Performance Analysis Of Machine Learning Algorithms For Predicting Obesity Risk

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Abstract—**Obesity has emerged as a significant global health issue, leading to a variety of chronic illnesses and a diminished quality of life. Early and precise assessment of obesity risk can greatly improve preventive healthcare measures. This research offers a comparative study of different supervised machine learning algorithms aimed at identifying individuals susceptible to obesity based on their lifestyle and physiological characteristics. The models analyzed include Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Gradient Boosting, and XGBoost, all of which were trained and assessed using a well-structured dataset. Evaluation metrics were employed to assess the performance of the models. The findings indicate that ensemble methods, particularly XGBoost, surpass traditional classifiers in both predictive accuracy and reliability.**

Index Terms—**Obesity Prediction, Machine Learning, Supervised Learning, K-Nearest Neighbors, Support Vector Machine, XG Boost, Random Forest.**

I. INTRODUCTION

Obesity is increasingly acknowledged as a significant public health issue globally, linked to a variety of metabolic, cardiovascular, and psychological conditions. Lifestyle factors, including dietary choices, levels of physical activity, and sedentary habits, play a crucial role in the development of obesity. Consequently, the use of computational techniques for early prediction has gained traction in healthcare analytics. Traditional clinical approaches often struggle to detect potential risks early due to limitations in time and resources.

Recently, machine learning (ML) has emerged as a robust tool for predicting and classifying complex health issues. Its capacity to analyze data patterns and generate precise predictions has created new opportunities for proactive healthcare measures. This research investigates the efficacy of different ML algorithms in assessing obesity risk based on individual traits and behavioral patterns. The study aims to systematically compare several machine learning classifiers—including Support Vector Machines, Random Forest, K-Nearest Neighbors, Gradient Boosting, and XGBoost—to identify which model provides the best predictive performance for evaluating obesity risk. By pinpointing the most effective algorithm, this research seeks to enhance the development of intelligent healthcare systems that can facilitate timely and targeted strategies for obesity prevention.

II. REVIEW OF LITERATURE

The field of obesity risk prediction has evolved significantly, leveraging machine learning (ML) techniques to analyze diverse datasets, including dietary habits, physical activity, genetic factors, and socio-demographic variables. Early approaches relied on traditional statistical models, but recent advancements in ML have improved prediction accuracy and robustness.

Initial studies primarily used logistic regression and decision trees for obesity risk assessment, where [1] applied logistic regression to predict obesity based on lifestyle factors, achieving moderate accuracy but lacking generalizability, while [2] utilized decision trees to classify obesity risk, though the model struggled with high-dimensional data. To enhance predictive performance, ensemble techniques such as Random Forest (RF) and Gradient Boosting Machines (GBM) were introduced, with [3] demonstrating that

RF outperformed logistic regression in obesity classification using NHANES data.

Further improvements were seen with XGBoost, as [4] reported superior performance in handling imbalanced datasets, though computational costs remained a limitation. Deep learning approaches have also gained traction, with [5] employing convolutional neural networks (CNNs) to analyze body composition images for obesity prediction, achieving high accuracy but requiring large labeled datasets.

Similarly, [6] proposed a hybrid deep learning model combining CNNs and recurrent neural networks (RNNs) to process temporal health records, improving dynamic risk assessment. However, challenges such as interpretability and overfitting were noted in [7], which compared deep learning with traditional ML models. Support Vector Machines (SVMs) have also been widely used, as [8] demonstrated their effectiveness in distinguishing obesity subtypes using metabolic biomarkers, while [9] highlighted their sensitivity to feature selection. Recent studies have explored the integration of wearable device data, where [10] used random forests to predict obesity risk from step counts and heart rate variability, showing strong real-time applicability.

