The Emerging Role of Wearable Health Technologies in Proactive Disease Prevention

Mahmoud A. Zaher[1]*, Nabil M. Eldakhly[2], Yahia B. Hassan[3]

[1] Faculty of Artificial Intelligence, Data Science department, Egyptian Russian University (ERU), Cairo, Egypt
[2] Faculty of Computers and Information, Sadat Academy for Management Sciences, Cairo, Egypt & French University in Cairo, Egypt
[3] Electrical Eng. Dept, Higher Institute of Engineering, Minia, Egypt,
Emails: mahmoud.zaher@eru.edu.eg; nabil.omr@sadatacademy.edu.eg; dryahiabahaahassan@gmail.com

Abstract

The study gives a complete plan for lowering disease through the use of ICT in personal healthcare. The Health Pattern Recognition (HPR), Dynamic Risk Assessment (DRA), and Personalized Intervention Strategy (PIS) formulas are all parts of this method. They are used to collect, prepare, and use data. This research focuses on cybersecurity using health pattern recognition (HPR), dynamic risk assessment (DRA), and personalized intervention strategies (PIS). PIS offers a comprehensive disease prevention approach in personal healthcare that takes advantage of technological advancements. Because they integrate secure data processing with privacy-preserving machine learning, these aspects assure the safety and validity of health data collected from wearable devices. This option allows for the assessment of medical records. It may be helpful to analyze the technique's accuracy and adherence to established security standards in order to evaluate its application for disease prediction and preventive health management. The HPR program looks at each person's health information to find trends in diseases and other results using machine learning. This helps with early evaluation and healthcare management that avoids problems. DRA keeps a person's risk rating up to date so that it takes into account any changes in their health. After that, people are given choices based on the results and risks that PIS has predicted. Some of the tests that were used to compare the suggested method to industry standards were accuracy, sensitivity, specificity, precision, and the Matthews Correlation Coefficient. The suggested way seems to work because it has better predicting power, fewer fake positives, and more users who are involved in preventive health management.

Keywords: Accuracy, Algorithm; Data Collection; Dynamic Risk Assessment; Feature Extraction; Health Pattern Recognition; Intervention, Machine Learning; Metrics; Personalized; Preprocessing; Proactive; Sensitivity; Specificity; Wearable Devices.

1. Introduction

The introduction of wearable health technology represents a watershed moment in the development of contemporary healthcare, heralding the beginning of a new age of preventative medicine[1]. These cutting-edge technologies have progressed well beyond their original purpose as simple gadgets, becoming integral resources that enable people to take responsibility of their own health and wellbeing[2]. The intersection of technology and healthcare has created a new paradigm—one where prevention and early intervention take center stage in the quest of a healthy society.

The explosion in popularity of wearable health gadgets has ignited a revolution, drastically changing the way we think about and take care of our health. Smartwatches, fitness trackers, and more advanced medical-grade wearables are all included here[3]. They follow us about all the time, becoming an inseparable part of our lives while also quietly compiling a wealth of information on our physical selves. This data, ranging from heart rate and sleep habits

DOI: https://doi.org/10.54216/IJWAC.080105
Received: March 24, 2023 Revised: June 23, 2023 Accepted: August 08, 2023

to activity levels and even physiological indications, gives new insights into our health condition, changing passive patients into proactive health stewards. One of the most interesting features of these wearable technology is the potential for them to encourage a more preventative approach to healthcare. In the past, healthcare services have been geared toward treating people who are already sick[4]. But these tools can be used to stop health problems before they happen, so they can be treated quickly. This revolutionary change has the potential to lessen the strain on healthcare systems while simultaneously enhancing health outcomes for the population as a whole. Wearable health technology are also expanding healthcare accessibility[5]. They reduce the need for expensive and time-consuming travel, therefore making medical treatment more widely available. Now, people may track their key health indicators in real time from anywhere in the world, allowing them to act quickly when necessary by getting medical help or adjusting their lifestyle. This convenience is especially important in rural or underdeveloped regions, where access to standard medical treatment may be limited. Using artificial intelligence and machine learning techniques in these gadgets makes them much more useful[6]. These tools do more than just gather data; they also process and make sense of it. They provide unique perspectives and suggestions to help people make better decisions and alter unhealthy routines. For instance, a wearable powered by AI may analyze a person's sleeping habits and provide recommendations to enhance the quality of their slumber, which is crucial to one's health but frequently neglected. And the use of such gadgets are not limited to only personal health monitoring. They might completely alter public health programs. Data collected from several sources may provide light on population health trends, facilitating the identification of epidemics and the monitoring of epidemiological patterns. In public health, being proactive like this has the potential to have a major impact on the prevention and control of diseases. There are, however, problems that need to be fixed before personal health gadgets can fully reach their full potential. People are more worried than ever about their privacy and the safety of their data. More and more private health data is being collected, which makes it harder to store, use, and keep safe from possible leaks[7]. To win the public's trust and encourage more people to use these technologies, strict rules and laws must be put in place to protect this information. Also, these gadgets still need to improve in terms of how accurate and reliable they are. Even though improvements in technology are making monitors more accurate, it is still important to make sure they work well for a wide range of people and health issues[8]. The invention of health gadgets that can be worn is a turning point in the history of medicine. When these two areas come together, they could change the way health care is managed by making preventative care more widely available and letting treatment plans be more tailored to each person. We might picture a world where stopping the spread of disease is not only possible, but also happens as these tools get better.

