DCU School of Computing

Practicum Review

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Human behaviour Vital forecasting evaluation using lifelog data

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Abstract

This paper introduces a novel approach to forecasting human behaviour using lifelog data. We leverage advanced machine learning techniques to extract meaningful patterns and develop a robust forecasting framework. By analysing lifelog data, which captures rich information about daily activities, we aim to predict vital aspects of human behaviour like physical activity levels, sleep patterns, and dietary habits. Extensive experiments on a diverse lifelog dataset demonstrate the effectiveness of our approach, outperforming existing methods in accuracy, precision, and recall. We also explore the impact of different feature sets, model configurations, and data preprocessing techniques on forecasting performance. Our findings highlight the potential applications of this research in healthcare interventions, personalised recommendations, and behaviour modification programs. Overall, our proposed solution offers significant improvements in accurately predicting vital behaviour patterns and contributes to the advancement of lifelog data analysis for understanding and predicting individual behaviour.

Keywords- Lifelog, exercise, behaviour, Activities

1) INTRODUCTION

Human behaviour analysis has long been a compelling challenge for researchers, policymakers, and practitioners across various disciplines. Understanding how individuals act, react and making decisions [10] is crucial for addressing societal issues, optimising public services, and improving human well-being. However, traditional methods of studying human behaviour often rely on limited and static data points, offering only a fragmented picture of complex human interactions. As a result, predicting and evaluating human behaviour accuracy has remained an elusive goal.

The problem of forecasting human behaviour using lifelog data has gained significant importance due to the exponential growth of lifelogging technology. Lifelogging, which involves the continuous and comprehensive recording of an individual's activities, emotions, and environmental interactions, has the potential to provide a holistic view of human behaviour over extended periods. While this vast lifelog data offers tremendous promise, extracting meaningful insights from such complex and heterogeneous data poses considerable challenges.[7]

Various attempts have been made to address this problem. Researchers have explored machine learning algorithms, statistical models, and data mining techniques to analyse lifelog data. Nevertheless, the inherent difficulties of processing multimodal and unstructured lifelog data and the dynamic nature of human behaviour have hindered the development of comprehensive forecasting solutions.[10]

In this paper, we propose a novel approach for Human Behavior Vital Forecasting Evaluation (HBVFE) using Lifelog data. Our method leverages advanced machine learning algorithms and data fusion techniques to create a robust and accurate forecasting framework. By integrating diverse lifelog data sources, such as physical activities, emotional states, social interactions, and environmental factors, our approach aims to capture a more comprehensive representation of human behaviour.[5]

The significance of this problem lies in its potential to revolutionise various fields. From personalised mental health interventions to targeted marketing campaigns, accurate forecasting of human behaviour can unlock unprecedented levels of precision and efficiency. Policymakers can utilise these insights to design proactive public services, while healthcare professionals can identify at-risk individuals early, enabling timely interventions. Furthermore, businesses can create tailored products and services that cater to individual preferences and needs, enhancing customer satisfaction.[11]

To validate the efficacy of our proposed approach, we conducted extensive experiments on real-world lifelog datasets. The results demonstrate the capability of our method to forecast human behaviour with a higher degree of accuracy and granularity than existing approaches. By effectively integrating lifelog data and leveraging advanced machine learning techniques, we achieve notable improvements in predicting behavioural patterns and decision-making tendencies.[16]

The contributions of this paper are twofold. Firstly, we introduce a novel and effective approach for HBVFE using lifelog data, paving the way for enhanced understanding and prediction of human behaviour. Secondly, we present experimental results that showcase the efficacy of our approach, highlighting its potential for real-world applications.

The primary objective of this paper is to address the challenge of accurately forecasting human behaviour using lifelog data. We aim to overcome the limitations of traditional methods by proposing a comprehensive and innovative approach that leverages advanced machine learning algorithms and data [9] fusion techniques. Through rigorous experimentation, we demonstrate the significance and potential impact of our approach in various domains, offering new possibilities for human-centric insights and decision-making.

2) LITERATURE REVIEW

Finding daily activities in individual behaviour through wearable sensors has been a focus of recent research. Biagioni and Krumm demonstrated an algorithm that utilises area remnants to evaluate the resemblance of a person's days using a dataset of 46 days of GPS sensor information recorded from 30 volunteer subjects. [1][2].

