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Human–AI Collaboration Models For Decision Support Systems

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Abstract
Human–Artificial Intelligence (AI) interaction in intelligent interfaces is crucial for developingcollaborative decision support between users and Machine Learning (ML) algorithms, particularly in applications involving smartwatches for healthcare. Nevertheless, the effects of interface design and interpretability techniques related to user trust, cognitive load, and decision quality in these types of applications have not been thoroughly investigated. The objective of the research is to design a human-centered intelligent interface and assess its interpretability, usability, and impact on decision-making performance, while increasing the accuracy of prediction results through a hybrid approach. The proposedGlow Worm Swarm Optimization- Dynamic K-NearestNeighbor (GWSO-DKNN) solution employs sensor data from smartwatches such as heart rate, movement, sleep, and activity information. Data preprocessing is performed using the Min-Max Normalization technique, whereas the Fast Fourier Transform (FFT) method is utilized for feature extraction in physiological time-series signals. An experiment is carried out to test multiple interface designs, while performance measures include accuracy, recall, F1-score, and log loss. The proposed GWSO-DKNN model demonstrates high precision of 96.77%, recall of 98.36%, F1-score of 97.56%, and low log loss of 5.62%, it can lead to improved user understanding. Both the development and evaluation of the proposed model are conducted within the Python programming environment. The proposed GWSO-DKNN classifier demonstrates higher performance compared to conventional classifiers like Random Forest (RF), Support Vector Machine (SVM), Naive Bayes, Logistic Regression (LR), and Perceptron.

Keywords: Human–AI Interaction, Intelligent Interfaces, Machine Learning, Decision Support Systems ,Smartwatch-Based Healthcare, Wearable Sensors.

1. Introduction

The use of information systems powered by AI technology is revolutionizing the way humans work; with the aid of firms utilizing interactive systems such as decision support and expert systems to effectively solve complex problems. Computing technology has evolved significantly in capability and human-machine interface with new developments [1, 2].As AI continues to become a part of everyday life, there is a need for knowledge on the psychological aspects of the interaction between AI and humans. AI technologies, particularly when designed to interact socially like ChatGPT, are very useful in assisting humans psychologically [3].The infrequent monitoring of vital signs can fail to detect abnormalities in time, leading to potential health hazards. With advancements in technology, wearable health monitoring devices have emerged to continuously monitor multiple physiological parameters, both in stationary conditions and during movement. These devices integrate sensors, microcontrollers, memory chips, radios, and battery power sources to form a wireless body area network, commonly referred to as a Wireless Body Area Network (WBAN) [4]. Walking can be effectively monitored using devices such as smartphones, smartwatches, and wearable accelerometers. It supports daily activities such as commuting, helps maintain a healthy body weight, and contributes to the prevention of various health conditions, including heart disease, high blood pressure, cognitive decline, and type 2 diabetes. Body-worn devices provide insights into quality of life and walking-related biomarkers, though large-scale implementation with open methods remains challenging [5].Healthcare monitoring devices enabled through innovations in electronics, materials science, biology, and Internet of Things (IoT) connectivity supportnon-invasive sampling of body fluids and transmission of information to mobilephones and medical practitioners [6].

Research aim: Research is intended to design a human-oriented adaptive interface model which utilizes the Human-AI Intelligent Interface dataset to monitor and predict physiological conditions and behavioral patterns in smartwatch-based healthcare systems. The proposed framework integrates Dynamic K-Nearest Neighbor (DKNN) with the Glowworm Swarm Optimization Algorithm (GWSO) to enhance prediction accuracy, improve Human-AI interaction in healthcare decision-making processes, and increase the interpretability, reliability, and trustworthiness of Human-AI systems.

Research organization: The structure of the research areas follows:Section 1 introduces the human-AI interaction and smartwatch healthcare systems. Section 2 presents the related work on wearable intelligence and intelligent Machine Learning (ML) methods. Section 3 outlines the methodology of collecting and analyzing the data, which includes data preprocessing, feature extraction, and the proposed hybrid intelligent system. Section 4 discusses the results and visualization analysis.Section 5 represents the conclusion and outlines future research directions.

