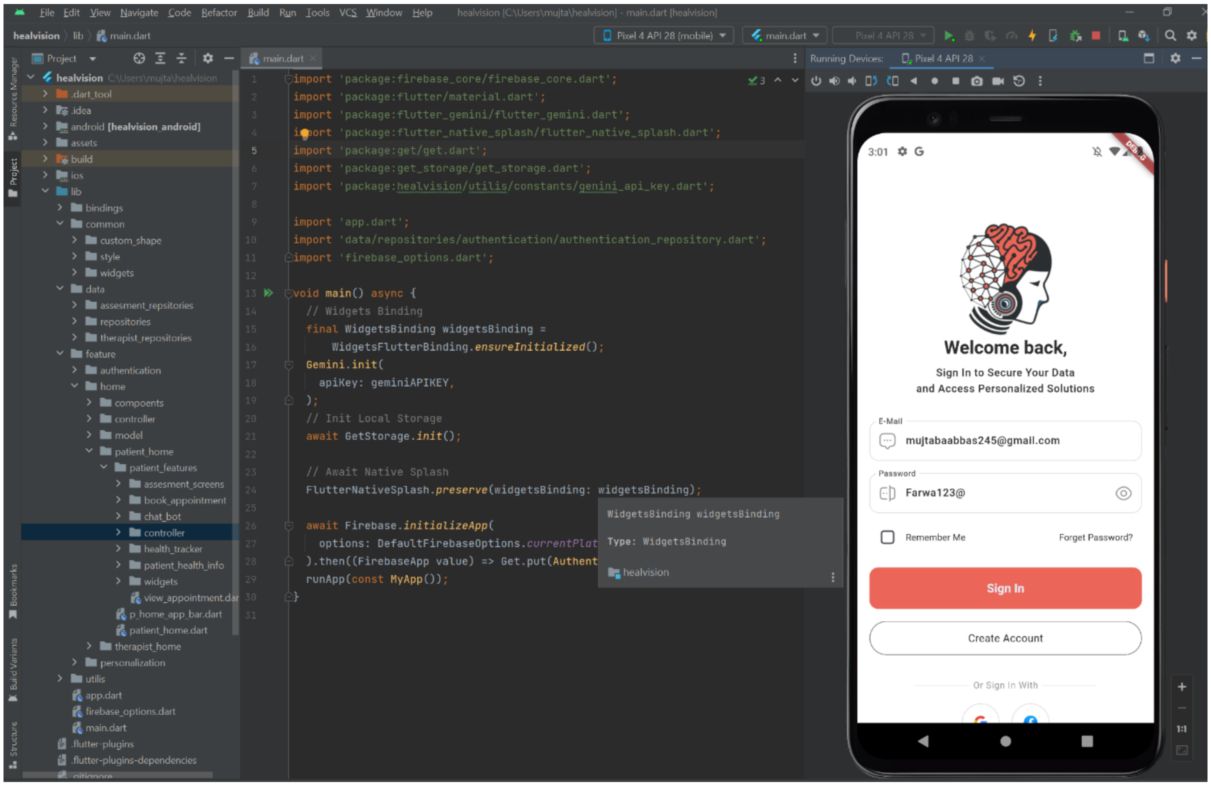


Figure 5.2: Sign In Screen

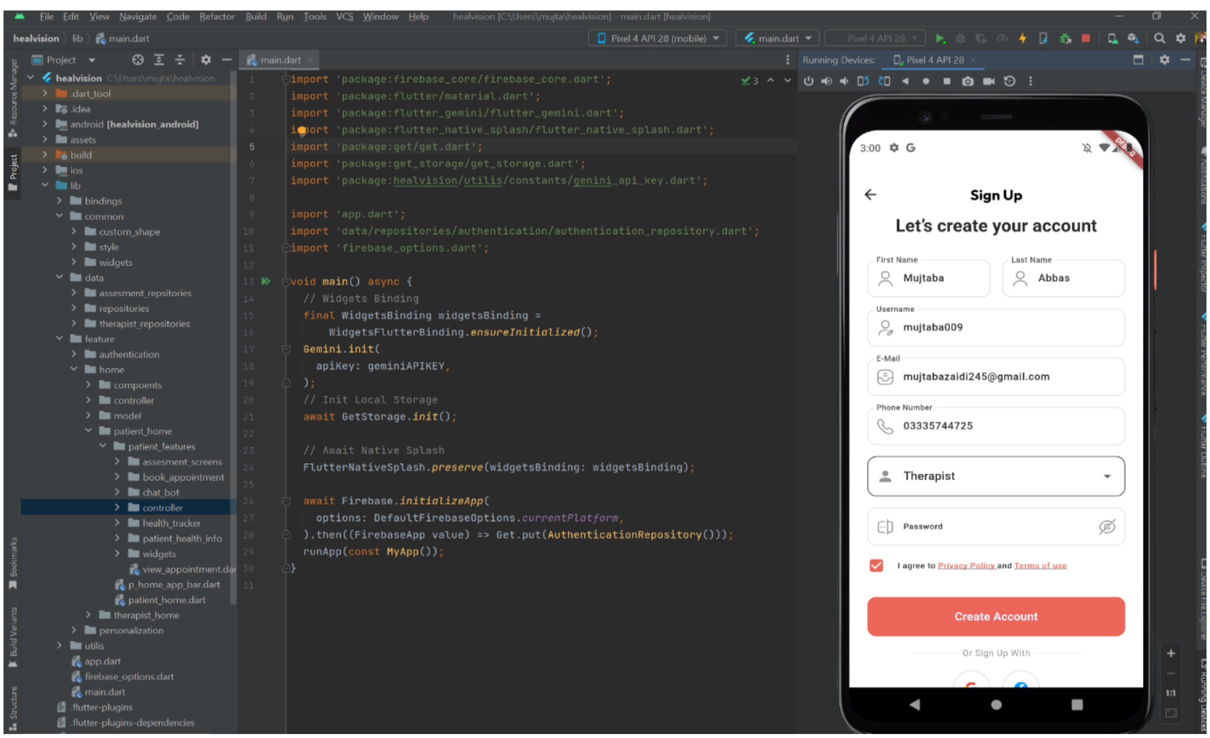


Figure 5.3: Sign-up Screen

The user will be exposed to the login page, where the user must enter an email address and password to access the specified dashboard, either patient or therapist. Users can sign in using their Google or Facebook accounts by clicking on the selected icons. If the user has no account, they must create one by clicking the create account icon and entering the required details. The user will be asked to verify the email address by opening the link sent to the user's email account.

6.1.3 Patient Dashboard

If a user has a patient account, the user will access the patient dashboard, as seen in the picture below.

Home Screen

Users can see upcoming appointments with a navigation bar where they can find a therapist, go to the health tracker, go to the assessment quiz, or click on the chatbot.

