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Sedentary behavior health outcomes and identifying the uncertain behavior patterns in adult

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Abstract
Uncertain sedentary behavior has evolved as a new health concern in recent periods. Being inactive for long periods is a significant risk factor among all the adult age groups, especially over-reliance on vehicles for mobility. Sensors are making it easier to monitor seating habits throughout the active period. However, experts are divided on the most appropriate objective metrics for capturing the cumulative information of sedentary time throughout the day. Due to discrepancies in measuring methods, data processing techniques, and the absence of fundamental outcome indicators like cumulative sedentary period, evaluating the several research studies sedentary patterns was unrealistic. In this research study, a novel design was suggested with adaptive computations, namely, fleeting granularity, to differentiate instances of daily human activities. Multivariate transitory information is acquired from sophisticated units (essential cells). Our proposed scalable algorithms can identify Frequent Behavior Patterns (FBPs) with a timeframe estimate by employing collected widespread multivariate data (fleeting granularity). It has been evidenced that the applicability of the example by differentiating proof computations on two certifiable datasets. The assessment of the relationships, accuracy, and applicability of sedentary factors is the primary subject of this research.

Keywords
uncertainty, sedentary behavior, time-series, reclining, multi-variate, accuracy, frequent behavior

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Последствия малоподвижного поведения для здоровья и выявление неопределенных моделей поведения у взрослых

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Аннотация
В последнее время неуверенное малоподвижное состояние человека превратилось в новую проблему для его здоровья. Бездействие в течение длительного времени является значительным фактором риска для всех взрослых возрастных групп людей, особенно чрезмерное использование транспортных средств для передвижения. Сенсоры упрощают отслеживание привычек сидения в течение всего активного периода. Тем не менее, эксперты расходятся во мнениях относительно наиболее подходящих объективных показателей для сбора совокупной информации о малоподвижном образе жизни человека в течение дня. Из-за расхождений в методах измерения и обработки данных, а также при отсутствии основных показателей результатов, таких как кумулятивный период малоподвижного образа жизни, оценка моделей малоподвижного образа жизни часто нереалистична. В работе предложен новый подход адаптивных вычислений (с мимолетной детализацией) для распознавания конкретных примеров повседневной деятельности человека. Многомерная переходная информация получена из сложных единиц (основных ячеек). Предлагаемые масштабируемые алгоритмы могут идентифицировать постоянные

модели поведения с оценкой временных рамок, используя собранные широко распространенные многомерные данные (мимолетная степень детализации). Подтверждена применимость разработанного подхода с помощью дифференцирования вычислений доказательства на двух подтвержденных наборах данных. Приведена оценка отношений, точности и применимости малоподвижных факторов.

Ключевые слова
неопределенность, малоподвижное поведение, временной ряд, полулежа, многовариантность, точность, частое поведение

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Introduction

Latest research has shown that sedentary lifestyles like reclining or sitting increase the incidence of non-communicable mortality and morbidity, regardless of physical exercise [1]. A sedentary existence is one wherein an individual's everyday routines do not significantly raise their energy consumption beyond that of their resting state. This research shows how significant Sedentary Behavior (SB) is in terms of fatality and other non-communicable risky diseases because of its prevalence, autonomy characteristics, and modifiability. The evaluation of sedentary behavioral patterns and correlations is necessary for the successful minimization of such behaviors through therapies or preventive healthcare interventions. In a recent systematic analysis [2], gender, age, obesity, exercise habits, emotion, and mood were all shown to be correlated with sedentary behavior. The determination of these covariates relies heavily on data from the regular populace, the majority of whom do not reach the acceptable levels of daily behavior. It is also possible that correlations between SB and other factors, such as prolonged working via sitting, transportation, etc [3]. Developing and implementing therapies addressing sedentary behavior requires a better knowledge of the correlations between sedentary activities and their distinct dimensions. Sequential sedentary-oriented uncertain [4] situations are described with expanded characteristics using the term "fleeting granularity or via multi-variant data aspects", which refers to a short-term condition. In research findings, the amount of time individuals spends on screen time and sitting down has been related to increased levels of abdominal obesity (relatively huge belly), fasting lipid profile, and glucose intolerance indicators (such as insulin sensitivity) distinct from abdominal obesity and workout duration [5]. Reclining for longer timeframes may lead to a reduction in triglyceride enzymatic hydrolysis and elimination of lipids, decreased absorption of plasma glucose, as well as less fructose insulin production. In addition, sedentary habits, such as watching programs on television, driving in automobiles for longer, and doing other sedentary activities, have been linked to an elevated risk of heart disease and sudden cardiac fatality. Sedentary behavior has traditionally been considered a wellness concern. However, these research observations show that extended reclining and light-intensity exercises could be encouraged [6].