2. Related work

Research [7] introduced a Three-layer Fog computing (tri-fog) health architecture based onFuzzy Adaptive Multi-Objective Optimization based on Ratio Analysis (FaMOORA),Robust Kernel Principal Component Analysis (RK-PCA), Two-Layer Two-Hidden Markov Model (2L-2HMM), and Spiking Quantum Network (SpikQ-Net) for analyzing wearable physiological data with a high accuracy rate and low latency, but still faces the problems of fog overload and emergency handling [7].ML-Based Rate-Adaptive Service Provisioning Framework(ML-RASPF) was proposed in this research [8], itminimizes latency and service delivery in IoT-enabled health care using the mist-edge-cloud model, where latency is minimized by 20%, delivery rateandincreased by 18%, and energy consumption is decreased by 19%. Research[9]suggested an AI-based wearable device monitoring system combined with Hyperledger Fabric blockchaintechnology for managing chronic diseases, which attained 96% accuracy, 91.79% precision, and 94.72% sensitivity. Research [10]proposed ML techniques for non-invasive sleep staging based on heart rate and motion features, reporting that ensemble-based algorithms can reach an accuracy of up to 82%, indicating the potential for long-term sleep analysis using wearable or even contactless devices. TheWEAR-ME research utilizes time-series data from wearable devices, standard biomarkers, and Deep Learning(DL) networks [11]to predict insulin resistance resulting inArea Under the Receiver Operating Characteristic Curve(AUROC) with 0.88, which indicates a project is scalable in predicting metabolic risks and recommending personalized changes to avoid type 2 diabetes. Transpose-Enhanced AutoEncoder Network (TEANet)[12] detects mental stress through Blood Volume Pulse (BVP) signals captured by wearables with an accuracy rate of up to 96.94 percent and a Cohen's Kappa score of 0.935, surpassing all existing models.Tree-basedMLwas used for spectrum sensing in cognitive radio-assisted smart healthcare. The research [13] intended to increase data transmission efficiency. The optimized tree can achieve the highest accuracy. However, it needs additional evaluation against DL models.

The research [14] suggested a knowledge distillation technique to perform human activity recognition using the sensor data from the smartwatch to enable Human Activity Recognition (HAR) using resource-constrained devices. The approach achieves an optimalaccuracy, although hardware constraints could impede the integration of multiple sensory inputs. A light one-dimensional Convolutional Neural Network (CNN) model with squeeze-and-excitation attention to detect arrhythmia based on beat-level electrocardiogram signals, with best accuracy levels, although very low-power devices can pose some challenges in terms of computation [15].The research in [16] enhances the protection in intelligent healthcare systems by integrating Artificial Intelligence (AI) and blockchain technology to detect malware and network attacks targeting wearable devices. In the performance analysis of different types of MLmodels, the Random Forest (RF) model gave the best result in terms of accuracy of 93%, while Support Vector Machine (SVM) scored 83% and Logistic Regression (LR) obtained only 44% accuracy, whereas Naïve Bayes(NB) scored 67% accuracy.

3. Methodology

The method starts by collecting data from the Human-AI Intelligent Interface dataset, which includes smartwatchsensor values like heart rate, motions, sleep, and physical activities data. The collected data is preprocessed with the help of the Min-Maxnormalization process, which results in acquiringclean healthcare data.The second stage includes the Fast Fourier Transform (FFT), whereby the signal information from the time domain is transformed to frequency domain to facilitate better feature extraction. These features will be used by the suggested GWSO-DKNN model to predict healthcare outcomes intelligently, as shown in Figure 1.

