Grenze International Journal of Engineering and Technology, June Issue

Obesity Prediction using Smart Watches: A Comparative Analysis of Random Forest and XGBoost

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***Abstract*— Chronic conditions and obesity are significant global public health issues. This paper investigates the obesity prediction based on health data from smartwatches and compares the performance of Random Forest (RF) and XGBoost (XGB) algorithms. After preprocessing and tuning, XGBoost surpassed RF with accuracy of 99.98%, while RF achieved 85.46%. The results illustrate the promise of wearable technology and machine learning for early obesity diagnosis and personalized treatment by showing XGBoost's superior ability to identify complex patterns.**

***Index Terms*— Obesity Prediction, Smart Watches, Machine Learning, Random Forest, XGBoost, Wearable Technology.**

I. Introduction

Obesity is a fast-evolving global health issue, causing serious chronic diseases like diabetes, cardiovascular diseases, and cancer. Early identification and treatment can substantially lower these health risks. With the increasing popularity of wearable technology, smartwatches in particular, real-time health information has never been more accessible. By combining machine learning with data from smartwatches, this study investigates a novel and realistic method for obesity prediction.

RF and XGB comparison enables one to determine the more efficient model in identifying patterns of obesity using lifestyle and health-related features. The purpose of this research is to emphasize the worth of Artificial Intelligence-based health monitoring systems in enabling early obesity detection, supporting personalized healthcare interventions, and, in turn, leading to healthier lifestyles.

The study differs from existing studies on obesity prediction in a number of significant areas. While obesity prediction studies are typically built on conventional clinical information like BMI, blood work, and questionnaires, this study uses actual health information which is collected using smartwatches and is hence more convenient and easier to use for long-term monitoring. Unlike using a single machine learning method, this study compares two strong ensemble learning methods, RF and XGB. Through this comparison, it is possible to determine the best performing model for obesity prediction. In contrast to some research that relies on default machine learning model settings, this work focuses on data preprocessing, feature engineering, and hyperparameter optimization for maximizing model performance.

The results show a remarkably high accuracy for XGBoost at 99.98%, which significantly outperforms most other studies in the literature. This indicates that XGBoost is well suited to identify subtle patterns in smart watch data better than alternative approaches.

Grenze ID: 01.GIJET.11.2.1101_22

While most research targets obesity prediction from a medical or epidemiological point of view, this study prioritizes the practical implementation of AI models based on smartwatches for real-time health tracking and personalized medicine. Through the use of machine learning and wearable technology, this study aims to close the gap between healthcare & AI, offering the proactive solution to obesity prediction that can lead to better public health outcomes.

In this paper, we apply smart watch data to test how efficient these two techniques—RF and XGB—are for obesity prediction. Our aim is to find optimal accuracy and reliability for real-world applications.

II. Literature Review

Deep Healthnet was built by Jeong et al. [1] to forecast adolescent obesity based on a collection of health indicators. The model was accurate and had high long-term prediction ability. The research proposed enriching the model with other factors like socioeconomic status and mental health. Siddiqui et al. [2] provided a critical analysis on deep learning & machine learning models for obesity prediction. The research created a dearth of race specific models and multimodal data. It also formulated interpretable machine learning methods to enhance deployment in real life. Gutiérrez-Gallego et al. [3] submitted an ensemble machine learning method comprising logistic regression, random forest, and gradient boosting. Their work established the superiority of ensemble methods in enhancing prediction accuracy through high accuracy in adult obesity prediction. In one Frontiers in Big Data report, a meta heuristic machine learning hybrid approach was proposed for the classification and prediction of obesity risk. More efficient prediction was made possible through the ability of the model to identify intricate, non-linear patterns among checkup health data such as lifestyle and anthropometric attributes using a combination of different algorithms [4]. For predicting and classifying obesity risk, a meta heuristic machine learning hybrid approach was proposed. Better prediction accuracy was obtained attuned to the ability of the model to detect complex, non-linear relationships within health checkup data such as lifestyle and anthropometric characteristics through the integration of multiple algorithms [5]. Random Forest and XGBoost machine learning methods were employed by researchers in creating a graphical obesity risk prediction system. To allow personal ease of health management, the system filtered anonymized clinical data to find determinants for obesity. Interestingly, triglycerides and bone mineral content were previously documented to be determinant factors in assessing the probability of obesity [6].