Sedentary activity is often measured in terms of the Metabolic Equivalent Task (MET). The timeframe MET rating determines the average amount of user action over the course of a specific timeframe. Fig. 1 depicts the MET range and important characteristics of movement and non-movement activities.

Formulation of the Problem

Sedentary patterns that have been identified may help individuals become more conscious of their own sedentary tendencies and adopt actions to address such habits. The user's physician may also utilize detected patterns to educate individuals to adapt to the necessary changes. Research on sedentary behavior has been done in the past. Sedentary behavior has been classified by [7] into four categories (behavior during transportation, employment, residence, and spare duration) and three contexts (environment) where it occurs (the residence, the worksite, and the commuting context). Personal (individualistic), community factors (interactional),

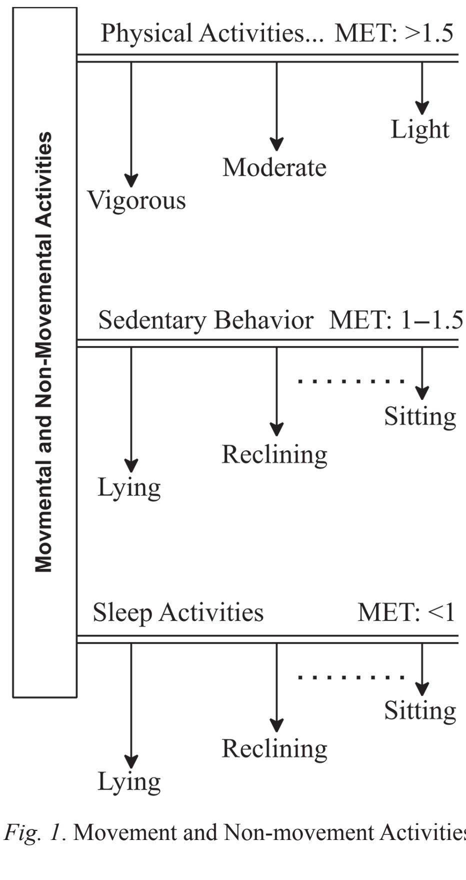

Fig. 1. Movement and Non-movement Activities

environmental characteristics (social contexts), external factors, and institutional features were characterized by [8] for a particular higher education institution population. Sedentary habits are clearly characterized, yet the particular causes that contribute to sedentary behaviors are unique to each individual. It is difficult for competent physicians to draw accurate subjective inferences since so many variables might be at play simultaneously, complicating the situation. By using automated and non-intrusive technologies to analyze the individual factors, healthcare professionals will be freed from such an arduous and time-consuming process. Timing (e.g., not having a sufficient workout schedule), daily routine (e.g., sitting in the workplace in a rhythm), and previous sedentary behaviors (e.g., watching television programs every day after work) are three significant key predictors of sedentary behavior [9]. Predicting sedentary habits specifically benefits preventative programming activities and relies on patterned behavior principles. A person affected by sedentary behavior is usually referred to as a "subject" and is more likely to engage in suggested sedentary behavior reduction activities, according to patterned behavior principles, if specific actions are incorporated into the subject's schedule. Recommending changes in one's strategies that might help one avoid or minimize sedentary activity, especially when the subject will be inactive or sedentary at some future stage. For example, many modern pieces of equipment have been developed that send an alert to a viewer who's likely to stay inactive for more than three hours when viewing television, prompting them to take some actions and move about during the commercials and other breaks. According to [10], subjects are more inclined to acknowledge notifications that are tailored to a particular scenario and provided ahead of time. Sometimes, a sedentary lifestyle has been linked to a greater risk of developing chronic health conditions. For example, being overweight may be linked to an increased dependence on private automobiles for mobility. The issue of personalized physical activity guidelines can only be solved using a cutting-edge learning approach that can create a conceptual model for an experience and understandable recommender techniques. Also, these courses help people learn how to use evaluation rules, especially when it comes to responding to the temporal characteristics of the subjects and the complicated interplay of improving their health. Usually, subjects' physical behaviors are monitored and organized using automated systems to regulate the health-oriented data systems. In this way, automated services can correctly adjust their workout regimens properly in a dynamic context. Furthermore, sedentary behavior and its associated health effects can be elaborately studied using an appropriate machine learning system. To uncover those three factors, we suggest a machine learning strategy, namely "Stacked-LSTM (Long Short-Term Memory)" which processes all the timestamp recordings of subjects' physical movement. As part of our approach, we examine a set of subjects' previous sedentary patterns (the "past inactive behavior predictor") in order to uncover patterns in time (the "everyday routine") which can be utilized to forecast their subsequent behavior (future patterns).

