Report On

Fitness Watch Analysis

Submitted in partial fulfillment of the requirements of the Course project in Semester of Second Year Artificial Intelligence and Data Science

by

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CERTIFICATE

This is to certify that the project entitled “Fitness Watch Analysis” is a bonafide work of "Kartik Joshi (Roll No.06), Divyah Mandavia (Roll No. 10), Arpit Mishra (Roll No. 14)," submitted to the University of Mumbai in partial fulfillment of the requirement for the Course project in semester III of Second Year Artificial Intelligence and Data Science engineering.

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Abstract

In an age where personal health and wellness are paramount, wearable fitness devices, such as fitness watches, have gained immense popularity. These devices continuously collect an abundance of health-related data, ranging from heart rate and step counts to sleep patterns and more. The intersection of big data and fitness technology presents a unique opportunity to leverage modern data analysis techniques to enhance our understanding of personal health and well-being. This research project focuses on harnessing the power of big data analytics to analyze the data generated by fitness watches. The objective is to extract valuable insights that can inform individuals about their physical health, activity patterns, and even predict potential health issues. With the ever-increasing volume of data generated by these devices, it is crucial to employ advanced data analysis methods to derive meaningful information.Ultimately, this research seeks to contribute to the field of health and fitness by offering a comprehensive analysis of the data produced by fitness watches, empowering individuals to make informed decisions about their well-being, and encouraging healthier lifestyle choices. The insights gained from this study may also have broader applications in healthcare, wellness programs, and the development of advanced fitness technologies.

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Problem Statement

In the era of wearable fitness devices like fitness watches, we face the challenge of unlocking valuable insights from the vast health and activity data they capture. The problem is to convert this data into actionable information for users, helping them make healthier choices and optimize their fitness routines. This study aims to use advanced data analysis and machine learning techniques to decipher patterns, correlations, and early health issue indicators in fitness watch data. We also need to address data privacy concerns, ensure user-friendliness, and encourage healthier lifestyles. The goal is to empower individuals to take charge of their well-being and explore broader applications in healthcare and fitness technology.

Additionally, the research will explore the challenge of balancing data privacy and the need for insightful data analysis, ensuring that individuals can trust the recommendations and insights derived from their fitness watches. The study also addresses the challenge of ensuring that the analysis is user-friendly and accessible to a broad audience, as it seeks to encourage healthier lifestyle choices.

2.1 Description and Working:

This study focuses on the exploration of health and fitness data gathered by wearable fitness devices, specifically fitness watches. The main objective is to leverage this abundant data to provide users with valuable insights into their health and well-being, thereby enhancing their fitness journey and lifestyle choices. The study's core components involve data analysis and machine learning techniques applied to fitness watch data to better understand personal health patterns and provide actionable recommendations.
The project acknowledges the growing importance of personal health and wellness in modern society and seeks to harness the potential of fitness watch data to contribute to individual well-being. Additionally, the insights derived from this study may have broader applications in healthcare, wellness programs, and the continued advancement of fitness technology.

1. **Data Collection:** Fitness watches continuously collect a wealth of data, including heart rate, step counts, sleep patterns, and more. The initial step is to collect and aggregate this data, ensuring its accuracy and completeness.
2. **Data Preprocessing:** Raw data may contain errors or inconsistencies that need to be cleaned and transformed into a suitable format for analysis.
3. **Data Analysis**: Advanced data analysis techniques and machine learning algorithms are employed to identify patterns and correlations within the data. This includes recognizing relationships between physical activity, physiological parameters, and sleep quality, among others.
4. **Predictive Modeling:** The study aims to develop predictive models that can anticipate potential health issues based on the collected data. These models may provide early indicators of health concerns, allowing users to take preventive measures.
5. **Personalized Recommendations:** The goal is to deliver personalized health and fitness recommendations to individual users. These recommendations may include exercise routines, dietary advice, and lifestyle adjustments tailored to the user's data.

