Daily Human behaviors Based Personalized health Recommendation

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Daily Human behaviors Based Personalized health Recommendation

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Abstract

Unhealth eating habits, poor sleep and lack of physical exercise have been causing the increase in diabetes, obesity and cardiovascular disease. The traditional health systems are weak in addressing such lifestyle related problems because these cannot provide to fit the individual needs. Moreover, the latest health tracking devices has limitations, and they often fail to take impact of daily behaviors such as drinking habit, meal timing and unstructured exercise on overall health and well-being. The most existing health system based on AI are rule based systems and based on the use of fixed recommendation which cannot adapted to daily behavior of individual. To address these limitations, a customize label dataset was created from fitbit wearable device. The data were collected formed based on real life measurements obtained through wearable which contain various features. Each simple data was labeled based on medical and behavioral health standards to detect unhealth behaviors. These identified features are used as input data to multiple Long Short Term Memory architectures such as simple LSTM, Deep LSTM and Bidirectional LSTM and trained with unhealthy habits using sequential patterns of daily activities. The proposed Deep LSTM model achieved accuracy of 89 percents which is the highest classification result. And then, Reinforcement Learning algorithm is developed to generated personalized and adaptive health advice using the result of deep LSTM classification and trained to enhance recommendation performance using simulated user feedback which achieved 16 percents of mean improvement rate. This finding has shown that the integration of LSTM based identification of habits and RL based adaptive recommendation can be healthcare interventions. It has potential to reduce the risk of chronic diseases and improve health outcomes by overcoming the known drawbacks of static recommendation systems.

1 Introduction

In the recent years, People have begun to face health issues such as unhealth eating, fitness issues and sleeping problems. Chronic diseases including diabetes, heart and obesity have also become a huge concern in the global killing approximately 40 million people per year (70 percent of all the world deaths) World Health Organization (2018).The causes of the diseases are closely connected to everyday routines such as exercise, food intake and sleep. This indicates that individuals require health solutions that are customized to them. Remaining healthy demands that every individual should have regular workout program and better lifestyle progress which are depending on bodies and mental health. Daily activities such as walking climbing stairs exercising are demonstrated to contribute significantly to health. As an example, the central institute of Mental Health (CIMH) discovered that participating in such activates can positively affect the well-being. They also discovered that through Using brain scans, individuals with smaller quantities of gray matter, who tend to be less active, may present a greater danger of mental health issues Karlsruher Institut für Technologie (KIT) (2020). Therefore, healthy lifestyle is beneficial both physically and mentally. The current use of new technologies such as smart phones and wearable devices allow tracking of health in real time. These devices accumulate plenty of health data, and may make it harder to make sense of all this data, and translate it into practical, individualized recommendations. This information is used by insurance companies and health organizations to enhance health and cope with expenses Bonato (2003). According to a survey conducted by a wearable firm 56 percent of individuals surveyed feel that these wearable devices would enable them to live 10 years longer, and 42 percent feel that it would make them more healthy Barnes et al. (2014). Conventional healthcare only provides broad guidance and does not offer attention to individual daily habits and mental health. New programs mostly revolve around exercise or dieting plans, and they usually neglect the routine aspects of the day such as how many steps one takes, the amount of sleep, number of glasses of water consumed in a day, the time of meals, and general movements during the day. These minor routines can be extremely influential to the overall well-being of the individual. Implementation of personalized healthcare has been proven to be beneficial through AI and has been used in many ways such as tracking health, disease prediction, and suggestions. Nevertheless, most of the existing systems provide only fixed recommendations and are unable to monitor numerous activities simultaneously. As a means to address these issues, it might become helpful to apply reinforcement learning to machine learning by suggesting health recommendations according to the daily routine. The results of previous research indicated that reinforcement learning can be useful regarding such areas as drug recommendations and cancer treatment plans, although there is still some difficulty because it cannot always access the required health datasets and cannot guarantee the safety and effectiveness of recommendations. The primary issue explored in this study is the question as "How can reinforcement learning give meaningful and helpful health advice for each person?" . The given research is a test of a system driven by RL that makes recommendations regarding which healthy habits should be done based on the daily activities of the individual such as steps, sleep, food, heart rate, and mental health indicators. The aim is to find out how RL can provide good real-time health advice according to the living people. The RL system will incorporate the feedback that people will give it in order to make more effective and personalized suggestions to prevent the disease and enable people to live a better life. Therefore, the study is expected to contribute to the future decrease of chronic diseases, enhancing of personalized health recommendations, and smarter health system through AI who learns and adapts over time.

2 Related Work

Chatterjee, A et al Chatterjee et al. (2023) have developed eCoaching for personalized recommendation modelling considering physical activity. They introduced a novel method by combining deep learning and semantic ontologies. This study employed time-series physical activity level classification method by evaluating deep learning algorithms including CNN, LSTM, GRU and MLP model. They used PMdata (public dataset) and

MOX2-5 activity (private dataset). In their experiment, CNN1D Model achieved highest accuracy of 97 percent and MLP model provide better performance that the other classifiers with 74 percents accuracy. Moreover, they evaluated the performance of the proposed OnoteCoach ontology model by measuring reasoning and query execution time. The result showed that their method provide affective plan and personalized recommendations. Additionally this study found that this ontology method can provide rule setting to improve interpretability.