Background

The use of Neural Network (NN) models has recently increased in the social healthcare sector. However, a systematic neural network technique must be developed in order to fully understand the effects of a sedentary lifestyle and how it affects health as well as the processes that may be at the root of multi-variant relationships. This section emphasizes the prevalence of the sedentary lifestyle and the impact created among various subjects and methods utilized to change the course of the lifestyle from sedentary mode. Wearable information via portable has already yielded a variety of information retrieval methods. Rawassizadeh et al. [11] studied adult behavioral patterns in a multidimensional time-series dataset using wearable devices and scalable techniques. Based on the assumption that the everyday activities of adults take place across discrete periods of time, researchers devised a strategy. Additionally, it leverages a mixture of multiple sensors rather than individual sensors to decrease uncertainty by employing only accessible active sensors. The techniques proposed can be applied to smart-watches without the need for cloud computing. Acquirement of contextual information through an acquisition engine, suggested by [12], relies on contextual buffering and contextual constraints to continuously monitor the subjects' wearable contextual state. Here, researchers imply that the acquisition engine might cut the total energy used. Depending on slide window methodology and anomaly evaluation, authors of [13] demonstrated the actual drug usage detection approach via sensing technology (biosensors). According to a study by [14], few novel approaches utilized to mine sensing information, and analysis of wearable electronic input are reliant upon the task needed to be executed. Recurrent immobile patterns using behavioral time analysis can be determined using a frequency-domain technique [15]. Trackers provide a list of user behaviors, but they don't alert the user to any harmful habits that have been observed. When applied to generic healthcare concerns, approaches such as NN, Support Vector Machines (SVM), and Decision Trees (DT) often provide adequate outcomes. However, when it comes to real-time condition monitoring in health sectors, the operational complexities of NN, generalized linear models, and synchronization analysis make them less effective than others. DT, rule-based, and analytical measures are frequently employed for actual data interpretation. Appropriate data labeling is a vital consideration when evaluating the use of data analysis in the medical sector. According to a recent evaluation [16] of wearable information extraction, security and privacy problems are emerging. As per the researchers, data mining methods must be tuned for efficiency and complexity minimization. The handheld technology should compute lightweight procedures rather than complex models that must be performed in the virtual ecosystem. It was shown in [17] research that conventional learning models, while implemented for a scientifically regulated population, had poor precision if deployed to an unrestricted (i.e., participants conduct their regular everyday activities) sample dataset. As a result, unrestricted information is vital for learning and training such methods, and can therefore be utilized whenever possible. Additionally, computational intelligence approaches have been used in the sleep-wake diagnosis and prediction process via inertial sensor acceleration and electrocardiographic information [18]. A learning algorithm called neighborhood functionality based LSTM was used to study the increased sampling frequency of motion and acceleration data as well as their temporal dependence. This led to the accurate detection and classification of sleep-wake behaviors that were elicited by [19].

Methodology

In this research, we presume that the sedentary activities are time-correlated since subjects' subsequent and prior behaviors are influenced by their present and past behaviors. So, we preferred a stacked LSTM neural network. LSTM network supports scalable factors and multi-variant transitory information. Moreover, its computational strategy relies on the previous and current input parametric values.

Dataset and Preprocessing

For the research purpose, we utilize two certifiable datasets derived from The Sedentary Behavior Research Network (Sedentary Research Database, n.d.) and Sedentary Behaviors Recognition[1]. This dataset includes time series logs/records of distinct behavior patterns/labels for our research purposes.

