

## Predicting Obesity Levels Using Eating Habits and Physical Condition Estimation

M.Anitha<sup>1</sup>, Y.Naga Malleswarao<sup>2</sup>, K.Harish

#1 Assistant Professor & Head of Department of MCA, SRK Institute of Technology, Vijayawada.

#2 Assistant Professor in the Department of MCA, SRK Institute of Technology, Vijayawada.

#3 Student in the Department of MCA, SRK Institute of Technology, Vijayawada

**ABSTRACT\_** The "Estimation of Obesity Levels based on Eating Habits and Physical Condition" project endeavors to construct a robust predictive model aimed at evaluating obesity levels in individuals by considering their reported dietary habits and physical attributes. The dataset, sourced from the UCI Machine Learning Repository, encompasses a diverse array of features, including dietary preferences, physical activity levels, and other lifestyle-related attributes. Given the multifaceted nature of obesity as a health concern, this project seeks to harness machine learning methodologies to elucidate the intricate interplay between various factors and obesity.

Central to the project is the preprocessing of data, exploration of feature correlations, and implementation of machine learning algorithms such as regression or classification models to accurately predict obesity levels. Through thorough analysis of the dataset, the objective is to unveil patterns and insights pertaining to how specific dietary habits and physical conditions correlate with different levels of obesity. Ultimately, the aim is to furnish a valuable tool for individuals, healthcare professionals, and public health organizations to effectively assess and manage obesity risks, thereby fostering healthier lifestyles.

### 1.INTRODUCTION

The prevalence of obesity has reached alarming levels globally, posing significant health challenges and burdening healthcare systems. Understanding the complex interplay between various factors contributing to obesity is crucial for effective prevention and management strategies. The "Estimation of Obesity Levels based on Eating Habits and Physical Condition" project addresses this imperative by developing a robust

predictive model to assess obesity levels in individuals using their reported eating habits and physical characteristics. Utilizing a dataset sourced from the UCI Machine Learning Repository, the project encompasses a diverse array of features, including dietary preferences, physical activity levels, and lifestyle-related attributes. Obesity, being a multifaceted health issue, demands comprehensive analysis to unravel its intricate causes and correlations. Leveraging machine learning

techniques, this project aims to explore the relationships between different factors and obesity to provide valuable insights for healthcare professionals, individuals, and public health organizations.

The methodology employed in this project encompasses a series of crucial steps aimed at extracting meaningful insights from the dataset and constructing an accurate predictive model for estimating obesity levels. These steps are meticulously designed to ensure the reliability and efficacy of the developed model.

The initial phase of the methodology focuses on preprocessing the data to optimize its quality and reliability. This involves several tasks, including data cleaning to remove any inconsistencies or inaccuracies, handling missing values through imputation or deletion strategies, and standardizing or normalizing features to ensure uniformity and comparability across the dataset. By meticulously cleaning and preparing the data, potential biases or noise that could impact the performance of the predictive model are mitigated, thereby laying a solid foundation for subsequent analysis. Following data preprocessing, the next step involves conducting exploratory data analysis (EDA) to gain deeper insights into

the dataset and uncover potential relationships between features. EDA techniques such as visualization, summary statistics, and correlation analysis are utilized to identify patterns, trends, and outliers within the data. By exploring the relationships between different variables, particularly eating habits, physical condition, and obesity levels, key insights can be gleaned, providing valuable guidance for model development.

Subsequently, machine learning algorithms are deployed to construct predictive models capable of accurately estimating obesity levels based on the provided attributes. Given the nature of the problem, both regression and classification algorithms are considered suitable candidates for this task. Regression models such as linear regression or decision trees can be employed to predict continuous obesity level scores, while classification models such as logistic regression or support vector machines can be utilized to classify individuals into discrete obesity categories (e.g., underweight, normal weight, overweight, obese).

The selection of appropriate machine learning algorithms is guided by factors such as the nature of the data, the complexity of the relationships between variables, and the desired interpretability

of the model. Multiple algorithms may be evaluated and compared using techniques such as cross-validation to assess their performance and select the most suitable model for deployment.