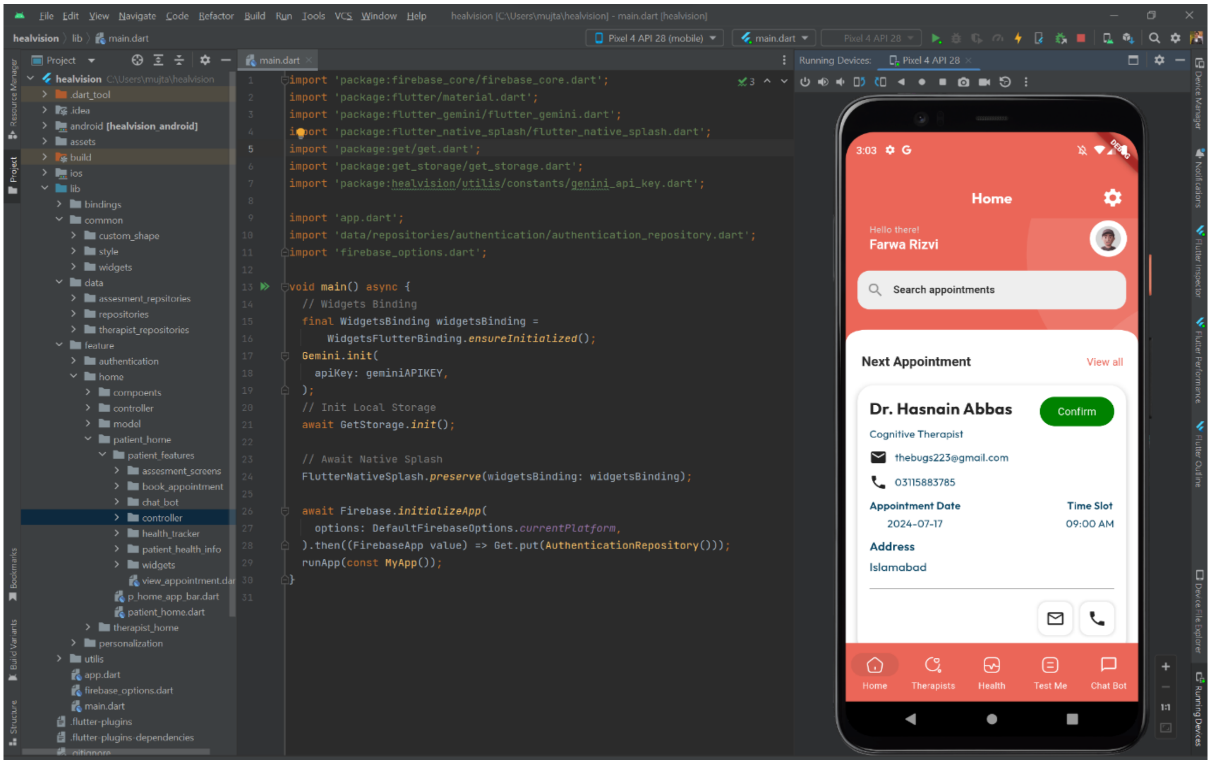


Figure 5.4: Patient Dashboard

Booking Appointment

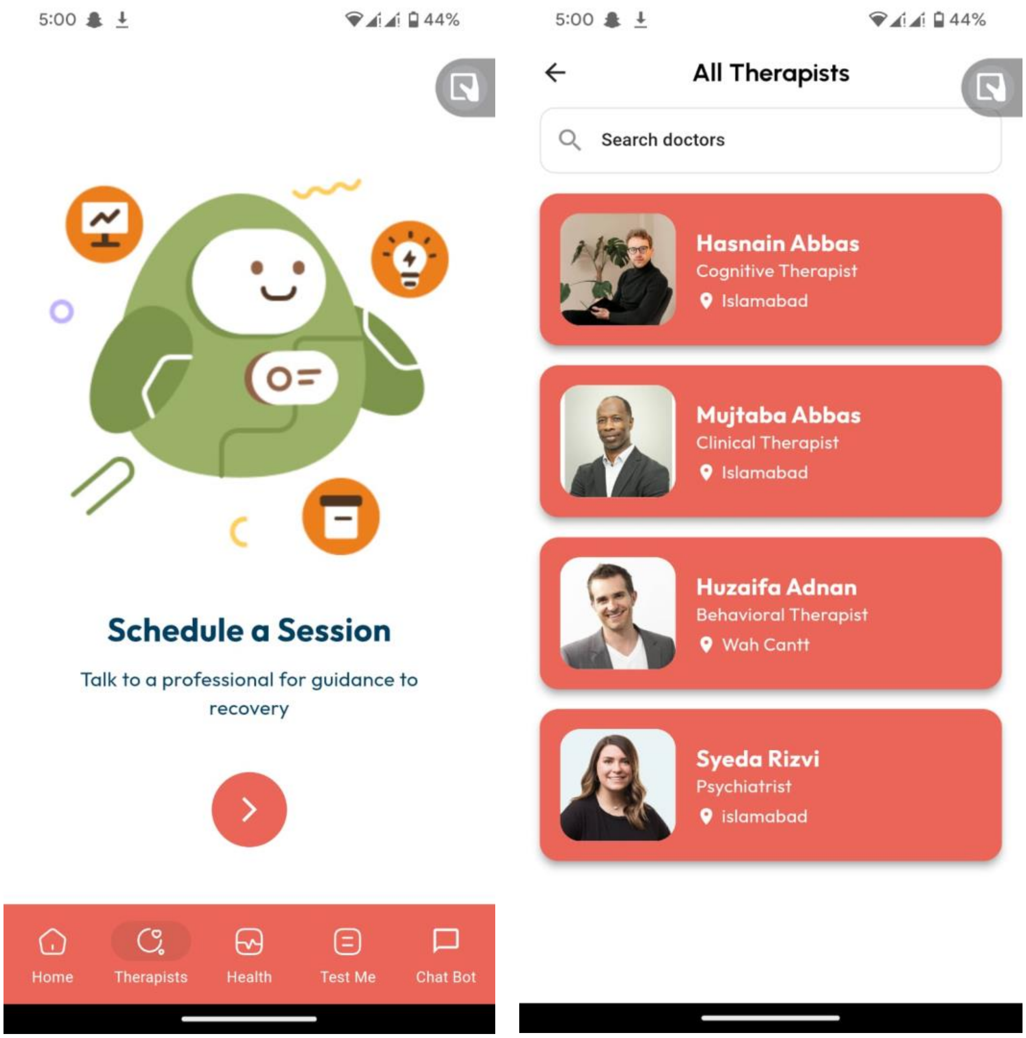


Figure 5.5: Book Appointment: Landing and Search for Therapists

After navigating to the therapist icon in the nav bar, the user will be exposed to the schedule a session screen, as seen above. After that, the user can access all available therapists, where a user can select the therapist of their preference. After clicking on the therapist tab, the User can see all the details about the therapist and a book appointment icon, as seen in the figure below.

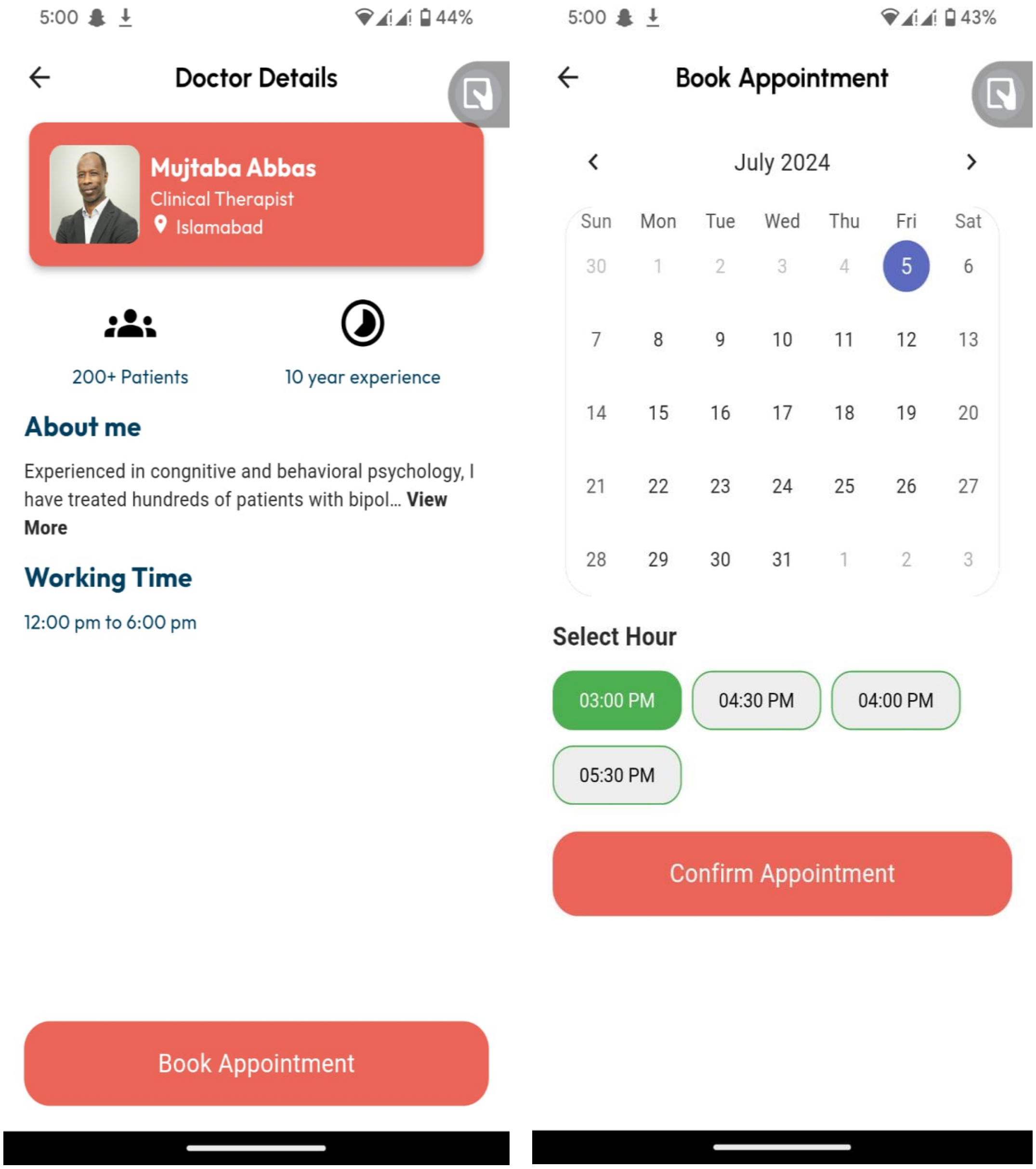


Figure 5.6: Book Appointment: Select and confirm

After clicking the 'Book Appointment', the User will be exposed to the calendar and the time slots available where a user can select the desired time slot and date to book an appointment with the doctor. After confirming the details, the appointment will go to the pending status until the therapist confirms it.

Health Tracker

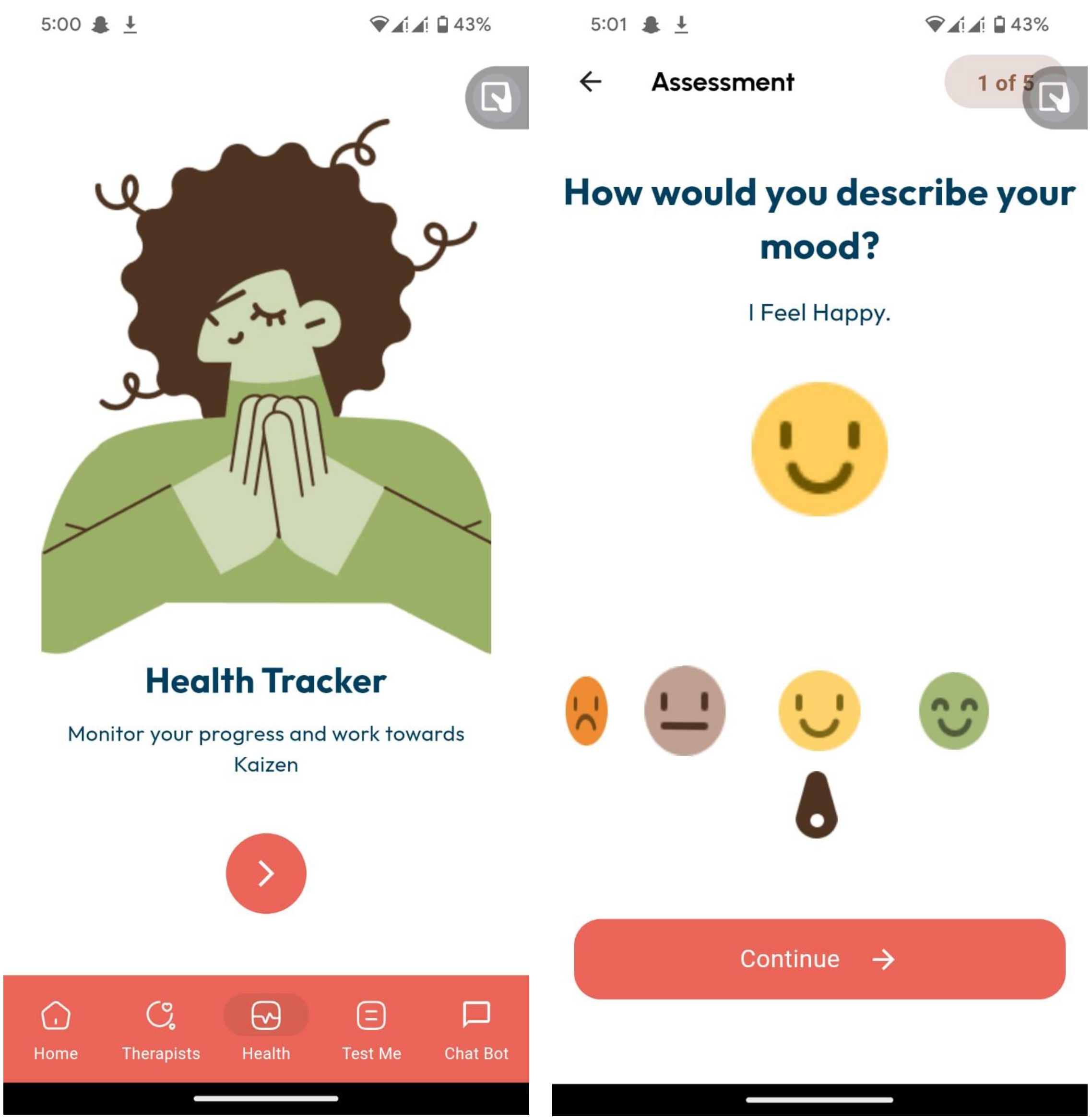


Figure 5.7: Health Tracker: Landing and Mood

Users can navigate to the health tracker by tapping on the health icon in the nav bar, where the user will be exposed to the health tracker screen, and by clicking on the following icon, the user will see an assessment screen where the user will be asked to describe their mood and click the continue icon where another screen as shown below will pop up asking for the sleep quality, physical distress, stress level, and substance use data the end. After submitting the data, the doctor can access patient data with a confirmed appointment.