Each record comprises a timestamp and set of sedentary activities like sitting for a long duration, watching television, riding in a bus or car, playing passive video games, playing on the computer, and sitting in a car seat or stroller. The most prominent features of the datasets are represented in Table 1. Next step is data preprocessing where the entire dataset is divided into time blocks for each observational day. Each time block is composed of 6 hours that are mentioned as for sessions. Since our goal is to identify recurrent patterns of sedentary behavior statistically, initially, we generate summary activity statistics for each time blocks from the datasets. For each block, we calculate the percentage of all activities performed by the subject that are sedentary. For instance, if the time block is 6 hours and the ratio of sedentary activity (SA) from the data record is computed in equation as

$$\mathrm{SA} = \vartheta^t_{B_i}/\delta^t_{B_i},\ i = \{1, 2, 3, 4\},$$

where $\vartheta^t_{B_i}$, represents the amount of time duration observed on SA in block (B_i) to the total amount of blocks time duration, $\delta^t_{B_i}$. For example, if the $\vartheta^t_{B_i}$= 16256 s against $\delta^t_{B_i}$ = 21600 s, then SA percentage is computed as 76.26. Using the unprocessed records, initially, a block-wise extraction of the required data is followed in each trial. Fig. 2 signifies a graphical depiction of the three dimensional multivariate sedentary vectors that are accounted for each block; they are state traits $\{S_1, S_2, \ldots, S_n\}$, previous action stacks $\{A_1, A_2, \ldots, A_n\}$, and duration $\{D_1, D_2, \ldots, D_n\}$. Activity intensity, encompassing degrees of weariness, exercise, fitness, and so on, is an element of state traits.

Table 1. List of Prominent Features of the Considered Subjects

Subject Features (n = 25)	Range	
Age	15–40	
Gender	Male & Female	
BMI (Body Mass Index), kg/m^2	Underweight	<18.5
	Normal	18.5–24.9
	Overweight	25.0–29.9
	Obese	>30.0
Smoking Status	Severe smoker	
	Occasional smoker	
	Rare smoker	
	No smoker	
Physical Activity, min/days	0 MET	
	1–500 MET	
	500–1000 MET	
	>1000 MET	
Health History	Diabetes	
	Heart Diseases	
	Hypertension	
	Cancer	
	Hypercholesterolemia	

Stacked LSTM

Based on the outlet efficiencies analyzed from past research work, stacked LSTM is a suitable choice for predicting multi-variate time-series patterns. It is feasible to portray a "stacked" LSTM structure via a standard LSTM [20] framework encompassing multilayer LSTMs. The layers stacked above other layers tend to give a sequence of outcomes instead of a single-valued outcome to the stacked layers below them. There is only one outcome for each input sampling interval, instead of a single-valued outcome for the overall input. It's also useful for ML-oriented applications that demand a graded stream over a lengthy span of time. LSTM NN schematic layout design is shown in Fig. 3.

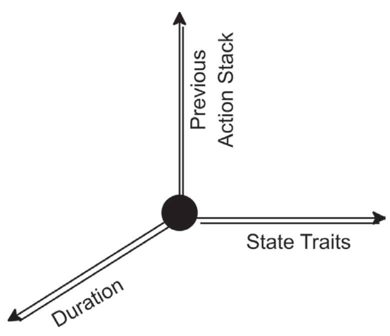

Fig. 2. Three Dimensional Multi-variate Sedentary Vectors

[1] WilliamPossos. New Dataset for Sedentary Behaviors Recognition. GitHub. 2020, February 18. https://github.com/WilliamPossos/sedentary-behaviors-dataset (Date of access: August 28, 2023).

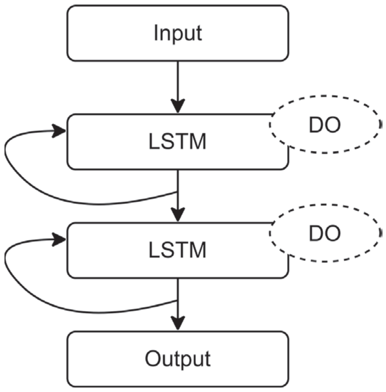

Fig. 3. Stacked LSTM Architecture

The next step is to build a fully connected neural network that can gain knowledge from the preceding stages and predict future sedentary behavior patterns. We present a new type of LSTM NN that utilizes multi-stacked hidden layers with significant neural nodes. The DropOut (DO) methodology is integrated with stacked LSTM to enhance the model generalization and solidity. Additionally, it features feedback links as reinforcement loops that let it train and predict the sequential relationships in multi-variate time-series input. Finally, the last layer of the LSTM is integrated with a completely connected NN that gains knowledge from the preceding stages and predicts future sedentary behavior patterns.

