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ORIGINAL

THE ROLE OF INTELLIGENT TECHNOLOGIES IN HEALTH MONITORING AND PERFORMANCE MANAGEMENT OF ATHLETES IN SPORTS MEDICINE AND HEALTH MANAGEMENT CENTERS

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ABSTRACT

Health management centres play a crucial role in managing and maintaining comprehensive health information systems, which include patient records, medical histories, and other vital data. Recent advancements in technology, including wireless communication networks, smart applications, and sensors, have significantly improved the quality of life by enabling more efficient health monitoring and management. Central to these advancements is the Internet of Things (IoT), which facilitates the processing, distribution, and access to essential data, thereby enhancing healthcare delivery. The purpose of this research is to develop a novel data processing system on an IoT platform specifically designed for real-time health monitoring of athletes within sports medicine and health management centres. The proposed system leverages public healthcare datasets stored in the cloud, which are pre-processed using Min-max normalization. Key features are extracted using Independent Component Analysis (ICA) to ensure accurate and relevant data processing. This study introduces a hybrid Magnetic Optimized Dynamic Support Vector Machine (HMO-DSVM) method, which is designed to optimize health monitoring for athletes by improving the accuracy and reliability of health assessments. The performance of the proposed system is evaluated against standard models, with experimentation conducted to validate the enhanced performance of the HMO-DSVM approach. Key performance metrics such as accuracy, precision, specificity, F1-score, and sensitivity are used to assess the effectiveness of the system. As intelligent technologies continue to evolve, their integration into sports medicine and athlete health management will be pivotal in shaping the future of healthcare delivery and monitoring, ultimately leading to improved health outcomes and enhanced athletic performance.

KEYWORDS: Health management; Health monitoring; Internet of Things (IoT); Independent Component Analysis (ICA); Hybrid Magnetic Optimized Dynamic Support Vector Machine (HMO-DSVM)

1. INTRODUCTION

The landscape of healthcare is rapidly evolving, driven by the integration of intelligent technologies that are reshaping how health data is collected, analysed, and utilized. Health management centres, which play a pivotal role in overseeing the health and well-being of individuals, have embraced these technological advancements to enhance their ability to manage vast and complex health information systems. These centres are responsible for maintaining comprehensive patient records, monitoring medical histories, and managing real-time health data. With the advent of the Internet of Things (IoT), smart applications, sensors, and advanced data processing techniques, the potential for improving health monitoring, particularly in specialized areas such as sports medicine, has never been greater. Athletes, due to the unique physical demands of their sport, represent a population that requires continuous, precise, and proactive health monitoring (Dorj et al., 2017; Lee & Yoon, 2021; Mani et al., 2020). The rigors of athletic training and competition place significant stress on the body, making athletes more susceptible to injuries and health issues that can impede their performance. In this context, the ability to monitor an athlete's health in real-time, assess their physical condition, and predict potential health risks is crucial. Traditional health monitoring methods, while valuable, often lack the real-time capabilities and comprehensive data integration needed to support the high-performance demands of athletes. Intelligent technologies, particularly those leveraging IoT, offer a transformative solution to these challenges. IoT enables the seamless integration of various health-monitoring devices, such as wearable sensors, that can track vital signs, physical activity levels, and other critical health indicators around the clock. These devices collect continuous streams of data, which can be transmitted in real-time to health management centres for analysis. For athletes, this means that every aspect of their physical condition—ranging from heart rate variability and oxygen saturation levels to muscle fatigue and recovery times—can be monitored with unprecedented precision. Moreover, the application of machine learning algorithms to this data allows for the development of sophisticated models that can predict potential health issues before they manifest, optimize training regimens, and tailor recovery protocols. For instance, machine learning models can analyse patterns in an athlete's heart rate and physical activity to predict the likelihood of an injury or to recommend adjustments in their training intensity to avoid overtraining. This level of proactive health management is critical for athletes who must maintain peak physical condition to perform at their best. The proposed research focuses on the development and implementation of a novel data processing system designed specifically for health management centres that cater to athletes (El Zouka & Hosni, 2021; Khatoon, 2020; Mehta et al., 2019). This system utilizes public healthcare datasets stored in the cloud, which are pre-processed using techniques like Min-max normalization to ensure data consistency and quality. Key features relevant to athletic performance and health are extracted using Independent Component Analysis (ICA), which isolates the most critical data points from the vast amounts of information collected. The core of this system is the hybrid Magnetic Optimized Dynamic Support Vector Machine (HMO-DSVM), an advanced machine learning method that optimizes the accuracy and reliability of health monitoring by dynamically adapting to the data it receives. By integrating these intelligent technologies, the proposed system aims to significantly enhance the capability of health management centres to monitor and manage the health of athletes. The system's ability to provide real-time, accurate assessments of an athlete's health status enables more informed decision-making by both healthcare providers and coaches. This, in turn, facilitates the early detection of potential health issues, allowing for timely interventions that can prevent injuries and other health complications. Additionally, the system's predictive capabilities can help optimize training and recovery strategies, ensuring that athletes are always in the best possible condition for competition.

