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# Harnessing Wearable Technology for Predictive Health Scoring: A Comparative Study of ML Models

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***Abstract:***

*In recent times, increasing reliance on technology and a lack of physical activity have contributed to a rise in health issues such as heart attacks, obesity, and diabetes. To maintain good health, individuals should follow a proper lifestyle and make conscious efforts to stay healthy. However, visiting hospitals frequently and undergoing medical tests can be time-consuming, which many people tend to avoid. Therefore, there is a need for a system that helps individuals monitor and improve their health conveniently.*

*Wearable devices like smart watches can play a significant role in this regard. These devices help users track their health in real time by displaying physical activity parameters such as step count, heart rate, flights climbed, blood oxygen level, calories burnt, and more. These health parameters enable users to monitor their well-being on a regular basis.*

*In this study, these parameters are considered, and machine learning (ML) algorithms are used to calculate the health status of an individual. ML algorithms such as Support Vector Machine (SVM), Gradient Boosting, and Extreme Gradient Boosting (XGBoost) are applied to predict the health score. The performance of all three algorithms is compared, and among them, the SVM algorithm shows the highest accuracy. This approach provides an efficient way to track and assess an individual's health status using wearable devices.*

***Keywords: Wearable Devices, Smart Watches, Health Tracking, Health Status***

## Introduction:

Wearable devices refer to smart gadgets that are worn on the body such as smart watches, wristbands, and rings or embedded within clothing to continuously monitor health and activity. These are electronic gadgets that utilize various technologies, including software, sensors, and network connections. The adoption of wearable products, such as activity trackers and body monitors, provides real-time information on the user's overall well-being. Wearable devices like smart watches and wristbands have gained increased popularity during the pandemic period when people have become more health-conscious. In today's fast-paced life, it's not feasible for individuals to visit the doctor daily for health check-ups. In such situations, wearable devices come into play, providing assistance in monitoring and tracking a person's health. In such scenarios, wearable devices are employed to assist individuals with health monitoring and tracking. These devices help track individuals' daily physical activities, including the number of steps taken; distance covered, calories burned, as well as monitor vital signs such as heart rate, blood pressure, and blood oxygen levels. These devices continuously monitor the above parameters, which is particularly valuable for the user. This continuous monitoring is crucial for assessing their health. The adoption of wearable products such as activity trackers and smart watch provide real-time information on the user's health and wellbeing.

The devices continuously monitor activities, allowing the user's fitness level to be assessed. The more frequently the user wears the device, the more data it can collect. To obtain a fully accurate health status, the user should wear the device for longer periods each day. Accurate data collection depends on the smart watch being correctly positioned on the wrist. To ensure precise health measurements, users must wear the device properly on their wrist, as improper placement can lead to inaccurate readings. The data is recorded on a daily basis and is considered over a span of one year to ensure accurate and reliable predictions.

A fitness wristwatch can be paired with a mobile application to offer key fitness-related information to the user. But the data generated by these devices is in a large amount. The accurate interpretation of data from wearable devices is important in advancing personalized healthcare and disease prevention. The health score predictions in this study are made by considering both geographical parameters such as age and gender, along with physiological parameters. The calculated health score is based on factors like Basal Metabolic Rate (BMR) and physical activity levels(PAL), tailored according to age and gender. Additionally, WHO standards are taken into account, including recommended minimum and maximum step counts, calories burnt, and heart rate ranges, all based on age and gender. This study explores the application of machine learning techniques to improve the interpretation of health metrics from wearable technology. To get a proper insight into the data, ML algorithms are used to analyse the data and help the user to easily track their health condition.

**Literature Review:**

**1.*Wearable activity trackers, accuracy, adoption, acceptance and health impact: A systematic literature review***

**Authors:** Grace Shin, Mohammad Hossein Jarrahi, Fei Y, Amir Karami, Nicci Gafinowitz, Ahjung Byun,

**Journal:** *Journal of Biomedical Informatics*

**Volume & Article ID:** Volume 93, Article 103153 (May 2019)

Wearable activity trackers (WAT) are electronic monitoring devices that enable users to track and monitor their health-related physical fitness metrics including steps taken, level of activity, walking distance, heartrate, and sleep patterns. Objective of the study is to understand the rich human-information interaction that is enabled by WAT adoption. In the study Topic modeling methods were used to identify six key themes of WAT research, namely Technology Focus, Patient Treatment and Medical Settings, Behavior Change, Acceptance and Adoption, Selfmonitoring Data Centered, and Privacy. This work raises interdisciplinary awareness about the current landscape of WAT use and the related diversity of interesting research opportunities and challenges. The study suggests that WAT devices are multi-dimensional technologies with complex impacts. Understanding WAT and their technological and non-technological aspects requires various research perspectives. This multi-dimensional framework highlights that WATs are not merely fitness devices but are embedded in complex human-information interactions. The review emphasizes the need for interdisciplinary approaches to fully understand the technological, behavioral, and ethical dimensions of WATs, and opens avenues for future research in both health informatics and user-centered design.

**2. Machine Learning for Healthcare Wearable Devices: The Big Picture**

**Authors:** Farida Sabry, Tamer Eltaras, Wadha Labda, Khawla Alzoubi, Qutaibah Malluhi

**Journal:** Journal of Healthcare Engineering (Hindawi)-2022

The paper highlights the Machine Learning Techniques used, the different modalities used, and the available datasets and the different challenges facing machine learning applications on wearable devices like deployment alternatives, power consumption, storage and memory, utility and user acceptance, data availability and reliability, communication, security and privacy were discussed while identifying possible solutions found in the literature. The objective of the study is to highlight the various ML techniques and the challenges in the deployment of wearable devices. The methods used are applied on datasets available for human activity recognition. K-NN, SVM, LR, Tree-based, Deep learning models are used for analysis of the data. Further research concerning data availability, reliability, and privacy to enable effective and efficient learning from data generated by wearable devices. The wearable devices are used for remote patient monitoring and detection of any irregularities with the human body

**3. Consumers' and Physicians' Perceptions about High Tech Wearable Health Products**

**Authors: Suphan Nasira, Yigit Yurdera- Istanbul University, Faculty of Economics**

**Journal/Conference: Procedia – Social and Behavioral Sciences**

**Volume: 195 (2015)**

This study aims to explore and compare the perceptions of both consumers and healthcare professionals (physicians) toward high-tech wearable health technologies, which include smartwatches, fitness trackers, and similar digital health-monitoring devices. Recognizing the growing popularity of wearable devices in personal healthcare, the authors seek to understand the underlying factors that influence the acceptance and adoption of such technologies among different user groups.

