BMI Analysis Pre-Covid And Post-Covid Using Machine Learning Algorithms

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Abstract**—** In this study, there is exploration of how people's BMI changed pre and post the onset of covid pandemic, considering factors like food habits (the nutritious value of what they eat) and physical activities. They not just eyeballing the data—system using super-smart computer techniques called Reinforcement Learning, specifically Deep Q Network and Random Forest Regression and Gradient Boost Regression. Before COVID-19, know people had certain eating habits and physical activities. Now, with the pandemic, those might have changed. Using Deep Q Network, our computer system learns from this data and figures out how these changes are linked to BMI. It's like teaching a computer to understand the consequences of different habits on weight. Gradient Boost Regression is another technique being used. It helps the computer learn not just from the data have but also by exploring possibilities like, what if someone changed their eating habits or exercise routines? This way, system not just looking at what happened but also predicting what could happen. By combining these techniques, study aim to unravel how food choices and physical activities during and after Covid-19 might have influenced BMI. It's like having a smart assistant to help us understand the connection between lifestyle changes and weight, shedding light on how they can stay healthy in this challenging time.

Keywords**—** Body Mass Index (BMI), Random Forest Regression, Gradient Boosting Regression, Deep Q-Network (DQN).

I. INTRODUCTION

In the wake of the COVID-19 pandemic, human's lives have undergone profound transformations, affecting everything from the work and social interactions to the dietary habits and exercise routines. Of particular interest amidst these changes is their potential impact on the health, specifically regarding Body Mass Index (BMI), a crucial indicator of overall health that considers body weight in relation to height. This study sets out to investigate the complexities surrounding BMI fluctuations before and after the onset of COVID-19, focusing on how lifestyle choices, including dietary habits (in terms of nutritional values) and physical activity, may have influenced these changes.

To navigate this intricate web of connections, system harness the power of Reinforcement Learning, employing advanced algorithms such as Deep-Q-Network and Random Forest Algorithms.

Before delving into the details of this study, it's essential to set the context. Prior to the pandemic, we had established routines, dietary preferences, and exercise habits. However, the pandemic disrupted these routines, leading to significant alterations in the daily lives. Factors such as remote work, limited outdoor activities, and changes in food availability and consumption likely influenced our lifestyles. Many individuals found themselves adopting new eating patterns during this time, whether as a conscious effort to prioritize nutritious foods or as a result of altered routines. Similarly, restrictions on movement and shifts in work dynamics may have impacted our physical activity levels, subsequently influencing our BMI.

Understanding the interplay between lifestyle changes during the pandemic and BMI fluctuations can provide valuable insights for public health strategies and individual choices. This study aims to go beyond mere numerical analysis, seeking to identify patterns and connections that illuminate the complex relationship between lifestyle choices and health outcomes. By leveraging Reinforcement Learning, model endeavor to uncover these intricate connections, offering insights into how choices made during challenging times can affect our health.

As it embarks on this exploration, it's important to recognize the vast complexities of human behavior and health. Our goal is to harness technology to distill meaningful insights, providing a clearer understanding of the relationship between lifestyle changes and BMI in the COVID-19 era. Stay tuned as the journey into the heart of health and well-being methods, contributing to a healthier, more informed future.

II. LITERATURE SURVEY

The intention of this study is to investigate the impact of the Wuhan lockdown on the Body Mass Index (BMI) of citizens, considering changes in food habits and lifestyle habits. They surveyed 11,223 residents using random digit dialing in July 2020. The results showed that residents who stayed in Wuhan during the isolation had a higher BMI compared to those who left the city [1]. This difference was most significant among younger age groups and overweight/obese individuals. Mediation analysis revealed that decreased physical activity played a role in this association. However, the lack of an association among residents aged 45+ was attributed to changes in food habits. In conclusion, the Wuhan lockdown increased BMI, particularly among younger or overweight/obese individuals, partly due to reduced lifestyle habits [2].

This study focuses on the impact of the covid 19 epidemic in India, with an emphasis on using machine learning models to predict its spread. The research uses various datasets and finds that the Transformer model is the most accurate in predictions. The Facebook mobility dataset proves valuable for predicting confirmed cases, but data from different sources are less effective in predicting COVID-19-related deaths. This study highlights the need for more attention to less developed countries like India in the context of pandemic research and technology [3].