The implications of these advancements are profound for the field of sports medicine. As athletes push the boundaries of human performance, the need for cutting-edge health monitoring and management tools becomes increasingly critical. Intelligent technologies not only support the immediate health needs of athletes but also contribute to their long-term well-being, allowing them to extend their careers and achieve their full potential. Furthermore, the integration of these technologies into health management centres represents a significant step forward in the broader field of healthcare, setting new standards for how health data is managed and utilized (AlShorman et al., 2020; Crowell et al., 2022; Lamonaca et al., 2018; Poongodi et al., 2021). In the application of intelligent technologies in health management centres, particularly in the context of sports medicine, offers a powerful tool for enhancing the health and performance of athletes. This study seeks to explore the potential of these technologies in creating a more responsive, accurate, and effective health monitoring system. By leveraging the capabilities of IoT, advanced data processing techniques, and machine learning, the proposed system aims to redefine how athlete health is managed, ultimately leading to better health outcomes and improved athletic performance. As the demands on athletes continue to grow, the role of intelligent technologies in supporting their health and well-being will become increasingly indispensable, paving the way for the next generation of sports medicine and health management practices.

2. Literature Review

The study (Doghri et al., 2022) provided a thorough analysis of wireless sensing and structural health monitoring (SHM) methods in the context of an effective CPS. Wireless sensor networks (WSNs) based SHM have the potential to lower the cost of building and maintaining public and private facilities. Due to the range of its application domains and its significance for public safety, WSN is attractive to many different types of studies that use SHM. The SAAPHO research used in the study (Azimi et al., 2017) suggested a strategy of intelligent healthcare services to support monitoring of elderly health. Here, the suggested healthcare services' definitions and design were provided while taking into account six distinct health criteria, including blood pressure, glucose, physical activity, pulse monitoring, weight monitoring and medication compliance. The research (Awotunde et al., 2022) suggested using IoT wearable with AI for real-time remote monitoring of elderly people. The physiological indicators of older people were recorded using a variety of wearable sensors and the data was stored in an IoT-based database in the cloud before processed by an AI model to aid in decision-making. Healthcare providers are able to provide preventative counsel to save lives since they are informed in real time on the health status of the elderly. The primary goal of the study (Zhao et al., 2019) was to examine and compile recent deep-learning studies on machine monitoring of health. The use cases of machine health using deep learning tracking structures are examined from the following perspectives: Auto-encoders (AE) along with its variations, variants Deep Belief Network (DBN), Restricted Boltzmann Machines (RBM), Deep Boltzmann Machines (DBM), Recurrent Neural Networks (RNN) and CNN. The article (Nancy et al., 2022) provided deep learning, a branch of machine learning that holds the transformational potential for analysing massive amounts of data at remarkable speeds, eliciting wise insights and resolving challenging problems. The proposed framework collected the IoT device data and the associated computerized history of the patient healthcare stored data in the cloud was analysed using predictive analytics. The creation of an intelligent digital twin (i-DT) in MATLAB/Simulink is used in the work (Venkatesan et al., 2019) to determine the build PMSM health monitoring and prognostic. To calculate the remaining useful life of a permanent magnet, an artificial neural network (ANN) fuzzy logic is used to map inputs such as distance and EV travel time to outcomes such as casing temperature and winding temperatures. The paper (Humayun et al., 2022) presented a framework for multi-agent health monitoring that consists of a collection of knowledgeable agents that collect data on patients, collaborate and recommend behaviours with patients as well as physicians working in a mobile environment. This system aims to improve the procedure for monitoring health. Using the introduction of a novel gadget that fuses healthcare with cutting-edge technology, the article (Kondaka et al., 2022) intended to build a bridge between the two. The suggested method presents iCloud Assisted Intensive Deep Learning (iCAIDL), a novel algorithm that supports healthcare providers and patients by using machine learning techniques and an intelligent cloud structure. The deep learning standards serve as the basis for this suggested method as the basis. The goal of the study (Rajan Jeyaraj & Nadar, 2022) was to promote the e-healthcare system by developing a unique IoT-based physiological signal monitoring system with applications. The proposed system was implemented using a deep neural network for exact estimation and prediction of signals method. An intelligent sensor is used for signal measurements in the proposed system and National Instrument myRIO was used for intelligent data collection. The article (Bajaj et al., 2023) used machine learning (ML) techniques to help categorize the state of the cutting tool while it is in use. The Support Vector Machine (SVM) is one such method that was used for data training. Choosing the best hyper-parameters for an SVM was crucial for creating a stable model. The modelling of tool settings using vibrations developed during machining requires to be treated carefully since intermittent cutting occurs in milling process. The architecture for patient health monitoring utilizing GSM was designed and implemented in the study (Baswa et al., 2017).

