Smart Routine Planner using Machine Learning

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***Abstract* - The disruptions caused by the COVID-19 pandemic have dramatically altered many of our normal routines, thus making it harder for most of us to cope with boredom, stress, and unpredictability. So, we came up with the idea of a smart routine planner, an application that will assist users to set realistic goals and create feasible plans to achieve them. Our goal is to bring a perfect balance between work and leisure by keeping a check on users' work efficiency, eating and sleeping patterns, fitness routine, hobbies, and other recreational activities.**

***Index Terms* - Personalized routine planner, task scheduler, data analysis, machine learning.**

I.INTRODUCTION

There are several applications on the web categorized as task managers, time-table schedulers, performance boosters, and so on. But they usually allow users to add, update, delete tasks, set reminders, evaluate users efficiency, and provide performance statistics. Unlike our application which not only analyzes the users' routine but also ensures that they follow a healthy one. 'Smart Routine Planner' will allow users to either plan timetables' daily or set up weekly milestones and assign estimated time for the completion of each goal. The planner will then arrange necessary tasks in a logical order and suggest a daily plan of action for the week. Another important feature is that in case the user is unable to complete a task on time then it suggests rescheduling it to a free slot later that day or keeps it for the following day.

Moreover, it will run a daily analysis on the user's routine and give suggestions to improve their performance by considering the routines of other users' of the same age group who have similar interests and working hours. Regional and occupational constraints can also be selected if required. Daily, weekly and monthly statistics will help the user by illustrating whether or not they have been productive or need to make adjustments to their schedule.

The application will also look for areas of improvement and make appropriate suggestions in case the user is inactive, eats in unhealthy intervals, lacks sleep, exercise, leisure, or hobbies. This is achieved through data analysis and machine learning by using appropriate methods and algorithms.

In this paper, we mainly focus on the following objectives:

1. Provide users with personalized routines based on their habits, and history of completion of previous tasks.
2. Suggest an optimal sleep schedule in case the user's routine deprives him/her of sleep.
3. Recommend appropriate hobbies as per users' interest by comparing their everyday schedule with other users of the same age group.
4. Encourage users to include physical activities and refreshment breaks in their daily routine.
5. Provide performance statistics on a regular basis.
6. Take feedback from users in order to improve the application's scheduling performance.

II.LITERATURE SURVEY

[1] In this paper, the authors put forth their ideas in developing an application that helps users achieve their daily physical activity target by analysing their previous activity data and adapting their activity plans accordingly. The number of steps taken is captured by the fitness tracker, which serves as a measure for physical activity. Daily goals are set by specifying the number of steps the user desires to walk that day. Random Forest algorithm is used to cluster users into different groups based on their daily activity patterns, according to which hourly plans are created for the day. User activity is monitored throughout the day and notifications are sent at appropriate intervals. If the

probability of achieving the target turns low then an alternate plan is suggested. This is done using the Linear–quadratic regulator algorithm.
The framework of this system consists of an online and an offline component. The offline component performs clustering and predictive model building from the user's data and stores it in persistent storage. The online component consists of an android mobile application, target probability prediction, and activity planning settings. The user's success probability of achieving the target is calculated on an hourly basis considering the steps completed so far. This computation is light-weight and makes use of pre-trained models using Neural Networks, Support Vector Machine, and Logistic Regression algorithms.

[2] In this paper, the authors propose the need for a tool that can analyze and manage the distribution of time towards meetings held by corporates, to ensure regularity and maximize productivity. So, they came up with MineTime Insight, an extension to the existing calendar application called MineTime. MineTime Insight is a visual analytics tool that reveals hidden patterns and meeting distributions in multivariate calendar data. It is designed to fit in the corporate environment targeting a broad audience of users with little or no visualization expertise. It quantifies the time a user spends with single persons or groups both in absolute and relative terms. It also provides a simplified statistical representation of the meeting periodicity to evaluate not only how often, but also how regularly, people have been met in the past. Moreover, it compares meeting patterns and gives an overview of a specific person's meeting history by identifying when meetings with a person occurred recently, what was discussed, and when upcoming meetings will take place. It also identifies retrogression or stagnation towards personal meeting goals and provides insights for improvement.