2.2 Software & Hardware used:

Software:

- Visual Studio Code
- Python 3.11
- Windows 10 OS

Google Colab Hardware:

- 64 bit Operating System
- 6gb RAM
- Intel i5 processor

Chapter # 3

3.1 Code:

```
import pandas as pd
import plotly.io as pio
import plotly.graph_objects as go
pio.templates.default = "plotly_white"
import plotly.express as px

data = pd.read_csv("Apple-Fitness-Data.csv")
print(data.head())
```

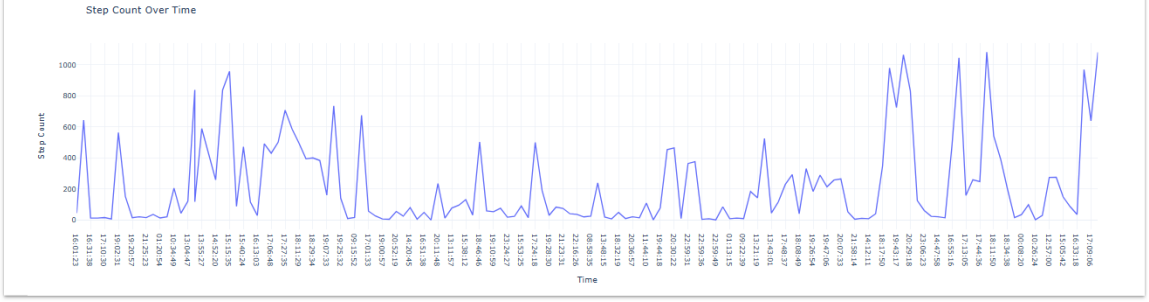
```
         Date      Time  Step Count  Distance  Energy Burned  \
0  2023-03-21  16:01:23          46   0.02543         14.620
1  2023-03-21  16:18:37         645   0.40041         14.722
2  2023-03-21  16:31:38          14   0.00996         14.603
3  2023-03-21  16:45:37          13   0.00901         14.811
4  2023-03-21  17:10:30          17   0.00904         15.153

   Flights Climbed  Walking Double Support Percentage  Walking Speed
0                3                             0.304          3.060
1                3                             0.309          3.852
2                4                             0.278          3.996
3                3                             0.278          5.040
4                3                             0.281          5.184
```

```
[3] print(data.isnull().sum())
```

```
Date                              0
Time                              0
Step Count                        0
Distance                          0
Energy Burned                     0
Flights Climbed                   0
Walking Double Support Percentage  0
Walking Speed                     0
dtype: int64
```

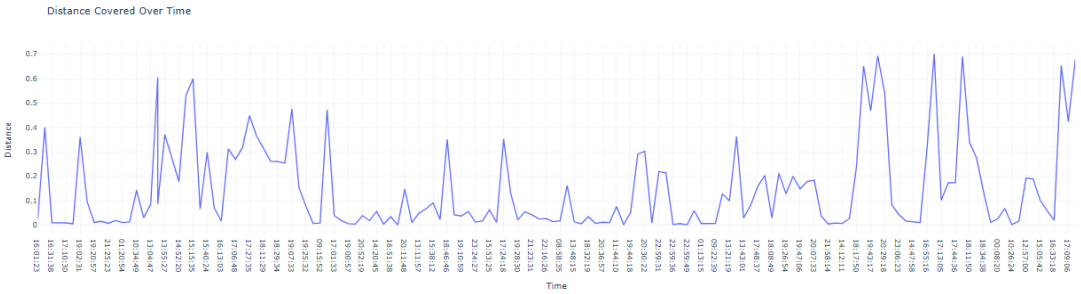
Step Count Over Time

```
fig1 = px.line(data, x="Time",
               y="Step Count",
               title="Step Count Over Time")
fig1.show()
```



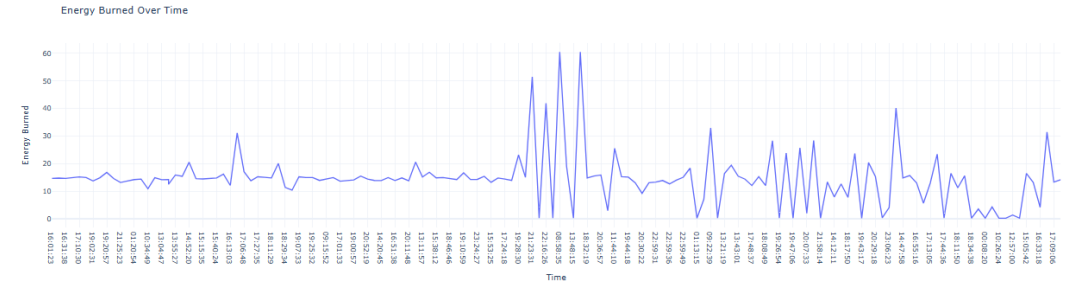
Distance Covered Over Time

```
fig2 = px.line(data, x="Time",
               y="Distance",
               title="Distance Covered Over Time")
fig2.show()
```