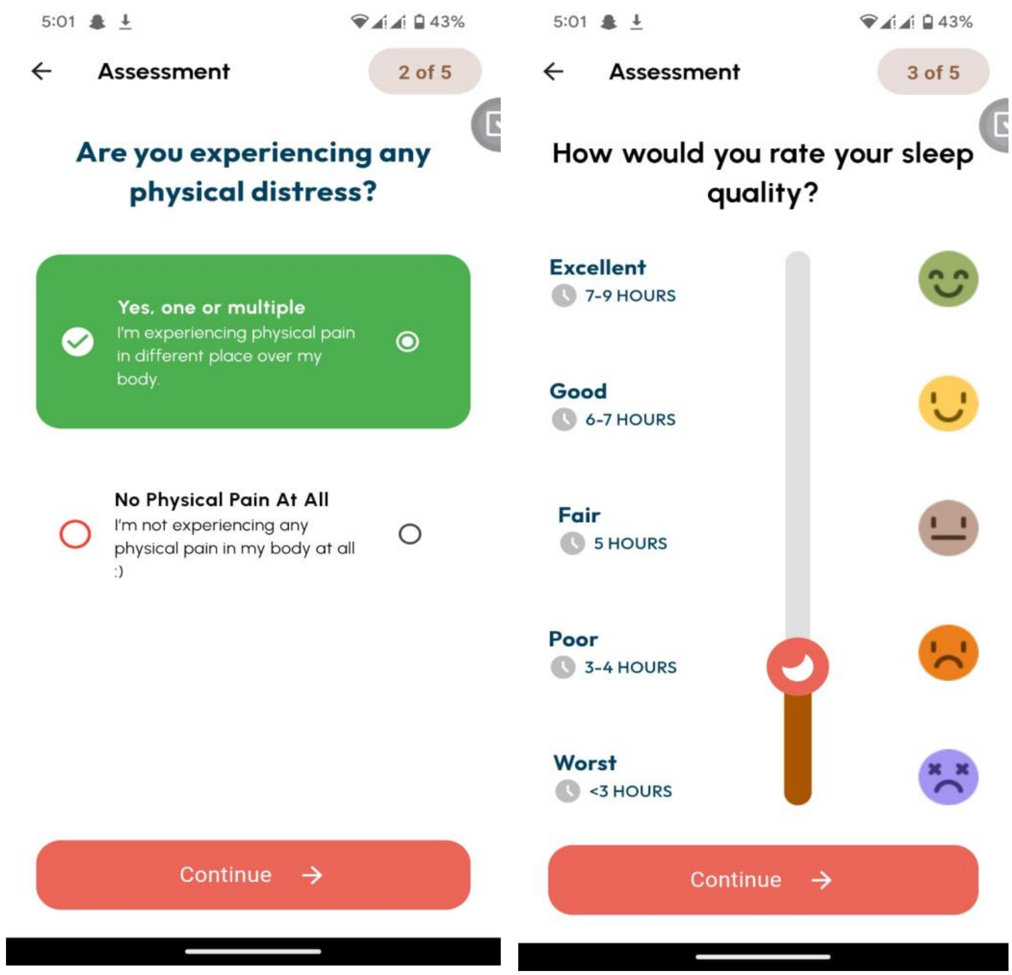


Figure 5.8: Health Tracker: physical distress

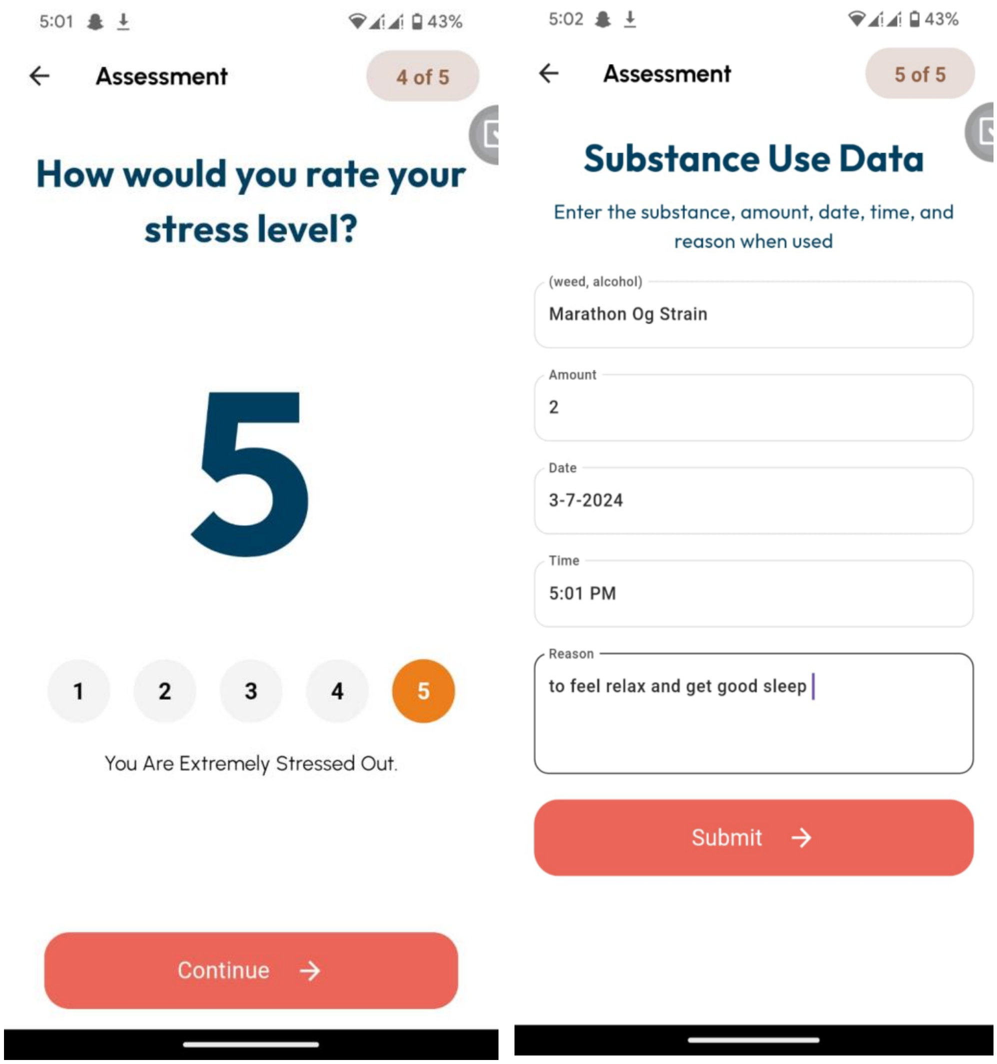


Figure 5.9: Health Tracker: Stress and info

Addiction Determination Quiz (Test me)