To analyse the current state of the patient's health, this was dependent on communication tools such as mobile phones and wireless sensor networks. The main objective is to create a structure that can help doctors by using tele-monitoring. The author (Islam et al., 2020) proposed a smart healthcare system for an IoT environment. The structure would be able to monitor a patient's vital signs and the state of the room in which they are located. Heart rate sensor, body temperature sensor, room temperature sensor, CO sensor and CO_2 sensor are the five sensors in this framework that were utilized to collect information about the hospital atmosphere. The article (Qing et al., 2019) gave a brief description of the SHM system technology based on piezoelectric transducers that have been established over the last 20 years for airplane applications. The pre-requisites for the actual use of health monitoring systems for structures and their utilization in airplanes were presented. Applications of the IoT involve improving operational effectiveness in industry, transportation, municipal management and physical exercise. The paper explored (Yeruva et al., 2022) its use in medical technology and offered a creative method for fusing the concepts of fog computing with the IoT. The IoT-based real-time remote patient monitoring system was suggested by this research to ensure the correctness of the crucial real-time signal. The suggested solution used the Message Queuing Telemetry Transport (MQTT) protocol to transmit crucial real-time signals to the web page (Alshammari, 2023). The article (Latchoumi et al., 2022) proposed a simple general population authentication methodology for MSNs and identified the challenging security vulnerabilities in current remote patient monitoring authentication approaches. The MSN networks were split into detectors, which offer measurements of a person's body and actuation, which take orders from medical personnel and respond in a certain manner. A hybrid safety and health monitoring WSN system with an Internet of Things connection was demonstrated in the study (Wu et al., 2018). The method aims to increase worker security for those who work outside. The suggested structure combines a wearable body area network (WBAN) for data collection from users with an LPWAN to connect the WBAN to the Internet. This article (Wu et al., 2020) described the layout of a tiny wearable sensor patchwork for monitoring various physiological signs, such as the body's temperature, photo plethysmography (PPG) and electrocardiogram (ECG).

2.1 Problem Statement

Intelligent technology integration is necessary to improve patient outcomes, reduce costs and meet the complex healthcare needs of a varied patient population. However, it is not integrated well enough, making it difficult to provide timely and individualized treatment. The amount of private patient data created and sent rises with the integration of intelligent technology into health management centres. Because of this, there is a greater chance of data breaches, cyber-attacks and illegal access to sensitive health information, endangering patient privacy and eroding healthcare system confidence.

3. Methodology

In this section, we discuss the intelligent technologies in health management centres on health monitoring. Figure 1 shows the flow of the suggested technique.

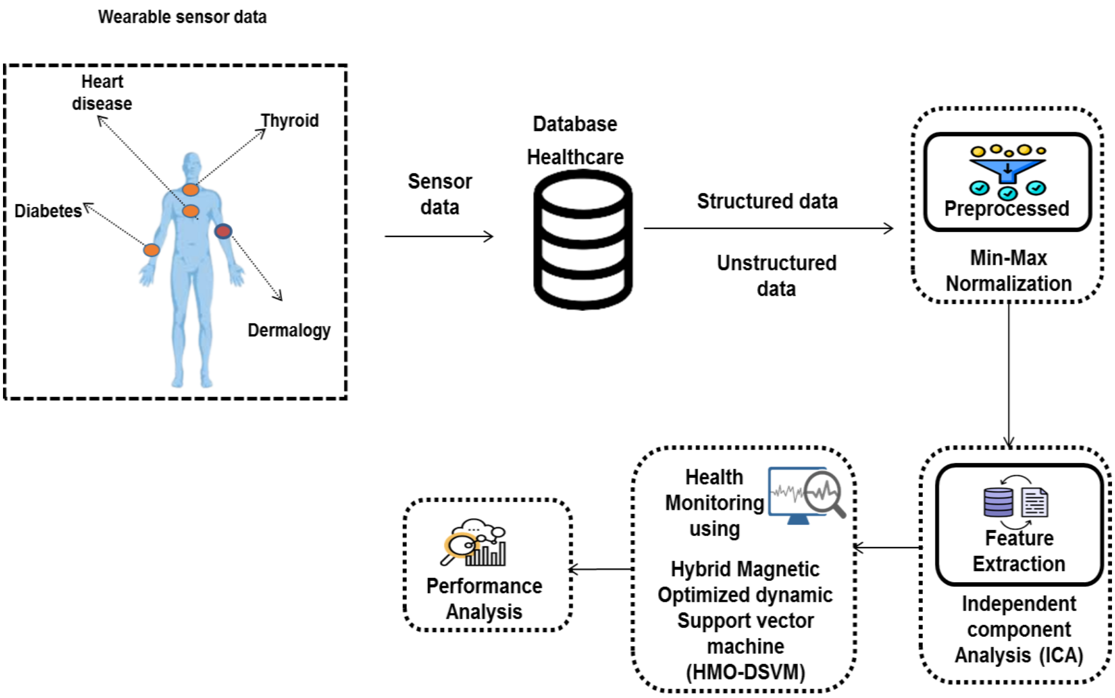

Figure 1: Flow diagram of the proposed method

3.1 Data Collection

As indicated in Table 1, the authors used a variety of publicly available datasets for various conditions, including thyroid, dermatology, diabetes and heart disease. Each disease's data set is split into training and testing datasets for experimental work, with 80% of the data serving as the training set and the remaining 20% serving as the testing set (Kaur et al., 2019).

