24-25J-109

PATIENT-CENTERED MOBILE APPLICATION FOR COMPREHENSIVE DIABETES SELF-MANAGEMENT AND OPTIMIZATION

Progress Review 2

OUR MEMBERS

Supervisor
Dr.Junius Anjana

Co-Supervisor
Ms.Gaya Thamali Dassanayake

Gunawardhana D.H.M.G

Kajeevan J

De Silva L.K.N

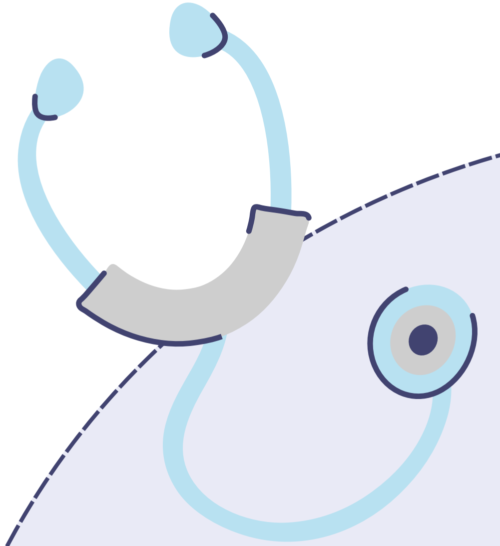
Wimansa P.P.S.D.

OUR EXTERNAL SUPERVISORS

Dr. RameshKumar Thevraj
Senior Registrar in Endocrinology
National Hospital Sri Lanka

DR.SOMESWARAPILLLAI PATHANTHAN
GRADE I MEDICAL OFFICER, NATIONAL HOSPITAL, SRILANKA.

INTRODUCTION



- Integrated mobile app for comprehensive management.
- Real-time data integration from devices.
- Feedback system to track progress and adjust recommendations.
- User-friendly interface to enhance patient engagement and education.

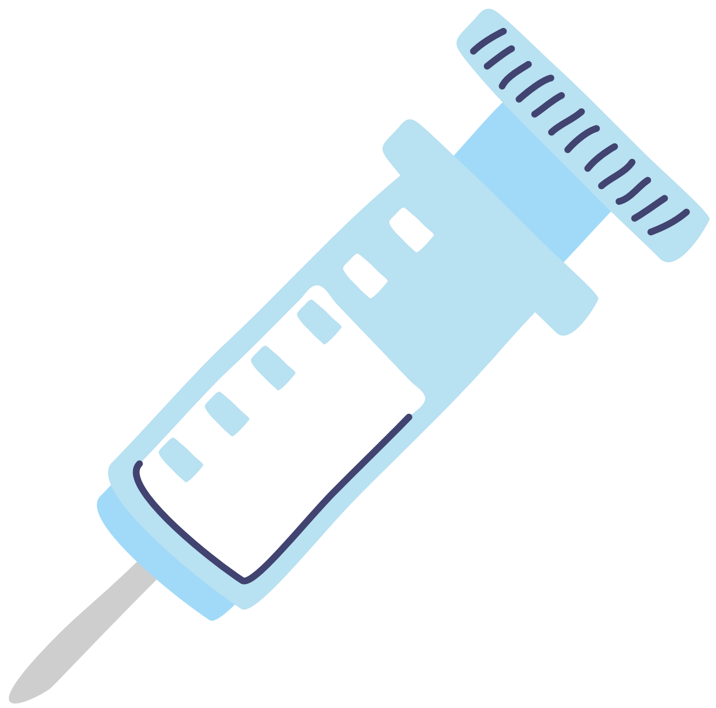
RESEARCH PROBLEM

Insulin Optimization

How can advanced machine learning algorithms be utilized to adjust insulin dosage effectively, minimizing the risks of hypo- and hyperglycemia?

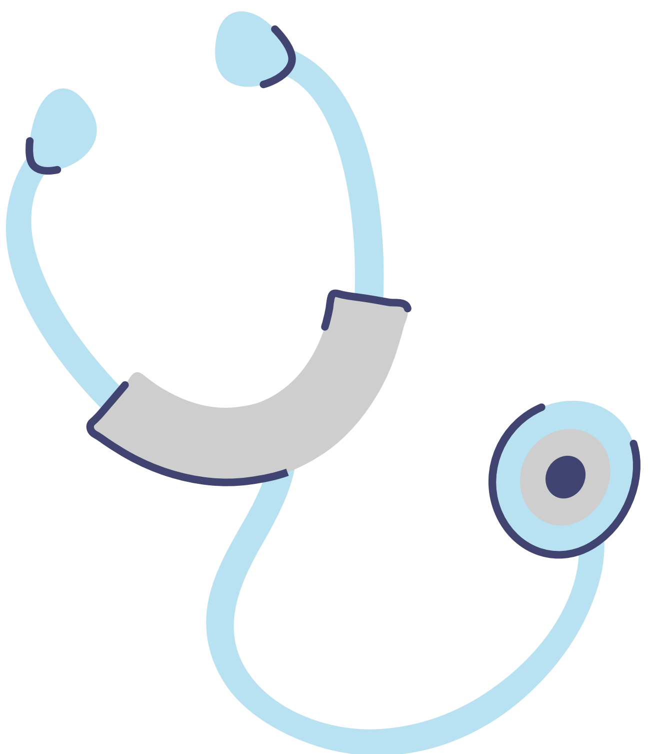
Side Effect Management

How can a system effectively monitor and manage side effects like hypoglycemia, weight gain, and cardiovascular issues?



Simplified Food Tracking

How can automated systems ensure accurate and user-friendly tracking of food intake for diabetes patients?



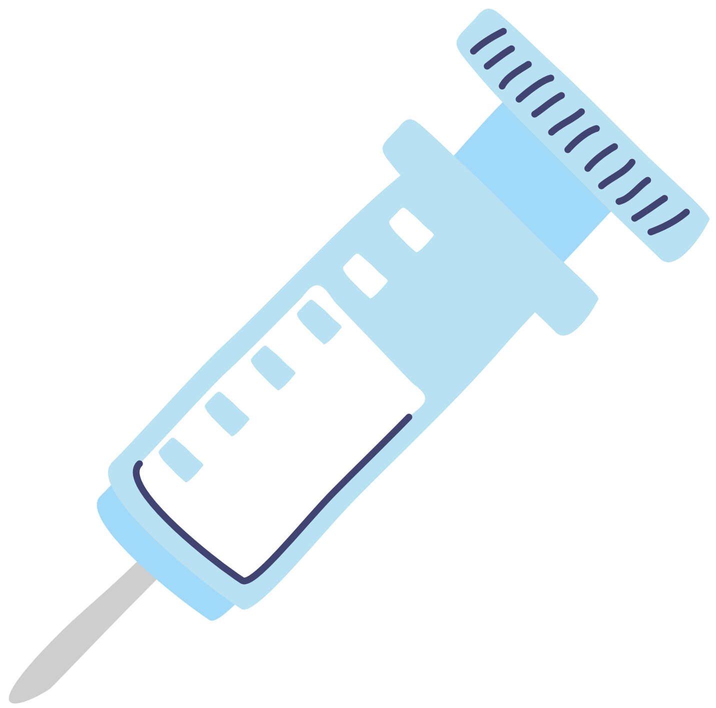
RESEARCH GAP

Limited Personalization

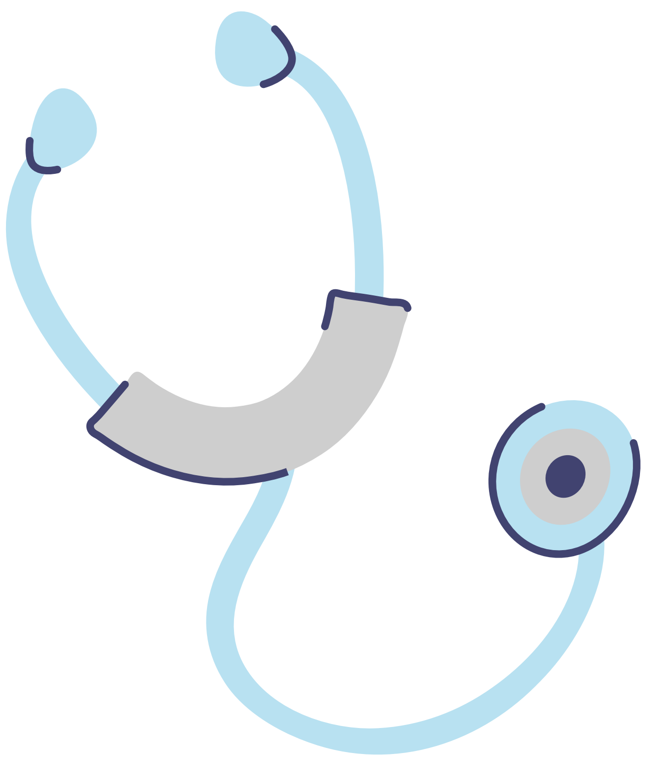
Data Overload Challenges

Side Effect Management

Inadequate Food Tracking Tools



Glycemic Variability Insights



Project Timeline: Gantt Chart

Commercializtion Plan

1. **Target Market & Value Proposition**
   - **Targeting Type 1 & Type 2 diabetes patients, healthcare providers, and clinics.**
   - **Real-time blood glucose prediction, insulin optimization, and personalized care using AI.**
2. **Product Development**
   - **Initial mobile app with cloud-based AI models.**
   - **Future integration with wearables and medical devices.**
3. **Marketing Strategy**
   - **Educational campaigns, social media influencers, and healthcare conferences.**
   - **Targeted advertising to patients and providers.**
4. **Scaling & Expansion**
   - **Strategic partnerships with tech and pharmaceutical companies.**
5. **Customer Support & Engagement**
   - **24/7 support and community building.**

6.Financial Projections

- **Initial Funding: Seek investment through venture capital, crowdfunding, or partnerships with healthcare organizations to fund product development and marketing.**

IT21289798 | GUNAWARDHANA D.H.M.G.

SPECIALIZATION - DATA SCIENCE

PERSONALIZED INSULIN AND MEDICATION PREDICTION WITH PATIENT ENGAGEMENT

INTRODUCTION

This innovative system leverages AI, time-series analysis, and real-time data processing to predict blood glucose levels and optimize insulin dosing, revolutionizing diabetes care. Built with React Native, Python, and Cloud Computing.

RESEARCH PROBLEM

Managing diabetes requires precise blood glucose predictions and insulin dosing. Current methods lack personalization and real-time accuracy, leading to suboptimal care.

RESEARCH SOLUTION

Develop a machine learning-powered system for accurate glucose prediction and insulin optimization using time-series analysis and real-time data, enabling better health outcomes and decision-making.

GUNAWARDHANA D.H.M.G. | IT21289798

RESEARCH GAP

Patient-Centered Design

Limited tools that provide personalized insights tailored to individual patient profiles and conditions.

Data Integration

Lack of systems that effectively combine diverse data sources (e.g., glucose levels, insulin doses, carbohydrate intake, and lifestyle factors).

Decision Support

Insufficient integration of actionable recommendations for healthcare providers and patients to improve treatment decisions.

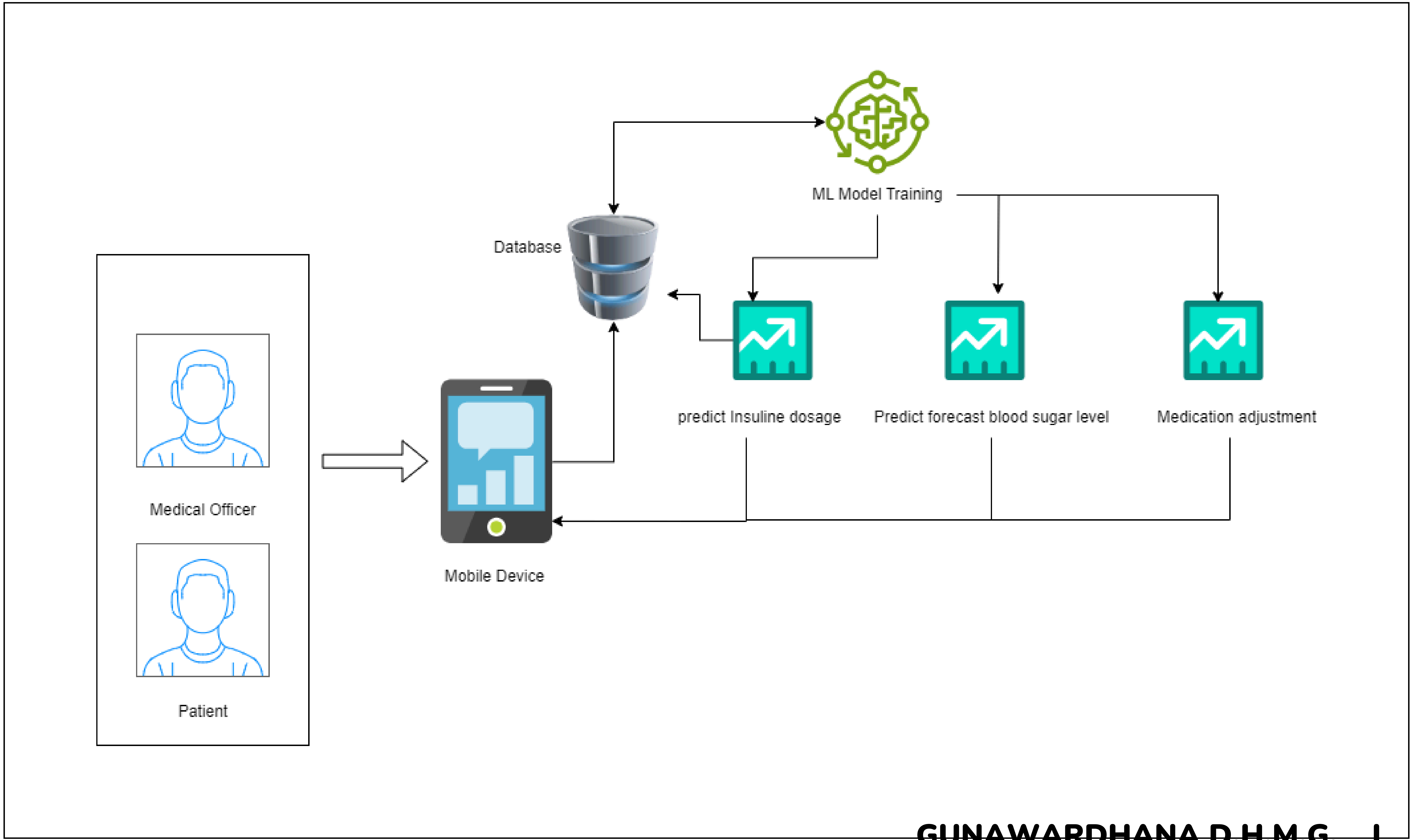
Technological Integration

Underutilization of advanced AI, time-series analysis, and cloud computing for seamless and scalable diabetes care solutions.

DATA SET

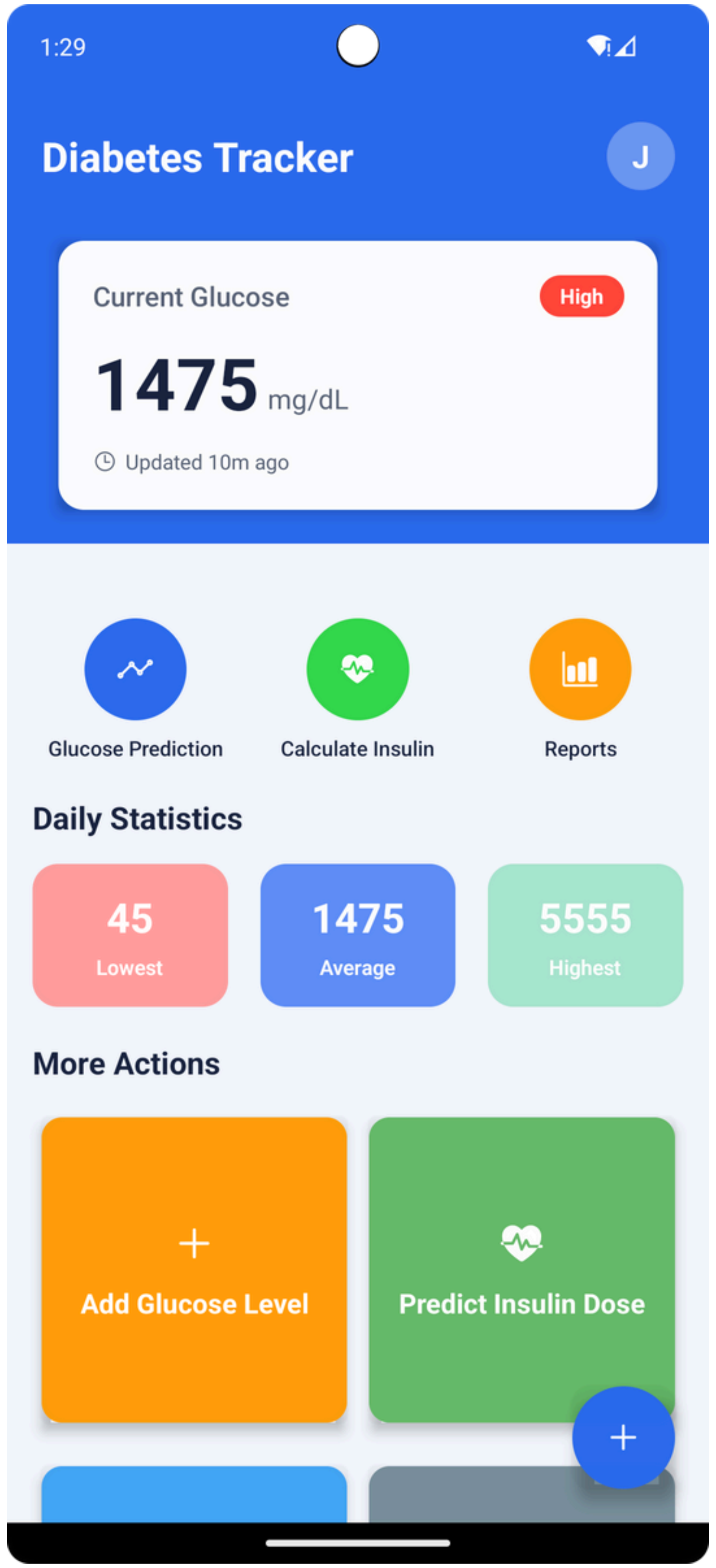
- Size: 269,768 rows and 104 columns
- Key Features:
- Timestamps: Track blood glucose and insulin changes over time.
- Blood Glucose Levels: Real-time glucose readings.
- Insulin Doses: Administered insulin amounts.
- Carbohydrate Intake: Records of carb consumption affecting glucose levels.
- Lag Variables: Previous values (e.g., glucose_lag_1) for predictive analysis.
- Patient Info: Details like weight and insulin type for personalized care.