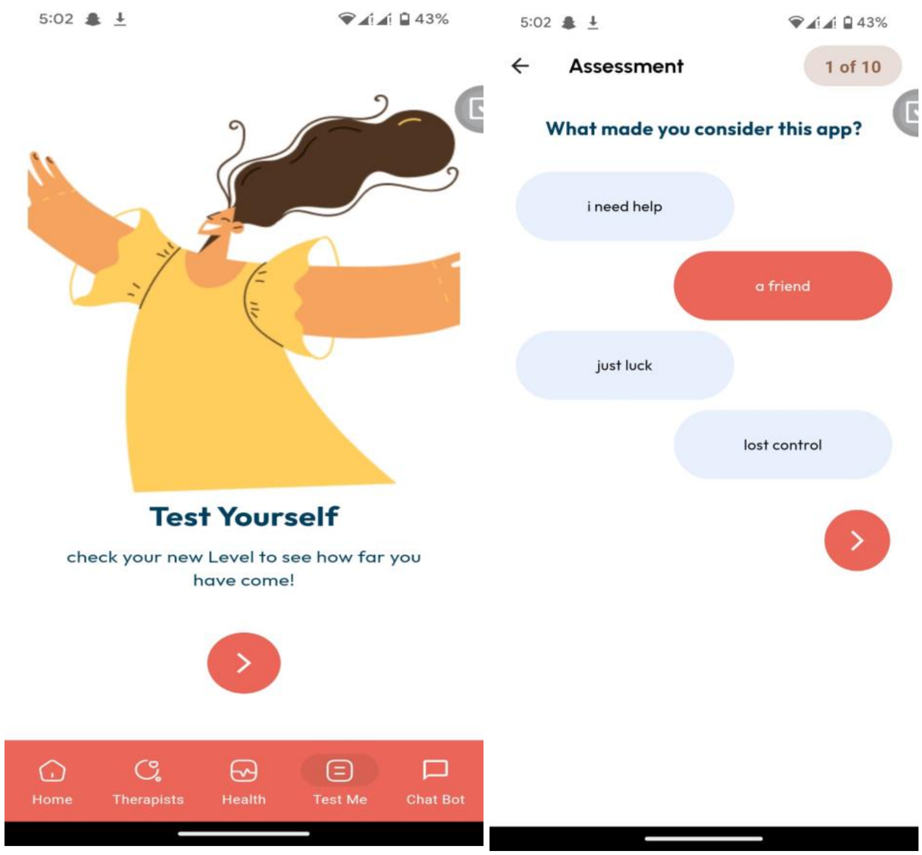


Figure 6.0: Quiz: Questionnaire selection

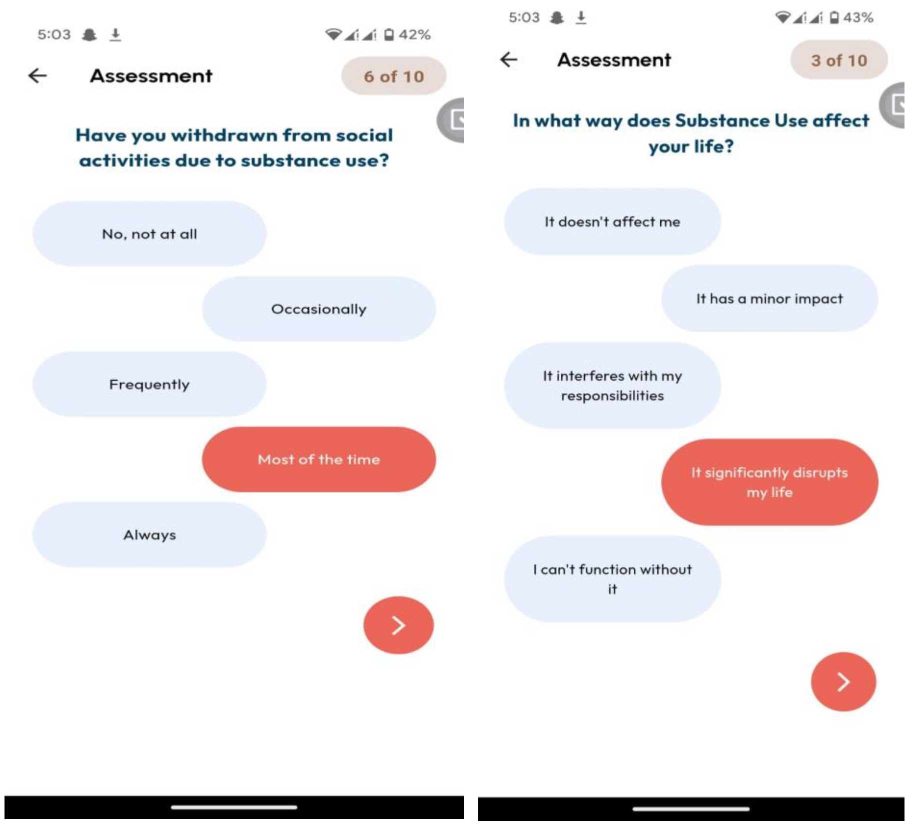


Figure 6.1: Quiz: Questionnaire selection 2

Users can give the addiction determination quiz by tapping the test me option in the nav bar, which will be shown with different assessment questions as shown above.

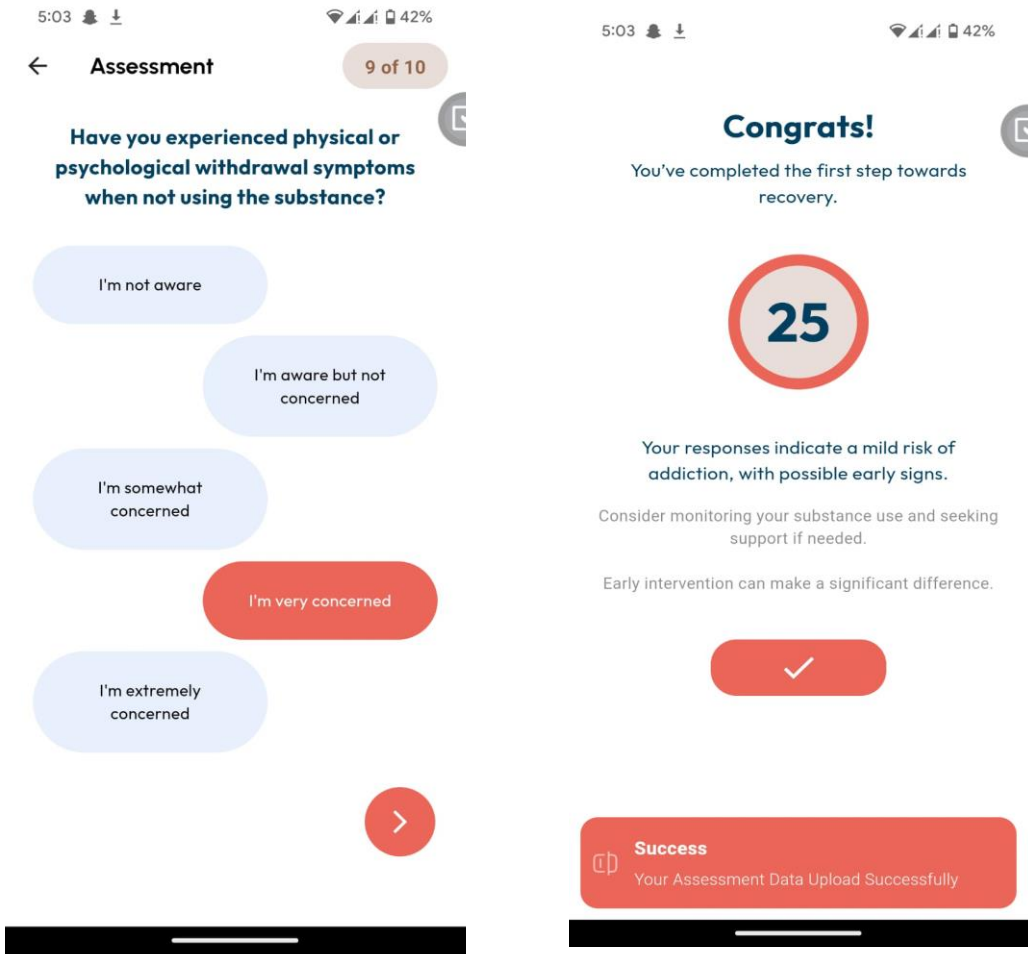


Figure 6.2: Quiz: Questionnaire selection and Score

After submitting the quiz, another screen will pop up, as shown above, where a user can see their score and some instructions.

Chatbot

Users can access the chatbot by tapping on the chatbot icon in the navigation bar. As seen in the picture below, the user can type and send the message. Meanwhile, the chatbot will reply in a few seconds. Chatbot is integrated with Gemini and responds according to the user prompt; meanwhile, our model will evaluate the message's emotional state and predict the message shown to the therapist.