Table 1: Dataset utilized in an experiment

DATASET	CLASS	NUMBER OF SAMPLES
DIABETES	2	768
HEART DISEASE	5	303
THYROID	6	9172
DERMATOLOGY	6	366

3.2 Data pre-processing using Min-max normalization

Min-max normalization is a common technique for scaling numerical properties within a certain range. It is used to prepare data for machine learning models. Min-max normalization can be used to normalize the input characteristics of the dataset monitoring healthcare. To enable a fair comparison of values before and after the operation, the normalization approach known as min-max normalization employs linear adjustments to the original data.

$$Z_{new} = \frac{z=min}{max(z)-min(z)} \quad (1)$$

Z_{new} =The adjusted value obtained after scaling the data; Z = outdated value; $max(z)$= Dataset's highest possible value; $min(z)$ = Dataset's lowest possible value

3.3 Feature extraction using for Independent component analysis (ICA)

An additional feature extraction technique, ICA, turns a multivariate random signal into a signal with independently varying elements. It is assumed that an equivalent amount of independent signals, measured signals and every measured signal is an inverse combination of every single independent signal. Consider that there are m linear combinations of the type $y_1, \ldots\ldots y_m$that we have seen. The mixes are m separate components combined linearly.

$$y_i = e_{i1}g_1 + e_{i2}g_2 + \cdots. + e_{im}g_m \quad (2)$$

When the search for independent components is represented by the variable t_l (l = 1 to m), the independent components and the mixture variables can be assumed to have a zero mean without losing generality. We can use the mixes $y_1, y_2 \ldots\ldots, y_m$ as symbols for y in vector format. The independent parts are designated here by the letter "t." The mixing model is expressed as $y = Bt$ if the mixing matrix is represented as "B". Independent Component Analysis is the term used to describe this model. Following the estimation of the matrix$B$, the inverse U can be calculated and the separate elements can be calculated as $t = Ut$. ICA takes the following steps:

Step 1: The technique of centring the data involves taking the mean out of the information. In order to guarantee that each of the elements have a zero mean.

Step 2: Another pre-processing technique is data whitening. During whitening, the mixture is changed to have unconnected elements and unity-sized deviations.

Step 3: Choosing the standards for independence: The independence criteria are determined by the data that is studied. Among the several techniques are ICA by maximizing non-normality, ICA by maximum or minimization of kurtosis, The FastICA algorithm and negentropy. In this investigation, the Negentropy approach was applied.

Step 4: Reconstitution of information: The output from using the independence criterion is divided by the product of whitening. After transposing the supplied data, this result is multiplied.

3.4 Hybrid Magnetic Optimized Dynamic support vector machine (HMO-DSVM)

To improve the SVM model's parameters and rate of convergence, this method incorporates magnetic optimization approaches that could have been influenced by magnetic field concepts. The system includes a DSVM, which allows SVM model parameters and structure to be adjusted in response to real-time alterations in health-related data. Leveraging this hybrid approach, the system seeks to enhance health monitoring systems' accuracy and reactivity, hence promoting more efficient health evaluation and management.

3.4.1 Dynamic Support vector machine (DSVM)

An efficient ML method for classifying data is the SVM. The DSVM is to create a hyperplane that divides two distinct groups of samples of data using the accessible information gathered and to maximize the "margin" of the closest data point from the hyperplane points in any class, as plainly seen in Figure 2. The DSVM might be used in a situation involving non-linear categorization by using the Kernel function as the function mapping's inner product and the input to a high-dimensional space of features. The space of feature mapping does not require any explicit evaluation.

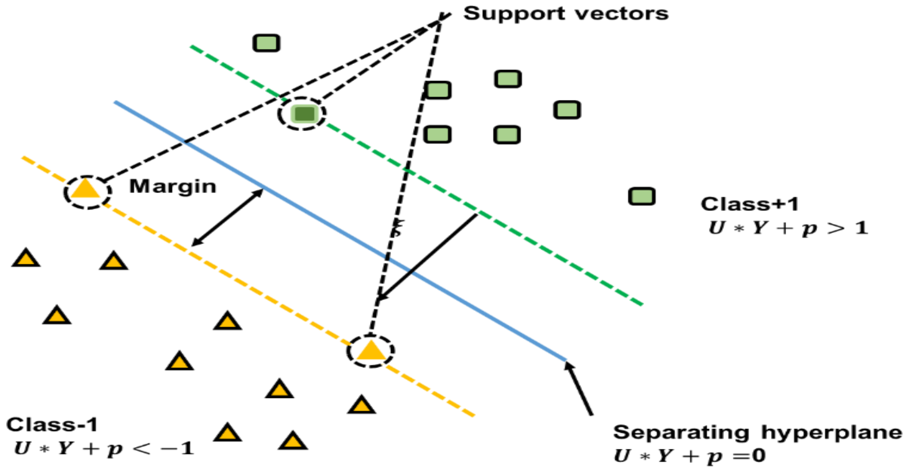

Figure 2: SVM's maximum of Margin Hyperplanes and Optimal Hyperplane

It is more logical to filter a small number of outlier points of data because it is not possible for the provided data to be separate. The slack variable$\xi_j$and the penalty for error C, which makes up the soft margin of the DSVM is necessary for its efficient operation, are described by

$$\text{Margin}= \frac{2}{\|u\|^2} \quad (3)$$

The optimization of the solution will be:

$$\text{Min}\left(\frac{1}{2}\|u\|^2 + V\sum_{j=1}^{M}\xi_j\right) \quad (4)$$

$$\text{Subject to} x_{j(u,Y)} + p \geq 1 - \xi_j, \xi_j \geq 0 \quad (5)$$

where u and $p$are the scalar and vector that are used to specify the hyperplane's location. $\xi_j$is a distance calculated between the hyperplanes that remain on their incorrect sides. The non-linear decision function will result from solving the dual optimization problem as shown by Equations (4) and (5) using the lagrange multipliers approach.

$$l(y) = sign\left(\sum_{j=1}^{M} e_j, x_j R(y, y_j) + p\right) \quad (6)$$

Where

$$R(y, y_j) = \exp\left(-\gamma\|y_j - y_i\|^2\right), \gamma > 0 \quad (7)$$

Where $R(y, y_j)$ is the kernel function, known as the Radial Basis Function (RBF). This kernel function allows it to examine data that is higher dimensional.