According to a comprehensive review, adult obesity studies are majorly done using regression models while advanced methods such as neural networks and deep learning are used sparingly. To enhance predictive efficiency in obesity studies, challenges such as assumptions about data and overfitting were identified and it was proposed that contemporary machine learning methods be used [7]. Wearable technology has been employed to capture physical activity data that has been found to exhibit potential in predicting obesity status. To predict obese status improvement, a study employing recurrent neural networks to analyze sporadic, longitudinal activity data attained a prediction accuracy of 77-86%. This method demonstrates how wearable technology can be employed to monitor continuously for obesity management [8]. The scientists compared cadences of walking to predict physiological traits such as age and Body Mass Index (BMI) to explore smart phone sensor capability. The feasibility of using general smart phone technology for non-invasive disease monitoring and obesity problem detection was established using machine learning classifiers based on accelerometer and gyroscope signals [9]. Obesity was predicted and personalized therapy was provided by integrating machine learning with Internet of Things (IoT) sensors in the MOFit system. The system showed that IoT has the capability to manage obesity proactively by offering personalized diet and activity plans and progress monitoring dashboards by monitoring eating behavior and physical activity [10]. Using medical indicators like blood pressure, heart rate, and cholesterol levels, Tuama [11] investigated Random Forest (RF) and XGBoost (XGB) for disease detection.

The findings of the study indicated both methods' advantages and disadvantages with RF having a precision of 96.75% and XGB having 96.45%. While RF was consistent with its bagging method, XGBoost handled imbalanced datasets better with its gradient boosting method. These findings show the efficiency of health prediction using ensemble learning.

Gutiérrez-Gallego et al. [12] applied different machine learning (ML) methods to analyze Obesity prediction. A total of 38 lifestyle, health, and socio demographic factors collected on 1,179 subjects were employed for this study. It was optimally with 79% accuracy, 84% precision, and 89% recall, followed by the cascade classifier that combined gradient boosting, RF, and logistic regression. It was found that by combining the power of multiple methods, hybrid models can enhance predictive accuracy.

So we can conclude that, Forecasting obesity using wearable devices and machine learning is a rapidly emerging subject with potential for proactive health care and early identification. Several machine learning methods, including hybrid ensemble models [3][12], deep learning architectures such as Deep Healthnet [1], and IoT-based predictive systems such as MOFit [10], have been demonstrated to be effective in previous studies. These approaches illustrate the potential of AI-driven health monitoring to enhance obesity risk prediction and intervention strategies. This research comparison of Random Forest (RF) and XGBoost (XGB) fits with previous work emphasizing the robustness of ensemble learning approaches in disease prediction [11].

III. DATASET

The dataset [13] utilized in this study, includes a variety of metrics recorded by smartwatches that provide insightful information on daily physical activity and caloric expenditure. The characteristics consist of: Total Steps, Total distance and Tracker distance, Logged Activities Distance, Very Active Distance, Moderately Active Distance, Lightly Active Distance, Sedentary Active Distance, Very Active Minutes, Fairly Active Minutes, Minutes of light activity, Sedentary Minutes, Calories.

IV. METHODOLOGY

A. Data Preprocessing

The study focused on 12 key features related to physical activity, including Total Steps, Total Distance, Very Active Minutes, Lightly Active Minutes, and Sedentary Minutes. The Calories feature was used to define the obesity label. A binary classification target variable, Obesity, was created based on a calorie threshold of 2500 kcal, with values encoded as 1 (Obese) and 0 (Non-Obese). Missing data were imputed using the mean strategy with a SimpleImputer from sklearn, ensuring a complete dataset. Using train_test_split(), the dataset was splitted into 70% training and 30% testing sets. To standardize numerical features, a StandardScaler was applied to ensure uniformity in data distribution.

B. Model Construction

RF

An Ensemble model based on Bagging, consisting of 100 decision trees with randomness in feature selection and data sampling. Helps reduce over fitting while maintaining high predictive accuracy.