Fig. 4 represents the operational structure of the proposed model. The LSTM networking mechanism is a version of the Recurrent Neural Network. It comprises two conditional stages as well as three gated operations in each LSTM cell, wherein the condition C_t is termed storage and remembering state (memory) and is employed to manage essential long-term correlations. The second conditional state ($\tilde{C}_t$) reflects the subject's activity at t. To regulate both M_t and $\tilde{C}_t$, LSTM uses the gated system of an input gate i_t, a forget gate f_t, and an output gate o_t. LSTM employs the gated technique and storage and remembering units to manage the process of aggregating subjects' input, which successfully overcomes the issue of the explosion of gradients or elimination in basic recursive NN. Thus, sequential time-series forecasting makes extensive use of such a technique. We designed a stacked LSTM NN model via stacking multiple hidden layers as well as neural cells in the LSTM approach. The LSTM NN schematic layout design is shown in Fig. 5 [13].

The variables shown in Fig. 4 are represented as follows:

Si is the hidden state of the LSTM cell at time step "i" in a stacked LSTM network carrying information from the previous step.

Ai is the activation of the input gate at time step "i" controlling the amount of new information added to the cell state.

Di refers to the activation of the forget gate at time step "i" determining which information from the previous hidden state should be forgotten.

Pi is the activation of the output gate at time step "i" deciding which part of the current cell state should be exposed as the output.

I/P signifies the input to the LSTM cell at time step "i" including current input data, the previous hidden state, and additional context.

O/P is the output of the LSTM cell at time step "i", which is the result or prediction for that time step.

Here, f_t is responsible for regulating the multi-variate data that deserves to be ignored in the activity state (internal), C_{t-1} of the subject at the time $t-1$. Then, i_t task is to regulate the quantity of storage and remember state C_t data that has to be stored at the moment, t. The sigmoidal function maps f_t and i_t to the range [0, 1], whereas the tanh activator maps C_t to the range [–1, 1]. However, both mappings are conditional on the non-linear function. The O_t regulates the set of subjects' data from the C_t and is sent to the h_t. Equation [13] expresses the correlation between the LSTM gates and states.

$$i_t = \sigma([(X_t), (h_{t-1})]\omega_{X_i} + \varphi_i)$$
$$f_t = \sigma([(X_t), (h_{t-1})]\omega_{X_f} + \varphi_f)$$
$$\tilde{C}_t = \tanh([(X_t), (h_{t-1})]\omega_{X_c} + \varphi_c)$$
$$C_t = [i_t \otimes \tilde{C}_t) + [f_t \otimes C_{t-1}]$$
$$O_t = \sigma([(X_t), (h_{t-1})]\omega_{X_o} + \varphi_o)$$
$$h_t = [O_t \otimes \tanh(C_t).$$

Here ω_{X_f}, ω_{X_i}, ω_{X_o}, ω_{X_c} signifies weight matrix of all forgot, input, output gates and storage and remembering state, respectively. Similarly, φ_f, φ_i, φ_o, φ_c denotes the bias of forgot, input, output gates and storage and

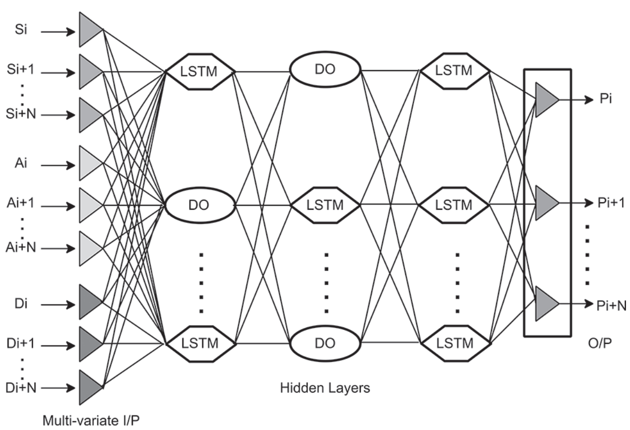

Fig. 4. Operational Structure of Proposed Model

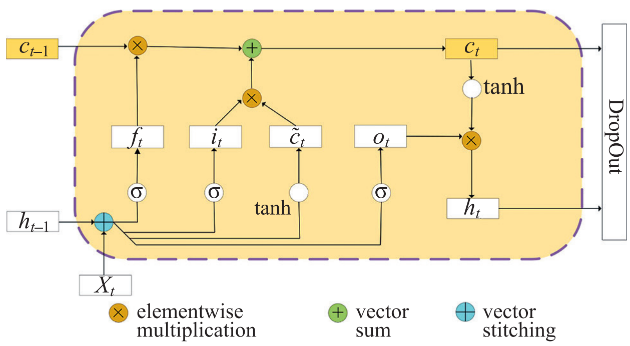

Fig. 5. Operation structure of LSTM Cell 13

remembering state, respectively. In addition to composite multiply '·' and component multiplication '⊗', $[X_t = \{S_{i+N}, A_{i+N}, D_{i+N}\}, h_{t-1}]$ is the process that links multivariate vectors of time-varying input, X_t and h_{t-1}, into a more extended vector matrix.