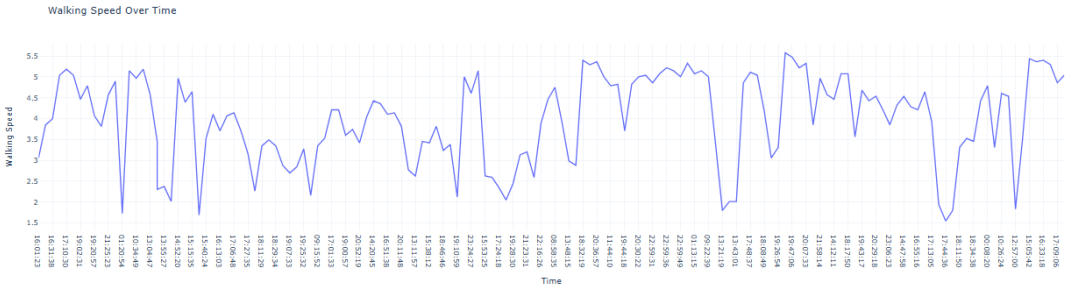
Energy Burned Over Time

```
[6] fig3 = px.line(data, x="Time",
                   y="Energy Burned",
                   title="Energy Burned Over Time")
    fig3.show()
```

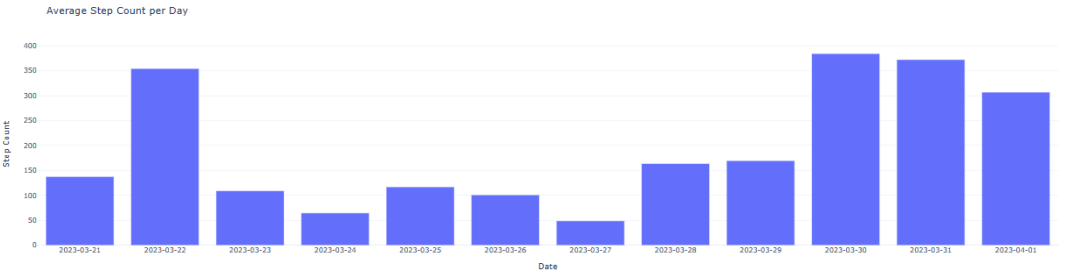


Walking Speed Over Time

```
fig4 = px.line(data, x="Time",
               y="Walking Speed",
               title="Walking Speed Over Time")
fig4.show()
```



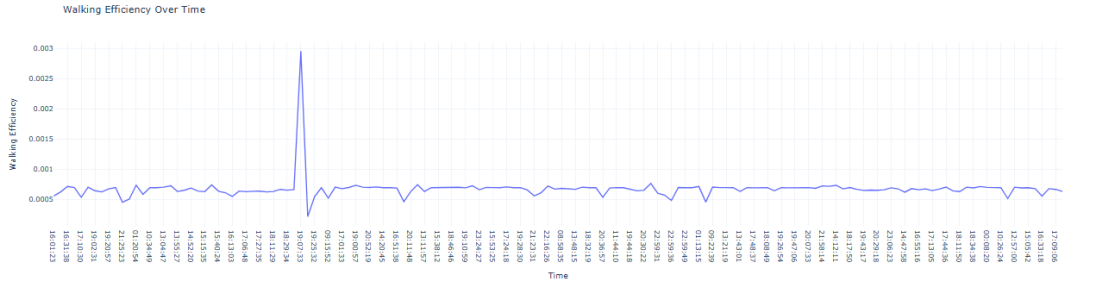

```
average_step_count_per_day = data.groupby("Date")["Step Count"].mean().reset_index()

fig5 = px.bar(average_step_count_per_day, x="Date",
              y="Step Count",
              title="Average Step Count per Day")
fig5.update_xaxes(type='category')
fig5.show()
```