3.4.2 Hybrid Magnetic Optimization Algorithm (HMOA)

One of nature's four basic interacting forces is the electromagnetic field, which is a notion. The interaction force among two electromagnetic components is inversely correlated with their distance, meaning that the farther apart the particles are, the less the force. The MOA simulates a system of agents, or particles of magnet that interact with one another to find a solution in an area of search, utilizing their magnetic fields or their fitness levels as shown in Algorithm 1. The meanings of MOA in mathematics are outlined as follows; agents are first distributed over the search space at random by MOA. Each agent is represented by a solution vector $Y_j \epsilon \Re^{\eth}$, where y_j^t represents the location of the agent in the t^{th} dimension and j designates the j^{th}agent. The solution vectors are analysed at each iteration of the method and their corresponding fitness values are saved in P_j, which stands for the particle's magnetic field value j. The mass $N_j$of every agent is supplied by

$$N_j = \propto + \rho P_j \qquad (8)$$

Where $\propto$ and ρ are values for constant parameters. Between two particles, the force of interaction j and $i$at dimension $t$is shown below:

$$L_{ji}^t = P_j \frac{y_i^t - y_j^t}{T(Y_i, Y_j)} \qquad (9)$$

In which $T(;.)$is a function of distance. Updates are made to each agent's location, velocity and acceleration by

$$e_j^t = \frac{L_i^t}{N_j}, \qquad (10)$$

$$c_j^t(d+1) = \theta c_j^t(d) + e_j^t \qquad (11)$$

$$y_j^t(d+1) = y_j^t(d) + cj^t \qquad (12)$$

where d is the iteration step and$\theta \sim U(0,1)$.

Algorithm 1: Hybrid Magnetic Optimization Algorithm (HMOA)

Start
$d = 0$

Step 1: initialize $Y^0$with a structured population
Step 2: even while there is no termination requirement
begin
d=d+1
Step 3:Analyze the component in $Y^d$and record their output in magnetic fields P^d
Step 4: Normalize P^d
Step 5: Assess the mass $N^d$for every particle as per

Step 6: for every particle y_{ji}^din Y^d do

Begin
Step 7: $L_{ji} = 0$
Step 8: find M_{ji}

Step 9: for all y_{wc}^d in M_{ji} do

Step 10: $L_{ji} = L_{ji} + \frac{\left(y_{wc}^d - y_{ji}^d\right) \times P_{wc}^d}{T(y_{ji}^d, y_{wc}^d)}$

end

Step 11: for all particles y_{ji}^d in Y^d do

begin

Step 12: $c_{ji,r}^{d+1} = \frac{L_{ji,r}}{N_{ji,r}} \times K(f_r, w_r)$

Step 13: $c_{ji,r}^{d+1} = c_{ji,r}^d + c_{ji,r}^{d+1}$

End
End
End

4. Result and Discussion

In this section, we discuss the application of intelligent technologies in health management centres on health monitoring. By placing different health sensors over a 1000x1000 m area in a simulation, the suggested model is confirmed. Windows 10 operating system and Python are used for experimentation and the network is made up of aggregate nodes and a sink that carry out various operations such as compression, transmission and decompression using the corresponding algorithms listed in the proposed work section.

The evaluation metrics are accuracy, precision, F1-score, sensitivity and specificity. The comparison of existing methods is Random forest (RF) (Ali et al., 2020), Naïve Bayes (NB) and Decision tree (Ali et al., 2020). Table 2 depicts the simulation parameters.

Table 2: Simulation parameters

S. NO	CONSTRAINT	VALUE
1.	Gateways	6
2.	Network area	1000x1000m
3.	Physical memory	512Mb
4.	Capacity	1Gb
5.	Number of devices	50
6.	Bandwidth	1Mbps
7.	Request per second	10

This indicates the system's capacity to continuously and dependably monitor and record health data. For chronic illnesses, regular monitoring is essential to identify trends as well as changes in health markers and enable successful management. Figure 3 and Table 3 depict the comparative study of accuracy in various methods. When compared, the proposed method achieves higher accuracy than the existing methods. In each dataset, our proposed (HMO-DSVM) approach reaches high accuracy.

Table 3: Outcomes of the accuracy

DATASET	ACCURACY (%)			
	RF (Ali et al., 2020)	NB (Ali et al., 2020)	DT (Ali et al., 2020)	HMO-DSVM [PROPOSED]
DIABETES	81.16	82.7	75.97	96.53
HEART DISEASE	55.73	68.7	52.45	85.14
THYROID	70.12	77.3	66.57	80.85
DERMATOLOGY	83.26	83.13	85.15	95.26