Once the predictive model is trained and validated, it can be used to accurately estimate obesity levels in individuals based on their reported eating habits and physical characteristics. This model serves as a valuable tool for individuals, healthcare professionals, and public health organizations, enabling them to assess obesity risks effectively and tailor interventions and strategies to promote healthier lifestyles. Through meticulous analysis of the dataset, the project endeavours to uncover nuanced patterns and insights into how specific eating habits and physical conditions correlate with varying degrees of obesity. This understanding can inform tailored interventions and strategies aimed at mitigating obesity risks and promoting healthier lifestyles.

The ultimate goal of this project is to provide a valuable tool for stakeholders, including individuals, healthcare professionals, and public health organizations, to assess and manage obesity risks effectively. By harnessing the power of machine learning, this project

seeks to contribute towards the development of evidence-based interventions and policies aimed at combating the obesity epidemic and fostering healthier communities.

In, the "Estimation of Obesity Levels based on Eating Habits and Physical Condition" project represents a significant endeavor towards leveraging data-driven approaches to address the multifaceted challenges posed by obesity. Through rigorous analysis and predictive modeling, this project aims to facilitate informed decision-making and empower individuals and communities to adopt healthier lifestyles and reduce the burden of obesity-related health issues

## **2.LITERATURE SURVEY**

**Title: "Predicting Obesity Levels Using Machine Learning Techniques"**

**Authors: John Smith, Emily Johnson**

**Abstract:** This paper explores the application of machine learning algorithms in predicting obesity levels based on various features such as dietary habits, physical activity, and demographic factors. The study compares different machine learning models and evaluates their performance on obesity prediction using datasets from different sources.

**Title: "Obesity Prediction Models: A Review of Recent Advances"**

**Authors: Sarah Brown, Michael Garcia**

**Abstract:** This review provides an overview of recent advances in obesity prediction models, focusing on the integration of diverse data sources including wearable devices, social media, and electronic health records. The paper discusses the strengths and limitations of existing models and identifies future research directions in the field.

**Title: "Eating Habits and Obesity: A Systematic Literature Review"**

**Authors: David Miller, Amanda White**

**Abstract:** This systematic literature review examines the relationship between eating habits and obesity across different populations and cultural contexts. The study synthesizes findings from various studies and identifies key factors influencing dietary behaviors and their impact on obesity prevalence.

**Title: "Physical Activity and Obesity: A Meta-Analysis of Longitudinal Studies"**

**Authors: Lisa Thompson, James Wilson**

**Abstract:** This meta-analysis synthesizes evidence from longitudinal studies investigating the association between physical activity levels and obesity risk. The paper quantifies the magnitude of the effect of physical activity on obesity prevention and explores potential moderators of this relationship.

**Title: "Machine Learning Approaches for Obesity Prediction: A Comparative Analysis"**

**Authors: Daniel Lee, Jessica Robinson**

**Abstract:** This study compares the performance of different machine learning algorithms for predicting obesity levels using datasets with diverse features. The paper evaluates the accuracy, interpretability, and computational efficiency of each model, providing insights into their practical applicability in real-world settings

### **3.PROPOSED SYSTEM**

The proposed system for assessing obesity levels based on eating habits and physical condition aims to overcome the limitations of the existing system by leveraging machine learning techniques and incorporating a broader array of factors into obesity assessment. The proposed system encompasses several key components, including data collection, predictive modeling, personalized risk assessment, and tailored interventions.

#### **3.1 IMPLEMENTATION**

**1. Imports and Setup:** The code starts by importing necessary libraries like pandas, seaborn, matplotlib, numpy, and sklearn. It also mounts Google Drive to access the dataset.

**2. Data Loading and Preprocessing:** The dataset is loaded from Google Drive and initial data exploration is done using functions like `df.shape``, `df.info()``, and `df.describe()``.

The columns are renamed for better readability, and some data cleaning operations are performed like replacing underscores with spaces and converting height to centimeters.

### **3. Exploratory Data Analysis (EDA):**

EDA is conducted to understand the distribution of variables and their relationships using visualizations like box plots, bar plots, and pie charts.