[3] In this paper, the authors have come up with a scheduling system called Intelligent Daily Scheduler, a mobile application that schedules personalized weekly timetables for users based on their everyday routine. The application collects data about users' lifestyles and uses the Deep Neural Network (DNN) model to predict patterns in their daily schedule. These patterns help in identifying different users' free time slots. To schedule tasks according to users' free time, they have developed a scheduling algorithm that minimizes task juggling and allocates continuous long intervals of time rather than small intervals so that users have sufficient time to complete their tasks with minimum interruption. Load Balancing schemas are used to distribute tasks evenly throughout the week so that no day is overscheduled. It also ensures that not more than one task is assigned at a given time. If users are not satisfied with the schedule generated then they can request a new schedule. Schedules will undergo modification until the user's requirements are satisfied. Moreover, the authors believe that users are the key elements in scheduling and thus, their overall success or failure depends on them.

[4] In this paper, the authors have developed a content-based recommendation system that assists users in planning their daily or weekly schedules. Tasks are suggested based on the user's previous task performance history. Users have to provide a set of tasks including their type like intellectual, physical, spiritual, social, errands or chores and the time required for the completion of each task. Users are asked to give a rating between 1 to 5, 1 being the lowest and 5 being the highest. This feedback is used to make the recommender system learn how to provide useful recommendations. The phi correlation coefficient is calculated for each task type by performing a correlation analysis between task type and user rating. Then ranks are assigned to each task type and the two highest positively ranked task types are recommended for the user's weekly plan, according to the selected time and day.

[5] This paper proposes a chatbot approach to introduce adaptive planning in a personal daily context by modelling it as a user story graph. The user story graph is initialized with a backlog of user stories that need to be done. Fibonacci sequence is used to assign story points to each user story, to indicate their relative size and complexity. Linked user stories makeup epics and segment the graph hierarchically, making multitasking possible. The bot plans the coming sprint by setting its duration and suggesting a list of user stories to fill the sprint time. This is followed by confirming finished user stories from the picked epic, updating the remaining story sizes, and calculating the sum of story points delivered from achieved releases in each sprint. This value is used to detect bottlenecks-

stories that are unable to finish after one sprint. Bottlenecks are either moved into later sprints or broken into smaller stories. If an epic in the previous sprint is completed, then new user stories are appended to the input to improve the progress of the epic.

[6] In this paper, the authors discuss choosing an optimal algorithm to generate smart time-table schedulers for universities, with minimal human intervention. Intelligent Timetabling Scheduler is a web-based application that not only generates exam timetables but also carefully chooses an arena considering the number of students attempting the exam and also appoints a supervising lecturer. For semester timetabling, it ensures that no professor or student is assigned to more than one class at the same time. And generally groups labs and webinars.
The authors have made a comparison of four algorithms- Genetic and Graph Coloring algorithms for examination timetabling and Heuristic and Iterated Local Search algorithms for semester timetabling. The Genetic Algorithm improved the solution iteratively until a global optimal was reached and proved to be very useful in allocating resources for examination. However, the Graph Coloring Algorithm was able to identify clashes and ensured that no duplicate allocations occurred. Both the Heuristic and Iterated Local Search Algorithms performed fairly well for a small group of instances. But with a medium and large group of instances, the Iterated Local Search Algorithm obtained a better number of feasible solutions compared to the heuristic algorithm.

[7] In this paper, the authors propose an algorithm to assist users in scheduling their daily routines according to certain constraints and dependencies. Temporal constraints ensure that no two activities start at the same time or intersect during their execution time. It also ensures that dependent activities are scheduled and executed appropriately. They have also used backtracking and back-jumping to ensure that all constraints are satisfied. The only drawback is that the algorithm has to complete all of its computational steps in case the user requests an alternative schedule. Thus, making it extremely time-consuming.

[8] In this paper, the authors propose an algorithm that finds an optimal agenda to fix appointments and finish tasks. It clusters the existing list of tasks, bins them according to spatial-temporal proximity to the new task, finds an optimal solution for the subset of tasks within the cluster closest to the new task and expands the search area if no solution is found, repeating the process until a valid schedule is reached. Agenda length, time, and distance are kept in check to provide the best results.

[9] In this paper, the authors have developed an Intelligent Calendar System that handles temporal inconsistencies in scheduling events. They have used distance-based heuristics for solving temporal inconsistencies between events based on their attributes. The distance between two events is calculated and the value is used to represent the distinction of similarity between those events. The lesser the distance between two events, the greater are the chances of them being in the same cluster. If an inconsistency is found in the strategy then a majority voting is performed to choose the best strategy. If the event occurred in the past, then the attributes will be revised and redistributed in order to make more accurate decisions in the future.

[10] In this paper, the authors have developed a user-friendly application that assists students in managing time for academics and part-time jobs. The application analyses the user's spending pattern, keeps track of their savings, time spent on academics, GPA scored, and gives appropriate suggestions for improvement. It also has a calendar and to-do list features.