Calculate Walking Efficiency

Calculate Walking Efficiency

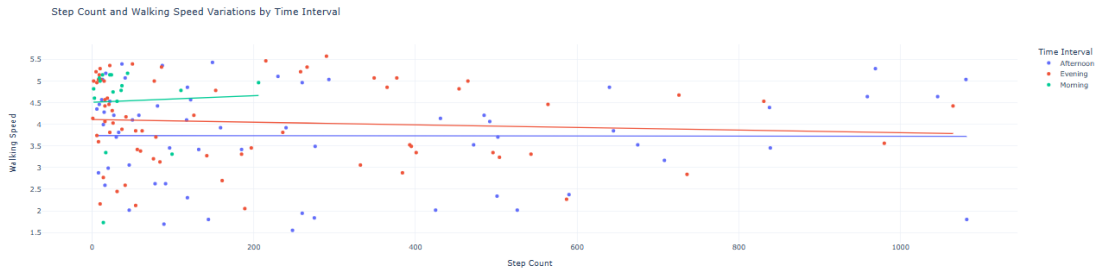
```
data["Walking Efficiency"] = data["Distance"] / data["Step Count"]

fig6 = px.line(data, x="Time",
               y="Walking Efficiency",
               title="Walking Efficiency Over Time")
fig6.show()
```



Create Time Intervals

Create Time Intervals

```
time_intervals = pd.cut(pd.to_datetime(data["Time"]).dt.hour,
                        bins=[0, 12, 18, 24],
                        labels=["Morning", "Afternoon", "Evening"],
                        right=False)

data["Time Interval"] = time_intervals

# Variations in Step Count and Walking Speed by Time Interval
fig7 = px.scatter(data, x="Step Count",
                  y="Walking Speed",
                  color="Time Interval",
                  title="Step Count and Walking Speed Variations by Time Interval",
                  trendline='ols')
fig7.show()
```



```
daily_avg_metrics = data.groupby("Date").mean().reset_index()

daily_avg_metrics_melted = daily_avg_metrics.melt(id_vars=["Date"],
                                                  value_vars=["Step Count", "Distance",
                                                              "Energy Burned", "Flights Climbed",
                                                              "Walking Double Support Percentage",
                                                              "Walking Speed"])

# Treemap of Daily Averages for Different Metrics Over Several Weeks
fig = px.treemap(daily_avg_metrics_melted,
                 path=["variable"],
                 values="value",
                 color="variable",
                 hover_data=["value"],
                 title="Daily Averages for Different Metrics")
fig.show()
```

```
<ipython-input-11-6b39c164a901>:1: FutureWarning:

The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
```


```
metrics_to_visualize = ["Distance", "Energy Burned", "Flights Climbed",
                        "Walking Double Support Percentage", "Walking Speed"]

# Reshape data for treemap
daily_avg_metrics_melted = daily_avg_metrics.melt(id_vars=["Date"], value_vars=metrics_to_visualize)

fig = px.treemap(daily_avg_metrics_melted,
                 path=["variable"],
                 values="value",
                 color="variable",
                 hover_data=["value"],
                 title="Daily Averages for Different Metrics (Excluding Step Count)")
fig.show()
```

3.3 CONCLUSION AND FUTURE SCOPE:

In conclusion, our exploration of fitness watch data has unveiled a wealth of insights into personal health and wellness, offering individuals the means to make informed choices about their well-being and optimize their fitness routines. The study underscores the potential of data-driven approaches in promoting healthier lifestyles and stands as a significant contribution to the field of health and fitness. Looking forward, several promising avenues for further research and development emerge. One key direction involves the enhancement of personalization in health and fitness recommendations. This entails refining algorithms to consider user preferences, individual characteristics, and even pre-existing health conditions, thereby tailoring guidance to a greater degree. Health predictions constitute another exciting frontier. Future research can focus on the creation of predictive models capable of anticipating health concerns, providing early warnings, and potentially preventing the development of serious health issues.
This proactive approach to health management has the potential to revolutionize healthcare. The challenge of data security and privacy remains paramount. Given the sensitive nature of personal health data, ongoing research should explore advanced encryption and anonymization techniques to ensure the confidentiality and protection of user information. Interoperability is a critical aspect to address, with efforts needed to ensure fitness watch data can seamlessly integrate with other health-related technologies, including electronic health records and telemedicine platforms. The integration of these systems can provide a more comprehensive and holistic view of an individual's health.

Chapter # 4

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