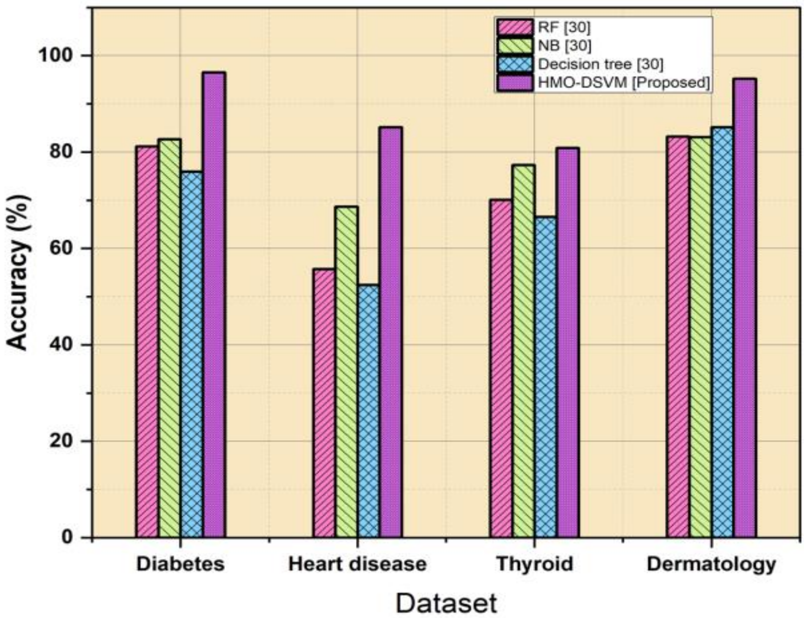

Figure 3: Comparison of accuracy in various datasets

A highly precise real-time monitoring system can detect any sudden changes or emergencies, allowing for immediate intervention and timely medical assistance. Figure 4 and Table 4 denote the comparative study of precision in various methods. In various datasets, we compared the proposed method to achieve greater precision than the other methods.

Table 4: Results of the precision

DATASET	PRECISION (%)			
	RF (Ali et al., 2020)	**NB (Ali et al., 2020)**	**Decision tree (Ali et al., 2020)**	**HMO-DSVM [PROPOSED]**
DIABETES	78.5	80.5	74.8	85.3
HEART DISEASE	73.8	79.7	82.21	88.44
THYROID	81.9	83.4	78.71	92.7
DERMATOLOGY	73.5	80.2	79.65	92.61

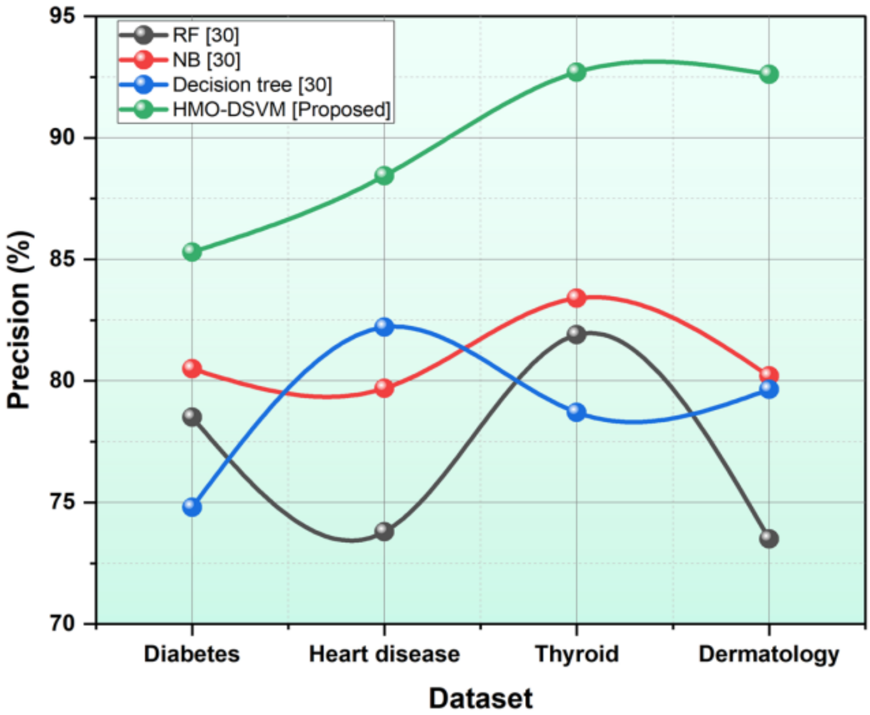

Figure 4: Comparison of precision in various datasets

The F1-score provides a fair evaluation of the model's overall performance, which is helpful when working with datasets that are unbalanced, making it a useful metric for health monitoring. A high F1-score in health monitoring shows that the system can reliably identify and detect health issues, limiting false positives along with false negatives and enhancing the accuracy as well as dependability of the procedure for monitoring. Compared with existing methodologies, the proposed method achieves a greater F1-score in several datasets. Figure 5 and Table 5 describe the comparison of the F1-score in various dataset.