This study investigates the effect of the covid 19 lockdown, especially amid the beginning isolation period (March to May 2020), on body weight and body mass record in both grown-ups and young people (>16). They think about surveyed 36 observational ponders and found that numerous people experienced expanded BW (11.1 to 72.4%), with a few announcing weight misfortunes (7.2 to 51.4%). There was a critical increment in both BW and BMI post-lockdown compared to some time recently the lockdown. Strikingly, one ponders in more seasoned grown-ups (>60) detailed critical body weight misfortune, proposing a hazard of lack of healthy sustenance in this populace [4]. The general increment in BW amid lockdown raises concerns about almost higher rates of overweight, weight, and related well-being issues. Advance inquiry is required to evaluate group-specific impacts, such as weight pick-up in more youthful individuals and the chance of weight misfortune, ailing health, and sarcopenia in more seasoned older adults [5].

In this study, the researchers used de-identified patient data from the QResearch database in England to analyze the impact of covid 19. They focused on patients aged 20 and older, registered in the database between January 24, 2020, and April 30, 2020, who had BMI data available. They collected information on demographics, clinical data, and SARS-CoV-2 test results gathered from Public Health England, as well as death certificates from the Office of National Statistics in England. The study assessed severe COVID-19 outcomes, such as hospitalization, ICU admission, and covid 19-related deaths. To determine the risk of severe covid19, they used Cox proportional hazard models and adjusted for demographic factors, behaviors, and comorbidities [6].

This study explores the use of Artificial Intelligence, particularly Deep learning and Reinforcement learning, to predict and optimize outcomes related to covid19. It specifically focuses on using a Modified Long Short-Term Memory (MLSTM) model to forecast the number of new cases, deaths, and recoveries in the coming days [7]. The research also suggests the use of deep learning reinforcement to enhance predictions based on symptoms. Real-world data was used to evaluate the system's effectiveness. The results indicate that this approach outperforms traditional models like Long Short-Term Memory (LSTM) and Logistic Regression (LR) in terms of prediction accuracy for the COVID-19 pandemic [8].

This study aimed to investigate how the COVID-19 pandemic affected the nutrition and physical activity behaviors of Dutch older adults. A total of 1,119 participants (aged 62 to 98) completed a questionnaire, and the results showed that around half of them reported a decrease in physical activity and exercise due to the pandemic. Additionally, a significant portion reported changes in nutrition behaviors, predisposing some to overnutrition and others to undernutrition. Those who had been in quarantine were more likely to report a negative impact. The study identifies subgroups of older adults at higher risk of being affected and suggests that these changes in behavior could increase the risk of malnutrition, frailty, sarcopenia, and disability in this population [9].

Efforts to enhance sample efficiency and maintain robustness in various machine learning and reinforcement learning algorithms have been ongoing in recent years. One approach involves the incorporation of off-policy samples, which are data points collected from policies different from the one currently being evaluated or improved upon. By leveraging off-policy samples, algorithms can potentially reuse data more effectively, leading to improved learning efficiency.
Moreover, higher-order variance reduction techniques have been explored to further enhance sample efficiency and stability. These techniques aim to mitigate the variance of estimators used in learning algorithms, which can be a significant challenge, especially in high-dimensional or complex environments [10].

The Deep Attention Q-Network (DAQN) represents a significant advancement in personalized treatment recommendation systems, particularly in healthcare applications. By integrating the Transformer architecture into a deep reinforcement learning (RL) framework, the DAQN can efficiently incorporate and process vast amounts of heterogeneous patient data, including medical histories, clinical notes, lab results, and treatment responses. This enables the model to generate personalized treatment recommendations tailored to individual patients' needs and characteristics. The Transformer architecture, originally proposed for natural language processing tasks, has gained widespread attention for its ability to capture long-range dependencies and relationships in sequential data efficiently. In the context of healthcare, where patient data is often sequential and multi-modal, the Transformer's self-attention mechanism proves invaluable [11].

The optimization model of urban emergency resource scheduling represents a critical aspect of emergency management systems, aiming to efficiently allocate limited resources to mitigate the impact of disasters or emergencies in urban areas [21]. By utilizing deep reinforcement learning (DRL) algorithms, this model can create a flexible and adaptive framework for emergency resource distribution, capable of dynamically adjusting resource allocations based on real-time information and evolving emergency scenarios. In the context of urban emergency resource scheduling, the deep reinforcement learning algorithm serves as the core decision-making engine, enabling the system to learn optimal resource allocation policies through interaction with the environment and feedback from past decisions [22]. The model's objective is to maximize the effectiveness of resource utilization while minimizing response time, resource wastage, and overall damage during emergency situations [12].