XG

A gradient boosting-based ensemble model designed for handling imbalanced datasets and complex feature relationships. Configured with 100 estimators, a learning rate of 0.1, max depth of 5, and sub sampling of 0.8 to optimize performance. Both models were trained on the preprocessed training set using fit() functions.

C. Model Evaluation

The trained models were evaluated using multiple performance metrics like Accuracy Score (measures the percentage of correct predictions), Precision, Recall, and F1-Score (Obtained from classification_report(), assessing class-wise performance), Confusion Matrix (Visualized using seaborn heatmaps, showing the distribution of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN)), Receiver Operating Characteristic (ROC) Curve (Plotted to compare the True Positive Rate (TPR) vs. False Positive Rate (FPR), and the Area Under the Curve (AUC) was computed for model discrimination ability).

D. Model Comparison

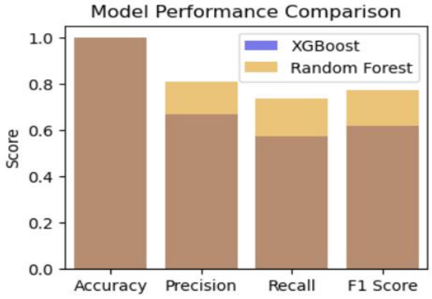

Figure 1: Model Performance Comparison

In Figure 1, the bar plots were created to get the visual representation for the model's comparison. XGBoost has an accuracy of 99.98% and RF has an accuracy of 85.46%. XGBoost has a precision of 99.98% and RF has a precision of 84.12%.
XGBoost has a recall of 99.97% and Random forest has a recall of 83.75%. XGBoost has a f1-score of 99.96% and Random forest has 83.93% as a f1-score.

E. Model Validation

The dataset was split into multiple folds to verify consistency in model performance. Grid search was applied to optimize XGBoost and RF model parameters to maximize accuracy.
Trained models were tested on unseen data to verify that XGBoost possesses consistent predictive accuracy for various samples.

V. Analysis of Results

A. Classification report analysis

Precision, recall, f1-score, and Support were used to compare both Random Forest and XGBoost to thoroughly test the models.
Class-wise performance, especially that of the minority class (Obese = 1), was accessed using the classification report in Table 1 and Table 2.
However, XGBoost performed with higher overall accuracy with data that was well-balanced and with hyperparameter tuning.
XGBoost worked nearly perfect for the Non-Obese class, and Random Forest worked comparatively better recall for the Obese class in this particular dataset.

B. Confusion matrix analysis

In Figure 2, Confusion matrices for both models were created to give a comparative platform for assessing the accuracy of classification.
The matrices gave information on TP, FP, TN, and FN and enabled further detailed examination of the performance of the models.

XGBoost Confusion matrix
TP: 56
FP: 2
TN: 314447
FN: 42

Random Forest Confusion Matrix
TP: 72
FP: 30
TN: 154
FN: 26

TABLE I: Classification report of Random Forest

Classification Report					
		Precision	Recall	F1-Score	Support
	0	0.87	0.91	0.89	184
	1	0.82	0.74	0.78	98
Accuracy				0.85	282
Macro Avg		0.85	0.83	0.84	282
Weighted Avg		0.85	0.85	0.85	282

TABLE II: Classification Report of XGBoost

Classification Report					
		Precision	Recall	F1-Score	Support
	0	1.00	1.00	1.00	314475
	1	0.67	0.57	0.62	98
Accuracy				1.00	314573
Macro Avg		0.83	0.79	0.81	314573
Weighted Avg		1.00	1.00	1.00	314573