To achieve this, the researchers extend the Technology Acceptance Model (TAM)—a widely used theoretical framework in technology adoption studies. While the original TAM focuses on perceived usefulness and perceived ease of use as the primary determinants of technology acceptance, this study enhances the model by incorporating two additional constructs: perceived risk and compatibility. Perceived risk refers to the concerns users may have regarding the reliability, privacy, or potential misuse of health data collected by wearable technologies. Compatibility assesses the degree to which wearable health technologies align with an individual's lifestyle, habits, and healthcare needs. By integrating these two constructs into TAM, the study offers a more comprehensive framework to examine how both psychological and practical considerations influence the decision-making process.

The study employs empirical data collection through surveys conducted with both consumers and physicians. The responses are analysed to identify patterns in perception and adoption behaviour.

**4. Wearable Sensors for Remote Health Monitoring**

**Authors:** Sumit Majumder, Tapas Mondal and M. Jamal Deen - Department of Electrical and Computer Engineering, McMaster University, Hamilton, Canada;

**Journal:** *Sensors* (an open-access journal published by MDPI)-2017

Remote health monitoring, based on non-invasive and wearable sensors, modern communication and information technologies offers an efficient and cost-effective solution that allows the elderly to continue to live in their comfortable home environment instead of expensive healthcare facilities. These systems will also allow healthcare personnel to monitor important physiological signs of their patients in real time, assess health conditions and provide feedback from distant facilities. In this paper, they have presented and compared several low-cost and non-invasive health and activity monitoring systems. Finally, compatibility of several communication technologies as well as future perspectives and research challenges in remote monitoring systems are discussed.

**5. Wearable data analysis, visualization and recommendations on the go using android middleware** -

**Authors:**Marios C.Angelides[1]•Lissette Andrea Cabello Wilson[1]•Paola Liliana Burneo Echeverría

**Journal** : Springer Journal-2018

The paper highlights the use of wearable device, the analysis and visualization of the wearer activity data it records. The paper showed the range of issues with wearable and grouped these issues under four categories, namely ethical/legal, economic, social and technological. It concluded with the recommendations generated using a Machine Learning Technique to support the wearer with monitoring their daily goals and activities.

The author did this in 9 steps and the steps are as follows:

1. The wearer configures their wearable and sets initial goals.
2. The wearable sensors track the wearer's daily activities and record data.
3. The wearable synchronizes with a smart device to transfer the wearable data recorded.
4. The raw data is forwarded by the smart phone to the wearable data server.
5. From the server it is retrieved and analyzed in comparison to community data to generate personal recommendations.
6. The results of the analysis and the recommendations are forwarded to the smart device.
7. Then they are visualized and offered to the wearer.
8. This assists the wearer with monitoring their daily goals and activities.
9. The smart phone synchronizes with the wearable to auto-update any revised goals

**Research Methodology:**

This research adopts a **supervised machine learning-based predictive methodology** to evaluate and compare the performance of Gradient Boosting, XGBoost, and Support Vector Machine (SVM) models in forecasting an individual's yearly health score based on physiological and activity data derived from wearable devices.

**Data Collection and Monitoring:**

The dataset was collected over a continuous period of **one year**, spanning **July to June**, for **300 individuals**, each monitored monthly. The data includes:

- **Step Count** (monthly total)
- **Calories Burnt** (monthly total)
- **Average Heart Rate**
- **Blood Oxygen Saturation**
- **Demographics:** Age and Gender
- **Health Score** (target variable)

The values were recorded consistently each month, creating a detailed time series per participant. Data was consolidated in CSV format and later preprocessed for machine learning analysis.

**Feature Engineering:**

From the raw monthly data, the following aggregated features were derived:

- Avg_Heart_Rate: Mean heart rate across all months
- Avg_Blood_Oxygen_Saturation: Average oxygen level across the year
- Total_Step_Count: Sum of step counts from July to June

- Total_Calories_Burnt: Annual total calorie expenditure
- Age and encoded Gender

These engineered features formed the independent variables (X), while Yearly_Health_Score was treated as the dependent variable (y).

**Data Pre-processing:**

The data was cleaned and normalized where needed. No significant missing values were reported. Categorical encoding was applied to Gender for model compatibility. The dataset was then split into **training (80%)** and **testing (20%)** subsets using stratified random sampling to preserve data balance.

**Model Selection and Training:**

To predict the *Yearly Health Score*, three widely used regression models were selected: **Gradient Boosting Regressor**, **XGBoost Regressor**, and **Support Vector Regressor (SVR)**. Each of these models represents a different approach to regression, enabling a comparative study across ensemble-based and margin-based learning strategies.

**1. Gradient Boosting Regressor (GBR):**

**Gradient Boosting** is an **ensemble method** that builds models sequentially by correcting the errors made by prior models. It uses decision trees as weak learners and improves the overall prediction by minimizing a specified loss function.

**Algorithmic Steps:**

1. Fit the first weak learner (usually a shallow tree) to the actual target values.
2. Calculate the residuals (errors).
3. Fit the next tree to the residuals.
4. Combine predictions from all trees in a weighted manner.

**Mathematical Formula:**

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Where:

- Fm(x)F_m(x)Fm(x): boosted model at iteration mmm
- hm(x)h_m(x)hm(x): new base learner fitted to residuals
- γm\gamma_mγm: learning rate (controls contribution of each tree)

**Expected Outcomes:**

- High accuracy due to error correction at each stage.
- Slower training time but excellent generalization.
- Can overfit if not regularized properly.

**2. XGBoost Regressor:**

**XGBoost (Extreme Gradient Boosting)** is a more advanced and **regularized version of Gradient Boosting** that includes enhancements for speed and accuracy. It supports parallel processing, shrinkage (learning rate), column subsampling, and L1/L2 regularization.