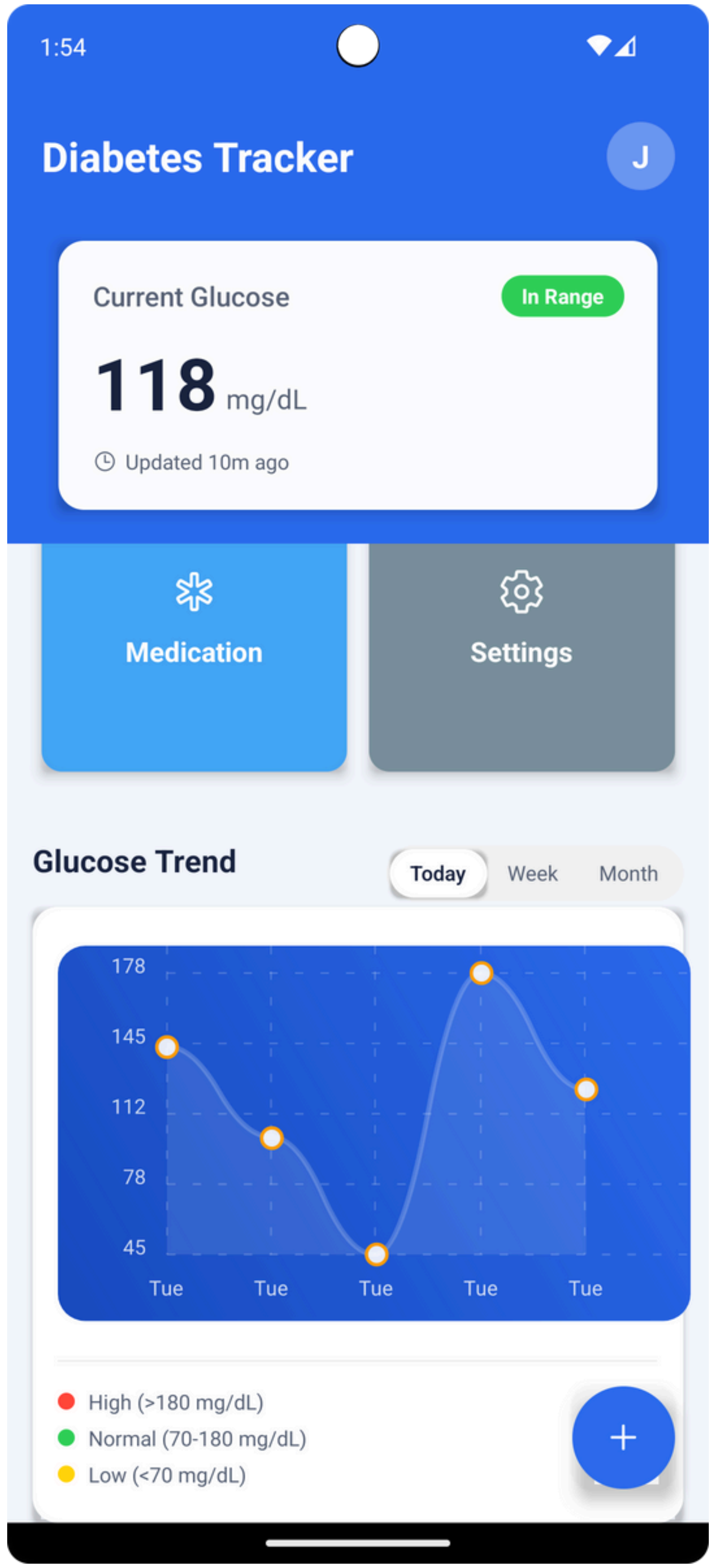
SYSTEM DIAGRAM

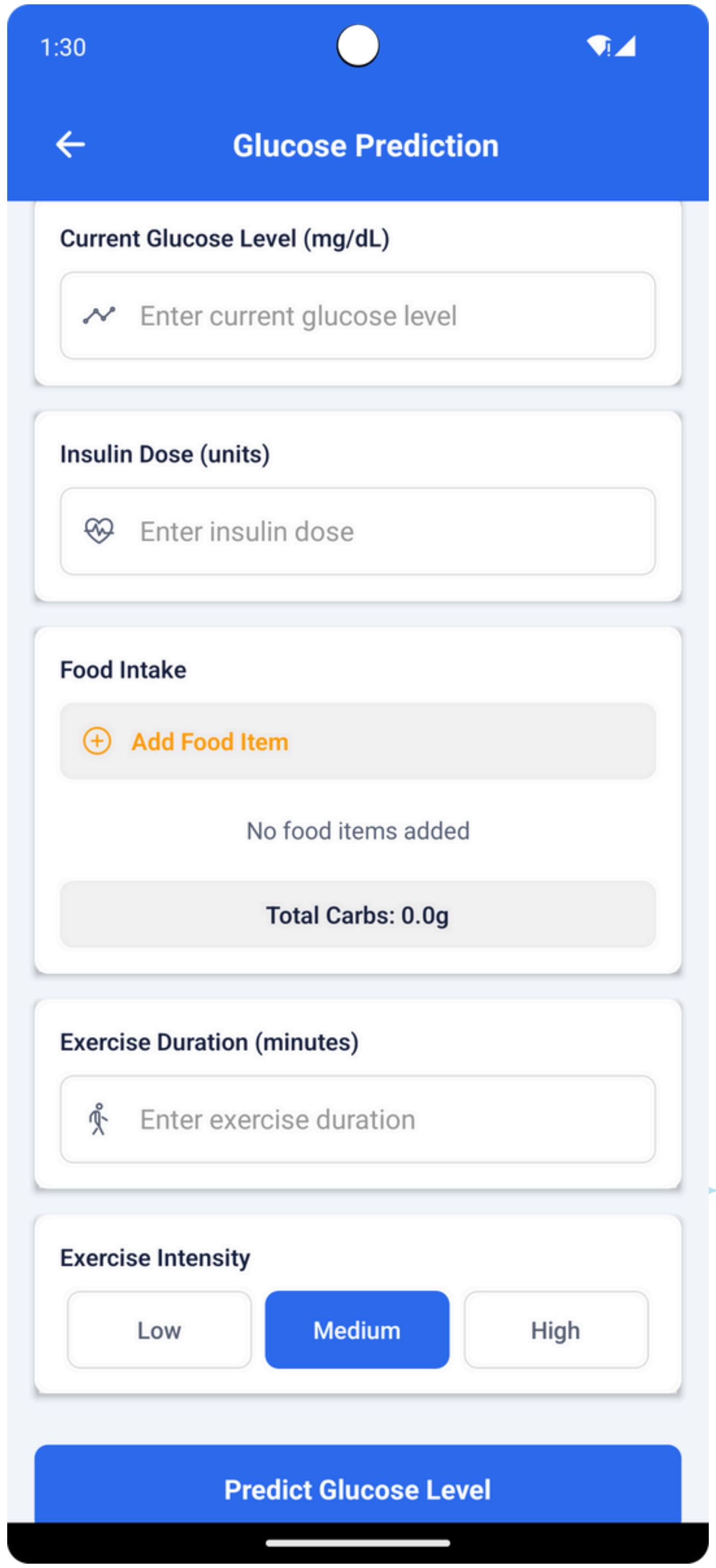


PROOF OF COMPLETION

MOBILE APPLICATION



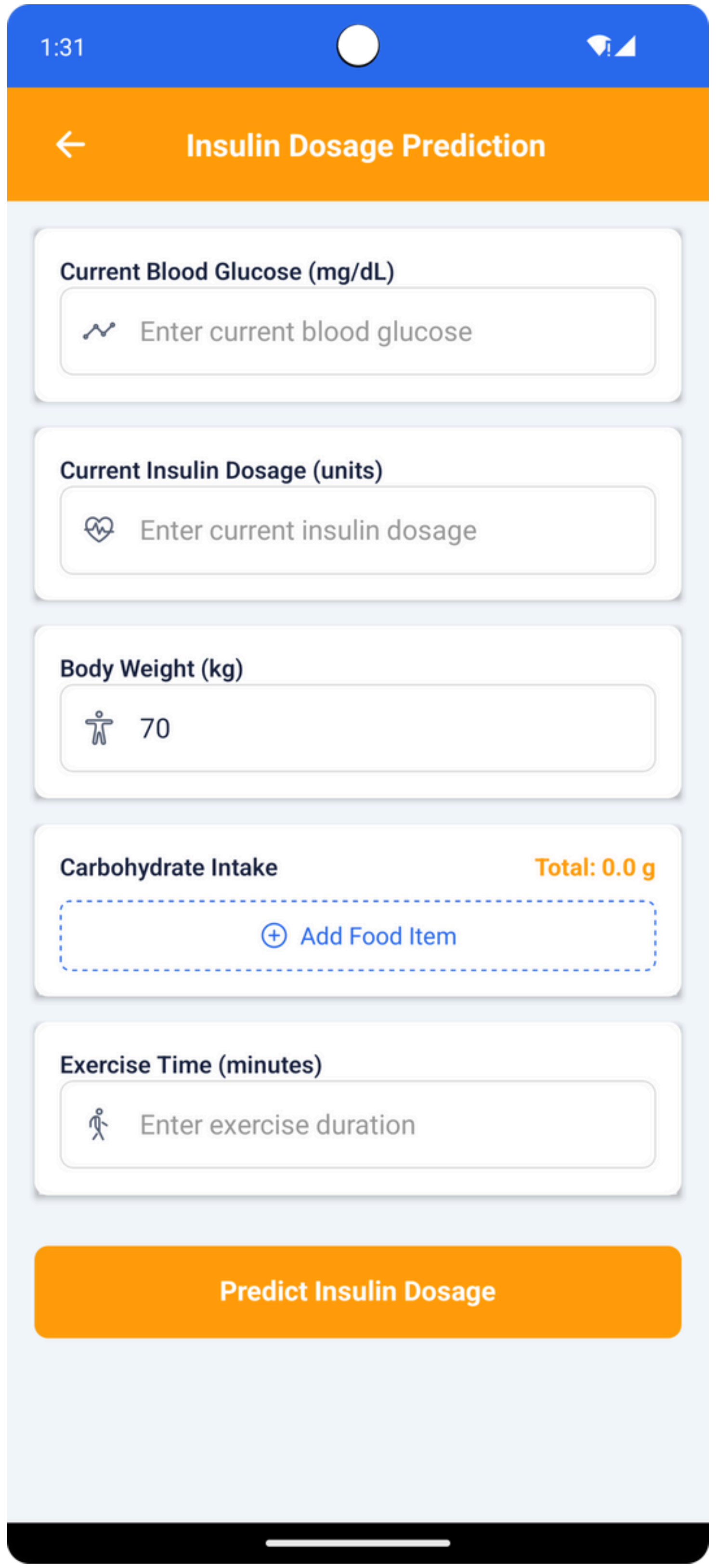


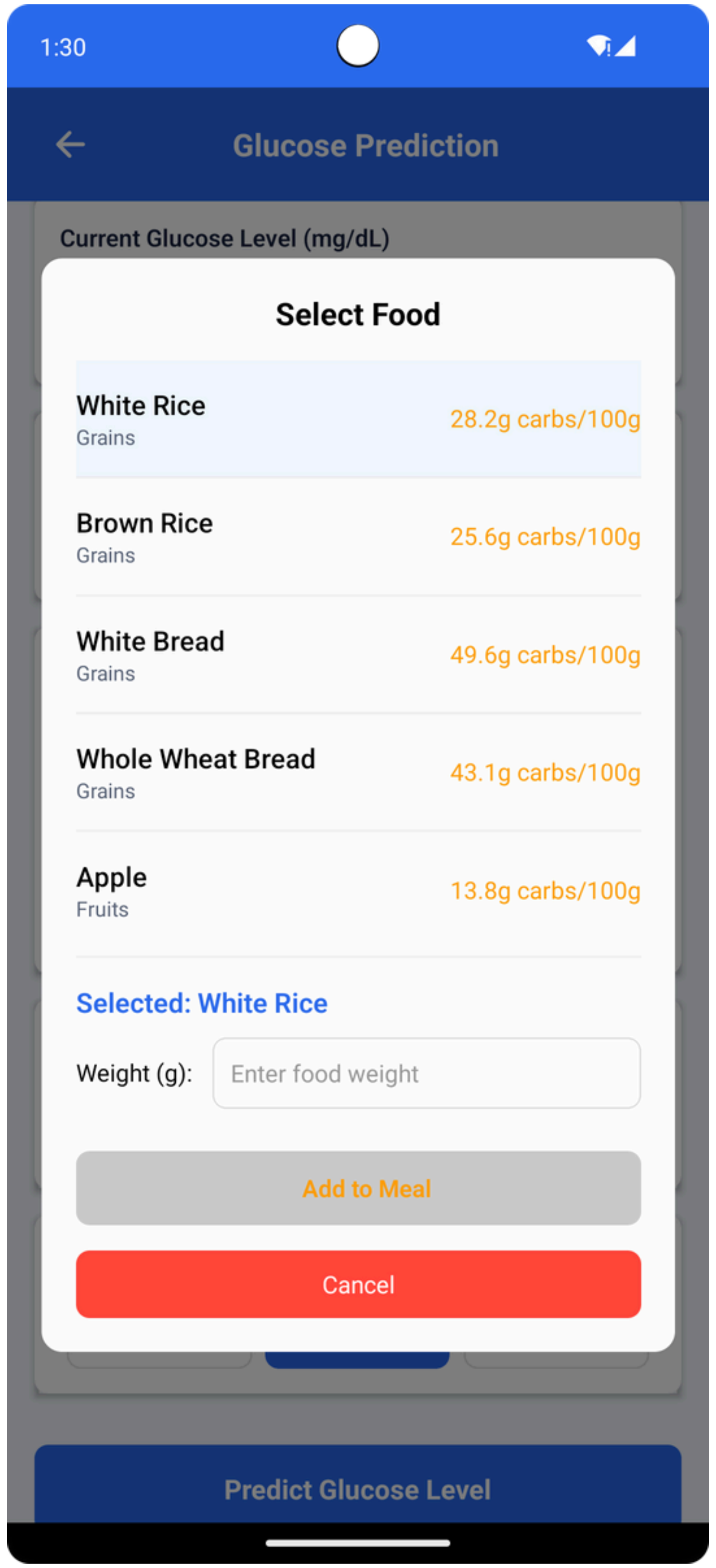


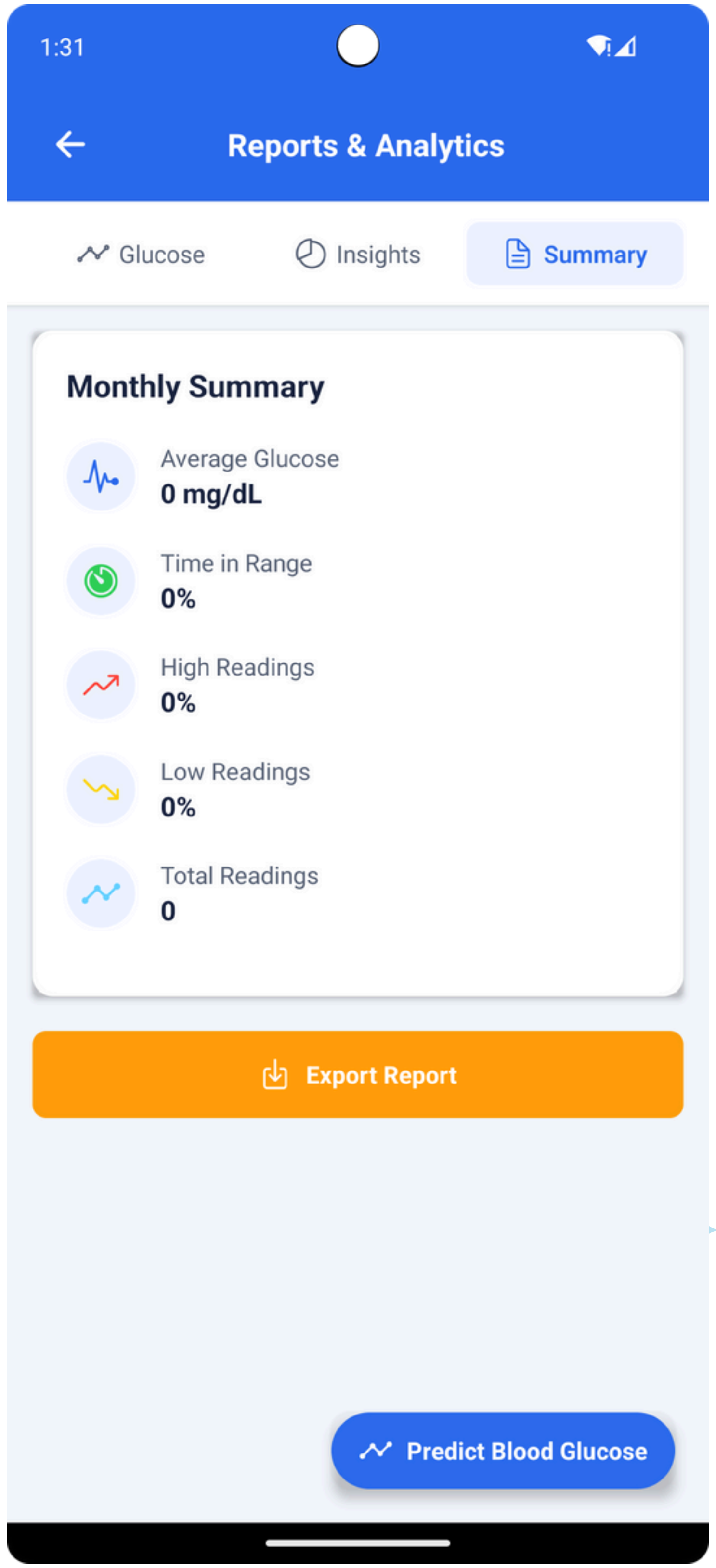
GUNAWARDHANA D.H.M.G. | IT21289798

PROOF OF COMPLETION

MOBILE APPLICATION



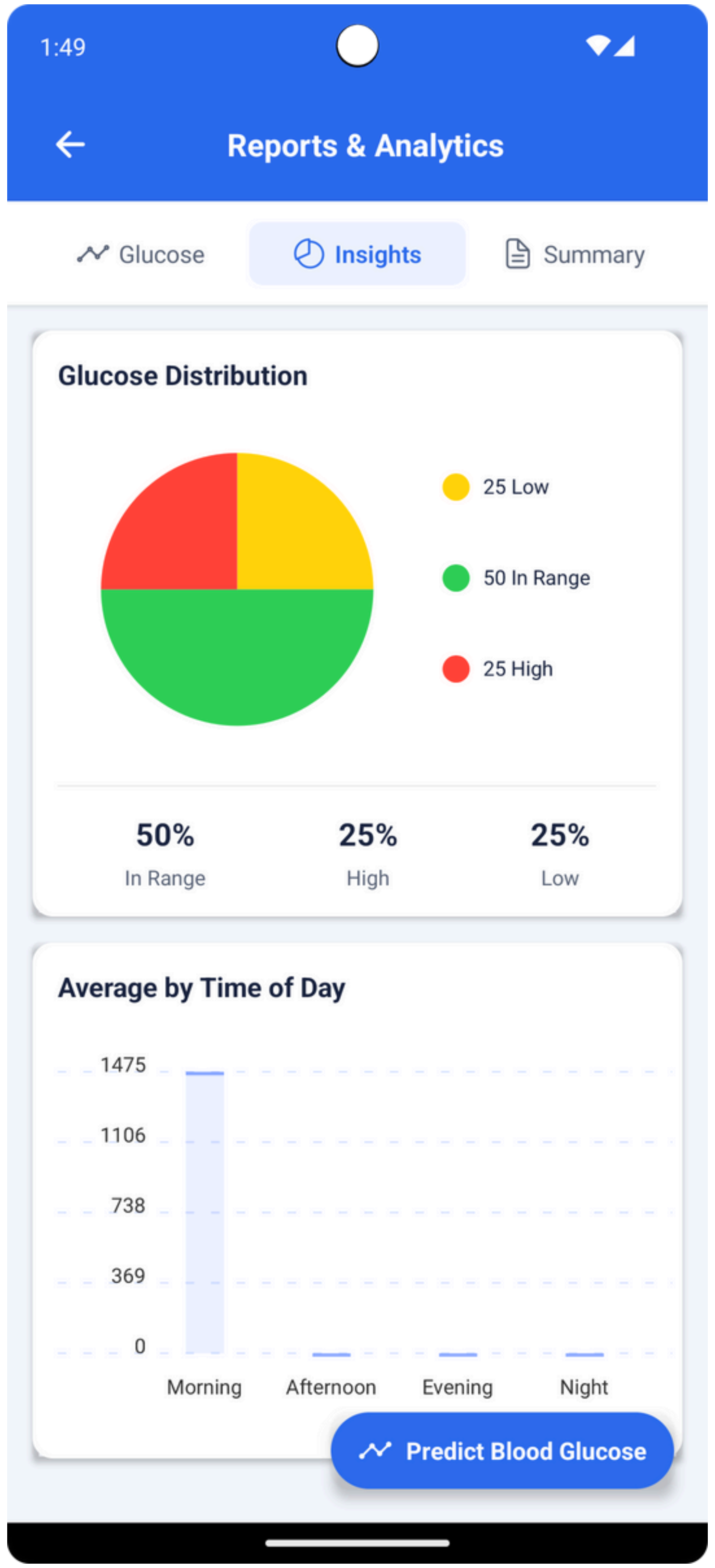


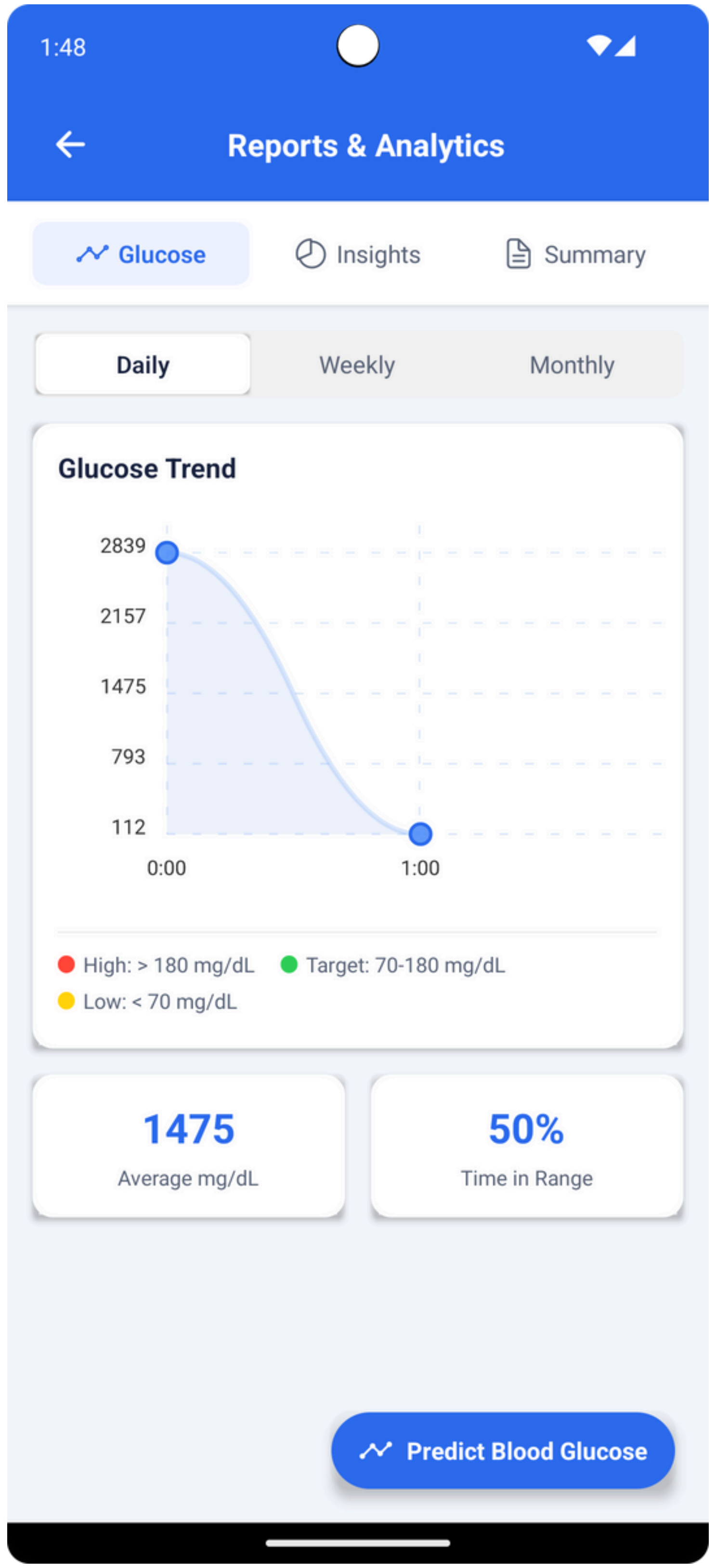


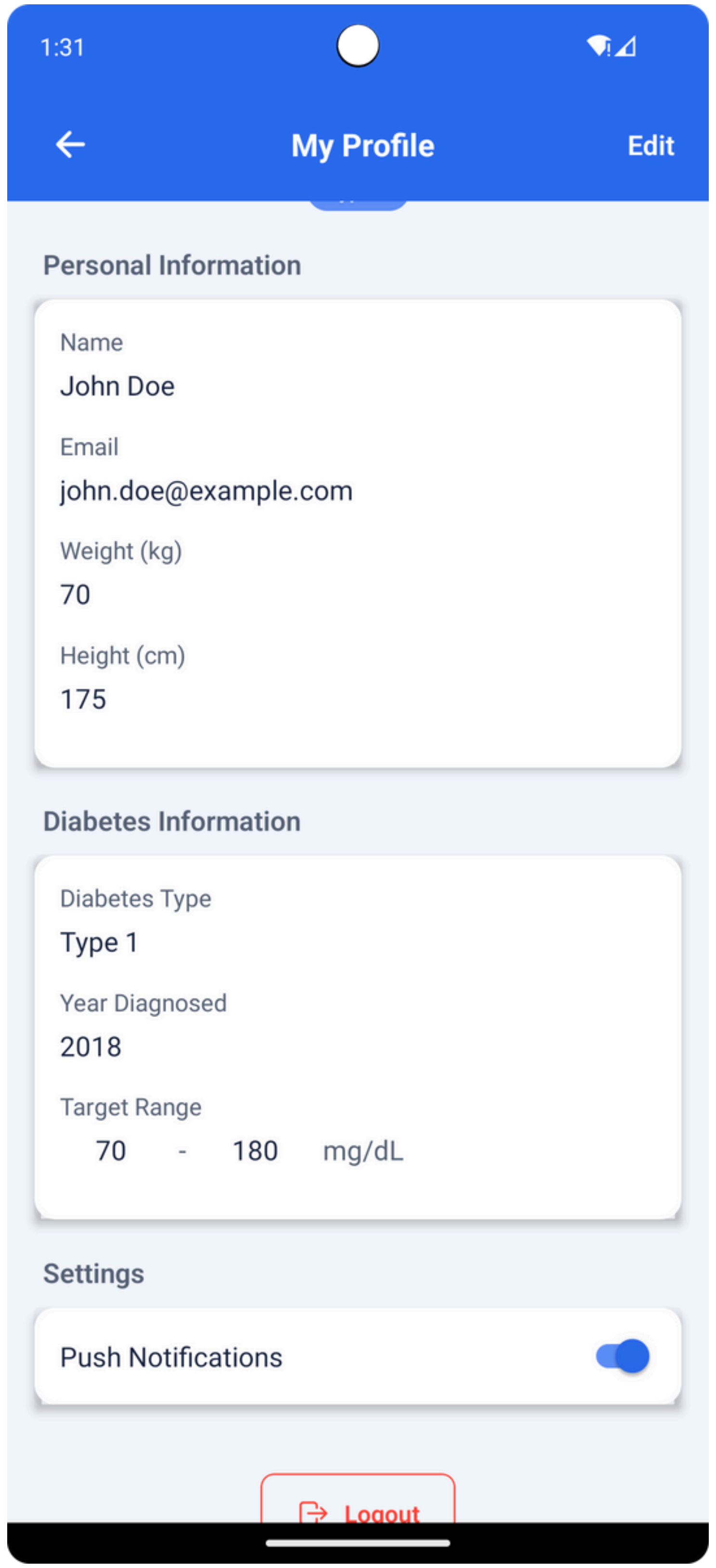
GUNAWARDHANA D.H.M.G. | IT21289798

PROOF OF COMPLETION

MOBILE APPLICATION







GUNAWARDHANA D.H.M.G. | IT21289798

FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS

FUNCTIONAL REQUIREMENTS

- USER MANAGEMENT
- GLUCOSE TRACKING
- INSULIN MANAGEMENT
- CARBOHYDRATE. TRACKING
- ANALYSIS & REPORTING

NON-FUNCTIONAL REQUIREMENTS

- PERFORMANCE & SCALABILITY
- SECURITY & PRIVACY
- AVAILABILITY & RELIABILITY
- USABILITY & ACCESSIBILITY

GUNWARDHANA D.H.M.G. | IT21289798

METHODOLOGY

Frontend
- React Native
- Responsive Design
- Intuitive User Interface

Backend
- Node.js with Express
- RESTful API Design

Database
- MongoDB
- Scalable Data Storage

Feature Engineering
- Time-series analysis
- Contextual feature extraction

Machine Learning Algorithms
- Random Forest
- Gradient Boosting

FUTURE WORKS

Fix Some bugs In frontend

Intergrate Mobile App

REFERENCES

- [1] C. R. Marling and R. C. Bunescu, "The OhioT1DM Dataset for Blood Glucose Level Prediction," Proceedings of the 3rd International Workshop on Knowledge Discovery in Healthcare Data, Stockholm, Sweden, 2018.
- [2] D. R. Zisser, J. E. Jovanovic, and M. D. Laffel, "Clinical Evaluation of a Continuous Glucose Monitoring System for Type 1 Diabetes," Journal of Diabetes Science and Technology, vol. 3, no. 4, pp. 1-8, 2009.
- [3] K. C. Santarcangelo, P. J. Johnson, and C. D. Garcia, "A Machine Learning Approach for Predicting Blood Glucose in Diabetes Management," Journal of Healthcare Engineering, vol. 2019, Article ID 2909471, 2019.
- [4] R. D. P. Haug, M. F. Gubbi, and S. P. George, "Optimizing Insulin Dosing: A Data-Driven Approach," IEEE Transactions on Biomedical Engineering, vol. 68, no. 3, pp. 1-10, Mar. 2021.
- [5] S. R. Basak, S. Ghosh, and A. K. Bhattacharya, "Predictive Models for Diabetes Management: A Review," Journal of Medical Systems, vol. 42, no. 6, pp. 23-45, 2018.
- [6] A. G. Ganaie and M. A. Ziarati, "Real-Time Blood Glucose Monitoring and Prediction using Machine Learning Algorithms," IEEE Access, vol. 8, pp. 150345-150353, 2020.
- [7] P. M. Santos and R. M. Lima, "Cloud-Based Healthcare System for Diabetes Management with AI Integration," Journal of Health Informatics, vol. 28, no. 2, pp. 58-70, 2022.
- [8] L. M. Greenfield, "Integrating Time-Series Data for Predictive Analytics in Healthcare," International Journal of Data Science and Analytics, vol. 5, no. 3, pp. 211-219, 2021.