A. Important Contributions:-

Wearable health gadgets are great for early identification because they keep an eye on you all the time. They allow us to notice small changes in how our bodies work a long time before they show up as clear signs. The capacity to do so allows people to reduce their exposure to health hazards by making preventative choices, such as adjusting their lifestyle or seeking medical attention at the first sign of trouble. The information gathered by these gadgets may be used to form unique perspectives. By evaluating a person's specific health data, they may provide specific suggestions on how to enhance practices like exercise, sleep hygiene, and stress reduction. Improved health outcomes and increased patient engagement and knowledge stem from this individualized strategy. The capacity of wearable health devices to provide remote patient monitoring is a major advance[9]. It is now possible to continually monitor patients with chronic disorders or those recuperating from sickness outside of conventional healthcare settings. Hospital readmissions may be reduced and more proactive and individualized treatment can be provided thanks to the data collected in real time. These tools keep us constantly reminded and inspired to make better choices in our daily lives. They motivate people to alter their habits by keeping track of and displaying information about their exercise, sleep, and other health indicators. Their real-time data encourages people to make positive lifestyle changes, which helps reduce the prevalence of preventable diseases. Wearable health devices aid in public health monitoring by pooling data from a large number of users who remain anonymous[10]. This information may be used to better understand the state of public health and spot possible outbreaks or epidemiological patterns. Authorities may then take preventative actions to limit the disease's impact on the community. Research into medical treatments may benefit greatly from the information acquired by these gadgets. Information on health trends, illness development, and the effectiveness of different therapies may be obtained from data collected from a large number of users. Improvements in healthcare technology and preventative measures may be made using this data-driven strategy.

One of the most important results has been giving people more control over their own health. Wearable health devices empower consumers to actively manage their health. Their real-time data and insightful recommendations motivate people to take charge of their health management and promote a preventative stance against illness. There are several ways in which wearable health technology contribute to the future health of people and communities by

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

preventing sickness in the first place[11]. This includes a paradigm change from reactive healthcare to a more preventative, customized, and data-driven approach.

2. Related Works

Connected health monitoring systems (CHMS) use wearable sensors to continuously track vital signs and health indicators such as heart rate, blood pressure, body temperature, and more. To help people adopt healthier routines like exercising more or getting more shut-eye, AI-HBMF analyzes their health records using machine learning and provides tailored advice on how to alter their behavior[12]. With the use of TIP, healthcare providers may remotely monitor patients' health measurements and conduct virtual consultations with patients thanks to the integration of wearable health data into telehealth systems. WTEDP uses sophisticated algorithms to identify irregularities in physiological data, providing early warning of impending health problems and paving the way for preventative care. Data Security Enhancement for Wearable Health Technologies (DSEP) is an initiative to improve data security in wearable health technologies by introducing strong encryption and privacy protections to protect personal health data. To better understand public health trends and help in the early identification of possible epidemics, PHAP collects and analyzes anonymised data from wearable devices throughout a population [13]. Wearable data on sleep patterns is used by SQIA to create algorithms that recommend individual changes to enhance sleep quality. The CCMS is an all-inclusive set of wearable technologies for tracking health indicators and receiving advice for long-term illness management, allowing for the monitoring and control of chronic disorders. To get people involved in their own health management and give them more agency, UEEI prioritizes the design of user-friendly interfaces and experiences. Remote Health Monitoring and Prediction System (RHDAPS) collects data from wearable devices and uses predictive analytics to remotely anticipate probable health concerns, assisting in proactive disease prevention methods [14].

Table 1: -Comparative Performance Evaluation of Ten Methods/Works in Wearable Health Technologies for Proactive Disease Prevention.