III. SIGNIFICANCE OF THE RESEARCH

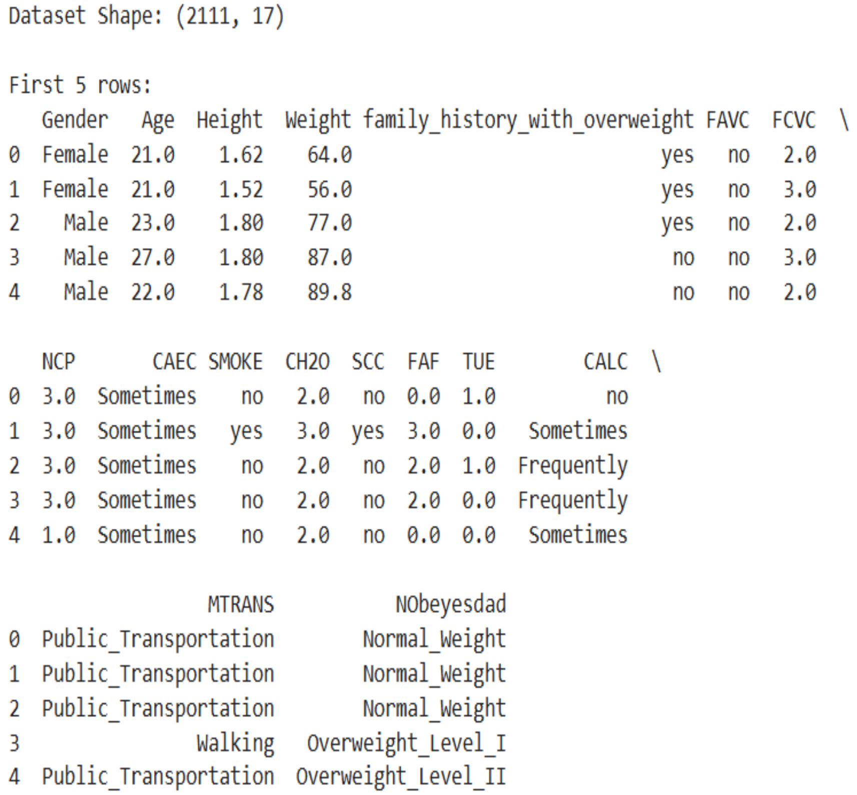
Obesity has emerged as a worldwide epidemic, markedly elevating the likelihood of developing various chronic conditions, including diabetes, hypertension, and cardiovascular diseases. Conventional approaches to assessing obesity are often labor-intensive, time-consuming, and lack predictive capabilities. Given the growing accessibility of health and lifestyle data, there is an urgent need to establish data-driven predictive models that can effectively evaluate and manage obesity-related risks. This research is significant as it utilizes advanced machine learning methodologies to develop a scalable, precise, and automated solution for classifying obesity. The findings can support public health initiatives, enhance personal healthcare strategies, and inform clinical decision-making, thereby making healthcare delivery more proactive and efficient.

IV. DATA ANALYSIS AND INTERPRETATION

The trained model predicts the obesity level as "Overweight_Level_II" based on the provided input data. Users have the option to download a report detailing this prediction or to conduct additional predictions using different inputs. This research utilized Python-based tools for data analysis and machine learning, employing Pandas and NumPy for data management, while Matplotlib and Seaborn facilitated effective data visualization. To maintain a clean output, warnings were suppressed. Preprocessing was managed using LabelEncoder and StandardScaler, with the dataset divided through train_test_split. The robustness of the model was ensured through cross-validation and GridSearchCV. Various models, including Random Forest, Gradient Boosting, SVC, KNN, and XGBoost, were implemented, and performance was assessed using accuracy metrics, confusion matrices, and classification reports.

