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Emergency Health Reporting App Based On Fitness Insights

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ABSTRACT

Our real-time smartwatch-based alerting system detects abnormal physiological and activity signals, such as heart rate and steps, that may indicate health risks using the elliptic envelope algorithm. We demonstrated the system's broad applicability by demonstrating its capability to identify anomalous signals prior to the onset of symptoms in a variety of health conditions through retrospective analysis. A dual-level warning mechanism notifies a proactive health management system when the heart rate significantly exceeds normal levels. Our proposal incorporates Fit-o-phile, a web application that offers personalized health recommendations and insights by visualizing and recording anomalous signal patterns while presenting a user-friendly visual interface. It also plans a medical consultation if significant irregularities are detected. It utilizes tailored assistance, reliable insights, and possible emergencies. This open-source, scalable method for early intervention and health monitoring may promote proactive health practices for a wide range of ailments.

Keywords: anomaly detection, heart rate, wearables, elliptic envelope, web application

I. INTRODUCTION

As a result of the assistance that wearable technology provides in the monitoring of healthcare, the medical profession is undergoing a transition. With the introduction of wearable technology, it is now possible to monitor vital signs in real-time. These vital signs include heart rate, the number of steps traveled, and other metrics like as elevation and calories [19]. By employing these instruments, it is feasible to perform uninterrupted and long-term monitoring of the physiological indicators that were previously mentioned. An inherent benefit of this type of technology is its ability to be employed at any given moment and in any given place.

Given the existence of supervised, unsupervised, and semi-supervised algorithms for anomaly detection, it is crucial to monitor people who are in optimal physical condition closely. These algorithms depend on continuous temporal data for analysis. In the process of discovering unexpected patterns, anomaly detection may on occasion produce false positives, which may or may not have any bearing on medical matters. In light of this, it is of the utmost importance to validate the outcomes that are generated by the utilization of anomaly detection techniques by comparing them with the information included in the user's electronic health record (EHR) [6].

The pace at which the heart beats is considered to be the typical vital sign because it reveals changes in the cycles of the heart. [20,21] Recent research has demonstrated that there has been an increase in the application of this essential characteristic for the goal of inferring a wide variety of heart illnesses. Such an increase has been observed. The application of heart rate data for the goal of assessing and preventing cardiovascular disease is receiving an increasing amount of support from the research that is being conducted. When a person has a high resting heart rate, they are at a greater risk of developing coronary artery disease (CAD) [22]. This is a correlation that exists between the two. Monitoring one's heart rate can provide useful information regarding the normal physiology of the heart, especially in individuals who are doing well physically.

II. DATASET

The dataset utilized in this study was originally collected for COVID-19 research purposes and is publicly available for download from the study data repository (https://storage.googleapis.com/gbsc-gcp-project-ipop_public/COVID-19/COVID-19-Wearables.zip) [1]. Although the primary objective of the dataset was to investigate early detection of COVID-19 using wearable technology, it has been repurposed for the specific focus of this research, which is highlighting abnormal heart rate data to users. The dataset includes de-identified raw heart rate, steps, and sleep data, providing a rich source of information for healthcare monitoring and anomaly detection beyond the scope of COVID-19 detection. By leveraging this dataset, we aim to extract valuable insights that can contribute to broader applications in healthcare analytics and personalized monitoring.

The participants employed various models of Fitbit smartwatches, like Fitbit Ionic, Charge 4, and Charge 3. The gathered data included measurements of heart rate, step count, and sleep duration. The heart rate, steps, and sleep data were collected in JSON format.

