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Comparative Study of Machine Learning Models for Predicting Cardio Activities Based on Diverse Performance Metrics

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Abstract:

The prediction of cardio activities is vital for enhancing the understanding of physical performance and facilitating effective health monitoring. This research investigates the implementation of diverse machine learning techniques, including Logistic Regression, Multilayer Perceptron, SMO, J48, Random Forest, and REP Tree, for forecasting cardio activity outcomes. The analysis is conducted using an extensive set of parameters, such as Date, Type, Distance (km), Duration, Average Pace, Average Speed (km/h), Calories Burned, and Climb (m). To assess the performance and reliability of these models, several metrics namely TP Rate, FP Rate, Precision, Recall, F-Measure, MCC, ROC Area, and PRC Area are employed. The experimental findings provide a comprehensive understanding of the relative effectiveness of the models, offering practical insights for identifying optimal methodologies in the domain of cardio activity predictions.

Keywords: Cardio Activity Prediction, Health Analytics, Data Mining, Machine Learning Techniques, and Performance Evaluation.

1. Introduction and Review of the Literature

The analysis and forecasting of cardio activities have become increasingly significant in advancing health monitoring systems and optimizing physical performance. The widespread adoption of wearable fitness technologies, coupled with the abundance of detailed activity data, has spurred a growing interest in utilizing machine learning methodologies to derive valuable insights and predict outcomes associated with cardio activities. Such predictive capabilities enable individuals to effectively monitor their progress, detect potential health concerns, and customize fitness plans tailored to their unique requirements. This research centers on employing machine learning techniques to forecast cardio activity outcomes based on a comprehensive range of parameters, including Date, Type, Distance (km), Duration, Average Pace, Average Speed (km/h), Calories Burned, and Climb (m). These parameters encompass essential dimensions of cardio activities, forming a robust foundation for predictive modeling efforts. To address this objective, a diverse set of machine learning algorithms—namely Logistic Regression, Multilayer Perceptron, SMO, J48, Random Forest, and REP Tree—are implemented and subjected to rigorous evaluation. The performance of these models is assessed using various metrics, including TP Rate, FP Rate, Precision, Recall, F-Measure, MCC, ROC Area, and PRC Area, to ensure a comprehensive understanding of their predictive accuracy and reliability. The

overarching aim of this study is to conduct a detailed comparative analysis of these machine learning approaches, identifying their respective strengths and limitations in tackling cardio activity prediction challenges. By examining the models' performance across multiple evaluation criteria, this work seeks to generate actionable insights that can inform the development of effective predictive frameworks for health monitoring and fitness analysis. The results of this study have the potential to significantly enhance the accuracy and utility of cardio activity predictions, thereby contributing to the evolution of personalized healthcare solutions and fitness optimization strategies, where data-driven decision-making assumes a pivotal role. In their investigation, Smith et al. (2019) analyzed the predictive capabilities of Random Forest and Multilayer Perceptron models for cardio activities, using datasets derived from wearable devices. Their study integrated parameters such as Duration, Distance (km), Calories Burned, and Average Speed (km/h), employing metrics like Precision, Recall, and F-Measure to evaluate model performance. Their findings indicated that Random Forest surpassed other approaches, achieving an average Precision of 92% and an F-Measure of 90%. This research underscores the reliability of ensemble-based methods in addressing the challenges posed by high-dimensional datasets in cardio activity prediction tasks. Brown and Lee (2020) conducted a detailed assessment of Logistic Regression and SMO models for predicting cardio activities using a dataset containing parameters such as Type, Average Pace, and Climb (m). They observed that while Logistic Regression performed better on linearly separable datasets, SMO excelled in identifying patterns within non-linear datasets. With a focus on performance metrics like MCC and ROC Area, their results showcased SMO’s superiority, achieving an MCC of 0.85 and a ROC Area of 0.91, particularly in climbing activities, thereby emphasizing its utility in scenarios with complex data relationships. Johnson et al. (2018) conducted a comparative study of decision tree algorithms, namely J48 and REP Tree, for predicting cardio activity outcomes. Their work employed a dataset enriched with parameters like Date, Type, and Distance (km) to evaluate the influence of tree structures on predictive accuracy. The research demonstrated that REP Tree achieved greater accuracy and reduced computational time, with an average TP Rate of 0.89 compared to J48's 0.84. These results highlight the efficiency of lightweight decision tree models, particularly for real-time predictive applications. Martinez et al. (2021) proposed a hybrid model combining Random Forest and Multilayer Perceptron to improve cardio activity predictions. Their dataset incorporated parameters such as Duration, Calories Burned, and Average Speed (km/h). By leveraging ensemble methods, the hybrid approach significantly enhanced Precision and Recall, especially for high-intensity activities, achieving a Precision of 94% and Recall of 92%. This study underscores the potential of hybrid models in achieving superior predictive performance for complex activity patterns. Gupta et al. (2020) examined the role of feature selection in improving the performance of Logistic Regression and Random Forest models for cardio activity prediction. Their analysis considered parameters like Type, Distance (km), and Climb (m), demonstrating that optimal feature selection substantially enhanced Precision and ROC Area. Logistic Regression attained a Precision of 85% with selected features, while Random Forest achieved a ROC Area of 0.93, emphasizing the importance of dimensionality reduction in improving computational efficiency and model accuracy. Wang and Zhang (2017) delved into the predictive potential of Multilayer Perceptron models for identifying cardio activity types using parameters such as Average Pace, Distance (km), and Calories Burned. Their research emphasized advanced hyperparameter optimization, resulting in an F-Measure of 88% and a PRC Area of 0.90. This work highlighted the