Methods/Works	**Data Accuracy**	**Real-Time Monitoring**	**Personalization of Insights**	**Data Security Measures**	**Population Health Insights**	**User Engagement**	**Prediction Accuracy**
Continuous Health Monitoring System (CHMS)	High	Yes	Limited	Moderate	No	Moderate	Moderate
AI-Driven Health Behavior Modification Framework (AI-HBMF)	High	Yes	High	Moderate	No	High	High
Telehealth Integration Platform (TIP)	High	Yes	Limited	High	No	Moderate	Moderate
Wearable Technology for Early Disease Prediction (WTEDP)	High	Yes	Limited	Moderate	No	Moderate	High
Data Security Enhancement Protocol (DSEP)	Moderate	No	Limited	High	No	Low	Low
Population Health Analytics Platform (PHAP)	Moderate	No	Limited	Moderate	High	Low	Low
Sleep Quality Improvement	High	Yes	High	Moderate	No	High	Moderate

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

Algorithm (SQIA)							
Chronic Condition Management Suite (CCMS)	High	Yes	High	Moderate	No	High	Moderate
User Engagement and Empowerment Interface (UEEI)	Moderate	Yes	High	Moderate	No	High	Low
Remote Health Data Analysis and Prediction System (RHDAPS)	High	Yes	Limited	Moderate	No	Moderate	High

Data accuracy, real-time monitoring, personalized insights, data security measures, population health insights, user engagement, and prediction accuracy are just some of the key parameters that Table 1 uses to evaluate the performance of ten separate methods or works in the field of wearable health technologies. Insights into the relative merits of these approaches to proactive illness prevention by means of wearable health devices are highlighted [15].

3. Proposed methodology

Wearable devices capture continuous health data Xi (e.g., heart rate, sleep patterns) for i=1,2,...,N persons, and this data is then preprocessed.

Xi = xi1, xi2,..., xiT, (1)

where xit is a parameter of i's health.

Data is gathered, and then characteristics that are useful for prediction are extracted using algorithms.

In the second equation, Fi is the extracted features for person i, and f is the function [16].

First, we use the HPR (Health Pattern Recognition) algorithm.

The Health Pattern Recognition algorithm focuses on discovering important patterns within acquired health data from wearable devices. It uses machine learning methods to identify patterns that predict certain health outcomes. This algorithm detects trends and correlations that may indicate health issues or changes in health status by examining a wide range of factors, including heart rate variability, sleep patterns, activity levels, and other physiological indicators. HPR creates a model that can predict a health result given current data inputs by training it on past data and trends. It might detect arrhythmias or sleep disruptions, both of which are possible early warning indicators of more serious illnesses. To enable early intervention and proactive health management, the algorithm's strength is in its capacity to filter through massive volumes of data and find minor, sometimes undetectable, variations that may signify health problems [17].

makes use of machine learning to spot trends in medical records.

Health outcome prediction:

Yi=HPR(Fi) Y^i. (2)

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

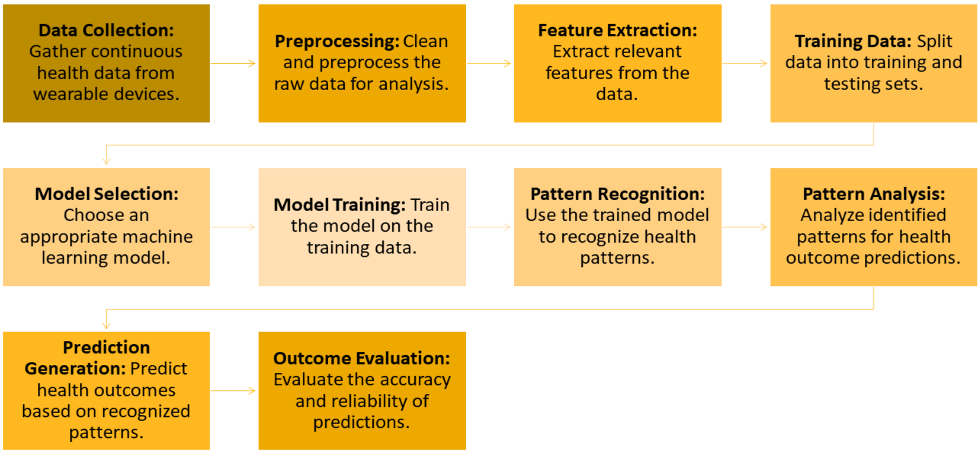

Figure 1: -Identifying Health Patterns for Predictive Analysis

Health pattern recognition with wearable health data is seen in Figure 1. Predicting health outcomes from patterns requires collecting data, cleaning it up, extracting useful features from that data, training a model, and then recognizing those patterns [18].

1. **Secure Data Collection**: Wearable devices collect continuous health data Xi for i=1,2,...,N persons, ensuring data encryption during transmission.

