CS GS Hackathon Project Report

Team: Hands-on 1

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Problem Statement

Topic M5: Predict Medical Emergencies: Use machine learning techniques to analyze real-time patient data and predict emergency events (like seizures or heart attacks), providing timely alerts for doctors.

Heart disease is one of the leading causes of mortality worldwide, and early detection of cardiac events, particularly heart attacks, can save lives. Wearable devices like smartwatches provide a non-invasive way to continuously monitor physiological metrics, including heart rate. By leveraging machine learning, it may be possible to predict potential heart attacks based on patterns in heart rate data. This project aims to develop a predictive model using Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN), to analyze heart rate time series data and forecast potential heart attack events. This system will provide timely alerts to healthcare providers, allowing for proactive intervention.

Approach

This project employs an LSTM model due to its ability to capture dependencies in time series data, making it ideal for analyzing sequential heart rate readings. The approach involves the following steps:

1. **Data Preprocessing**: Heart rate data collected at one-minute intervals is normalized using MinMax scaling. The data is segmented into sequences, where each sequence consists of 60-minute intervals used as input to predict the heart rate at the subsequent minute.
2. **LSTM Model Design**: The LSTM model consists of multiple layers: an input LSTM layer with 50 units, a dropout layer to prevent overfitting, a second LSTM layer, and a dense layer for final predictions. The model is compiled with a mean squared error loss function and the Adam optimizer.
3. **Model Training**: The model is trained on sequences generated from heart rate data. A supervised learning approach is used, where each sequence of 60 data points predicts the heart rate for the next time step. The model is trained with

multiple epochs to allow the network to learn dependencies in the heart rate fluctuations.

4. **Prediction and Alerting**: Once trained, the model is used to predict heart rate patterns. An alert mechanism can be integrated into a real-time system to notify healthcare providers if the predicted heart rate falls within ranges indicative of potential cardiac events.
5. **Real-time implementation:** After the model is trained and tested, it can now be deployed onto a system where it should be exposed to data from real time humans or patients so that it would be able to identify and predict an actual medical emergency.

3. Dataset Used

For the initial model training, we used a combination of real-world and simulated data to emulate heart rate sequences. The primary dataset was derived from the **MIT-BIH Arrhythmia Database**, which provides labeled ECG recordings, including heart rate data and cardiac event annotations. This database was used to simulate possible scenarios and establish baseline prediction performance. To tailor the model to smartwatch heart rate data, the real-time data collected from a wearable device at one-minute intervals is used in conjunction with historical data from the MIT-BIH dataset.

Code Snippet

```
# Imports

import numpy as np

import pandas as pd

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import LSTM, Dense, Dropout

from sklearn.preprocessing import MinMaxScaler

# Building and Training LSTM model

model = Sequential([

    LSTM(50, return_sequences=True, input_shape=(X.shape[1], 1)),

    Dropout(0.2),
```

```
    LSTM(50, return_sequences=False),

    Dropout(0.2),

    Dense(25),

    Dense(1)

])

model.compile(optimizer='adam', loss='mean_squared_error')

model.fit(X, y, batch_size=32, epochs=10)
```

5. Conclusion

This project successfully demonstrates that an LSTM-based predictive model can be developed to analyze heart rate data for potential early warning signs of heart attacks. Through experimentation, the LSTM model shows promise in recognizing patterns within heart rate data that might precede a cardiac event, potentially assisting healthcare providers in proactive intervention.

While the current model provides a foundational approach, further refinements are required to increase prediction accuracy and robustness. External validation with real-time patient data is essential to determine its efficacy in a clinical setting.

6. Future Enhancements

Future work on this project can focus on the following enhancements:

1. **Incorporating Additional Physiological Signals**: Adding more parameters like oxygen saturation, blood pressure, and ECG data can improve model accuracy.
2. **Anomaly Detection**: Implementing anomaly detection to identify irregular heart rate patterns even in the absence of direct labels, potentially capturing early warning signs not identified in the training data.
3. **Extended Model Validation**: Testing the model on larger and more diverse datasets to assess generalizability and accuracy across different demographics and health conditions.
4. **Mobile and Web Application Interface**: Developing a user-friendly interface for healthcare providers to view predictions and alerts in real time.

By advancing these enhancements, the project can evolve into a fully functional predictive healthcare tool, potentially contributing to life-saving early interventions.