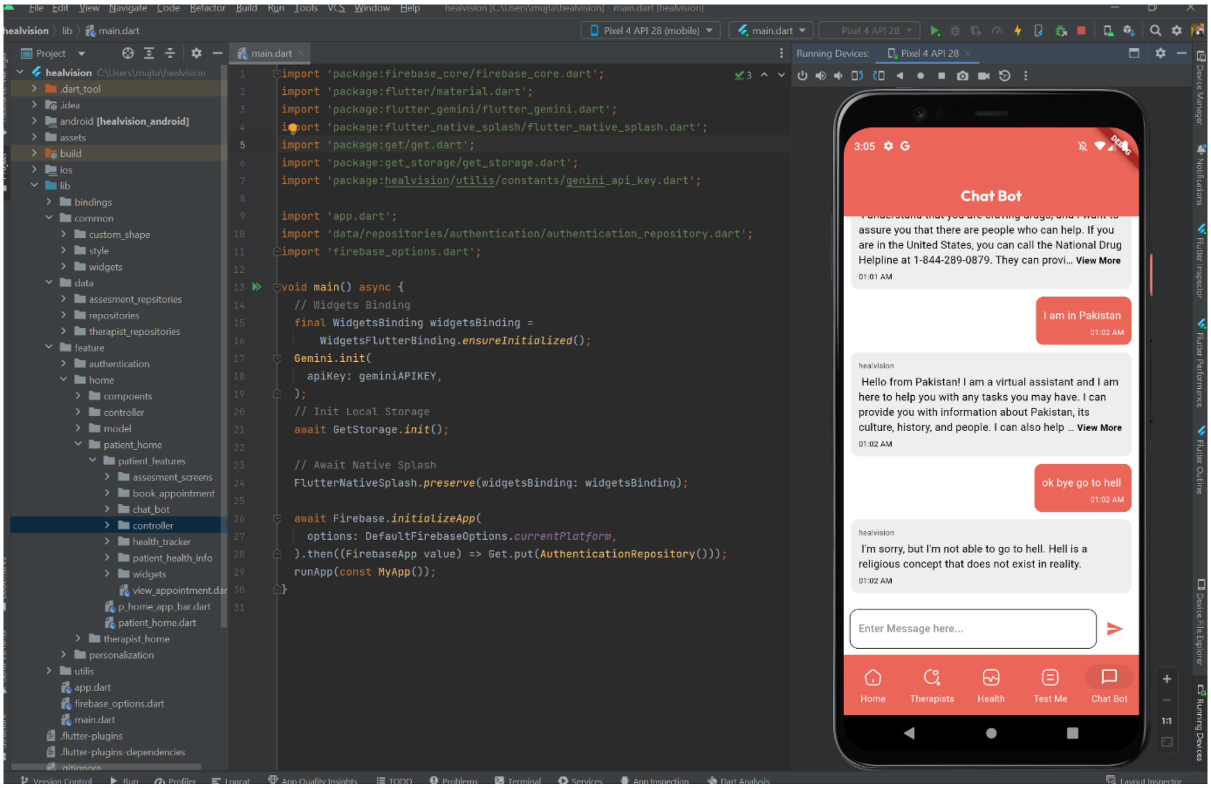


Figure 6.3: Chatbot

Settings

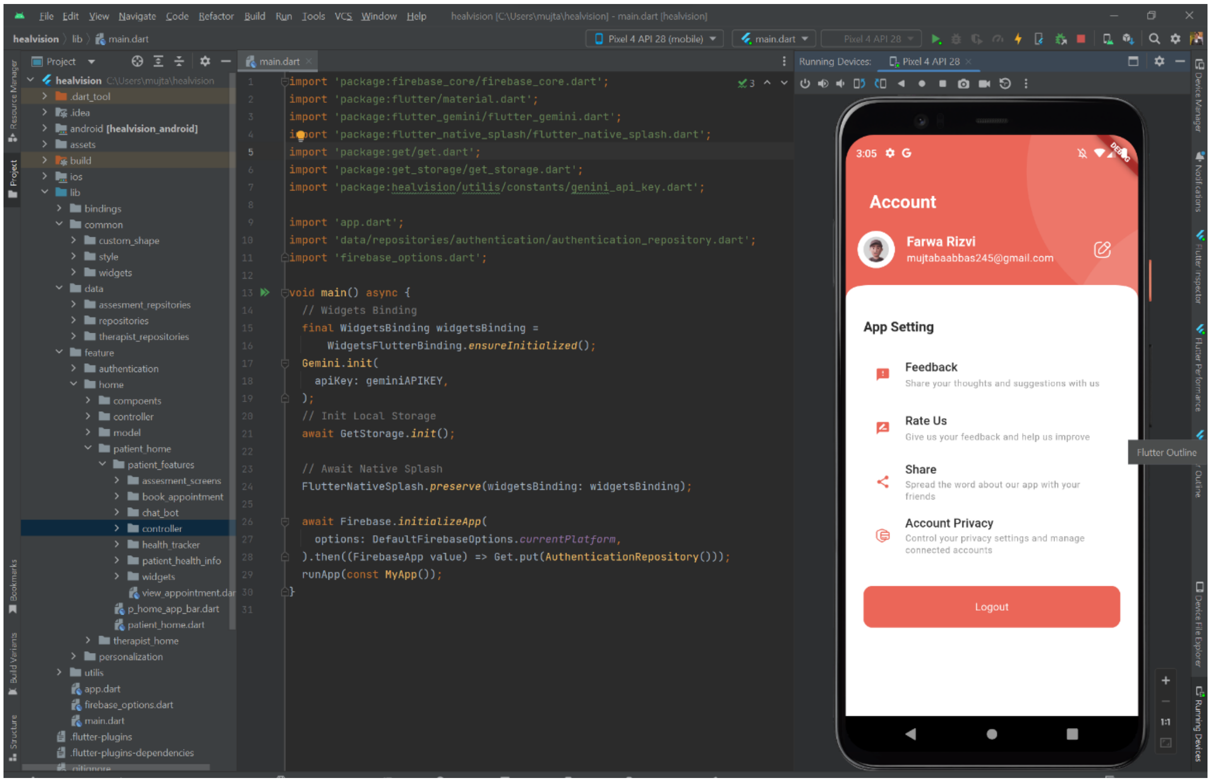


Figure 6.4: Settings

Users can go to settings by navigating to the settings icon on the top right bottom of the header. The above picture shows that the user can log out and edit the profile details by navigating to the edit icon.

6.1.4 Therapist Dashboard

If a user has a therapist account, the user will access the therapist dashboard, as seen in the picture below.

Home Screen

The therapist can see upcoming appointments with a navigation bar where the therapist can check the appointment, go to monitor, and their profile screen.

