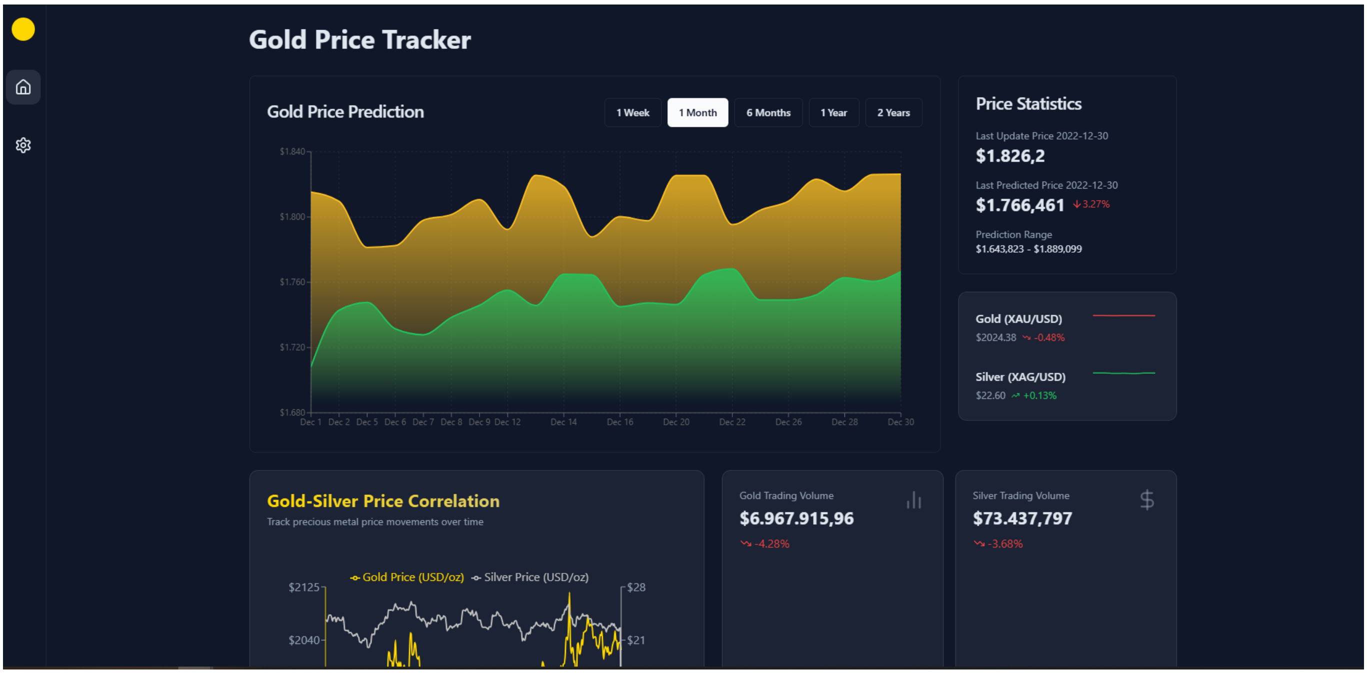
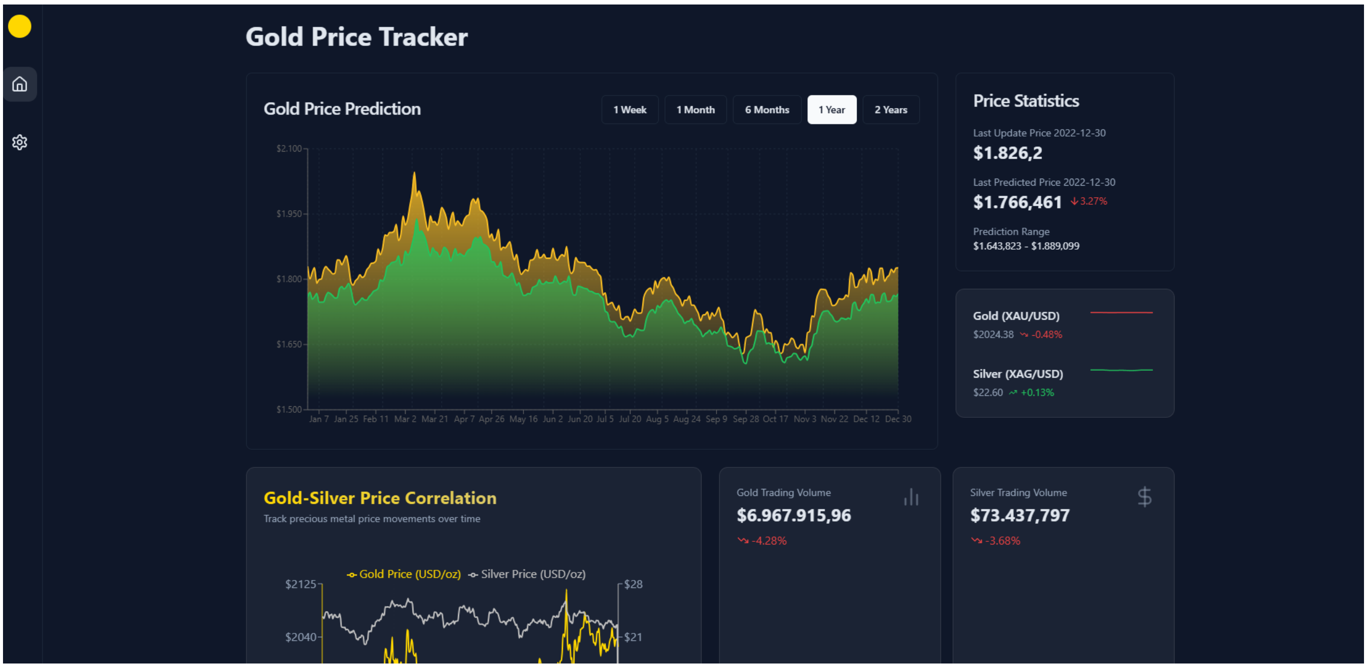