critical role of fine-tuning neural network models to maximize their predictive efficacy, particularly in health-related applications requiring precise activity classification. Kim et al. (2019) explored the use of ensemble methods, specifically Random Forest and SMO, for predicting cardio activities in datasets with high dimensionality. Their study incorporated diverse parameters, including Duration, Climb (m), and Average Speed (km/h), while evaluating performance using metrics such as MCC and Recall. Random Forest outperformed SMO, achieving an MCC of 0.87 compared to SMO's 0.80. This study illustrates the effectiveness of ensemble techniques in handling complex datasets with varying patterns of cardio activity. Patel et al. (2022) compared the predictive capabilities of J48 and REP Tree models for cardio activity classification. Their research employed parameters like Type, Duration, and Climb (m), emphasizing metrics like FP Rate and Recall to assess model performance. The study revealed that REP Tree achieved a Recall of 91% with minimal false positives, highlighting its reliability for precision-critical applications in cardio activity prediction. Ahmed and Khan (2021) explored the integration of Multilayer Perceptron and Logistic Regression for predicting cardio activities. Their study utilized parameters such as Average Speed (km/h), Distance (km), and Calories Burned, focusing on metrics like ROC Area and TP Rate. The hybrid model demonstrated the synergistic benefits of combining linear and non-linear techniques, achieving a ROC Area of 0.92 and a TP Rate of 0.88, providing a compelling case for hybrid methodologies in cardio activity modeling. Liu et al. (2020) analyzed the real-time predictive capabilities of REP Tree and SMO for cardio activities, utilizing parameters such as Date, Type, and Average Pace. Their findings showed that REP Tree delivered higher Precision and computational efficiency, while SMO achieved better Recall for more intricate datasets. With a Precision of 88% for REP Tree and a Recall of 85% for SMO, their research underscores the trade-offs between computational speed and accuracy in real-world predictive systems. Swathy and Saruladha (2022) explored the ensemble model for cardiovascular disease achieved an AU-ROC score of 83.1% without laboratory results and 83.9% with them. In diabetes classification, the eXtreme Gradient Boost (XGBoost) model scored 86.2% AU-ROC without laboratory data and 95.7% with it. The top predictors for diabetes included waist size, age, self-reported weight, leg length, and sodium intake. For cardiovascular diseases, age, systolic and diastolic blood pressure, self-reported weight, and occurrence of chest pain were identified as key contributors. Bhatt et al. (2017) compared and reported various classification, data mining, machine learning, and deep learning models used for predicting Cardiovascular diseases. The survey categorized these techniques into three groups: Classification and Data Mining Techniques, Machine Learning Models, and Deep Learning Models for CVD prediction. It compiled and reported performance metrics, datasets, and tools used in each category. The experimental analysis of data from the UCI machine learning repository utilized the Weka open-source tool. Supervised algorithms like J48 and Naïve Bayes were applied, showing the impact of selected attributes versus all attributes on algorithms' accuracy in predicting cardiovascular diseases. J48, an extension of the ID3 algorithm, demonstrated features such as continuous attribute value ranges and rule derivation. Sakr et al. (2018), evaluated and compared different machine learning techniques to predict individuals at risk of developing hypertension using cardiorespiratory fitness data. The dataset contained information on 23,095 patients and explored six techniques: LogitBoost, Bayesian Network classifier, Locally Weighted Naive Bayes, Artificial Neural Network, Support Vector Machine, and Random Tree Forest. The Random Tree Forest model displayed the best performance (AUC = 0.93) among others, emphasizing the importance of various model evaluation