This survey delves into the extensive applications of reinforcement learning (RL) techniques within healthcare domains, aiming to address existing challenges and explore novel methodologies. RL, a subfield of machine learning, offers a versatile framework for optimizing sequential decision-making processes, making it particularly well-suited for various healthcare applications where decision-making plays a crucial role in patient care, treatment planning, and resource allocation. The healthcare industry presents a myriad of challenges, ranging from personalized treatment recommendation and patient monitoring to healthcare operations management and policy optimization. RL techniques have been increasingly leveraged to tackle these challenges, offering innovative solutions that enhance patient outcomes, streamline healthcare delivery, and improve overall system efficiency [13].

III. METHODOLOGY

Proposed System: The proposed system is like having a health detective powered by super-smart computers. Using Reinforcement Learning buddies, Deep Q Network and other algorithms like Random Forest Regression and Gradient Boost Regression, main aim to crack the code on how humans' lifestyles during and after covid-19 influence BMI. It's not just about tracking weight changes but understanding the 'why' behind it. Deep Q Network learns from the health history, like a friend who's seen it all, connecting the dots between food choices, physical activities, and BMI [23]. Deep Q Network is the adventurer, helping to explore different scenarios—what if we change our habits? Together, they form a dynamic duo, dissecting the complex puzzle of health in the pandemic era. The proposed system isn't just about numbers; it's a breakthrough in decoding how the daily choices impact their well-being, paving the way for personalized health strategies.

A. *System Architecture*

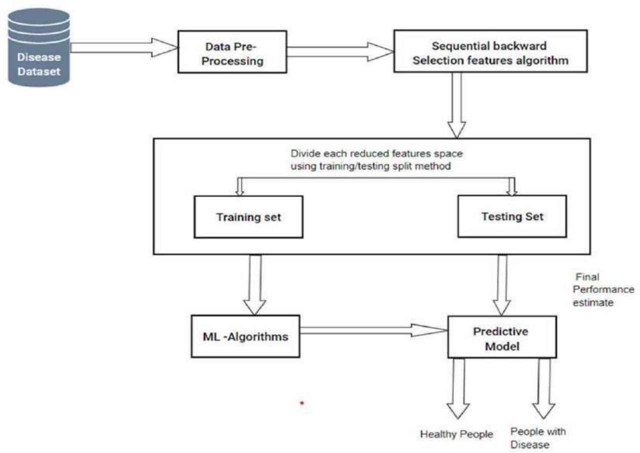


Fig. 1. System Architecture

1. Data Collection: The initial step involves gathering a comprehensive dataset comprising weight measurements, information on underlying diseases, dietary habits, physical activity levels, and other relevant factors.

2. Data Preprocessing: This stage involves cleaning and preprocessing the collected dataset to handle missing values, outliers, and inconsistencies, ensuring that the data is suitable for analysis.

3. Dataset Splitting: The dataset is divided into training and test sets to facilitate model training and evaluation while maintaining the integrity of the analysis.

4. Model Architecture Design: The next step is to design the architecture of the Deep-Q Network and Soft Actor-Critic model, considering the complexity of the data and the specific objectives of the analysis.

5. Model Training: The designed models are trained using the training set, allowing them to learn patterns and relationships within the data.

6. Model Evaluation: The performance of the trained models is evaluated using the test set to assess their effectiveness in predicting BMI changes accurately.

7. Visualization: Visualizations are generated to compare the actual and predicted BMI changes, providing insights into the model's performance and highlighting any discrepancies or areas for improvement.

8. Prediction: Utilizing the trained models, predictions are made regarding BMI changes resulting from the lockdown, considering factors such as weight categories (normal, underweight, overweight/obese), dietary habits, and physical activities. These predictions offer valuable insights into the impact of these factors on BMI changes during the lockdown period.