IT21286032 | KAJEEVAN J

SPECIALIZATION - DATA SCIENCE

REAL-TIME GLYCEMIC EVENT PREDICTION AND MANAGEMENT TOOL.

Introduction

Diabetes is a growing health challenge in Sri Lanka, with prevalence rising to 8.7% and affecting over 1.2 million individuals. Effective management requires continuous monitoring of blood glucose levels to prevent dangerous glycemic events.

➤ **Problem**: Existing healthcare solutions lack real-time predictive capabilities and personalized management options, leading to preventable complications.

➤ **Our solution**: Transforming diabetes care through AI-powered prediction of glycemic events and personalized management tools.

➤ **Implementation progress**: Our initial prototype has evolved into a functional mobile application with 90% of planned features completed, demonstrating the practical application of machine learning for healthcare.

Research Question

How can CGM data and machine learning predict and manage glycemic events in real-time for diabetes patients in Sri Lanka?

What technologies best support real-time glucose monitoring, predictive analytics, and personalized recommendations?

Objectives

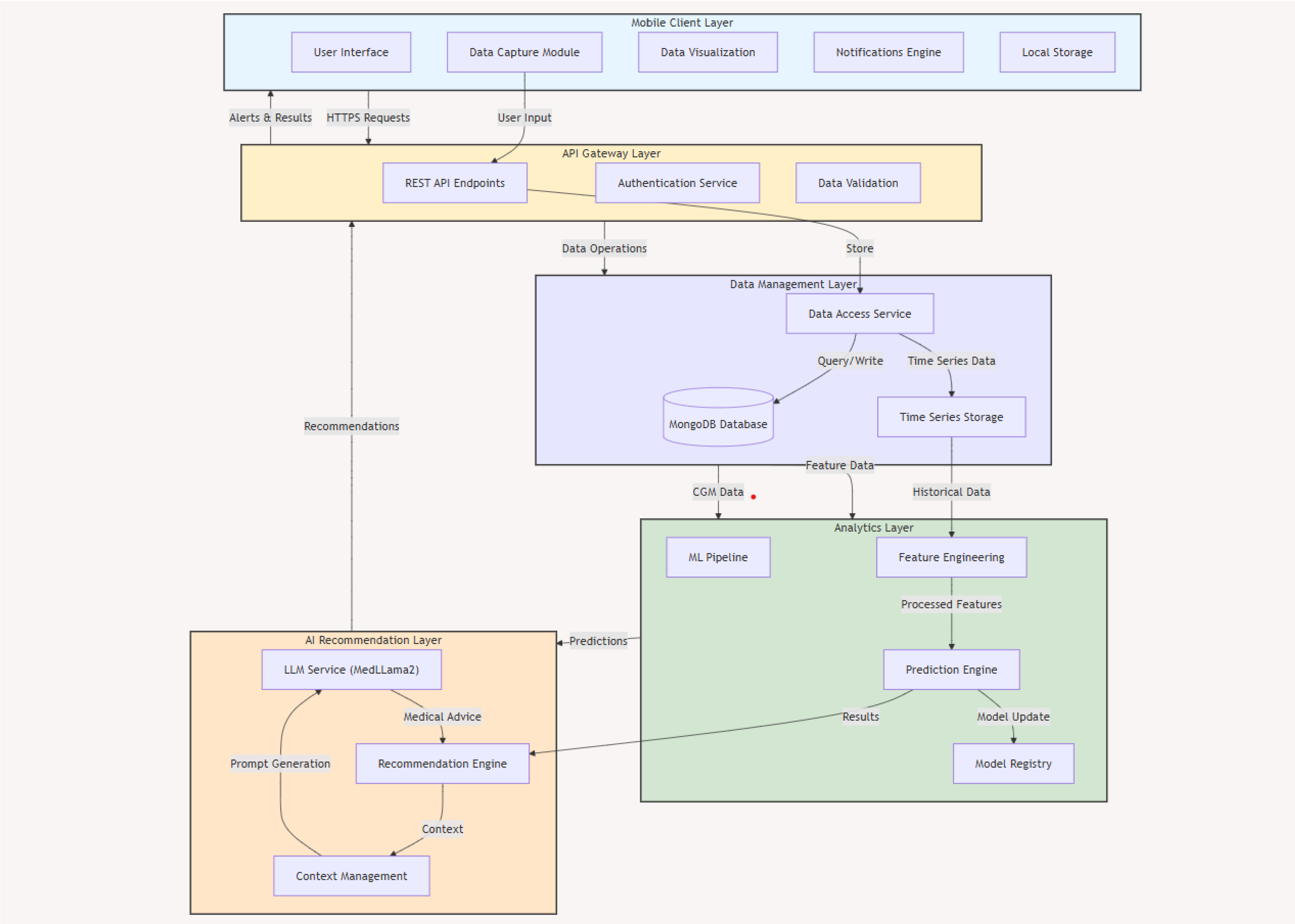
Specific Objectives

- Develop Predictive Algorithms & Management System for Glycemic Events

Sub Objectives

- Integrate CGM data with insulin, activity, and diet.
- Develop predictive models for accurate event forecasting.
- Create a recommendation system for real-time management.

Component Diagram



What I Have Finished:

- Time Series Machine Learning Model
- UI Implementation
- Backend API Services
- MongoDB Integration
- Prediction Engine
- Medlama based Recommendation System

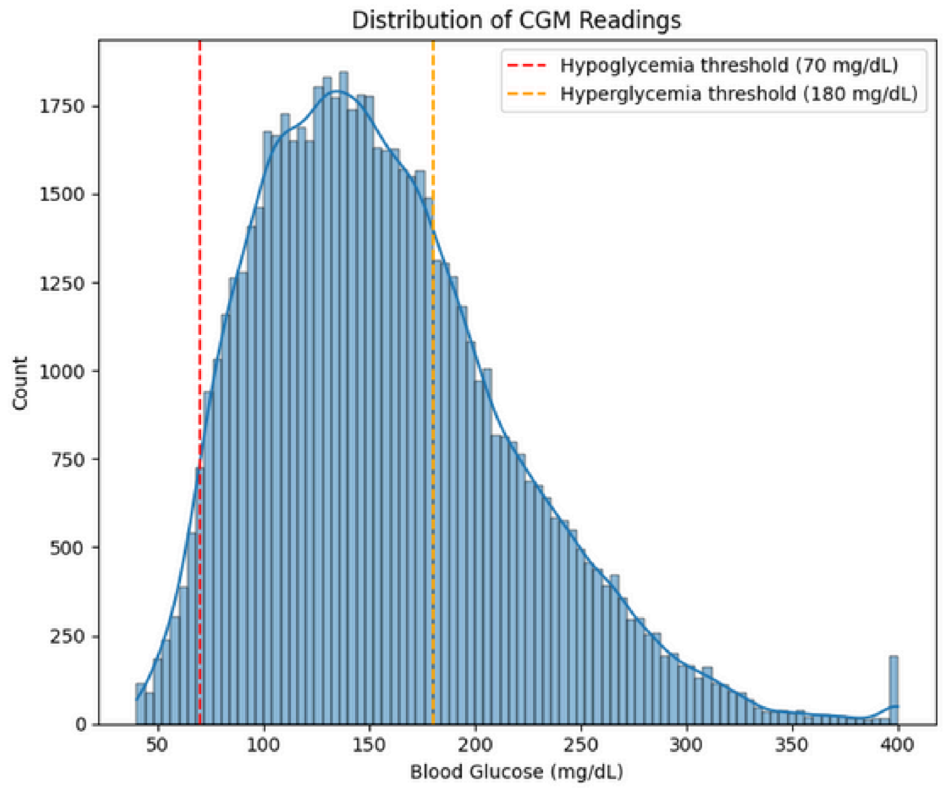
What I Need to Finish:

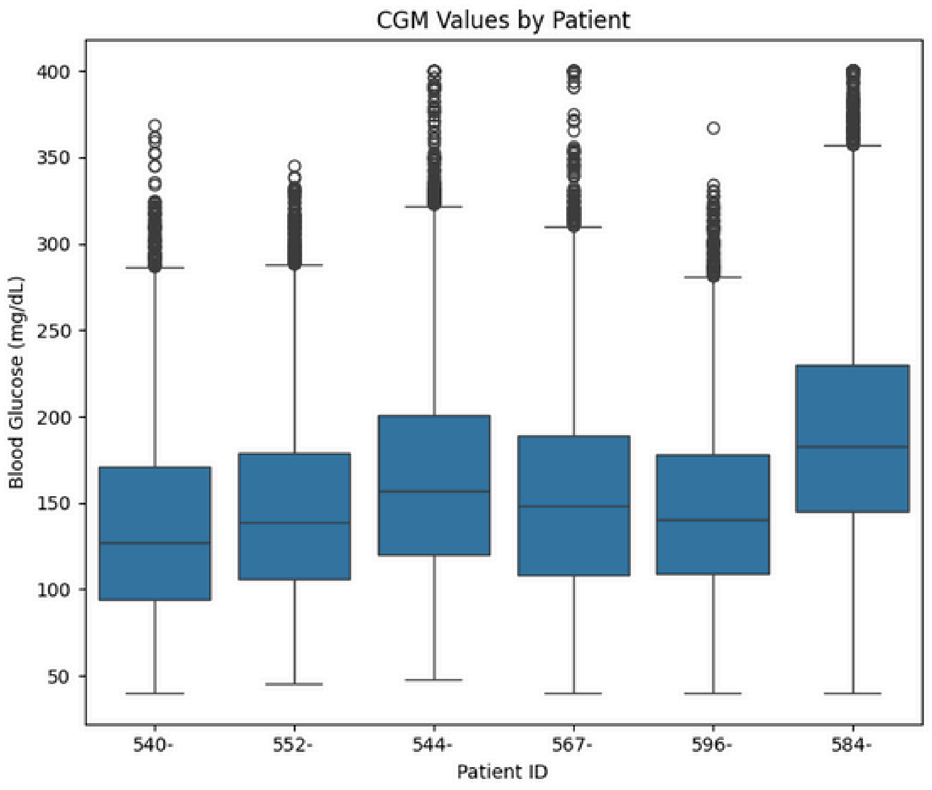
- Real-Time CGM Device Integration
- Kubernetes Deployment
- HIPAA-Compliant Security Implementation

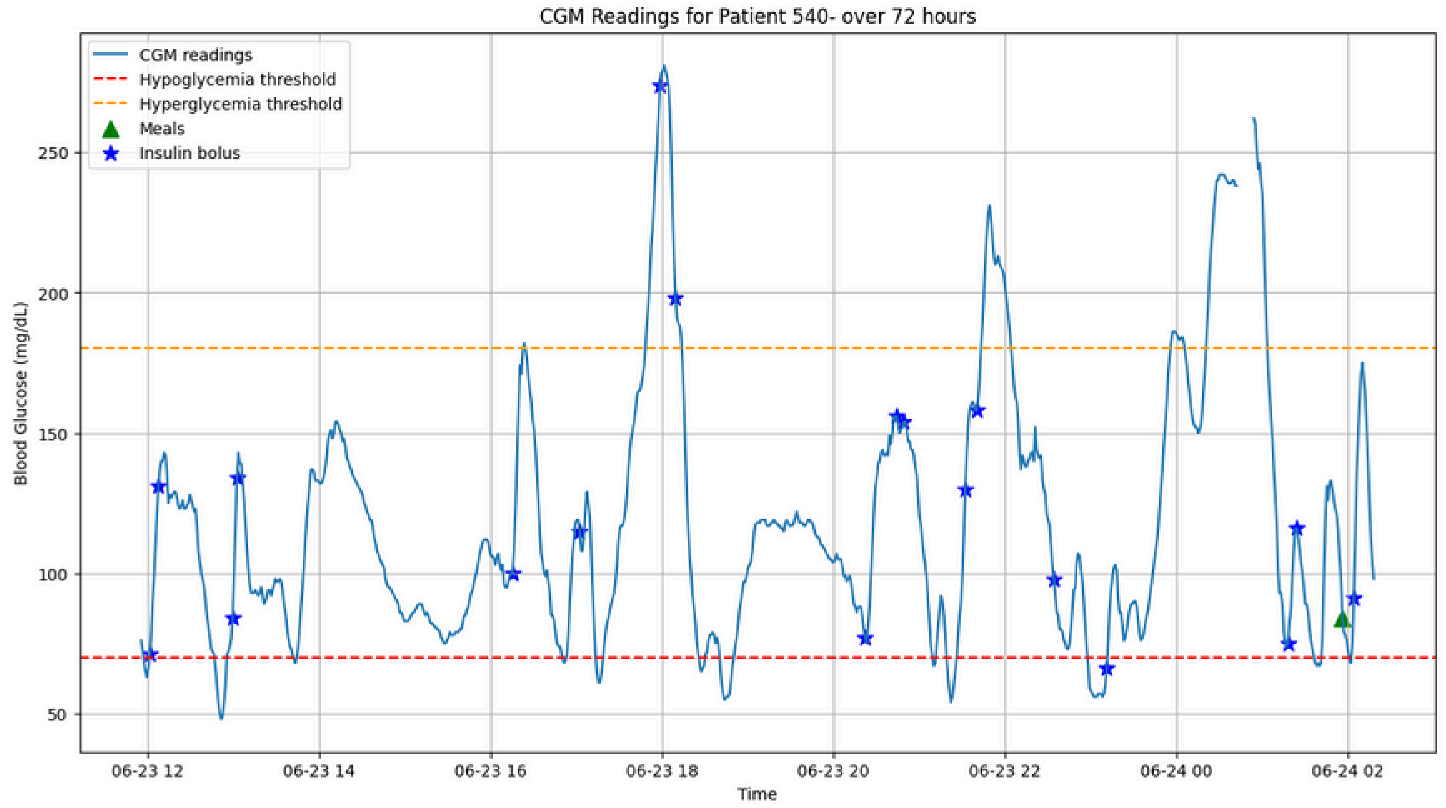
Technologies

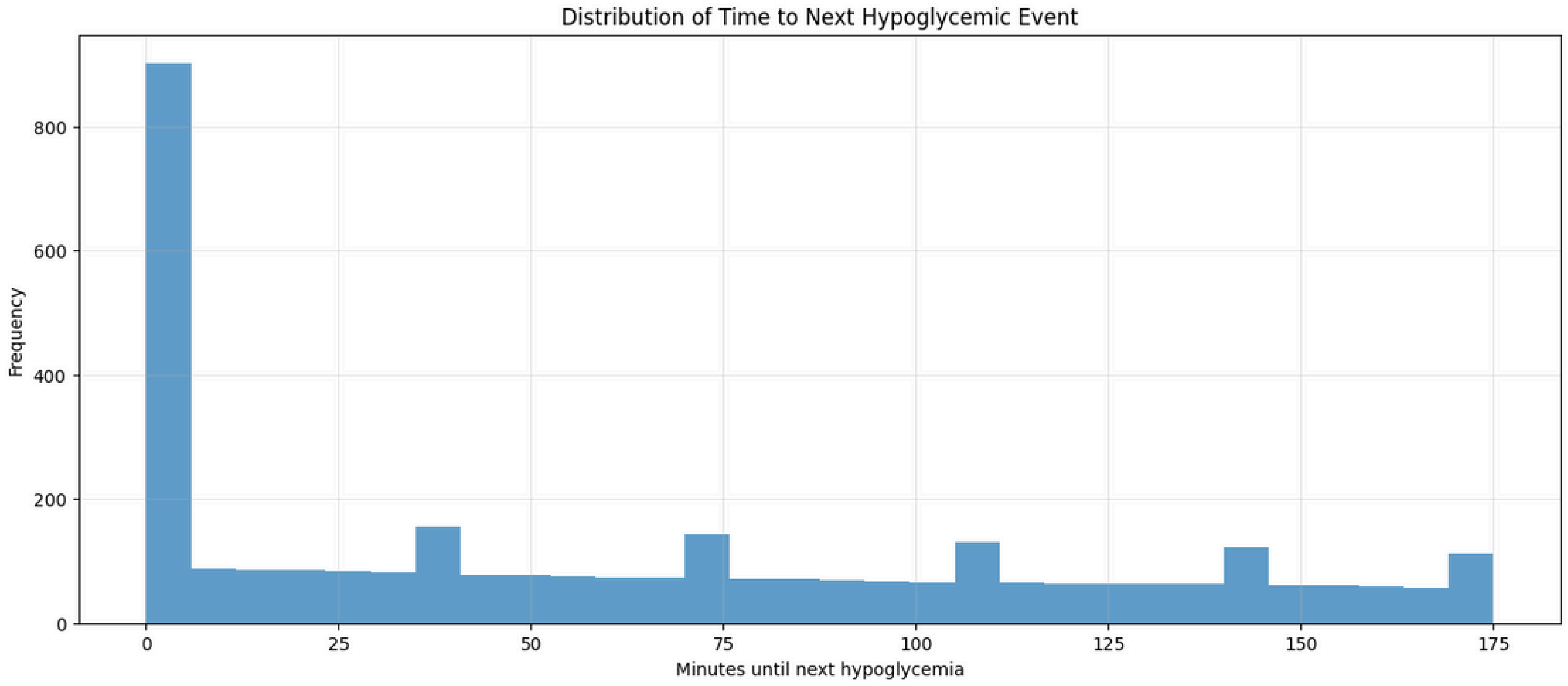
- Backend: Python with Flask APIs, MongoDB for data storage
- Frontend: React Native with Expo Router
- Machine Learning: Keras with TensorFlow (GRU for time series prediction)
- AI Recommendation: MedLLama2 on Ollama for medical advice
- Data Integration: CGM devices, fitness bands (via APIs)
- Deployment: Kubernetes for scalability and reliability
- Security: OAuth2, data encryption, HIPAA compliance measures
- Analytics: Time-series data processing pipelin