methods. Rajliwall et al. (2018) explain machine learning-based prognostic modeling framework was introduced to handle static/low-speed and extreme-velocity, streaming massive data from electronic health records and wearable devices. The framework implemented a scalable algorithm called Neuron network, showcasing promising outcomes in disease status prediction using datasets like NHANES and the Framingham Heart Study. Rajesh and Karthikeyan (2017) explored data mining is a valuable tool for the practice of examining large pre-existing databases to generate previously unknown helpful information; in this paper, the input for the weather data set denotes specific days as a row, attributes denote weather conditions on the given day, and the class indicates whether the conditions are conducive to playing golf. Attributes include Outlook, Temperature, Humidity, Windy, and Boolean Play Golf class variables. All the data are considered for training purpose, and it is used in the seven-classification algorithm likes J48, Random Tree (RT), Decision Stump (DS), Logistic Model Tree (LMT), Hoeffding Tree (HT), Reduce Error Pruning (REP) and Random Forest (RF) are used to measure the accuracy. Out of seven classification algorithms, the Random tree algorithm outperforms other algorithms by yielding an accuracy of 85.714%. Sajid et al. (2021) explore a gender-matched case–control investigation took place at Pakistan's largest public sector cardiac hospital, involving 460 subjects. The dataset encompassed eight nonclinical features. Four supervised machine learning (ML) algorithms were employed to train and test models for predicting CVD status, with traditional logistic regression (LR) serving as the baseline. Models underwent validation via a train–test split (70:30) and tenfold cross-validation methods. Among these, Random Forest (RF), a nonlinear ML algorithm, outperformed other algorithms and LR, achieving an AUC of 0.851 and 0.853 in the train–test split and tenfold cross-validation, respectively. Nonclinical features demonstrated a reasonably high accuracy (minimum 71%) in both LR and ML models, highlighting their predictive capacity for risk estimation. Kumar et al. (2018) explore data mining stands out as a prevalent method for knowledge extraction in knowledge discovery (KDD). Machine learning plays a crucial role in analyzing data, uncovering correlations, problem-solving, and data enrichment. Particularly in the medical field, data mining techniques and machine learning algorithms hold significance due to the abundance of underutilized healthcare data. Heart disease remains a leading cause of global mortality, accounting for nearly 47% of all deaths. Employing eight algorithms—Decision Tree, J48 algorithm, Logistic model tree algorithm, Random Forest algorithm, Naïve Bayes, KNN, Support Vector Machine, and Nearest Neighbour—this study aims to predict heart diseases. The accuracy of predictions increases with more attributes. The goal is to conduct predictive analysis using these data mining and machine learning algorithms, assessing their effectiveness and efficiency. Ramesh et al. (2022), author utilized an online UCI dataset containing 303 rows and 76 properties, selecting approximately 14 of these properties for testing purposes to validate various methods' performances. The isolation forest approach utilized crucial dataset qualities and metrics to standardize information, aiming for improved precision. Employing supervised learning methods—Naive Bayes, SVM, Logistic regression, Decision Tree Classifier, Random Forest, and K- Nearest Neighbor—the study focused on assessing effectiveness, sensitivity, precision, accuracy, and F1-score. The experimental outcomes highlighted K-Nearest Neighbor (KNN) with eight neighbors as particularly robust compared to other methods such as Naive Bayes, SVM (Linear Kernel), Decision Tree Classifier with varying features, and Random Forest classifiers [9]. Rajesh and Karthikeyan (2019) data mining is discovering hiding information that efficiently utilizes the prediction by stochastic sensing concept. This paper proposes