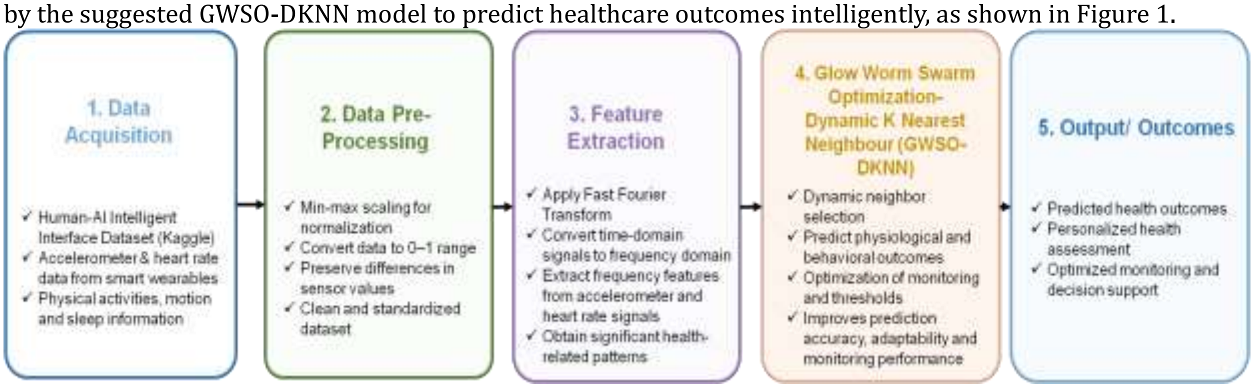

Figure 1: Methodology flow of the proposed model

3.1 Data Acquisition

Dataset used in this research was taken from the Kaggle source (https://www.kaggle.com/datasets/zara2099/human-ai-intelligent-interface-dataset/data), which has 4000 readings taken from smart wearable's such as accelerometers and heart rate monitors. The dataset includes information on human activities and their interactions with intelligent interfaces, which can be used to analyze the level of physical activities and motion behavior. To conduct an effective evaluation of the system, that use 80% of the dataset for training while leaving 20% for the test dataset.

3.2 Data Preprocessing using Min-Max scaling

The min-max scaling technique is applied to scale the sensor data to a standardized scale, usually from zero to one, while preserving the differential between the data. In the Human-AI Intelligent Interface dataset, Min-Maxscaling is employed to normalize features in the sensor data to facilitate a fair comparison for analysis of Human-AI interaction in a healthcare system through wearable technology. As a result of normalization, all features can play an equal role in the analysis process.

$$f' = \frac{f - \min(\max_k - \min_k)}{\max - \min} + \min_k \quad (1)$$

In Equation (1), f'denotesthe normalized value of the smartwatch health care feature, f refers to the original value of the smartwatch feature,min and max are the minimum values and maximum values respectively,$\max_k$ and $\min_k$ refer to the minimum value of feature attribute, and maximum value of the healthcare feature attribute, and k represents the feature of the healthcare.

3.3 Feature extraction using Fast Fourier Transform (FFT)

The FFT changes time domain signals to frequency domain signals, which helps in the accurate analysis of physiological signals generated by smart wearable devices. The acceleration sensors and heart rate sensors from the Human-AI Intelligent Interface Dataset help in identifying patterns related to physical activities, gait analysis, and other health-related functions. The FFT formula is given by Equation (2).

$$W(l) = \sum_{m=0}^{M-1} w(m) X_M^{ml}, \quad l = 0,1,\ldots,M-1 \quad (2)$$

Where $w(m)$ denotes the discrete smartwatch health care signal, $W(l)$ refers to the frequency domain signal obtained from the smartwatch health care signal, $\frac{i2\pi}{M}$ refers to the number of sensor samples obtained from smartwatches, $\sum_{m=0}^{M-1}$ denotes the summation of all sensor reading and X_M^{ml} refers to the twiddle factor is depicted as Equation (3).

$X_M^{ml} = f - \frac{i2\pi}{M}.ml = f^{-i\theta} = (\cos\theta - i\sin\theta)$ (3)

Where, m denotes the frequency corresponding to physiological activities, l denotes the discrete sampling time of smartwatch sensor data,i represents to the imaginary component in signal processing, f^{-}refers to the sensor signal, $\cos\theta$ refers to the original component of frequency,$\sin\theta$ refers to the imaginary component of frequency,θ refers to the phase angle of the signal, X denotes the coefficient of the frequency transformation, and π denotes the circumference of the circle .The Complicated signal sample is denoted by Equation (4).

$w(m) = BQ + iBJ$ (4)

Where w(m) denotes the discrete smartwatch health care signal, BQ and BJ represent the real and imaginary components of the sensor.In Equation (5), where X_M denotes the factor of the FFT.