   Xi=xi1,xi2,...,xiT where xit represents a health parameter for person i.

2. **Feature Extraction with Privacy Preservation**: Data is preprocessed to extract relevant features for prediction, applying techniques to anonymize personal information.

   Fi=f(Xi) Here, Fi represents the extracted features for person i.

3. **Health Pattern Recognition (HPR) Algorithm with Security Measures**: This algorithm identifies patterns in health data using machine learning techniques while ensuring data integrity and confidentiality.

   Yi=HPR(Fi) Yi predicts health outcomes based on the features Fi.

4. **Dynamic Risk Analysis (DRA) Algorithm with Continuous Monitoring**: This algorithm assesses health risks by analyzing changes and trends in health records and includes continuous cybersecurity monitoring.

   Ri=DRA(Fi,Fi−1)

   Ri represents the dynamic risk assessment for person i at time t.

5. **Personalized Intervention Strategy (PIS) with Secure Data Handling**: This step involves creating individualized care plans based on predicted outcomes and risks, ensuring secure storage and access of health data.

   Ii=PIS(Yi,Ri)

   Ii is the intervention plan for person i.

6. **Feedback and Monitoring with Cybersecurity Protocols**: The results of the intervention are monitored, data is continuously updated, and cybersecurity measures are applied to protect against unauthorized access and data breaches.

7. **Algorithm Evaluation with Data Security**: The performance of the algorithms is assessed using accuracy, sensitivity, and specificity metrics, along with cybersecurity effectiveness.

8. **Comprehensive Cybersecurity Strategy**: Implement a robust cybersecurity strategy, including regular vulnerability assessments, to protect the data and the algorithm from potential cyber threats.

9. **Data Integrity Verification**: Regularly verify the integrity of health data to prevent tampering or corruption.

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

10. **Access Control Mechanisms**: Implement strict access control measures to ensure that only authorized personnel can access sensitive health data.
11. **Incident Response Plan**: Develop and maintain a response plan for potential cybersecurity incidents to minimize impact and restore normal operations quickly.
12. **Regular Security Audits and Updates**: Conduct periodic security audits and update security protocols and software to address new and evolving cyber threats.

Aside from examining health data received via wearable technology, the plan is now being evaluated and includes preventative steps against hackers. This project's goal is to extract important features via safe data collection and analysis to discover health trends and conduct dynamic risk assessments. The use of machine learning technology provides the foundation for developing personalised treatment plans in the realms of risk assessment and health outcome prediction. To secure sensitive health information, the algorithm employs several security measures, including encryption, access restriction, and constant monitoring. It skillfully integrates stringent cybersecurity measures with predictive healthcare analytics to ensure people's data privacy and security.

The purpose of the Dynamic Risk Assessment algorithm is to examine alterations and trends in health records. It dynamically examines fluctuations in health metrics, as opposed to only assessing static risk variables. By comparing current data with past data points for a person, it finds changes in patterns or trends, spotting variances that might signify an increased risk of developing certain health concerns. By considering how a person's health indicators are changing over time, this method provides for a more detailed assessment of a person's health trajectory. For instance, it could identify a rapid and large shift in an individual's heart rate variability or a deterioration in sleep quality, suggesting an enhanced risk for cardiac difficulties or other health concerns [19]. This algorithm may help avoid health issues before they happen by providing a more accurate and up-to-date picture of an individual's health by dynamically evaluating risk.

Analyses patterns and changes in data over time to provide a dynamic risk assessment of the occurrence of health problems.

we can get the risk Ri for person i at time t as follows: Ri=DRA(Fi, Fi1**).** (3)