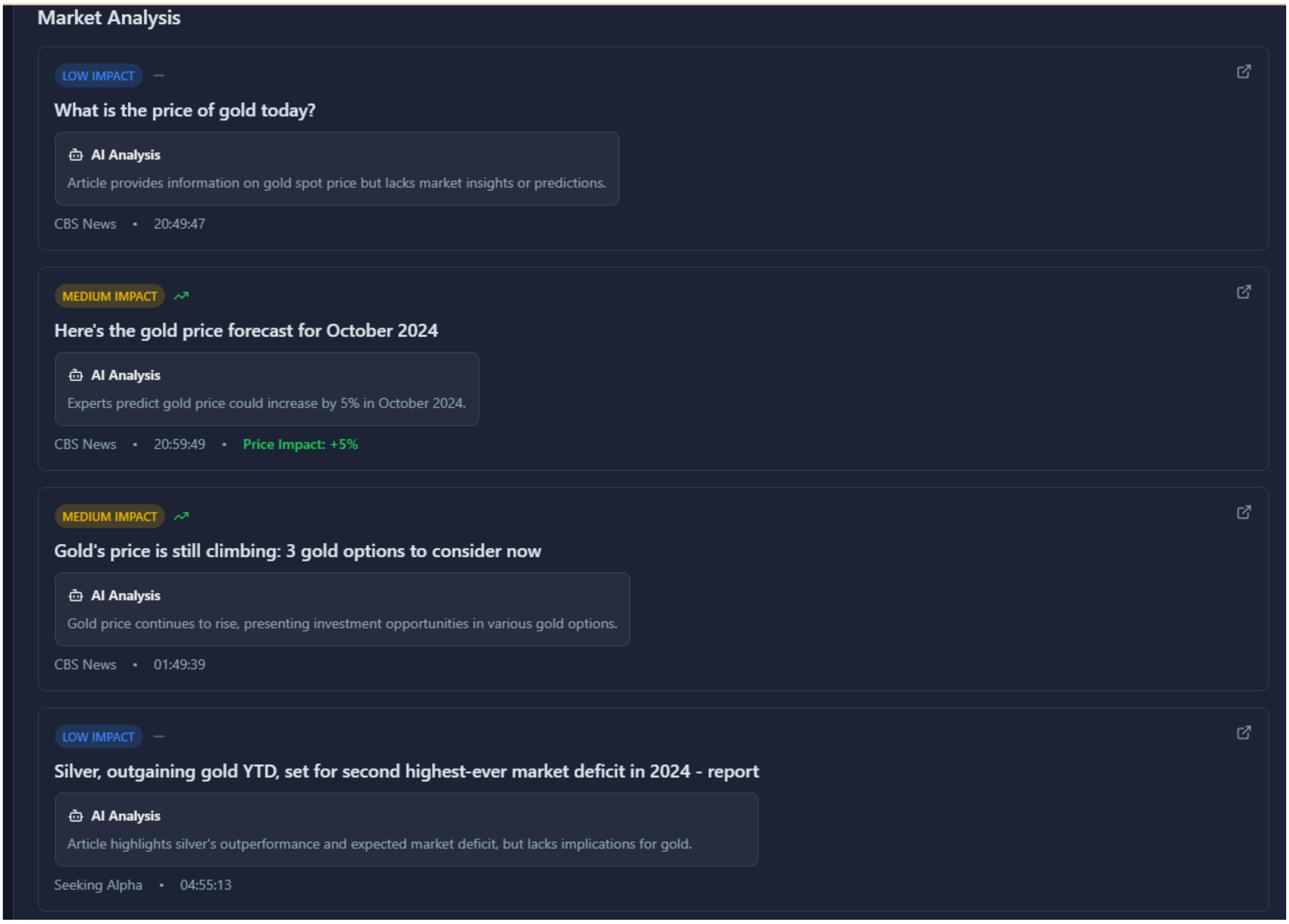
# Gold Price Tracker