$w(m) \times X_M = (BQ\cos\theta + BJ\sin\theta) + i(BJ\cos\theta - BQ\sin\theta)$ (5)

3.4 Smartwatch-based health monitoring system

The proposed GWSO-DKNN model improves the intelligent health monitoring process throughthe use of smartwatch sensors that gather data from Human-AI Intelligent Interface Dataset. The DKNN model makes predictions about physiological and behavioral results using data gathered through smartwatch sensors related to healthcare features like heartbeat rate, motion level, sleep activity, and physical exercises. The GWSO model increases the efficiency of prediction using intelligent knowledge update, interaction, and optimization of neighbor selection in healthcare nodes. The new hybrid model improves health prediction, adaptability learning, and monitoring performance in the Human-AI healthcare interface.

Healthcare Monitoring prediction using Dynamic K-Nearest Neighbor (DKNN): DKNN represents a modified form of the conventional KNN algorithm, designed specifically for predicting physiological and behavioral outcomes using wearable smart devices in healthcare. The algorithm relies on the Human-AI Intelligent Interface dataset, which comprises sensor data collected from various wearable devices, including smartwatches and accelerometers, recording physiological parameters like physical activities, heartbeat, and motion characteristics.

$\hat{\eta}_i = \sum_{L=L_{min}}^{L_{max}} X_i^L \eta_i^L$ (6)

In Equation (6), where $\hat{\eta}_i$ denotes the outcome of prediction in healthcare system, X_i^L refers to the weight of the features in the smartwatch, η_i^Lrepresents the value of features in the healthcare dataset,L_{max} and L_{min} are the maximum and minimum level of features,$i$refers the index of the dataset sample,Xdenotes coefficient of the feature, L refers to the level of the layers in features, and η refers to the parameter of prediction.

Hyperparameter tuning with Glow Worm Swarm Optimization (GWSO): In this research, GWSO is utilized for hyperparameter tuning to optimize the performance of machine learning models by selecting the most suitable parameter combinations from behavioral and physiological data collected through wearable technology. The integration of GWSO-based hyperparameter tuning enhances individualized health monitoring, improves intelligent interface responsiveness, and supports more accurate decision-making in wearable healthcare applications.

$K_j(s) = (1-o)K_j(s-1) + \gamma^I\left(W_j(s)\right)$ (7)

In Equation (7), where $K_j(s)$ represents the knowledge improvement in healthcare system,$o$denotes the rate of learning, $K_j(s-1)$represents the state of prior knowledge,γ^I denotes the activation function of intelligence I,$W_j(s)$denotes the input of sensor in smart watches,j denotes the index of the features in dataset, $s$denotesiteration of the time step, Irefers to the level of intelligence, K is the representation of knowledge, γ refers to theadaptive function in health prediction,K_j is the state of knowledge of the feature index, W_j refers to the data collected from the sensor with index j and the W represents the sensor data.

$M_j(s) = \{i \backslash c_{ji} \le q_c^j \Lambda K_i(s) \ge K_j(s)\}$ (8)

In Equation (8), where $M_j(s)$ represents the set of monitoring health data, q_c^jrefers to the value of threshold,$K_i(s)$ represents the state of the knowledge from the neighbor, i denotes the index of smart devices, M represents the group that monitor the health-related activities, q is the parameter of threshold, c denotes the cost of computation of sensors,c_{ji} refers to the cost computation among nodes,Λ denotes the operator of logical condition,$\le$ and $\ge$ denotes the lesser than and greater than operations.

$$Prob_{ji} = \frac{k_i - k_j(s)}{\sum_{l \in M_j(s)} k_l(s) - k_j(s)} \quad (9)$$

In equation (9), $Prob_{ji}$ refers to the probability of interaction of the nodes,k_i refers to the value of knowledge from the neighbor, $k_l(s)$ denotes the knowledge of the neighbor in health prediction, l denotes the index of neighbor nodes, and$\sum_{l \in M_j(s)}$ refers to the aggregation function of health monitoring.

$$W_j(s+1) = W_j(s) + t\left(\frac{W_i(s) - W_j(s)}{\|W_i(s) - W_j(s)\|}\right) \quad (10)$$

In Equation (10),$W_j(s)$denotes the input of sensor in smart watches,$W_j(s+1)$ represents the state of healthcare improvement, $W_i(s)$denotes the state of neighbor in healthcare, and$\|W_i(s) - W_j(s)\|$ represents the state of distance.

$$q_c^j(s+1) = min\,[qt, max\{0, q_c^j(s) + \beta(ms - |M_j(s)|\}] \quad (11)$$

In Equation (11), β denotes the factor of adaptive adjustment,ms refers to the number of arrivals,$|M_j(s)|$ denotes the current count of monitoring, max and min denotes the maximum and minimum values, $q_c^j(s)$ denotes the queue length, $q_c^j(s+1)$ refers to the updatedqueue value and t denotes the step of adaptation.
GWSO-DKNN improves the efficiency of Human-AI intelligent healthcare prediction systems using smartwatches, as depicted in the Algorithm 1.