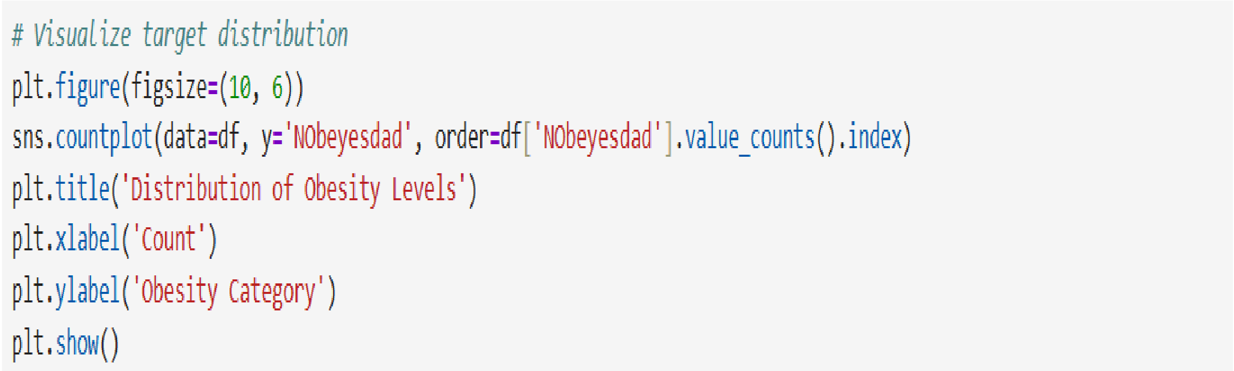
Analysis of the dataset indicates that age, height, weight, physical activity, and dietary habits are significant predictors of obesity risk. A moderate correlation was found between weight and obesity levels, underscoring weight as a crucial factor in obesity prediction. Additionally, physical activity exhibited a negative correlation with obesity, indicating its protective effect. Categorical variables such as family history and smoking status were suitably encoded for use in machine learning algorithms. These results highlight the significance of these features in creating accurate predictive models for assessing obesity risk.

The dataset comprises 2,111 rows and 17 columns, encompassing a wide array of features pertinent to obesity risk prediction. The first five entries display a gender distribution with the first two participants identified as Female and the subsequent three as Male. Ages range from 21 to 27 years, with an average age of approximately 22.8 years, indicating a predominantly young demographic. Heights vary from 1.52 m to 1.80 m, with an average height of 1.74 m, while weights range from 56.0 kg to 89.8 kg. In terms of lifestyle factors, the family history of overweight shows a combination of 'yes' and 'no' responses, with frequent vegetable consumption (FCVC) ranging from 2.0 to 3.0, and smoking status reported