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Monitoring Body Mass Index (BMI) Pre & Post Covid-19 Outbreak: A Comprehensive study in Healthcare

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Abstract— **A comprehensive health monitoring & analyzing system that provides personalized recommendations, goal setting, and tracking based on relevant factors related to BMI & COVID-19. System aims to analyze attack obesity through prediction, prevention and ongoing monitoring through appropriate predictive analytical system. The system's Risk Assessment component categorizes individuals by their risk levels using factors like age, gender, medical history, and behavior related to pre & post covid-19 related to BMI, then relates appropriate connections in human body. The wellness solution includes features such as fitness tracking, data integration, personalized metrics, and predictive analytics to create a holistic approach for predictive analytics health management. The system healthcare monitoring and analyzing system is a groundbreaking solution that leverages predictive analytics to promote a healthy lifestyle, combat obesity, and enhance overall well-being. By considering a range of factors and employing cutting-edge technology, we empower individuals to take control of their health, achieve their fitness objectives, and mitigate health risks.**

Keywords— BMI, COVID-19, Obesity, Predictive Analysis, Healthcare.

I. Introduction

The standard health organizations legitimately formulated COVID-19 as a pandemic period in 2020's onwards, numerous initial investigations have delved into the connection between increased visceral fat and the repercussions for individuals afflicted by this virus. In a prospective cohort study conducted in Italy, involving 233 COVID-19 patients, Giacomelli's findings revealed that those with obesity faced a significantly heightened three-fold risk of mortality compared to individuals with a BMI less than 30 kg/m2. Similarly, study of COVID-19 patients demonstrated that severe obesity, defined by a BMI of 35 kg/m2 or higher, was linked to a higher rate of in-hospital mortality, even when accounting for other potentially influential factors. In France, Simonnet's research illustrated a notably higher prevalence of obesity observed in infected persons with higher care units grappling with SARS-CoV-2-related pneumonia.

The primary goal of our current systematic review is to ascertain the association between BMI and the severity of COVID-19 and its outcomes. Additionally, we aim to offer a conceptual perspective on the advantages and constraints associated with conducting early systematic reviews in the context of a rapidly evolving pandemic with shifting epidemiological patterns. Strong evidence supporting the validity of worries about the pandemic's potential effects on children's health has been produced by recently completed research in the United States. Woolford et al. in Southern California and Lange et al. (who looked at data from youngsters across the country) used medical records to show a marked increase in the rate of weight gain and body mass index (BMI) during the pandemic. This was especially clear in a study of kids whose weight and height were recorded at school, which revealed that even among those who were originally placed in the healthy BMI range, weight increase during the pandemic year outpaced that of the pre-pandemic years.

Risk Assessment is a fundamental part of our system. It considers age, gender, medical history, and pre- and post-COVID-19 habits, all of which are connected to BMI, to assess health risks. This helps us understand how diverse circumstances affect an individual's health by establishing appropriate bodily linkages.

Our healthcare solution includes Fitness Tracking, Data Integration, Personalised Metrics, and Predictive Analytics. These components integrate smoothly to develop a predictive analytics-based health management strategy. Fitness Tracking lets users track their workouts and progress towards fitness objectives. Personalised Metrics reflect the individual's health requirements and objectives, whereas Predictive Analytics uses data to provide suggestions.

In recent years, healthcare prediction has saved many lives. In healthcare, smart systems that assess complicated data correlations and turn them into predictive evidence have grown rapidly. Artificial intelligence is rapidly changing healthcare. This emphasises the importance of ML & DL systems in clinical data and image-based diagnosis and illness prediction procedures. Predictive analytics has become essential in healthcare since it may improve illness predictions and save lives. The importance of accurate illness prediction and estimate is highlighted by the fact that inaccurate forecasts might endanger patients [1]. The research evaluates the current ML & DL healthcare prediction technique to highlight the challenges of using these algorithms [2].