Algorithm 1: Proposed GWSO-DKNN Model

Input: Smartwatch sensor dataset DDD, train-test ratio (70:30), k=1k = 1k=1 to 151515, GWSO parameters
Output: Predicted class YpredY_{pred}Ypred, Accuracy, Recall, F1-score, and Log-loss
Begin

1. Load smartwatch sensor dataset.
2. Preprocess the datawith Min-Max normalization.
3. Extract frequency-domain features using FFT.
4. Splitting of dataset into training (80 %) and testing (20 %) sets.
5. Initialize GWSO parameters and glowworm population.
6. Perform GWSO optimization to:
   - Update luciferin values
   - Select neighboring glowworms
   - Update glowworm positions
   - Determine optimal features and kkk value
7. Apply DKNN classification by:
   - Computing Euclidean distances
   - Selecting nearest neighbors
   - Predicting the class using weighted majority voting
8. Evaluate the performance of the model using Recall, F1-score,Log-loss, and Accuracy.

End

Hyperparameter of the proposed model: For GWSO, parameters such as population size and iteration number are set to 30 and 100 respectively. For luciferin, which signifies glow intensity, the initial value is 5 with an enhancement constant of 0.6, while the decay factor is set to 0.4. The step size and neighborhood radius are set to 0.03 and 5 respectively, with the number of candidate neighbors varying from 1 to 15. Euclidean distance determines the direction of movement for the agents.

4. Result

The implementation was carried out resulting inhighperformance computer setup that consists ofNVIDIA GeForce RTX 3060 GPU,512 GB SSD Drive, 16 GB RAM, andan Intel Core i7 Processor. The proposed architecture is implemented using the Python programming language version 3.11 in the Jupyter Notebook. Some of the popular libraries include Scikit-learn, NumPy, Pandas, and Matplotlib.

Explorative Data Analysis: Figure 2 represents the analysis of smartwatch health data, patterns, and evaluation of Human-AI interaction.Figure 2(a) depicts the signal variation of smartwatches during healthcare data analysis processes. Figure 2(b) describes the distribution of sleep times collected using wearable healthcare devices. Figure 2(c) showcases statistics on monitoring samples collected using smartwatch healthcare databases. Figure 2(d) exhibits healthcare attribute correlations for the Human-AI smartwatch interaction analysis process.