[11] In this paper, the authors have implemented a systematic human activity recognition method that analyses basic activities (BA) and transitional activities (TA) in a continuous sensor data stream. The raw sensor data is segmented into fragments using a sliding window, characteristics and attributes are built based on window segmentation. Clustering is done using the K-Means algorithm to aggregate the activity fragments into periods. Finally, a random forest classifier is used to accurately classify BA and TA.

[12] In this paper, the authors have made a survey on the techniques used in personalized real-time physical activity coaching systems. They have developed a data extraction tool to analyze the systems based on general characteristics, personalization, design foundations, and various evaluation methods. They have come to a

conclusion that most of the applications are not referring to the theory and practice in the field, use very simple forms of personalization, lack proper evaluation of the effects of particular personalization strategies and overall system effectiveness, self-learning, and context awareness.

[13] In this paper, the authors have designed a nutritional recommender system that generates daily personalized meal plans for users based on their history, nutrition needs, and food preferences. AHP Sort is used to remove foods that are not suitable for the user and an optimization-based approach is used to generate the food menu. They have also used a probabilistic approach for generating an alternative menu considering the foods which the user disliked earlier or in the initial menu.

[14] Activities of Daily Living (ADL) describes a person's lifestyle and habits. This paper focuses on learning ADL routines by making use of a neural network model called Spatiotemporal ADL Adaptive Resonance Theory (STADLART) which is a 3-Layer ART network. In their experiment, the STADLART outperformed the K Nearest Neighbors (KNN) algorithm and the K-Means algorithm. The STADLART-NC, a variation of the STADLART normalizes and customizes ADL weights for various ADLs in regular routines, making learning more meaningful. The STADLART model is utilized to create an intelligent system that learns users' ADL and detects abnormalities in it. It is also used to advise and recommend activities.

III.METHODOLOGY

We aim to create a mobile application that will be able to provide users with personalized schedules. Initially, users will be asked to mention their age which is mandatory and other details like interests, region, and occupation, which are optional. While scheduling tasks for the day or week, users will have to select categories that best fit their task. The categories are as follows- fitness, social, work, chores, refreshment break, leisure, hobby, sleep, and others. The application will suggest the user to allot time for physical activities, refreshment breaks, and sleep if at all their routine seems to ignore these essentials. A timer will be used to remind users about upcoming and pending tasks. Users can mark tasks as completed as per their convenience.

We will use an Artificial Neural Network (ANN) model to predict the user's general lifestyle. The input variables to the ANN model include task name, task category, and status (i.e., completed or pending). This data is very useful in making predictions about whether or not the user will be able to complete a specific task at a given day and time. It will also give insights about the user's free time slots which can be used to schedule tasks accordingly.

Users will be grouped according to their age. The age ranges are as follows:

Category I	15 years >= age < 25 years
Category II	25 years >= age < 35 years
Category III	35 years >= age < 45 years
Category IV	45 years >= age < 55 years
Category V	55 years >= age < 65 years

Users will be clustered in groups using the K- Means algorithm. They will be clustered according to their age band, working hours, interests, and hobbies. If desired the user can configure their settings to include region and occupation also in the clustering process.

Consider the following case where user X works for an average of 7 hours and has free-time of approximately 4 hours per day but pursues no hobby. In this case, the application will match user X's interests with that of other users in the same cluster and suggest a suitable list of hobbies that user X may like. If at all user X has not provided the system with a set of interests, then X's working hours will be matched with other users in the cluster and X will be asked to pick an interest from the suggested list of interests. These suggestions can also be narrowed down according to region and occupation. Interest and hobby suggestions are done using Artificial Neural Networks (ANN).

As discussed in [15], pattern classification becomes more complex as data dimensionality increases. But with deep learning algorithms like Deep Artificial Neural Networks, it becomes easier to make predictions and obtain satisfyingly accurate results by training models on large datasets.

IV.CONCLUSION

Proper planning helps in reducing stress to a great extent. A feasible plan with attainable goals helps ease one's mind by giving them confidence and direction.
Thus, the Smart Routine Planner is like a supportive friend who helps one to achieve their goals by making the best use of their time, keeping work and leisure in perfect balance and also ensures that they follow a healthy routine. Thereby, implementing a structure to their day that not only gives them a sense of control but also improves their focus, organization, and productivity.