II. PREDICTIVE ANALYTICS

Predictive analytics is a complex data analysis area that predicts unknown future occurrences. It analyses data and predicts future occurrences using data mining, statistical analysis, modelling, ML, and AI in many applications [3]. The "predictor," variable used to predict future behaviour or consequences, is the core of predictive analytics. These predictors accurately estimate future probability. Machine learning and regression are the key predictive analytics methods [4]. Machine learning approaches have grown in popularity owing to their capacity to manage large datasets with diverse properties and noisy data. Machine learning is ideal for predictive modelling because it finds detailed patterns in large datasets, according to several observational studies. These predictive algorithms are used to estimate pricing, assess risks, predict consumer behaviour, and classify documents. In essence, predictive analytics harnesses a diverse set of cutting-edge tools and methodologies to sift through historical data, discern patterns, and employ these patterns to anticipate future occurrences.

III. HEALTHCARE PREDICTIVE ANALYTICS

Predictive analytics plays pivotal role across various facets of the healthcare and life sciences sectors, providing invaluable support. Its primary objectives encompass precise disease diagnosis, the enhancement of patient care, efficient allocation of resources, and the overall improvement of clinical outcomes. By leveraging the power of predictive analytics, healthcare organizations can proactively prepare for the challenges of their industry while simultaneously optimizing costs. The achievements of predictive analytics in this domain are poised to deliver significant benefits, notably by elevating the quality of healthcare services. Looking ahead, it's evident that predictive analytics has the potential to usher in a transformative era within the healthcare industry, promising a future marked by profound changes and advancements.

IV. MACHINE LEARNING

Before Machine Learning, in its traditional sense, can be defined as the process through which a computer program enhances its ability to perform tasks within a specific domain by learning from prior experiences [5]. These experiences are denoted as "E," while the tasks it aims to improve in are referred to as "T," and the criteria used to gauge its progress is "P."

ML automates analytical model creation. Iterative techniques enable computers to learn from data without programming instructions. This allows robots to reveal hidden knowledge, aiding decision-making and problem-solving across disciplines. Machine Learning has transformed how computers process and interpret data, providing significant solutions in a data-driven environment [6,7].

A. *Steps to apply machine learning to data*

1. Data collection: All information must be collected in a digital form that can be examined, in a database. An algorithm will learn from this data to offer meaningful insights

2. Examining and getting ready the data: Data quality is key to machine learning project success. This is when machine learning requires a lot of human interaction. A significant portion of this time is given to data exploration, or learning more about the complexities of the data.

3. Model training: The particular machine learning job will guide the choice of a suitable method, which will then use the data to create a model representation.

4. Analyzing prototypical performance: Since every machine learning model gives a biased result, determining how effectively the algorithm learns from the history. Depending on the model, a test dataset may assess accuracy.

5. Enhancing model performance: If the model's performance has to be raised, then it is essential to use sophisticated tactics. It could sometimes be necessary to switch to a new kind of model altogether.

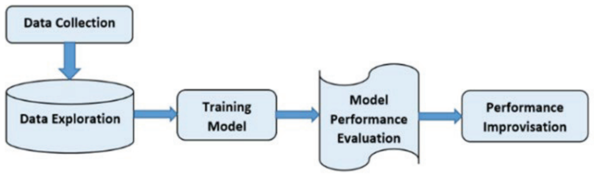

Fig. 1. Machine Learning Process

If the model seems to be functioning well after completing these stages, it may be used for the intended purpose. The model may be used to automate operations, offer score data for forecasts, project financial data, and provide relevant knowledge for marketing or research. The deployed model's triumphs and setbacks may even provide more information needed to train the model that comes out next.

B. *Reinforcement Learning (RL)*

This learning teaches the machine to make accurate business decisions to maximise efficiency (performance). This rigorous approach to learning optimises efficiency while reducing human proficiency. Robotics, games, and navigation use reinforcement learning. The system employs reinforcement learning to find the most rewarding tasks via trial and error.

Decision-making is scientifically called Reinforcement Learning (RL) [8]. Maximising knowledge. teaching reinforcement. It involves choosing the appropriate action to maximise rewards. Just as young infants study their surroundings and develop skills to attain goals, this ideal conduct is learnt by interacting with the environment and watching how it reacts.