Gold Price Tracker is a web application that predicts the future price of gold based on historical data. The application uses a Long Short-Term Memory (LSTM) neural network to model the complex relationships in gold prices. Users can input a date range and receive a forecasted price for the end of the period. The model is trained on gold prices from 2017 to 2021 and provides a reliable estimate of future trends.

## Demo




## Business Requirements

### Data Accuracy

- Real-time gold price updates with < 1-minute delay
- Historical data accuracy verified against multiple sources
- News sourced from reputable financial outlets

- AI analysis confidence scoring system

### Performance

- Initial page load < 3 seconds
- Real-time updates < 500ms
- Caching strategy:
  - Price data: 1 minute
  - News analysis: 30 minutes
  - Historical data: 24 hours

## Features

### Real-time Market Data

- Live gold price tracking
- Historical price charts with customizable timeframes
- Price statistics and trend analysis
- Related trading pairs monitoring

### AI-Powered Market Analysis

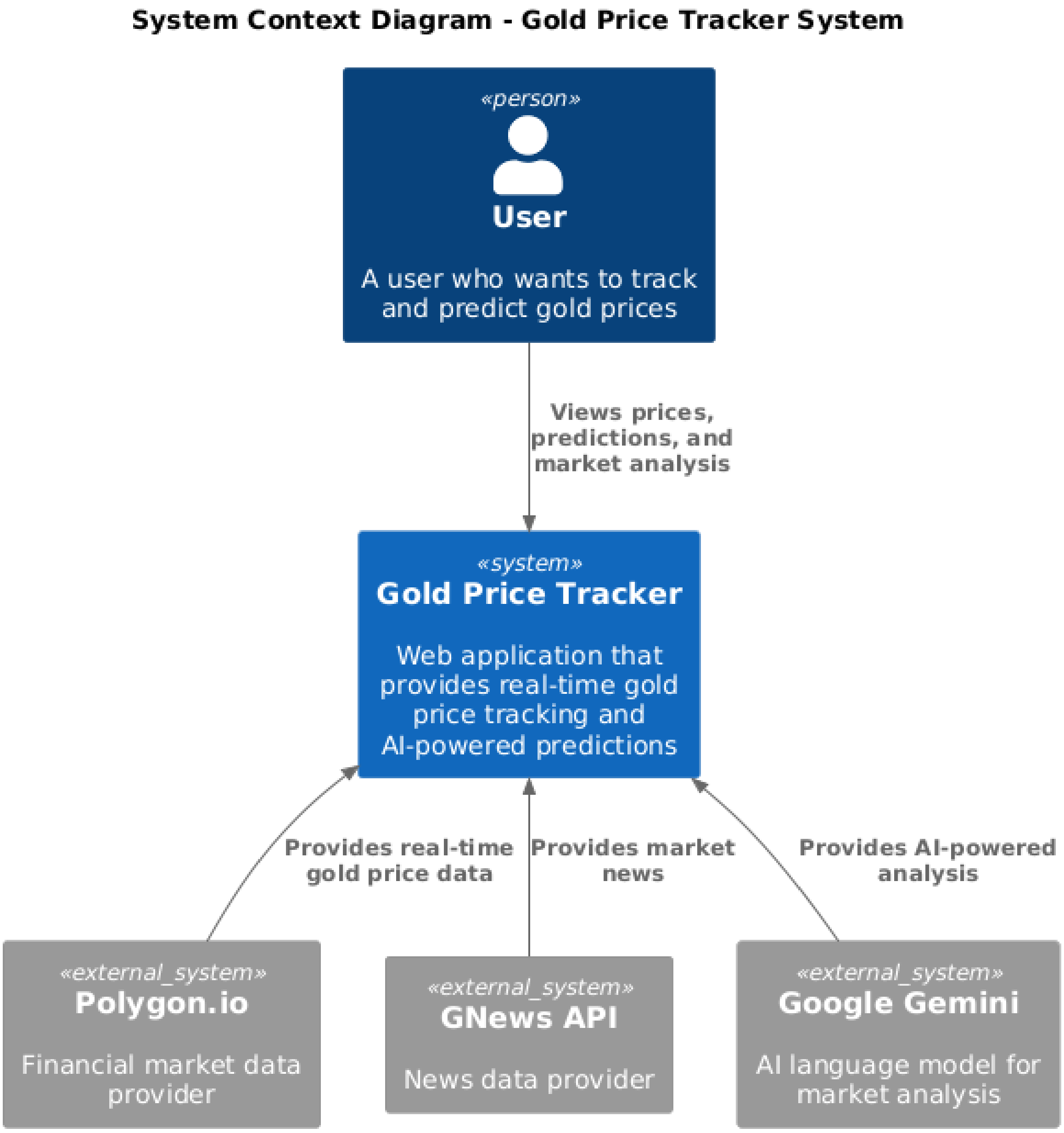
- Real-time news aggregation from reliable sources
- AI-driven sentiment analysis of market news
- Impact assessment on gold prices
- Price movement predictions based on news events