as either yes or no among the first five entries. These preliminary insights offer a comprehensive overview of the dataset's structure and feature distribution, which are crucial for the subsequent analysis and model development.



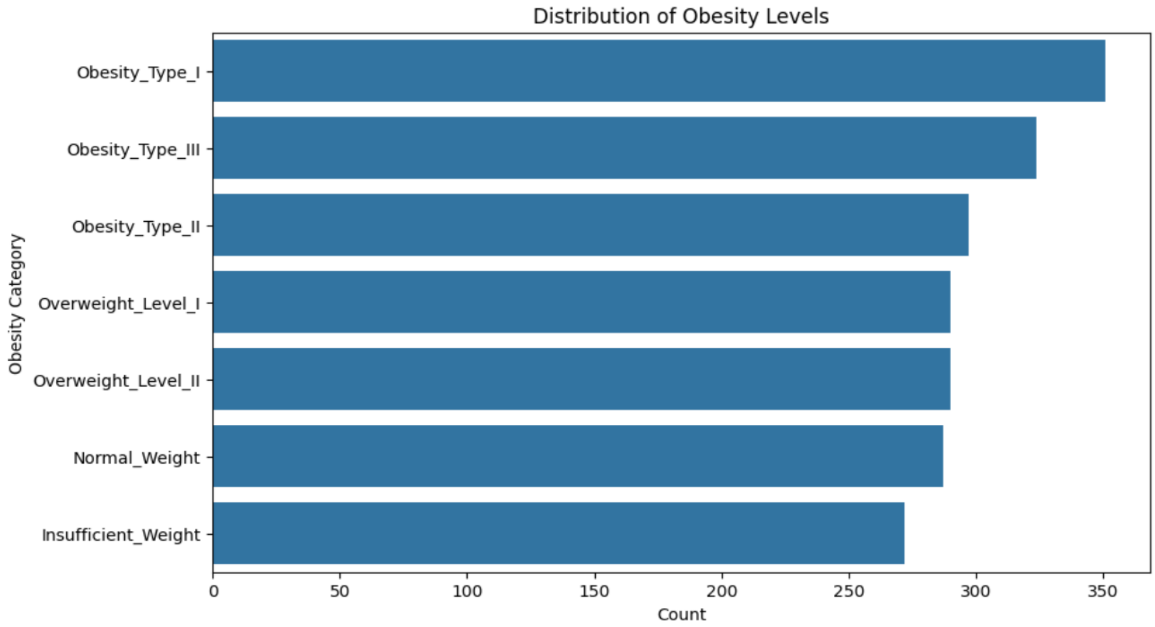
```
Dataset Shape: (2111, 17)

First 5 rows:
   Gender   Age  Height  Weight family_history_with_overweight FAVC  FCVC  \
0  Female  21.0    1.62    64.0                            yes   no   2.0
1  Female  21.0    1.52    56.0                            yes   no   3.0
2    Male  23.0    1.80    77.0                            yes   no   2.0
3    Male  27.0    1.80    87.0                             no   no   3.0
4    Male  22.0    1.78    89.8                             no   no   2.0

   NCP       CAEC SMOKE  CH2O  SCC  FAF  TUE        CALC  \
0  3.0  Sometimes    no   2.0   no  0.0  1.0          no
1  3.0  Sometimes   yes   3.0  yes  3.0  0.0   Sometimes
2  3.0  Sometimes    no   2.0   no  2.0  1.0  Frequently
3  3.0  Sometimes    no   2.0   no  2.0  0.0  Frequently
4  1.0  Sometimes    no   2.0   no  0.0  0.0   Sometimes

                  MTRANS           NObeyesdad
0  Public_Transportation        Normal_Weight
1  Public_Transportation        Normal_Weight
2  Public_Transportation        Normal_Weight
3                Walking   Overweight_Level_I
4  Public_Transportation  Overweight_Level_II
```