Proof Of Completion- EDA





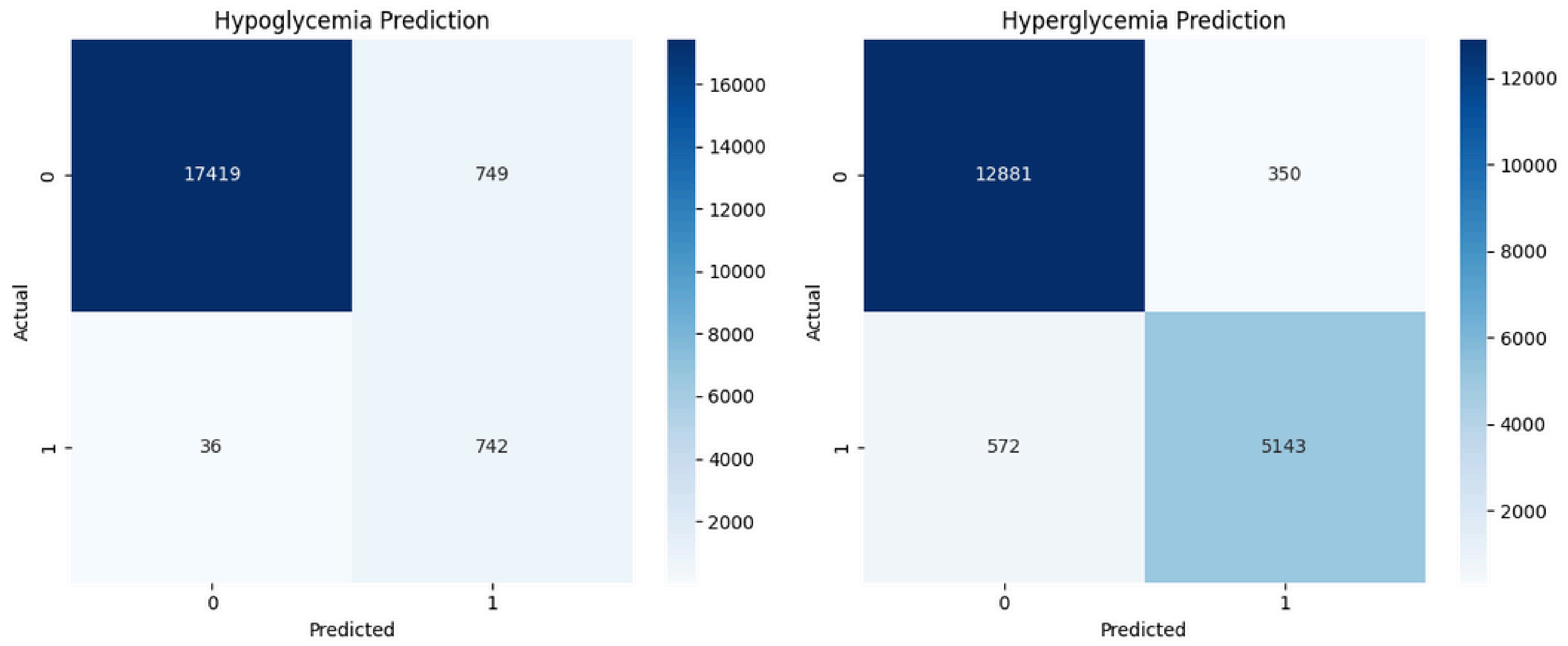




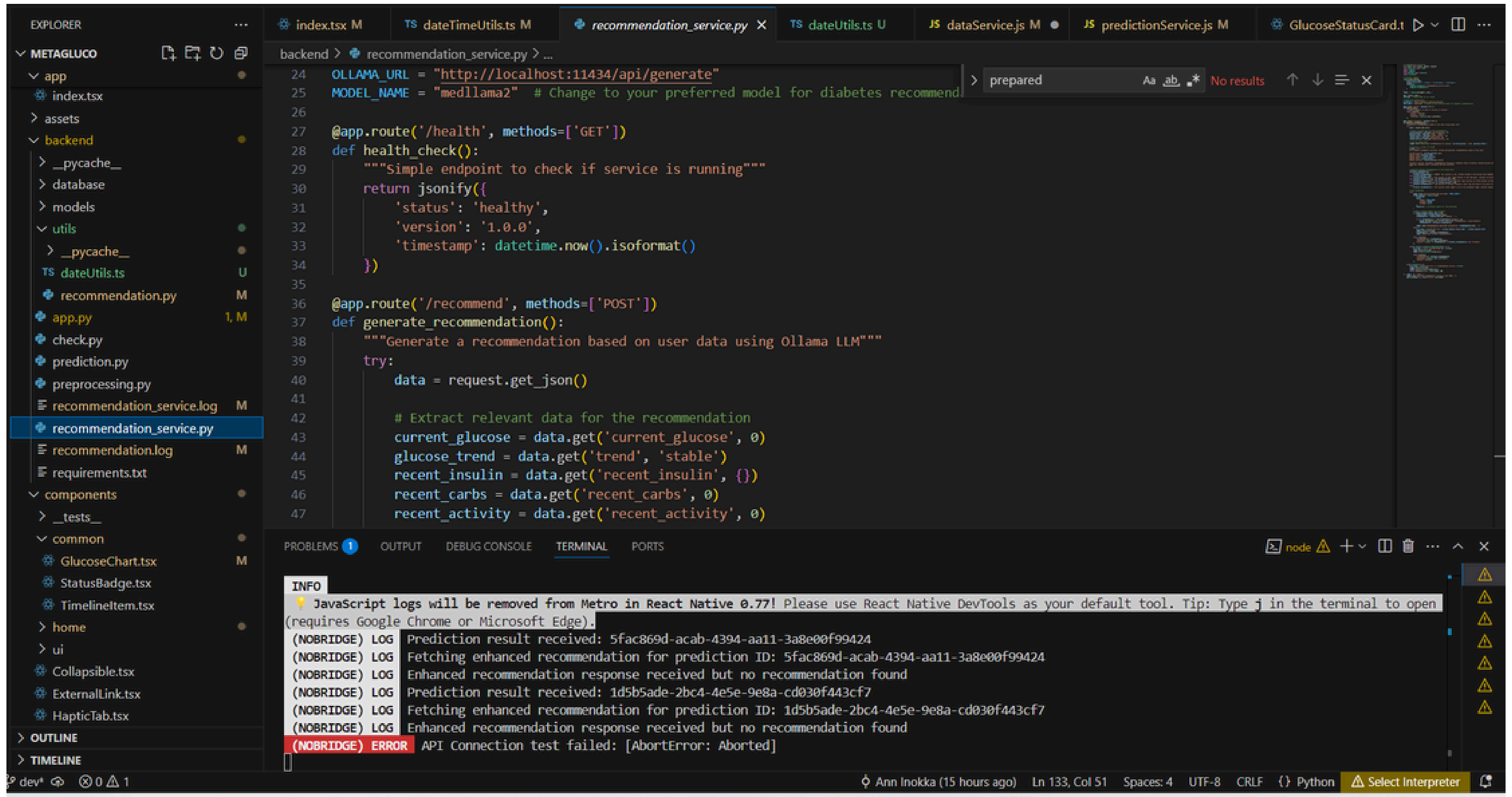
Proof Of Completion

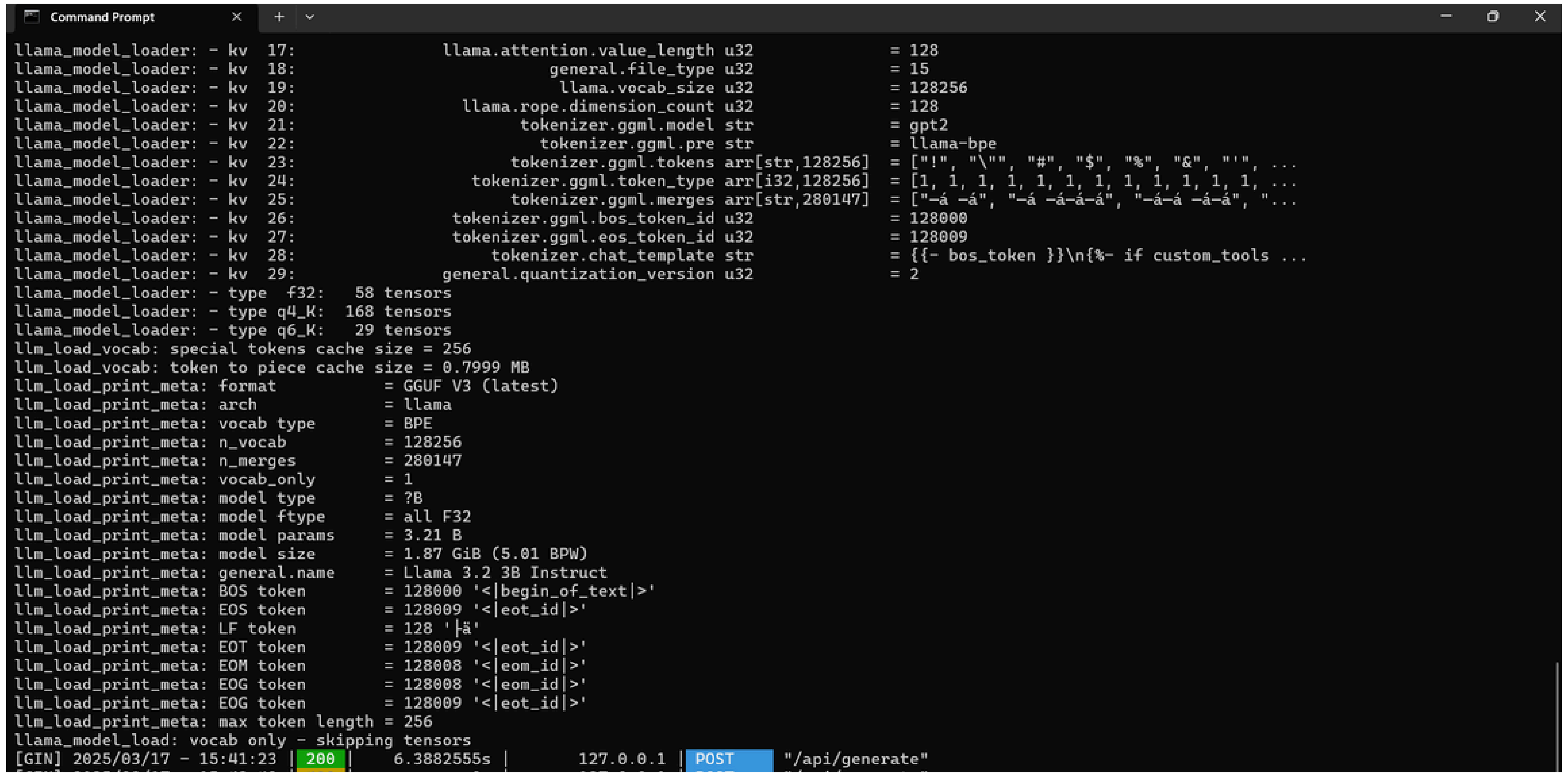
Model Training

```
3685/3685 ━━━━━━━━━━━━━━━━━━━━ 82s 16ms/step - loss: 0.0506 - mae: 0.0663 - val_loss: 0.2106 - val_mae: 0.1233
Epoch 10/50
3685/3685 ━━━━━━━━━━━━━━━━━━━━ 80s 15ms/step - loss: 0.0487 - mae: 0.0649 - val_loss: 0.2096 - val_mae: 0.1224
Epoch 11/50
3685/3685 ━━━━━━━━━━━━━━━━━━━━ 59s 16ms/step - loss: 0.0464 - mae: 0.0635 - val_loss: 0.2229 - val_mae: 0.1281
Epoch 12/50
3685/3685 ━━━━━━━━━━━━━━━━━━━━ 80s 15ms/step - loss: 0.0445 - mae: 0.0624 - val_loss: 0.2303 - val_mae: 0.1300
Epoch 13/50
3685/3685 ━━━━━━━━━━━━━━━━━━━━ 83s 16ms/step - loss: 0.0427 - mae: 0.0614 - val_loss: 0.2303 - val_mae: 0.1267
Evaluating model...
593/593 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step

Hypoglycemia Prediction Performance:
              precision    recall  f1-score   support

           0       1.00      0.96      0.98     18168
           1       0.50      0.95      0.65       778

    accuracy                           0.96     18946
   macro avg       0.75      0.96      0.82     18946
weighted avg       0.98      0.96      0.96     18946


Hyperglycemia Prediction Performance:
              precision    recall  f1-score   support

           0       0.96      0.97      0.97     13231
           1       0.94      0.90      0.92      5715

    accuracy                           0.95     18946
   macro avg       0.95      0.94      0.94     18946
weighted avg       0.95      0.95      0.95     18946
```

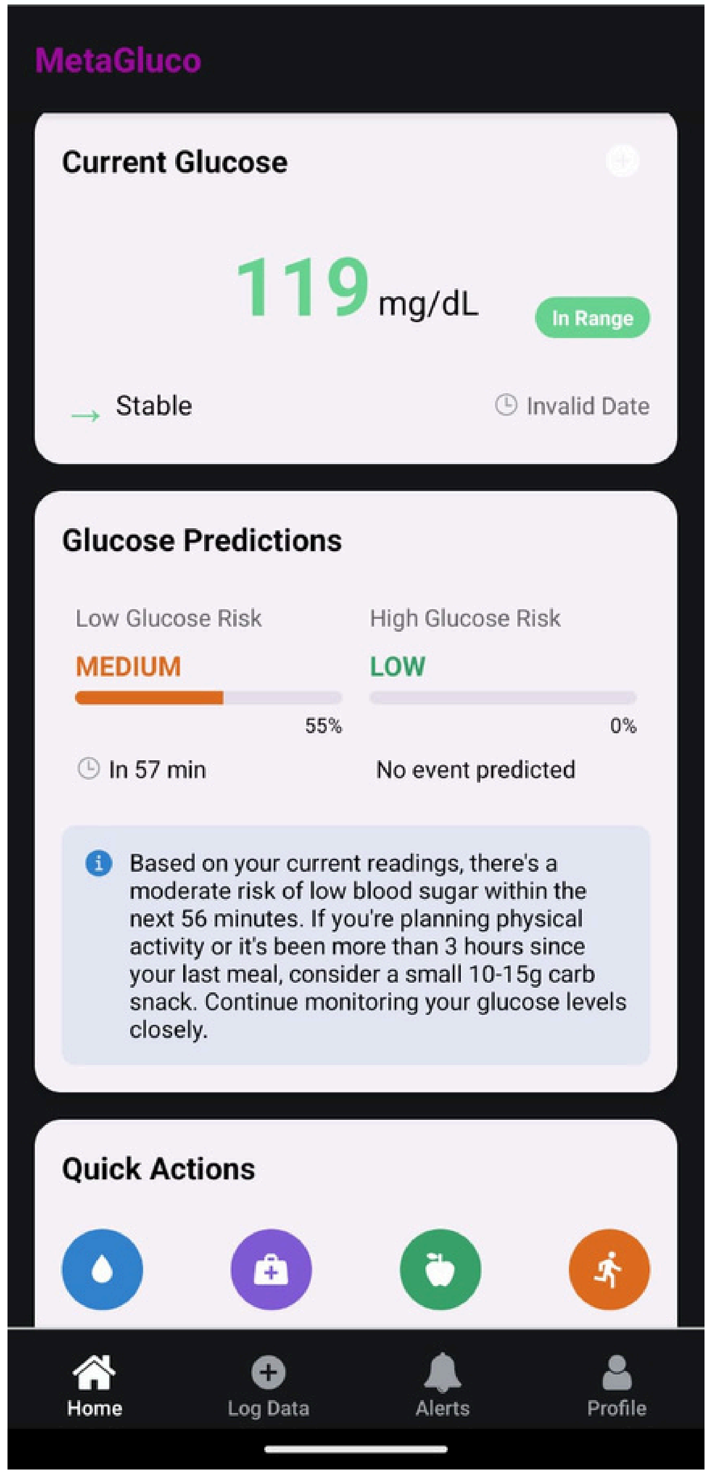


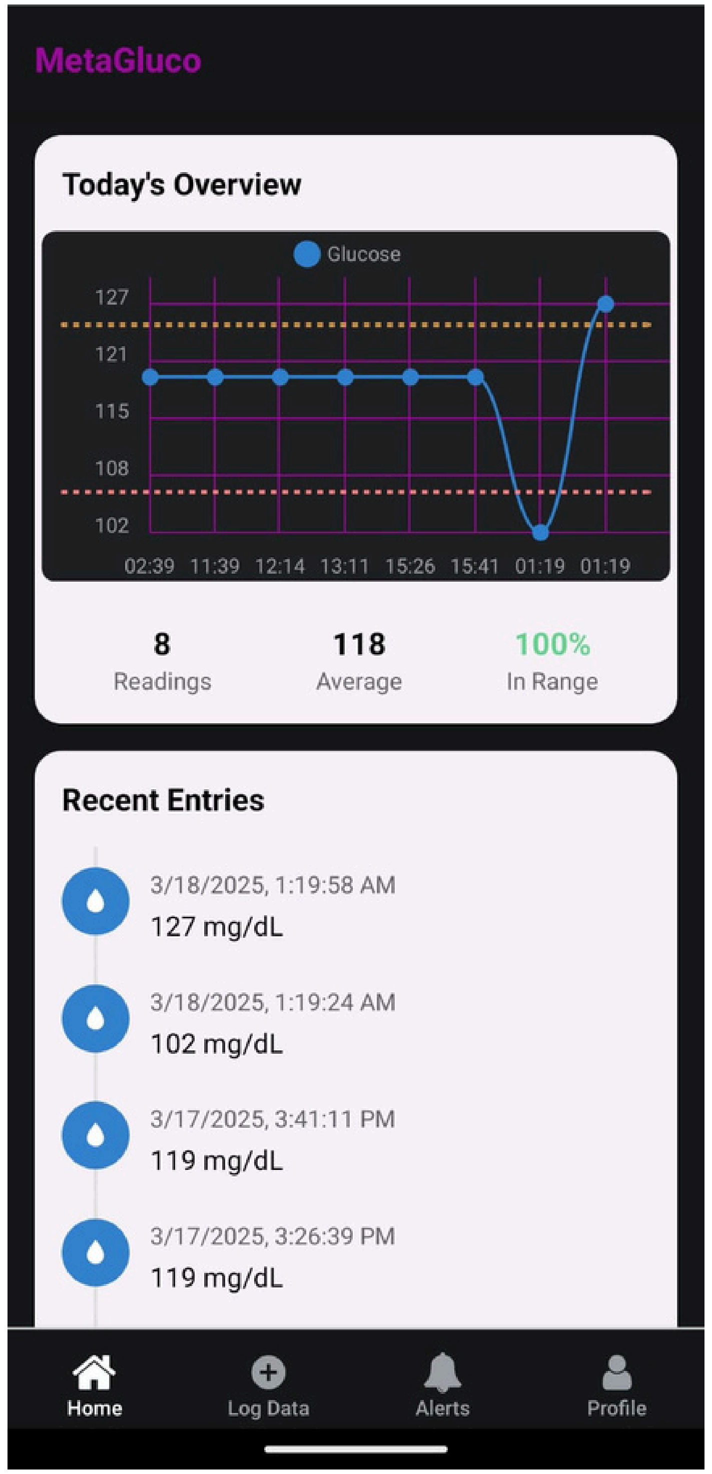
Medllama2 Implementation

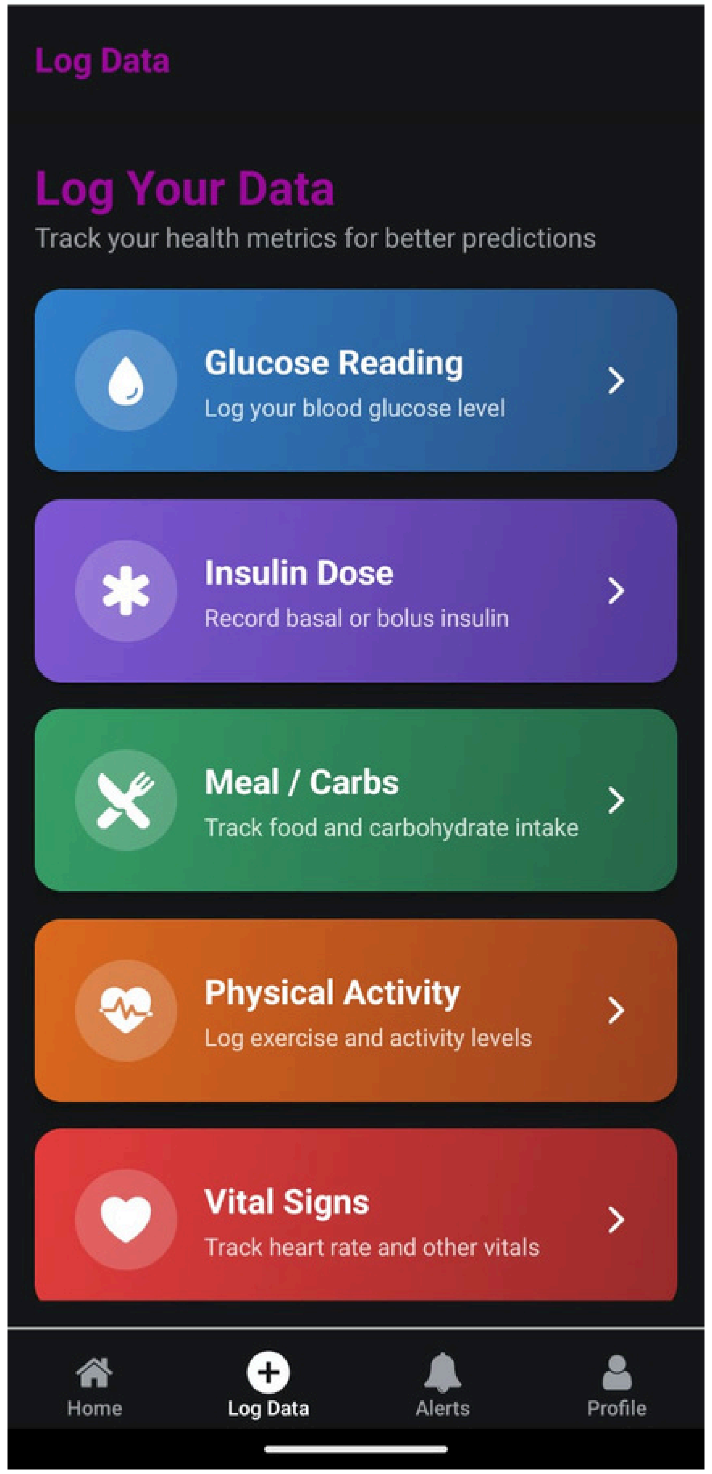




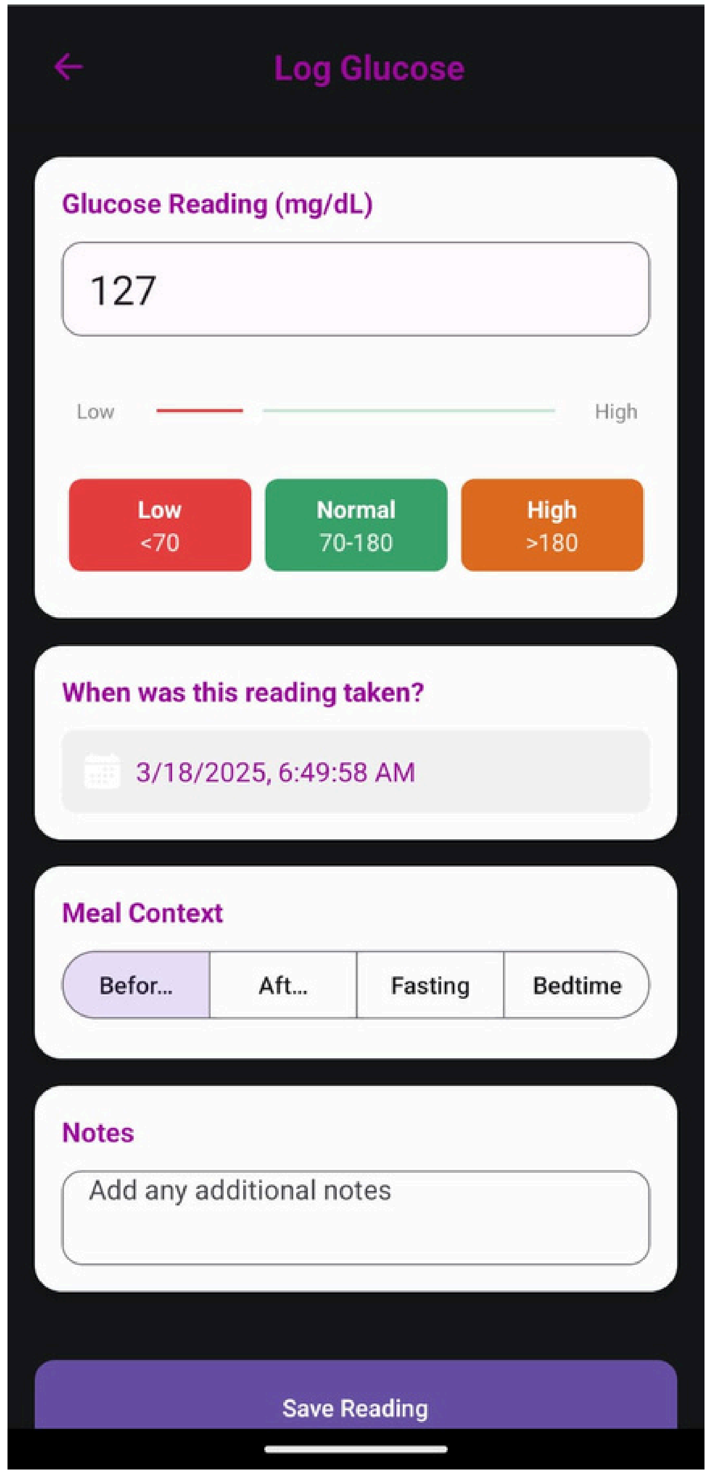
Frontend

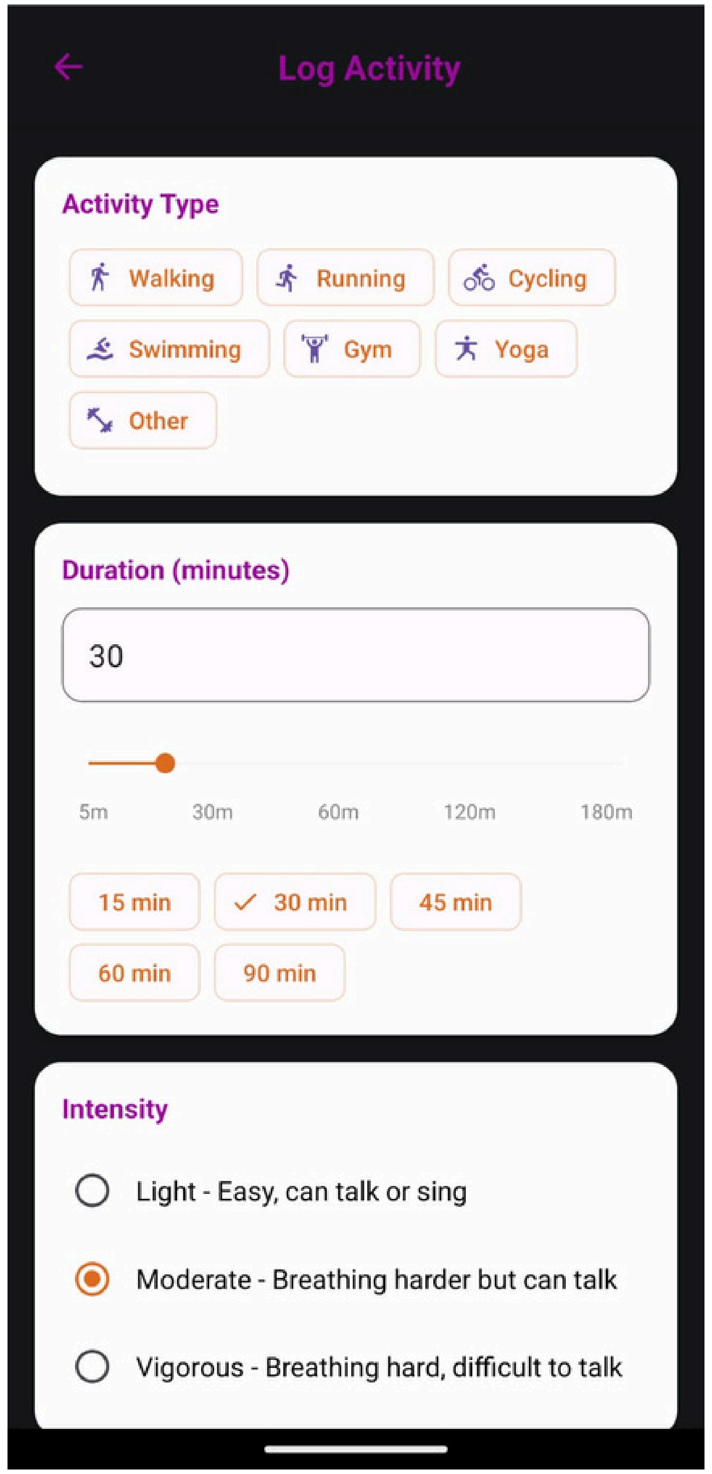

MetaGluco
Current Glucose
119 mg/dL
In Range
Stable
Invalid Date
Glucose Predictions
Low Glucose Risk
MEDIUM
55%
In 57 min
High Glucose Risk
LOW
0%
No event predicted
Based on your current readings, there's a moderate risk of low blood sugar within the next 56 minutes. If you're planning physical activity or it's been more than 3 hours since your last meal, consider a small 10-15g carb snack. Continue monitoring your glucose levels closely.
Quick Actions
Home
Log Data
Alerts
Profile