The learner must determine for himself what actions to do in order to maximize the reward when there is no supervisor present. This search method is akin to conducting an iterative search. Because reinforcement learning may learn the actions that ultimately result in success in an unseen environment without the help of a supervisor, it is a very powerful algorithm [9] decision process

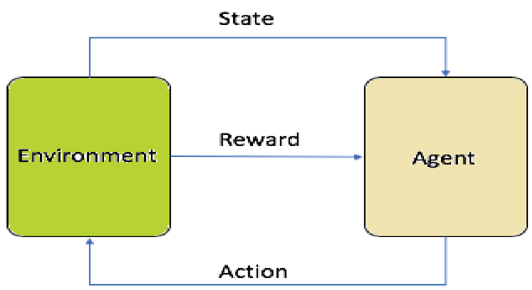

Fig. 2. Reinforcement learning approach

The following important words sum up the fundamental components of an RL problematic :

- Agent- ML algorithm, often known as the autonomous system.

- Environment- The adaptive problem space, or environment, has elements including variables, boundary values, rules, and appropriate behaviours.
- Action- A move that the real-time agent makes in order to move about.
- State- The environment at a specific moment in time.
- Reward- The performing an action can be any positive, negative, or zero value; it can also be thought of as a penalty.
- Cumulative reward- The total of all prizes or the end value.

C. Chain of Markov

Assume that Z0, Z1, Z2... is a series of random items. The sequence is considered Markov if, for each

$t \in \{1, 2, \cdots,\}$,

$P(Z_t \in \cdot \mid Z_0 = z_0, Z_1 = z_1, \ldots, Z_{t-1} = z_{t-1}) =$

$P(Z_t \in \cdot \mid Z_{t-1} = z_{t-1})$,

for any sequence $z_0, z_1 \ldots, z_{t-1}$.

In alternate universes, a Markov chain's future remains independent of its history, provided that 't' denotes time steps.

D. Linear Regression (Supervised learining model)

In linear regression, the response value is estimated and the relationship between two variables is described using a line-of-best-fit. Algorithm was made to perform basic linear regression using a single predictor variable (X) and a single respondent (Y).

$$Y = mX + b,- \tag{1}$$

where Y is the response (dependent) variable, X is the predictor (independent) variable, m is the predicted slope, and b is the estimated intercept.

The predictor or explanatory variable that does not change as a result of changes in other variables is also known as the independent variable. However, the dependent variable changes with oscillations in the independent variable. The response or result variable under study is the dependent variable, and the regression model predicts its value.

E. K- menas Clustering (Unsupervised learining model)

A wide number of techniques are available for finding observational subgroups within a data collection, including clustering. When we cluster data, we want observations within the same group to be similar and observations across groups to be different. Unsupervised as it does not rely on a response variable for training; rather, it looks for correlations between the observations on its own. By grouping observations together, we may determine which ones are similar and perhaps group them together. K-means clustering is a straightforward and widely used clustering method that divides a dataset into a set of k groups.

F. Methods

This research report delves into the comprehensive methodology of the study and provides a detailed overview of the study [10] design, participants, and data collection process. The survey was carried out in multiple City, spanning from July 3rd to July 31st, 2020, and was spearheaded by the national health organization. The actual survey was administered using a computer-aided telephone interview platform and conducted by trained interviewers. Before proceeding with formal interviews, strict adherence to eligibility criteria, which included age and the participant's location within their family, was confirmed. Additionally, each telephone conversation was meticulously recorded and reviewed by a supervisor. The survey questionnaire encompassed various critical aspects [10], including:

a) Evaluations of the COVID-19 pandemic-related government countermeasures.

b) Assessments of respondents' self-protective behaviours and risk perceptions in relation to the COVID-19 pandemic.

c) Enquiries about the respondent's city of residence during the lockdown.

d) Details on the respondent's family members' COVID-19 status [11].

e) Information on the COVID-19 situation in the neighbourhood of the respondent.

f) An evaluation of the respondents' physical and mental health conditions during the outbreak.

g) The participants' demographic details. [12,13,14].