Table 5: Outcomes of the F1-score

Dataset	F1-SCORE (%)			
	RF (Ali et al., 2020)	**NB (Ali et al., 2020)**	**Decision tree (Ali et al., 2020)**	**HMO-DSVM [PROPOSED]**
DIABETES	72.6	80.3	74.7	83.77
HEART DISEASE	69.3	79.51	78.51	87.8
THYROID	77.6	85.35	82.35	90.5
DERMATOLOGY	83.5	77.78	81.56	94.82

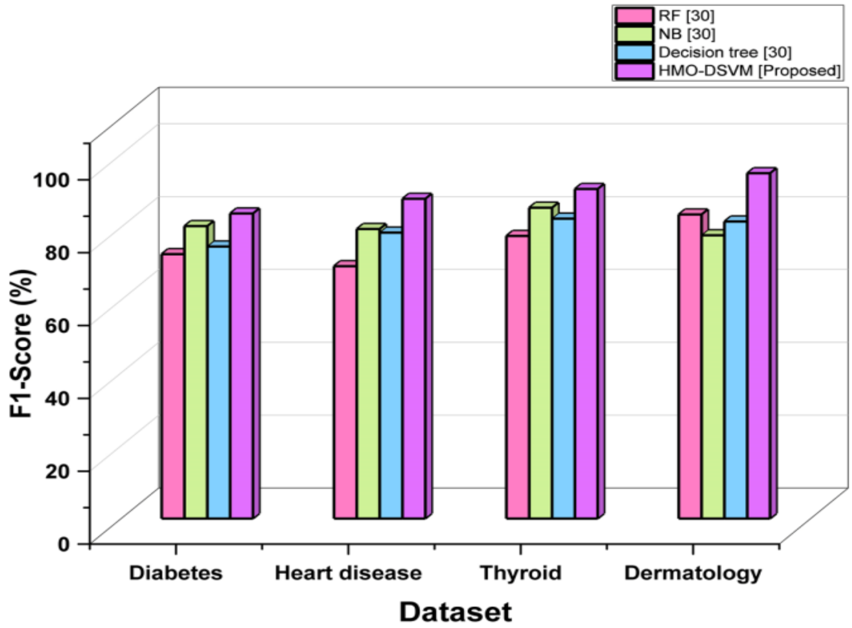

Figure 5: Comparison of F1-score in various datasets

For health monitoring systems to be useful and reliable, particularly in identifying and treating various health disorders, the sensitivity parameter must be evaluated. Healthcare workers can improve patient care and general health outcomes by focusing on sensitivity to make sure that monitoring systems are capable of recognizing people who need additional examination and action. Figure 6 and Table 6 demonstrate the comparative study of sensitivity in various methods. We evaluated the suggested technique with existing methods on a variety of datasets and the proposed method achieved a high level of sensitivity.

Table 6: Result of the Sensitivity

Dataset	SENSITIVITY (%)			
	RF (Ali et al., 2020)	**NB (Ali et al., 2020)**	**Decision tree (Ali et al., 2020)**	**HMO-DSVM [PROPOSED]**
DIABETES	77.76	79.7	77.8	85.41
HEART DISEASE	80.25	82.3	82.35	86.8
THYROID	82.41	84.57	80.41	90.3
DERMATOLOGY	83.67	88.5	86.3	92.7

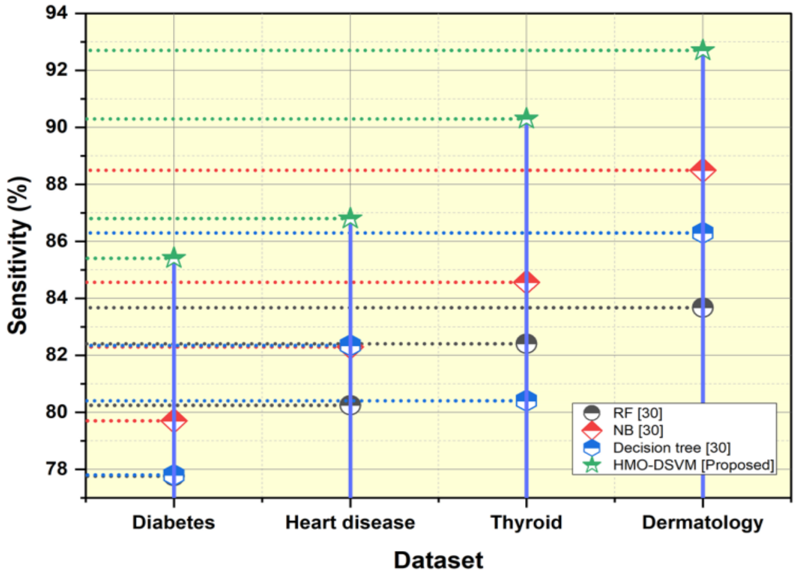

Figure 6: Comparison of sensitivity in various datasets

The specificity parameter is essential for assuring the accuracy and efficacy of health monitoring systems in establishing the absence of certain health problems. By focusing on specificity, healthcare professionals can raise their level of trust in the accuracy of the monitoring systems and raise the standard of care provided to patients as a whole. Figure 7 and Table 7 present the comparative study of specificity in various methods.

Table 7: Result of the Specificity

DATASET	SPECIFICITY (%)			
	RF (Ali et al., 2020)	**NB (Ali et al., 2020)**	**Decision tree (Ali et al., 2020)**	**HMO-DSVM [PROPOSED]**
DIABETES	79.4	79.57	80.21	90.5
HEART DISEASE	80.2	83.4	81.5	92.3
THYROID	81.41	84.3	79.7	89.81
DERMATOLOGY	87.5	85.56	86.87	94.3