### User Experience

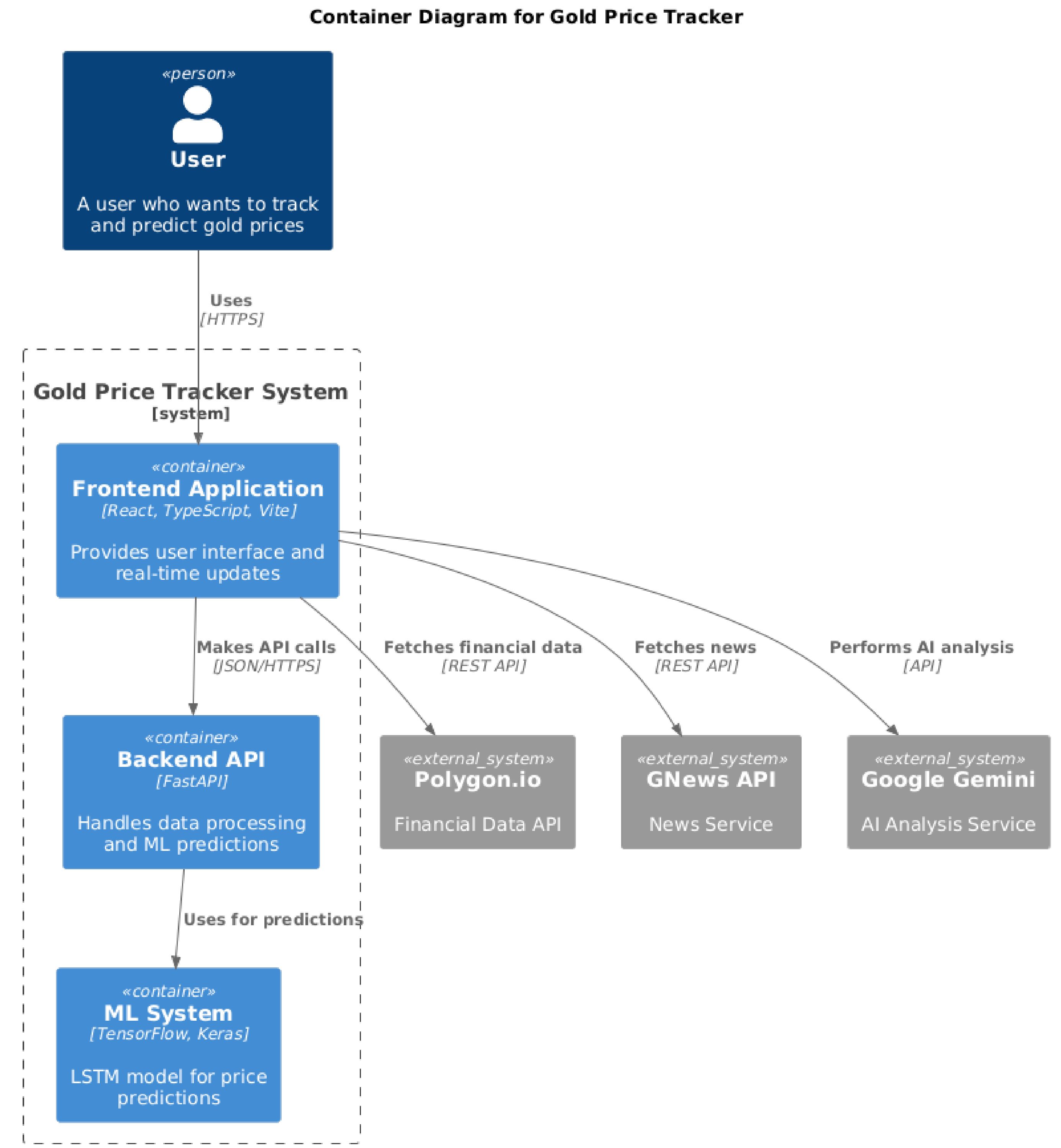
- Responsive design for all devices
- Dark/light theme support
- Customizable dashboard layout
- Real-time data updates
- Efficient caching system to prevent rate limiting

