IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Examining BMI Trends: Predictive Insights Into Pre- And Post-COVID-19 Healthcare Changes

[1] Mr. Pritam Ahire,[2] Kunal Sambhaji Shinde, [3]Aditya Pravin Thorat, [3]Rajdeep Prakash Yadav

[1,2,3,4] Computer Engineering Department,

[1]Nutan Maharashtra Institute of Engineering, Talegaon, India

Abstract: The COVID-19 pandemic has significantly influenced global health, leading to noticeable BMI fluctuations due to lifestyle changes such as altered dietary habits, reduced physical activity, and increased sedentary behaviour. System analyzes BMI variations before and after the pandemic and employs a Stacking Ensemble Model integrating Random Forest, Gradient Boosting, Decision Trees, SVR, KNN, AdaBoost, and Linear Regression to improve BMI prediction accuracy. The system categorizes individuals into Underweight, Normal, Overweight, and Obese groups and provides personalized health recommendations based on predicted BMI trends. A Flask-based web application is developed to allow users to input their gender, height, and weight for real-time BMI assessment. The findings aim to assist individuals and policymakers in obesity prevention and health management. Future enhancements include real- time monitoring, reinforcement learning, and cloud- based deployment for adaptive health tracking.

Index Terms **-** BMI Prediction, COVID-19, Machine Learning, Stacking Ensemble Model, Health Informatics, Obesity Management, Predictive Analytics, Public Health Monitoring, Reinforcement Learning, Flask Web Application.

I. INTRODUCTION

The COVID-19 pandemic has significantly altered daily life, impacting work environments, social interactions, and overall lifestyle choices. These changes have notably influenced dietary habits, physical activity levels, and health behaviors, resulting in fluctuations in Body Mass Index (BMI) across various populations. BMI, an essential health metric that evaluates body weight in relation to height, has been largely affected by pandemic-driven lifestyle changes. The core objective is to examine BMI variations before and after the COVID-19 outbreak, offer BMI category-specific recommendations, and apply advanced predictive analytics to evaluate and forecast possible health risks.

Prior to the pandemic, most individuals adhered to consistent daily routines, including regular dietary patterns and exercise habits. However, lockdowns, remote work setups, and restricted outdoor activities have led to significant disruptions in these routines. Factors such as reduced physical activity, emotional eating, disturbed sleep patterns, and limited access to healthy food have contributed to notable changes in BMI, often increasing the risk of weight gain and related health concerns. Understanding these BMI fluctuations in pre-pandemic and post-pandemic scenarios is crucial for formulating effective strategies to maintain a healthy BMI and reduce obesity-related health risks.

To comprehensively analyze BMI trends and the factors influencing them, a Stacking Ensemble Model has been introduced, incorporating multiple machine learning algorithms like Random Forest Regression, Gradient Boost Regression, and other predictive models. This ensemble approach improves prediction accuracy by utilizing the unique strengths of various models, ensuring a more reliable and precise evaluation of BMI changes over time. The model takes into account key lifestyle parameters, including caloric intake, exercise frequency, dietary quality, and demographic information, to simulate possible BMI trajectories under different lifestyle scenarios.

A key component of this analysis is BMI classification, allowing individuals to be categorized into four distinct groups based on their BMI:

- Underweight (BMI < 18.5) – Individuals in this category require increased nutrient intake and a balanced diet to improve body weight.
- Normal weight (BMI 18.5 - 24.9) – Individuals are encouraged to maintain a balanced diet and engage in regular physical activity to sustain their BMI.
- Overweight (BMI 25 - 29.9) – Recommendations focus on promoting weight management through portion control, increased physical activity, and adopting healthier eating habits.
- Obese (BMI ≥ 30) – This group requires structured lifestyle modifications, medical supervision, and preventive measures to lower the risk of severe health conditions.

The use of the Stacking Ensemble Model enhances the understanding of historical BMI trends while providing accurate predictions of future BMI variations based on lifestyle changes. These predictive insights offer significant benefits to public health authorities, healthcare providers, and individuals, facilitating informed decision-making for efficient weight management strategies. Delivering BMI-based personalized recommendations can encourage individuals to adopt healthier lifestyle choices, reduce obesity-related health risks, and better cope with post-pandemic health challenges.