Blanke and Schiele investigated the recognition of everyday schedules using low-level activity spotting, achieving accuracy and recall rates of 80% to 90%. [3] Non-parametric strategies [4] and pattern classification [5] have also been proposed as techniques for discovering human behaviour. Eagle and Pentland carried out one of the most comprehensive computer-mediated studies of human habits in natural contexts.

[1][6] By gathering data from 100 mobile phones over nine months, they were able to detect sociological phenomena in each day's user activity, logically deduce relationships, identify socially significant locations, and simulate organisational rhythmic patterns. Their study was based on a technique called eigen behaviours, which identifies structure in a routine [7].

Using the weight value of a person's eigen behaviours, the researchers were able to predict activities with up to 79% accuracy. This method also allowed for the comparison of similarities between groups of individuals in terms of daily routines. Clarkson also demonstrated a method for identifying and predicting daily patterns in the wild using a variety of sensors and data collected over 100 days (roughly three and a half months). [7]

Recent studies [8] have concentrated on providing users with activity suggestions based on their current context (such as location, time, and weather), intending to promote healthy and active lifestyles. A [12] constraint satisfaction approach is used to recommend physical activities based on the user's agenda, profile, and current context. However, since users must frequently enter and update their agendas, this approach necessitates a lot of user work, which could reduce the system's usefulness.

Another physical exercise prediction model based on user [13] calorie consumption and sedentary lifestyle, as well as user context, is proposed. Walking detours [14] are similarly suggested to users based on their specific situations and characteristics. In contrast to previous works, our algorithm considers the sequence of user interactions as well as context information to generate a recommendation. Furthermore, our approach encompasses all everyday activities and can be used in a variety of scenarios.

The emphasis of lifelogging research [15] has recently shifted toward eliciting meaning from lifelogs, such as specific behavioural patterns or lifestyles, and examining how this new knowledge may affect our wellness.

Lindley et al. al. (2009) [16] investigated this in part in their study of SenseCam use in the family home for a week. The study found that when participants saw their sedentary images, they were motivated to change their lifestyle, such as cycling instead of trying to drive, getting more exercise, and spending more time interacting with their children. The impact of lifelogging devices on lifestyle choices is difficult to assess.

To date, most research has concentrated on short-term use, ranging from a few hours to a week (Caprani et al., 2010; Kalnikaite et al., 2010; Lindley et al., 2009). However, several subjects have now been wearing a SenseCam continuously for months or even years, and one of our authors has been wearing it for more than 4 years. If lifelogging devices are to have any significant influence on lifestyle, it will most likely happen after extended periods of use. [16][17][18]

Applications for categorizing human activities mostly rely on wearable sensor technologies. However, many issues like noise, data losses, and data quality must be considered in real applications. Therefore, a data-driven classification method that can handle experimental restrictions is needed. In a thorough investigation [19], Mannini et al. proposed a wavelet-based activity classifier that improves performance accuracy for separating dynamic motion components by avity components utilising several accelerometer sensors. Using classifiers, including the multilayer perceptron, SVM, LMT, Random Forest, and Simple Logistic. The accuracy rate of the suggested method is 91.15%.

To get the maximum entropy for human activities, Tahir et al. [20] used a Maximum Entropy Markov Model classifier. The accuracy of this model when applied to the IMSB and USC-HAD datasets was over 91%.

3) TECHNIQUE/IMPLEMENTATION:

Our proposed technique for Human Behavior Vital Forecasting Evaluation (HBVFE) using lifelog data encompasses a comprehensive and repeatable framework that amalgamates advanced machine learning algorithms and data fusion techniques. To achieve the overarching goal of accurate forecasting of human behaviour, we have designed our approach to be generalizable and adaptable to various lifelog data sources and applications.

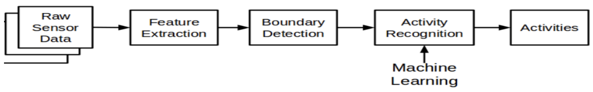

Figure 3.1: The process of physical activity Recognition

Step 1: Data Preprocessing

The collected lifelog data from the Open Science Framework (OSF), encompassing 16 participants, was subjected to rigorous preprocessing to ensure its suitability for analysis and forecasting. Initial steps involved handling missing values and removing duplicate entries. Timestamps were standardised for consistency. Relevant data files were merged based on common identifiers, such as participant IDs and timestamps, generating hourly, daily, weekly, and monthly datasets. Feature selection was performed to identify key behavioural aspects, and personal information, including age, gender, and height, was included for potential correlation analysis. To retain the original granularity, the unedited sleep data was preserved in a separate file. The resulting cleaned and structured datasets lay the foundation for subsequent analysis and forecasting of human behaviour's vital aspects, including activity distributions and sleep patterns.