## Diagram

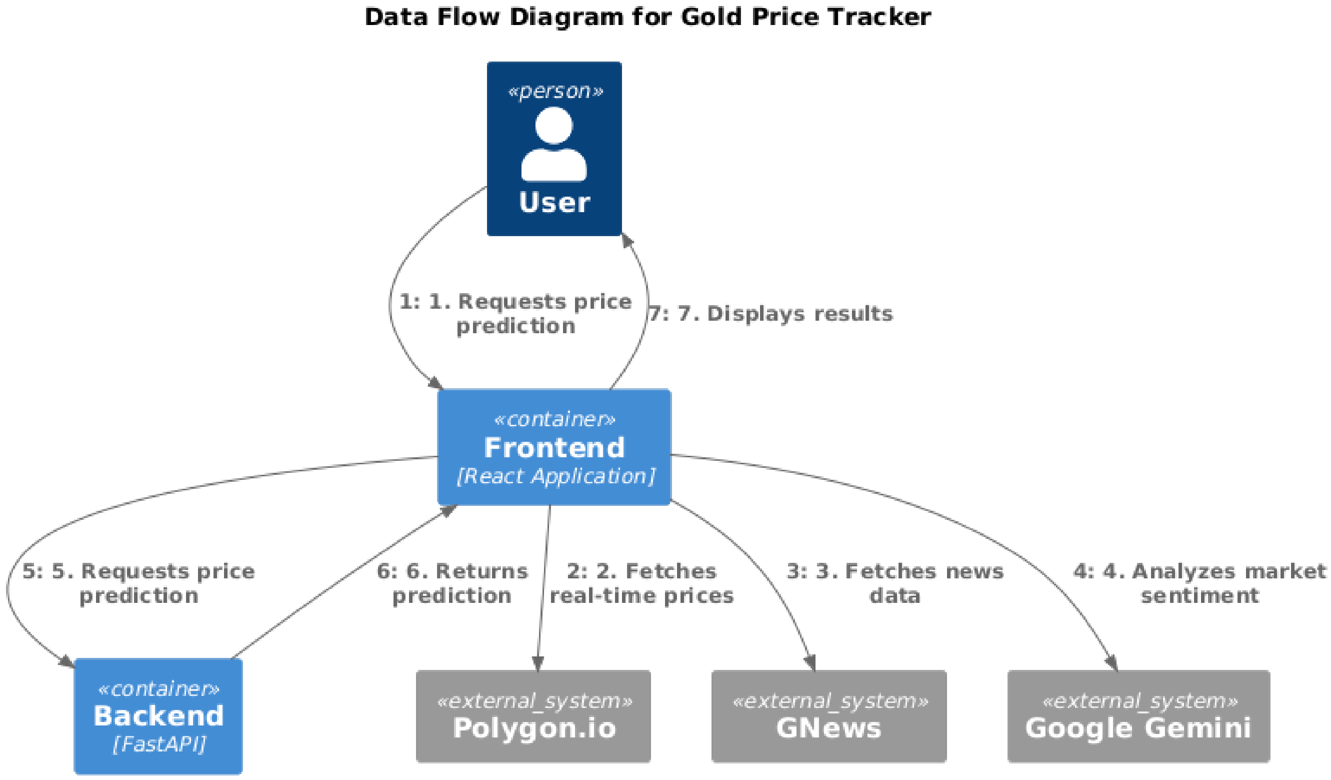
### C1: System Context Diagram




C2: Container Diagram

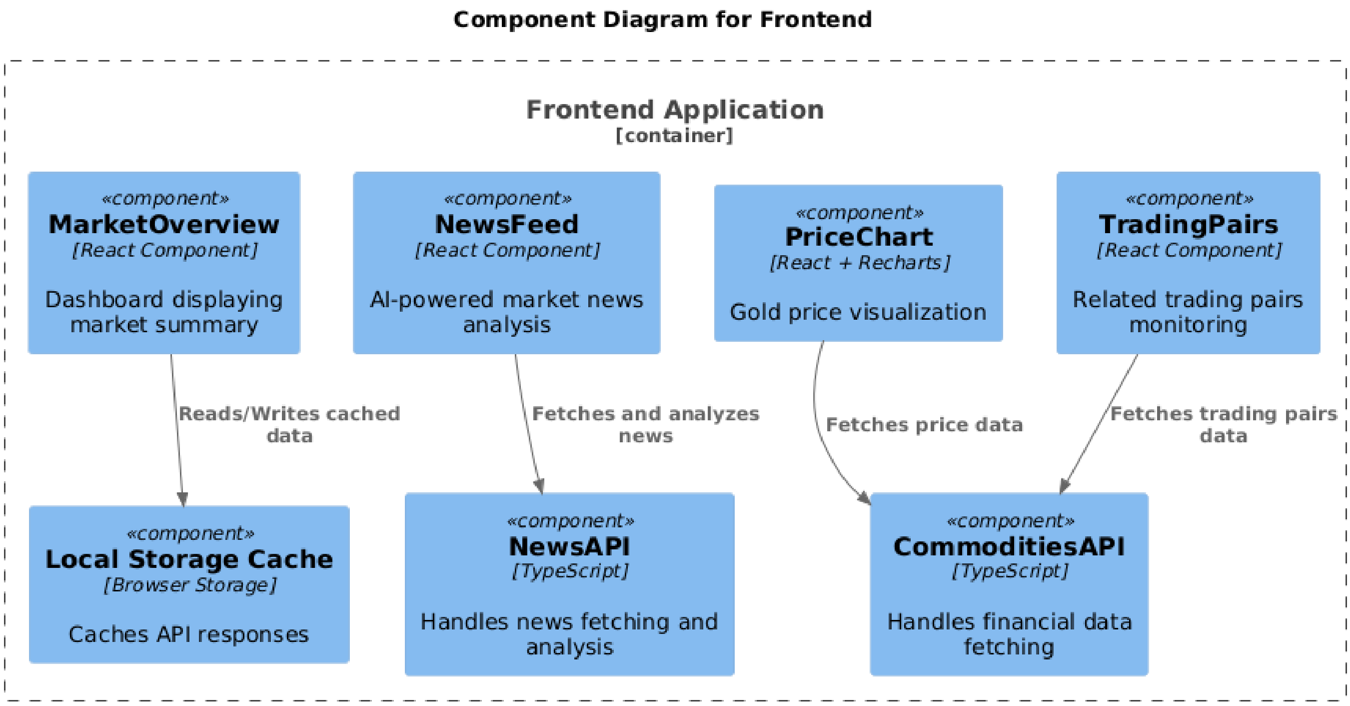

Container Diagram for Gold Price Tracker
«person»
User
A user who wants to track and predict gold prices
Uses
[HTTPS]
Gold Price Tracker System
[system]
«container»
Frontend Application
[React, TypeScript, Vite]
Provides user interface and real-time updates
Makes API calls
[JSON/HTTPS]
Fetches financial data
[REST API]
Fetches news
[REST API]
Performs AI analysis
[API]
«container»
Backend API
[FastAPI]
Handles data processing and ML predictions
«external_system»
Polygon.io
Financial Data API
«external_system»
GNews API
News Service
«external_system»
Google Gemini
AI Analysis Service
Uses for predictions
«container»
ML System
[TensorFlow, Keras]
LSTM model for price predictions