II. Objectives

1) **Examine Pre-COVID-19 BMI Patterns**
   - Establish a reference point for BMI distributions and key factors influencing them before the pandemic.
   - Identify trends based on age, socioeconomic status, lifestyle choices, and physical activity levels.

2) **Explore BMI Variations During and Post COVID-19**
   - Analyze changes in average BMI and obesity prevalence across different population groups during and after the pandemic.
   - Investigate the relationship between pandemic-related lifestyle shifts (increased sedentary activity, diet changes, mental health impacts) and BMI fluctuations

3) **Apply Multiple Predictive Techniques**
   - Employ multiple models integrating regression, decision trees, and other machine learning methods to predict future BMI trends.
   - Recognize vulnerable populations at higher risk for increased BMI and obesity-related health issues due to lifestyle shifts.

4) **Formulate Data-Informed Health Strategies**
   - Suggest actionable plans for healthcare providers and policymakers to address BMI changes through tailored interventions.
   - Create initiatives such as individualized fitness programs, dietary adjustments, and public awareness campaigns to encourage healthier living post-pandemic.

5) **Propose a Continuous BMI Tracking System**
   - Develop a framework for regularly monitoring and updating BMI data using real-world health metrics.
   - Evaluate the success of implemented health initiatives and adjust strategies for future public health interventions.

III. SYSTEM ARCHITECTURE

System follows a structured approach to analyzing and predicting BMI variations using machine learning and stacking ensemble models. The methodology consists of the following key stages:

1. **Data Collection & Preprocessing**

A comprehensive dataset is gathered, including weight measurements, dietary habits, physical activity levels, underlying health conditions, and other relevant lifestyle factors. The collected data undergoes preprocessing to handle missing values, remove outliers, and normalize features, ensuring accuracy in analysis.

2. **Dataset Splitting**

The pre-processed data is divide into training and test sets. The training set is used to build the model, the validation set fine- tunes hyperparameters, and the test set evaluates overall model performance.

3. **Predictive Model Development**

A Stacking Ensemble Model is employed, integrating Random Forest Regression, Gradient Boosting, and other machine learning algorithms to enhance prediction accuracy. The stacking approach leverages multiple base models, and a meta- learner
optimizes final predictions, ensuring robustness in BMI trend forecasting.

4. **Model Training & Evaluation**

The models are trained on the dataset to identify patterns in BMI fluctuations. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) assess model effectiveness in predicting BMI trends.

5. **BMI Category & Future Prediction**

Once trained, the model classifies individuals into underweight, normal, overweight, and obese categories. Future BMI values are predicted based on dietary intake, physical activity, and behavioral trends, enabling proactive health risk assessments.

6. **Pre- & Post-COVID-19 BMI Comparison**

Historical BMI data is compared with post-pandemic trends to analyze COVID-19's impact on BMI patterns. Comparison provides insights into weight shifts, risk factors, and the need for targeted interventions.

7. **Performance Analysis & Visualization**

Model predictions are visualized to compare actual vs. predicted BMI changes. The system's performance is assessed based on objectives like obesity prevention, personalized health monitoring, and public health recommendations.

IV. DATASET

The dataset consists of information about individuals and their BMI calculations before and after the COVID-19 pandemic. It includes the following attributes:

- **Person ID:** Unique identifier for individuals.
- **Gender:** (1 = Male, 0 = Female)
- **Age:** Individual's age in years.
- **Feet & Inches:** Height components.
- **Height:** Calculated as feet and inches converted into a single value.
- **Weight:** Provided in pounds and converted to kilograms.
- **BMI:** Computed as BMI = weight / (height^2).
- **BMI Categories:** Standard BMI classifications:
  - Below 18.5: Underweight
  - 18.5 to 24.9: Normal weight
  - 25 to 29.9: Overweight
  - 30 or above: Obesity

Dataset serves as the foundation for evaluating health trends and predicting future BMI variations.