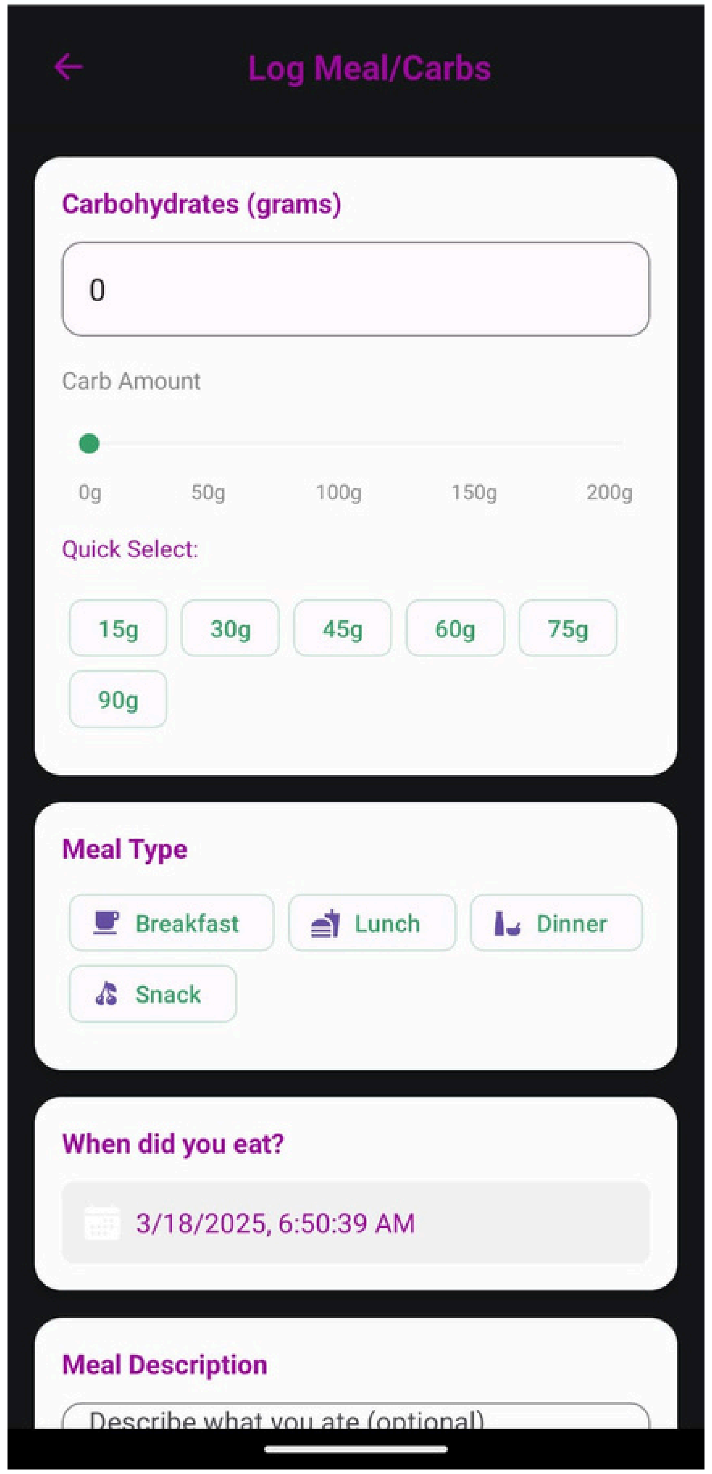

MetaGluco
Today's Overview
Glucose
127
121
115
108
102
02:39
11:39
12:14
13:11
15:26
15:41
01:19
01:19
8
Readings
118
Average
100%
In Range
Recent Entries
3/18/2025, 1:19:58 AM
127 mg/dL
3/18/2025, 1:19:24 AM
102 mg/dL
3/17/2025, 3:41:11 PM
119 mg/dL
3/17/2025, 3:26:39 PM
119 mg/dL
Home
Log Data
Alerts
Profile

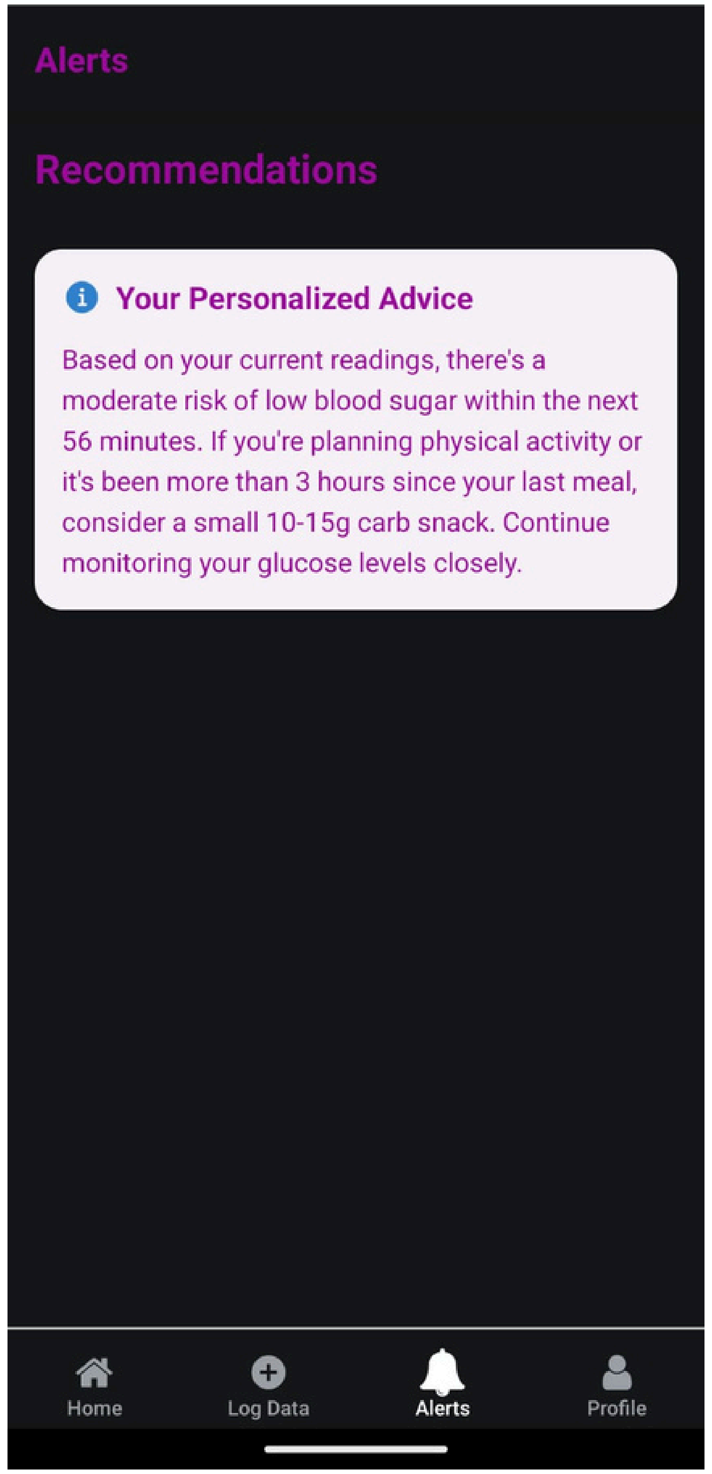

Log Data
Log Your Data
Track your health metrics for better predictions
Glucose Reading
Log your blood glucose level
Insulin Dose
Record basal or bolus insulin
Meal / Carbs
Track food and carbohydrate intake
Physical Activity
Log exercise and activity levels
Vital Signs
Track heart rate and other vitals
Home
Log Data
Alerts
Profile

Frontend

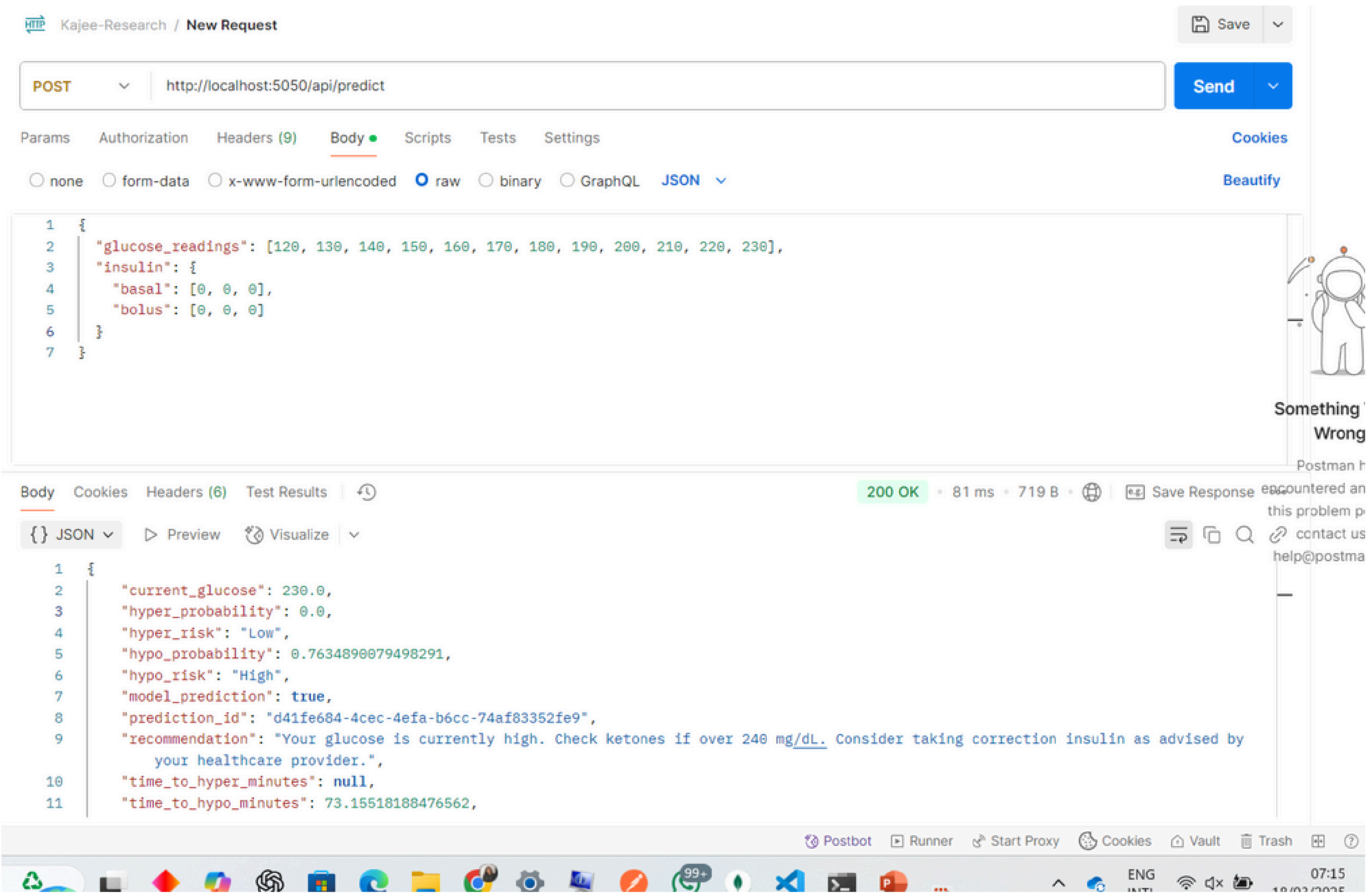

Log Glucose
Glucose Reading (mg/dL)
127
Low
High
Low <70
Normal 70-180
High >180
When was this reading taken?
3/18/2025, 6:49:58 AM
Meal Context
Befor...
Aft...
Fasting
Bedtime
Notes
Add any additional notes
Save Reading

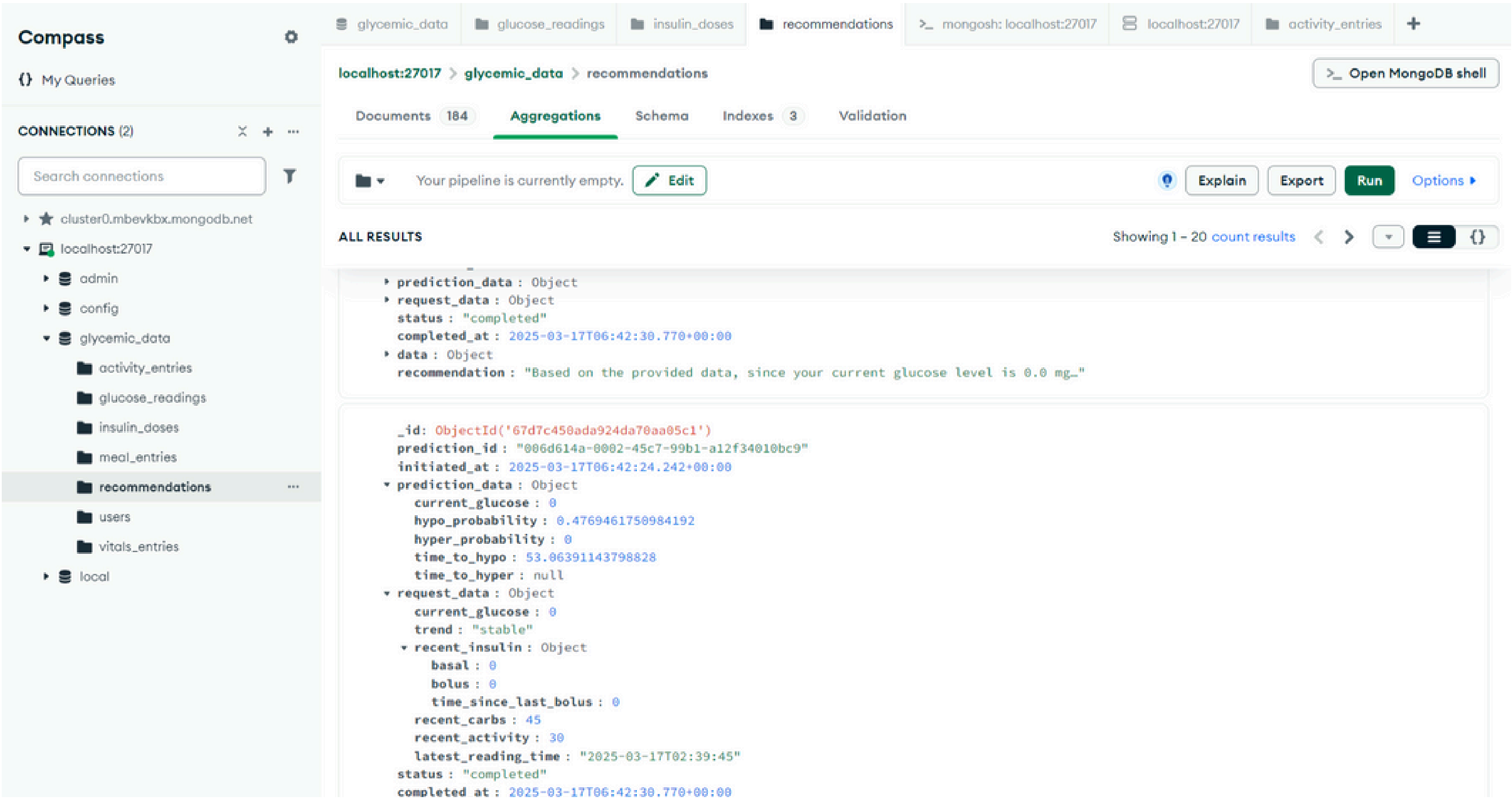

Log Activity
Activity Type
Walking
Running
Cycling
Swimming
Gym
Yoga
Other
Duration (minutes)
30
5m
30m
60m
120m
180m
15 min
30 min
45 min
60 min
90 min
Intensity
Light - Easy, can talk or sing
Moderate - Breathing harder but can talk
Vigorous - Breathing hard, difficult to talk


Log Meal/Carbs
Carbohydrates (grams)
0
Carb Amount
0g
50g
100g
150g
200g
Quick Select:
15g
30g
45g
60g
75g
90g
Meal Type
Breakfast
Lunch
Dinner
Snack
When did you eat?
3/18/2025, 6:50:39 AM
Meal Description
Describe what you ate (optional)


Alerts
Recommendations
Your Personalized Advice
Based on your current readings, there's a moderate risk of low blood sugar within the next 56 minutes. If you're planning physical activity or it's been more than 3 hours since your last meal, consider a small 10-15g carb snack. Continue monitoring your glucose levels closely.
Home
Log Data
Alerts
Profile

Testing and Validation





Standards and Best Practices

- Mobile: React Native component architecture with reusable UI elements
- Backend: RESTful API design with proper endpoint naming and HTTP methods
- ML: Time-series data processing for continuous CGM readings
- AI: MedLLama2 prompt engineering for accurate medical recommendations
- Data: Real-time data streaming architecture for CGM integration
- Security: Encrypted medical data storage following healthcare standards
- Testing: Model validation with historical glucose datasets
- Prediction: Confidence intervals for glycemic event predictions
- Ethics: Responsible AI implementation with human oversigh

Commercialization Potential

- Market Size: 1.2 million diabetes patients in Sri Lanka (8.7% prevalence rate)
- Growth Rate: 4.7% annual increase in diabetes diagnoses
- Target Users: 35% of patients use smartphones for health management
- Cost Savings: Potential 30% reduction in hospitalization costs
- Revenue Model: Freemium subscription ($5/month premium features)
- Expansion Potential: Adaptable to neighboring countries (India, Bangladesh)
- Competitive Edge: 15-20 minute earlier prediction than existing solutions
- ROI: Good return on development and maintenance costs within few months

References

- M. Gadaleta, A. Facchinetti, E. Grisan, and M. Rossi, "Prediction of Adverse Glycemic Events From Continuous Glucose Monitoring Signal," IEEE Journal of Biomedical and Health Informatics, vol. PP, no. 99, pp. 1-1, April 2018, doi: 10.1109/JBHI.2018.2823763. [1]
- N. Nuwarapaksha, H.M.R.K.G. Nandasena, and N. Nanayakkara, "Prevalence of Long-term Complications among Type 2 Diabetes Mellitus Patients at National Hospital - Kandy, Sri Lanka," Diabetes Research and Clinical Practice, vol. 186S, p. 109535, January 2022. [2]
- Deldjoo, Y., He, Z., & McAuley, J., "A Review of Modern Recommender Systems Using Generative Models (Gen-RecSys)," Polytechnic University of Bari, Bari, Italy; University of California, La Jolla, USA.[3]
- Lin, Y., Liu, Y., Lin, F., Miao, C., "A Survey on Reinforcement Learning for Recommender Systems," September 2021.[4]
- Syafrudin, M., Alfian, G., Fitriyani, N. L., Anshari, M., "Future Glycemic Events Prediction Model Based On Artificial Neural Network," 2022 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), November 2022, [5]
- Crilly, P., Uddin, N., "A mixed method study investigating the use of the Sugar Smart app to help community pharmacists reduce public sugar intake," Royal Pharmaceutical Society (RPS) Winter Summit 2017, London, December 2017.[6]
- Zhu, Y., Yi, J., Xie, J., Chen, Z., "Deep Causal Reasoning for Recommendations," arXiv preprint arXiv:2201.01593, 6 Jan 2022 (v1), last revised 21 Nov 2022 (v2).[7]

IT21287718 | WIMANSA P.P.H.S.D.

SPECIALIZATION - DATA SCIENCE

SIDE EFFECTS PREDICTION AND ALERT MECHANISM FOR DIABETES TREATMENT

INTRODUCTION

- Diabetes affects 537M adults worldwide (IDF 2021)
- Medication side effects reduce treatment adherence
- Existing solutions focus on glucose monitoring, not side effect prediction
- Research goal: Predict and alert side effects in real time

RESEARCH PROBLEM

- Side effects of diabetes treatment affect patient adherence

- Current systems reactively manage side effects, not predict them

- Existing machine learning models focus on diagnosis, not treatment effects

RESEARCH OBJECTIVES

- Develop an ML-based system for side effect prediction

- Train a robust model for personalized prediction

- Design an intuitive mobile interface for logging symptoms and receiving alerts

WIMANSA P.P.H.S.D. | IT21287718

DATA SET

CDTOD Diabetes Side Effects Prediction Dataset

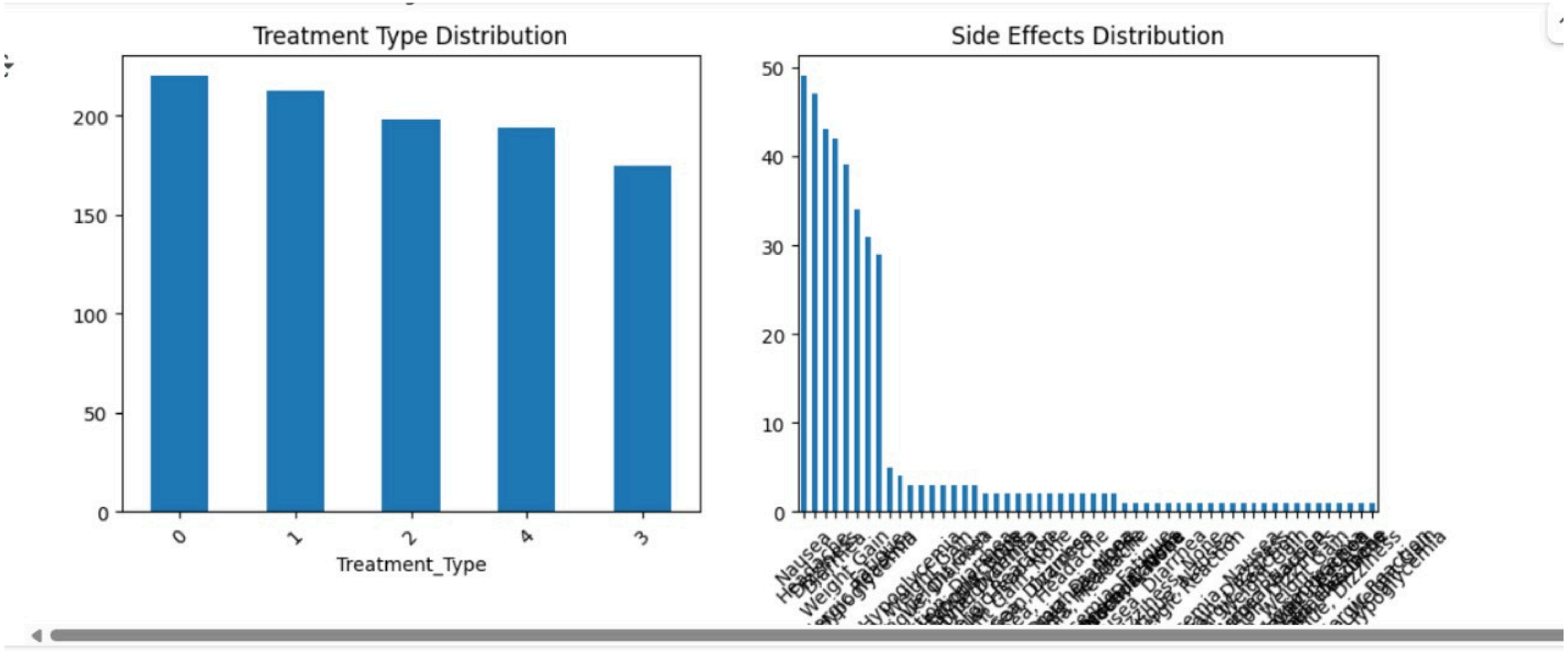
- **Patient demographics (ID, Date, Age, Gender, BMI)**
- **Health metrics (Glucose, Insulin levels)**
- **Reported side effects (Headache, Nausea, Dizziness, Fatigue, etc.)**
- **Lifestyle factors (Sleep Hours, Diet Quality)**