## Data flow




## Project Structure

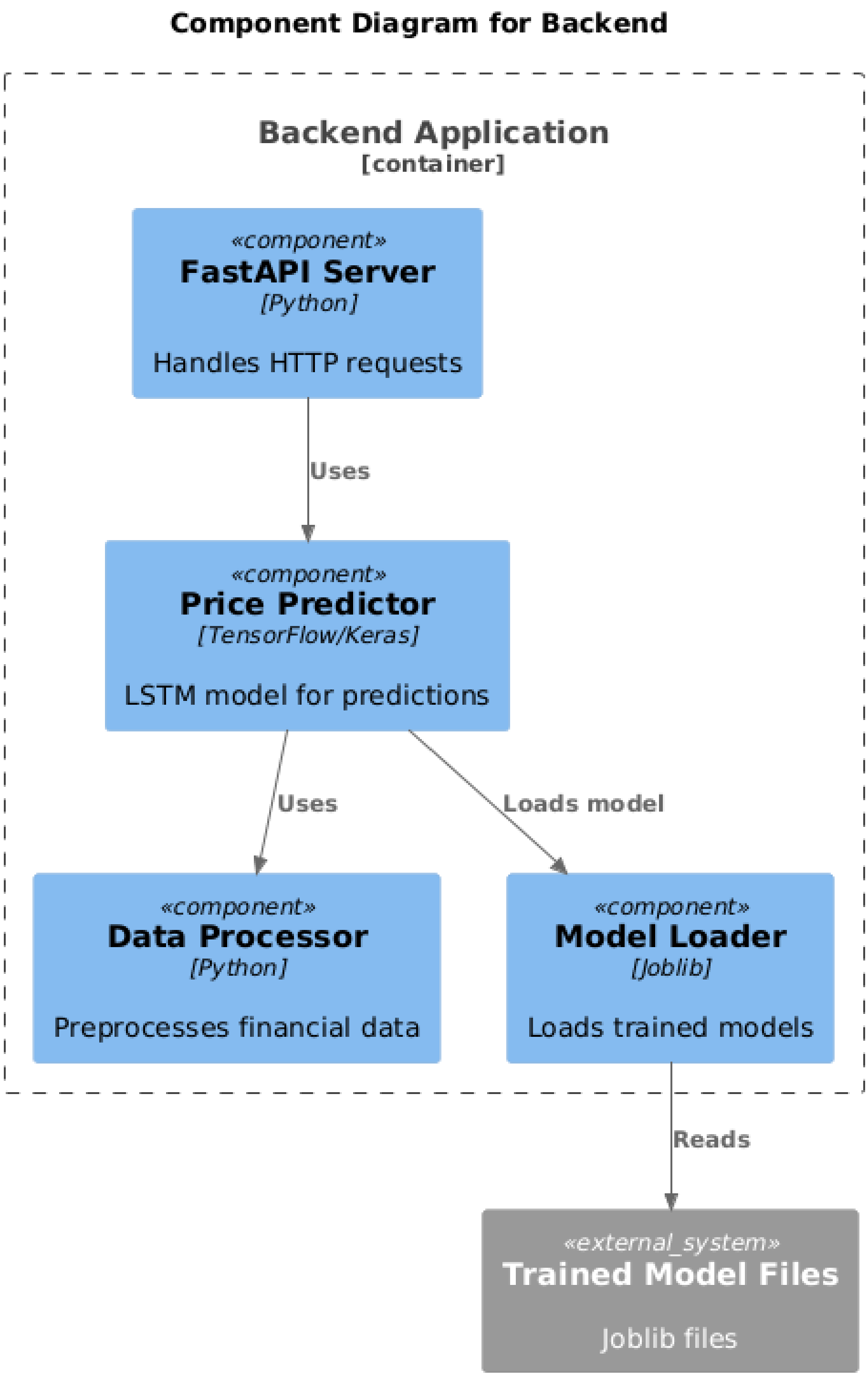
### Frontend




```
frontend/
├── src/
│   ├── components/
│   │   ├── NewsFeed.tsx        # AI-powered market news analysis
│   │   ├── NewsItem.tsx        # Individual news item display
│   │   ├── PriceChart.tsx      # Gold price visualization
```

```
│       │       ├── PriceStats.tsx      # Price statistics and metrics
│       │       ├── MarketOverview.tsx  # Market summary dashboard
│       │       ├── TradingPairs.tsx    # Related trading pairs
│       │       └── ui/                 # Reusable UI components
│       ├── lib/
│       │       ├── newsApi.ts          # News fetching and analysis
│       │       ├── commoditiesApi.ts   # Gold price data fetching
│       │       └── cache.ts            # Caching utilities
│       └── pages/
│               ├── Index.tsx           # Main dashboard page
│               └── Settings.tsx        # User preferences
```