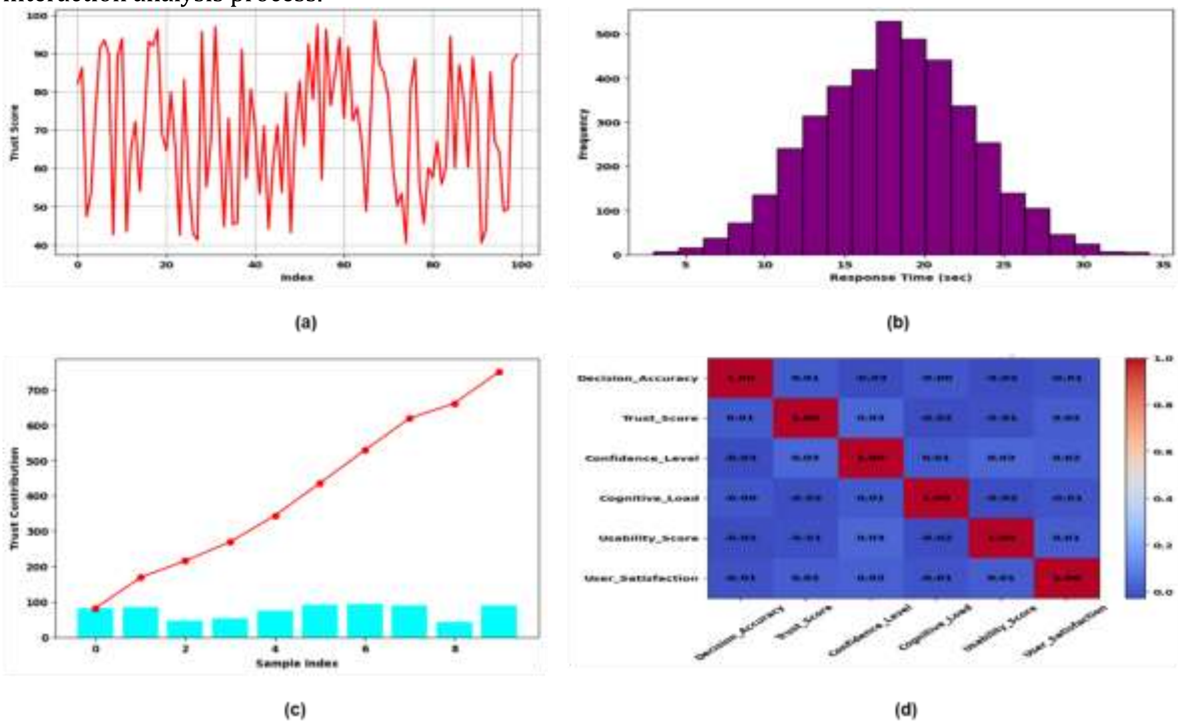

Figure 2: Visualization of (a) Smartwatch Signal Variation, (b) Sleep Pattern Time Distribution, (c) Trust Analysis, and (d) Correlation Matrix of Healthcare Features

Evaluation metrics: The evaluation is done using recall, precision, log-loss, and F1-score methods, which wereused for evaluating classification performance in the case of health prediction via Human-AI smartwatches. Precision is the percentage of the true positives out among all the positives predicted. Recall refers to ratio of correctly detected true positive by the classifier. F1 score refers to the calculated as a balance between precision and recall to give an overall classification measure. Log loss assesses the accuracy of predictions through penalties for inaccurate probability predictions in classification problems.

Performance analysis: Table 1 and Figure 3 provide the comparisons of several classification algorithms using recall, log loss,accuracy, and f-score values. RF classifier is highly effective, while SVM and naive Bayes classifiers provide average results. On the other hand, logistic regression and perceptron classifiers prove to have low efficiency due to their inability to capture complex data patterns in health care and wearables. The performance of the GWSO-DKNN is better than other classification methods, as its precision, recall, f-score values, and Log-Loss Score are 96.77%, 98.36%, 97.56%, and 5.62%respectively.

Table 1: Performance Analysis of ML methods with theProposedmethod

Algorithm	Precision (%)	Recall (%)	Log-Loss Score (%)	F1 Score (%)
RF [16]	93.24	92.99	6.34	93.67
SVM [16]	82.13	82.78	14.19	82.90
Naïve Bayes [16]	66.89	65.13	32.84	67.12
LR [16]	42.56	43.60	48.67	44.02
Perceptron [16]	32.90	33.53	69.89	33.19
GWSO-DKNN[Proposed]	96.77	98.36	5.62	97.56