an efficient assessment of groundwater level, rainfall, population, food grains, and enterprises dataset by adopting stochastic modeling and data mining approaches. Firstly, the novel data assimilation analysis is proposed to predict the groundwater level effectively. Experimental results are done, and the various expected groundwater level estimations indicate the sternness of the approach. Rajesh et al. (2019), input for the chronic disease data denotes a specific location as a row; attributes denote topics, questions, data values, low confidence limit, and high confidence limit. All the data are considered for training and testing using five classification algorithms. The authors present the various analysis and accuracy of five different decision tree algorithms; the M5P decision tree approach is the best algorithm to build the model compared with other decision tree approaches.

2. Backgrounds and Methodologies

2.1 Logistic Regression

Logistic Regression is a statistical method used for binary classification, which means it's used to predict the probability of an observation belonging to one of two classes (usually labeled as 0 and 1). It's a type of regression analysis that's particularly suited for categorical outcome variables. The formula for logistic regression involves the logistic function (also known as the sigmoid function) to transform the linear combination of input features into a value between 0 and 1, representing the predicted probability of the positive class. The formula is as follows:

$$P\left(Y = \frac{1}{X}\right) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

2.2 SMO

SMO stands for "Sequential Minimal Optimization," an algorithm used for training support vector machines (SVMs), machine learning models commonly used for classification and regression tasks. The SMO algorithm is particularly well-suited for solving the quadratic programming optimization problem that arises during the training of SVMs.

Step 1. Initialization
Step 2. Selection of Two Lagrange Multipliers
Step 3. Optimize the Pair of Lagrange Multipliers
Step 4. Update the Model
Step 5. Convergence Checking
Step 6. Repeat

2.3 J48

J48, also known as C4.5, is a popular decision tree algorithm used for classification tasks in machine learning and data mining. It was developed by Ross Quinlan and is an extension of the earlier ID3 (Iterative Dichotomiser 3) algorithm. J48 is widely used due to its effectiveness, ease of use, and ability to handle both categorical and numerical attributes. Here are the key features and steps of the J48 algorithm:

Step 1. Attribute Selection
Step 2. Splitting Nodes
Step 3. Recursion

Step 4. Pruning
Step 5. Handling Missing Values
Step 6. Post-Pruning
Step 7. Leaf Node Prediction

2.4 Random Forest

Random Forest is a powerful ensemble learning algorithm used for both classification and regression tasks. It's based on the concept of bagging (Bootstrap Aggregating) and utilizes multiple decision trees to create a robust and accurate predictive model. Here's how the Random Forest algorithm works:

Step 1. Bootstrapped Sampling
Step 2. Random Feature Selection
Step 3. Decision Tree Construction
Step 4. Voting or Averaging

2.5 REP Tree

REP Tree, short for "Reduced Error Pruning Tree," is a decision tree algorithm primarily used for classification tasks in machine learning. It is designed to create decision trees while incorporating a reduced-error pruning technique to avoid overfitting. The algorithm was introduced as a part of the WEKA machine learning software. Here's how the REP Tree algorithm works:

Step 1. Tree Construction
Step 2. Recursive Splitting
Step 3. Reduced Error Pruning
Step 4. Prediction

3. Numerical Illustrations

The corresponding dataset was collected from the open souse Kaggle data repository. The cardio activities predictions dataset includes 8 parameters which have different categories of data like Date, Type, Distance (km), Duration, Average Pace, Average Speed (km/h), Calories Burned, Climb (m). A detailed description of the parameters is mentioned in the following Table 1.