III.RELATED WORK

Heart rate and step counts were used by Mishra et al. (2020) in a recent study to detect COVID-19 incidents. They looked at exercise and physiological data from over 5200 participants, 32 of whom had COVID-19 infections identified. The results of the investigation showed that the subjects' resting heart rates were greater than average. To deal with the missing results, two algorithms were created: one that concentrated on heart rate over steps anomaly detection (HROS-AD) and the other on resting heart rate differential (RHR-diff). To observe baseline residuals, one method was to standardize the resting heart rate over a predetermined period. In HROS-AD, an elliptic envelope technique based on machine learning was used to merge the steps and heart rate data. The approach measured the separation between each HROS point and the overall mean in order to identify univariate and multivariate outliers, assuming that the data had a Gaussian distribution. When a point considerably deviates from the predicted Gaussian distribution, it is regarded as an outlier [1].

Another study on anomaly identification[7] in wearable data highlights the importance of swiftly recognizing anomalies and the need for accurate automated methods. Various studies have suggested different procedures, including both traditional statistical methods and advanced machine learning algorithms, to tackle difficulties such as missing data and establishing anomalous bounds. These observations provide the foundation for incorporating advanced anomaly detection algorithms into emergency health reporting applications, allowing for prompt identification of health issues for rapid intervention.

Studies on workout detection[5] using machine learning algorithms have revealed the effectiveness of utilizing wristband-type wearable sensors. These research highlight the capacity of wearable technology to analyze biological data and identify important characteristics like as sleep status, skin temperature, and pulse rate. This can enhance the accuracy of workout recognition algorithms. By incorporating comparable methods into emergency health reporting applications, it is possible to enhance the immediate identification of physical activity during emergencies. This can offer healthcare professionals responding to critical situations with crucial background information.

Systematic reviews and meta-analyses[12] have demonstrated the efficacy of interventions that utilize Fitbit devices in achieving positive outcomes related to a healthy lifestyle. Participants using Fitbit devices have shown notable enhancements in their daily step count, physical activity, and weight management. Integrating Fitbit data into emergency health reporting applications might offer significant insights into individuals' physical activity levels, enabling healthcare professionals to customize interventions and deliver individualized health advice during emergencies using up-to-date fitness data.

Research on machine learning models and evaluation metrics[7,15] highlights the significance of thorough assessment in validating models. Performance fitness and error metrics (PFEMs) are now recognized as essential tools for assessing the validity of models and the accuracy of predictions. By utilizing PFEMs (Portable Field Emission Microscopes) and sophisticated machine learning algorithms in emergency health reporting applications, it guarantees precise and dependable health monitoring that relies on fitness data derived from wearable devices. Moreover, it is recommended to promote interdisciplinary collaboration and implement comprehensive integration and validation methods in order to strengthen the performance evaluation process, thus increasing the overall effectiveness of health monitoring systems.

Previous studies on fatigue detection[14] have heavily relied on intricate EEG equipment, which has restricted its practicality in real-world situations. Recent developments in wearable technology have made it possible to gather physiological data, such as sleep patterns and heart rate, that are closely related to degrees of exhaustion. Researchers seek to automate tiredness detection tasks by utilizing machine learning algorithms and gathering data from widely-used fitness monitors such as Fitbit. This approach shows potential for enhancing safety and well-being across many industries and leisure activities by allowing for the prompt detection of dangers associated with weariness.

Incorporating fitness data from wearable devices into emergency health reporting applications shows great potential for boosting health surveillance and enhancing patient outcomes in critical circumstances. By integrating advanced anomaly detection algorithms such as elliptical envelope[15], and Fitbit data analysis into these applications, healthcare professionals can obtain invaluable insights into individuals' health and fitness levels. This allows for more informed decision-making and targeted interventions in emergencies using . Furthermore, utilizing sophisticated machine learning models such as elliptical envelope[15] to assess performance guarantees the dependability and precision of health monitoring using data from wearable devices, hence augmenting the usefulness of emergency health reporting applications in proactive health management.