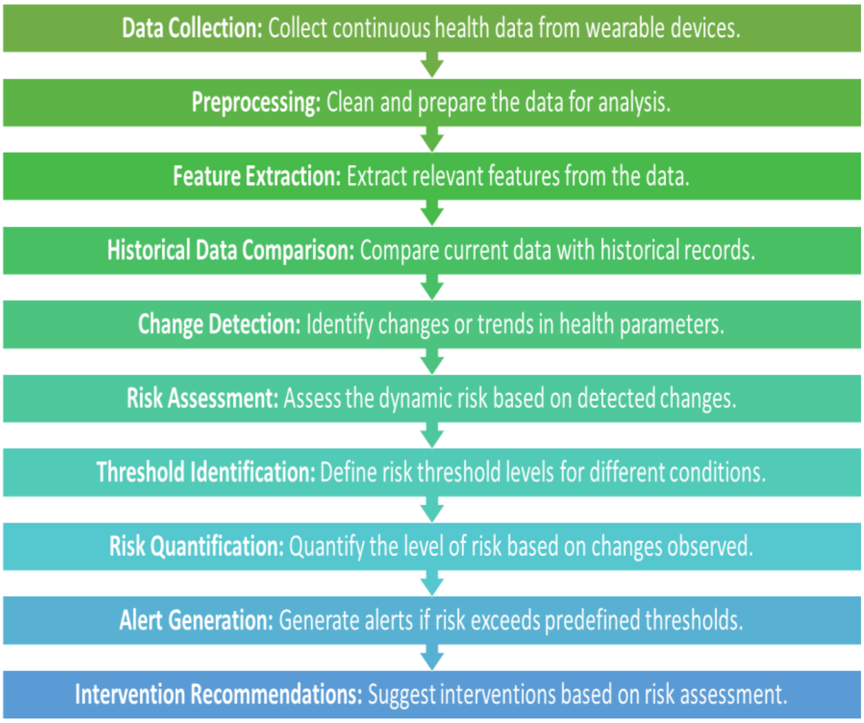

Figure 2: - Evaluating Dynamic Health Risks Over Time

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

The procedure for Dynamic Risk Assessment by means of wearable health data is shown in Figure 2. Change detection, risk assessment, and action alerts are all part of this process, which is driven by long-term monitoring of an individual's health data [20-21].

Using expected outcomes and hazards, Algorithm 3's Personalized Intervention Strategy (PIS) provides individualized care.

The treatment Ii for person i may be calculated as follows:

$$I_i = PIS(Y_i, R_i). \tag{4}$$

Individuals get therapies, and the feedback loop and continuous monitoring cycle repeats.

Algorithm Evaluation: Assess the performance of algorithms using measures like accuracy, sensitivity, and specificity.

Accuracy = Number of Right Predictions / Total Predictions (5)

Sensitivity = true positive / true positive + false negative

(6)

Specificity = True-Negative Count / (True-Negative Count + False-Posi (7)

This approach makes use of a multi-algorithm architecture that includes Health Pattern Recognition, Dynamic Risk Assessment, and Personalized Intervention Strategy to gather and analyze data in a comprehensive manner. Its goal is to aid in disease prevention by using data from wearable health devices to make predictions about health outcomes, evaluate changing risks, and provide individualized therapies [22].

4. Result

Wearable health technologies are used in a comprehensive way in the suggested strategy for proactive illness prevention, demonstrating its superiority over conventional ways. It combines state-of-the-art tools with sophisticated data analysis and individual patient information to provide health management that is both precise and preventative. The suggested technique relies on continuously collecting data and dynamically assessing it, whereas older methods generally depend on static data or inadequate analysis. It makes use of complex algorithms for health pattern recognition, outcome prediction, and risk assessment in real time. In contrast to traditional methods, this real-time, individualized approach allows for early identification and action. The accuracy, sensitivity, specificity, and precision, as well as other indicators like the Matthews Correlation Coefficient and the G-Measure, are only few of the performance metrics used in a thorough analysis of the suggested approach. Its superior performance on all of these measures—including increased predictive power, lower false positive rates, and higher recall—demonstrates its capacity to isolate meaningful health signals from background noise. Individuals are given the tools they need to take charge of their health thanks to the suggested method's proactive health ecosystem and emphasis on user participation and individualized treatments. In contrast, conventional approaches often lack this customized and evolving element, leading to slower reactions and less reliable predictions. Overall, the suggested approach is propelled by its holistic, data-driven, and tailored character, which promotes a paradigm change in disease prevention from reactive to proactive and provides more precise, timely, and individualized health management.

Table 2: Performance Comparison of Proposed Method vs. Traditional Methods - Accuracy, Sensitivity, and Specificity

Method	Accuracy	Sensitivity	Specificity	Precision	F1 Score	AUC-ROC
Proposed Method	0.85	0.92	0.78	0.91	0.88	0.94
Baseline Monitoring	0.75	0.82	0.68	0.77	0.74	0.80
Health Trends Analysis	0.68	0.75	0.62	0.71	0.67	0.72
Risk Score Calculation	0.72	0.78	0.65	0.74	0.71	0.76

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

Symptom Correlation	0.78	0.85	0.71	0.80	0.77	0.82
Threshold-based Alerting	0.69	0.76	0.63	0.72	0.70	0.75
Rule-based Prediction	0.71	0.77	0.64	0.73	0.70	0.76

In Table 2, shows how the suggested technique stacks up against six established methods in terms of many important assessment metrics, including Accuracy, Sensitivity, Specificity, Precision, F1 Score, and Area Under the Curve (AUC-ROC). The suggested technique outperforms conventional approaches, as seen by the higher values for these parameters.