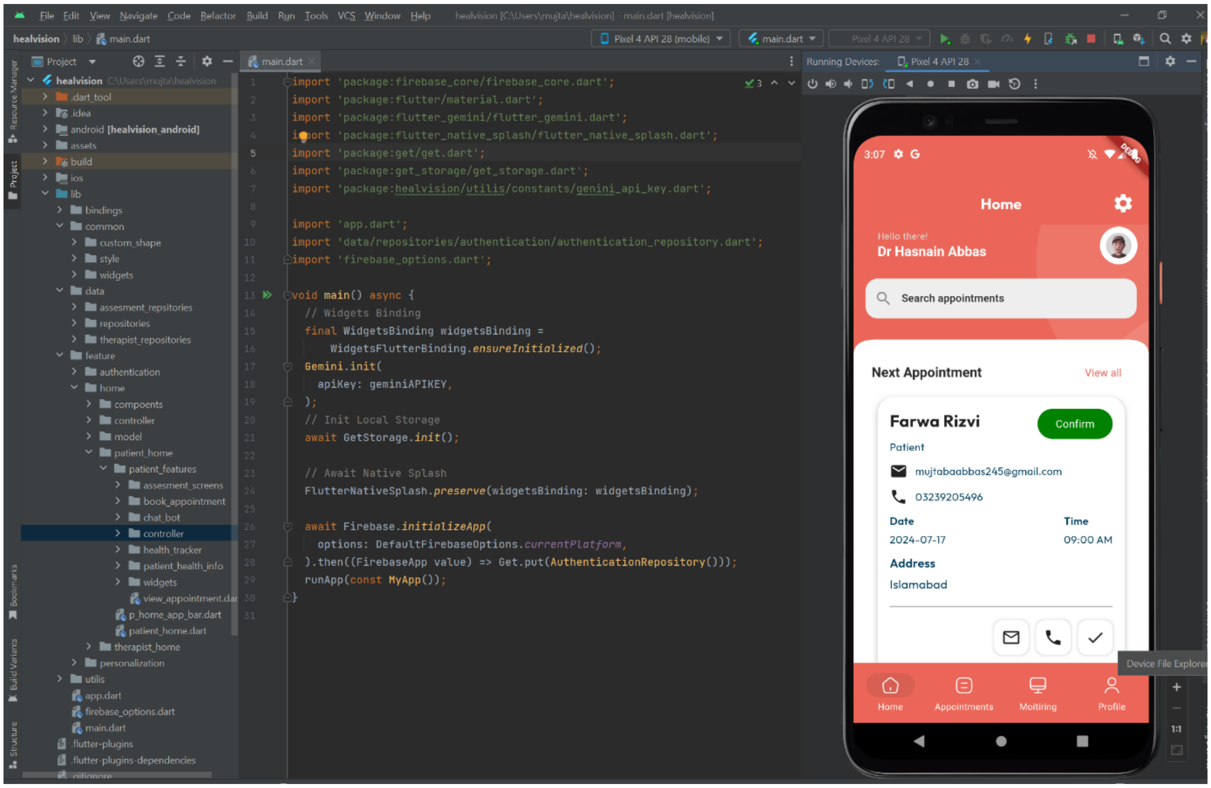


Figure 6.4: Therapist Dashboard

Appointment Status

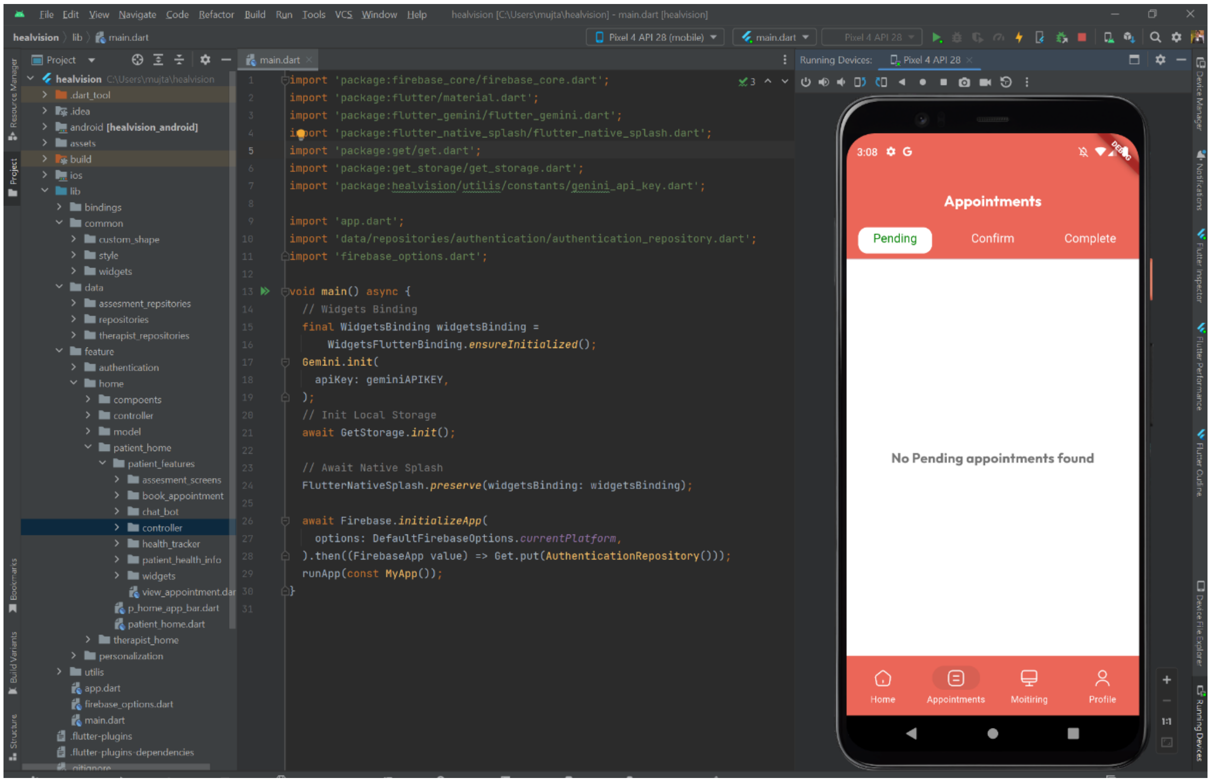


Figure 6.5: Appointments Pending

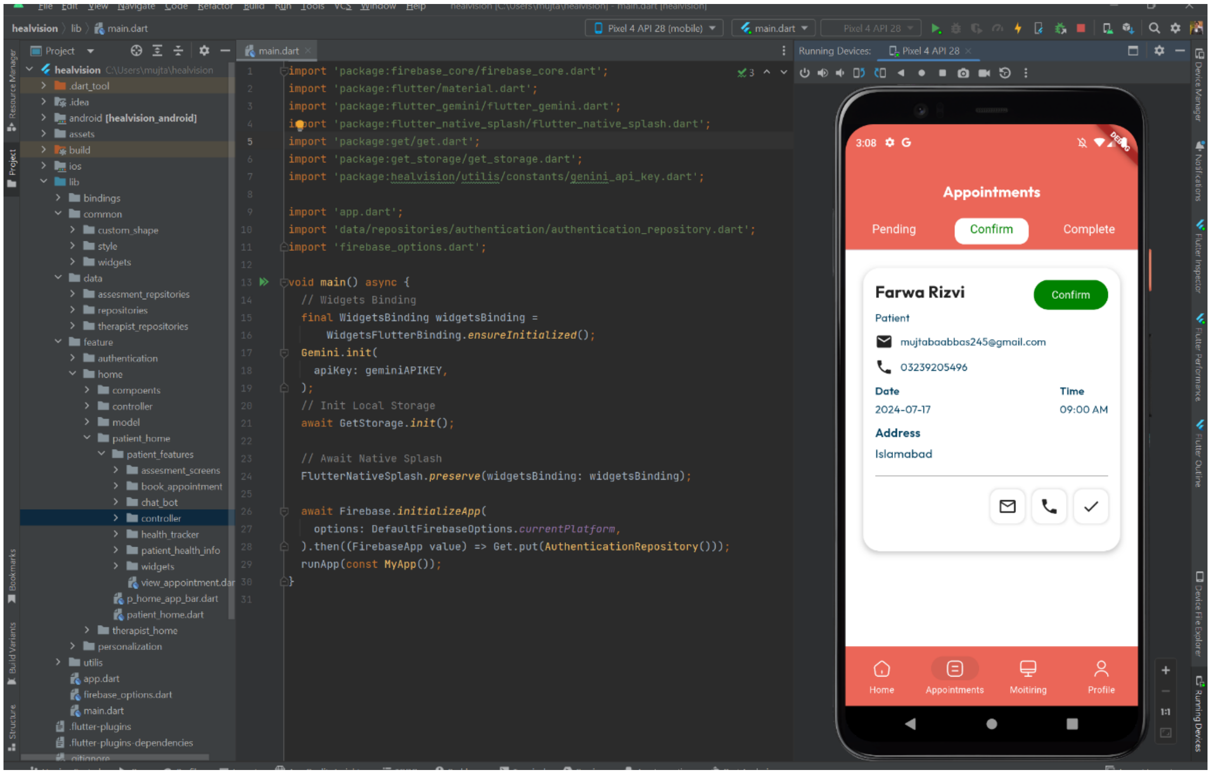


Figure 6.6: Appointments Confirmed

As seen in the above pictures, the therapist can see the pending, confirmed, and completed appointments by navigating to the options above and changing the appointment status by clicking the tick icon.

Monitor Progress

Navigating to the monitoring option will enable the therapist to see the patient's health, assessment, and chat data. The therapist can only see data if the appointment is confirmed.

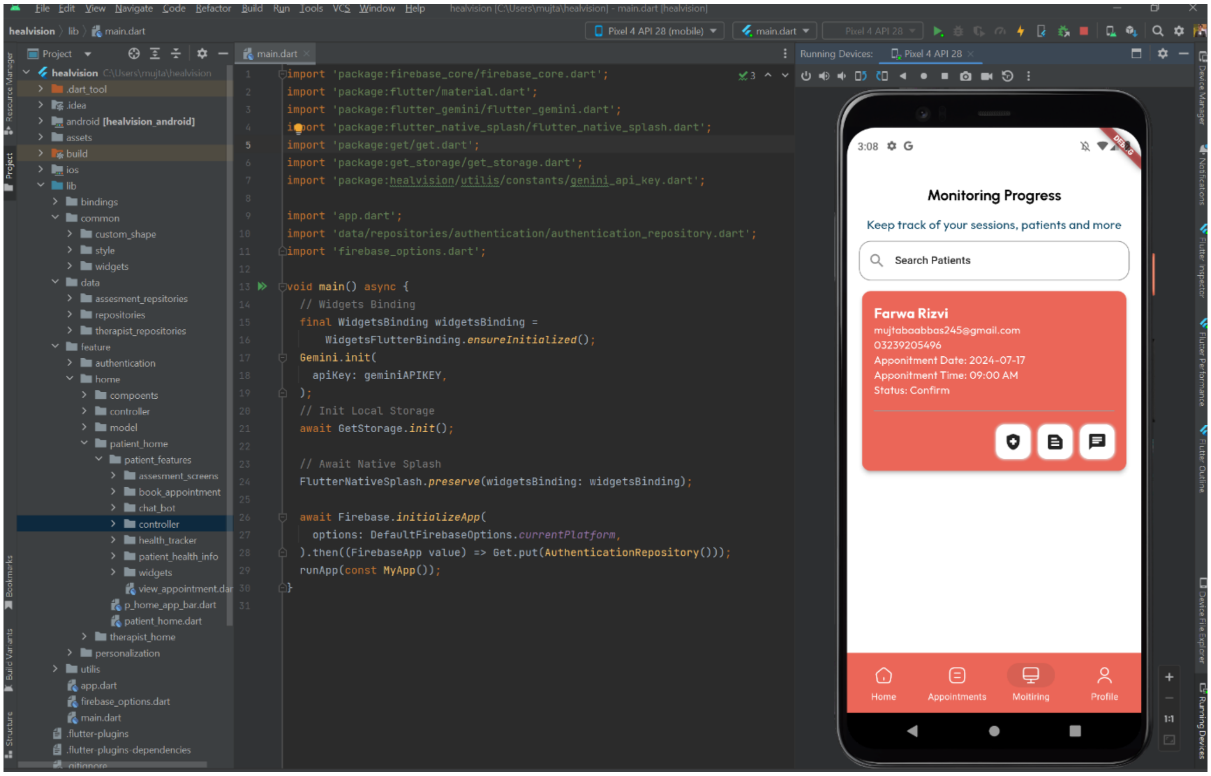


Figure 6.7: Patient Records – Monitoring Progress

As seen in the above picture, patient records are shown with three icons at the bottom of the widget: one for health data, the second for assessment data, and the third for chatbot data. The therapist will be exposed to the desired screens by clicking on any of the options, as seen in the pictures attached below. A therapist can see the patient chat with the Gemini bot and the emotion prediction below every message.