IV. METHODOLOGY

- **Fit-O-Phile Web Application**

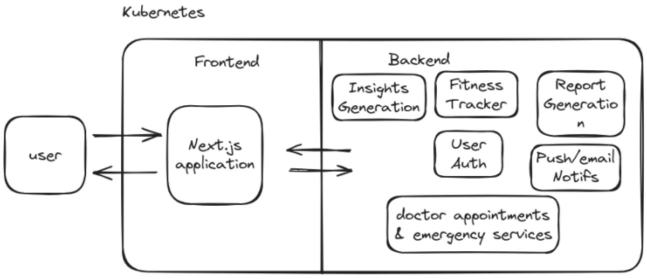


Fig 1: Architecture diagram

Our project uses backend and API development, which is powered by Express and Node.js. Express provides a streamlined approach to routing and middleware management, facilitating the creation of RESTful APIs. Node.js, known for its non-blocking I/O and scalability, complements Express by handling concurrent requests efficiently. Together, these technologies form the foundation of our backend architecture, ensuring robustness and responsiveness in handling data operations and client requests.

Moving on to data storage, we utilize MongoDB as our database solution. MongoDB's NoSQL nature offers flexibility in handling complex data structures and allows for seamless integration with Node.js through libraries like Mongoose. Its document-based storage model simplifies data management and retrieval, making it ideal for applications requiring dynamic and scalable data storage capabilities.

For the user interface development, we employ Next.js, a React framework known for its server-side rendering (SSR) capabilities. Next.js enhances React applications by providing SEO-friendly SSR, improved performance, and efficient routing. This enables us to create dynamic and interactive user interfaces that deliver fast page loads and optimal front-end user experience.

Incorporating machine learning functionality into our application, we integrate FastAPI, a Python web framework designed for building APIs with high performance and asynchronous capabilities. FastAPI's automatic API documentation generation, along with its efficient handling of HTTP requests, makes it well-suited for integrating machine learning models and exposing them through RESTful APIs within our application.

Our application architecture follows a microservices approach, dividing functionalities into smaller, independent services that communicate via APIs. This microservices architecture enhances scalability, flexibility, and maintainability by allowing each service to be developed, deployed, and scaled independently, ensuring optimal performance and resource utilization.

For authentication and authorization, we rely on Keycloak, an open-source identity and access management system. Keycloak provides robust features for user authentication, authorization, and single sign-on (SSO), ensuring secure access control and role-based permissions management within our application.

- **HROS-AD**

The Elliptic Envelope technique, used for anomaly detection, employs Gaussian density estimation to accurately predict the covariance of the data. Outliers are detected by examining data that follows a multivariate Gaussian distribution and identifying instances that go outside the robust covariance estimate. Consequently, this algorithm generates a fictitious ellipsoid encircling a provided dataset. Values falling within the envelope are regarded as representative/normal data, whereas any value outside the envelope is categorized as an outlier[18]. It computes the Mahalanobis distance [2] for each observation from the expected distribution and identifies data that surpass a specified threshold as anomalies. The algorithm's simplicity stems from its capacity to find both univariate and multivariate outliers, rendering it a powerful instrument for pinpointing exceptional data points in datasets. This method improves data analysis by identifying anomalies that could distort results or suggest abnormalities in the underlying distribution of data.In real-world datasets, it is common for the dimensions (columns in the dataset) to be correlated with each other.When circumstances like these arise, depending on the distribution of points as measured by the Euclidean distance between a given point and the cluster's center may yield imprecise or inadequate data regarding the point's actual proximity to the cluster. Mahalanobis distance is preferred over Euclidean distance because it first transforms the columns into uncorrelated variables, then scales the columns to equalize their variances, and last calculates the Euclidean distance.[23]

By leveraging these technologies and architectural principles, our methodology ensures the development of a scalable, performant, and secure web application capable of handling complex functionalities and delivering an exceptional user experience.

- **Working:**

1. Data Preprocessing:

- The heart rate (HR) and steps data are loaded from CSV files into pandas dataframes - The HROS (Heart Rate Over Steps) feature is calculated by dividing the heart rate by the steps data, filtering data points where steps are zero and also 12 minutes ahead.
- Moving averages (mean = 400 hours) are applied to smoothen the HROS data, followed by downsampling to one-hour intervals to obtain average values.