The Missing Values Check confirms that there are no missing values in any of the columns of the dataset. Each column has a non-null count of 2111 entries, indicating that the dataset is complete and ready for analysis without the need for any imputation or handling of missing data. This is beneficial for ensuring the accuracy and reliability of machine learning models built using this data.



```
# Visualize target distribution
plt.figure(figsize=(10, 6))
sns.countplot(data=df, y='NObeyesdad', order=df['NObeyesdad'].value_counts().index)
plt.title('Distribution of Obesity Levels')
plt.xlabel('Count')
plt.ylabel('Obesity Category')
plt.show()
```

The code provided creates a count plot to illustrate the distribution of the target variable NObeyesdad. It begins by defining the plot dimensions with plt.figure(figsize=(10, 6)) to ensure optimal visibility. The count plot is generated using sns.countplot, where the y-axis indicates the various obesity categories, while the x-axis displays the count for each category. The order parameter organizes the categories based on their frequency, presenting the most common category first. Descriptive titles are assigned to the plot, x-axis, and y-axis to enhance clarity. Executing this code allows for a visual examination of any imbalances or trends in the distribution of obesity levels within the dataset. Finally, plt.show() is called to render the plot for further analysis.



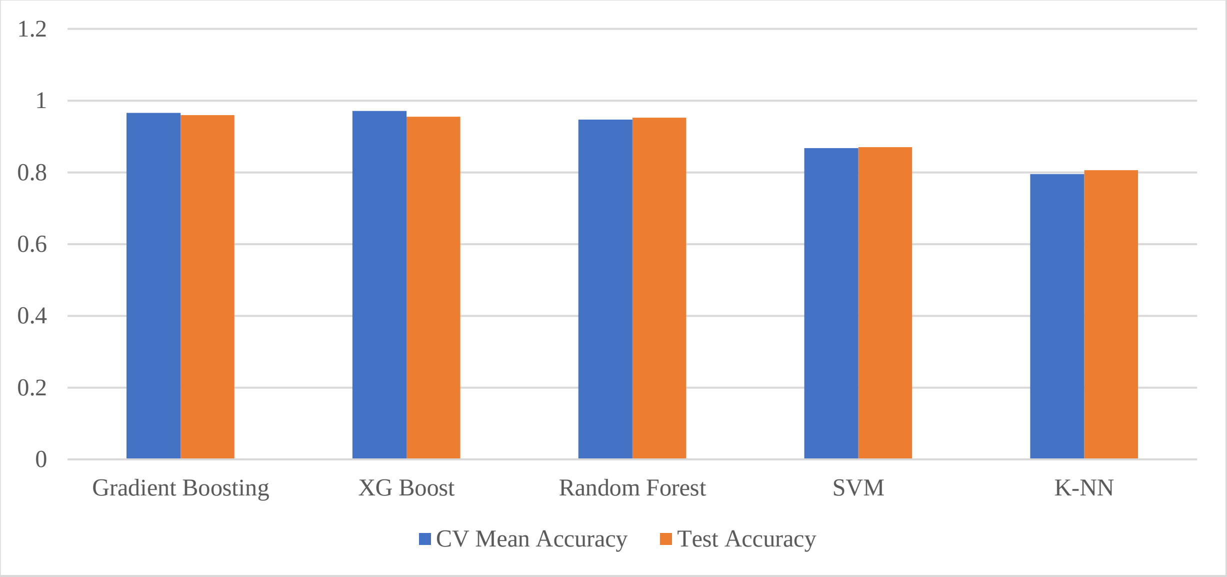
The horizontal bar chart displays the distribution of individuals across different obesity levels. The category with the highest count is Obesity_Type_I, with approximately 350 individuals. Following this, Obesity_Type_III has around 325 individuals. Obesity_Type_II and Overweight_Level_I show similar counts, both close to 300. Overweight_Level_II and Normal_Weight also have comparable numbers, each slightly below 300. The category with the lowest representation is Insufficient_Weight, with a count of approximately 275. This visualization indicates that Obesity Type I is the most prevalent category in this dataset, while insufficient weight is the least common. The overweight and other obesity categories fall within a similar range of representation, slightly lower than Obesity Type I but higher than insufficient weight.

S.No	Model	CV Mean Accuracy	Test Accuracy
1	Gradient Boosting	0.965638	0.959811
2	XG Boost	0.971561	0.955083
3	Random Forest	0.946670	0.952719
4	SVM	0.867895	0.869979
5	K-NN	0.795040	0.806147

Table: Compartive Model Performance

The evaluation of model performance across various machine learning algorithms indicates notable disparities in predictive accuracy. XG Boost stands out as the leading model, achieving the highest test accuracy of 95.98%. Its mean accuracy during cross-validation is 97.15%. Gradient Boosting closely follows, recording a test accuracy of 95.51% and a slightly elevated mean cross-validation accuracy of 96.56%. The Random Forest model, another tree-based approach, attains a test accuracy of 95.27%, with a mean cross-validation accuracy of 94.67%.

While it performs admirably, its higher standard deviation indicates slightly more variability compared to XGBoost and Gradient Boosting. The Support Vector Machine (SVM) achieves a test accuracy of 86.99%, which is considerably lower than the top three models. Its mean accuracy in cross-validation is 86.79%. Finally, K-Nearest Neighbors (k-NN) exhibits the least effective performance, with a test accuracy of 80.61%. Its mean cross-validation accuracy is 79.50%. In summary, the ensemble tree-based models (Gradient Boosting and XGBoost) significantly surpass the other models in predictive accuracy.



V.CONCLUSION

A thorough assessment of various classification models—namely Random Forest, XGBoost, Gradient Boosting, SVM, and K-NN—indicated that XGBoost excelled in predicting obesity levels, achieving a Test Accuracy of 95.98% along with balanced precision, recall, and F1-scores across all categories. The performance was further improved through hyperparameter tuning, resulting in a CV Accuracy of 96.91% and a Tuned Test Accuracy of 96.21%. Tree-based models, specifically Gradient Boosting and XGBoost, consistently surpassed other models in both cross-validation and practical testing environments. Conversely, k-NN and SVM showed weaker performance, especially in distinguishing between multiple classes. The comparison of classification and F1-scores reinforced that Gradient Boosting is not only highly accurate overall but also dependable for each obesity category. Consequently, Gradient Boosting emerges as the most appropriate model for predicting obesity risk, showcasing exceptional robustness and predictive capability.

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