**Mathematical Objective Function:**

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k)$$

**Expected Outcomes:**

- Superior accuracy and performance
- More robust to overfitting
- Often yields best results in regression problems

**3. Support Vector Regressor (SVR):**

**SVR** is a variant of Support Vector Machines (SVM) used for regression tasks. It attempts to fit a function that deviates from actual target values by a maximum margin ε\varepsilonε, while being as flat as possible.

**Optimization Goal:**

Minimize:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

Subject to:

$$\begin{cases} y_i - (w \cdot x_i + b) \leq \varepsilon + \xi_i \\ (w \cdot x_i + b) - y_i \leq \varepsilon + \xi_i^* \end{cases}$$

Where:

- CCC: penalty parameter (regularization)
- ε\varepsilonε: tube size (acceptable error)
- ξi\xi_iξi, ξi∗\xi_i^*ξi∗: slack variables for tolerance

**Expected Outcomes:**

- Works well for smaller or simpler datasets
- Requires feature scaling (sensitive to magnitudes)
- Struggles with large feature spread or complex non-linear relationships
- Slower training for large datasets

**Data Overview:**

The dataset used in this research was collected over a continuous **one-year period**, covering health-related metrics of **300 individuals**. Each individual's data was recorded monthly from **July to June**, ensuring consistency and completeness across all entries. The primary aim was to capture longitudinal trends in physical activity and vital signs that contribute to overall health.

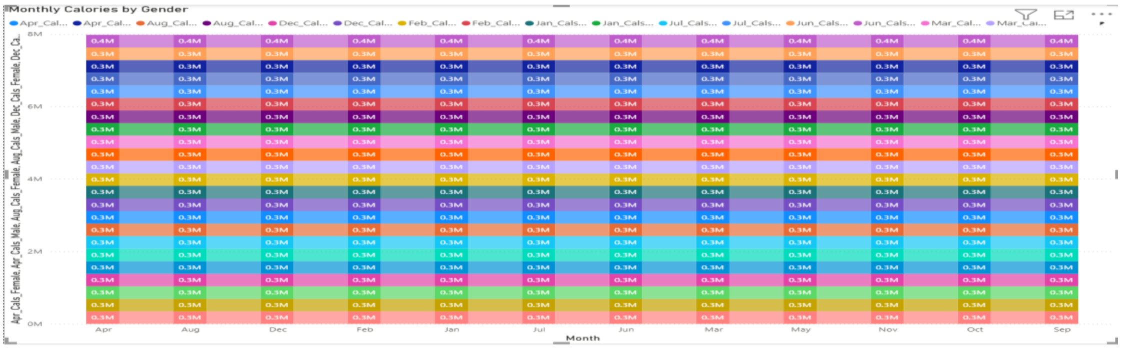
The dataset includes key physiological and activity-based indicators such as **monthly step count**, **calories burnt**, **average heart rate**, and **blood oxygen saturation**. Demographic details like **age** and **gender** were also included to study potential variations in health score patterns across different population segments. The central focus of the analysis is the **Yearly Health Score**, which acts as the target variable for prediction.

To prepare the data for analysis, the raw monthly readings were aggregated to create meaningful features such as **total annual step count**, **average heart rate across the year**, **cumulative calories burnt**, and **mean blood oxygen levels**. This aggregation ensured dimensional consistency and improved the quality of the feature set used for machine learning models. Categorical encoding was applied to the gender variable to make it model-compatible.

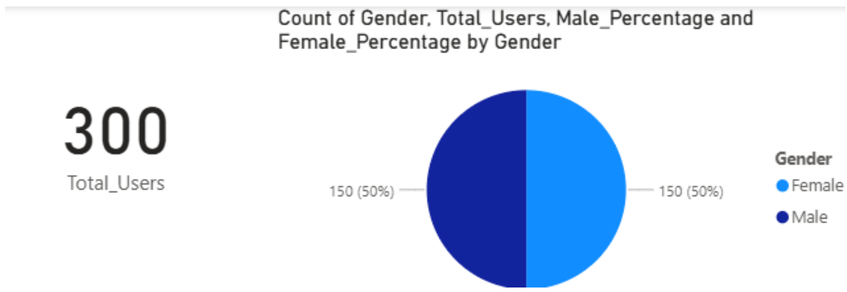
The dataset exhibited a balanced gender distribution and a healthy spread across various age groups, making it suitable for generalizable modeling. No major missing values or anomalies were detected, minimizing the need for imputation. The dataset's time-bound and structured nature made it highly appropriate for supervised machine learning tasks like regression, providing a reliable foundation for comparing multiple prediction models.

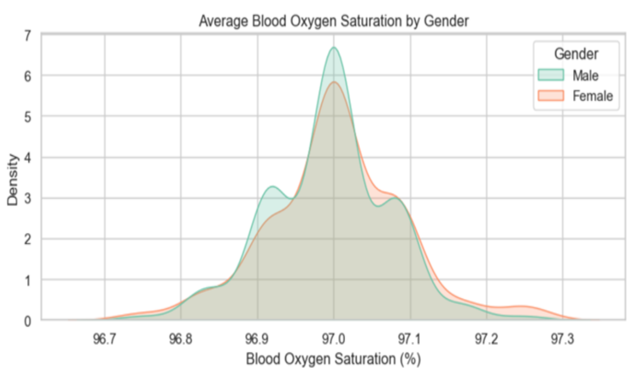
**Exploratory Data Analysis (EDA) with Visualizations:**

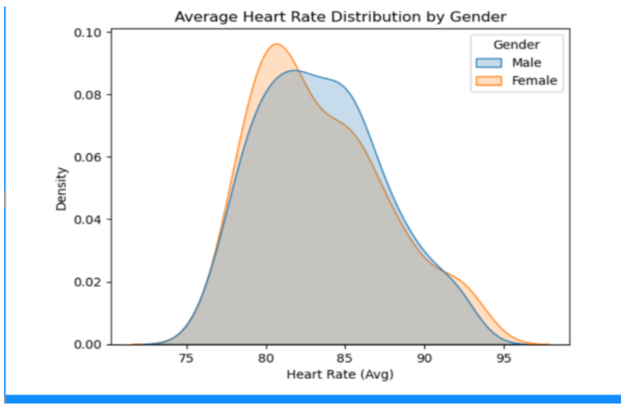
Exploratory Data Analysis (EDA) was conducted to understand the distributions, patterns, and relationships among the features before applying machine learning models. It played a vital role in identifying key predictors for the yearly health score, checking for data quality issues, and preparing visual insights that could be compared across gender and age groups.