2. Seasonality Correction:

- Seasonal decomposition is performed on the HROS data using the seasonal_decompose function from statsmodels.
- The trend and residual components are extracted from the decomposition to correct for any seasonality effects in the data.

3. Standardization:

- The seasonality-corrected data is standardized using the StandardScaler() function from sklearn.preprocessing to have a zero mean and unit variance (Z-score normalization).

4. Anomaly Detection with Elliptic Envelope:

- Anomaly detection is carried out using the EllipticEnvelope class from sklearn.covariance, which fits a Gaussian distribution to the standardized data and identifies outliers/anomalies.
- The contamination parameter is set to the specified outliers_fraction (e.g., 0.1) to control the proportion of outliers detected.

5. Visualization and Results Saving:

- The results of anomaly detection are visualized using matplotlib to plot the standardized HROS data with detected anomalies highlighted.
- Anomalies are saved to both a PDF file for visualization and a CSV file for further analysis.

- The visualization includes markers for symptom date and diagnosis date if provided, aiding in understanding the temporal context of anomalies.

6. Web interface:

- Alongside visualizations, the code implements alert notifications triggered by anomalies, ensuring timely intervention and healthcare provider engagement, user profiles, etc
- Analytics dashboards present aggregated reports derived from the input data, highlighting trends, patterns, and abnormalities for comprehensive health monitoring and furthermore directing patients to schedule a doctor appointment.

- **MATHEMATICAL EQUATION**

The Elliptic Envelope algorithm fits a robust covariance estimate to the data, considering observations that are consistent with a multivariate Gaussian distribution and identifying outliers as observations lying outside the robust covariance estimate. The key equation involved in this algorithm is:

$$\text{EllipticEnvelope}(X) = \begin{cases} 1 & \text{if } (X-\mu)^T\Sigma^{-1}(X-\mu) \le \chi^2_{p,\alpha} \\ -1 & \text{otherwise} \end{cases}$$

Where:

- (X) is the input data matrix with (n) observations and (p) features.
- (μ) is the estimated mean vector.
- (Σ) is the estimated covariance matrix.
- $(\chi^2_{p,\alpha})$ is the threshold value based on the Chi-square distribution with (p) degrees of freedom at significance level (α).

This equation represents the decision boundary used by the Elliptic Envelope algorithm to classify observations as normal (inliers) or anomalous (outliers) based on their Mahalanobis distance from the estimated distribution. An observation with a Mahalanobis distance exceeding the threshold $(\chi^2_{p,\alpha})$ is considered an outlier.