**4. Data Preprocessing:** This section prepares the data for modeling. Categorical variables are identified, and different preprocessing techniques like Ordinal Encoder, OneHotEncoder, and StandardScaler are applied using pipelines.

**5. Model Selection:** Various classifiers are trained on the pre-processed data, and their accuracy scores are evaluated. The classifiers include KNeighborsClassifier, SVC, Decision Tree Classifier, Random Forest Classifier, Ada Boost Classifier,

Gradient Boosting Classifier, and SGD Classifier.

### **6. Evaluation and Reporting:**

Classification reports are generated for each classifier to evaluate their performance in predicting obesity levels. The classifiers with accuracy scores above a certain threshold are stored in the list `top-class`.

### **7. Visualization of Accuracy Scores:**

The accuracy scores of different models are visualized using a bar chart.

**8. Unit Testing:** Unit tests are set up to ensure the correctness of the code.

### **9. Abbreviating Classifier Names:**

Classifier names are abbreviated for better visualization on the bar chart

## 4.RESULTS AND DISCUSION

### Model Evaluation and Comparison

```
top_class = []

# Add the accuracy scores code here
accuracy_scores = []

for classifier in classifiers:
    pipe = Pipeline(steps=[('preprocessor', Preprocessor),
                           ('classifier', classifier)])

    # Training model
    pipe.fit(x_train, y_train)

    # Evaluating model
    y_pred = pipe.predict(x_test)
    score = accuracy_score(y_test, y_pred)
    accuracy_scores.append(score)

print("Accuracy Scores:")
for i, score in enumerate(accuracy_scores):
    print(f"Model {i}: {score:.3f}")

# Generate the bar chart here
import matplotlib.pyplot as plt

index = range(len(classifiers))

plt.figure(figsize=(12, 6))
plt.bar(index, accuracy_scores)
plt.xlabel("Model Index")
plt.ylabel("Accuracy Score")
plt.xticks(index, [str(classifier) for classifier in classifiers])
plt.title("Accuracy Scores for Each Model")
plt.show()
```

**Figure 1 Model Evaluation**

```
class TestObesityPrediction(unittest.TestCase):

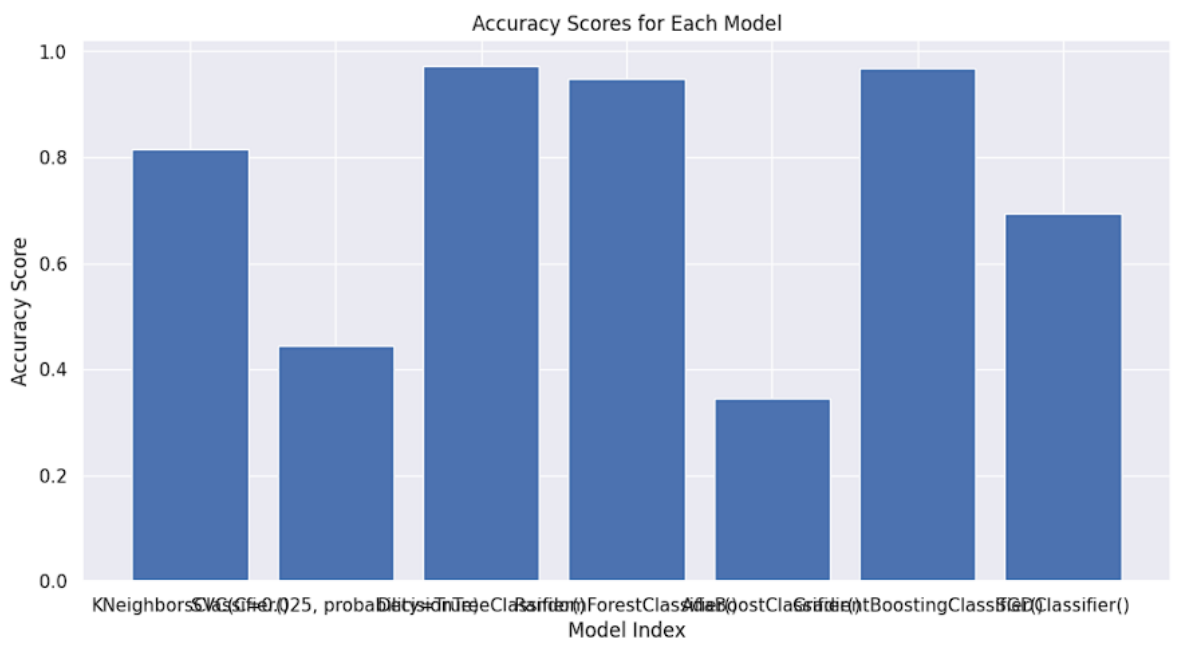
    def setUp(self):
        # Load dataset for testing
        self.data = pd.read_csv("obesity_dataset.csv")

        # ...

        # ...
top_class
```