The first step of EDA involved a **correlation heatmap** to examine interdependencies among variables. It was observed that Avg_Heart_Rate and Total_Calories_Burnt showed moderate positive correlation with the Yearly_Health_Score, indicating their significance in predicting overall wellness. On the other hand, Avg_Blood_Oxygen_Saturation remained relatively stable, contributing less directly to score variance but still relevant as a physiological marker.

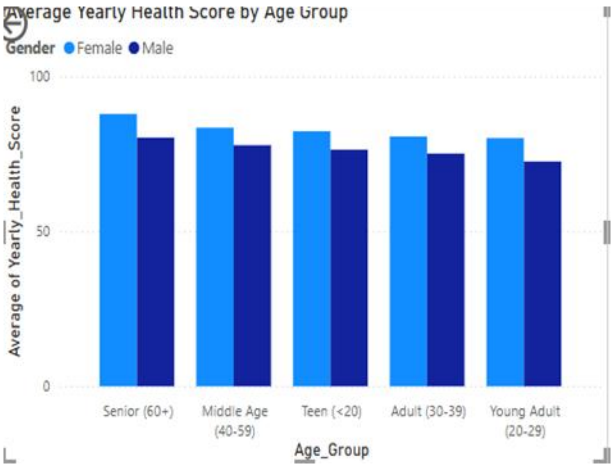


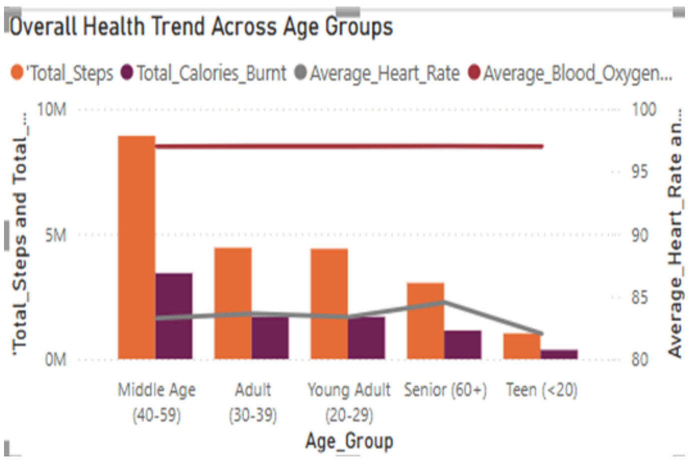



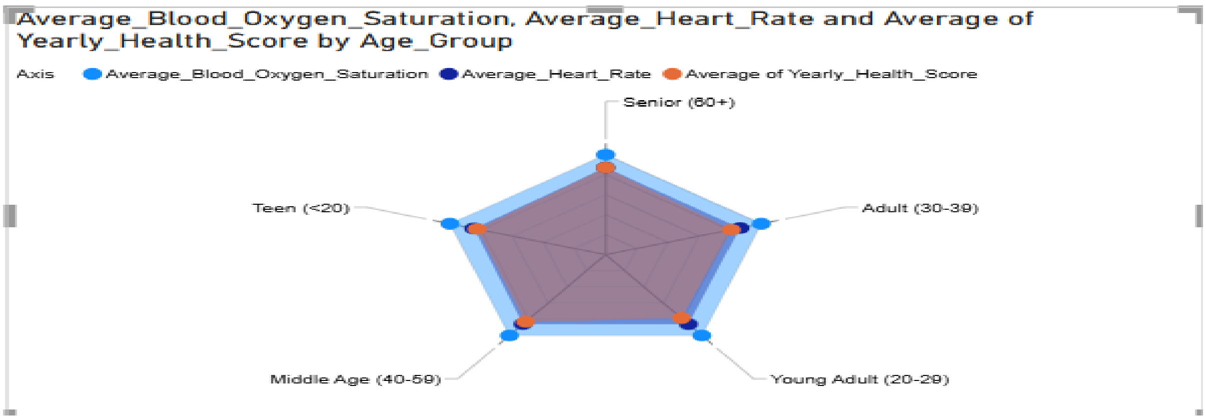



To explore gender-wise patterns, **box plots** were created for total calories burnt and average heart rate. These visuals highlighted that males had a slightly wider range and higher mean calorie expenditure compared to females, whereas heart rate distributions remained similar across both groups. **Pie charts** were used to verify the gender distribution (150 male, 150 female), confirming balance in representation. Age distribution was visualized using a **histogram**, showing that most participants fell within the 20–40 age range.

Further EDA focused on **age-based trends**, where a **line chart** was plotted to show changes in Avg_Heart_Rate and Avg_Blood_Oxygen across age intervals (e.g., 20–30, 31–40, etc.). The analysis revealed that average heart rate tends to decline slightly with age, while oxygen saturation remains consistently high, regardless of age group. Additionally, a **scatter plot** was created to assess the relationship between Yearly_Health_Score and Total_Calories_Burnt, which showed a mild upward trend, confirming that physically active individuals tend to achieve better health scores.




**Model Development:**

The machine learning models selected for this study were: **Gradient Boosting Regressor**, **XGBoost Regressor**, and **Support Vector Regressor (SVR)**. These models were chosen to compare the performance of ensemble-based tree methods with a margin-based kernel model. The goal was to accurately predict the Yearly Health Score using a set of engineered features derived from one year's worth of physiological and activity data.