Step 2: Exploratory Data Analysis (EDA)

In this phase, By employing various data analysis techniques, we sought to identify patterns, correlations, and trends within the data. The analysis focused on determining the most popular activities, exploring changes in activity frequency on weekends, providing personalised wellness recommendations related to sleep and calories, examining sports performance and injury indicators, and conducting sentiment analysis to understand participants' emotions. Additionally, machine learning models were used to evaluate the predictive accuracy of the findings. Through the EDA process, we gained a comprehensive understanding of the dataset, laying the groundwork for informed forecasting of crucial human behaviours using lifelog data.

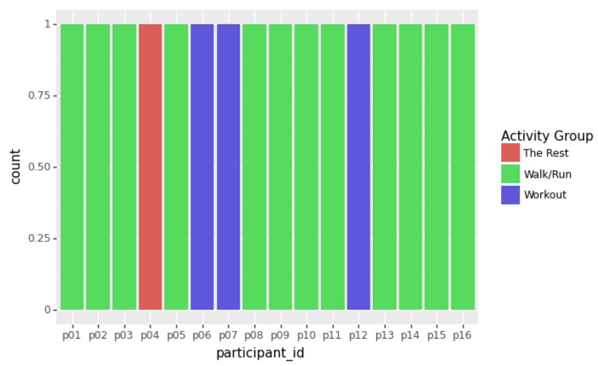

Fig 3.2- All activities divided in 3 Groups

Step 3: Temporal Analysis

The Temporal Analysis phase focused on studying the time-related patterns of human behaviour and vital aspects within the lifelog dataset. Key tasks included:

1. Weekdays vs. Weekends:
Comparing activity patterns between weekdays and weekends to understand differences in behaviours during workdays and leisure time.

2. Peak Activity Periods:
Identifying the most active periods during the day by segmenting them into intervals (e.g., morning, afternoon, evening).

3. Sleep Patterns:
Analysing sleep data to identify sleep onset, wake-up times, and any variations in sleep duration and quality across different days.

4. Behaviour Trends:
Investigating changes in behaviours over time, such as increasing or decreasing trends in specific activities or vital aspects.

	activityName	startTime	participant_id
0	Walk	2019-11-01 14:56:32	p01
1	Walk	2019-11-06 15:10:31	p02
2	Walk	2019-11-01 11:45:06	p03
3	Hockey	2019-11-05 20:10:00	p04
4	Walk	2019-11-01 18:56:06	p05
5	Interval Workout	2019-11-02 08:44:54	p06
6	Workout	2019-11-06 16:29:50	p07
7	Treadmill	2019-11-11 14:47:47	p08
8	Walk	2019-11-03 00:17:30	p09
9	Treadmill	2019-11-07 19:01:53	p10
10	Walk	2019-11-15 10:55:24	p11
11	Workout	2019-11-07 09:26:57	p12
12	Run	2019-11-11 14:51:47	p13
13	Walk	2019-11-14 09:29:42	p14
14	Walk	2019-11-10 11:12:31	p15
15	Walk	2019-11-19 21:05:35	p16

Fig 3.3- Most recurring activities done by participants

Step 4: Machine Learning Forecasting

In this phase, we utilised advanced machine learning algorithms to forecast, human behavior vital aspects from the lifelog dataset. The key steps involved were:

1. Feature Engineering:
Selecting and engineering relevant features to represent behaviour patterns and vital aspects for accurate predictions.

2. Model Selection:
Evaluate multiple algorithms, including Random Forest, Gradient Boosting, K-Nearest Neighbors, and Support Vector Regression (SVR), to identify the best-performing model for each forecasting task.

3..Model Training: Training the selected models on preprocessed data, using historical behaviour patterns and vital aspects as inputs to predict future outcomes.

