International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 07 July 2024
Page No: 2041- 2051
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0279

Obesity Guard: Machine Learning for Early Detection & Preventioning

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Abstract

Obesity has become a global health concern, with its prevalence reaching alarming levels in recent year. Obesity Guard is an innovative idea aimed at addressing the pressing global issue of obesity through the application of machine learning technology. Obesity poses significant health risks and is a growing concern worldwide, affecting millions of individuals and straining healthcare systems. Early detection and prevention are crucial in combating this epidemic, and Obesity Guard offers a proactive solution leveraging advanced machine learning algorithms. This revolves around the development of a comprehensive system capable of detecting early signs of obesity and providing personalized prevention strategies. Machine learning algorithms are at the core of Obesity Guard, enabling the system to process vast amounts of data efficiently and extract actionable insights. These algorithms utilize predictive analytics to identify patterns and trends indicative of obesity risk factors. By employing techniques such as classification, regression, and clustering, Obesity Guard can generate personalized recommendations tailored to each user's specific needs and goals. The implementation of Obesity Guard has the potential to revolutionize obesity management by shifting the focus from reactive treatments to proactive prevention. By empowering individuals with actionable insights and support, Obesity Guard aims to reduce the burden of obesity-related diseases and improve overall health outcomes. Obesity Guard represents a novel approach to addressing the obesity epidemic through the application of machine learning and personalized healthcare technologies. Obesity Guard represents a significant advancement in the field of preventive healthcare, offering a proactive approach to addressing the global obesity epidemic. By harnessing the power of machine learning and wearable technology, this has the potential to empower individuals to take control of their health, reduce obesity rates, and improve overall well-being. In our proposed work, we compare four supervised ML classifiers i.e. support Vector Machine, Decision Tree, Random Forest, Logistic Regression. Further ensemble learning technique is used to develop a hybrid model for obesity prediction. After analysis, the Random Forest (RF) model has achieved 100% accuracy than other models.

Keywords: *Obesity, Machine Learning, Support Vector Machine, Decision Tree, Random Forest, Logistic Regression*

1. Introduction

Obesity is a multifaceted global health issue that continues to escalate in prevalence, posing significant challenges to individuals, healthcare systems, and societies worldwide. Defined by the World Health Organization (WHO) as abnormal or excessive fat accumulation that presents a risk to health, obesity contributes to a myriad of chronic diseases, including cardiovascular disorders, type 2 diabetes, certain cancers, and musculoskeletal conditions. The complex interplay of genetic, environmental, behavioural, and socio-economic factors underscores the need for comprehensive approaches to tackle this epidemic. Despite increasing awareness of the health risks associated with obesity, its prevalence continues to rise unabated. The latest statistics from the WHO indicate that globally, overweight and obesity affect nearly 2 billion adults, with obesity rates more than tripling since 1975. Furthermore, childhood obesity has become a particularly alarming concern, with approximately 38 million children under the age of five classified as overweight or obese in 2020. These trends not only threaten individual health and well-being but also strain healthcare systems and impose substantial economic burdens on societies. Addressing the obesity epidemic requires a multifaceted strategy that encompasses prevention, early detection, and personalized intervention. Traditional approaches to obesity management often focus on lifestyle modifications, such as diet and exercise, alongside medical interventions like pharmacotherapy and bariatric surgery. While these interventions are essential components of obesity treatment, they predominantly target individuals already diagnosed with obesity or related comorbidities. Consequently, there is a critical need to shift towards proactive, preventative measures that identify individuals at risk of obesity before it progresses to a clinically significant stage. Advancements in technology, particularly in the fields of machine learning and wearable devices, offer unprecedented opportunities to revolutionize obesity prevention and management. By harnessing the power of data analytics and artificial intelligence, it becomes possible to develop innovative solutions that facilitate early detection, personalized intervention, and behaviour modification. "Obesity Guard" represents a pioneering initiative aimed at leveraging machine learning techniques to address the obesity epidemic comprehensively. The primary objective of Obesity Guard is to develop a sophisticated yet user-friendly system that empowers individuals to monitor, manage, and prevent obesity in real time. By integrating wearable devices, mobile applications, and cloud-based analytics, Obesity Guard offers a holistic approach to obesity management that extends beyond conventional methods. Central to the Obesity Guard platform are its machine learning algorithms, which analyse diverse datasets, including physical activity levels, dietary patterns, metabolic parameters, and genetic predispositions, to identify individuals at risk of obesity. Moreover, Obesity Guard employs personalized coaching and behavioural interventions to promote healthier lifestyles and prevent the onset or progression of obesity related complications. Through continuous monitoring and feedback, users receive tailored recommendations and support, fostering sustainable behaviour change and long-term adherence to healthy habits. Additionally, Obesity Guard incorporates social networking and gamification elements to enhance user engagement, motivation, and adherence to the program. In summary, Obesity Guard represents a pioneering initiative in the field of obesity prevention and management, leveraging cutting-edge technologies to address a pressing global health challenge. By combining machine learning algorithms with wearable devices and personalized coaching, Obesity Guard offers a comprehensive solution that empowers individuals to take proactive control of their health and well-being [1-6]. Through early detection, personalized intervention, and behavioural modification, Obesity Guard aims to mitigate the burden of obesity related diseases and promote healthier lifestyles on a global scale.