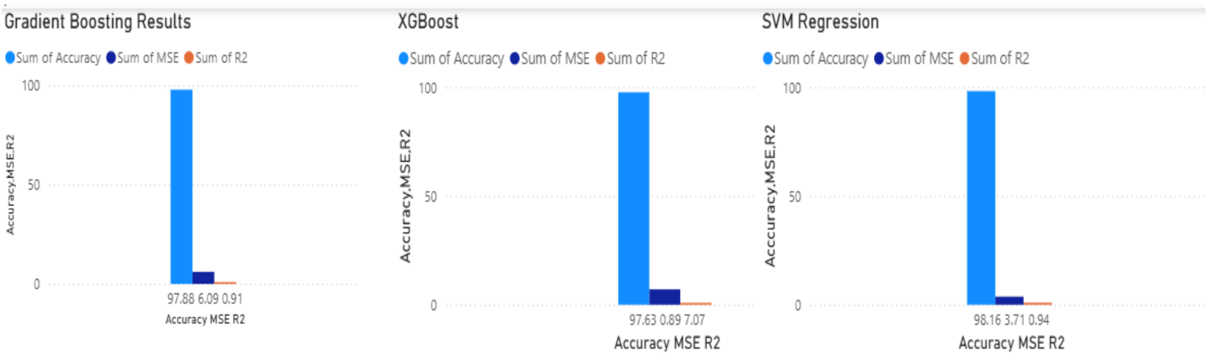
Each model was trained using the preprocessed dataset split into **80% training** and **20% testing** sets. Feature columns included: Total_Calories_Burnt, Total_Step_Count, Avg_Heart_Rate, Avg_Blood_Oxygen_Saturation, Age, and encoded Gender. These features were selected based on insights from EDA that showed moderate correlation and explanatory potential regarding the target variable. Hyperparameter tuning was applied where necessary using techniques such as grid search to enhance model performance and reduce overfitting.

Gradient Boosting and XGBoost used decision tree ensembles to sequentially minimize residual errors, with XGBoost offering additional speed and regularization benefits. SVR, on the other hand, was implemented using a radial basis function kernel after scaling features. All models were evaluated using regression metrics including **$R^2$ Score**, **Mean Squared Error (MSE)**, **Mean Absolute Error (MAE)**, and a custom **Accuracy %** metric. These values were later visualized and compared using Power BI for a clearer interpretation of model strengths and limitations.

**Results and Outcome:**

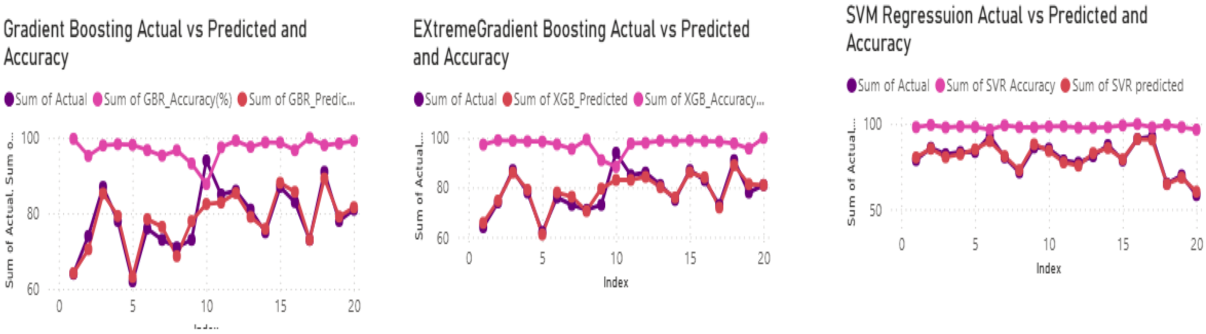
The predictive performance of Support Vector Regression (SVR), XGBoost, and Gradient Boosting models was evaluated using standard regression metrics: **Mean Squared Error (MSE)**, **$R^2$ Score**, and a custom-defined **Accuracy (%)**. The outcomes were visualized using Power BI to facilitate an intuitive comparison. Below are the key visualizations and their insights:

- Graph 1: Clustered Column Chart: Comparing Models on Accuracy, MSE, and $R^2$



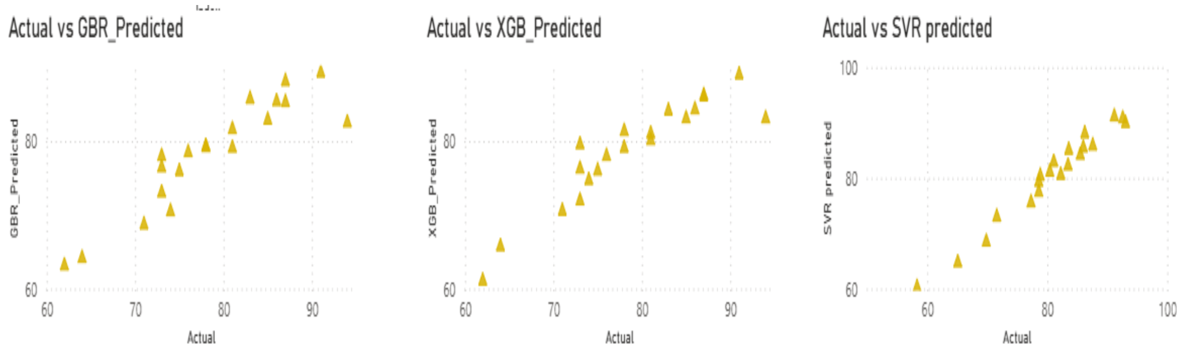

This graph places all three models side-by-side for major evaluation metrics. SVR leads with the **highest accuracy and $R^2$ score**, and the **lowest MSE**, indicating its superior performance. XGBoost and Gradient Boosting follow.

- Graph 2: Line Chart with Markers: Actual vs Predicted with Accuracy (3 Models)



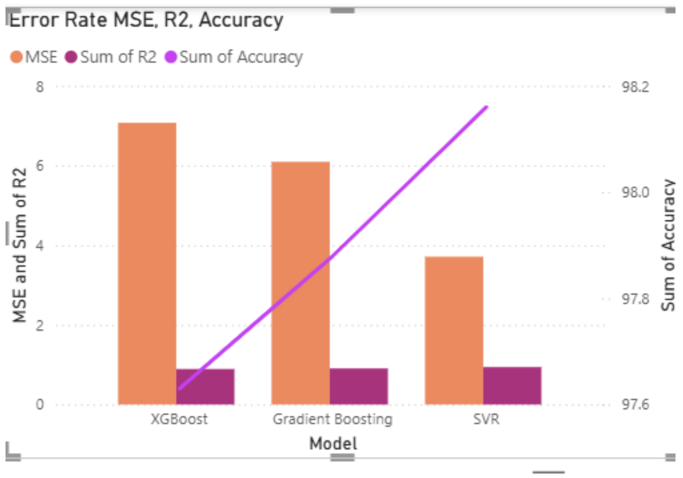

This chart highlights how each model's predictions align with actual values over 20 test records. SVR lines remain closest to the actual trend, visually affirming its strong accuracy.