Ji Fang et al Fang et al. (2024) have researched for improvement of digital health services by using machine learning technique to personalized exercise goal setting. They proposed to implement dynamically adapt exercise recommendation for each user by integrating fitness-fatigue theory and deep reinforcement learning. They collected publicly available datasets including personalized exercise data and biometric data. They designed deep reinforcement learning by integrating LSTM networks in an asynchronous advantage actor-critic algorithm and reinforcement learning. This study showed that that actor-critic algorithm allows to determine the optimal exercise by presenting the performance with 95 percents confidence. Moreover, they found the adaptability of machine learning algorithm to individual behaviours in exercise goal setting.

The paper has been proposed physical activity recommendation system based on deep learning. The purpose of this study is preventing respiratory diseases and enhancing the immune system. They collected the data by accessing questionaries, test reports and hospital records such as X-rays, scans and prescriptions from doctors. They applied clustering approach to define the individual behaviour and the Restricted Boltzmann Machine (RBM) model. This study introduced two evaluation methods such as assessing questionaries and measuring performance with metrics. Moreover, they applied feature-based similarity and clustering method to refines recommendations based on comparable users. The study demonstrated their proposed approach outperforms compare to other classifiers such as random forests, K-nearest neighbours, support vector machines and decision trees. However, the collected dataset is small 658 individuals that would be limitation the model's generalizability Bhimavarapu et al. (2022).

Shoaib et al. (2015) proposed such a method using data provided by smartphone and smartwatch sensors to detect complex human activities. Their research revealed that although smartphone sensors are enough in terms of recognizing basic activities like walking or jogging, the combination of smartwatch data prolongs the effect of recognizing complex activities which require motions of fine movements of hands like smoking, eating, or drinking a cup of coffee. They used simple statistical features based on the data of accelerometers and gyroscopes: using machine learning classifiers, SVM, KNN, and decision trees. Even though the research was characterized by high accuracy of classification, it still features a small sample size and the controlled conditions of the experiment, which can reflect the decreased applicability of the findings in the real world. Furthermore, the interest was narrowed merely to classifying activity with no aim at analyzing behavior over an extended period or its monitoring as well as adaptation to individual variability. This study can be improved in future studies by enhancing the size and diversity of the participants used and also examining the possibility of the multi-modal integration component of wider use related to health issues Shoaib et al. (2015).

The paper proposed to develop RL model to optimize physical for just in time adaptive interventions (JITAIs). They aim to promote physical activity in individual user with stage 1 hypertension. This paper investigated HeartSteps V2 mobile health application based on data collected HeartSteps V1 by integrating RL algorithm to send activity suggestion five times per day. The proposed RL model is trained continuously update treatment policies based on ongoing data collection. They applied data from HeartSteps V1 in the training process to improve performance and address the data scarcity. They applied proxy Makov Decision Process to handle model delayed effects. Moreover, they implemented randomized probabilities to allow for valid secondary analyses. There are limited assumptions of the RL model such as relying on low-dimensional linear models, minimal interacting between actions and most state variables. The small dataset in HeartStepsV1 with 37 participants which limited to train and validate to applied in real world. The proposed algorithm lacks mechanisms to detect life style changes such as illness etc. The model is trained as fully personalized for each user which has limitation to share knowledge between similar users which need to take time be fully personalized especially for new user Liao et al. (2020).

A system to help introduce personalized digital health support to the real-world, PH-RL (Personalized Health using Reinforcement Learning) which is described in the paper. The authors presented it by embedding it in an application on mental health referred to as MoodBuster. The aim was to deliver motivational messages that are timely, customized according to habits and needs of each individual to engage them into using the app. The study addresses the following major problems of integrating healthcare and AI privacy-related issues, the unavailability of large real-data sets, and uncompromised suggestions. There are three such personalization levels provided the system including the same message to all, messages to a groups of similar users , messages to each individual. It employs both batch learning and online learning, to enhance its adaptation with time. MoodBuster was used to test the system with 30 participants who participated in the real world. The findings implied that effective communication with the mental health app was higher when promoting timely, personalized text messages that align with the past studies. Nevertheless, the authors state that the system must be tested on more and various patients with real mental health issues to be able to fully realize its usefulness in healthcare el Hassouni et al. (2023).