The dropout technique is included in the suggested stacked LSTM architecture to increase generalizability. Throughout the training procedures of NN, the Dropout technique arbitrarily excludes neurons having a specific likelihood in order to avoid cross-adaptation between neurons. In other words, the 'p' fold population of initial neurons is triggered on average. On the other hand, the testing process tends to trigger all integrated neurons, resulting in unstable network outcomes. To find a solution to this issue, it is necessary to multiply the value that is processed by each neuron, especially during the testing process, multiplied with p. The optimum values were obtained whenever $p = 0.5$. As a result, some neurons are eliminated as well as adapted during activation. Consequently, the network mechanism gets high resiliency due to the arbitrary diversification of processed outcomes. This dropout approach is also a useful way to deal with over-fitting issues in the LSTM model since it reduces the system complexity.

Performance evaluation

The degree of B_i is defined based on the subject's behavior which is influenced by the specific duration of the subject's exposure to past data. To put it another way, if a subject's actions in the following hour (X_{t+2}) rely on their present activity and the subject's activities in the preceding three hours (X_{t+1}, X_t and X_{t-1}), then the degree of B_i (ζ) necessary to predict their behavior is three hours. The model could best explain a wide range of behavioral patterns in different subjects with varying degrees. To verify the performance of the proposed stacked LSTM model, we compare the performance with scalable algorithm and Frequency domain algorithm. In this analysis, we randomly have chosen ten subjects for testing purposes with different blocks.

We examine the suggested stacked LSTM model performance with that of a scalable method and a frequency domain algorithm (discussed in section 2) to