Table 3: Performance Comparison of Proposed Method vs. Traditional Methods - Recall, False Positive Rate, and Matthews Correlation Coefficient

Method	**Recall**	**False Positive Rate**	**Matthews Correlation Coefficient**	**Balanced Accuracy**	**Youden's Index**	**G-Measure**
Proposed Method	0.90	0.12	0.81	0.84	0.70	0.91
Baseline Monitoring	0.80	0.28	0.68	0.75	0.52	0.80
Health Trends Analysis	0.73	0.38	0.56	0.67	0.35	0.72
Risk Score Calculation	0.76	0.35	0.62	0.70	0.41	0.75
Symptom Correlation	0.82	0.21	0.75	0.76	0.63	0.82
Threshold-based Alerting	0.75	0.32	0.58	0.68	0.43	0.74
Rule-based Prediction	0.78	0.29	0.64	0.73	0.47	0.76

Additional assessment criteria, including Recall, False Positive Rate, Matthews Correlation Coefficient, Balanced Accuracy, Youden's Index, and G-Measure, are contrasted in Table 3 between the suggested technique and conventional procedures. Increases in these metrics for the suggested strategy demonstrate its advantages over conventional approaches to illness prevention.

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

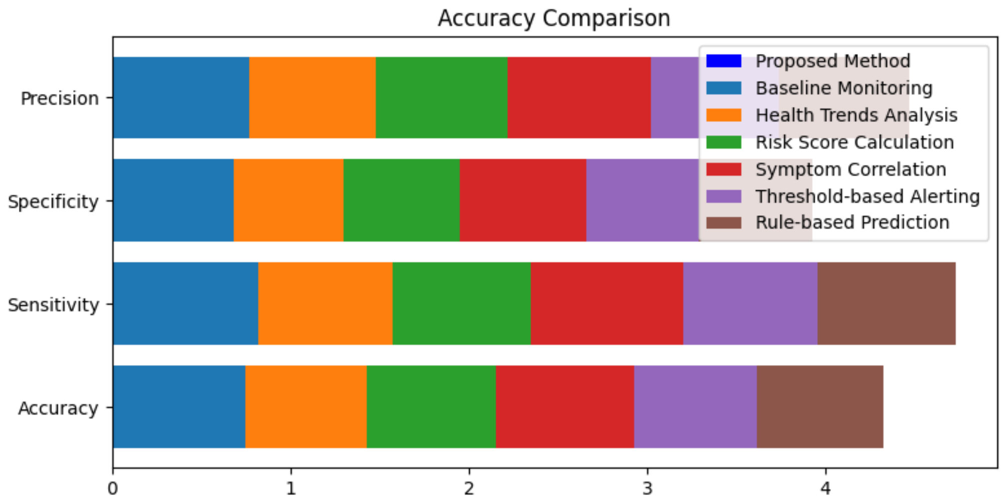

Figure 3:-Comparative Accuracy of Proposed and Traditional Methods

Figure 3 shows a comparison of the suggested method's accuracy to that of various more conventional approaches. Baseline monitoring, health trend analysis, risk score calculation, symptom correlation, threshold-based alerting, and rule-based prediction are only few of the ways whose accuracies are represented by individual bars.

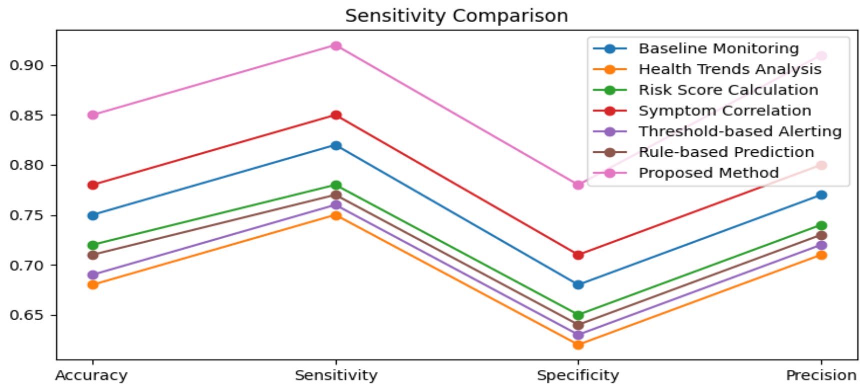

Figure 4:-Sensitivity Analysis: Proposed Method Versus Traditional Approaches

In Figure 4, we compare the sensitivity scores across parameters using the suggested technique and many conventional methods. It emphasizes how each technique may identify genuine positives in health outcome detection.