The research paper presented a novel deep reinforcement learning framework by Liu et al. (2022). The purpose is to address the challenge of personalized treatment recommendation in medicine. Their proposed model is implemented using Markov Decision Process (MDP) which able to learn sequentially from evolving patient data. Although the study shows higher performance compared to supervised baselines on various datasets including GDSC and CCLE, there are a number of limitations that are very crucial. First, there is the issue of the dependency on complicated genomic and drug feature information that lends this real-world clinical translation to become difficult given the lack of such molecular data in non-cancer health areas. Second, the method, as dynamic as it is, mainly works in simulated or cell-line material data, which puts on question generalizability of the approach to real records of patients history. Lastly, reward design is closely integrated with the form of reward, which may constrain the option of other clinical outcomes. The study found that the important contribution by implementing reinforcement learning which can adaptive treatment recommendations Liu et al. (2022)
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The paper aims to implement reinforcement learning based fitness framework which provide personalized exercise recommendation to users. This paper's goal is to promote physical activities to maintain physical and mental health through personalized workouts recommendation, especially during the COVID 19 pandemic. This system is designed to increase long term user engagement by aligning with EU's recommendation and the national HEPA strategies. This proposed RL framework able to generates personalized workout sessions depend on user bodyweight and feedback without predefining workout plans. This paper presented a user simulator which allow to train model realistic user behavior and feedback. This feature enables effective RL model training. In the evaluation, researcher evaluated the model using not only simulations but also real-world trail with 69 users and 559 workout sessions. The proposed RL model is trained using synthetic data which is generated by the user simulator thus their system lack of large-scale real-world data. Moreover, the RL model does not learn fully user behaviors because it is trained in a simulated environment. They designed short term train for 15 weeks which limits to allow long-term user engagement Tragos et al. (2023).

The purpose of the paper is to develop a personalized physical activity recommendation system for mobile health services. This system is designed dynamically to an individual's behaviour, fitness goals and health states. They aims the system to optimize long term health outcomes by recommending exercise plans using Deep reinforcement learning combining Long short term Memory (LSTM) and deep Neural (DNN) with Asynchronous Advantage Actor-Critic algorithm to learn optimal exercise policies from time series data. The paper presented a novel use of fitness fatigue model to detect the user's exercise performance, balancing benefits and strain. This system is implemented using DRL model integrating LSTM and DNN. Moreover, this system able to updates recommendations in real time based on continuous data from wearable devices. DRl model is trained and validated using data which is five years of running data such as Marathon dataset. This system may limit in generalizability because its evaluation is based on simulated environments using historical running data without using live and diverse user trials. This system lack real time user interaction which could not provide insight into usability and actual behavioural outcomes Fang et al. (2022).

The purpose of the paper is to classify individual's daily lifestyles categorized such as lightly active, moderately active and active using body activity data which are collected from wearable fitness devices such as Fitbit, Xiaomi Band and Huawei Band. This system's model is train data combining from multiple wearable brands which offers more generalized evaluation across devices. Activity data was collected 3 to 9 months from 10 users which provide real world long term data inputs. In the experiment, they evaluated three machine learning algorithms such as k-NN, SVM and Naïve Bayes to determine effective classification method. The k-NN achieved highest accuracy 98.37 percents which showing best performance in this application. This dataset is including only 10 user which is a limitation to generalize of the result. They implemented the system based on narrow set of features such as steps taken, distance, time active, resting heart rate. There are no include some potentially informative features such as sleep, diet etc. The proposed model lacks dynamic adaptation to user behaviour and changing life style Abdul Halim et al. (2022).

This paper proposed a machine learning based system to monitor and classify physical activities using data from wearable sensors. This paper amins to promote physical activity for healthy living. They investigated the impact of class imbalance on the performance of machine learning classifiers. The study explore the effect of multi-class imbalance in physical activity classification. They presented comparison of six machine learning model such as SVM, gradient Boosting, XGBoost, CatBoost, AdaBoost with decision tree and AdaBoost with Random Forest. This paper demonstrated SVM with adaptive weighting which achieve best performance result among other models under class imbalance conditions. They introduced data communication and classification framework using wearable sensors and cloud based systems. The study only focuses on machine leaning models. Therefore , they acknowledges deep learning methods to improve better performance and should be explore in the future work Alsareii et al. (2022).

The paper purposed AI4foodDB by implementing personalized e-Health nutrition and lifestyle monitoring. They aim to collect data from nutritional weight loss intervention involving 100 overweight and obese users. They collect first data by integrating food images, wearable sensor data, validated questionaries and biological samples. They introduced a crossover design by providing comparison between traditional clinical and detail AI based data collection methods. The proposed dataset includes 10 distinct datasets such as spanning anthropometry, biomarkers, gut microbiome, sleep , physical activity, emotional state and etc. the dataset is designed to unable into training AL and machine learning models.There is data loss because of human error and technical issues 10 percents and 15 percents of smartwatch data and 23 percents of meal photos ware missing Romero-Tapiador et al. (2023).

T.D.M. Perera have developed ensemble model to predict the lifestyle status of a person based on deep learning technology. They amins to maintain sustainability of each well-being and to achieve balanced lifestyle. Therefore, they used an open source dataset from Kaggle including 15000 samples and applied data preprocessing techniques. They applied SMOTE for balancing the dataset and PCA for dimensionality reduction. In their experiments, they implemented ensemble models including ANN, LSTM, CNN and SVM by combining into an ensemble. They implemented rules-based majority voting and a weighted average method to compare performance. This research demonstrated a weighted average ensemble model by combining four deep learning classifier which achieved best performance accuracy 94.51 percents by reducing overfitting and bias Perera et al. (2024).

The paper introduced human activity classification based on wearable IMU sensor data using deep LSTM neural network. The research of purpose is to address challenges in HAR including limitation of labelled data and data imbalance. They proposed a new feature extraction method based on spectrograms of raw IMU data. Moreover, a feature space data augmentation method was demonstrated by addressing problems such as class imbalance and limited data. The one of the novelties is using of spectrograms derived from raw IMU data. The researched shown that usability of their proposed methods by demonstrating improvement of classification performance when dealing with small data and imbalanced datasets. This paper does not present the experiment of different classification performance to provide more comprehensive understanding and effectiveness Steven Eyobu and Han (2018).