- Graph 3: Multi-Series Line Chart: Actual vs Predicted (3 Models)



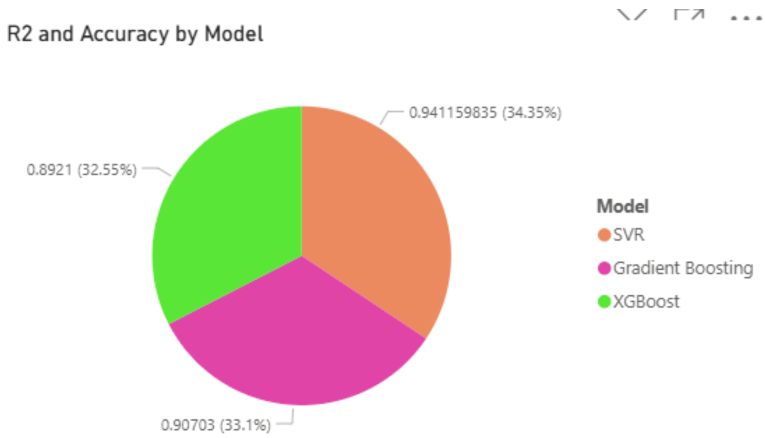

Compares the overall prediction pattern of each model. SVR consistently mirrors the actual score curve, outperforming XGBoost and Gradient Boosting in most instances.

- Graph 4: Stacked Column with Line Overlay: **MSE and R² Comparison with Accuracy Line**



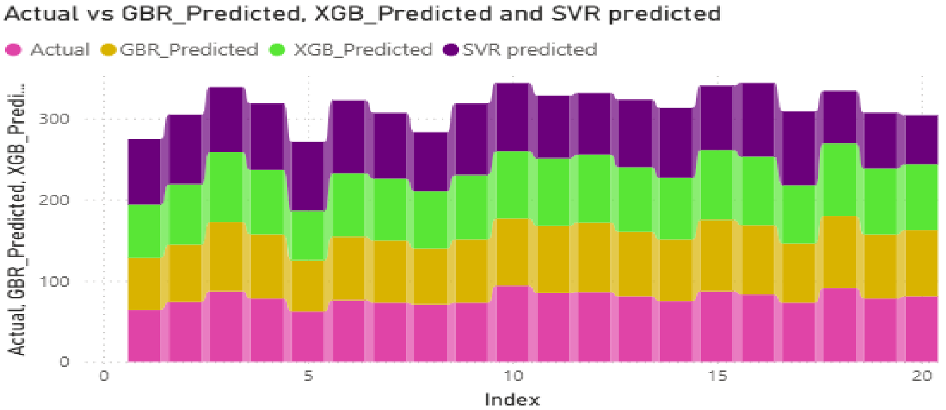

Here, SVR shows a distinct advantage with **lowest MSE** and **highest R²**, while the overlayed line for accuracy shows a peak for SVR over other models.

- Graph 5: Pie Chart: Model Accuracy Proportions



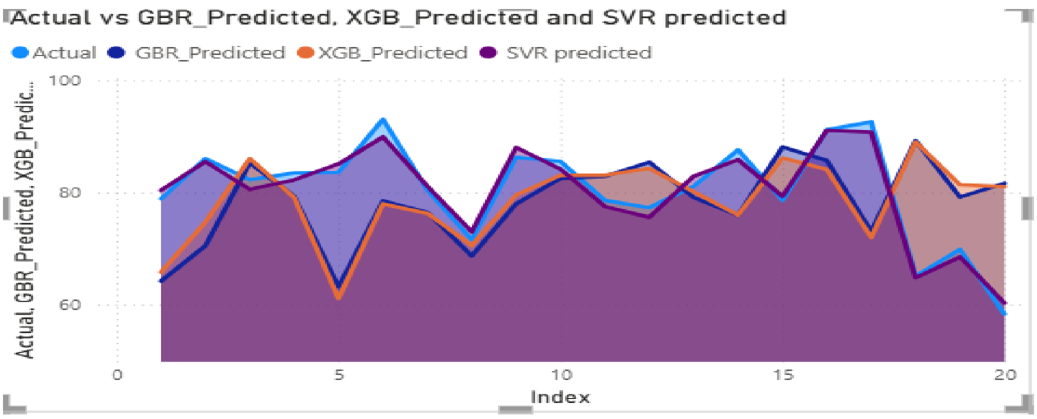
Displays the distribution of total model accuracy. SVR contributes the largest slice, followed by XGBoost and then Gradient Boosting.

- Graph 6: Stacked Column Chart :Actual vs Predicted Visual Coverage



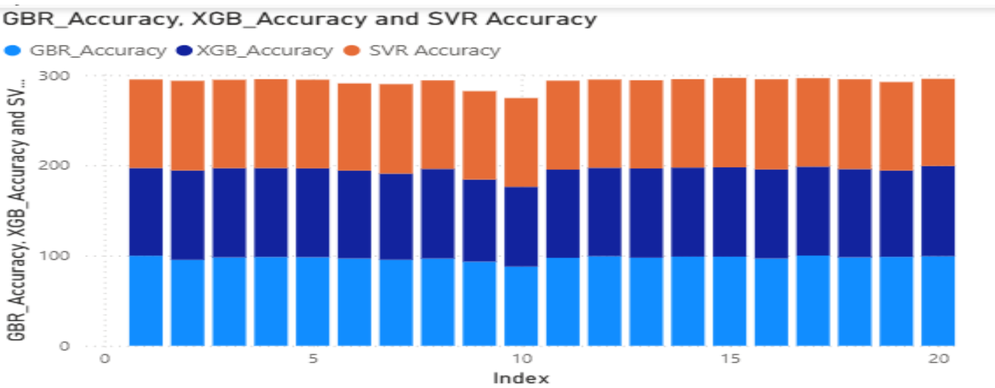

The pink base shaded ribbon shows the coumn with actual data .The size determine data .SVR predictions remain tightly aligned with the actual shaded baseline, while other models exhibit noticeable deviations.