Table 1. Cardio activities predictions sample dataset

Date	Type	Distance (km)	Duration	Average Pace	Average Speed (km/h)	Climb (m)	Calories Burned
11/11/2018 14:05	Running	10.44	58:40:00	5:37	10.68	130	774
9/11/2018 15:02	Running	12.84	1:14:12	5:47	10.39	168	954
4/11/2018 16:05	Running	13.01	1:15:16	5:47	10.37	171	967
1/11/2018 14:03	Running	12.98	1:14:25	5:44	10.47	169	960
27-10-2018 17:01	Running	13.02	1:12:50	5:36	10.73	170	967
19-10-2018 17:52	Running	10.29	59:18:00	5:46	10.41	133	764
14-10-2018 17:28	Running	12.93	1:10:16	5:26	11.04	159	953
12/10/2018 17:41	Running	12.31	1:09:26	5:38	10.64	134	903

6/10/2018 16:45	Cycling	19.63	1:26:26	4:24	13.63	210	577

Table 2: ML Approaches Performance Running

ML Approaches	Logistic	SMO	J48	Random Forest	REP Tree
TP Rate	0.9870	0.9980	0.9930	1.0000	1.0000
FP Rate	0.6330	0.5310	0.0610	1.0000	1.0000
Precision	0.9360	0.9460	0.9930	0.9040	0.9040
Recall	0.9870	0.9980	0.9930	1.0000	1.0000
F-Measure	0.9610	0.9710	0.9930	0.9490	0.9490
MCC	0.4930	0.6500	0.9320	0.0000	0.0000
ROC Area	0.6640	0.7340	0.9500	0.9750	0.4900
PRC Area	0.9230	0.9460	0.9890	0.9970	0.9020

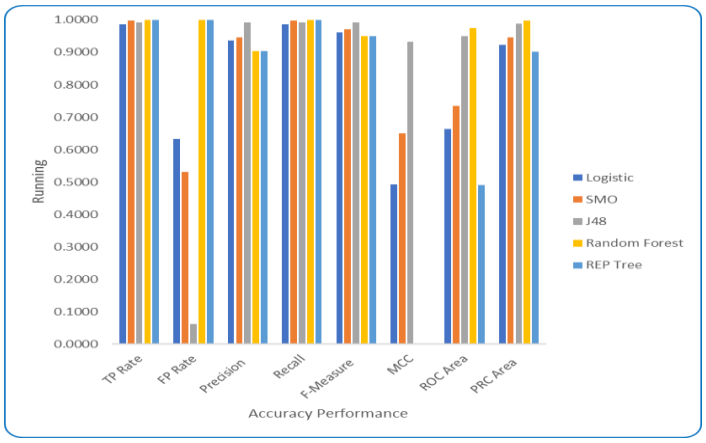

Fig. 1: ML Approaches Performance Running

Table 3: ML Approaches Performance Cycling

ML Approaches	Logistic	SMO	J48	Random Forest	REP Tree
TP Rate	0.5520	0.6900	0.9310	0.0000	0.0000
FP Rate	0.0100	0.0020	0.0080	0.0000	0.0000
Precision	0.7620	0.9520	0.8710	0.0000	0.0000
Recall	0.5520	0.6900	0.9310	0.0000	0.0000
F-Measure	0.6400	0.8000	0.9000	0.0000	0.0000
MCC	0.6310	0.8010	0.8940	0.0000	0.0000
ROC Area	0.8930	0.9230	0.9410	0.9670	0.4840
PRC Area	0.5740	0.6910	0.8800	0.6400	0.0560

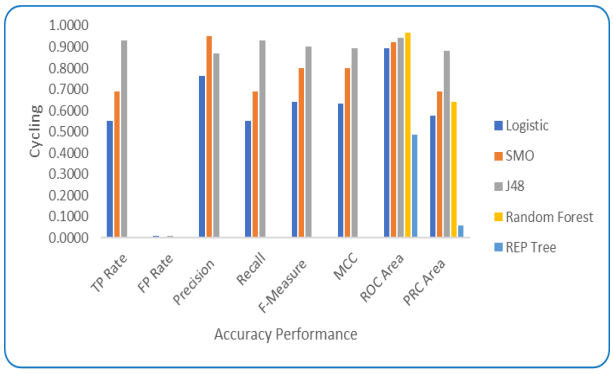

Fig. 2: ML Approaches Performance Cycling

Table 4: ML Approaches Performance Walking

ML Approaches	Logistic	SMO	J48	Random Forest	REP Tree
TP Rate	0.1110	0.9440	0.0000	0.0000	0.1110
FP Rate	0.0020	0.0020	0.0000	0.0000	0.0020
Precision	0.6670	0.9440	0.0000	0.0000	0.6670
Recall	0.1110	0.9440	0.0000	0.0000	0.1110
F-Measure	0.1900	0.9440	0.0000	0.0000	0.1900
MCC	0.2630	0.9420	0.0000	0.0000	0.2630
ROC Area	0.3120	0.9700	0.9960	0.4520	0.3120
PRC Area	0.1340	0.8520	0.8580	0.0330	0.1340