V. RESULTS AND DISCUSSION

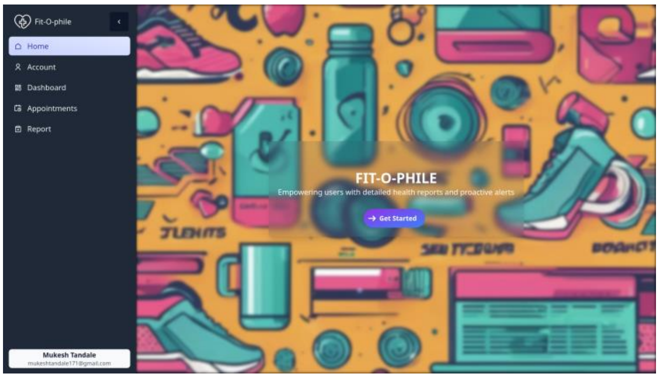


Fig 2: Home page of Web App

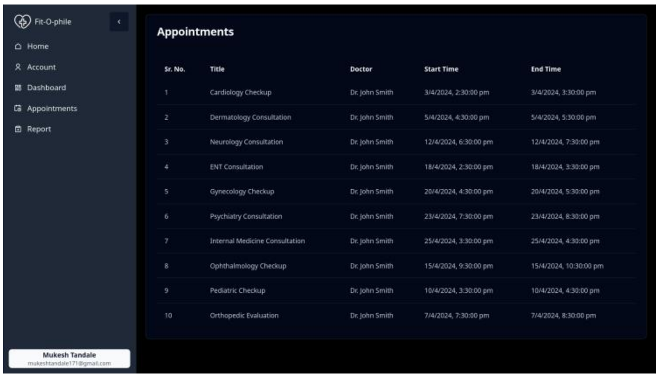


Fig 3: Appointments Page

Fig 4: Dashboard

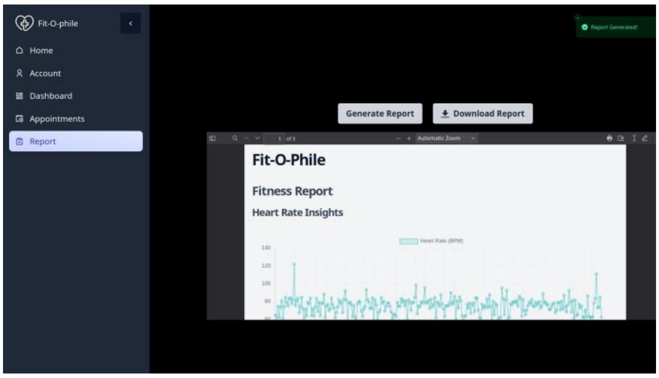
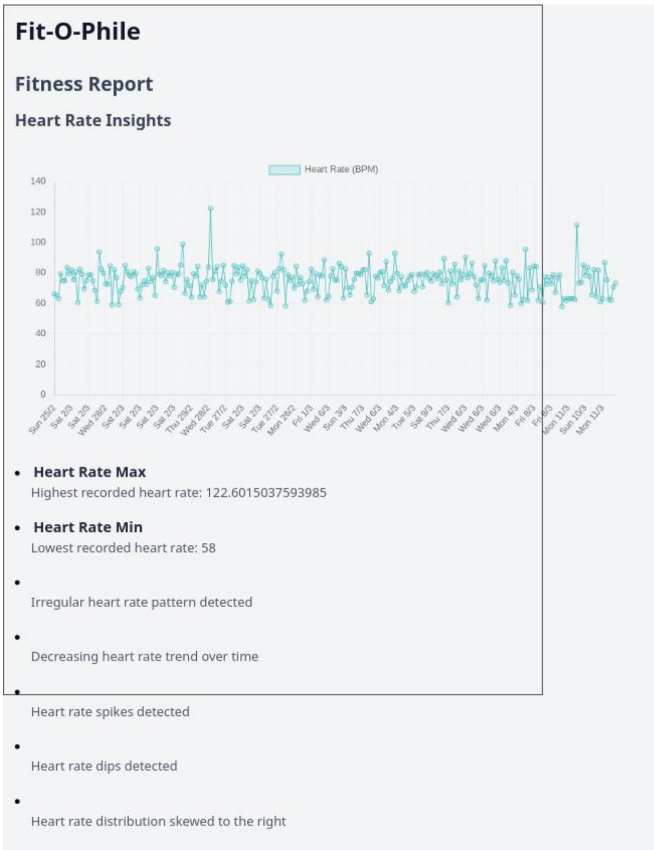