Backend



```
backend/
│
├── main.py                  # FastAPI
├── requirements.txt          # Python dependencies
├── data.csv                  # Gold Price 2017 - 2021
├── gold_price_model.joblib      # Trained model
├── gold_price_scaler.joblib     # Data scaler
```

# Tech Stack

## Frontend

- React with TypeScript
- Vite for build tooling
- Tailwind CSS for styling
- shadcn/ui for components
- Recharts for data visualization
- Google Gemini for AI analysis
- Tanstack Query for data fetching

## Backend

## Machine Learning Stack

- Core Libraries
  - Deep Learning:
    - TensorFlow (Neural Network)
    - Keras (High-level Neural Network API)
- Scientific Computing:
  - NumPy (Numerical computations)
  - Pandas (Data manipulation)
- Machine Learning:
  - Scikit-learn
    - MinMaxScaler (Data normalization)
    - train_test_split (Data splitting)
    - mean_absolute_percentage_error (Evaluation metric)
- Model Serialization:
  - Joblib (Model and scaler saving/loading)

# Model Details

## Algorithm Choice

LSTM (Long Short-Term Memory)

- Memory Mechanism

  - Can capture long-term dependencies

    - Remembers important information over extended periods
    - Critical for financial time series where past events significantly impact future prices

- Non-linear Pattern Recognition

    - Captures complex, non-linear relationships
    - Understands intricate market dynamics
    - Can learn from:
        - Historical price movements
        - Seasonal patterns
        - Subtle market signals

```
input1 = tf.keras.layers.Input(shape=(self.window_size, 1))
x = tf.keras.layers.LSTM(64, return_sequences=True)(input1)
x = tf.keras.layers.Dropout(0.2)(x)
x = tf.keras.layers.LSTM(64, return_sequences=True)(x)
x = tf.keras.layers.Dropout(0.2)(x)
x = tf.keras.layers.LSTM(64)(x)
x = tf.keras.layers.Dropout(0.2)(x)
x = tf.keras.layers.Dense(32, activation='relu')(x)
output = tf.keras.layers.Dense(1)(x)
```

Architecture Breakdown

- Multiple LSTM Layers (64 units)

    - First layer: Processes sequential data
    - Subsequent layers: Extract higher-level representations
    - Each layer adds complexity and depth to learning

- Dropout Layers (0.2)

    - Prevents overfitting
    - Forces network to learn robust, generalized features
    - Reduces model's dependency on specific training instances

- Dense Layers

    - Final layers for regression output
    - Transforms learned representations into price prediction

**Core Features**

**Engineered Features**

### Data Preprocessing Considerations

- Window Size Selection (356 * 2 = 712 days)

    - Approximately 2 years of historical data

- Captures:
  - Annual market cycles
  - Seasonal price variations
  - Medium-term economic trends

- Loads CSV data

- Cleans and transforms price data

- Uses MinMaxScaler for data normalization

- Creates sliding window approach for time series prediction

**Data Transformation Techniques**

1. Price Normalization

```
scaler = MinMaxScaler()
scaled_prices = scaler.fit_transform(df.Price.values.reshape(-1, 1))
```

- Scales prices to [0, 1] range
- Ensures all features contribute equally
- Prevents dominance of larger numerical values

2. Sliding Window Approach

```
X, y = [], []
for i in range(self.window_size, len(scaled_prices)):
    X.append(scaled_prices[i-self.window_size:i, 0])
    y.append(scaled_prices[i, 0])
```

- Creates sequences of historical prices
- Each prediction uses previous 712 days' data
- Allows model to learn temporal patterns

## Model Pros and Cons

**Pros**

- Captures complex temporal patterns
- Handles non-linear relationships
- Provides uncertainty estimates
- Robust to market volatility
- Reproducible via fixed random seed

**Cons**

- Computationally expensive
- Requires substantial historical data
- Sensitive to window size selection
- May struggle with sudden market disruptions
- Potential overfitting risk

### Limitations and Considerations

- Not predictive of extreme black swan events
- Assumes past patterns will somewhat repeat
- Should be used as one of multiple decision-making tools
- Regular retraining recommended

### Model Pipeline

### Data Sources

- `data.csv`: Gold Price 2017 - 2021

## Installation

1. Install dependencies:

```
//Go to the frontend directory
cd frontend
npm install

//Go to the backend directory
cd backend
python install -r requirements.txt
```

2. Start the development server:

```


//Go to the frontend directory
cd frontend
npm run dev

//Now it available on localhost:5173

//Go to the backend directory

cd backend
python main.py
```