2. Literature Review

For obesity detection & classification we studied several parameters like age, gender, BMI, height, weight, etc. by using various machine learning algorithms such as SVM, DT, LR, RF, etc. There is a predictive model for obesity using machine learning techniques applied to a public clinical dataset. Five algorithms were employed, including Gboost Classifier, Random Forest Classifier, Decision Tree Classifier, K-Nearest Neighbour, and Support Vector Machine. The results indicate promising accuracy, with Gboost Classifier achieving the highest accuracy of 99.05% and K-Nearest Neighbour showing a strong accuracy of 95.74%. This automated approach offers a potential solution for early prediction of obesity, facilitating timely intervention and prevention strategies [Musa Fati Anisat.,2022]. The rising global issue of obesity and overweight, exploring how machine learning (ML) and deep learning (DL) algorithms can aid nutritionists and dieticians in addressing this challenge. Through a systematic review of 17 articles, it finds that while ML and DL show promise, traditional methods remain predominant in practice. ML models are noted for their time-consuming data cleaning processes but excel in automatically modelling large datasets, surpassing traditional statistics in this aspect. Overall, the study provides valuable insights into the evolving role of ML and DL in nutrition and dietetics, highlighting the need for further exploration and integration of these technologies [Antonio Ferreras.,2023]. The system addresses the pressing issue of obesity by utilizing machine learning algorithms to predict the risk of obesity. With data collected from over 1100 individuals of varying ages, the study employs nine prominent machine learning algorithms, including k-nearest neighbour, random forest, logistic regression, and more. Through comprehensive performance evaluation, it is found that the Logistic Regression Algorithm achieves the highest accuracy of 97.09%, providing insights into obesity risk levels categorizing them into high, medium, and low. The findings underscore the potential of machine learning in identifying and addressing the complexities of obesity, offering valuable insights for preventive healthcare strategies [Faria Ferdowsy.,2021]. Utilization of national panel data to develop a prediction model for obesity risk in 10-year-olds, identifying 10 key factors including child's gender, eating habits, activity levels, previous BMI, maternal education, and self-esteem. Boys with higher BMI, less indoor activity, and mothers with high self-esteem are more likely to develop obesity. These findings underscore the importance of early screening and targeted preventive interventions to mitigate childhood obesity risks, contributing to a healthier future generation [Heemoon Lim.,2023]. The escalating issue of obesity among women aged 19-35, highlighting its detrimental effects such as infertility, heart diseases, and diabetes. By collecting and analysing datasets from various sources, the study focuses on identifying risk factors contributing to obesity. Applying the Naive Bayes algorithm, the research demonstrates promising accuracy in predicting obesity, offering valuable insights for healthcare professionals, patients, and biomedical researchers [7-12]. Ultimately, the aim is to raise awareness about the consequences of obesity and provide early intervention strategies to mitigate its impact on women's health [Rakshitha Kiran P.,2019]. The deep learning model for predicting childhood obesity patterns using longitudinal electronic health records (EHR) data. Leveraging a large dataset from a paediatric health system, the model employs LSTM network architecture to capture temporal dependencies in the data. By training on both dynamic and static EHR data, the model predicts obesity risk for ages 2-20 years. Comparative analysis with traditional machine learning methods highlights the efficacy of the LSTM model in utilizing longitudinal data for accurate predictions. Additionally, the inclusion of an attention layer enhances interpretability by ranking features at each timestamp based on attention scores [Mehak Gupta.,2019]. The study explores the application of machine learning techniques to develop a predictive model for identifying individuals with obesity or overweight based on physical condition and eating habits data. Eight classification algorithms were tested, with random forest exhibiting the best performance, achieving 78% accuracy, 79% precision, 78% recall, and 78% F1-score. The study highlights the potential of machine learning in healthcare decision-making, providing a valuable tool for specialists to identify and address overweight and obesity as public health concerns [Elias Rodrigueza.,2021]. The study aims to develop an intelligent eCoach system to address obesity, focusing on personalized wellness goals and early risk prediction. Future efforts will involve designing and testing the system with data collected from a controlled trial in south Norway, offering automated, personalized recommendations to participants aged >20 and <60 to manage a healthy lifestyle effectively [Ayan Chatterjee.,2020]. The fuzzy rapid obesity chest-pain assessment and classification system for unstable angina, integrating physical activity, event