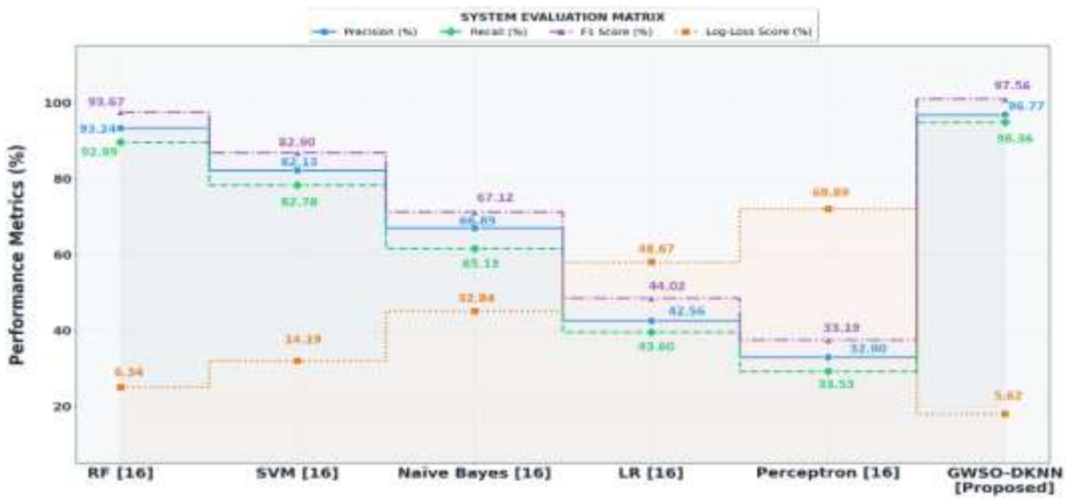

Figure 3: Performance Comparison of existing and proposed models

Using the Human–AI Intelligent Interface Dataset from Kaggle, all existing and proposed models were retrained and evaluated under the same experimental setup and training–testing splitting strategy to ensure a fair comparative analysis. Identical preprocessing procedures, feature extraction settings, and evaluation metrics were applied to all models. The comparative results show that the proposed GWSO-DKNN model outperformed all existing models under the same experimental setup and training–testing splitting conditions. The proposed model achieved the highest Recall,F1-Score, and Precision, while obtaining the lowest Log-Loss score, demonstrating improved prediction capability and classification robustness (Table 2).

Table 2:Retrained Analysis of Existing and Proposed Models

Algorithm	Precision (%)	Recall (%)	Log-Loss Score (%)	F1 Score (%)
RF	94.82	94.11	5.94	94.46
SVM	86.37	85.92	12.76	86.14
Naïve Bayes	71.45	70.88	28.31	71.16
LR	48.29	47.63	41.52	47.95
Perceptron	39.84	38.92	61.47	39.37
GWSO-DKNN [Proposed]	96.77	98.36	5.62	97.56

4.1 Discussion

The GWSO-DKNN model is superior to the existing models ofclassification because it improves accuracy, flexibility, and reliability in smartwatch-based Human-AI health monitoring through better management of complex, non-linear data patterns. RF [16] can become very computation-demanding when handling a higher level of feature complexity, while SVM [16] depends highly on the choice of kernels and is vulnerable to noisy high-dimensional input. Moreover, Naïve Bayes [16] assumes that features have no dependencies, making it impossible to apply to physiological data. LR [16] and Perceptron [16] models cannot effectively capture complex relationships betweenbehavioral and health-associated data. To overcome the drawbacks the suggested GWSO-DKNN model provides improvements to accuracy, adaptability, and robustness by detecting non-linearity in smartwatch data, overcoming computational constraints, and being superior to current classifiers in Human-AI interaction-based health monitoring systems.

5. Conclusion

A Human-AI interaction model was proposed for intelligent interfaces by making use of healthcare data via the application of smartwatch. DKNN and Glowworm Swarm Optimization have been used to develop the proposed model with the purpose of predicting behavioral and physiological patterns. Data preprocessing involved Min-Max normalization along with the FFT technique for feature extraction to effectively represent signals from wearable devices. Evaluation metrics of precision (96.77%), recall (98.36 %), F1-score (97.56%), and log-loss score (5.62%) showed that the GWSO-DKNN algorithm outperformed the traditional classifiers, which comprise of RF, Perceptron, SVM, LR, and Naive Bayes. GWSO-DKNN is more adaptable than other classifiers due to the complexities associated with nonlinear smartwatch data. Limitations of the research include dataset size, experimental control settings, and the use of pre-defined attributes of sensors. The future direction of this research will be towards the implementation of these techniques in real-world operational settings, the utilization of deep learning algorithms, multi-sensor fusion, and increasing scalability and interpretability in various healthcare settings.