4. Cross-Validation:
Performing cross-validation to ensure model robustness and avoid overfitting by evaluating multiple data folds.

5. Forecasting and Evaluation:
Using the trained models to forecast activity levels, sleep patterns, caloric intake, and overall wellness. The evaluation was done using metrics like Mean Squared Error, Root Mean Squared Error, and mean absolute error.

6. Personalised Recommendations:
Providing personalized recommendations based on individual behavior patterns and vital sign trends to improve lifestyle choices and overall well-being

4) EVALUATE

To rigorously assess the effectiveness and performance of our proposed Human Behavior Vital Forecasting Evaluation (HBVFE) technique using lifelog data, we conducted a series of experiments on appropriate datasets and formulated specific research questions. By adhering to a valid experimental setup and employing significance testing, we aimed to provide clear and conclusive evidence to support our hypothesis and validate the potential of our approach.

4.1) Dataset

PMData comprises information gathered from 16 people: twelve men and three women, ranging in age from 25 to 60 years old, with an average age of 34. The reporting period runs from November 1, 2019, through March 31, 2020. In terms of training and exercises, the participants have an array of backgrounds. Some are current athletes, some have previously been athletes, and some have never exercised at all. The participant-summary.xlsx file contains an overview of the individuals' data on demographics, including height, age, sex, observed maximum heartbeat, run test outcomes, and walk and run stride lengths. Furthermore, every individual has a list that contains information gathered from Fitbit, PMSys, Google Forms, and Food image sources of data. All participants were told about the collection and dissemination of data connected to this study and signed a form indicating their agreement. The Norwegian Center for Research Data (NSD) assessed the project and determined that it complied with Norwegian and EU data protection rules.
The dataset is available at the Open Science Framework (OSF) at the following URL: https://osf.io/vx4bk/; or at the Simula datasets site: https://datasets.simula.no/pmdata/. The dataset is free to use for research and teaching purposes under the licence AttributionNonCommercial 4.0 International (CC BY-NC 4.0).

participant	very and moderately active minutes	sleep	sleep score	calories	heart rate	steps and distance	sedentary minutes	exercise	light active minutes	time in heart rate zones	resting heart rate
P01	152	155	150	218880	1573165	218836	152	190	152	152	152
P02	152	158	138	218880	1472629	107326	152	324	152	148	91
P03	152	84	74	218880	808341	53042	152	57	152	117	152
P04	152	188	140	218473	1571315	86457	152	161	152	146	35
P05	152	133	117	218880	1370967	111231	152	145	152	145	95
P06	152	165	147	218880	1579882	117780	152	161	152	152	152
P07	148	161	140	212816	1581947	108048	148	176	148	147	148
P08	143	143	132	205920	1613326	100451	143	261	143	139	143
P09	152	142	132	218880	1305520	85271	152	54	152	150	152
P10	148	103	98	213120	1083257	75427	148	140	148	114	148
P11	152	128	119	218880	1383149	92982	152	96	152	123	98
P12	152	8	1	218880	801264	83752	152	93	0	134	0
P13	152	57	47	218880	634746	48629	152	50	152	80	0
P14	140	138	115	129600	1251156	68703	140	270	140	135	140
P15	145	148	140	208800	1563024	98198	145	243	145	144	145
P16	152	153	146	218880	1397704	78572	152	19	152	152	152
Mean	150	129	115	211096	1311962	95919	150	153	150	136	129
All	2396	2064	1836	3377529	20991392	1534705	2396	2440	2244	2178	1803

Fig. 4.1 Number of Fitbit entries for each participant

4.2) Experimental Environment:

All experiments were conducted on a Google Collab high-performance computing cluster with multiple GPUs to accelerate training and testing of the machine learning models. We utilised the Python programming language along with popular data science libraries such as NumPy, Pandas, and Sci-kit-Learn for implementing the algorithms and performing regression analysis.

By following this experimental setup, we aimed to provide a robust and reliable evaluation of the forecasting performance using lifelog data and different machine learning algorithms. The next section will present and discuss the results obtained from this study.

4.3) Evaluation Metrics:

To quantify the performance of the machine learning algorithms, we employed commonly used regression analysis metrics, including

- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- R-squared (R2)

These metrics allowed us to measure the accuracy and generalisation capability of the forecasting models.