REFERENCES

[1] Z. Li, S. Das, J. Codella, T. Hao, K. Lin, C. Maduri and C. Chen, "An Adaptive, Data-Driven Personalized Advisor for Increasing Physical Activity," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 3, pp. 999-1010, May 2019, doi: 10.1109/JBHI.2018.2879805.

[2] M. Ancona, M. Beyeler, M. Gross and T. Guenther, "MineTime Insight: Visualizing Meeting Habits to Promote Informed Scheduling Decisions," in IEEE Transactions on Visualization and Computer Graphics, doi: 10.1109/TVCG.2019.2941208.

[3] J. Geetha, B. S. Akanksh and A. S. Koushik, "Intelligent Daily Scheduler," 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Bangalore, 2018, pp. 2308-2312, doi: 10.1109/ICACCI.2018.8554485.

[4] M. A. Kuhail and N. S. S. Gurram, "TaskDo: A Daily Task Recommender System," 2019 International Conference on Computational Intelligence in Data Science (ICCIDS), Chennai, India, 2019, pp. 1-5, doi: 10.1109/ICCIDS.2019.8862073.

[5] Y. Li, H. Shibata and Y. Takama, "User Story Driven Adaptive Planning Framework in Personal Daily Context," 2020 International Symposium on Community-centric Systems (CcS), Hachioji, Tokyo, Japan, 2020, pp. 1-6, doi: 10.1109/CcS49175.2020.9231325.

[6] T. W. Ekanayake, P. Subasinghe, S. Ragel, A. Gamage and S. Attanayaka, "Intelligent Timetable Scheduler: A Comparison of Genetic, Graph Coloring, Heuristic and Iterated Local Search Algorithms," 2019 International Conference on Advancements in Computing (ICAC), Malabe, Sri Lanka, 2019, pp. 85-90, doi: 10.1109/ICAC49085.2019.9103403.

[7] F. S. Alhaijawy and A. M. Florea, "Scheduling People's Daily Activities Using Temporal Constraints Satisfaction Problem," 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT), Thessaloniki, 2018, pp. 876-881, doi: 10.1109/CoDIT.2018.8394957.

[8] Stephanie Rosenthal and Laura M. Hiatt. 2020. Human-Centered Decision Support for Agenda Scheduling. In Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems (AAMAS '20). International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 1161–1168.

[9] T. JiaHua and D. Zhang, "SmartCalendar: Improving Scheduling Through Overcoming Temporal Inconsistencies," 2018 IEEE 17th International Conference on Cognitive Informatics & Cognitive Computing (ICCI*CC), Berkeley, CA, 2018, pp. 30-37, doi: 10.1109/ICCI-CC.2018.8482075.

[10] J. L. Yeo, P. S. JosephNg, K. A. Alezabi, H. C. Eaw and K. Y. Phan, "Time Scheduling and Finance Management: University Student Survival Kit," 2020 IEEE Student Conference on Research and Development (SCOReD), Batu Pahat, Johor, Malaysia, 2020, pp. 1-6, doi: 10.1109/SCOReD50371.2020.9250969.

[11] J. Li, L. Tian, H. Wang, Y. An, K. Wang and L. Yu, "Segmentation and Recognition of Basic and Transitional Activities for Continuous Physical Human Activity," in IEEE Access, vol. 7, pp. 42565-42576, 2019, doi: 10.1109/ACCESS.2019.2905575.

[12] Monteiro-Guerra F, Rivera-Romero O, Fernandez-Luque L, Caulfield B. Personalization in Real-Time Physical Activity Coaching Using Mobile Applications: A Scoping Review. IEEE J Biomed Health Inform. 2020 Jun;24(6):1738-1751. doi: 10.1109/JBHI.2019.2947243. Epub 2019 Nov 19. PMID: 31751254.

[13] R. Yera Toledo, A. A. Alzahrani and L. Martínez, "A Food Recommender System Considering Nutritional Information and User Preferences," in

IEEE Access, vol. 7, pp. 96695-96711, 2019, doi: 10.1109/ACCESS.2019.2929413.

[14] S. Gao, A. -H. Tan and R. Setchi, "Learning ADL Daily Routines with Spatiotemporal Neural Networks," in IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 1, pp. 143-153, 1 Jan. 2021, doi: 10.1109/TKDE.2019.2924623.

[15] I. Arel, D. C. Rose and T. P. Karnowski, "Deep Machine Learning - A New Frontier in Artificial Intelligence Research [Research Frontier]," in IEEE Computational Intelligence Magazine, vol. 5, no. 4, pp. 13-18, Nov. 2010, doi: 10.1109/MCI.2010.938364.