Fig 5: Report Page



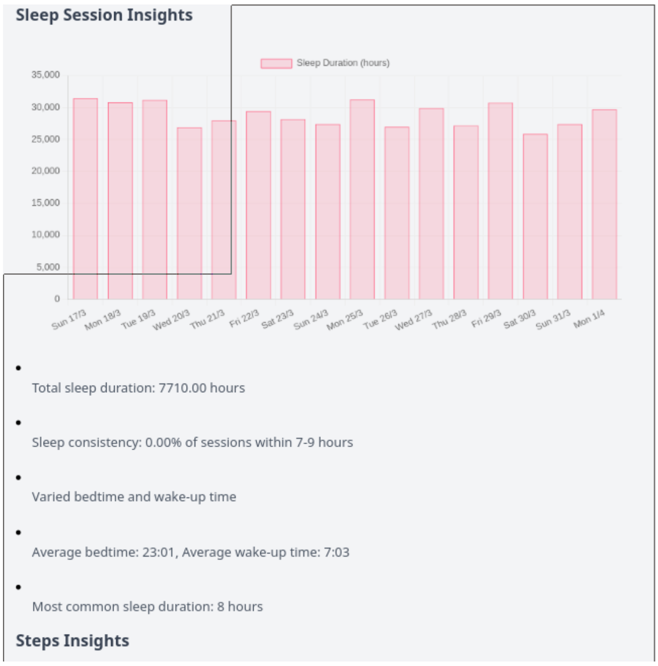
Fit-O-Phile

Fitness Report

Heart Rate Insights

- **Heart Rate Max**
  Highest recorded heart rate: 122.6015037593985
- **Heart Rate Min**
  Lowest recorded heart rate: 58
- Irregular heart rate pattern detected
- Decreasing heart rate trend over time
- Heart rate spikes detected
- Heart rate dips detected
- Heart rate distribution skewed to the right

Fig 6: PDF Report Page 1



Sleep Session Insights

- Total sleep duration: 7710.00 hours
- Sleep consistency: 0.00% of sessions within 7-9 hours
- Varied bedtime and wake-up time
- Average bedtime: 23:01, Average wake-up time: 7:03
- Most common sleep duration: 8 hours

Steps Insights

Fig 7: PDF Report Page 2

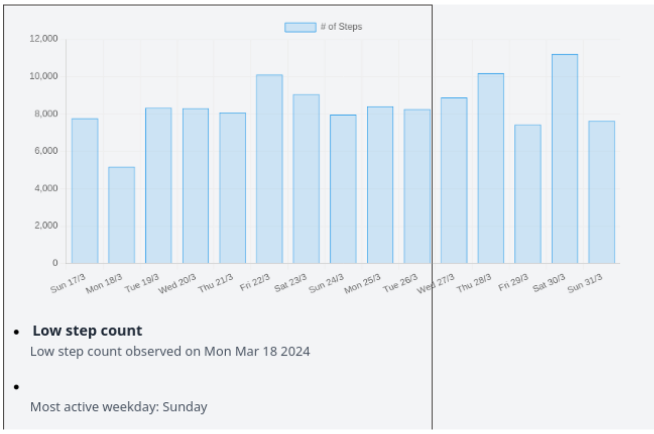


Fig 8: PDF Report Page 3

VI. CONCLUSION

Our project has developed a robust anomaly detection method, HROS-AD, leveraging the combination of elliptic envelope and Gaussian density estimation techniques. This approach effectively identifies anomalies in heart rate over steps (HROS) data, providing valuable insights into physiological irregularities. Additionally, we have integrated a user-friendly web application interface that allows users to interact with the system, including functionalities such as booking appointments with healthcare providers upon anomaly detection. The web app also features an analytics dashboard that offers personalized insights based on user input, ensuring a proactive approach to healthcare monitoring. Furthermore, alert notifications are triggered in real time if abnormalities are detected, enabling prompt intervention and management. In terms of future scope, integrating GPS services can enhance the system's capabilities by incorporating location-based data for contextual analysis. Additionally, modeling patients with pre-existing ailments such as high blood pressure and diabetes can further refine anomaly detection algorithms, tailoring them to specific health conditions. Overall, our project presents a comprehensive solution for proactive healthcare monitoring, bridging the gap between data analytics, user interface, and clinical intervention for improved patient outcomes and healthcare efficiency.

VII. ACKNOWLEDGEMENT

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