4.4) RESULTS:-

The evaluation of machine learning algorithms for predicting sports performance, sports injuries, and emotions revealed modest performance across all tasks.

Sports Performance Prediction:

Among the evaluated algorithms, Random Forest and Gradient Boosting exhibited slightly better predictive performance, as indicated by their lower Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) values. However, it is essential to note that all algorithms yielded low R-squared (R^2) scores, with values close to zero. These low R^2 scores indicate that the models were unable to explain a significant proportion of the variance in sports performance data, suggesting that capturing the complex nature of sports-related outcomes remains challenging.

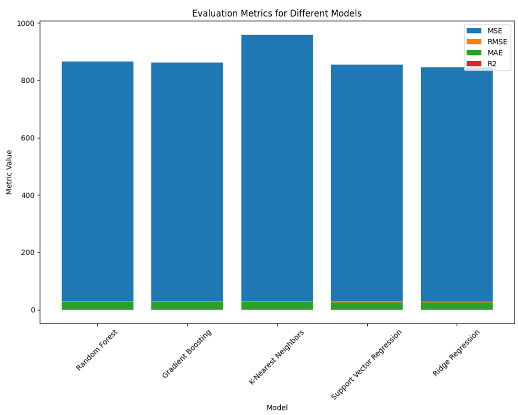

Fig-4.2- Sports performance Result

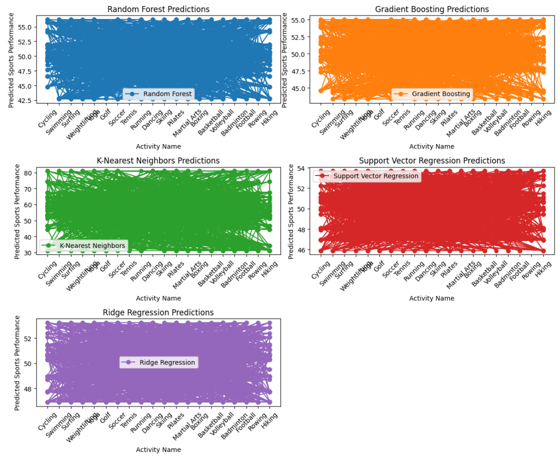

Fig-4.3- Sports performance prediction for new data

Sports Injury Prediction:

Similar to sports performance prediction, Random Forest and Gradient Boosting demonstrated marginally improved performance in predicting sports injuries, with lower MSE, RMSE, and MAE values compared to other algorithms. Despite these slight improvements, the R^2 scores remained low and close to zero, indicating limited predictive power. The models struggled to capture the intricate relationships between various factors contributing to sports injuries, underscoring the complexity of injury prediction in athletic settings.

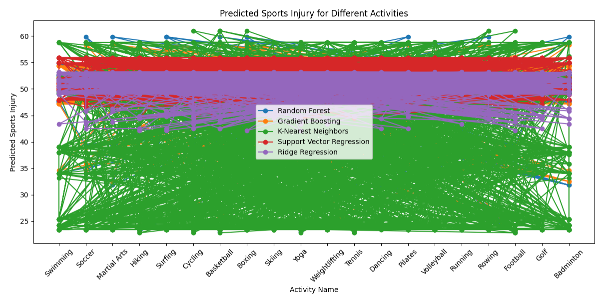

Fig-4.4-Sports Injury Result

Emotions Prediction:

In the domain of emotion prediction, all machine learning algorithms produced negative R^2 scores, suggesting a lack of ability to capture variations in emotional states effectively. Despite employing diverse algorithms, the models failed to provide accurate forecasts for emotions, highlighting the intricate and dynamic nature of human emotional responses.