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	
1	PatientID	Day	Glucose	Insulin	BloodPres	HeartRate	Headache	Nausea	Vomiting	BlurryVisio	Sweating	Fatigue	Dizziness	Irritability	Cough	StomachU	JointPain	Age	Gender	Weight	Hypertensi	KidneyDise	Neuropath	Me
2	1	Day 1	91	14	97	83	0	0	0	0	0	0	1	0	0	0	0	68	Male	118	0	0	0	Ins
3	1	Day 2	159	7	134	62	0	0	0	0	0	0	0	0	0	0	1	68	Male	118	0	0	0	Ins
4	1	Day 3	98	36	98	71	0	0	1	0	0	0	0	1	1	0	0	68	Male	118	0	0	0	Ins
5	1	Day 4	148	29	92	92	0	0	0	0	1	0	0	1	0	0	1	68	Male	118	0	0	0	Ins
6	1	Day 5	187	48	98	80	0	0	0	0	0	0	0	0	0	0	0	68	Male	118	0	0	0	Ins
7	1	Day 6	161	15	112	107	0	0	0	0	0	0	0	0	0	0	0	68	Male	118	0	0	0	Ins
8	1	Day 7	227	5	97	114	0	0	0	0	0	0	0	0	0	0	1	68	Male	118	0	0	0	Ins
9	1	Day 8	118	13	124	119	0	0	0	0	0	0	0	0	0	0	0	68	Male	118	0	0	0	Ins
10	1	Day 9	109	18	109	108	0	0	0	0	0	0	1	0	0	0	1	68	Male	118	0	0	0	Ins
11	1	Day 10	142	13	108	106	0	0	0	0	0	0	0	0	0	0	0	68	Male	118	0	0	0	Ins
12	1	Day 11	157	34	130	63	0	0	0	0	0	1	0	0	0	0	0	68	Male	118	0	0	0	Ins
13	1	Day 12	90	25	110	64	0	0	0	0	0	0	0	0	1	0	0	68	Male	118	0	0	0	Ins
14	1	Day 13	247	16	101	105	0	0	0	0	0	0	0	0	0	0	0	68	Male	118	0	0	0	Ins
15	1	Day 14	229	16	134	62	0	1	0	0	0	0	0	0	0	0	0	68	Male	118	0	0	0	Ins
16	1	Day 15	215	23	131	60	0	0	0	0	0	0	0	0	0	0	1	68	Male	118	0	0	0	Ins

DATA SET

A	B	C	D	E	F	G	H	I	J	K
Patient_ID	Age	Gender	Diabetes_T	Treatment_	Medicatior	Dosage	Treatment_	Side_Effec	Severity_Score	
1	56	Male	Gestationa	Insulin	Glargine	68.92	36	Allergic Re	9	
2	69	Male	Type 1	Metformin	Sitagliptin	12.71	20	None	0	
3	46	Female	Gestationa	Insulin	Glipizide	95.39	18	None	0	
4	32	Male	Type 1	GLP-1 rece	Liraglutide	84.66	38	None	0	
5	60	Male	Gestationa	Insulin	Metformin	81.48	67	Hypoglyce	8	
6	25	Female	Type 2	DPP-4 inhi	Metformin	83.18	23	Headache	3	
7	78	Male	Gestationa	Insulin	Sitagliptin	93.61	96	Nausea	4	
8	38	Male	Gestationa	GLP-1 rece	Lispro	56.7	109	None	0	
9	56	Male	Type 1	DPP-4 inhi	Metformin	24.03	16	Headache	3	
10	75	Male	Type 2	Sulfonylure	Liraglutide	63.59	59	None	0	
11	36	Male	Gestationa	Sulfonylure	Sitagliptin	75.57	69	None	0	
12	40	Female	Type 2	Insulin	Glipizide	75.1	68	None	0	
13	28	Male	Gestationa	Insulin	Liraglutide	54.54	21	Allergic Re	9	
14	28	Male	Gestationa	GLP-1 rece	Sitagliptin	11.5	104	Headache	3	
15	41	Male	Type 2	GLP-1 rece	Liraglutide	40.26	115	None	0	
16	70	Male	Gestationa	Metformin	Metformin	92.47	78	None	0	
17	53	Male	Type 2	GLP-1 rece	Glipizide	60.52	103	Nausea	4	
18	57	Female	Gestationa	Metformin	Sitagliptin	56.14	95	None	0	
19	41	Male	Type 1	DPP-4 inhi	Glargine	30.54	78	Dizziness,	4	
20	20	Female	Type 2	Insulin	Glipizide	40	70	None	0	
21	39	Female	Gestationa	DPP-4 inhi	Glargine	90.06	12	None	0	
22	70	Male	Gestationa	GLP-1 rece	Liraglutide	68.31	16	None	0	
23	19	Male	Type 1	DPP-4 inhi	Lispro	79.8	81	None	0	
24	41	Male	Type 2	DPP-4 inhi	Glipizide	48.16	109	Headache	3	
25	61	Male	Gestationa	DPP-4 inhi	Liraglutide	64.87	87	None	0	
26	47	Female	Type 1	GLP-1 rece	Glargine	28.6	14	Headache	3	
27	55	Male	Gestationa	DPP-4 inhi	Metformin	72.02	61	None	0	

DATA SET



Treatment Type Distribution
0
50
100
150
200
0
1
2
4
3
Treatment_Type
Side Effects Distribution
0
10
20
30
40
50

TRAINING MODELS

Model Used - LSTM (Long Short-Term Memory).

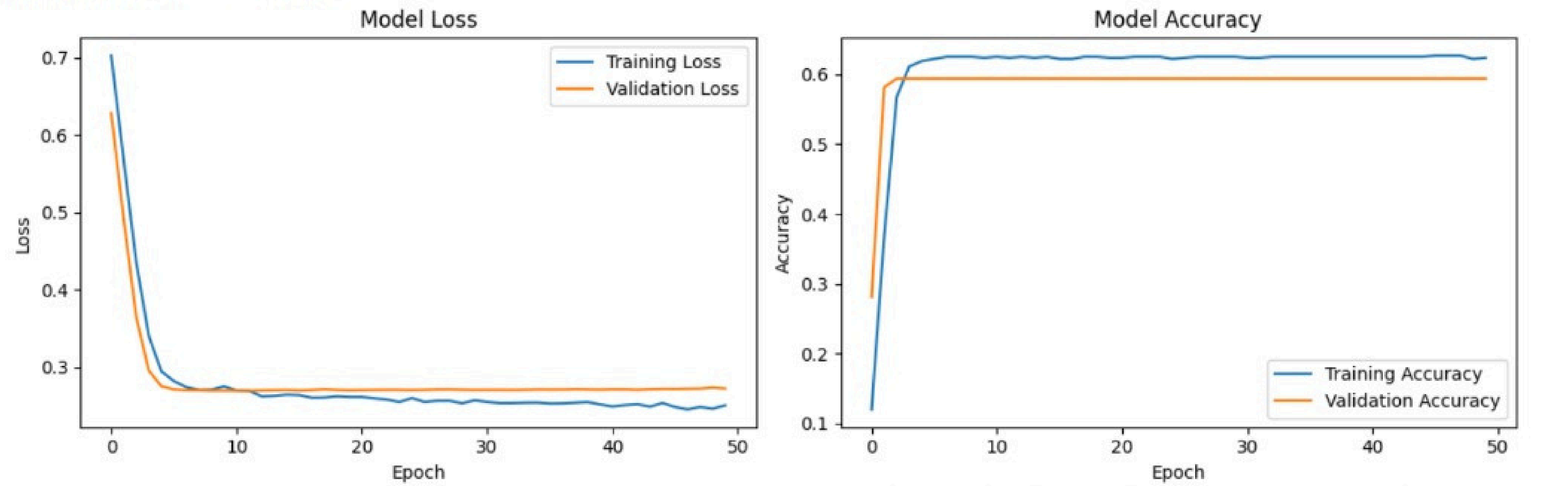
Why LSTM?

- **Captures sequential trends in daily symptom logs.**
- **This model learns from 30-day patient history to predict tomorrow's side effects.**
- **Handles sequential dependencies, capturing patterns in glucose, insulin, and symptoms.**

```
[9] # Build LSTM model
    input_layer = Input(shape=(X_train_scaled.shape[1], 1))
    bi_lstm = Bidirectional(LSTM(64, return_sequences=True))(input_layer)
    attention = MultiHeadAttention(num_heads=4, key_dim=64)(bi_lstm, bi_lstm)
    norm = LayerNormalization()(attention)
    flatten = Flatten()(norm)
    dropout = Dropout(0.3)(flatten)
    output_layer = Dense(11, activation='sigmoid')(dropout)

    model = Model(inputs=input_layer, outputs=output_layer)
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

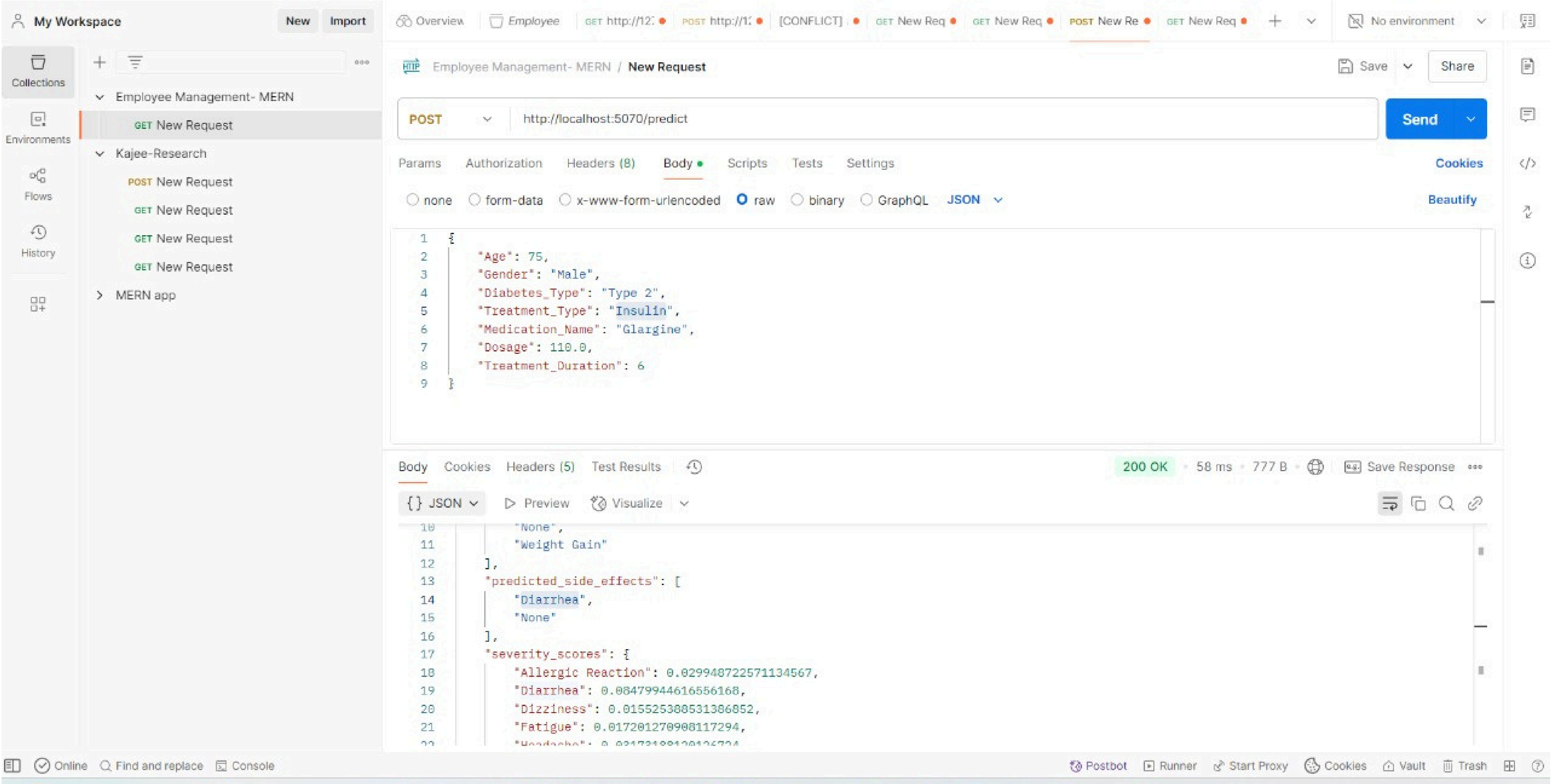
```
# Train model
history = model.fit(X_train_scaled, y_train, epochs=20, batch_size=32, validation_data=(X_test_scaled, y_test))
```

TRAINING MODELS



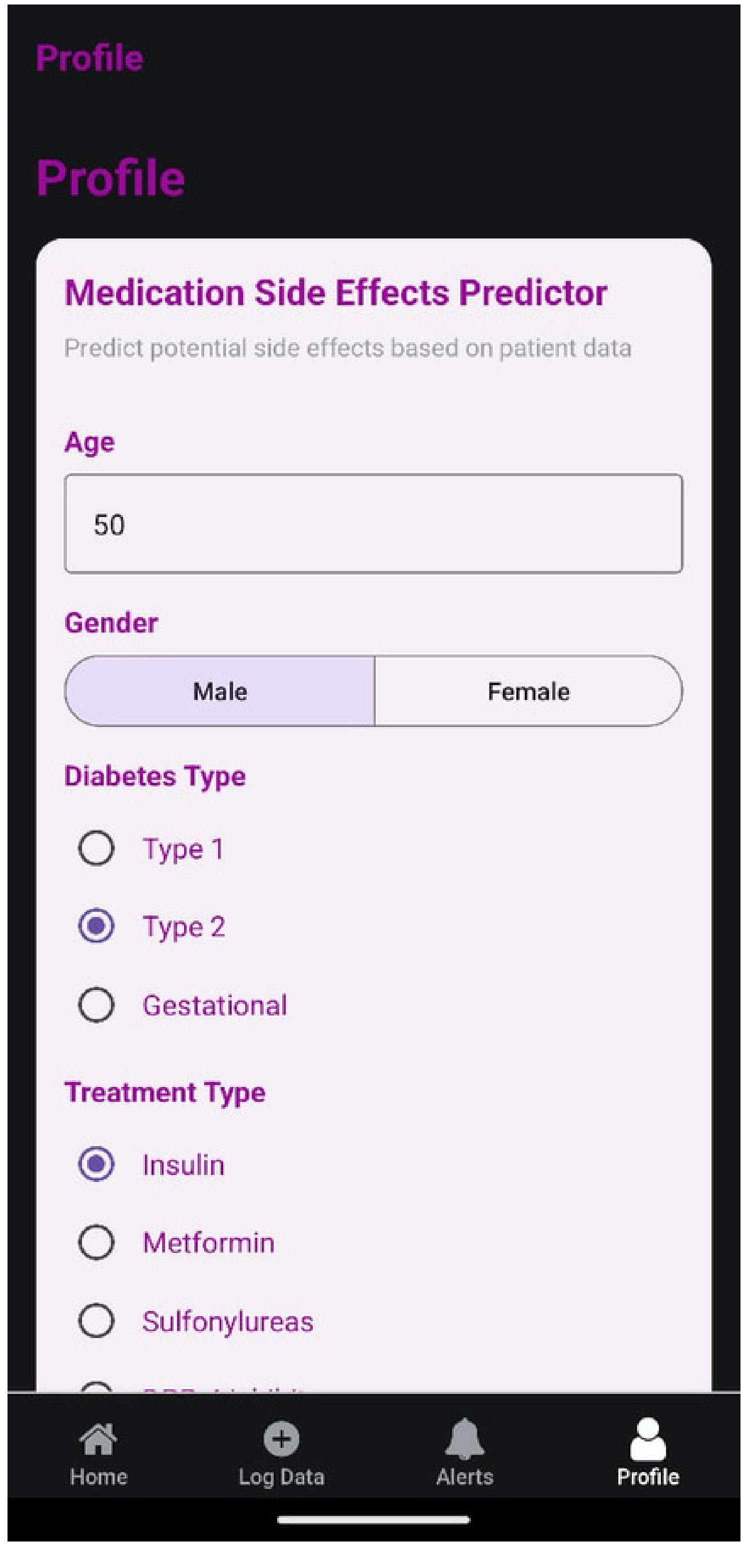

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the r
Model and preprocessing objects saved successfully!
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
```

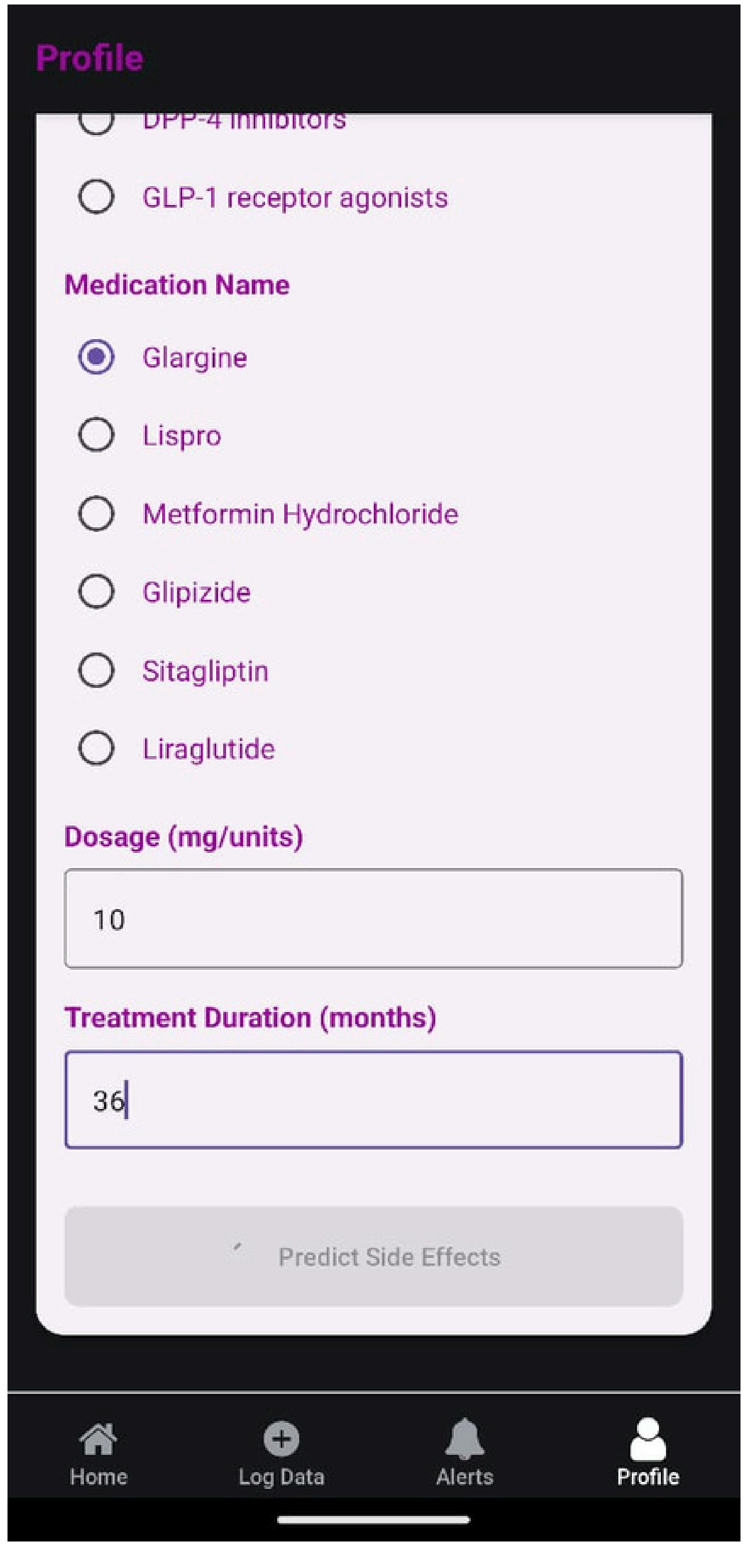
PROOF OF COMPLETION

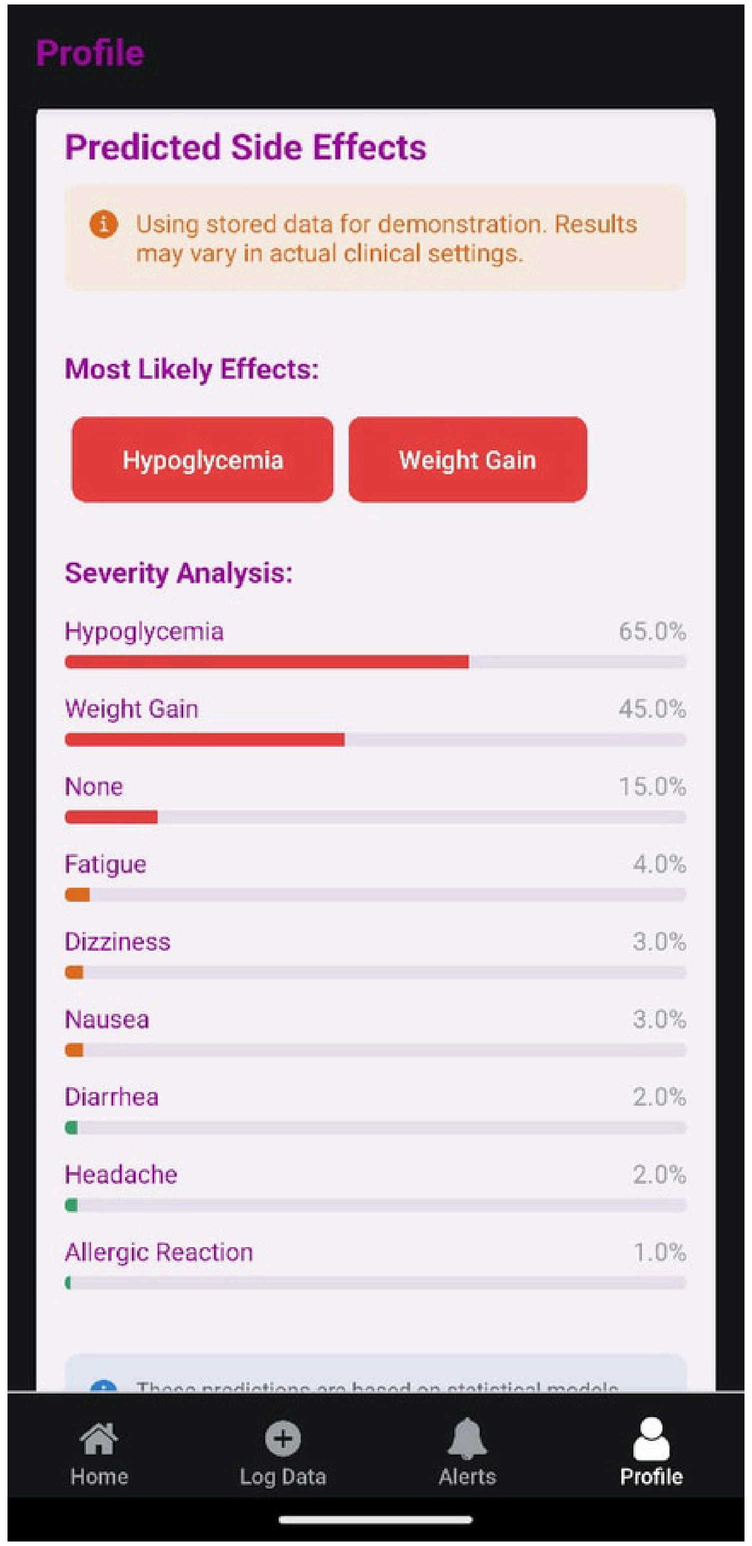


WIMANSA P.P.H.S.D. | IT21287718

PROOF OF COMPLETION







WIMANSA P.P.H.S.D. | IT21287718

REFERENCES

M. S. Abdul Rahman, S. M. Rahimifard, and M. M. Al-Shami, "Prediction of DiabetesRelated Complications Using Machine Learning Algorithms: A Comprehensive Review," in 2021 IEEE International Conference on Artificial Intelligence and Machine Learning (AIML), 2021, pp. 1-6.

N. Jothi and A. A. N. Islam, "A Framework for Predicting Adverse Drug Reactions in Diabetic Patients Using Machine Learning Techniques," in 2021 IEEE International Conference on Biomedical Engineering and Sciences (IECBES), 2021, pp. 212-217

R. Al-Mahdi, M. Elshamli, and A. S. Mokhtar, "A Machine Learning Approach for RealTime Prediction of Side Effects in Diabetes Treatment," in 2022 IEEE International Conference on Healthcare Informatics (ICHI), 2022, pp. 45-50.