3 Methodology

3.1 Data collection and preparation

The dataset is applied for this study was collected from a publicly available Fitbit fitness tracker dataset provided by Kaggle arashnic (2016) . This dataset included individual activity measurements sample at minute records. The data preprocessing consisted of standardization of timestamps, handling missing values, make sure consistent of data for all user recodes. Moreover, more synthetic data are added to expand dataset size to create realistic variation in user behaviors by relying statistical properties such as mean, standard deviation observed in original dataset. After initial cleaning and analyzing this dataset, it was aggregated into daily intervals by computing minutes data for each feature which ensure compatibility with the multi label model's sequential input requirements. The daily Fitbit dataset features consist of step count, sleep duration, heat rate and calories burned. However, the original dataset cannot provide to meet project requirement for training multi labels classification. Therefore, python script was implemented to label each data sample to enable supervise multi label classification by aligning healthcare guidelines and thresholds. The dataset was labeled with binary values such as 0 or 1 which indicating specific unhealth habits as detailed in Figure 3.1. These labelling method offers the model to effectively classify occurrences of multiple unhealthy behaviors.

Table 1: Health Habit Labeling Criteria

Habit Label	**Feature**	**Label Condition**	**Reference / Evidence**
Lack of Exercise	Steps per day	1 if steps < 5000, else 0	US CDC Hajna et al. (2018)
Poor Sleep	Sleep per day	1 if sleep < 6 hours, else 0	National Sleep Foundation **?**
High Heart Rate	Heart rate per hour	1 if heart rate > 85 bpm	Mayo Clinic Mayo Clinic (2025)
High Calorie Intake	Calories per day	1 if calories > 3000 kcal, else 0	NIH Osilla et al. (2022)

3.2 Long Short Term Memory architectures

This study required to predict for individual unhealthy habits based on daily behaviors including steps counts, sleeping patterns, heart rate and calorie. Therefore, three type of LSTM architectures was applied to design sequential data to understand how user's habits and how it correlates with health conditions. LSTM Models will be trained to detect unhealth behaviors such as lack of exercise, poor sleep, high heart rate and high calories. In pervious research have been demonstrated, LSTM model has ability as adaptive functionality which allows to enhance their operation. The proposed three type of LSTM models will be evaluated each performance and will be choose best model to integrate with reinforcement learning agent. Simple LSTM architecture was implemented with one LSTM layer and one dense output layer. This architecture is not capable of overfitting with smaller datasets makes it successful in working with basic sequential tasks with data. However, previous studies have already used simple LSTM frameworks in the medical field, including the predictions of the health status of patients and the recognition of activities based on the data gathered using wearable devices Zhang et al. (2022).

Deep LSTM architecture was built with multiple LSTM layers which allow model to capture complex temporal relationships more effectively. Deep LSTMs are especially applicable to complex tasks who have more than a single layer of temporal dependencies. In previous research, Deep LSTM models tend to perform better than simple models when it comes to solving complex tasks of prediction of sequences, like predicting daily activities or health conditions of humans based on the sensor data gathered Zhang et al. (2019).

Bi-LSTM random access memory is a two-way processing of data sequences both forward and backward at the same time. This architecture enables the model to learn the contextual data of previous and next data points and hence greatly increase the accuracy of predicting such a model to perform sequential data tasks. Bidirectional LSTMs have demonstrated greater performance in healthcare issues like prediction of patient conditions, early diagnosis, anomaly detection in health, and so on due to capturing the past and future relationships Zhao et al. (2017).

3.3 Reinforcement learning

Reinforcement learning was employed in this study to recommend adaptive daily health habit recommendations base on daily lifestyle. RL model offers the agent to learn optimal behaviour polices. making the agent to interact with the environment and obtaining a reward in response to a positive performance. This will make it possible to personalize advice as the behaviour of the users changes. Daily health features like the number of steps, amount of sleep, calories, and average heart rate are also present in the state. These are the measures of the health condition of the user on a given day which are fed into the RL agent. An action chosen by the agent is one of the recommendations on health habits including "Walking more" Have a good sleep "Eat well" Try to relax more. The reward depends on the simulated feedback that has been made once the user makes use of the recommendation. In case the user health gets better for example steps count rises, the quality of sleep improves , a positive reward is given to the agent +1 otherwise penalized -1. In this paper, the value-based RL method is employed, namely, a Deep Q-Network (DQN) Mnih et al. (2015). The Q-network approximates the Q-values with the neural network that would be trained in such a way, to reduce the loss in the temporal-difference sense.

Loss:

$L() = E[(r + \max Q(s, a;)\ \ Q(s, a;))^2]$ Sutton and Barto (2018)

Where:

- are the network parameters,
- s and s are current and next states,
- a and a are actions, • r is the observed reward,
- is the discount factor.

A batch of daily data in the form of sequential outputs of LSTM classifier is trained on the RL model. Every training session is an approximation of a daily health experience of a user as time progresses. The Q-network is continuously updated depending on the feedback of the user behaviours Tragos et al. (2023).