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frequency, time intervals, and fuzzy body mass index variables into three severity classes. By leveraging fuzzy set theory and logic, the system enables handling imperfect information in diagnosing coronary heart disease patients with obesity risk factors. Overcoming limitations of existing classification methods, it offers a comprehensive approach, including obesity comorbidity risk, making it a viable option for healthcare assistance, particularly in primary care settings [Thiego Orsi.,2020]. The study emphasizes the importance of attribute selection in achieving better performance in SNP-related data analysis. It highlights classification accuracy rate and rate of reduction as common performance measures, with sensitivity and specificity being crucial in SNP-related data analysis. The choice between high sensitivity and specificity depends on the application context, such as disease prediction or SNP identification. Additionally, the paper underscores the significance of area under the curve (AUC), positive predictive rate, and negative predictive rate in evaluating the performance of the proposed technique, FARNeM, which demonstrates superiority over other methods in terms of predictive accuracy [Phaik-Ling Ong.,2019]. The system focuses on early detection of obesity-related diseases, addressing drawbacks of existing systems. After extensive research and expert consultation, machine learning algorithms like Random Forest and AdaBoost were implemented with exceptional accuracy. A tailored model for the Indian population considers various parameters rated by medical practitioners to categorize individuals based on obesity risk. The system conducts tests and provides personalized health insights, including identifying potential diseases and facilitating easy document access. Future enhancements include doctor-patient communication and OCR integration for prescription analysis, promising improved healthcare outcomes and patient engagement [Naomi Christianne.,2019]. Childhood obesity is a public health concern in the United States. Consequences of childhood obesity include metabolic disease and heart, lung, kidney, and other health-related comorbidities. Therefore, the early determination of obesity risk is needed and predicting the trend of a child's body mass index (BMI) at an early age is crucial. Early identification of obesity can lead to early prevention. Multiple methods have been tested and evaluated to assess obesity trends in children. Available growth charts help determine a child's current obesity level but do not predict future obesity risk. The present methods of predicting obesity include regression analysis and machine learning-based classifications and risk factor (threshold)-based categorizations based on specific criteria [Pritom Kumar.,2020]. Obesity is a significant public health issue worldwide, with an increasing number of people being affected by it. The problem has become a leading cause of several life-threatening health conditions such as diabetes, cardiovascular disease, and cancer. Early detection and intervention are crucial for obesity prevention and management. Machine learning (ML) techniques can help to address this issue by providing advanced tools for monitoring and predicting obesity [O mar M.T.,2019]. Obesity is a risk factor contributing to severe health problems including hypertension, cardiovascular diseases, type 2 diabetes mellitus and cancer.1–4 Childhood clinical and environmental factors are known to influence obesity risk after in life. Estimates of BMI heritability range from 40% to 70%,11,12 and genome wide association studies have identified several loci for BMI and obesity 13–17. For instance, a recent study reported 97 single-nucleotide polymorphisms (SNPs) associated with BMI in over 100000 genotyped individuals [Fatemeh seyednasrollah.,2018]. Obesity is strongly associated with multiple risk factors. It is significantly contributing to an increased risk of chronic disease morbidity and mortality worldwide. There are various challenges to better understand the association between risk factors and the occurrence of obesity. The traditional regression approach limits analysis to a small number of predictors and imposes assumptions of independence and linearity. Machine Learning (ML) methods are an alternative that provide information with a unique approach to the application stage of data analysis on obesity. This study aims to assess the ability of ML methods, namely Logistic Regression, Classification and Regression Trees (CART), and Naïve Bayes to identify the presence of obesity using publicly available health data, using a novel approach with sophisticated ML methods to predict obesity as an attempt to go beyond traditional prediction models, and to compare the performance of three different methods [Sri Astuti Thamrin.,2018]

3. Methodology

This section involves a structured approach to building a machine learning model that can effectively classify individuals as obese or non-obese based on relevant features.