J. Wu, J. Zhang, and Z. Li, "Mobile Health Application for Diabetes Management: RealTime Prediction of Blood Glucose Levels and Side Effects," in 2021 IEEE International Conference on Health Informatics (ICHI), 2021, pp. 74-80.

IT21283062 | DE SILVA L.K.N.

SPECIALIZATION - DATA SCIENCE

NUTRITIONAL GUIDANCE SYSTEM WITH PERSONALIZED MEAL PLANS

INTRODUCTION

Managing diabetes requires a careful balance of nutrition and lifestyle adjustments. This research proposes a machine learning-based personalized meal recommendation system designed for diabetic patients. The system uses patient profiles, including health metrics, dietary preferences, and allergies, to generate meal plans tailored to their diabetes type and other variables.

RESEARCH PROBLEMS

Lack of real-time data utilization for dynamically adjusting meal plans

Generic recommendations with insufficient deep personalization for individual users.

Inaccurate or non-personalized predictive models for glucose response to meals.

SPECIFIC OBJECTIVE

To create a personalized nutritional guidance system that uses dietary, medical, and activity data to provide optimized meal plans for better diabetes management.

SUB OBJECTIVES

- *Comprehensive Data Integration*
- *Personalized Nutritional Guidance*
- *Optimization of Meal Plans*
- *Improvement of Diabetes Management Outcomes*

DATA COLLECTION

```python
datapath = 'diabetes_user_profiles_with_mealID.csv'
df = pd.read_csv(datapath)
df
```

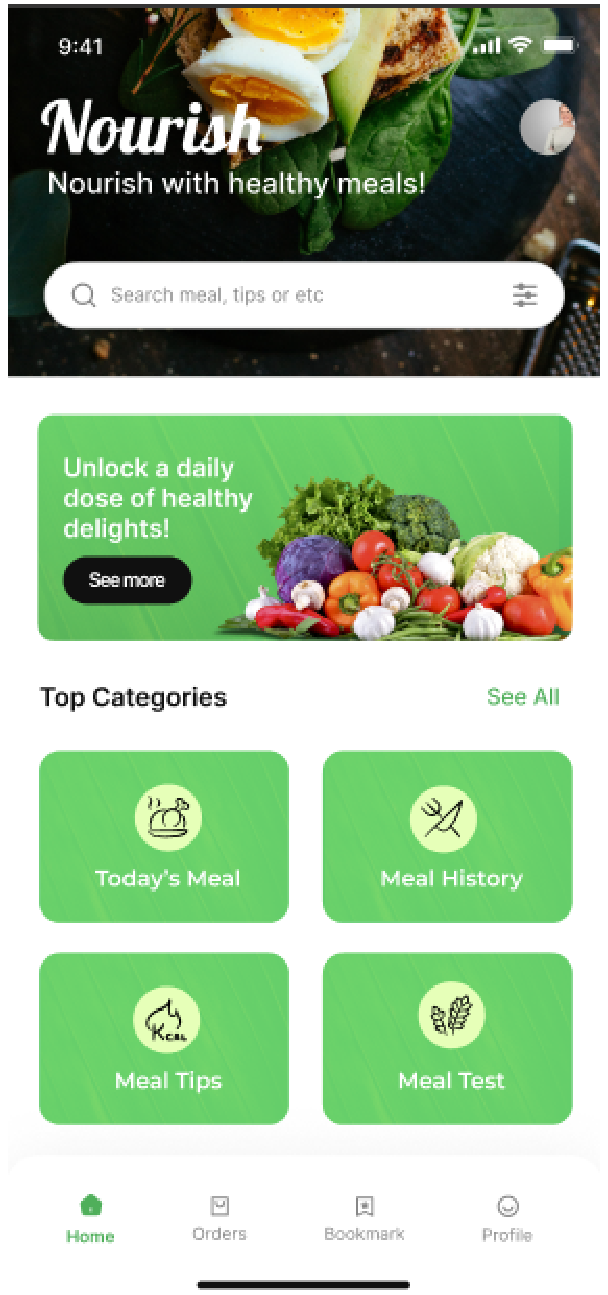
Python

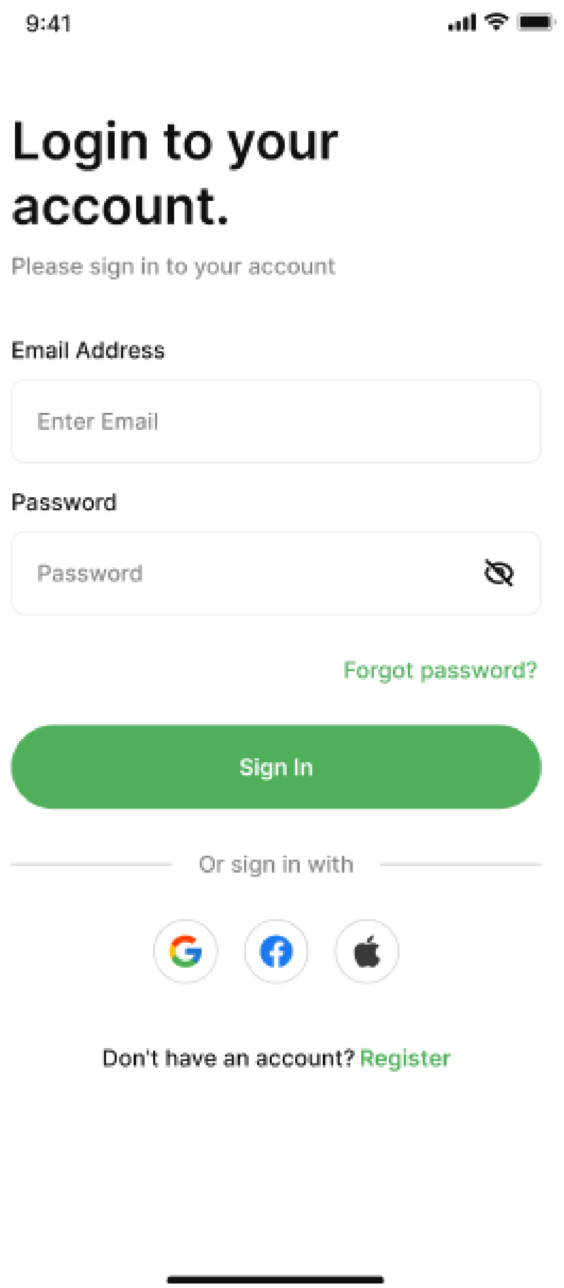
	RecordID	Name	Age	Gender	Height	Weight	Location	Occupation	DiabetesType	DiagnosedYearsAgo	...	DietFollowed	TriggerFoods	Allergies	Int
0	1	Nimal Fernando	64	Male	168	80	Jaffna	Homemaker	Gestational	2	...	Vegetarian	NaN	Dairy	
1	2	Kumari Rathnayake	55	Female	178	96	Kandy	Office worker	Type 1	14	...	Low-carb	Sugary snacks	Nuts	
2	3	Anjali Perera	57	Female	180	55	Jaffna	Homemaker	Type 1	10	...	NaN	Sugary snacks	Dairy	
3	4	Amara Wijesinghe	48	Female	156	56	Colombo	Office worker	Type 1	4	...	Vegetarian	Sugary snacks	Dairy	
4	5	Kumari Rathnayake	70	Female	175	50	Colombo	Homemaker	Type 2	5	...	Vegetarian	White bread	NaN	

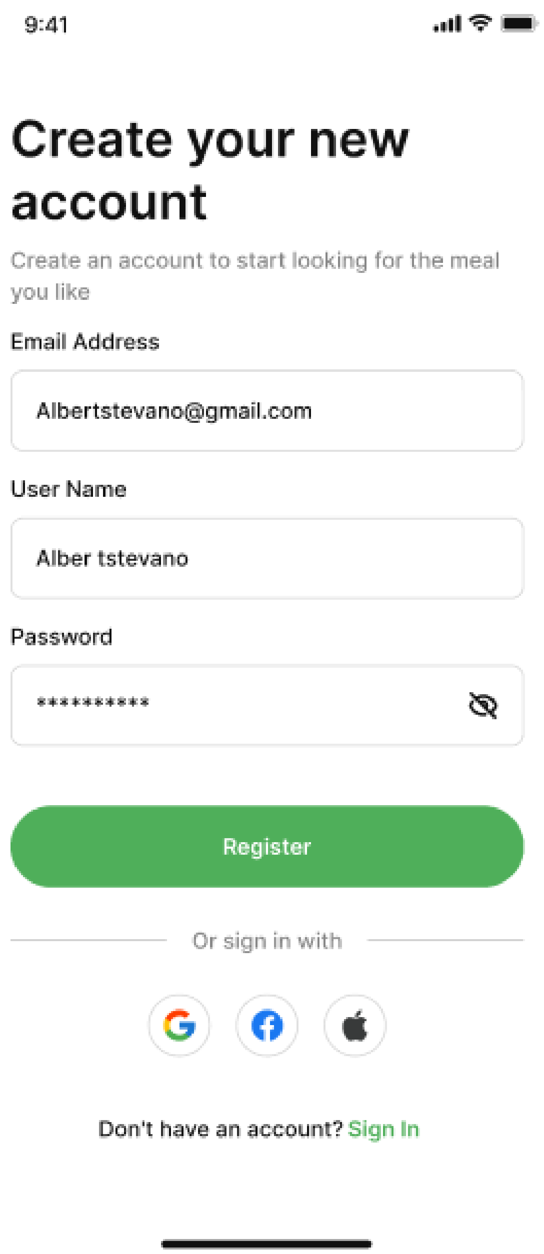
MealID	MealName	MealDetails	CalorieCount	AllergyStatus	Preferences	Type
1	Traditional Sri Lankan Breakfast	String hoppers, pol sambol, dhal curry	350	Contains coconut	Vegetarian	Breakfast
1	Rice and Curry Lunch	White rice, fish curry, mallung, papadam	600	Contains fish, gluten	Non-Vegetarian	Lunch
1	Light Dinner	Vegetable soup, brown bread	250	Contains gluten	Vegetarian	Dinner
2	Coconut Milk Rice Breakfast	Kiribath, lunu miris	300	Contains coconut	Vegetarian	Breakfast
2	Seafood Curry Lunch	White rice, prawn curry, gotukola salad	650	Contains shellfish	Non-Vegetarian	Lunch
2	String Hopper Dinner	String hoppers, chicken curry	450	Contains gluten	Non-Vegetarian	Dinner
3	Healthy Breakfast	Oats porridge, banana, nuts	320	Contains nuts	Vegetarian	Breakfast
3	Chicken Fried Rice Lunch	Brown rice, chicken, vegetables	700	Contains egg, soy	Non-Vegetarian	Lunch
3	Vegetable Roti Dinner	Whole wheat roti, mixed vegetables	400	Contains gluten	Vegetarian	Dinner
4	Spicy Breakfast	Hoppers, lunu miris, dhal curry	300	Contains coconut	Vegetarian	Breakfast
4	Fish Curry Lunch	Red rice, fish curry, beetroot salad	550	Contains fish	Non-Vegetarian	Lunch