B. *Algorithms*

1) *Reinforcement Learning:*

Reinforcement Learning is a feedback-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions [24]. For each good action, the agent gets positive feedback, and for each bad action, the agent gets negative feedback or penalty. Reinforcement learning (RL) is typically used for dynamic decision-making tasks, where an agent interacts with an environment to learn optimal actions. As we are using Dynamic dataset for the BMI prediction, Reinforcement Learning technique is a good choice.

2) *Deep Q-Network (DQN):*

What it does: A Deep Q-Network (DQN) is like a smart system that learns how to make better decisions over time. It's often used in situations where there are different choices to make, and you want to pick the best one.
How to use it: You can use DQN to pick the best choices for things like what to eat and how much to exercise. It's good when you have clear options to choose from, like different diets or exercise routines. DQNs are like helpful guides that adjust your choices based on what's happening. They aim to help you maintain a healthy BMI, and they learn from your experiences to do better over time.
In this dynamic approach, the DQN learns over time which actions are most likely to lead to a decrease or increase in BMI based on the observed state transitions and rewards. It dynamically adjusts its predictions and actions as it accumulates more experience, helping individuals make

healthier choices with respect to their nutritional values and physical activity.

Components:

• State (S):
  - Initial BMI
  - Nutritional values
  - Physical activity

• Action (A):
  - Increase activity
  - Change diet

• Reward Function (R):
  - $R(S, A) = (BMI_{new} - BMI_{initial}) - Cost(A)$

• Q-Value Function (Q(S, A)):
  - $Q(S, A) = E[R(S, A)] = E[(BMI_{new} - BMI_{initial}) - Cost(A)]$

• DQN Loss Function:
  - $Loss = |Q(S, A) - (R(S, A) + \gamma * \max(Q(S', A')))|^2$
  - γ : Discount factor

3) *Gradient Boost Regression:*

Gradient Boosting is an ensemble learning technique that has gained widespread popularity in machine learning due to its high predictive accuracy and versatility across various tasks. Unlike traditional boosting methods that focus on optimizing the overall model, Gradient Boosting aims to minimize the errors of the model by sequentially fitting new models to the residuals (errors) made by the previous ones.

Gradient Boosting sequentially builds an ensemble of weak learners to minimize a loss function:

$F_i(x)=F_{i-1}(x)+\alpha.h_i(x)$

$F_i(x)$= is the current ensemble prediction after i iterations. $F_{i-1}(x)$=is the prediction from the previous iteration.

α=is the learning rate.

$h_i(x)$=is the prediction from the newly trained weak learner.

4) *Random Forest Regression:*

What it does: Random Forest Regression (RFR) is a machine learning technique used for predicting continuous numerical values. It constructs an ensemble of decision trees and aggregates their predictions to make accurate forecasts.

How to use it: RFR can assist in choosing the best dietary and exercise options by analyzing clear choices like different diets or exercise routines [25]. RFR aims to help individuals maintain a healthy BMI by leveraging its predictive capabilities. It learns from past experiences, adapting its predictions over time to promote healthier choices in terms of nutrition and physical activity.

IV. USE CASE DIAGRAMS

A. *Use Case Diagram*

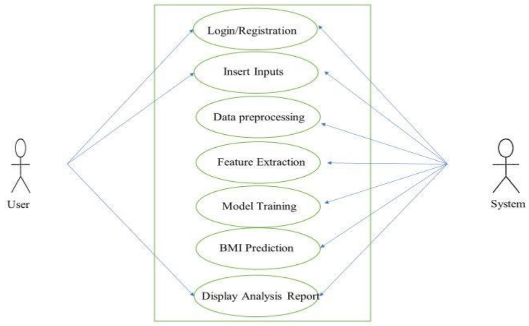


Fig. 2. System User Interaction Diagram

B. *Class Diagram*

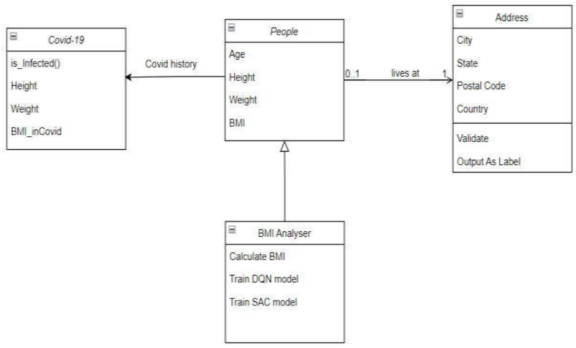


Fig. 3. System Class Diagram

V. ADVANTAGES

A. *Advantages*

1.**Personalized Health Insights:** The analysis enables the provision of personalized health insights. By understanding individual responses to changes in food habits and physical activities, tailored recommendations can be generated, promoting a more personalized approach to health.