V. SYSTM ARCHITECTURE

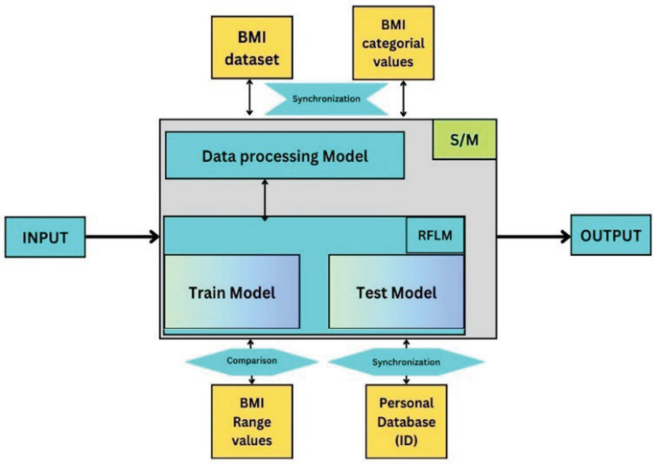

Fig. 3. Architectural Model

a) Collect BMI Data & Data Pre-processing:

In this stage, data related to BMI (Body Mass Index) is collected from various sources [15]. The collected data is then pre-processed to clean, transform, and prepare it for machine learning.

b) Reinforcement learning model:

Machine learning models are designed to predict BMI values. To do this, separate the data into sets for testing, validation, and training. Model performance is evaluated by the testing set, model parameters are adjusted with the help of the validation set, and models are trained using the training set.

c) Predict BMI Categories and Future BMI Values:

Once the machine learning models are trained and validated, they are employed to predict not only BMI categories (underweight, normal, overweight, obese) but also future BMI values. This is achieved by applying ML algorithms to the pre-processed data.

d) Compare BMI Value Data Pre & Post COVID-19:

In this stage, BMI data from before and after the COVID-19 pandemic are compared. To determine how the pandemic affected people's BMI patterns, historical BMI data and post-COVID-19 BMI forecasts were compared.

e) Performance Analysis:

This is a critical phase where the outcomes of the BMI prediction system are analysed and evaluated. The system's performance is assessed with respect to multiple objectives [16] like personalized health monitoring, predict obesity prevention & intervention, research and epidemiology, fitness and wellness tracking [17].

A. Dataset

The dataset with information related to individuals and their Body Mass Index (BMI) calculations before the COVID-19 pandemic [18]. Here's a breakdown of the columns:

- Person ID: An identifier for each individual in the dataset.
- Gender: Indicates the gender of the person. It appears to use the following coding: (1-male, 0-female)
- Age: The age of the individual in years.
- Feet: The feet part of the height in feet and inches.
- Inches: The inch's part of the height in feet and inches.
- Pounds: The weight of the individual in pounds.
- Height: The height of the individual, calculated as the sum of feet and inches converted to a single measurement (e.g., 5 feet 10 inches becomes 5.83 feet).
- Weight: The weight of the individual in kilograms (approximately, as 1 pound is approximately 0.45 kilograms).
- BMI: The Body Mass Index of the individual, which is a calculated value based on their height and weight. (Formula for BMI = weight / (height^2)).

The BMI values in the table indicate the level of obesity or underweight for each individual. Here's a brief description of BMI standard ranges like "Below 18.5: Underweight", "18.5 to 24.9: Normal weight", "25 to 29.9: Overweight", "30 or above: Obesity".

The table seems to contain data for 25 individuals, including their gender, age, height, weight, and BMI before the COVID-19 pandemic there are various BMI performance indexes can be referred [19,20] . It can be used for various health and medical analyses and is often used to assess the overall health of an individual based on their weight relative to their height.

The table includes data for 25 individuals, with information such as gender, age, height, weight, and their calculated BMI. When evaluating a person's health and wellness, the BMI readings may be utilized to determine if they are underweight or overweight, or whether they fall within a healthy weight range.

https://www.kaggle.com/datasets/prahire/pre-post-covid-bmi

VI. RESULT

TABLE I. BMI COMPARTAISON BETWEEN PRE & POST COVID-19

Person ID A1	Pre-Covid-19 BMI	Predicted Post-Covid-19 BMI (RL output)
1	35.04	40.80
2	24.01	24.28
3	23.17	23.86
4	17.22	16.36
5	27.75	22.73
6	19.37	21.79
7	23.40	23.56
8	33.64	27.84
9	21.11	22.43
10	19.53	20.08
11	24.39	24.39
12	25.10	25.52
13	31.09	34.02
14	29.29	24.63
15	42.68	41.23
16	18.43	18.43
17	26.46	26.61
18	25.10	25.24
19	17.86	15.82
20	21.57	21.18
21	25.40	25.54
22	24.81	24.81
23	23.48	23.35
24	25.24	25.70
25	29.60	29.76

The BMI of several people both PRE and POST the Covid-19 epidemic is shown in the table. A person's BMI indicates how much weight they have with respect to their height and is frequently used to determine if they are underweight, normal weight, overweight, or obese.