3.1. A. Dataset Collection

This involves collecting data formats: text input For that we have taken dataset from Kaggle website in two formats. First dataset for text input is with 500 text snippets with information about obesity levels. The second dataset contains 2878

3.2. B. Feature Extraction

Feature extraction in an obesity classification machine learning project involves identifying and extracting relevant features from data to accurately classify individuals based on obesity levels. This process requires careful consideration of various factors that contribute to obesity, including demographic, medical, and genetic data from that we have extracted demographic features such as age, gender, height, weight medical features such as BMI etc.

3.3. Algorithms

3.3.1. Support Vector Machine

In this SVM classifier for obesity detection using a CSV dataset. It starts by importing the necessary libraries and defining the Model_Training function. This function loads the dataset, removes missing values, and separates the features (x) from the target variable (y). The data is split into training and testing sets using a 80-20 split. An SVM classifier with a linear kernel is trained on the training data and used to make predictions on the test data. The model's performance is evaluated using a classification report and accuracy score, which are printed to the console. The trained model is saved as "SVM_wt.joblib" using joblib.dump.The script then loads the saved model and a pre-fitted scaler from "scaler.pkl". The features are scaled using this scaler before making predictions. Finally, the classification report and accuracy score for the test data are printed, providing a detailed evaluation of the model's performance.

3.3.2. Decision Tree

Decision Tree model to classify obesity based on a dataset in a CSV file. It first loads and cleans the data, removing rows with missing values. Then, it separates the data into features (excluding the target class label) and the target variable itself. The code splits the data into training and testing sets for model evaluation. Next, it creates a Decision Tree Classifier and trains it on the training data. It predicts labels for unseen test data and evaluates the model's performance using classification report and accuracy score. The code also creates a confusion matrix to visualize how well the model classified different categories. Finally, it saves the trained model for future use.

3.3.3. Random Forest

In this, we implemented a Random Forest Classifier for obesity classification using a dataset loaded into a Pandas Data Frame. Missing values were handled with dropna (), and features were separated from the target variable, excluding the "Class" column. We split the data into training and testing sets with a 20% test size. A Random Forest Classifier with 20 decision trees and the entropy criterion was trained on the training data, Figure 1.

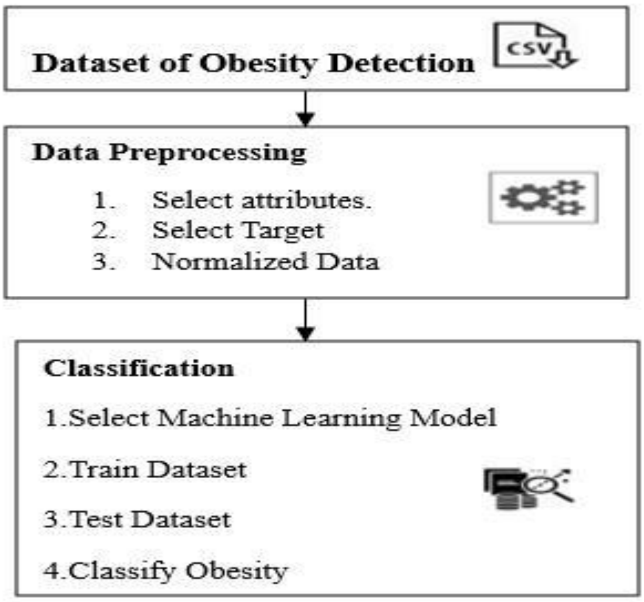

Figure 1 **Dataset of Obesity Detection**

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Performance was evaluated using predictions on the test data, with metrics such as confusion matrix, classification report, and accuracy score. The trained model was saved with joblib. dump for future use. This approach demonstrated effective obesity classification and provided a robust framework for further enhancements.

3.3.4. Logistic Regression

In this captures video from a webcam and processes it to extract and record pose and face landmarks using MediaPipe's holistic model. The script begins by importing the necessary libraries: CSV, OS, numpy, media pipe, and cv2. It initializes MediaPipe's drawing utilities and holistic model for landmark detection. We defined the number of coordinates to be extracted (num_coords), set to 501, and prepared a list of landmark labels (landmarks) that include x, y, z, and visibility coordinates for each landmark. A CSV file named coords1.csv is created with headers corresponding to these landmarks. We set a class label (class_name = "high") and began video capture using OpenCV. Within the video capture loop, each frame is converted from BGR to RGB and processed by the holistic model to detect pose and face landmarks. The landmarks are then drawn on the frame for visualization. If landmarks are detected, their coordinates and visibility scores are extracted, flattened, and combined into a single row, which is appended with the class label. This row is then written to the CSV file. The script displays the video feed with the drawn landmarks, and the loop continues until the 'q' key is pressed. Finally, the video capture is released, and all OpenCV windows are closed [13-14]. This approach facilitates real-time capture and storage of landmark data for further analysis or machine learning applications.