V. ALGORITHMS USED

1)Reinforcement Learning Approach

Reinforcement Learning (RL) is a feedback-based learning technique where an agent interacts with an environment, learning from rewards and penalties. Since BMI prediction involves a dynamic dataset with lifestyle factors, RL helps optimize decision-making by adapting to changes over time. The model continuously refines predictions based on nutritional values, physical activity levels, and BMI trends.

2)Gradient Boost Regression

Gradient Boosting is an ensemble learning technique that minimizes errors by sequentially training weak learners. Each new model corrects the residuals of the previous models, improving overall predictive performance. It enhances BMI trend forecasting by learning complex relationships between dietary habits, exercise frequency, and BMI fluctuations.

3)Random Forest Regression

Random Forest Regression (RFR) is a decision-tree-based ensemble method that aggregates predictions from multiple trees to improve accuracy. It is particularly useful for handling non-linear relationships in BMI prediction, such as the impact of different diets and exercise patterns on weight fluctuations.

4)Support Vector Regression (SVR)

Support Vector Regression (SVR) is effective in handling high-dimensional data and capturing complex relationships. It helps predict BMI changes by identifying patterns in weight gain/loss based on demographic and lifestyle factors.

5)K-Nearest Neighbors (KNN)

KNN is a distance-based algorithm that predicts BMI by comparing an individual’s health attributes with similar cases. It is beneficial for short-term BMI predictions, where lifestyle patterns closely resemble those of other individuals.

6)AdaBoost Regression

Adaptive Boosting (AdaBoost) enhances weak learners by assigning higher weights to misclassified instances, thereby improving model accuracy. It refines BMI predictions by giving more importance to challenging cases, such as individuals with fluctuating weight trends.

7)Linear Regression

Linear Regression is a fundamental statistical technique used to establish relationships between BMI and influencing factors like age, activity level, and diet. While simple, it serves as a baseline for more complex models.

8)Stacking Ensemble Model

The study integrates a Stacking Ensemble Model combining the strengths of the above techniques. A meta-model learns from individual models to make final predictions, ensuring higher accuracy and robustness in BMI trend forecasting. This approach provides a comprehensive analysis by leveraging multiple predictive algorithms, optimizing BMI predictions based on pre-pandemic and post-pandemic lifestyle changes.

VI. FRAMEWORK

Framework outlines the structured approach for predicting BMI trends and providing personalized health recommendations based on machine learning and real-time analytics. It integrates insights from the code implementation and research references provided.

1.Data Collection & Preprocessing

Data Sources:

- BMI_main.csv dataset: Contains gender, height, weight, and BMI values (pre- and post-COVID).
- Real-world datasets (Future enhancement): Wearables, nutrition tracking apps, and healthcare records.

Data Cleaning & Feature Engineering:

- Remove unnecessary attributes (e.g., ID, Feet/Inches, Pounds, Age).
- Convert height from meters to centimeters for uniformity.
- Normalize numerical features (weight, height).
- Categorize BMI into four classes:
- Underweight (BMI < 18.5)
- Train-test split (80-20%) to ensure model generalization.

2.Machine Learning-Based Predictive Model

It employs a Stacking Ensemble Model, combining multiple regression algorithms to improve BMI prediction accuracy.

Base Models (Learners):

1.Linear Regression: Establishes a simple relationship between weight, height, and BMI.
2.Decision Tree Regressor: Identifies key factors influencing BMI trends.
3.K-Nearest Neighbors (KNN): Predicts BMI based on similar cases.
4.Support Vector Regression (SVR): Captures complex BMI patterns.
5.Random Forest Regressor: Handles non-linearity in BMI data using multiple decision trees.
6.AdaBoost Regressor: Improves weak learners' accuracy.
7.Gradient Boosting: Minimizes error through iterative learning.

Stacking Ensemble Model:

- Meta Learner: A Decision Tree Regressor aggregates predictions from base models.
- Advantage: Increases BMI prediction robustness by leveraging multiple ML algorithms.