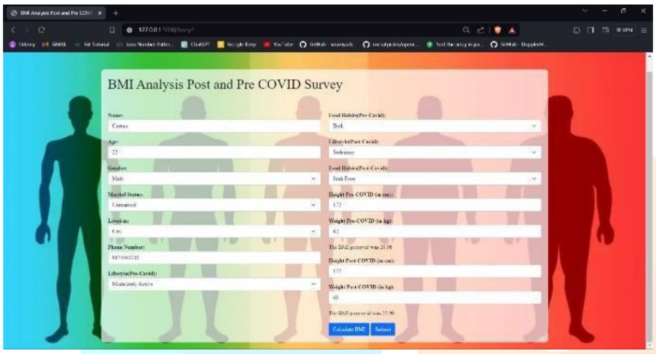
2.**Dynamic Adaptability:** The use of Reinforcement Learning, especially Soft Actor Critic, allows for dynamic adaptability. The system can continuously learn and adjust its recommendations based on real-time data, accommodating changes in lifestyle and habits over time.

3.**Risk Assessment and Prevention:** By identifying patterns and correlations between BMI changes and lifestyle factors, the analysis can contribute to early risk assessment and preventive measures. This proactive approach aids in addressing health risks before they escalate [26].

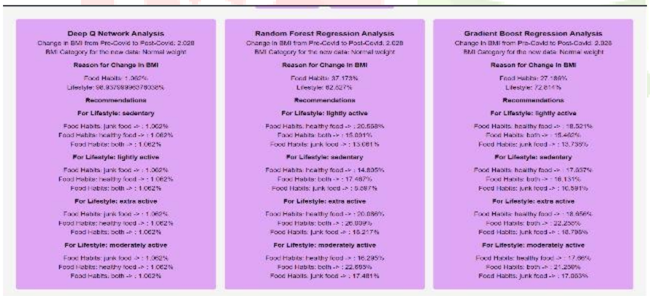
4.**User-Friendly Applications:** The insights derived from the analysis can be translated into user-friendly applications. These applications can provide individuals with easy-to-understand feedback, making it simpler for them to make informed choices about their health.

VI. RESULTS

A. *Frontend*



B. *Backend*



VII. CONCLUSION

In conclusion, our investigation into the analysis of Body Mass Index (BMI) before and after the COVID-19 pandemic, examining the influence of dietary habits and physical activity through Reinforcement Learning with Deep Q Network and complementary algorithms like Random Forest Regression and Gradient Boost Regression, has revealed a compelling narrative. Our journey through this project has transcended mere data analysis, delving into the intricate interplay between our lifestyles and health outcomes. As we navigate the post-pandemic landscape, our findings shed light on the nuanced ways in which our choices impact BMI. The application of advanced machine learning techniques has not only enabled us to decipher these intricate patterns but has also paved the way for a future where health management becomes personalized, dynamic, and easily accessible. With further refinement and expansion, our system holds the potential to evolve into a comprehensive tool, guiding individuals towards healthier choices in real-time.

VIII. FUTURE SCOPE

Looking ahead, the future prospects for our BMI analysis system are brimming with promising opportunities. Beyond the examination of COVID-19's impact on Body Mass Index (BMI), there lies potential to refine and broaden our understanding of how dietary habits and physical activity influence overall health.

We envision delving deeper into diverse datasets from various demographics, taking into account cultural nuances and regional disparities to ensure our insights are inclusive and relevant. Furthermore, the integration of real-time data could revolutionize our system into a dynamic tool. Imagine having a system that adapts to changes in your lifestyle and provides immediate, tailored feedback. This adaptability could transform our analysis into a proactive health advisor, offering timely suggestions for maintaining a healthy lifestyle.

As technology continues to advance, our system has the potential to evolve into a comprehensive health management platform. By incorporating more advanced machine learning techniques and collaborating with healthcare professionals, we can contribute to the development of preventive healthcare strategies.

Ultimately, the future scope of our BMI analysis transcends the current scenario, promising a journey towards a more personalized, adaptable, and user-centric approach to health and well-being.

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