3.4. Performance Parameters

The confusion matrix serves as a pivotal tool in assessing the effectiveness of algorithms, particularly in the realm of obesity classification. This matrix encapsulates essential information regarding predicted and actual class labels, facilitating a clear visualization of the model's performance. By delineating the instances of correctly and incorrectly predicted values, the confusion matrix provides a comprehensive snapshot of how well a classifier distinguishes between obese and non-obese of obesity detection levels. The matrix becomes instrumental in gauging the precision, recall, and overall accuracy of the algorithm, enabling practitioners to make informed decisions about its suitability for real-world applications, Figure 2. This visual representation enhances the interpretability of results, aiding researchers and clinicians in refining and optimizing obesity detection and classification model, shown in Figure 3 & Figure 4. The various performance parameters which are used to evaluate the performance of model are:

a) **Accuracy:** The accuracy is a widely used measure to evaluate how well a model performs. It's calculated by taking the number of correct predictions and dividing it by the total predictions made by the model. In simpler terms, accuracy tells us the percentage of times the model got it right among all the predictions it made. The accuracy is calculated using the following equation.

$$\textbf{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

b) **Precision:** The precision is a measure that tells us how many of the predicted positive instances are true positives. It's the ratio of correctly predicted positive observations to the total predicted positives. The precision is calculated using the following equation.

$$\textbf{Precision} = TP \div (TP + FP)$$

c) **Recall/Sensitivity:** It measures how well a model captures and correctly identifies all the actual positive instances and it is represented with the following equation.

$$\textbf{Recall} = TP \div (TP + FN)$$

d) **F1 Score:** The F1 score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. It is calculated using the following equation.

$$1-Sc = 2(\text{precision} * \text{Recall}) / (\text{precision} + \text{Recall})$$

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```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       0.92      1.00      0.96        11
           2       1.00      0.80      0.89         5
           3       1.00      1.00      1.00         5

    accuracy                           0.97        33
Accuracy : 96.96969696969697%
Model saved as SVM_wt.joblib
```

Figure 2 Performance of SVM Algorithm

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         6
           1       0.75      1.00      0.86         6
           2       1.00      0.67      0.80         6
           3       1.00      1.00      1.00         4

    accuracy                           0.91        22

Accuracy : 90.9090909090909%
Model saved as DT_wt.joblib
```

Figure 3 Performance of DT Algorithm

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         4
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         2
           3       1.00      1.00      1.00         2