4 Design Specification

The propose system will provide individual daily health habits recommendation based on integration of sequential LSTM prediction with reinforcement learning to develop a health habits. These three main components of the architecture include data preprocessing and labelling, multi-label unhealthy habit classification based on the Long Short-Term Memory (LSTM) , and the production of the adaptive recommendations with the help of an RL agent. The system is used to find several unhealthy behaviours using data in wearable devices through multi-label classification. Raw Fitbit records are restructured into daily recordings that contain the following features; steps completed, sleep hours, heart rates, and calorie burning. All the records collected each day are tagged with binary tags that indicate particular bad behaviors including lack of exercise, poor sleep, high heat rate, and high calorie that were collected through accepted healthcare standards. This pre-processing step allows to supervise the models that can reveal a number of behaviours within one day. Three LSTM-based designs are considered Simple LSTM, Deep LSTM and Bidirectional LSTM (Bi-LSTM). The LSTM networks learn temporal dependences in the sequential data with the Deep LSTM offering more depth to learning complex patterns and the Bi-LSTM processing the information forward and backward directions. Each LSTM model will be trained and generate result independently. The Reinforcement Learning agent uses the results of the LSTM classifier. The generation of these outputs constitutes the "state" input output of which is selected by the RL agent as an act or recommendation to the individual regarding their health. The user feedback, positive and negative flows to the RL policy where in a dynamic way the adjustments can be made accordingly. This system's functional requirements are data processing and labelling, Behaviour classification, best model selection, recommendation.

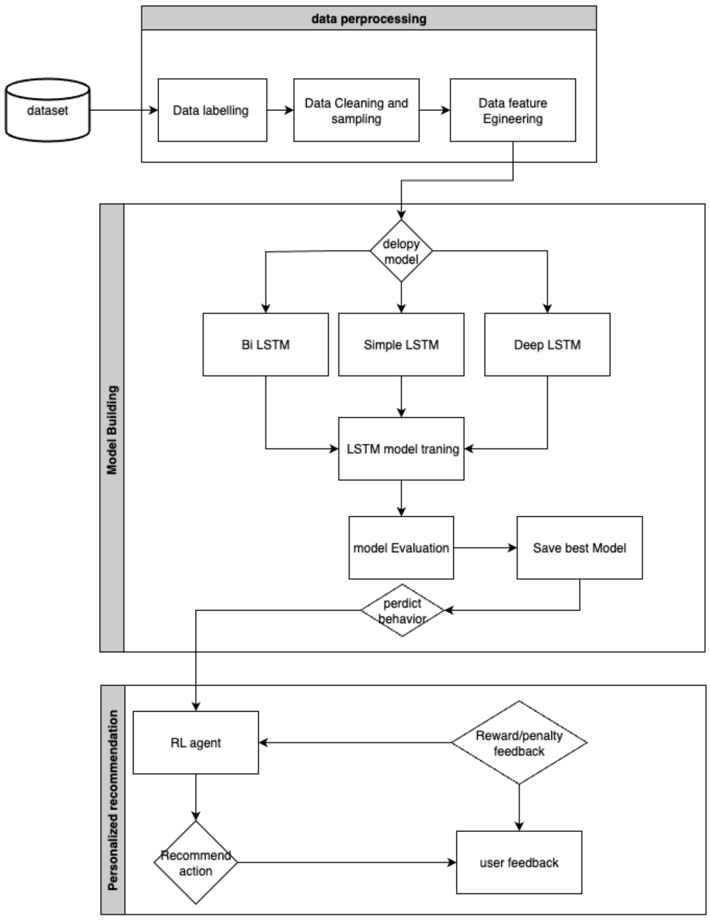

Figure 1: System Architecture Design

5 Implementation

The last phase of the project was the complete development including model training and integration of AI driven personalized health habit recommendation system. The important outputs were generated in the phase such as cleaned and labelled dataset, optimized

LSTM model to classify unhealthy habit, reinforcement learning (RL) agent providing adaptive recommendations and performance evaluation results to be provided with visual analytics. This project started with raw Fitbit activity dataset and transformed into a structured into daily sequences to align with LSTM model training requirements. Binary multi-label labels, based on accepted health-related guidelines and thresholds, were included in each daily record including lack of exercise, poor sleep, high heart rate, high calorie. This labelling procedure allowed supervised multi-label recognition and allowed the system to identify more than one unhealthy habit occurring at a day. The training of the model and integration with RL were based on the resulting labelled dataset. After data preparation, three deep learning architectures was implemented, trained and compared performance result such as simple LSTM, deep LSTM and bidirectional LSTM. The models were developed by Python with deep learning libraries such as TensorFlow and Keras. Pandas and NumPy were used to manipulate data and labelling logic, and performance evaluation metrics such as accuracy, f1-score, and classification reports were calculated using the scikit-learn. In this step, the best trained models was stored in the form of .h5 that the most efficient architecture could be selected to integrate into the RL pipeline. The Deep LSTM, which provided the best results was integrated into a reinforcement learning setup. Therefore, it could make tailored behaviour-specific health recommendations. he RL agent received as its system state the daily classification output generated by the LSTM network and replied with an action in the form of a health recommendation such as walk more, sleep earlier, reduce calories, relax. The simulated user feedback environment was developed which the agent would be rewarded or punished based on changes. The implementation of the RL model was in Python, using Keras-RL and reinforcement learning self-written scripts to train and update the agents and define exploration algorithms. The final system produced output in the form of the annotated dataset, optimized Deep LSTM, trained RL agent, comparisons of the visual performance across all of the LSTM architectures and reports presenting the classification accuracy, F1-score histograms, and the level of improvement using the RL. This deployment is the functional structure of the end-to-end pipeline that can process the data of wearable devices, classify various unhealthy habits and generate adaptive daily health recommendations based on reinforcement learning.