PROOF OF COMPLETION

MOBILE APPLICATION



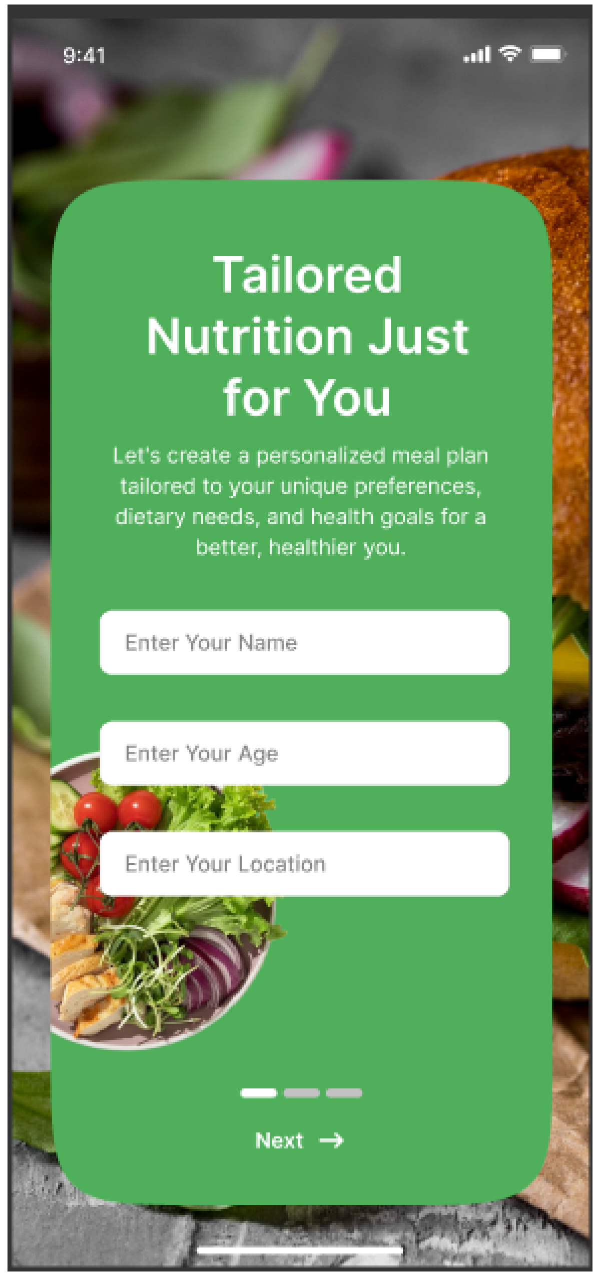


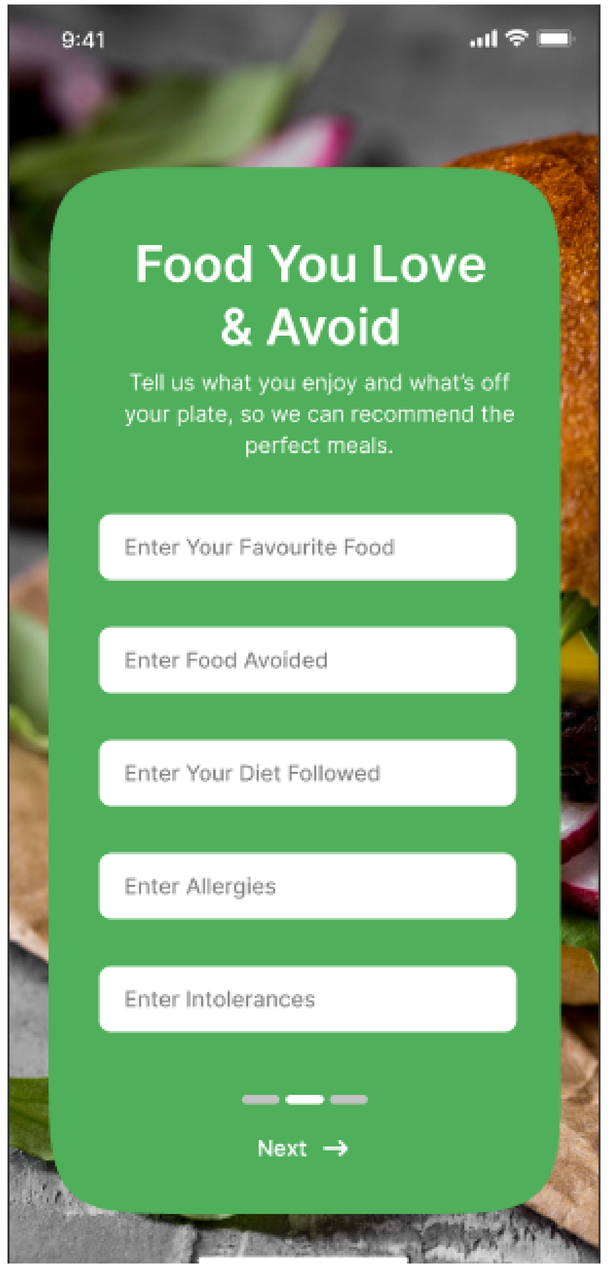


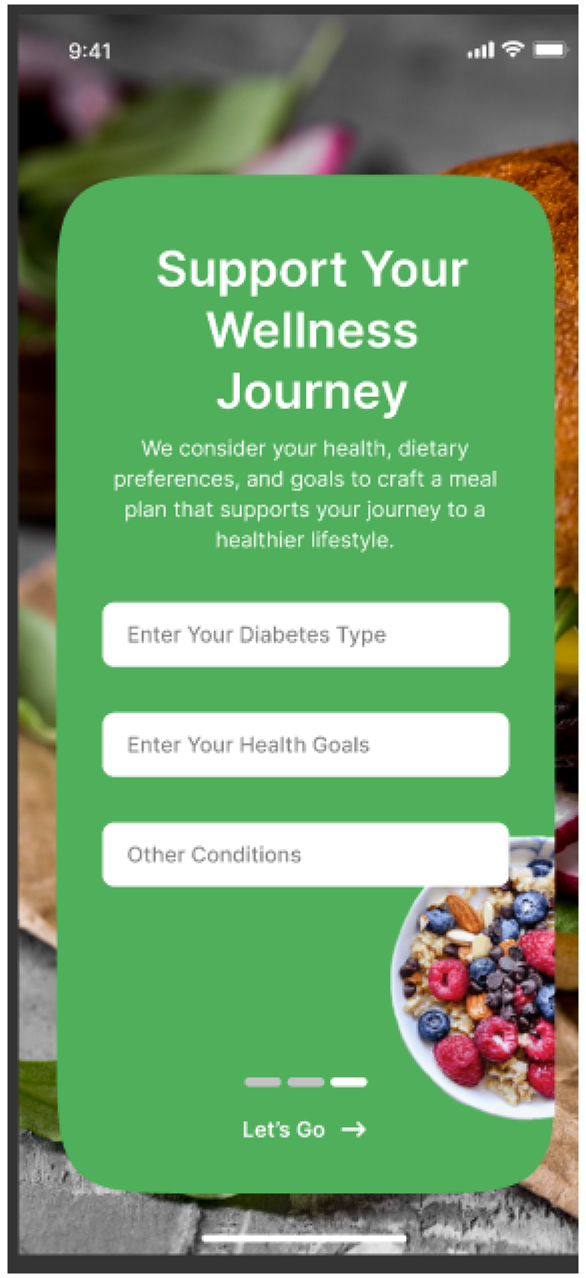
DE SILVA L.K.N. | IT21283062

PROOF OF COMPLETION

MOBILE APPLICATION



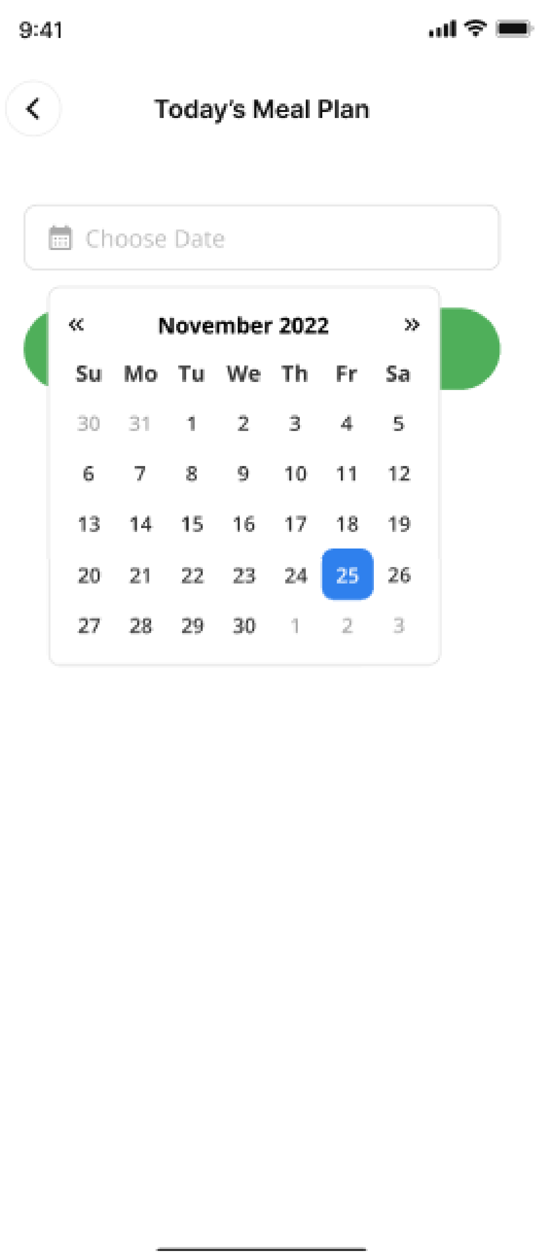


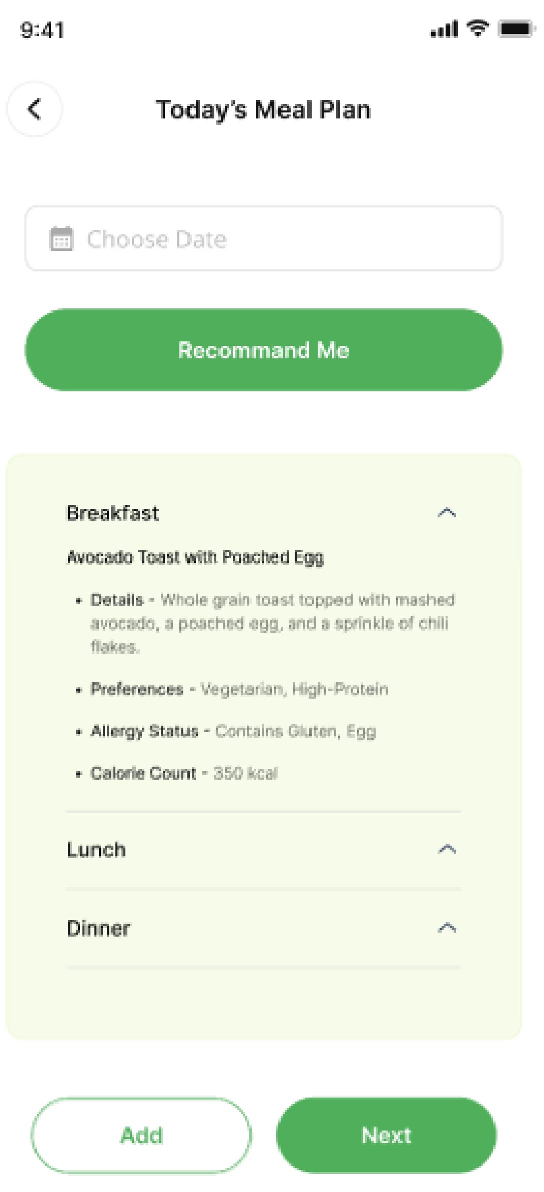


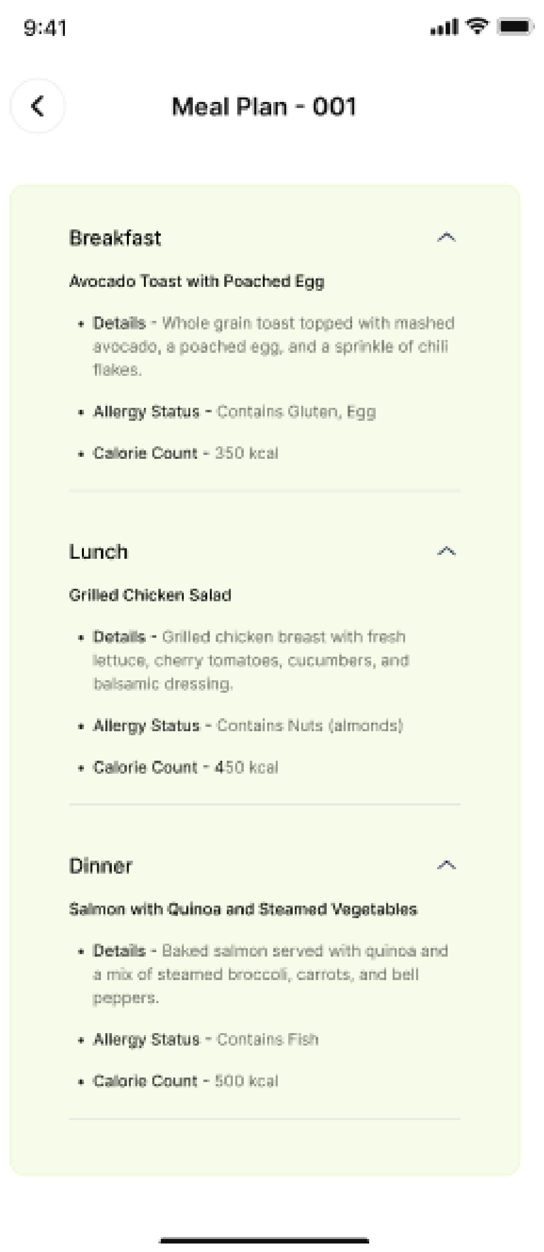
DE SILVA L.K.N. | IT21283062

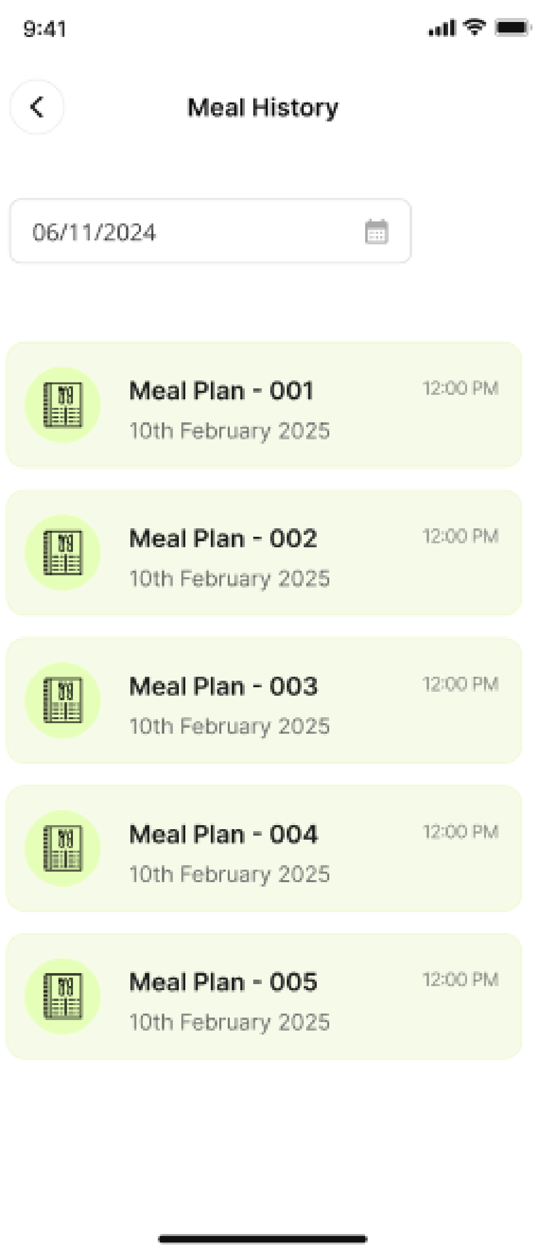
PROOF OF COMPLETION

MOBILE APPLICATION





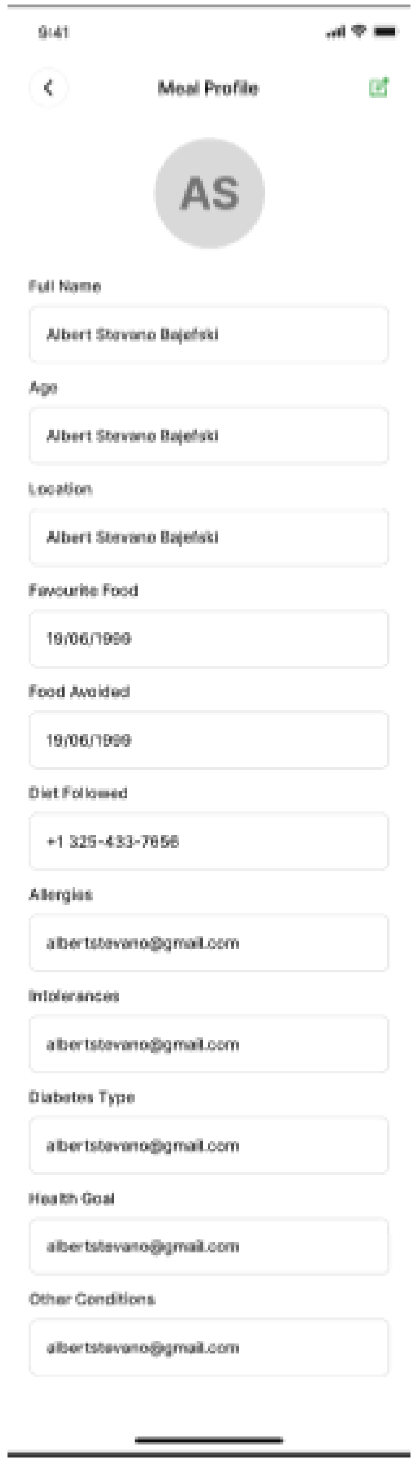


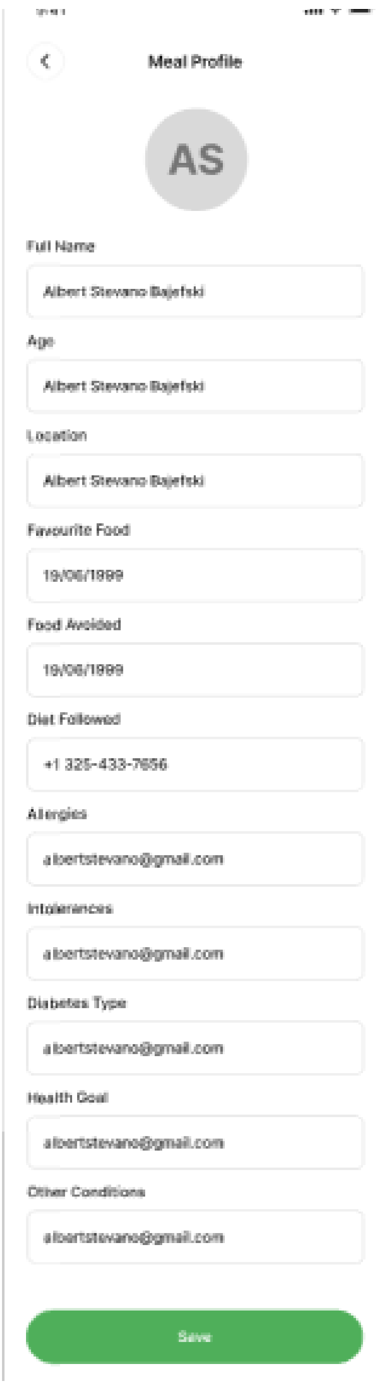


DE SILVA L.K.N. | IT21283062

PROOF OF COMPLETION

MOBILE APPLICATION





PROOF OF COMPLETION

IMPLEMENTATION - CATBOOSTCLASSIFIER MODEL

- ENSEMBLE LEARNING - BOOSTING FRAMEWORK
- CLASSIFICATION TASKS
- CATEGORICAL DATA

```python
cat = CatBoostClassifier(
                        iterations=200,
                        learning_rate=0.1,
                        loss_function='MultiClass',
                        depth=6
                        )
cat.fit(
        X, Y,
        eval_set=(
                  X_test,
                  Y_test
                  ),
        verbose=100
        )
```

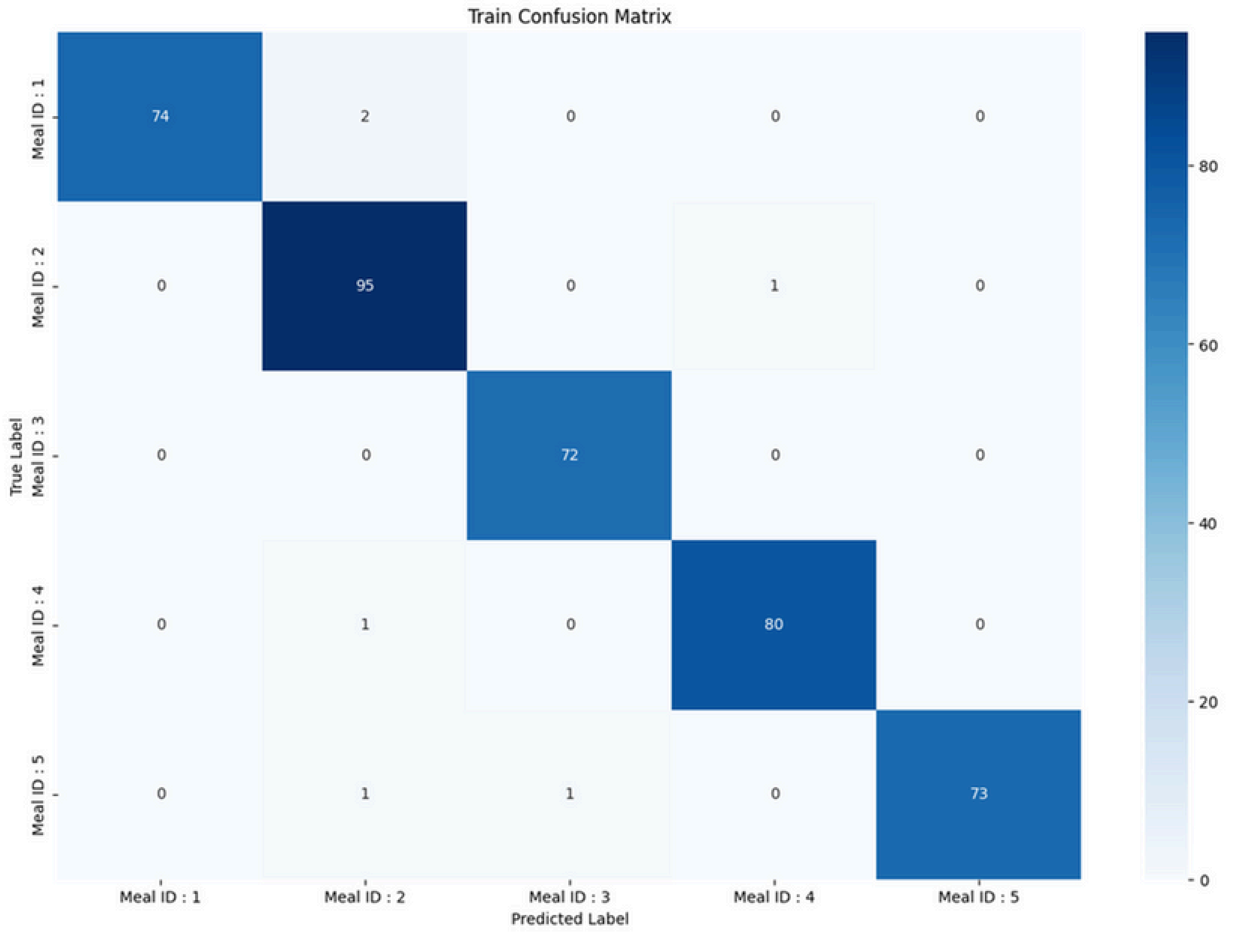
54] ✓ 0.5s

------------------------ Train CLS REPORT ------------------------

	precision	recall	f1-score	support
Meal ID : 1	1.00	0.97	0.99	76
Meal ID : 2	0.96	0.99	0.97	96
Meal ID : 3	0.99	1.00	0.99	72
Meal ID : 4	0.99	0.99	0.99	81
Meal ID : 5	1.00	0.97	0.99	75
accuracy			0.98	400
macro avg	0.99	0.98	0.99	400
weighted avg	0.99	0.98	0.99	400

------------------------ Test CLS REPORT ------------------------

	precision	recall	f1-score	support
Meal ID : 1	1.00	1.00	1.00	22
Meal ID : 2	0.95	1.00	0.98	20
Meal ID : 3	1.00	1.00	1.00	26
Meal ID : 4	1.00	1.00	1.00	16
Meal ID : 5	1.00	0.94	0.97	16
accuracy			0.99	100
macro avg	0.99	0.99	0.99	100
weighted avg	0.99	0.99	0.99	100



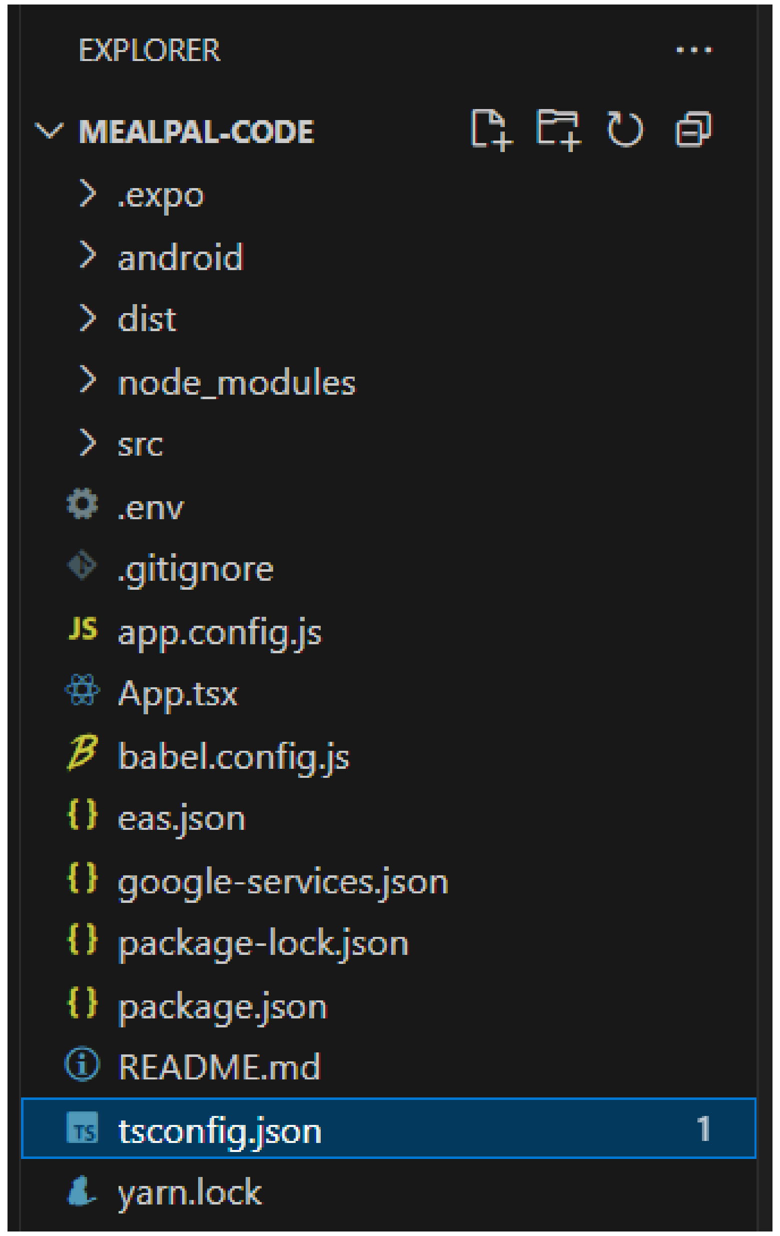
EVALUATING THE MODEL

- CLASSIFICATION REPORT
- CONFUSION MATRIX

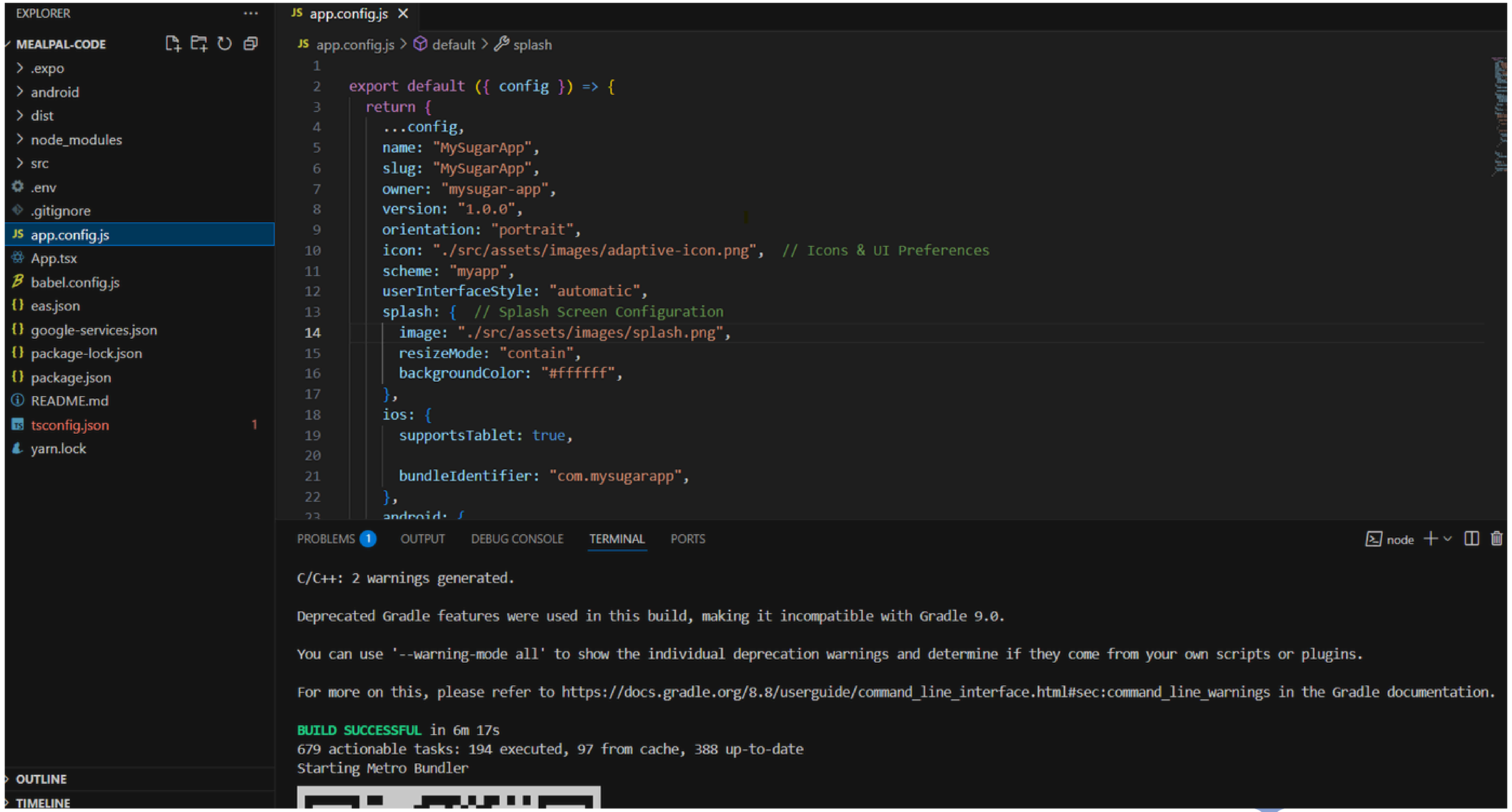
DE SILVA L.K.N. | IT21283062

PROOF OF COMPLETION

IMPLEMENTATION - CODE SNIPPETS



Code Structure



App.config.js

PROOF OF COMPLETION

IMPLEMENTATION - CODE SNIPPETS

DetailsScreenOne.tsx 2

src > screens > auth > DetailsScreenOne.tsx > ...

```tsx
import React from "react";
import { Image, ImageBackground, StyleSheet, Text, View } from "react-native";
import { Button } from "react-native-paper";
import { Formik } from "formik";
import * as Yup from "yup";
import ScrollViewWrapper from "@/components/wrappers/ScrollViewWrapper";
import { LightPalette } from "@/theme";
import { CustomTextInput } from "@/components/customComponents/VhTextInput";
import StepperIndicator from "@/components/customComponents/StepperIndicator";
import { routeKeys } from "@/navigation/config";
import { useCustomNavigation } from "@/hooks";
import CustomDropdown from "@/components/customComponents/CustomDropdown";
import { useRoute } from "@react-navigation/native";

//validation rules
const validationSchema = Yup.object().shape({
  Name: Yup.string().required("Name is required"),
  Age: Yup.number().required("Age is required"),
  Location: Yup.string().required("Location is required"),
  Weight: Yup.string().required("Weight is required"),
});

const DetailsScreenOne = () => {
  const navigation = useCustomNavigation();
  const route = useRoute();

  return (
    <ImageBackground
      source={require("../../assets/images/details-bg.png")}
      style={styles.background}
    >
```

DetailsScreenOne.tsx

getMeals.ts 1

src > services > getMeals.ts > ...

```ts
// services/postService.ts

import { storage } from "@/localStorage";
import { getData, postData } from "@/query/config";
import { ToastAndroid } from "react-native";

// API function to fetch posts
export const getMeals = async (data) => {
  try {
    const response = await postData("predict_meal", data);
    // console.log("Users", response);
    return response; // Return response data
  } catch (error) {
    ToastAndroid.show("An error occurred getting data", 1000);

    throw error; // Rethrow error for React Query to handle
  }
};
```

getMeals.js

PROOF OF COMPLETION

IMPLEMENTATION - CODE SNIPPETS

{} google-services.json ×

{} google-services.json > ...

```json
{
  "project_info": {
    "project_number": "799795395727",
    "project_id": "mealplan-6e07d",
    "storage_bucket": "mealplan-6e07d.firebasestorage.app"
  },
  "client": [
    {
      "client_info": {
        "mobilesdk_app_id": "1:799795395727:android:a5c7a1f72661d5011604fa",
        "android_client_info": {
          "package_name": "com.mysugarapp"
        }
      },
      "oauth_client": [],
      "api_key": [
        {
          "current_key": "AIzaSyB6cnlUomTi6kAVZYk5nZvkh7rlfN0P8aY"
        }
      ],
      "services": {
        "appinvite_service": {
          "other_platform_oauth_client": []
        }
      }
    }
  ],
  "configuration_version": "1"
}
```

google-service.json

TodaysMealScreen.tsx 1 ×

src > screens > home > TodaysMealScreen.tsx > ...

```tsx
import { StyleSheet, ToastAndroid, View } from "react-native";
import React, { useEffect, useState } from "react";
import ScrollViewWrapper from "@/components/wrappers/ScrollViewWrapper";
import CustomHeader from "@/components/customComponents/CustomHeader";
import { CustomButton } from "@/components/customComponents/CustomButton";
import MealAccordion from "@/components/customComponents/MealAccordion";
import { getMeals } from "@/services/getMeals";
import { storage, storageKeys } from "@/localStorage";
import { getFormattedDate } from "@/utils/getFormattedDate";
import { useMMKVObject } from "react-native-mmkv";

const TodaysMealScreen = () => {
  const [todaysMeal, setTodaysMeal] = useState([]);
  const [loading, setLoading] = useState(true);
  const [userDetails, setUserDetails] = useMMKVObject(storageKeys.USER_DETAILS);

  const getTodayMeal = async () => {
    try {
      setTodaysMeal([]);
      setLoading(true);

      const todayMeal = await getMeals(userDetails);

      setTodaysMeal(todayMeal.Meals);
      setLoading(false);
    } catch (error) {
      console.log("EEE", error);
      setLoading(false);
    }
```

TodayMealScreen.tsx

DE SILVA L.K.N. | IT21283062

COMPLETED TASKS

- Data Cleaning and Preprocessing & Data Analysis
- Created a model to generate and recommend meal plan
- Improved the model accuracy for better performance.
- Designed Wireframes & UI/UX Designs.
- Developed a mobile app for meal recommendation.

FUTURE WORKS

- develop feedback system for future improvement.
- Mobile app Intergration

METHODOLOGY

FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS

FUNCTIONAL REQUIREMENTS

- USER MANAGEMENT
- DATA COLLECTION & INTEGRATION
- MEAL PLAN RECOMMENDATION
- MOBILE APP FEATURES
- BLOOD GLUCOSE PREDICTION & ANALYSIS

NON-FUNCTIONAL REQUIREMENTS

- PERFORMANCE & SCALABILITY
- SECURITY & PRIVACY
- AVAILABILITY & RELIABILITY
- USABILITY & ACCESSIBILITY

REFERENCES

- "Mobile health applications for managing diabetes: A systematic review" by El-Gayar, O., Timsina, P., Nawar, N., & Eid, W. (2013). Journal of Diabetes Science and Technology.
- "Data preprocessing techniques for classification without noise in real-world" by García, S., Luengo, J., & Herrera, F. (2015). Knowledge and Information Systems.
- "Collaborative filtering for dietary recommendations" by Harvey, M., Ludwig, B., & Elsweiler, D. (2013). Proceedings of the 7th ACM conference on Recommender systems
- "Adaptive learning algorithms for personalized diet recommendations" by Ueta, T., Koizumi, Y., & Shirota, S. (2019). IEEE Access

THANK YOU!