    accuracy                           1.00        11

Accuracy : 100.0%
Model saved as RF_wt.joblib
```

Figure 4 Performance of RF Algorithm

4. System Architecture

Block Diagram: The system operates through two primary avenues for assessing obesity: visual detection using a camera and prediction based on textual data. In the initial stage of data acquisition, users have the option to provide input either through real-time images captured by a camera or through text entry containing relevant information for obesity prediction. Once acquired, the data undergoes pre-processing tailored to each input type. For camera input, this involves resizing images, potentially converting them to grayscale, and normalizing pixel values to ensure consistency, Figure 5. Meanwhile, textual data is subjected to pre-processing steps such as removing irrelevant characters, converting text to lowercase, and identifying key phrases related to obesity risk factors. Following pre-processing, separate machine learning models are trained for each input option. For camera input, a model, learns from a dataset of labelled images, discerning features indicative of obesity, such as body proportions or pose. Conversely, for textual input, algorithms like Support Vector Machines (SVMs), Random Forests, or Decision Trees are employed to identify patterns in the text data associated with obesity risk.

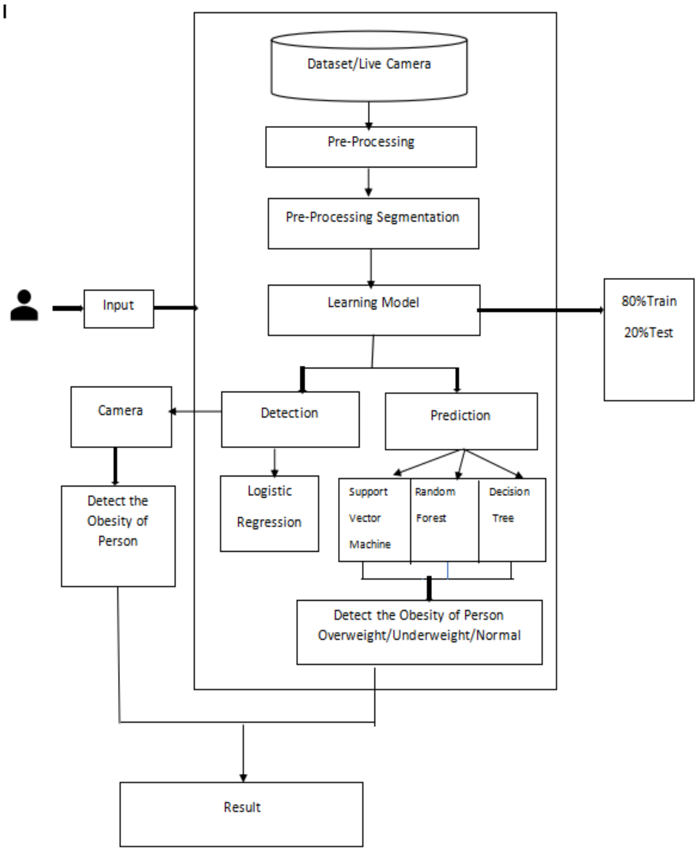

Figure 5 Block Diagram

Data splitting is conducted to segregate the pre-processed data into training and testing sets, facilitating model training and subsequent evaluation. Once trained, the models are deployed for detection or prediction tasks. For camera input, the image-based model analyses new images to predict

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https://doi.org/10.47392/IRJAEH.2024.0279

weight or BMI based on learned features, while the textual model processes user-provided text to assess the risk of obesity. The system generates results based on the chosen method, such as categorizing weight or BMI values for camera input or providing a risk assessment for textual input. However, it's essential to recognize potential limitations, including the accuracy of both methods, privacy concerns associated with camera-based systems, and the potential for biases in the training data. Despite these considerations, this dual-option system offers flexibility in obesity assessment, although careful attention must be paid to ethical implications and real-world deployment challenges Figure 6.