6 Evaluation

6.1 LSTM model Evaluation

In this study, three LSTM architectures including were evaluated and compared to choose the most effective architecture for multi-label health habit classification. All the models were trained in the same conditions, with the same labelled dataset to be as comparable and fair as possible. The aim was to determine what type of LSTM performs better in relation to the recognition of the behavioural patterns and predicting the various health states. Each model was evaluated suing standard metrics including accuracy, precision, recall and F1 score. The results were visualized using bar chars by show the comparative strengths of each model. The Deep LSTM has performed best in terms of subset accuracy 89 percents which is significantly higher than that of the Simple LSTM 65.6 percents and Bidirectional LSTM 70 percents which shows a greater capacity to correctly identify all unhealthy behaviours in individual user. By Health habit label, Deep LSTM performed better than other models at distinguishing between people with and people without the labels of Lack of Exercise (F1 = 1.00), High Heart Rate (F1 = 0.84) but all models failed terribly at differentiating between people with and people without the label of Poor Sleep (F1 = 0.00) probably due to class imbalance with features. This indicated that there were good and unique patterns in this behaviours as all models did very well in the "High Calorie." Such insights indicate the assessment of model depth which is providing the greatest performance increase to this application. In the given case, it is possible to choose that Deep LSTM is the best model to be implemented in the recommendation system based on reinforcement learning, even the issues about the underrepresented behaviours remain unchanged, which is why the further studies should be devoted to the way to deal with the data imbalance and use the model improvements.

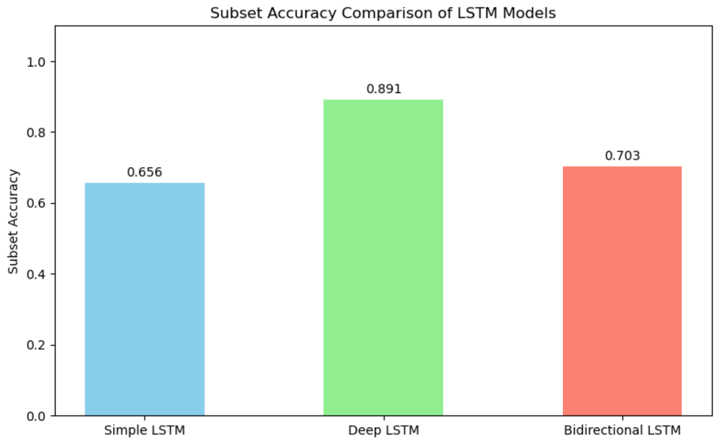

Figure 2: Accuracy Comparison of LSTM Models

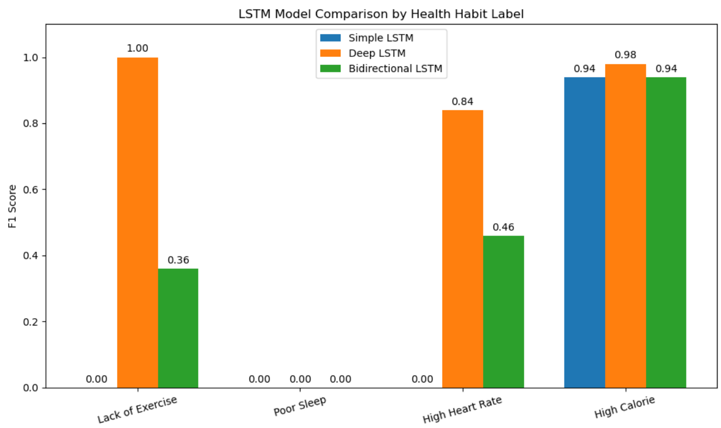

Figure 3: F1 score Comparison of LSTM models

6.2 RL evaluation

After the optimal LSTM architecture was found to detect an unhealthy habit, a Reinforcement Learning (RL) framework has been implemented to give personalized daily health-related recommendation of habits. The success of such an RL agent should be systematically estimated to make certain that the recommendations made by it actually help to support healthier users behaviours in the long term. It was based on a Daily Habit Feedback Checklist reading, where feedback of the user is simulated against each recommendation forward by the agent. This kind of feedback was used to get information on whether the user had been using the suggestion and whether they saw improvement in the health behaviours. The RL agent learn the state of the user as the LSTM output every day, it would then pick a recommendation on a health habit to change such as increase walking, go to bed earlier, or lessen food consumption and it would get imaginary feedback. The positive feedback reward for the agent whereas lack of improvement led to penalty. Accordingly, the policy of the agent was repeatedly updated during the repeating episodes. The metrics that were used to measure the performance of the models were the average reward , improvement rate and the coverage of the various health habit recommendations. During the undertaken experiments the RL system reached the mean improvement rate amounting to 0.16, and 2,002 of all 12,153 recommendations are leading positive changes to the user habits. This shown that the agent can in some cases strengthen positive behaviours but the low-middle improvement rate reveals that the recommendation policy may need additional optimization. The improvements can be made in such a way that the reward structure can be redesigned to be more detailed and realistic feedback reviewing systems can be included and the learning techniques can be personalized to meet different user characteristics. However, although RL agent shows promising adaptive learning power further development and testing is required with consideration to maximizing the effect of long-term health behaviour change.