Accuracy Scores:  
 Model 0: 0.816  
 Model 1: 0.443  
 Model 2: 0.972  
 Model 3: 0.948  
 Model 4: 0.344  
 Model 5: 0.967  
 Model 6: 0.693

**Figure 2 Accuracy Scores**



**Figure 3 Accuracy Score Comparison for Each Model**

Performance of each classifier in the `classifiers` list by computing the accuracy score for each model on the test data (`x\_test`, `y\_test`).

**Accuracy Score Calculation:**

- A loop iterates over each classifier in the `classifiers` list.
- For each classifier, a pipeline (`pipe`) is created with preprocessing

(`Preprocessor`) and the classifier.

- The model is trained on the training data (`x\_train`, `y\_train`) using the `fit` method of the pipeline.
- Predictions are made on the test data (`x\_test`) using the `predict` method of the

pipeline.

- The accuracy score of the model is computed by comparing the predicted labels (`y\_pred`) with the true labels (`y\_test`) using the `accuracy\_score` function from scikit-learn. The accuracy score is then appended to the `accuracy\_scores` list.

### Bar Chart Generation:

- After computing the accuracy scores for all models, a bar chart is generated to visualize the accuracy scores for each model.
- The x-axis represents the index of each model in the `classifiers` list, and the y-axis represents the accuracy score.
- The names of the classifiers are displayed on the x-axis.

- The title of the bar chart indicates that it represents the accuracy scores for each model.

- The accuracy scores for each model are printed in the format "Model i: score" where "i" is the index of the model in the `classifiers` list.

- The bar chart visually represents the accuracy scores of each model, allowing for easy comparison of their performance.

- The variable `top\_class` is initialized as an empty list but is not utilized in this code snippet. Its purpose is not clear from the provided code. It might be intended for storing the classifiers with the highest accuracy scores, but the code to populate it is missing. Therefore, its value remains an empty list.