Table 1 Performance of Various Algorithms

Algorithm	Accuracy	Precision	Recall	F1 Score
Decision Tree	90.9	0.93	0.91	0.91
Random Forest	100	1	1	1
SVM	96.9	0.98	0.95	0.96

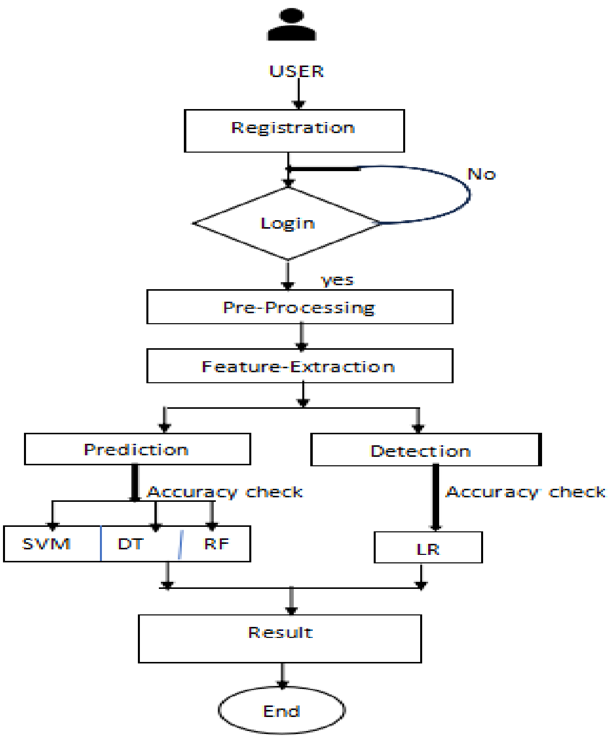

Figure 6 Flow Chart

5. Result & Analysis

The Obesity Guard system classifies individuals into obesity levels such as low weight, medium weight, and high weight, and provides personalized dietary and exercise plans based on their obesity level. This classification is determined using parameters such as age, height, weight, and BMI. For live camera inputs, the system detects the individual's weight level using logistic regression. The textual data is analysed using machine learning algorithms including Support Vector Machine, Random Forest, and Decision Tree. The dataset, sourced from Kaggle, undergoes thorough preprocessing and feature extraction to enhance accuracy. The system achieves an overall average accuracy of 96%, shown in Figure 7, Figure 8, Figure 9 & Figure 10.

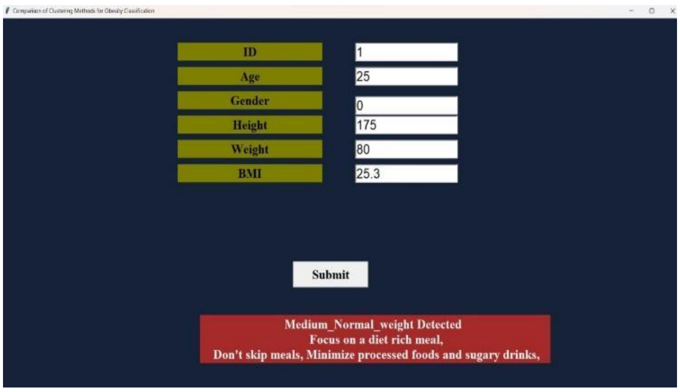

Figure 7 Flow Chart

In this we have taken parameters like age, height, weight, gender, and BMI and the system detected the medium obese person and gave a personalized recommendation.

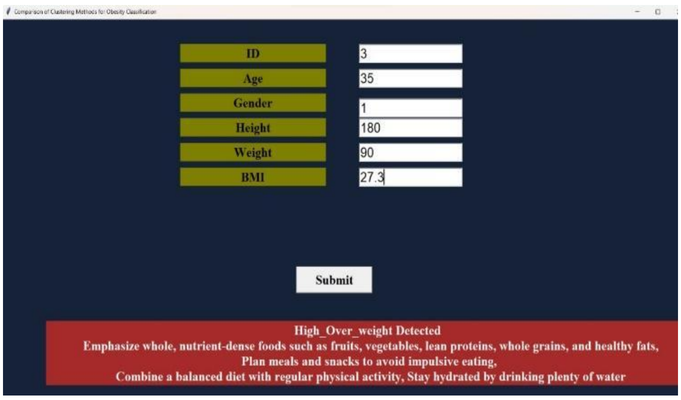

Figure 8 Flow Chart

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https://doi.org/10.47392/IRJAEH.2024.0279

In this we have taken parameters like age, height, weight, gender, and BMI and the system detected the High_over_weight obese person and gave a personalized recommendation as their detection.

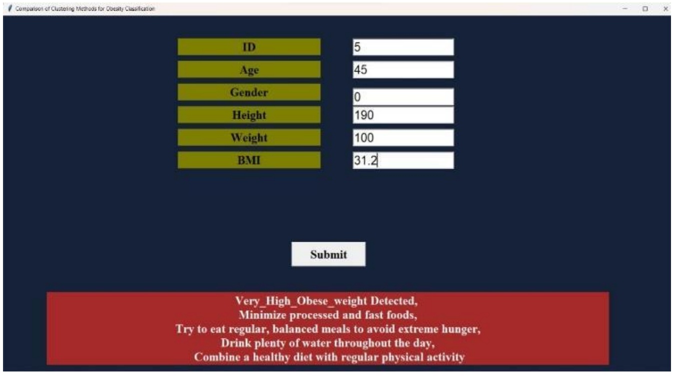

Figure 9 Flow Chart

In this we have taken parameters like age, height, weight, gender, and BMI and the system detected the Vey_High_over_weight obese person and gave a personalized recommendation as their detection.

Figure 10 Flow Chart

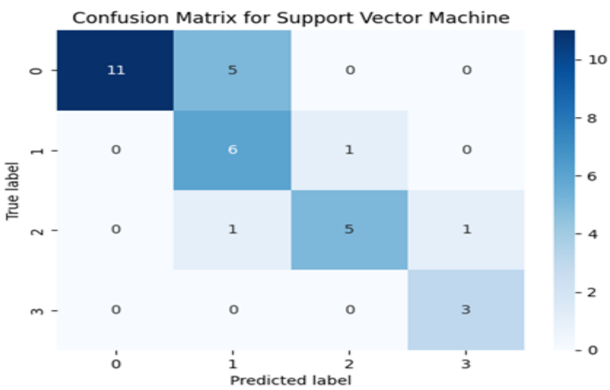

Figure 11 Confusion Matrix using SVM Algorithm

Confusion Matrix for Various Algorithms: In this we have taken parameters like age, height, weight, gender, and BMI and the system detected the Normal_weight so there is not any recommended change in their habit, Figure 11.

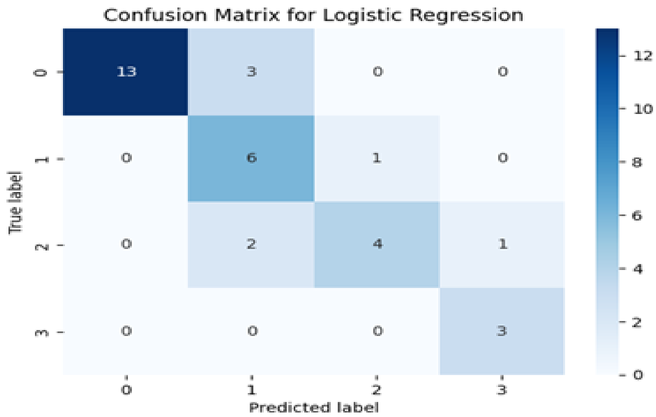

Figure 12 Confusion Matrix using LR Algorithm

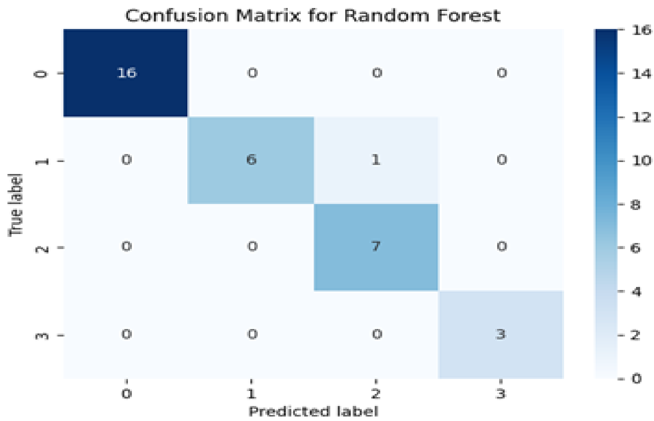

Figure 13 Confusion Matrix using RF Algorithm