References

1. Vann Yaroson, E., Abadie, A. and Roux, M., 2025. Human-artificial intelligence collaboration in supply chain outcomes: the mediating role of responsible artificial intelligence. Annals of Operations Research, 354(1), pp.35-69..https://doi.org/10.1007/s10479-025-06534-7
2. Vössing, M., Kühl, N., Lind, M. and Satzger, G., 2022. Designing transparency for effective human-AI collaboration. Information Systems Frontiers, 24(3), pp.877-895.https://doi.org/10.1007/s10796-022-10284-3
3. Yang, F. and Oshio, A., 2025. Using attachment theory to conceptualize and measure the experiences in human-AI relationships. Current Psychology, 44(11), pp.10658-10669.https://doi.org/10.1007/s12144-025-07917-6
4. Alzahrani, S., Nadershah, M., Alghamdi, M., Baabdullah, R., Bayoumi, M., Bawajeeh, O., Alghamdi, A. and Bayoumi, A., 2025. The use of Apple smartwatches to obtain vital signs readings in surgical patients. Scientific Reports, 15(1), p.10920. https://doi.org/10.1038/s41598-024-84459-0
5. Straczkiewicz, M., Huang, E.J. and Onnela, J.P., 2023. A "one-size-fits-most" walking recognition method for smartphones, smartwatches, and wearable accelerometers. NPJ digital medicine, 6(1), p.29. https://doi.org/10.1038/s41746-022-00745-z
6. Mastoi, Q.U.A., Alqahtani, A., Almakdi, S., Sulaiman, A., Rajab, A., Shaikh, A. and Alqhtani, S.M., 2024. Heart patient health monitoring system using invasive and non-invasive measurement. Scientific Reports, 14(1), p.9614.https://doi.org/10.1038/s41598-024-60500-0
7. Ijaz, M., Li, G., Wang, H., El-Sherbeeny, A.M., Moro Awelisah, Y., Lin, L., Koubaa, A. and Noor, A., 2020. Intelligent fog-enabled smart healthcare system for wearable physiological parameter detection. Electronics, 9(12), p.2015. https://doi.org/10.3390/electronics9122015
8. Rafique, W., 2025. Ml-raspf: A machine learning-based rate-adaptive framework for dynamic resource allocation in smart healthcare iot. Algorithms, 18(6), p.325. https://doi.org/10.3390/a18060325
9. Saxena, S., Saxena, S., Tahilramani, N. and Charanarur, P., 2025. Blockchain enhanced smart healthcare management for chronic diseases. Discover Computing, 28(1), p.112. https://doi.org/10.1007/s10791-025-09574-6
10. Sabbatini, L., Belli, A., Bruschi, S., Esposito, M., Raggiunto, S. and Pierleoni, P., 2026. Non-Invasive Sleep Stage Classification with Imbalance-Aware Machine Learning for Healthcare Monitoring. Big Data and Cognitive Computing, 10(4), p.116.https://doi.org/10.3390/bdcc10040116
11. Metwally, A.A., Heydari, A.A., McDuff, D., Solot, A., Esmaeilpour, Z., Faranesh, A.Z., Zhou, M., Narayanswamy, G., Xu, M.A., Liu, X. and Yang, Y., 2026. Insulin resistance prediction from wearables and routine blood biomarkers. Nature, 652(8109), pp.451-461.https://doi.org/10.1038/s41586-026-10179-2
12. Santo Ali, M., Bipro, S.S., Motin, M.A., Kabir, S., Sharma, M. and Chowdhury, M.E., 2026. TEANet: A Transpose-Enhanced Autoencoder Network for Stress Monitoring on Resource-Constrained Wearable Device. IEEE Access, 14, pp.9560-9571.https://doi.org/10.1109/ACCESS.2025.3644400
13. Raza, A., Ali, M., Ehsan, M.K. and Sodhro, A.H., 2023. Spectrum evaluation in CR-based smart healthcare systems using optimizable tree machine learning approach. Sensors, 23(17), p.7456.https://doi.org/10.3390/s23177456
14. Fan, Y., Phaphan, W., Jitpattanakul, A. and Mekruksavanich, S., 2026. Knowledge Distillation for Efficient Human Activity Recognition on Resource-Constrained Smartwatches. IEEE Access, 14, pp.25854-25870.https://doi.org/10.1109/ACCESS.2026.3664977
15. Tahsin, M.S., Adarbah, H.Y. and Noore, A., 2026. A Lightweight Channel-Attention CNN for Robust Beat-Level Arrhythmia Detection. IEEE Access, 14, pp.62803-62817. https://doi.org/10.1109/ACCESS.2026.3686810
16. Alabdulatif, A., Khalil, I. and Saidur Rahman, M., 2022. Security of blockchain and AI-empowered smart healthcare: application-based analysis. Applied Sciences, 12(21), p.11039 .https://doi.org/10.3390/app122111039