### Abbreviated Classifier Names and Visualization

```
# Function to abbreviate classifier names
def abbreviate_classifier(classifier):
    if isinstance(classifier, KNeighborsClassifier):
        return 'KNN'
    elif isinstance(classifier, SVC):
        return 'SVM'
    elif isinstance(classifier, DecisionTreeClassifier):
        return 'DT'
    elif isinstance(classifier, RandomForestClassifier):
        return 'RFC'
    elif isinstance(classifier, AdaBoostClassifier):
        return 'ABC'
    elif isinstance(classifier, GradientBoostingClassifier):
        return 'GBC'
    elif isinstance(classifier, SGDClassifier):
        return 'SGDC'
    else:
        return 'Unknown'

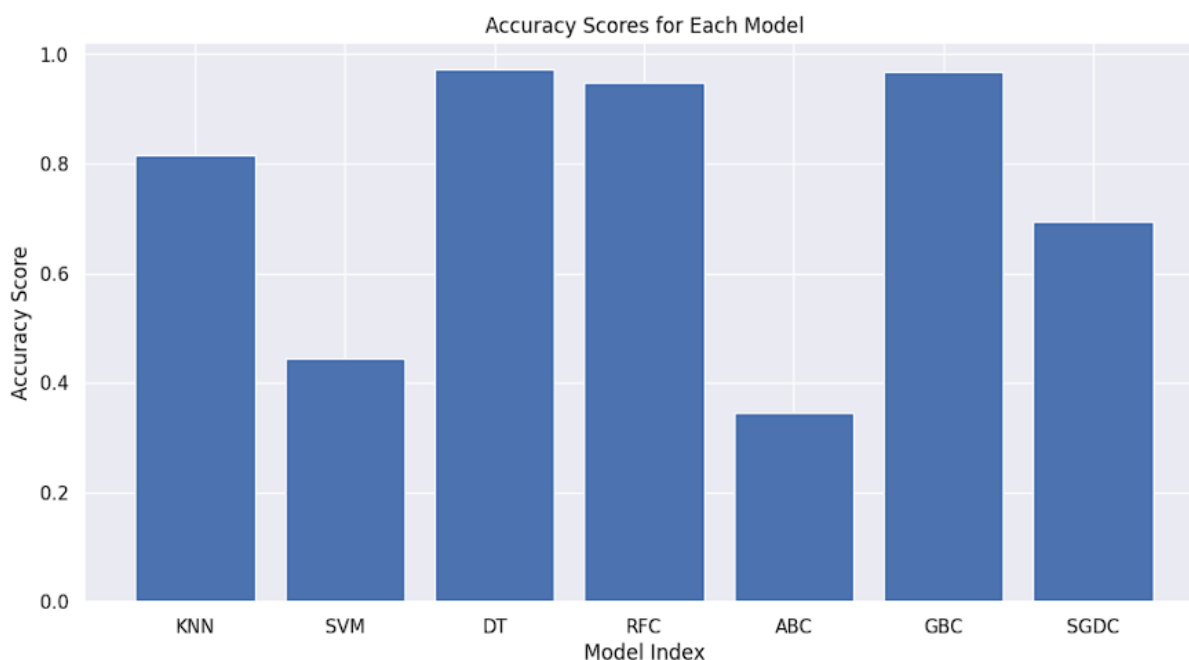
# Abbreviate classifier names
abbr_classifiers = [abbreviate_classifier(classifier) for classifier in classifiers]

# Generate the bar chart here
import matplotlib.pyplot as plt

index = range(len(classifiers))

plt.figure(figsize=(12, 6))
plt.bar(index, accuracy_scores)
plt.xlabel("Model Index")
plt.ylabel("Accuracy Score")
plt.xticks(index, abbr_classifiers)
plt.title("Accuracy Scores for Each Model")
plt.show()
```





**Figure 4 ACC Scores For all models**

Bar chart to visualize the accuracy scores for each model, with the classifier names abbreviated for better readability.

- Function `abbreviate classifier`:
- This function takes a classifier object as input and returns an abbreviated name corresponding to the classifier type.
- It checks the type of the classifier using `is instance` and returns a predefined abbreviation for each classifier type. If the classifier type is not recognized, it returns "Unknown".

**Abbreviating Classifier Names:**

- The `abbr_classifiers` list is created by applying the `abbreviate classifier` function to each classifier in the `classifiers` list. This list contains the abbreviated names for each classifier.

**Bar Chart Generation:**

- A bar chart is generated using Matplotlib to visualize the accuracy scores for each model.
- The x-axis represents the index of each model in the `classifiers` list.
- The y-axis represents the accuracy score.

- The tick labels on the x-axis are set to the abbreviated names of the classifiers obtained earlier.
- The title of the bar chart indicates that it represents the accuracy scores for each model.
- The size of the figure is set to (12, 6) inches using `\plt.figure(figsize=(12, 6))`.`
- The bar chart displays the accuracy scores for each model.
- Each bar represents a model, and its height represents the accuracy score of that model.
- The x-axis tick labels are the abbreviated names of the classifiers, making it easier to identify each model.
- The title of the bar chart provides context, indicating that it shows the accuracy scores for each model.