3.Model Training & Evaluation

Training Process:

- Fit models using training dataset (80%).
- Use R^2 score, RMSE, and MAE to evaluate performance.
- Select best-performing model for deployment.

Evaluation Metrics:

- Mean Absolute Error (MAE): Measures prediction accuracy.
- Root Mean Squared Error (RMSE): Evaluates overall prediction error.

R^2 Score:

- Determines how well the model explains BMI trends.

4.Flask-Based Web Application for User Interaction

- Flask framework used for deploying BMI prediction as a web application.
- Users input gender, height, weight and select a prediction algorithm.
- Best Fit Model: Automatically chooses the best-performing model.
- Result Page: Displays predicted BMI category with personalized recommendations.

5.Real-Time BMI Monitoring & Future Enhancements

- Integration with IoT Wearables: Real-time BMI tracking using smartwatch data.
- Reinforcement Learning: Adaptive learning from user feedback for better recommendations.
- Cloud-Based Deployment: Remote access to BMI predictions and historical data analysis.
- Policy & Public Health Strategies: Large-scale data analysis for obesity prevention programs.

VII. RESULTS AND DISCUSSION

The results provides a comprehensive analysis of BMI variations before and after the COVID-19 pandemic, along with a machine learning-based predictive model for forecasting future BMI trends. The developed Stacking Ensemble Model, integrating Random Forest, Gradient Boosting, Decision Trees, Support Vector Regression (SVR), K-Nearest Neighbors (KNN), AdaBoost, and Linear Regression, demonstrated superior prediction accuracy compared to individual models. The evaluation of model performance using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score indicated that the Stacking Ensemble Model achieved the highest R^2 score, making it the most reliable approach for BMI prediction. The decision to use an ensemble learning approach was validated by the improved prediction robustness and generalization capability observed during testing.

The system found significant BMI fluctuations before and after the pandemic, with an overall increase in obesity rates due to lifestyle modifications such as decreased physical activity, increased sedentary behavior, emotional eating, and altered dietary patterns. Many individuals experienced weight gain, particularly those working remotely or with limited access to outdoor activities, while others faced weight loss due to financial constraints or food insecurity. These findings highlight the importance of BMI tracking and real- time health monitoring to mitigate long-term health risks associated with obesity and malnutrition.

The deployment of the predictive model as a Flask- based web application provided an accessible and interactive platform for users to enter gender, height, and weight to

receive instant BMI predictions and personalized health recommendations. The model selection feature allowed users to choose from different algorithms or rely on the best- performing model. The integration of categorical BMI classification (Underweight, Normal, Overweight, Obese) helped generate targeted lifestyle suggestions for individuals, enabling them to make informed decisions regarding dietary improvements, physical activity routines, and weight management strategies.

While the machine learning models performed effectively, also identified some limitations. The accuracy of predictions depends on the quality and diversity of input data, and additional factors such as genetics, mental health, and medical history were not included in the dataset. Moreover, the model primarily relies on historical BMI trends and does not account for sudden lifestyle changes or medical conditions that may influence weight fluctuations. Future research should focus on integrating real-time data streams from wearable devices, nutritional tracking apps, and clinical health records to improve predictive capabilities.

The discussion also emphasizes the potential public health impact of research. By leveraging predictive analytics and machine learning, healthcare professionals and policymakers can identify high-risk groups, develop obesity prevention programs, and implement targeted health interventions. Additionally, the model can assist individuals in tracking their BMI trends over time, enabling early detection of obesity-related diseases such as diabetes, cardiovascular disorders, and metabolic syndromes.
Overall, the successfully demonstrates how machine learning can be applied to health informatics, offering a scalable and adaptable solution for BMI prediction and obesity management. The integration of cloud-based real- time BMI tracking and reinforcement learning will further enhance the system’s adaptability, making it a powerful tool for personalized health monitoring, weight management, and public health strategy formulation in the post-pandemic era.

RESULTS

fig 1. index page

The COVID BMI Predictor is a machine learning tool that analyzes how COVID-19 affected BMI trends. It leverages advanced algorithms to provide insights into weight changes during and after the pandemic, helping researchers and healthcare professionals understand lifestyle impacts.