- Graph 7: Filled Area Chart: Predicted Coverage vs Actual (Overall Area)




**Blue Overlay** shows area covered as actual data .Visually demonstrates that SVR's predictions cover the majority of the actual health score area, supporting its top performance claim.

- Graph 8: Stacked Column Chart – Accuracy Focus: Comparing Accuracy Across Models




This chart clearly shows **SVR with the highest accuracy**, followed by XGBoost and Gradient Boosting, further validating its effectiveness.

In conclusion, **SVR emerged as the most effective regression model** in this study, outperforming both ensemble-based methods—XGBoost and Gradient Boosting—across all major performance indicators. However, it is important to note that **XGBoost and Gradient Boosting also demonstrated reliable predictive capabilities**. Their slightly lower performance could be attributed to factors such as **dataset size, feature variance, or the nature of underlying relationships**, which may have been better suited to SVR's kernel-based approach in this context.

📌 First 10 Predictions:

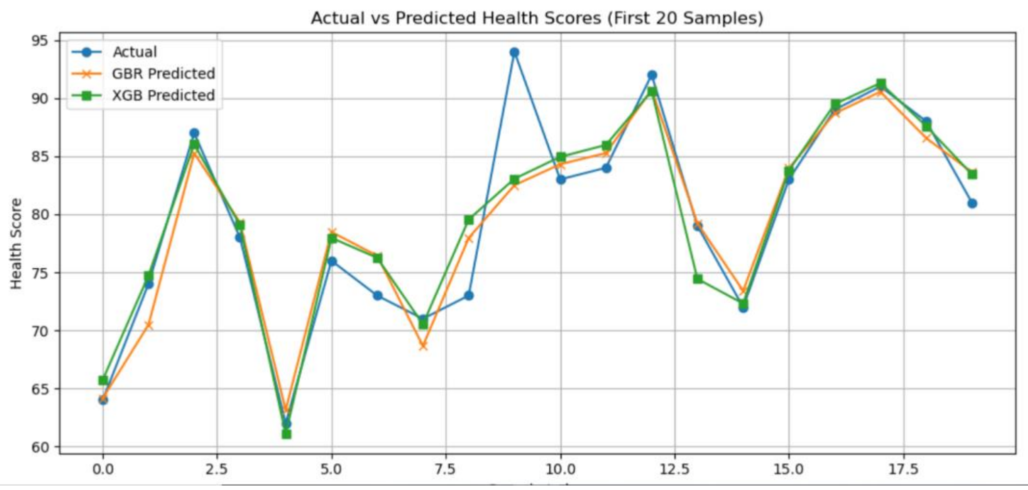
| Actual | GBR_Predicted | XGB_Predicted | GBR_Accuracy(%) | XGB_Accuracy(%) |
|---|---|---|---|---|
| 64 | 64.16 | 65.730003 | 99.75 | 97.30 |
| 74 | 70.47 | 74.699997 | 95.23 | 99.05 |
| 87 | 85.25 | 86.019997 | 97.99 | 98.88 |
| 78 | 79.31 | 79.070000 | 98.33 | 98.63 |
| 62 | 63.14 | 61.080002 | 98.15 | 98.51 |
| 76 | 78.47 | 77.970001 | 96.75 | 97.41 |
| 73 | 76.43 | 76.250000 | 95.30 | 95.54 |
| 71 | 68.67 | 70.529999 | 96.71 | 99.34 |
| 73 | 77.96 | 79.540001 | 93.21 | 91.04 |
| 94 | 82.50 | 83.059998 | 87.77 | 88.36 |

📌 Last 10 Predictions:

| Actual | GBR_Predicted | XGB_Predicted | GBR_Accuracy(%) | XGB_Accuracy(%) |
|---|---|---|---|---|
| 85 | 82.87 | 83.070000 | 97.49 | 97.73 |
| 86 | 85.38 | 84.269997 | 99.28 | 97.99 |
| 81 | 79.08 | 80.110001 | 97.63 | 98.90 |
| 75 | 75.90 | 75.980003 | 98.80 | 98.69 |
| 87 | 88.08 | 86.139999 | 98.76 | 99.02 |
| 83 | 85.69 | 84.099998 | 96.75 | 98.67 |
| 73 | 73.02 | 71.940002 | 99.98 | 98.55 |
| 91 | 89.24 | 88.989998 | 98.07 | 97.79 |
| 78 | 79.16 | 81.339996 | 98.51 | 95.72 |
| 81 | 81.61 | 81.000000 | 99.25 | 99.99 |

**Table 7.1** displays the first and last 10 predictions made by two regression models: Gradient Boosting Regressor (GBR) and XGBoost Regressor (XGB). Each row includes the actual value, the values predicted by each model, and their respective accuracy percentages. The table reveals that both models perform strongly, with XGB slightly outperforming GBR in most cases, especially in the latter predictions where XGB consistently shows accuracy above 97%. GBR also demonstrates robust predictions, though with slightly more variation in accuracy, particularly in the first 10 records. This suggests both models are reliable, but XGB may provide slightly more stable performance on this dataset.

The graph below illustrates the actual values against the predicted values by GBR, XGB models, clearly highlighting their accuracy levels. The plotted data points confirm that the models closely follow the actual trends,exhibiting higher predictive stability across the observed range.



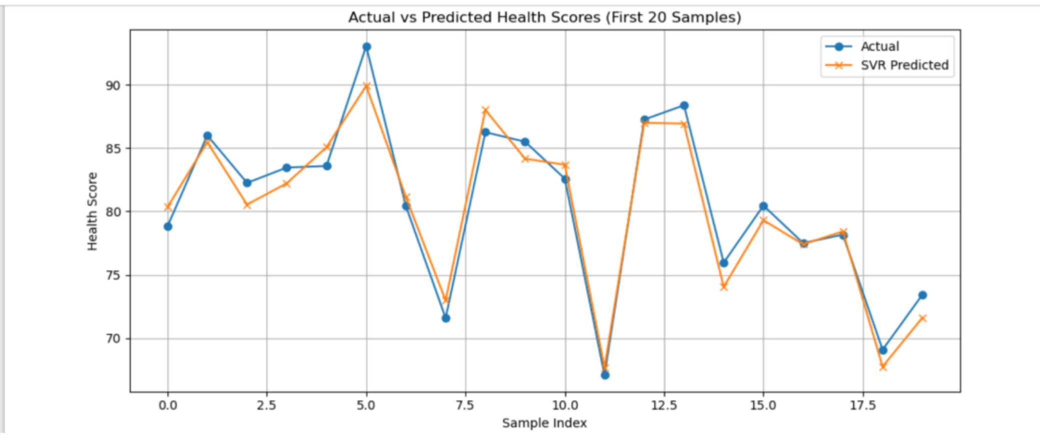
First 10 Predictions:

| Actual | SVR_Predicted | Accuracy(%) |
|---|---|---|
| 78.83 | 80.35 | 98.08 |
| 86.00 | 85.47 | 99.38 |
| 82.25 | 80.54 | 97.92 |
| 83.46 | 82.22 | 98.51 |
| 83.58 | 85.06 | 98.23 |
| 93.04 | 89.90 | 96.63 |
| 80.42 | 81.12 | 99.13 |
| 71.58 | 72.97 | 98.06 |
| 86.25 | 88.01 | 97.96 |
| 85.50 | 84.16 | 98.44 |

Last 10 Predictions:

| Actual | SVR_Predicted | Accuracy(%) |
|---|---|---|
| 78.58 | 77.47 | 98.59 |
| 77.29 | 75.56 | 97.76 |
| 81.08 | 82.88 | 97.78 |
| 87.58 | 85.82 | 97.99 |
| 78.58 | 79.29 | 99.11 |
| 91.17 | 91.08 | 99.91 |
| 92.58 | 90.74 | 98.01 |
| 65.08 | 64.74 | 99.47 |
| 69.83 | 68.49 | 98.08 |
| 58.29 | 60.25 | 96.64 |

**Table 7.2** presents similar information but for the Support Vector Regressor (SVR) model. The SVR model predictions are compared against actual values, accompanied by the accuracy of each prediction. SVR demonstrates high consistency across its predictions, maintaining accuracy above 96% in all cases, with many values near or above 98%. This suggests that SVR is a strong contender in regression performance, rivaling GBR and XGB in precision. The relatively tight range in accuracy indicates minimal deviation in its prediction behavior. The graph below illustrates the actual values against the predicted values by SVR models, clearly highlighting their accuracy levels. The plotted data points confirm that the models closely follow the actual trends,exhibiting higher predictive stability across the observed range.




**Discussion:**

The comparative analysis of the three models reveals that Support Vector Regression (SVR) outperformed both XGBoost and Gradient Boosting in predicting the Yearly Health Score. This can be attributed to SVR's capability to handle non-linear relationships effectively through its kernel functions, making it well-suited for the subtle and individualized patterns present in physiological and activity-based data.

Despite their slightly lower scores, both XGBoost and Gradient Boosting exhibited strong predictive capabilities and followed the actual data trends with reasonable accuracy. The minor performance gap could be due to model sensitivity to the dataset's size, noise, or the scale of features. Ensemble methods like XGBoost may show better results with larger or more diverse datasets. The results indicate that model selection should be context-aware, considering both the data characteristics and computational constraints.

**Limitations:**

The study, while methodologically sound, faced the following limitations:

1. **Limited Sample Size:** The dataset included only 300 participants, which may not capture the diversity of a larger or more heterogeneous population.
2. **Missing Lifestyle Factors:** Key health-influencing variables such as sleep quality, diet, stress levels, and medical history were not available.
3. **Single-Year Data Window:** The data was collected over a one-year period, restricting the ability to observe long-term health trends or seasonality effects.
4. **Model-Specific Limitations:** SVR, though most accurate in this case, may not scale well to larger datasets due to its computational demands.
5. **Generalization Constraint:** The models were not tested on real-world deployment scenarios or external validation datasets, which may affect reliability in live applications.

**Future Works:**

To enhance the study and its real-world applicability, the following future directions are recommended:

1. **Integrate Lifestyle and Clinical Data:** Include variables like sleep patterns, stress levels, and known health conditions for holistic health prediction.
2. **Expand Sample Size and Duration:** Use multi-year datasets with larger populations to improve generalizability and temporal analysis.
3. **Incorporate Deep Learning Models:** Evaluate neural networks or LSTM-based models for real-time and sequential health tracking.

**Conclusion:**

1. **SVR Emerged as the Most Effective Model:** Among the three models tested, Support Vector Regression (SVR) demonstrated the highest prediction accuracy and $R^2$ score while maintaining the lowest mean squared error (MSE), making it the most suitable model for this dataset.
2. **XGBoost and Gradient Boosting Remain Strong Contenders:** Although slightly outperformed by SVR, both XGBoost and Gradient Boosting models achieved robust results. Their consistent performance suggests they remain valuable choices, particularly for larger datasets or when scalability is prioritized.
3. **Importance of Feature Engineering:** The transformation of monthly metrics into aggregated features such as annual heart rate average and total steps was crucial. These engineered variables improved model input quality and made the predictions more stable.

4. **Exploratory Data Analysis Added Insight:** Visual EDA using Power BI helped uncover underlying data trends, identify feature importance, and confirm the dataset's quality. It also reinforced the impact of age and gender on overall health scores.
5. **Year-Long Monitoring is Sufficient for Trend Detection:** The use of a single year of wearable device data provided enough temporal resolution to detect meaningful health patterns and variations, validating the potential of such data for predictive modeling.
6. **Balanced Demographic Distribution Supported Fair Modeling:** An equal distribution of male and female participants contributed to unbiased model training and reliable comparative analysis across gender groups.
7. **SVR Captured Non-Linear Health Patterns Well:** The kernel-based learning approach of SVR allowed it to adapt to complex relationships in physiological data, which ensemble tree methods may not have captured as effectively within this dataset.
8. **Power BI Visualizations Enhanced Interpretability:** Integrating Power BI into the analysis pipeline added a powerful layer of interpretability, making it easier to communicate the results through intuitive graphs and dashboards.
9. **Predictive Health Scoring Shows Real-World Potential:** The models, particularly SVR, showed strong promise for real-time health scoring systems powered by wearable devices, which could be used for preventive health monitoring and personalized insights.
10. **Scalable Framework for Digital Health Applications:** The research establishes a scalable and adaptable framework that can be expanded with larger datasets, more features, and deeper models for broader use in health analytics, insurance scoring, and wellness programs.

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