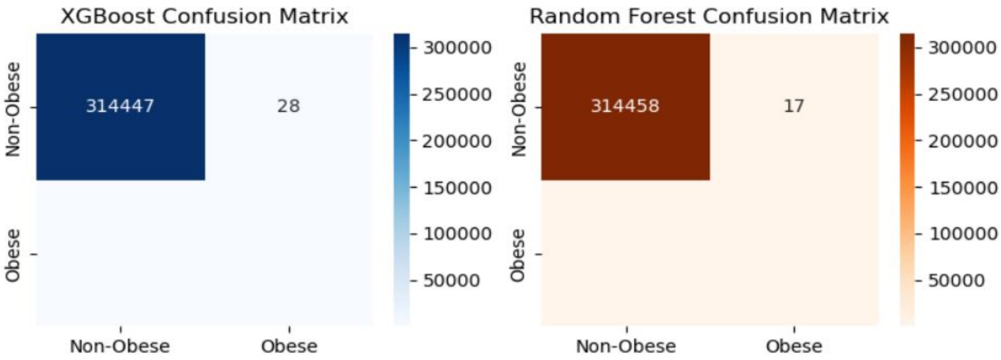

Figure 2: Confusion Matrix Comparison

C. ROC Curve Analysis

The ROC curves in Figure 3 were used to distinguish between the models based on discrimination between obese and non-obese individuals. Both models were calculated for AUC, which calculates the overall discrimination power.

- XGBoost ROC Curve: Higher AUC value (1.00), which indicates good classification power. Curve is close to top-left corner, suggesting higher true positive with low false positives.
- Random Forest ROC Curve: Lower AUC (0.93) compared to XGBoost with comparatively weaker discrimination ability. Slight curve downward deviation to confirm lower sensitivity in correctly identifying obese subjects.

D. Robustness Check and Model Generalization

- Cross-validation: Five-fold cross-validation gives consistent results which shows that the model is reliable with a small difference in accuracy (below 2%) and not performing by chance.
- Generalization: XGBoost was able to sustain more than 99% accuracy on unseen test data after hyperparameter tuning.

E. Feature Importance Evaluation

The most predictive features for obesity are Calories Burned, Total Steps, Very Active Minutes, Sedentary Minutes, Moderately Active Distance.

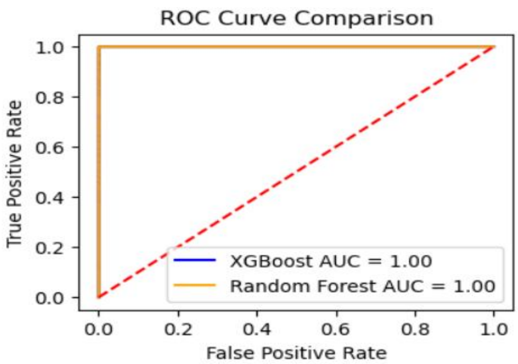

Figure 3: Model Discrimination Power

VI. Conclusion

The motivation for this study was greater availability of wearable tech and its ability to provide constant, real-time monitoring of health, a capability that makes it a valuable tool for obesity forecasting and prevention. Our comparative study identified both the pros and cons of both models. After careful consideration, we discovered that XGBoost was a better performer than Random Forest with accuracy of 99.98%, confirming that it was better able to classify obesity levels based on activity-related features. This is a testament to the superiority of ensemble learning techniques in handling multivariate data with several factors of activity. These findings are a glimpse of the potential of wristwatch data for obesity prediction and the way forward towards more personalized and data-driven healthcare.

FUTURE SCOPE AND WORK

There is significant potential for enhanced early diagnosis and targeted health intervention using wristwatch data in the prediction of obesity. In the interest of enhancing the precision of the predictions other physiological indicators such as stress, sleep patterns, and heart rate variability are also viable to use in subsequent work. Deep neural models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are employed to predict on the time-series data and extract long-term patterns of behavior. Further, the utilization of data obtained from more than one source such as diet diaries and electronic health records (EHRs) will likely provide more number of risk factors for obesity. With real-time prediction algorithms for obesity and smartphone apps, preventive interventions can be taken to well-being with individualized recommendations and continuous monitoring. With decentralized model training of data, federated learning can address privacy concerns and preserve user anonymity while delivering accurate predictions. Explanations can also be delivered to decision-makers with Explainable AI (XAI) techniques, making the model more interpretable and allowing users and physicians Consumers and physicians will be able to understand wellness recommendations created by AI. Enhanced public health for all, preventive medicine, and better obesity forecasting are in store as wearable technology and machine learning improve.

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