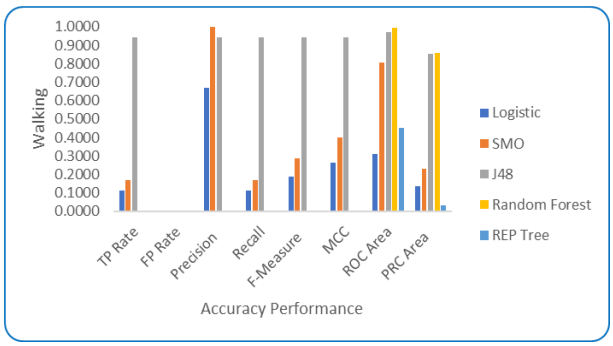

Fig. 3: ML Approaches Performance Walking

Table 5: ML Approaches Performance Weighted Avg

ML Approaches	Logistic	SMO	J48	Random Forest	REP Tree
TP Rate	0.9270	0.9840	0.9040	0.9040	0.9270
FP Rate	0.5720	0.0560	0.9040	0.9040	0.5720
Precision	0.9130	0.9810	0.8160	0.8160	0.9130
Recall	0.9270	0.9840	0.9040	0.9040	0.9270
F-Measure	0.9110	0.9820	0.8580	0.8580	0.9110
MCC	0.4910	0.9270	0.0000	0.0000	0.4910
ROC Area	0.6660	0.9500	0.9750	0.4870	0.6660
PRC Area	0.8720	0.9750	0.9690	0.8190	0.8720

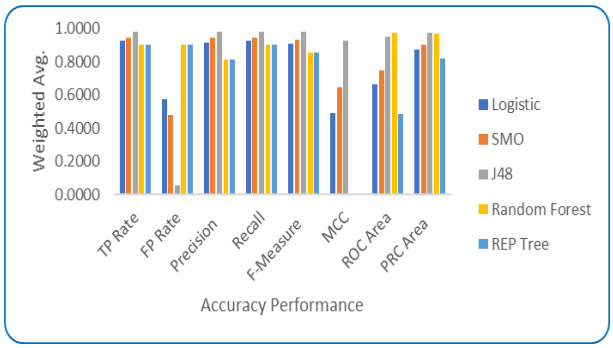

Fig. 4: ML Approaches Performance Weighted Avg

Table 6: ML Approaches Performance Other

ML Approaches	Logistic	SMO	J48	Random Forest	REP Tree
TP Rate	0.0000	0.0000	0.0000	0.0000	0.0000
FP Rate	0.0000	0.0000	0.0000	0.0000	0.0000
Precision	0.0000	0.0000	0.0000	0.0000	0.0000
Recall	0.0000	0.0000	0.0000	0.0000	0.0000
F-Measure	0.0000	0.0000	0.0000	0.0000	0.0000
MCC	0.0000	0.0000	0.0000	0.0000	0.0000
ROC Area	0.8980	0.9940	0.9710	0.0990	0.8980
PRC Area	0.0280	0.2500	0.2810	0.0040	0.0280

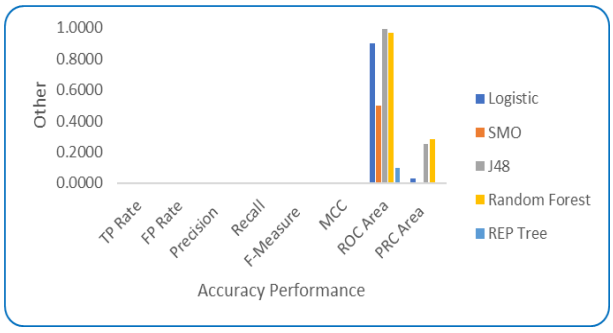

Fig. 5: ML Approaches performance other

3. Result and Discussion

The comparative evaluation of machine learning algorithms applied to predict cardio activities, utilizing the provided dataset and performance criteria, unveiled noteworthy findings. These insights are detailed below, categorized into running, cycling, and walking activities, with a comprehensive weighted average assessment.