Here is description of the columns in the table:

- Person ID: This column simply assigns a unique identifier to each individual, presumably for tracking and reference.
- Pre-Covid-19 BMI: This column shows the BMI of each individual before the Covid-19 pandemic.
- Predicted Post-Covid-19 BMI (RL output): This column shows the BMI of each individual after the Covid-19 pandemic. It is also calculated using the RL-ML model.

The data in these columns represent the BMI of 25 individuals. It appears that some individuals have gained weight (their BMI increased) after the Covid-19 pandemic [21], while others maintained their weight or even experienced a decrease in BMI. The table may be used to observe the effect of the pandemic on individuals' patient weight & health, which could be important for public health studies or interventions related to nutrition and lifestyle.

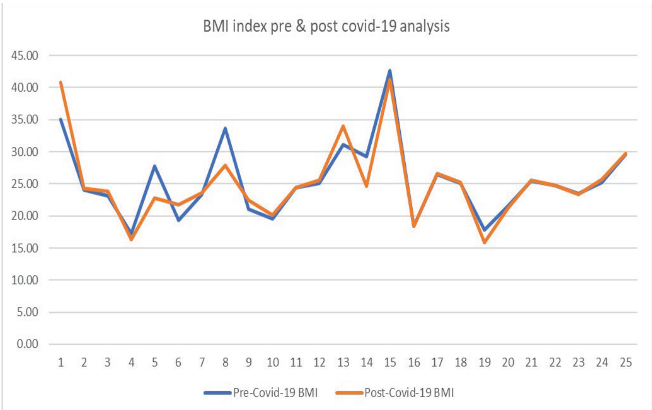

Fig. 4. BMI analysis

A. *Comparing results using linear regression model (Supervised learning approach)*

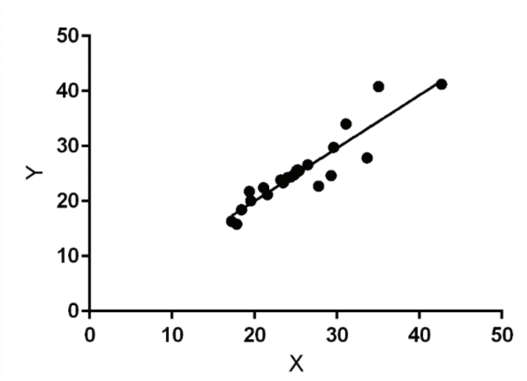

Fig. 5. BMI linear regression analysis

- Best-fit values: Slope- 0.9616 ± 0.08483, Y-intercept- 0.7827 ± 2.208, X-intercept- -0.8139, 1/Slope- 1.040.
- 95% Confidence Intervals: Slope- 0.7861 to 1.137, Y-intercept- -3.786 to 5.351, X-intercept- -6.778 to 3.344.
- Goodness of Fit: R square- 0.8482, Sy.x- 2.435.
- Is slope significantly non-zero?
- F - 128.5, DFn,DFd- 1,23, P Value- < 0.0001, Deviation from horizontal? - Significant
- Data: Number of XY pairs- 25, Equation- Y = 0.9616*X + 0.7827

B. *Comparing results using K-means clustering model (Un-Supervised learning approach)*

Number of clusters (k value): 2

Number of iterations: 10

TABLE II. COMPUTED SAMPLE VALUE & CENTROID INDEX

Sample value	Centroid index	Sample value	Centroid index
35.04,40.8	1	29.29,24.63	2
24.01,24.28	2	42.68,41.23	1
23.17,23.86	2	18.43,18.43	2
17.22,16.36	2	26.46,26.61	2
27.75,22.73	2	25.1,25.24	2
19.37,21.79	2	17.86,15.82	2
23.4,23.56	2	21.57,21.18	2
33.64,27.84	1	25.4,25.54	2
21.11,22.43	2	24.81,24.81	2
19.53,20.08	2	23.48,23.35	2
24.39,24.39	2	25.24,25.7	2
25.1,25.52	2	29.6,29.76	1
31.09,34.02	1		