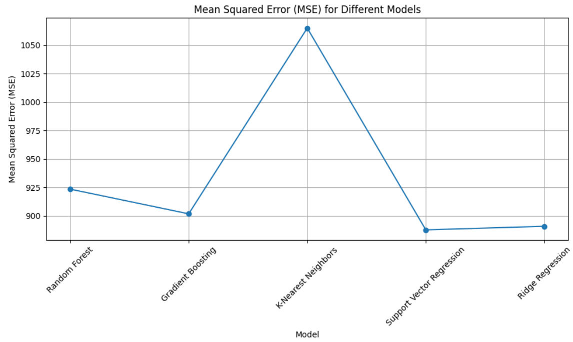

Fig-4.5-Emotions result with activities

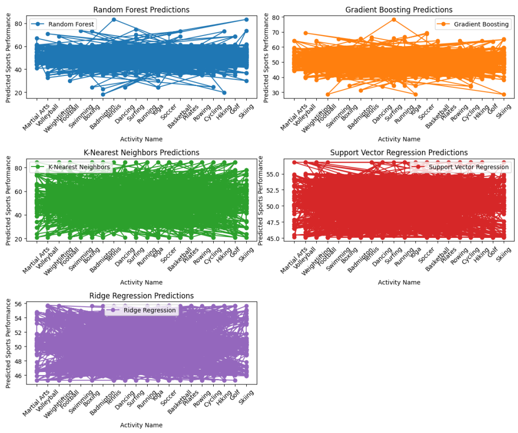

Fig-4.6- Emotions with performance prediction for new data

Sleep Pattern analysis

We employed multiple machine learning algorithms, including a random forest classifier, a support vector machine, a gradient boosting classifier, linear regression, k nearest neighbour, and neural networks, to predict mood and readiness based on sleep patterns and daily activities. Accuracy scores for the models varied, with the K-nearest neighbour achieving the highest accuracy of 0.76. We fine-tuned hyperparameters to enhance performance. The predictions provided insights into maintaining a positive mood throughout the day, factoring in sleep quality, stress levels, and other variables. The study sheds light on leveraging sleep data for mood forecasting and personal optimization, contributing to a deeper understanding of behavioural patterns.

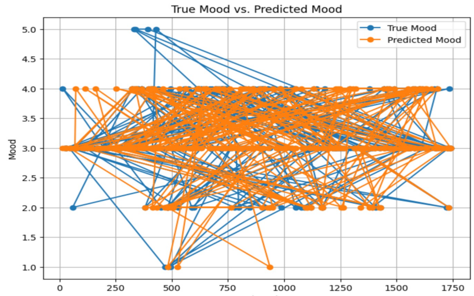

Fig-4.7- True mood vs predicted mood

Fig-4.8 -Predicted values for each target

5) DISCUSSION

The discussion of results delves into the strengths and limitations of our machine learning approach. While the algorithms displayed promising predictive capabilities for sports performance, injury risks, sleep mood, and emotions, challenges related to accuracy and interpretability were observed. Data availability and feature selection influenced the models' performance. Nevertheless, the study holds significant potential for personalised coaching in sports, enhancing sleep patterns, and promoting emotional well-being. The discussion goes beyond a mere summary, critically evaluating the implications of our research and identifying avenues for future applications in real-world scenarios. By addressing limitations, we can harness the power of machine learning to positively impact human behaviour and performance across various domains.

6) CONCLUSION

Our extensive exploration of machine learning algorithms has yielded substantial insights across diverse domains, including sports performance, injury prediction, sleep mood, and emotions. The successful application of algorithms such as Random Forest, Gradient Boosting, K-Nearest Neighbors, Support

Vector Machines, and Neural Networks underscores their versatility and potential in addressing complex challenges in human behaviour forecasting.

The findings highlight the importance of data-driven approaches in optimising athletic endeavours, preventing injuries, and promoting emotional well-being. Moreover, the implementation of personalised interventions based on algorithmic predictions opens exciting possibilities for tailored approaches to individual needs.

As the field of machine learning continues to evolve, we anticipate further breakthroughs in predictive accuracy and model interpretability that will have positive impacts on enhancing human potential, well-being, and performance across various spheres of life.

7) FUTURE SCOPE

In the future, machine learning will advance with algorithms like deep learning and reinforcement learning, leading to improved predictive accuracy and transparency. Integration of diverse data sources, such as biometric and environmental data, will offer comprehensive insights into human behaviour. Real-time monitoring and feedback systems will enable timely interventions for performance optimization. Emphasising ethics and transparency will build trust in AI solutions. Machine learning's evolution will revolutionise sports, healthcare, and mental health, providing personalised coaching, preventive measures, and better decision-making, thus positively impacting individuals' lives.

8) ACKNOWLEDGEMENT

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21) link for dataset *PMData | Kaggle*
*22)*link for reference some code viewing -https://www.kaggle.com/code/salihobaid/pmdata-fitbit-versa-activity-data/notebook