Health Tracker Data

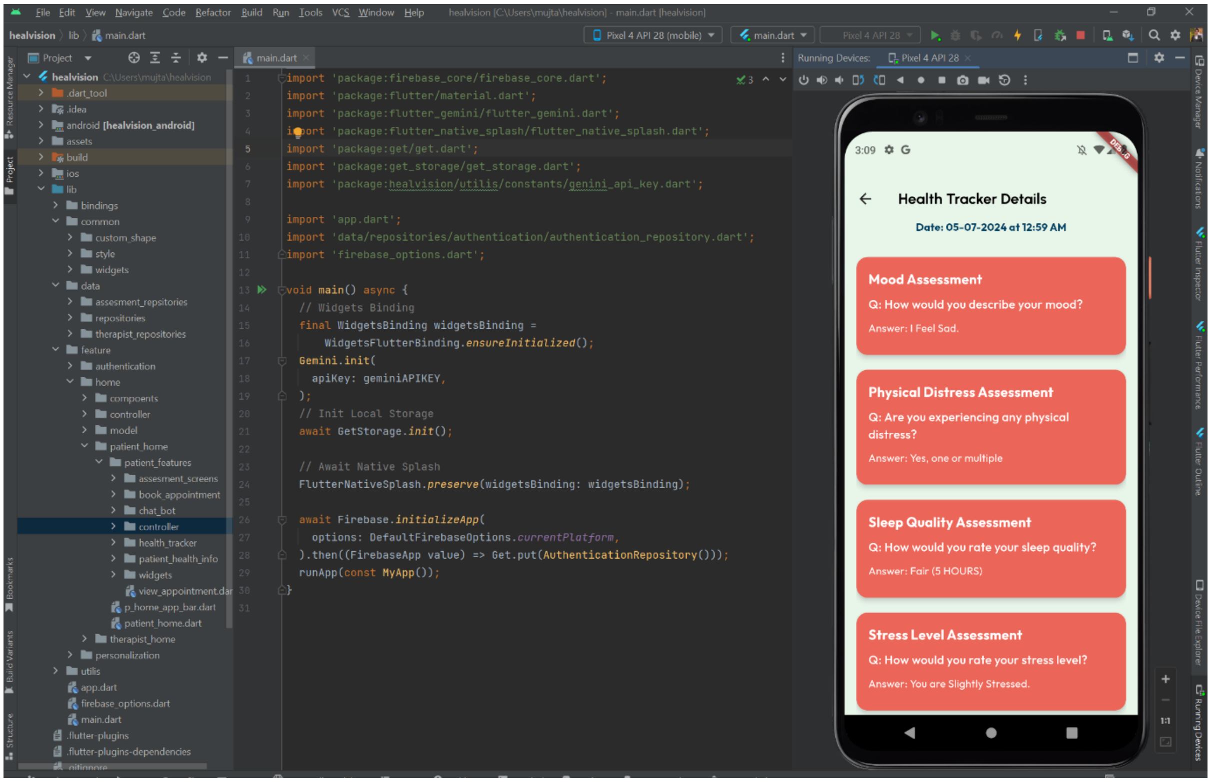


Figure 6.8: Monitoring Progress - Health Tracker

Assessment Data

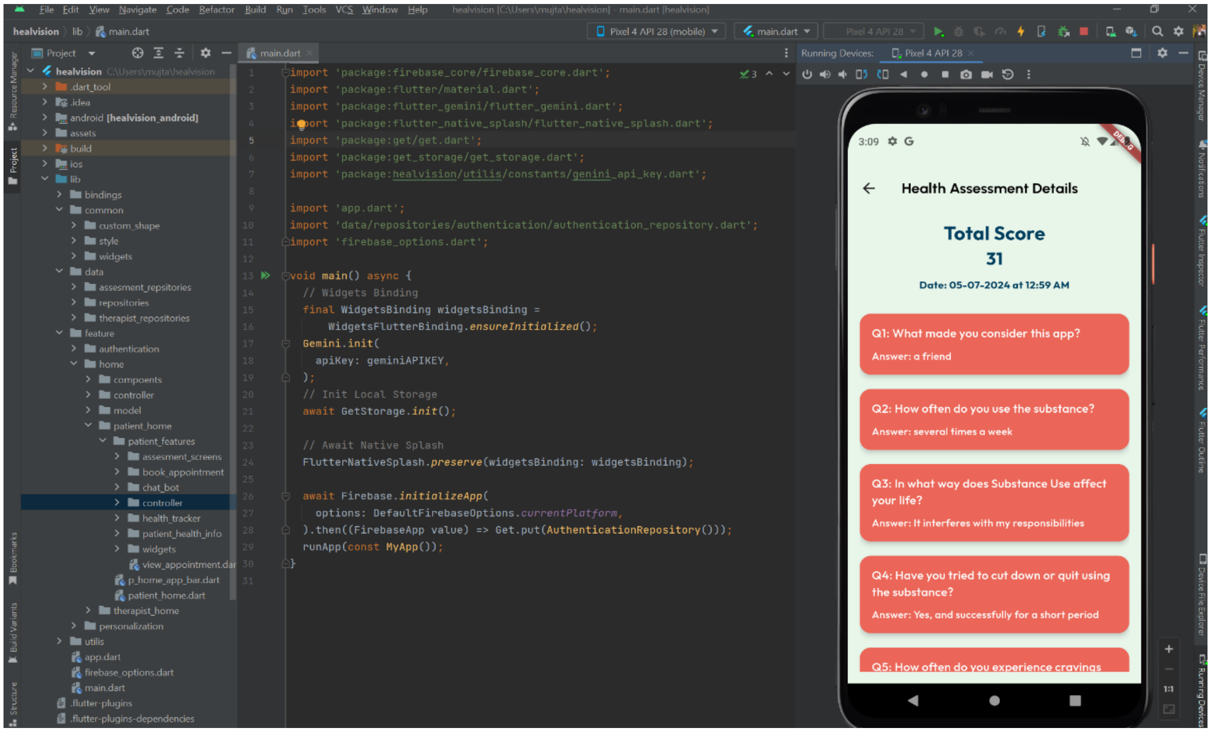


Figure 6.9: Monitoring Progress – Addiction Level

Chatbot Data

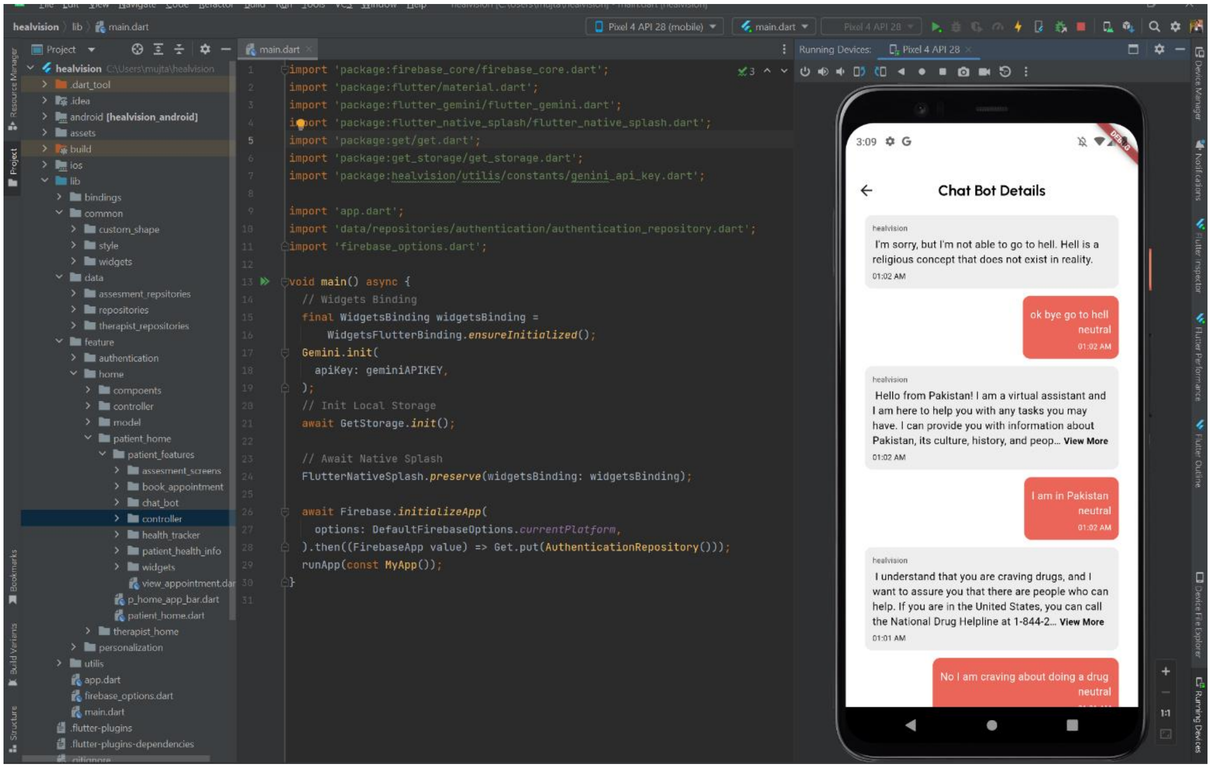


Figure 7.0: Monitoring Progress – Chatbot Prediction and History

Profile Screen

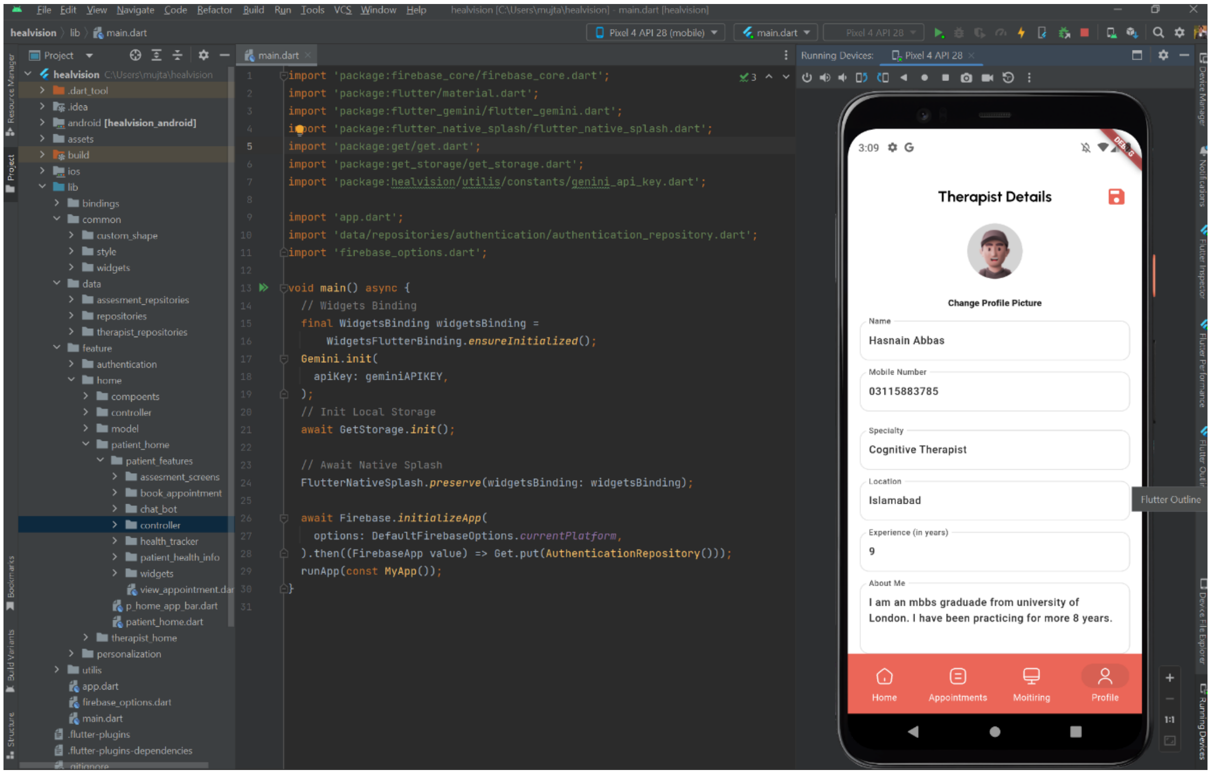


Figure 7.1: Therapist Profile

6.2. Model

The primary outperforming model results, namely FNN (version 4) and BERT-ANN (Version 2), are further studied in this section. Although the BERT-ANN (Version 2) appears to be performing less than FNN (Version 4), when testing the model, BERT-ANN was able to give more accurate results.

Table 2: Model Results Comparision

The summary of parts of various models and datasets applied are recorded.

	Model		Accuracy (%) Training	Accuracy (%) Testing
	Balanced			
Emotions-6000	BERT Based	*Simple*	58.66	58
		ANN Version 1	99.97	78.66
		ANN Version 2	99.88	79.33
Emotions	FNN	*Version 1*	99.43	92.08
		Version 2	98.79	92.04
		Version 3	99.54	91.11
		Version 4	99.69	**92.17**
	GloVe Based	*GloVe-LSTM*	16.6	16.16
		GloVe-NN	80.85	51.25
		GloVe-CNN	99.41	56.17
	Naive-Bayes		84.2	84.18
	Random Forest		90.95	90.93
	Imbalanced			
	FNN	*Version 1*	99.62	85.04
		Version 2	98.79	85.58
	Naive-Bayes		85.10	85.06
	Random Forest		85.29	85.28
	Convolutional NN		13.88	13.84
	Recurring NN		11.11	11.10
	Support Vector Machine		84.66	84.14
	Logistic Regression		89.01	88.06

The detailed results of different models on both datasets can be seen in Table 2. The integration of the model was executed by creating an API for the model and accessing the API through the Flutter application. Fast API is used to manage the model and can be tested directly. If an input like the one shown in fig 7.2 is given to the predict-emotion method defined by the public URL (provided by Ngrok Tunnel)/predict-emotion. The output shown in fig 7.3 is the response prediction.