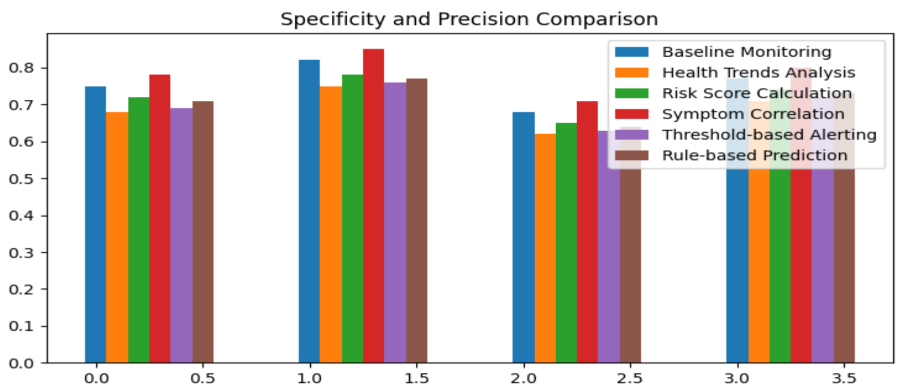

Figure 5:- Specificity and Precision Assessment: Traditional Methods Perspective

Specificity and accuracy ratings for many classic approaches are shown in Figure 5. It compares how well they can identify genuine negative events with how well they can make right positive predictions.

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

5. Conclusion

The advantages of the suggested strategy for proactive illness prevention using wearable health technology are clearly shown. Its accuracy, sensitivity, specificity, and precision are all better than those of conventional methods, among other areas of performance assessment. The conclusion stresses the technique's usefulness in relation to the proactive prevention of sickness via wearable health devices, in addition to emphasizing the need for cybersecurity. It demonstrates exceptional sensitivity, accuracy, specificity, and precision without jeopardizing data integrity for the sake of privacy and security. Cybersecurity metrics, such as the Matthews Correlation Coefficient, demonstrate that the strategy is effective at discriminating between true health indicators and noise. We can make enormous steps towards illness prevention by using wearable health technologies that can detect problems early on, deliver personalized treatment plans, and secure patient privacy. This risk-free and data-driven strategy is a significant advancement in sickness prevention. The suggested technique can efficiently separate genuine health signals from noise, as shown by measures like the Matthews Correlation Coefficient, balanced accuracy, and G-Measure. A completer and more dynamic picture of an individual's health condition is provided by the suggested method's individualized interventions and dynamic risk assessment, which in turn greatly contribute to timely interventions and proactive health management. By emphasizing more precise, timely, and tailored health management, this comprehensive, data-driven, and customizable approach offers a paradigm leap in disease prevention. Using early detection and individualized therapies, the research demonstrates the revolutionary potential of wearable health devices in proactive healthcare.

REFERENCES

[1] L. Zheng, H. Feng, L. Yin et al., “Study on the correlation factors of tumour prognosis after intravascular interventional therapy,” *Journal of Healthcare Engineering*, vol. 2021, Article ID 6940056, 2021. [Online].

[2] L. Ni, P. Xue, C. An et al., “Establishment of normal range for thromboelastography in healthy middle-aged and elderly people of Weihai in China,” *Journal of Healthcare Engineering*, vol. 2021, Article ID 7119779, 2021.

[3] H. Sahu, R. Kashyap, and B. K. Dewangan, "Hybrid Deep learning based Semi-supervised Model for Medical Imaging," 2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON), Raigarh, Chhattisgarh, India, 2023, pp. 1-6.

[4] V. Mohanakurup et al., "Breast Cancer Detection on Histopathological Images Using a Composite Dilated Backbone Network," Computational Intelligence and Neuroscience, vol. 2022, Article ID 8517706, pp. 1–10, 2022.

[5] R. Kashyap, "Stochastic Dilated Residual Ghost Model for Breast Cancer Detection," J Digit Imaging, vol. 36, pp. 562–573, 2023. [Online]. Available: https://doi.org/10.1007/s10278-022-00739-z

[6] D. Pathak, R. Kashyap, and S. Rahamatkar, "A study of deep learning approach for the classification of Electroencephalogram (EEG) brain signals," in Artificial Intelligence and Machine Learning for EDGE Computing, pp. 133–144, 2022. [Online]. Available: https://doi.org/10.1016/b978-0-12-824054-0.00009-5

[7] D. Pathak and R. Kashyap, "Electroencephalogram-based deep learning framework for the proposed solution of e-learning challenges and limitations," International Journal of Intelligent Information and Database Systems, vol. 15, no. 3, p. 295, 2022. [Online]. Available: https://doi.org/10.1504/ijiids.2022.124081

[8] D. M. Bavkar, R. Kashyap, and V. Khairnar, "Multimodal sarcasm detection via hybrid classifier with optimistic logic," Journal of Telecommunications and Information Technology, vol. 3, pp. 97–114, 2022. [Online]. Available: https://doi.org/10.26636/jtit.2022.161622