6.3 Discussion

The experimental of the proposed project provide major insights regarding the multi label classification and reinforcement learning. Among of proposed LSTM network designs, the deep LSTM achieved highest accuracy and F1 scores on a majority of labels compared to alternative models. This findings was aligns in previous research which deep neutral network can better capture more complex temporal dependencies in health time series data. The high achievement of Deep model shown that its applicability to both sequential and multi-label dataset of health behaviour classification. However, the outcomes showed good performance in some labels especially high calorie and lack of exercise but models performance poor in poor sleep labels which resulting in F1 score of zero. This problem can be due to two reasons (1) imbalance of the dataset (2) limited available of sleeping features and related processed. The Bidirectional LSTM is theoretically superior in regard to modelling the dependencies in both time directions, but it failed to outperform the Deep LSTM. In some cases, Bi-LSTM provided small gains on selected labels, which means that it has the potential to be used in integration with feature augmentation. The RL component also showed the ability to adjust its recommendations in accordance with the simulated user feedback with an average improvement rate of 0.16 after each interaction. Although this suggests that a certain model of the reinforcement of the behaviour was achieved, the rate of improvement is less than expected in comparison with other healthcare-oriented studies of the use of RL Yu et al. (2021) Abdellatif et al. (2021) . The performance gap can probably be explained by the inadequacy of the simulated feedback, which does not likely represent the complexity of human behaviours in the real world as well as the simplicity of the reward function used. As proposed design, selecting the best LSTM architecture before integrating RL pipeline was efficient which served the most stable classification for the recommendation.

7 Conclusion and Future Work

In this study, a personalized health habit recommendation system has been developed using sequential deep learning and reinforcement learning. A Deep Multi-label LSTM architecture achieved outperform in prediction of unhealth behaviours from wearable device data. The combination of LSTM model and reinforcement learning provide adaptive recommendation by demonstrating the agent's potential to offer positive behavioural change for each user. However, several challenges are remaining. The models were always having difficulties with lowly-tagged examples like "poor sleep", which showed the drawback that is brought forth by the class imbalance and the ineffectiveness of features that are not specific enough. Also, the training progress of the RL agent could be improved further as it did not show a large increase. As a future work, should towards gathering more representative and multi-faceted data sets especially in cases where rare or poor labelled behaviour is required. Model accuracy could be further improvement in future by optimizing features engineering, solving unbalance issues. Moreover, the experiments of real world user would give more valid insights and achievements into RL training and testing which provide developing more realistic approaches in recommendation. And in the end, it is possible that these advancements will lead to the development of a successful and consistent digital health companion that will positively influence its user and make a healthy change in their lifestyles.

References

Abdellatif, A. A., Mhaisen, N., Chkirbene, Z., Mohamed, A., Erbad, A. and Guizani, M. (2021). Reinforcement learning for intelligent healthcare systems: A comprehensive survey.
URL: *https://arxiv.org/abs/2108.04087*

Abdul Halim, N., Mohd Ali, A., Nordin, S. and Osman, R. (2022). Classification of daily lifestyle based on body activities obtained from wearable devices, *in* R. Alfred and Y. Lim (eds), *Proceedings of the 8th International Conference on Computational Science and Technology*, Vol. 835 of *Lecture Notes in Electrical Engineering*, Springer, Singapore, pp. 231–240.
URL: *https://doi.org/10.1007/978-981-16-8515-6*$_2$0

Alsareii, S., Awais, M., Alamri, A., AlAsmari, M., Irfan, M., Aslam, N. and Raza, M. (2022). Physical activity monitoring and classification using machine learning techniques, *Life* **12**(8): 1103.
URL: *https://doi.org/10.3390/life12081103*

arashnic (2016). Fitbit fitness tracker data.

Barnes, K., Kauffman, V. and Connolly, C. (2014). Health wearables: Early days, *Technical report*, PwC Health Research Institute. PwC Health Research Institute Report.

Bhimavarapu, U., Sreedevi, M., Chintalapudi, N. and Battineni, G. (2022). Physical activity recommendation system based on deep learning to prevent respiratory diseases,

Computers **11**(10): 150.
URL: *https://doi.org/10.3390/computers11100150*

Bonato, P. (2003). Wearable sensors/systems and their impact on biomedical engineering, *IEEE Engineering in Medicine and Biology Magazine* **22**(3): 18–20.