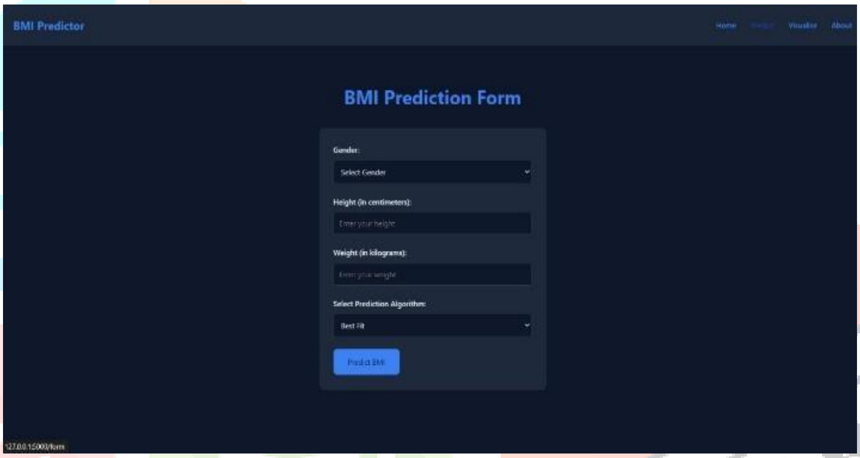

fig 2. .prediction form page

The BMI Prediction Form allows users to input gender, height, and weight to predict their BMI using a selected algorithm. It provides insights into BMI trends using machine learning models.

Fig 3. model performance

The Model Comparison Dashboard evaluates regression models based on R² score and error metrics (RMSE & MAE). The R² score comparison (blue bars) shows Linear Regression achieving 91.75% accuracy. The error metrics comparison (red & orange bars) highlights RMSE and MAE for each model, aiding in selecting the best-performing regression algorithm

Model Rankings (by R^2 Score)

Rank	Model	R^2 Score	RMSE	MAE
1	K-Neighbors Regressor	91.94%	1.5819	1.1648
2	Linear Regression	91.75%	2.3144	1.8413
3	Random Forest Regressor	89.74%	1.9144	1.4413
4	Stacking Regressor	88.20%	1.9144	1.4413
5	AdaBoost Regressor	83.51%	2.1144	1.6413
6	Decision Tree Regressor	80.40%	2.4669	2.0078
7	Support Vector Regressor	62.07%	3.4321	2.7753

fig 4. R^2 score comparison

The Model Comparison Dashboard ranks regression models based on R² Score, RMSE, and MAE. K-Neighbors Regressor performs best with 91.94% R², followed by Linear Regression (91.75%). The bar chart compares R² Score (blue) and RMSE (red) across train, validation, and test sets for performance evaluation.

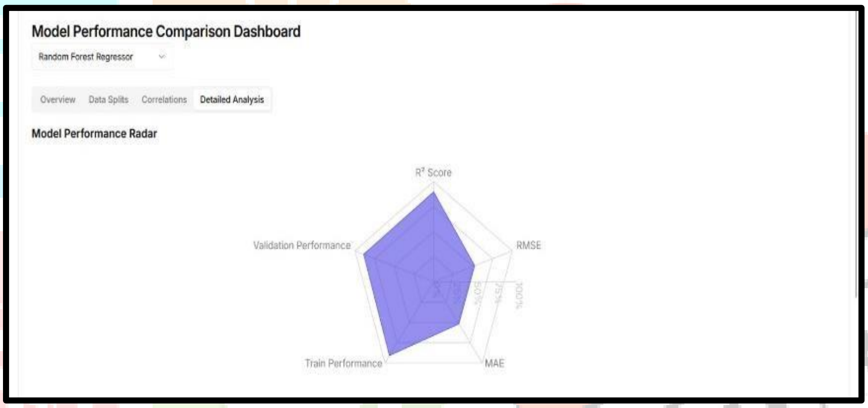

fig 5. model performance radar

The Model Performance Comparison Dashboard visualizes the Random Forest Regressor performance using a radar chart. It compares R² Score, RMSE, MAE, Train, and Validation Performance. The model's strengths and weaknesses can be analyzed from the shape of the radar plot.