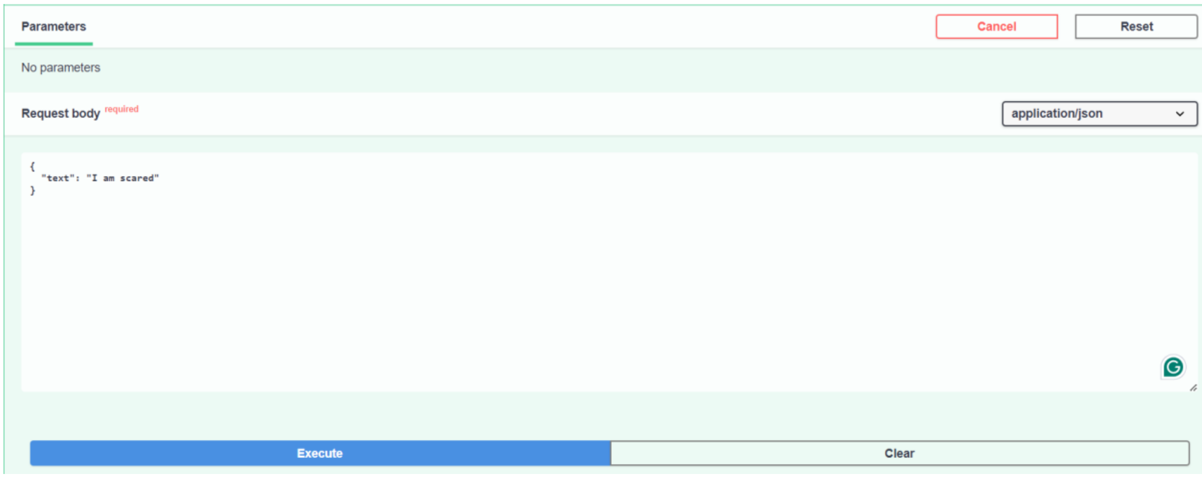


Figure 7.2: Fast API Input Stream

Enter: "I am scared."

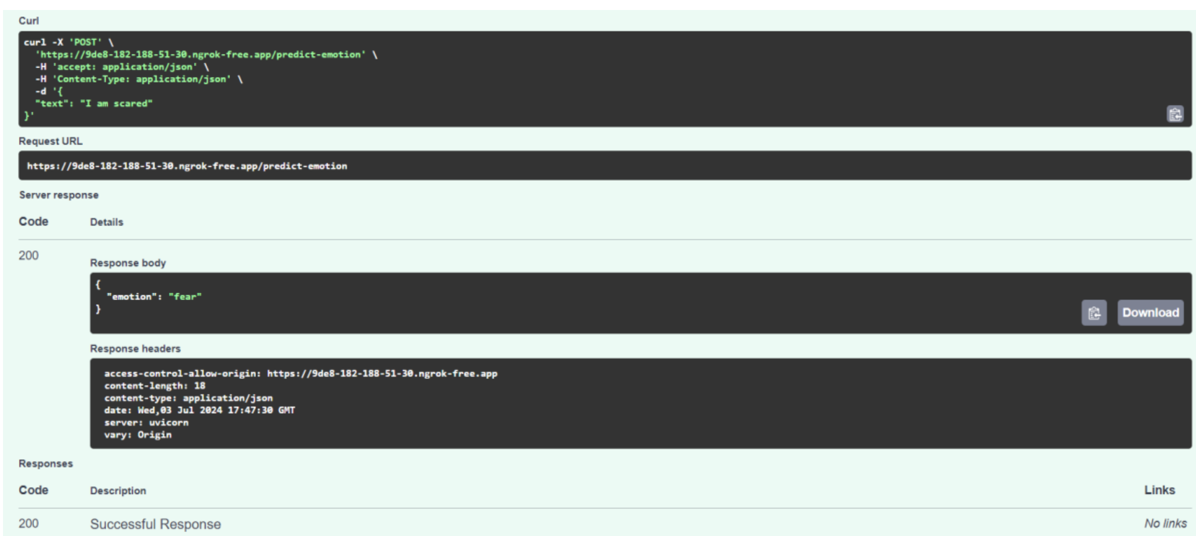


Figure 7.3: Fast API Response Stream

Response: "Fear"

6.2.1. Feed Forward Neural Network - Emotions Dataset (Balanced)

As Figure 7.4 suggests, the final version of NN on the 'Emotions' Dataset proved to have the highest training and testing accuracy compared to the previous Feed-forward Neural Network Models. Version 2 is the poorest-performing model.

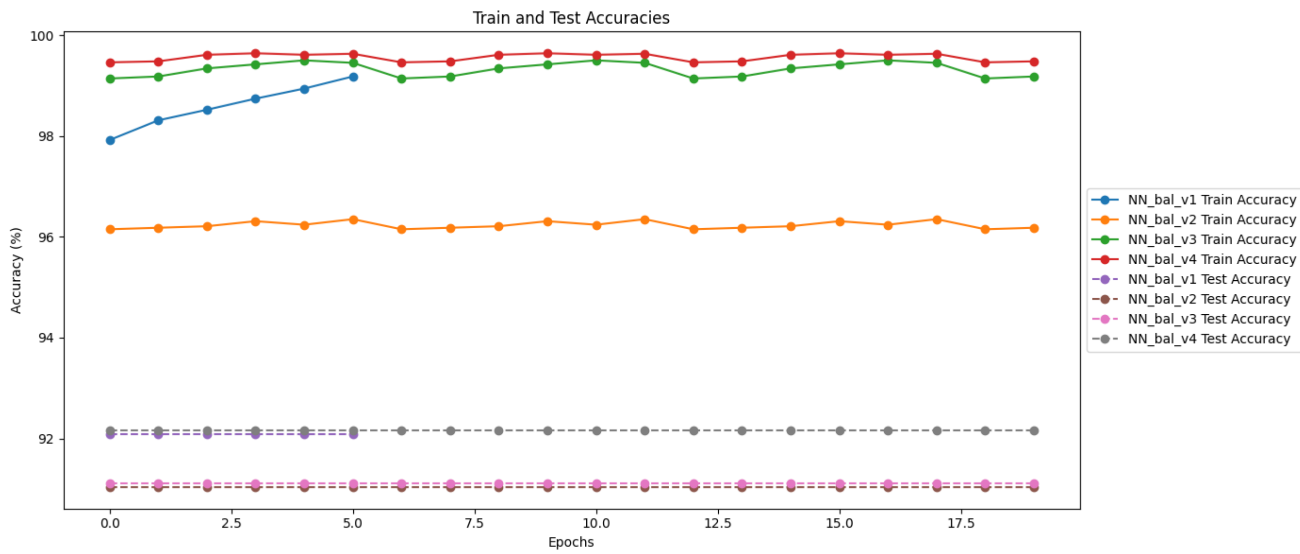


Figure 7.4: FNN Versions Comparison on *Emotions*

Balancing the dataset and tuning the model resulted in significant improvements in the Neural Network implementation of the Emotions dataset.

Almost all alternative models, like BERT, GLoVE, ANN, LSTM, Naive Bayes, Random Forest Classifier, Convolutional Neural Networks, RNNs, SVM, and Logistic Regression, were experimented with on both the imbalanced and balanced datasets, with their results shown in fig 7.4. As predicted, the results of the balanced dataset were significantly higher than those of the imbalanced dataset, which highlights the importance of balanced datasets.

BERT-based Artificial Neural Network - Emotions 6000 Dataset (Custom)

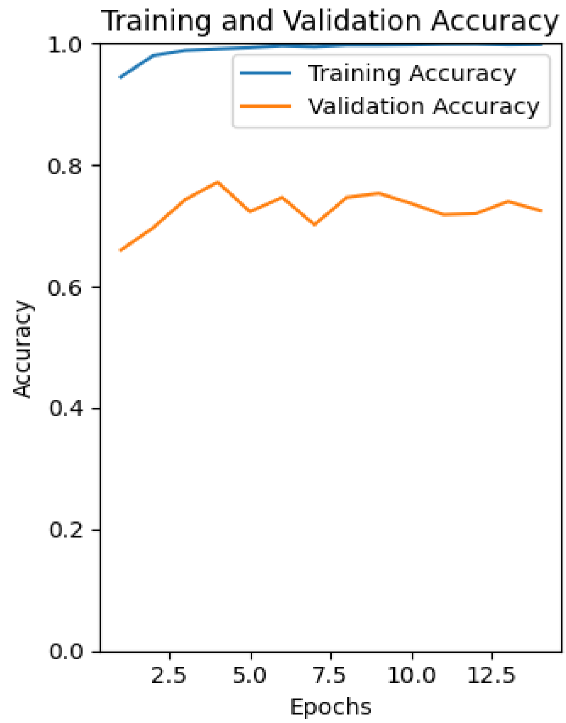


Figure 7.5: BERT-ANN Version 2 Results

Amongst the two versions, the ***BERT-ANN Version 2*** achieved a higher training and testing accuracy of 99.88% and 79.33%, respectively.

6.2.1.1. BERT-ANN Version Comparision

1. Model Complexity: The first model has reduced complexity due to fewer neurons than the second. This implies that *Version 2* can learn more patterns in the Emotions-6000 dataset than *Version 1*.
2. Dropout - Regularization: The second version was set to a lower dropout rate of 10%, which, although it may overfit, also increases the model's chances of learning complex patterns compared to version 1, which improves accuracy.

7. CONCLUSION AND FUTURE WORK

In conclusion, our study mainly focused on the emotional analysis of individuals battling with Substance Use Disorder and personalized mobile application to aid them in their recovery journey. After a detailed review of related work, we identified several strategies and techniques to mitigate these issues. To resolve these challenges, we proposed an AI-driven solution that uses models such as ANN, BERT, GloVe, feed-forward NN, Naïve Bayes, and Random forest to precisely predict the emotions of individuals with SUD based on the textual messages and a personalized mobile application that includes addiction determination through an interactive quiz, appointment system, health tracker, and emotion detection-based chat module using our feed-forward NN model and a chatbot. Our research showed that our method was adequate, with the NN model achieving an impressive accuracy of 92.17\% %, followed by Random Forest at 90.93\% % and Naïve Bayes at 84.18\% %. With 98.99% and 77.33% for training and testing of BERT-ANN, respectively, with custom Emotions Dataset. This robust implementation signifies the value of our approach in precisely detecting emotions, aiding therapists in understanding and addressing their patients' moods, and making it easier for people struggling with SUD to start their recovery journey with our personalized mobile application with AI.

Future research should emphasize refining and optimizing our indicated method, examining more AI algorithms, and undertaking real-world testing to evaluate its usefulness in the mental health world. Moreover, our mobile application incorporates support groups and daily tasks to make it more personalized and helpful for patients and therapists. By following advancements, we can support the concept of digital therapy instead of traditional therapy for all individuals struggling with SUD.

8. REFERENCES

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