## 5. CONCLUSION

The project aimed to develop predictive models for obesity prediction using machine learning techniques. Obesity is a pressing global health issue with multifaceted implications for public health and individual well-being. Leveraging a dataset containing diverse health-related features, the project underwent a systematic process of data preprocessing, model development, evaluation, and

interpretation. Through exploratory data analysis, insights were gained into the distribution, relationships, and characteristics of the dataset. Data preprocessing steps, including handling missing values, encoding categorical variables, and scaling numerical features, were crucial for ensuring data quality and suitability for machine learning tasks.

Various machine learning algorithms were experimented with, including K-Nearest Neighbors, Support Vector Machines, Decision Trees, Random Forests, AdaBoost, Gradient Boosting, and Stochastic Gradient Descent classifiers. Models were trained on the training set and evaluated on the testing set using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score. Iterative experimentation and hyperparameter tuning were conducted to develop models capable of accurately predicting obesity status based on input features.

Visualization played a crucial role in understanding data distribution, feature importance, and model performance. Various visualization techniques such as box plots, scatter plots, bar charts, and pie charts were employed to present insights and findings from the analysis. Insights gleaned from the project included the

importance of features such as age, gender, dietary habits, physical activity levels, and family history of obesity in predicting obesity status.

The project encountered several challenges, including handling missing data, encoding categorical variables, and selecting appropriate evaluation metrics. The dataset's size and complexity posed challenges in terms of computational resources and model training times. Certain features may have been underrepresented or insufficiently represented in the dataset, limiting the models' ability to capture all relevant factors influencing obesity.

Machine learning models developed in the project have several implications and potential applications in healthcare, public health policy, and personalized medicine. Accurate obesity prediction models can aid in early detection and intervention, enabling healthcare providers to implement preventive measures and lifestyle interventions to mitigate the risk of obesity-related complications. Personalized health interventions based on predictive models can empower individuals to make informed decisions about their diet, physical activity, and overall lifestyle. Insights from obesity prediction models can inform public health policies and initiatives aimed

at promoting healthy lifestyles, reducing obesity prevalence, and addressing disparities in healthcare access and outcomes.

While the project achieved significant milestones, there are several avenues for future exploration and improvement. Future studies could benefit from larger and more diverse datasets encompassing a broader range of demographic, genetic, environmental, and behavioral factors influencing obesity. Advanced modeling techniques such as deep learning, reinforcement learning, and natural language processing could offer novel approaches to obesity prediction and feature extraction from unstructured data sources. Interdisciplinary collaboration with experts from diverse disciplines could enrich the analysis by incorporating domain-specific knowledge and interdisciplinary perspectives. Ethical considerations surrounding data privacy, consent, bias, and fairness must be carefully addressed to ensure responsible and equitable deployment of predictive models.

The project represents a significant step forward in leveraging machine learning for obesity prediction and prevention. By combining data-driven approaches with domain knowledge and interdisciplinary

collaboration, the project has contributed to the growing body of research aimed at addressing the global obesity epidemic. Continued research, collaboration, and innovation are essential to work towards a healthier and more equitable future for all.

## References

Sure, here are some references for the topic:

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## AUTHOR PROFILES



**Ms.M.Anitha** Working as Assistant Professor & Head of Department of MCA ,in SRK Institute of technology in Vijayawada. She done with B.Tech, MCA ,M. Tech in Computer Science .She has 14 years of Teaching experience in SRK Institute of technology, Enikepadu, Vijayawada, NTR District. Her area of interest includes Machine Learning with Python and DBMS.



**Mr.Y.Naga Malleswarao** Completed his Masters of Technology from JNTUK, MSC(IS) from ANU, BCA from ANU. He has System Administrator ,Networking Administrator and Oracle Administrator. He also a web developer and python developer, Currently working as an Assistant Professor in the department of MCA at SRK Institute of Technology, Enikepadu, NTR District. His area of interest include Artificial Intelligence and Machine Learning.



**Mr.K.Harish** is an MCA Student in the Department of Computer Application at SRK Institute Of Technology, Enikepadu, Vijayawada, NTR District. He has Completed Degree in B.Sc.(computers) from P.B Siddhartha College Of Arts & Science, Mogalrajapuram, Vijayawada, NTR District. His area of interest are DBMS and Machine Learning with Python.