The confusion matrix is a fundamental tool in the evaluation of classification models. It provides a comprehensive view of how well a model is performing by breaking down the predictions into four categories: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The evaluation of each model's performance involves the utilization of its respective confusion matrix to derive key performance metrics. Through this process, we have computed various performance parameters for each model, offering a comprehensive understanding of their effectiveness in classification tasks, shown in Figure 12, Figure 13 & Figure 14.

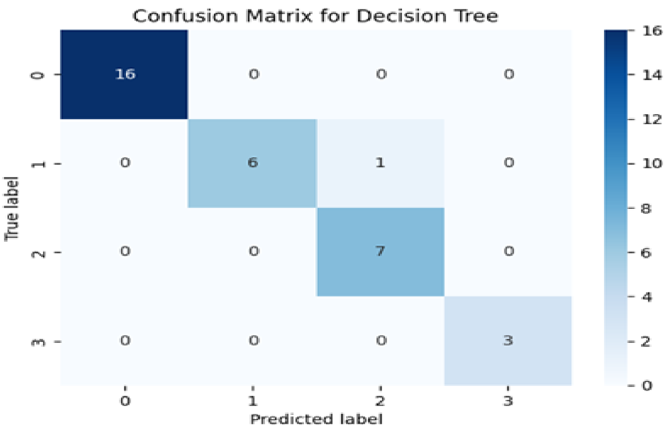

Figure 14 Confusion Matrix using DT Algorithm

Conclusion

In conclusion, the proposed system for obesity assessment presents a promising approach to addressing the global health challenge of obesity. Prediction is based on textual data; the system offers flexibility and adaptability to diverse user preferences and scenarios. Through meticulous data acquisition, preprocessing, model training, and evaluation processes, the system aims to provide accurate and personalized assessments of obesity risk. However, while the system demonstrates potential benefits, several considerations must be acknowledged. The accuracy of both visual and textual methods may be limited, and biases can arise if the training data is not representative of the population. Additionally, privacy concerns associated with camera-based systems, especially in public settings, require careful attention. Despite these challenges, the system holds promise for empowering individuals to take proactive steps towards managing their weight and overall health. By providing actionable insights and personalized recommendations, the system can support users in adopting healthier lifestyles and reducing their risk of obesity-related complications. Moving forward, further research and development are needed to refine the system's algorithms, improve accuracy, address ethical considerations, and ensure accessibility for all user demographics. By continuing to innovate and collaborate across interdisciplinary domains, we can harness the power of technology to combat the obesity epidemic and promote health and well-being worldwide.

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International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 07 July 2024
Page No: 2041- 2051
https://irjaeh.com
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