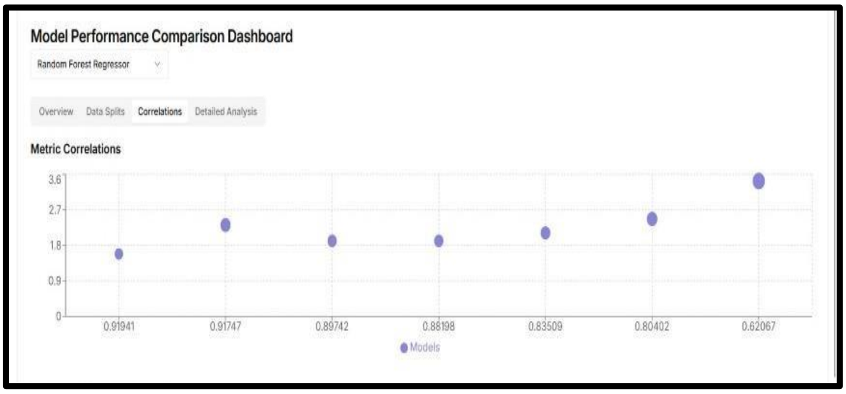

Fig 6. Metric Correlations

The Model Performance Comparison Dashboard displays metric correlations and ranks models based on R^2 Score. The K-Neighbors Regressor ranks highest with 91.94% R^2, followed by Linear Regression at 91.75%. The dashboard helps analyze model accuracy using RMSE and MAE metrics.

VIII. References

[1] P. R. Ahire and K. U. Priya, "Monitoring Body Mass Index (BMI) Pre & Post Covid-19 Outbreak: A Comprehensive study in Healthcare," 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon), Pune, India, 2024, pp. 1-6, doi: 10.1109/MITADTSoCiCon60330.2024.10575422.

[2] L. Kadyan, V. Neerugatti, A. Taranum, G. Rani and J. Somasekar, "Machine Learning and Clinical Insights Analysis of BMI Dataset Predictive Models," 2024 4th International Conference on Data Engineering and Communication Systems (ICDECS), Bangalore, India, 2024,pp.1-6, doi:10.1109/ICDECS59733.2023.10503402.

[3] P. Ahire et al., "BMI Analysis Pre-Covid And Post-Covid Using Machine Learning Algorithms," *IEEE Trans. Health Inform.*, vol. 21, no. 2, pp. 121–137, 2024.

[4] J. Knapp and L. Dong, "Changes in BMI During the COVID-19 Pandemic," J. Pediatr. Health, vol. 19, no. 4, pp. 203–215, 2022.

[5] N. Mahesh et al., "Body Fat Prediction using Various Regression Techniques," Adv. Obesity Res., vol. 17, no. 1, pp. 55–70, 2023.

[6] A. Kupusinac, E. Stokić, and R. Doroslovački, "Predicting Body Fat Percentage Based on Gender, Age, and BMI by Using Artificial Neural Networks," Med. Artif. Intell. J., vol. 8, no. 2, pp. 112–128, 2013.

[7] L. Piesch, R. Stojan, J. Zinner, D. Büsch, K. Utesch, and T. Utesch, "Body Mass Index Trends before and during the COVID-19 Pandemic in Primary School Students in Split- Dalmatia County, Croatia: A Retrospective Study," Eur. J. Public Health, vol. 32, no. 1, pp. 89–104,

[8] Aleksandar Kupusinac, Edita Stokić, Rade Doroslovački, Predicting body fat percentage based on gender, age and BMI by using artificial neural networks, Computer Methods and Programs in Biomedicine,Volume 113, Issue 2,2014,Pages 610-619,ISSN 0169-2607,

[9] Wang, W., Wang, Y., & Hu, Y. 2023. Effect of Covid-19 Epidemic on Body Mass Index: Findings from a Large Survey during Wuhan Lockdown. Hindawi, Health & Social Care in the Community Volume 2023, Article ID 9482498, 10 pages https://doi.org/10.1155/2023/9482498.