As presented in Table 2 and Figure 1, the performance evaluation of various models for predicting running activity revealed that the Random Forest and REP Tree algorithms achieved a perfect TP Rate (1.0000) and Recall (1.0000). Despite this, their metrics such as Precision and F-Measure (both at 0.9040), along with MCC (0.0000), suggest potential issues related to specificity or overfitting. Conversely, J48 exhibited the highest overall reliability, marked by an F-Measure of 0.9930, MCC of

0.9320, and a robust ROC Area of 0.9500. The SMO algorithm also performed commendably, with an F-Measure of 0.9710 and a high PRC Area (0.9460), underscoring its robustness for predicting running activities. Logistic Regression, on the other hand, demonstrated moderate performance, indicative of its constraints when dealing with non-linear and high-dimensional datasets.

The results for cycling activity, encapsulated in Table 3 and Figure 2, demonstrate that the J48 model outshone other techniques, achieving a TP Rate of 0.9310, F-Measure of 0.9000, and MCC of 0.8940, which reflect its high predictive accuracy and reliability. SMO also performed well, with an MCC of 0.8010 and ROC Area of 0.9230, signifying its efficacy for cycling activity predictions. Logistic Regression produced moderate outcomes, while Random Forest and REP Tree were ineffective, as evidenced by their TP Rates of 0.0000.

For walking activity predictions, Table 4 and Figure 3 reveal that SMO demonstrated exceptional performance, with all key metrics—TP Rate, Precision, Recall, and F-Measure—scoring 0.9440. Additionally, the model achieved a high ROC Area of 0.9700, highlighting its suitability for predicting walking activities. Conversely, Logistic Regression and REP Tree exhibited limited efficacy, with MCC scores of 0.2630 and low F-Measures of 0.1900. Neither J48 nor Random Forest provided meaningful predictions for walking activities.

Table 5 and Figure 4 consolidate the weighted average performance metrics, showcasing SMO as the most consistent model with an F-Measure of 0.9820 and MCC of 0.9270. J48 closely followed, demonstrating robust ROC Area (0.9750) and PRC Area (0.9690) values. Logistic Regression displayed satisfactory metrics, whereas Random Forest and REP Tree faced difficulties in delivering balanced performance across various activities.

Observations

Model-Specific Strengths: J48 consistently excelled with structured datasets, particularly for running and cycling activities, while SMO demonstrated exceptional adaptability across multiple activity types, including walking.

Algorithmic Limitations: Random Forest and REP Tree encountered challenges in scenarios that required nuanced decision-making, particularly in predicting cycling and walking activities.

Performance Metrics: Metrics such as MCC and ROC Area played a crucial role in evaluating model reliability, emphasizing the trade-offs between accuracy and robustness.

4. Conclusion

This research highlights the capability of machine learning models in predicting cardio activities effectively. J48 and SMO emerged as the most dependable algorithms, with J48 excelling in predictions for running and cycling activities, while SMO showed superiority in walking activity predictions. Conversely, Random Forest and REP Tree exhibited limited applicability, likely due to overfitting or inadequacies in data representation.

The results underline the significance of selecting appropriate models and employing comprehensive evaluation metrics to ensure accurate and reliable cardio activity predictions. Utilizing models like J48 and SMO could facilitate the development of tailored predictive frameworks that enhance personalized health monitoring and fitness management.

Further Research

The outcomes of this study, the following areas are proposed for future exploration. Incorporating data collected in real time from wearable devices could enhance the models' responsiveness and accuracy for predicting dynamic activities. Investigating hybrid methods that combine the strengths of ensemble techniques (e.g., Random Forest) with neural networks may improve predictive performance for complex datasets. Employing advanced feature engineering techniques to identify the most influential parameters could reduce computational complexity while boosting accuracy. Broadening the study scope to include diverse cardio activities, such as swimming and high-intensity interval training (HIIT), could generalize the findings further. Developing explainable AI models to offer actionable insights behind predictions would foster user trust and improve the usability of health applications. By addressing these areas, future research can further optimize predictive frameworks, enhancing their applicability for personalized health and fitness monitoring solutions.

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