Chatterjee, A., Prinz, A., Riegler, M. A. et al. (2023). An automatic and personalized recommendation modelling in activity ecoaching with deep learning and ontology, *Scientific Reports* **13**: 10182.
URL: *https://doi.org/10.1038/s41598-023-37233-7*

el Hassouni, A., Hoogendoorn, M., Ciharova, M., Kleiboer, A., Amarti, K., Muhonen, V., Riper, H. and Eiben, A. E. (2023). ph-rl: A personalization architecture to bring reinforcement learning to health practice, *Technical report*, Vrije Universiteit Amsterdam and Mobiquity Inc., Amsterdam, The Netherlands.

Fang, J., Lee, V., Ji, H. and Wang, H. (2024). Enhancing digital health services: A machine learning approach to personalized exercise goal setting, *Digital Health* **10**.
URL: *https://doi.org/10.1177/20552076241233247*

Fang, J., Lee, V. and Wang, H. (2022). Dynamic physical activity recommendation on personalised mobile health information service: A deep reinforcement learning approach.
URL: *https://arxiv.org/abs/2204.00961*

Hajna, S., Ross, N. A. and Dasgupta, K. (2018). Steps, moderate-to-vigorous physical activity, and cardiometabolic profiles, *Preventive Medicine* **107**: 69–74.
URL: *https://doi.org/10.1016/j.ypmed.2017.11.007*

Karlsruher Institut für Technologie (KIT) (2020). Everyday activities enhance personal well-being, ScienceDaily.
URL: *https://www.sciencedaily.com/releases/2020/11/201125104348.htm*

Liao, P., Greenewald, K., Klasnja, P. and Murphy, S. (2020). Personalized heartsteps: A reinforcement learning algorithm for optimizing physical activity, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* **4**(1): 1–22. Article 18.

Liu, M., Shen, X. and Pan, W. (2022). Deep reinforcement learning for personalized treatment recommendation, *Statistics in Medicine* **41**(20): 4034–4056.
URL: *https://doi.org/10.1002/sim.9491*

Mayo Clinic (2025). What's a normal resting heart rate?, Mayo Clinic Website.
URL: *https://www.mayoclinic.org/healthy-lifestyle/fitness/expert-answers/heart-rate/faq-20057979*

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S. and Hassabis, D. (2015). Human-level control through deep reinforcement learning, *Nature* **518**: 529–533.
URL: *https://doi.org/10.1038/nature14236*

Osilla, E. V., Safadi, A. O. and Sharma, S. (2022). Calories, StatPearls [Internet]. Last updated September 12, 2022;.
URL: *https://www.ncbi.nlm.nih.gov/books/NBK499909/*

Perera, T., Rupasingha, R. and Kumara, B. T. G. S. (2024). Deep learning-based ensemble model for predicting the lifestyle status of a person, *2024 4th International Conference on Advanced Research in Computing (ICARC)*, pp. 25–30.

Romero-Tapiador, S., Lacruz-Pleguezuelos, B., Tolosana, R. et al. (2023). Ai4fooddb: A database for personalized e-health nutrition and lifestyle through wearable devices and artificial intelligence, *Database* **2023**: baad049.
URL: *https://doi.org/10.1093/database/baad049*

Shoaib, M., Bosch, S., Scholten, H., Havinga, P. J. M. and Incel, O. D. (2015). Towards detection of bad habits by fusing smartphone and smartwatch sensors, *Proceedings of the Workshop on Sensing Systems and Applications Using Wrist Worn Smart Devices*.

Steven Eyobu, O. and Han, D. S. (2018). Feature representation and data augmentation for human activity classification based on wearable imu sensor data using a deep lstm neural network, *Sensors* **18**(9).
URL: *https://www.mdpi.com/1424-8220/18/9/2892*

Sutton, R. S. and Barto, A. G. (2018). *Reinforcement Learning: An Introduction*, 2nd edn, MIT Press.
URL: *http://incompleteideas.net/book/the-book-2nd.html*

Tragos, E., O'Reilly-Morgan, D., Geraci, J., Shi, B., Smyth, B., Doherty, C., Lawlor, A. and Hurley, N. (2023). Keeping people active and healthy at home using a reinforcement learning-based fitness recommendation framework, *Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (IJCAI)*, AI for Good, pp. 6237–6245.
URL: *https://doi.org/10.24963/ijcai.2023/692*

World Health Organization (2018). Noncommunicable diseases, `https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases`.

Yu, C., Liu, J., Nemati, S. and Yin, H. (2021). Reinforcement learning in healthcare: A survey, *ACM Computing Surveys* **55**(1): 1–36.

Zhang, S., Li, Y., Zhang, S., Shahabi, F., Xia, S., Deng, Y. and Alshurafa, N. (2022). Deep learning in human activity recognition with wearable sensors: A review on advances, *Sensors* **22**(4): 1476.
URL: *https://doi.org/10.3390/s22041476*

Zhang, Y., Yang, Z., Lan, K., Liu, X., Zhang, Z., Li, P., Cao, D., Zheng, J. and Pan, J. (2019). Sleep stage classification using bidirectional lstm in wearable multi-sensor systems, *IEEE INFOCOM 2019 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 443–448.

Zhao, R., Yan, R., Wang, J. and Mao, K. (2017). Learning to monitor machine health with convolutional bi-directional lstm networks, *Sensors* **17**(2): 273.
URL: *https://doi.org/10.3390/s17020273*