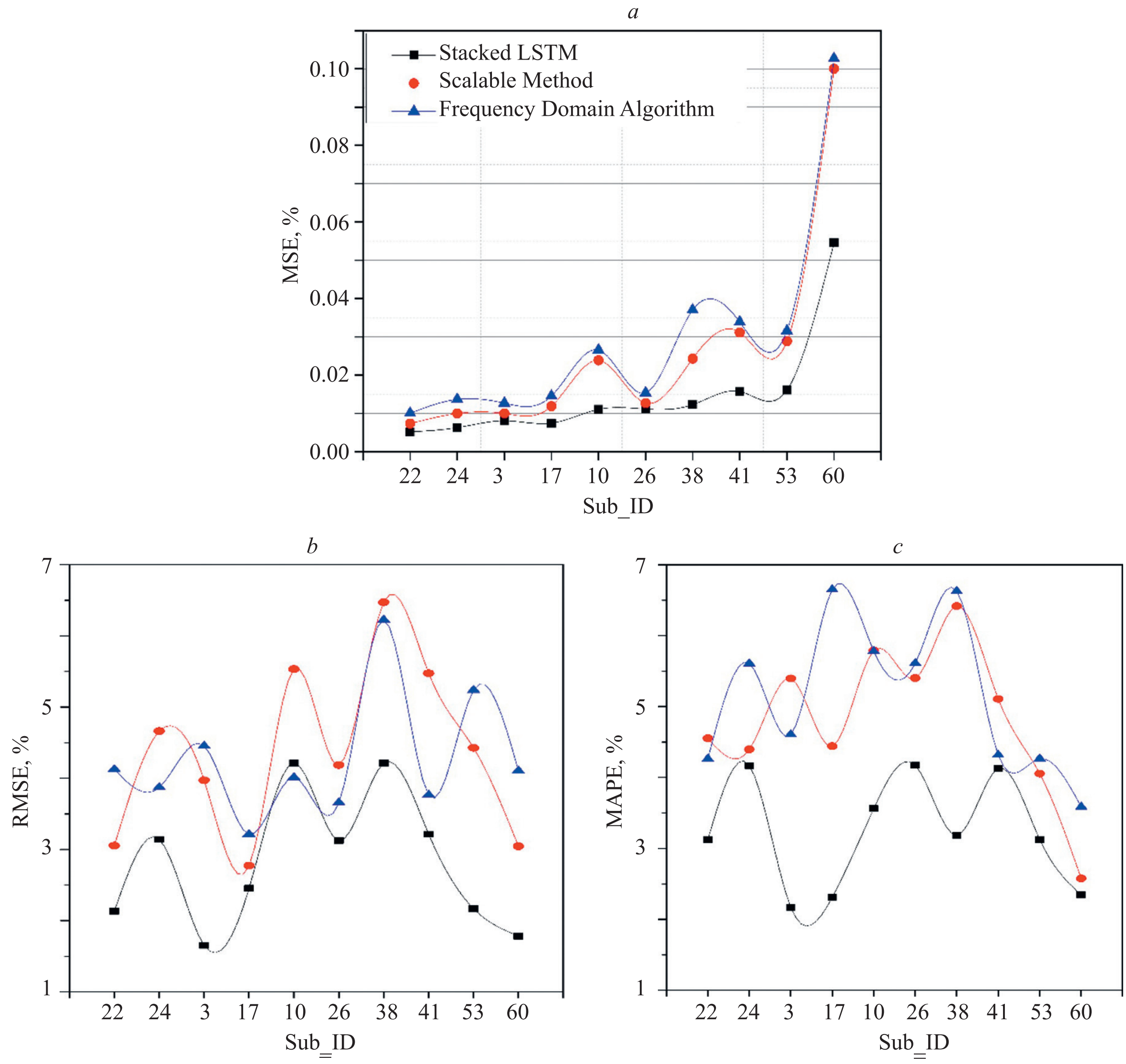

Fig. 6. Analysis of MSE (*a*), RMSE (*b*) and MAPE (*c*)

prove its effectiveness. For the purpose of evaluating the effectiveness of the suggested approach, various analytical indicators are employed: the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), the r-correlation coefficient, and the Mean Absolute Per cent Error (MAPE). The following equations below describe these indicators:

$$\mathrm{MAE} = 1/d\sum_{t=1}^{T}|(a_t - \hat{a}_t)|$$

$$\mathrm{RMSE} = \sqrt{1/d\sum_{t=1}^{T}(a_t - \hat{a}_t)^2}$$

$$r = \frac{\sum_{0}^{T}[(a_t - \bar{a}_t)(\hat{a}_t - \bar{\hat{a}}_t)]}{\sqrt{\sum_{0}^{T}[(a_t - \bar{a}_t)^2} \cdot \sqrt{\sum_{0}^{T}[(\hat{a}_t - \bar{\hat{a}}_t)^2}}$$

$$\mathrm{MAPE} = 1/d\sum_{t=1}^{T}\left|\frac{|(a_t - \hat{a}_t)|}{a_t}\right| \times 100,$$

where d is the total volume of behavioral information, a_t is the actual value at t, $\hat{a}_t$ is the forecasted range of sedentary behavior, $\hat{a}_t$ and $\bar{\hat{a}}$ are the mean of real and predicted values, respectively.

Fig. 6 exemplifies the best-fitting (MSE < 0.01 at $\zeta = 3$ and <0.02 at $\zeta = 6$) stacked LSTM for inactive subjects. Our method tests all concerned subjects in four blocks (B_i), and the block size that yields the best Mean Square Error (MSE) is selected. Block length with minimum MSE is six hours; further implying the optimal forecast for subject 22 sedentary behaviors at timescales of 6 hours from 6 AM to 12 PM (block-1), then from 12 PM until 6 AM (block-2), then from 12 AM until 12 AM (block-3), and then from 6 PM until 12 PM (block-4).

It is noticeable from the findings in Fig. 6, *a* that subjects are more likely to remain sedentary for shorter periods of time ($\zeta = 3$) than for longer periods of time ($\zeta = 6$). Although they had irregular sedentary behaviors at various B_i, this suggests that each subject did not engage in recurrent reclining.

Subjects 17, 22, and 24 had the finest fitting models and the minimum MSEs among all other subjects. As seen in Fig. 6, *a*, the models had MSEs of 0.007454, 0.051888, and 0.006266, respectively, along with the pattern of proportion deviations (or mistakes). The stacked LSTM factors (S_n, A_n, D_n) influence the pattern change at which it converges and the quality of its learning, both of which may be tuned via trials. We tested how well the suggested stacked LSTM model could learn by changing the values of the hidden neurons. The parameters of the suggested model were then calculated.