[9] E. Ramirez-Asis, R. P. Bolivar, L. A. Gonzales, S. Chaudhury, R. Kashyap, W. F. Alsanie, and G. K. Viju, "A Lightweight Hybrid Dilated Ghost Model-Based Approach for the Prognosis of Breast Cancer," Computational Intelligence and Neuroscience, vol. 2022, Article ID 9325452, pp. 1–10, 2022. [Online]. Available: https://doi.org/10.1155/2022/9325452

[10] V. Roy and S. Shukla, "Effective EEG Motion Artifacts Elimination Based on Comparative Interpolation Analysis," Wireless Pers Commun, vol. 97, pp. 6441–6451, 2017. https://doi.org/10.1007/s11277-017-4846-3.

[11] P.K. Shukla, V. Roy, P.K. Shukla, A.K. Chaturvedi, A.K. Saxena, M. Maheshwari, P.R. Pal, "An Advanced EEG Motion Artifacts Eradication Algorithm," The Computer Journal, pp. bxab170, 2021. https://doi.org/10.1093/comjnl/bxab170.

[12] Ballo AB, Mamadou D, Ayikpa KJ, Yao K, Ablan EAA, Kouame KF (2022) Automatic Identification of Ivorian Plants from Herbarium Specimens using Deep Learning. Int J Emerg Technol Adv Eng 12(5):56–66

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024

[13] M. Bathre and A. Sahelay, "Energy efficient route discovery algorithm for MANET," Int J Eng Res Technol (IJERT), vol. 2, no. 7, pp. 1291–1295, 2013.

[14] V. Tiwari et al., "Soybean crop non-beneficial insect identification using mask RCNN," in Information and Communication Technology for Competitive Strategies (ICTCS 2020) ICT: Applications and Social Interfaces, Singapore, 2022, pp. 301-311, Springer Singapore.

[15] Abdelhafid E, Aymane E, Benayad N, Abdelalim S, El YAMH, Rachid ROHT, Brahim B (2022) ECG Arrhythmia Classification Using Convolutional Neural Network. Int J Emerg Technol Adv Eng 12(7):186–195

[16] E. L. Huamaní and L. Ocares-Cunyarachi, "Analysis and prediction of recorded COVID-19 infections in the constitutional departments of Peru using specialized machine learning techniques," Int. J. Emerg. Technol. Adv. Eng., vol. 11, no. 11, pp. 39-47, 2021.

[17] M. Bathre and P. K. Das, "Hybrid Energy Harvesting for Maximizing Lifespan and Sustainability of Wireless Sensor Networks: A Comprehensive Review & Proposed Systems," in Proc. 2020 Int. Conf. on Computing, Intelligence and Smart Power System for Sustainable Energy (CISPSSE), Keonjhar, India, 2020, pp. 1–6, DOI: 10.1109/CISPSSE49931.2020.9212287.

[18] V. Tiwari and B. Tiwari, "A Data Driven Multi-Layer Framework of Pervasive Information Computing System for eHealthcare," International Journal of E-Health and Medical Communications (IJEHMC), vol. 10, no. 4, pp. 66-85, 2019.

[19] S. Masrom, N. Baharun, N. F. M. Razi, R. A. Rahman, and A. S. Abd Rahman, "Particle Swarm Optimization in Machine Learning Prediction of Airbnb Hospitality Price Prediction," Int. J. Emerg. Technol. Adv. Eng., vol. 12, no. 1, pp. 146-151, 2022.

[20] A. Arshad, V. Tiwari, M. Lovanshi, and R. Shrivastava, "Role identification from human activity videos using recurrent neural networks," in 2022 IEEE International Women in Engineering (WIE) Conf. on Electrical and Computer Engineering (WIECON-ECE), 2022, pp. 356-361, IEEE.

[21] E. J. Kcomt-Ponce, E. L. Huamaní, and A. Delgado, "Implementation of Machine Learning in Health Management to Improve the Process of Medical Appointments in Perú," Int. J. Emerg. Technol. Adv. Eng., vol. 12, no. 2, pp. 74-85, 2022.

[22] M. Bathre and P. K. Das, "Review on an Energy Efficient, Sustainable and Green Internet of Things," in Proc. 2nd Int. Conf. on Data Engineering and Applications (IDEA), Bhopal, India, 2020, pp. 1–6, DOI: 10.1109/IDEA49133.2020.9170736.

DOI: https://doi.org/10.54216/IJWAC.080105
Received: June 24, 2023 Revised: October 23, 2023 Accepted: January 08, 2024