Resultant output as below,

TABLE III. RESULTANT OUTPUT

Centroid index	Centroid value
1	34.410,34.730
2	23.135,22.816

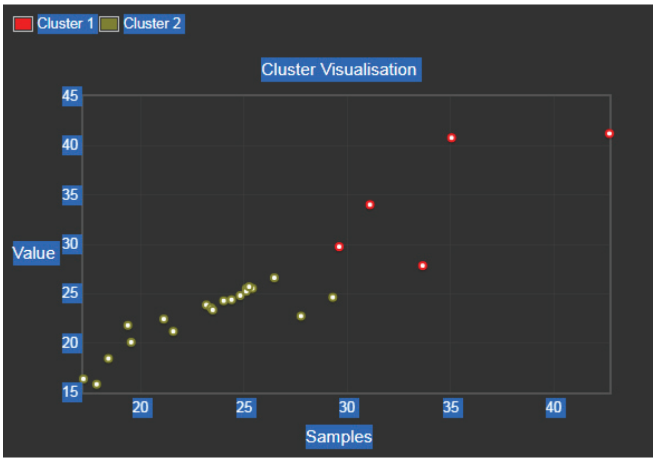

Fig. 6. Clustering analysis

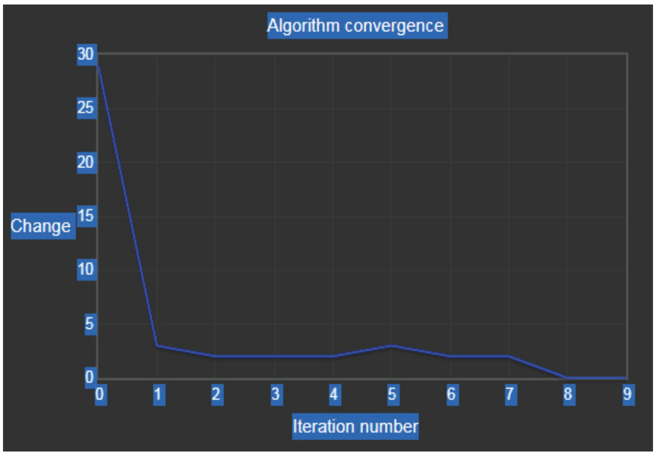

Fig. 7. Algorithm convergence

a) Bad observation:

TABLE IV. BAD OBSERVATION IN BMI BETWEEN PRE & POST COVID-19

Person ID	Pre Covid-19	Post Covid-19	Observations
1	35.04	40.80	Obesity increased in the higher range.
13	31.09	34.02	Obesity increased in the higher range.
19	17.86	15.82	Underweight decreases the range.

b) Good observation:

TABLE V. GOOD OBSERVATION IN BMI BETWEEN PRE & POST COVID-19

Person ID	Pre Covid-19	Post Covid-19	Observations
5	27.75	22.73	Overweight to normal weight
8	33.64	27.84	Obesity to overweight
14	29.29	24.63	Overweight to normal weight

c) Analysis:

After observing all results below mention analysis of all outcome in detail:

2) Outcome 1. Personalized Health Monitoring: The system aims to provide personalized health monitoring by predicting and tracking individuals' BMI values. Users can monitor their BMI trends and make informed health decisions.

3) Outcome 2. Predict Obesity Prevention & Intervention: By analyzing BMI data, the system can help predict the risk of obesity and provide early intervention suggestions to prevent its onset.

VII. CONCLUSION

This research revealed a connection between the COVID-19 lockdown and higher body weight or obesity in urban areas, particularly among young people or those who were already overweight or obese. This association was partly because physical activity decreased during the lockdown. In the broader context of social and economic development, implementing measures to increase physical activity and improve nutrition during lockdowns can be advantageous in preventing overweight and obesity. These measures also help in reducing and postponing the onset of non-communicable chronic diseases within the population. This research shows that within our national cohort of persons, BMI increased during the COVID-19 pandemic. We draw attention to the need of focused interventions, especially in higher-risk areas, to counteract the COVID-19 pandemic's negative effects on physical and mental health. We can expect an acceleration of the global obesity pandemic in the absence of more forceful action.

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