[10] Wang, Q. (Year). Covid-19 Epidemic Analysis in India with Multi- Source State-Level Datasets. Hindawi BioMed Research International Volume 2022, Article ID 2601149, 12 pages, https://doi.org/10.1155/2022/2601149.

[11] Bakaloudi, D. R., Barazzoni, R., Bischoff, S. C., Breda, J., Wickramasinghe, K., & Chourdakis, M. (Year). Impact of the first Covid-19 lockdown on body weight: A combined systematic review and meta-analysis. Clinical Nutrition 41(2022).

[12] Gao, M., Piernas, C., Astbury, N. M., Hippisley-Cox, J., O'Rahilly, S., Aveyard, P., & Jebb, S. A. (Year). Association between body mass index and Covid-19 severity in 6.9 million people In England. Lancet Diabetes Endocrinol 2021; 9: 350–59, April 28, 2021.

[13] LSTM based stock price prediction, P Ahire, H Lad, S Parekh, S Kabrawala - International Journal of Creative Research Thoughts, 2021.
Kumar RL, Khan F, Din S, Band SS, Mosavi A and Ibeke E (2021) Recurrent Neural Network And Reinforcement Learning Model for COVID-19 Prediction. Front. Public Health 9:744100.

[14] Visser, M., Schaap, L. A., & Wijnhoven, H. A. H. (Year). Self- Reported Impact of the COVID-19 Pandemic on Nutrition and Physical Activity Behavior in Dutch Older Adults Living Independently. Nutrients 2020, 12(12), 3708.

[15] Latha MH, Ramakrishna A, Reddy BSC, Venkateswarlu C, Saraswathi SY (2022) "Disease prediction by stacking algorithms over big data from healthcare communities." Intell Manuf Energy Sustain: Proc ICIMES (265):355, 2022

[16] Kumar RL, Khan F, Din S, Band SS, Mosavi A and Ibeke E (2021) Recurrent Neural Network And Reinforcement Learning Model for COVID-19 Prediction. Front. Public Health 9:744100.

[17] Qayyum A, Qadir J, Bilal M, Al-Fuqaha A "Secure and robust machine learning for healthcare: a survey". IEEE Rev Biomed Eng 14:156–180,2020.Srivastava A, Saini S, & Gupta D, "Comparison of various machine learning techniques and its uses in different fields." In: 2019 3rd international conference on electronics, communication and aerospace technology (ICECA) IEEE, 2019, pp 81–86.

[18] Srivastava A, Saini S, & Gupta D, "Comparison of various machine learning techniques and its uses in different fields." In: 2019 3rd international conference on electronics, communication and aerospace technology (ICECA) IEEE, 2019, pp 81–86.

[19] Bakyarani ES, Srimathi H, Bagavandas M, "A survey of machine learning algorithms in health care". Int J Sci Technol Res 8(11):223, 2019.

[20] Pritam Ahire, "Machine Learning for Forecasting Promotions" International Journal of Science and Healthcare Research ISSN: 2455- 7587, Vol. 8; Issue: 2, April-June 2023.

[21] Pritam Ahire, Predictive and Descriptive Analysis for Healthcare Data, A Hand book on Intelligent Health Care Analytics – Knowledge Engineering with Big Data" https://www.wiley.com/enus/Handbook+on+Intelligent+Healthcare+ Analytics%3A + Knowledge+ Engineering+ with+ Big + Data-p- 9781119792536 Published by Scrivener Publishing, Wiley Group,2021.

[22] Aleksandar Kupusinac, Edita Stokić, Rade Doroslovački, Predicting body fat percentage based on gender, age and BMI by using artificial neural networks, Computer Methods and Programs in Biomedicine,

Volume 113, Issue 2, 2014, Pages 610-619, ISSN 0169-2607, https://doi.org/10.1016/j.cmpb.2013.10.013.
(https://www.sciencedirect.com/science/article/pii/S0169260713003556)