Each subject's RMSE and MAPE are shown in Fig. 6, *b*, *c*. Subjects 3 and 22 exhibited the lowest RMSE and MAPE highlighting the prospective usefulness of multi-variate sequential datasets that were not included in earlier models. Furthermore, the study primary shortcoming was the absence of a criteria assessment of posture throughout the reclining period which is a severe flaw in all approaches. As a result, any 1.5 MET behaviors were classified as sedentary activity, regardless of positional gestures performed while sitting or lying.

Our earlier representations focused on multi-variate sequential patterns since it is essential to note that repeated behaviors may emerge at any time. We considered a time-series-based stacking LSTM model to capture correlations on all different timescales, particularly hourly, apart from weekly and monthly recurrent trends. Examining all reasonable timeframes may lead to an extensive investigation of all recurring patterns. It is, therefore, inefficient. When looking for recurring trends/patterns, we look at the proportion of time spent sitting as a continuous signal whose process is dependent on the frequency with which sitting is done. Therefore, it is fair to investigate the information in the time-frequency because temporal iterations are continuous.

Sedentary behavior is more common among individuals of all ages and genders who practice lower physical activity, and this is a problem that affects everyone equally. Conversely, individuals who have a salaried position are more likely to be sedentary. Fig. 7 shows that the three multi-variate components (S_n, A_n, and D_n) have a positive and statistically significant link with a lower health perception and physical inactivity, as shown in the findings (r-correlation value is nearer to 1). In other investigations, this correlation has not been found. The fourth block has very low work intensity, which indicates that the timeframe is always in sleep mode. This may be attributable to the reality that the person is sedentary in some conditions, which raises the possibility that low-intensity workout regimens will be accomplished. Individuals who have difficulty completing high-intensity workout routines may get demoralized by their specific challenges.

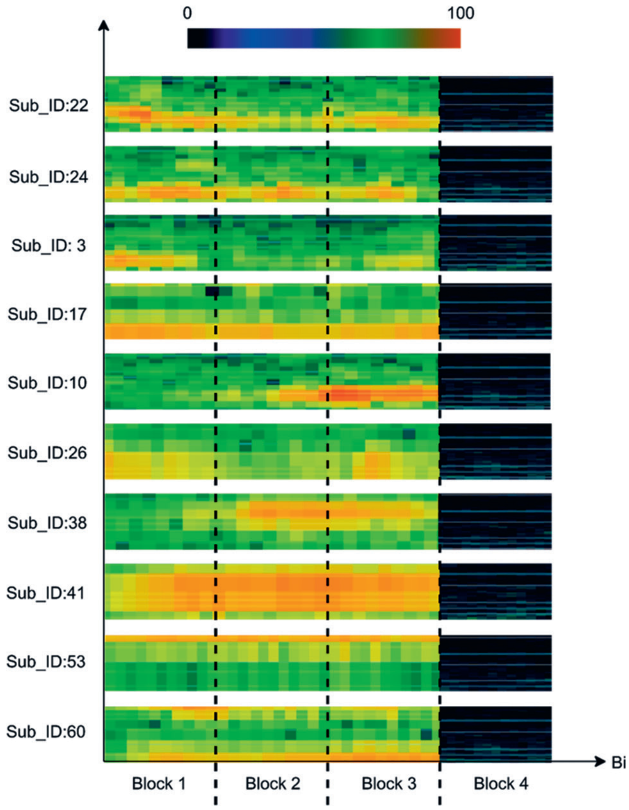

Fig. 7. Behavior Pattern of Various Subjects

Conclusion

According to this research, sedentary behavior in adults is highly linked to previous 6-hour window blocks of sedentary activity and demonstrates repeating sedentary trends. Therefore, we used a stacked LSTM model to simulate such sedentary tendencies in predicting prospective sedentary behavior based on previous behavior. Utilizing unprocessed activity records as a starting point, we went through the preprocessing procedure, establishing the stacking LSTM model sequence, exploring event traces for the appropriate activities and passivity characteristics, and then evaluating the conceptual approach using MSE, RMSE, MAPE, and *r*-correlation metrics. Finally, we were able to use our stacked LSTM model to simulate the three most significant individual predictors of sedentary behavior (state traits, previous action stacks, and duration) through which a 99 % accuracy level was attained.

Our present research is entirely focused on two predetermined datasets (adults). In future work, we expect to evaluate our model on a broader range of demographics as well as a larger sample size. In addition, wearable equipment will be supplied to subjects to monitor their physical activity around the clock in order to collect a real-time dataset.

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