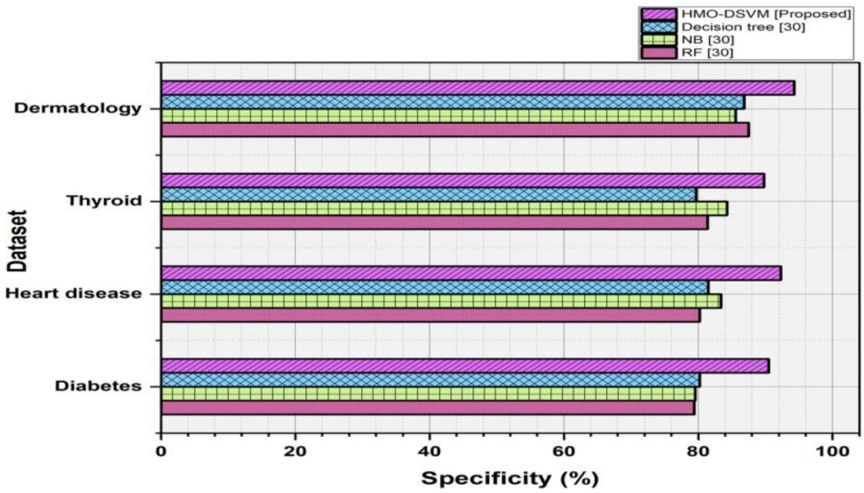

Figure 7: Comparison of specificity in various datasets

4.1 Discussion

A complete technology system that uses data analysis and real-time monitoring to forecast and prevent heart illnesses is called an Intelligent Healthcare Tracking System to Predict Heart Disease. The system's goal is to monitor and evaluate pertinent health metrics by using a variety of smart devices, including wearable sensors, mobile apps and cloud-based platforms. Naïve Bayes (Ali et al., 2020), decision tree (Ali et al., 2020) and random forest (Ali et al., 2020) have lower accuracy in the health monitoring in different dataset than the proposed method. The system uses sophisticated algorithms and machine learning methods to gather and analyse data on vital signs, physical activities, dietary habits and medical history to anticipate the development of heart disease in people and identify possible risk factors. Furthermore, it offers tailored advice with actions, enabling patients as well as medical professionals to take proactive measures to control and reduce the risk of heart-related issues. Decrease in face-to-face communication between patients and physicians. The technology cannot replace the knowledge and individualized treatment given by healthcare experts; it can provide insightful analysis and data-driven forecasts. In treating complicated health problems like heart disease, relying on automated monitoring and predictive analytics can possibly diminish the value of human judgment, empathy and customized treatment strategies. Furthermore, an over-reliance on technology can lead to a lack of comprehensive knowledge about a patient's general health, thereby missing significant non-measurable aspects that influence their condition. Our proposed HMO-DSVM method tackles these issues. Personalized treatments can lead to better health management and more effective outcomes for individuals with diverse health conditions. IoT devices can help the early detection of health issues, cost-effective healthcare delivery and a more proactive approach to managing individual and population health.

5. Conclusion

The integration of intelligent technologies into health management centres, particularly within the realm of sports medicine, offers significant potential for enhancing the monitoring and management of athlete health. The novel data processing system developed in this study, based on IoT architecture and utilizing the hybrid Magnetic Optimized Dynamic Support Vector Machine (HMO-DSVM) method, demonstrates substantial improvements in the accuracy, precision, and reliability of real-time health monitoring for athletes. By effectively processing and analysing health data, the proposed system enables more informed decision-making, which is crucial for optimizing athletic performance and ensuring timely interventions. The study's findings confirm that the application of advanced technologies such as IoT and machine learning algorithms can lead to better health outcomes by providing more precise and timely health assessments. This is particularly important in sports medicine, where the ability to monitor and respond to an athlete's health in real-time can significantly impact their performance and overall well-being. As these intelligent technologies continue to evolve, their further integration into health management centres will be essential for advancing the field of sports medicine. The successful implementation of such systems not only promises to improve individual health outcomes but also has the potential to set new standards for athlete care, making it a critical area of focus for future research and development. By embracing these innovations, sports medicine practitioners can ensure that athletes receive the best possible care, ultimately leading to enhanced performance and prolonged athletic careers.

Reference

Ali, F., El-Sappagh, S., Islam, S. R., Kwak, D., Ali, A., Imran, M., & Kwak, K.-S. (2020). A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. *Information Fusion*, *63*, 208-222.

Alshammari, H. H. (2023). The internet of things healthcare monitoring system based on MQTT protocol. *Alexandria Engineering Journal*, *69*, 275-287.

AlShorman, O., AlShorman, B., Alkhassaweneh, M., & Alkahtani, F. (2020). A review of internet of medical things (IoMT)-based remote health monitoring through wearable sensors: a case study for diabetic patients. *Indonesian Journal of Electrical Engineering and Computer Science*, *20*(1), 414-422.

Awotunde, J. B., Ajagbe, S. A., & Florez, H. (2022). Internet of things with wearable devices and artificial intelligence for elderly uninterrupted healthcare monitoring systems. International Conference on Applied Informatics,

Azimi, I., Rahmani, A. M., Liljeberg, P., & Tenhunen, H. (2017). Internet of things for remote elderly monitoring: a study from user-centered perspective. *Journal of Ambient Intelligence and Humanized Computing*, *8*, 273-289.

Bajaj, N. S., Patange, A. D., Jegadeeshwaran, R., Pardeshi, S. S., Kulkarni, K. A., & Ghatpande, R. S. (2023). Application of metaheuristic optimization based support vector machine for milling cutter health monitoring. *Intelligent Systems with Applications*, *18*, 200196.

Baswa, M., Karthik, R., Natarajan, P., Jyothi, K., & Annapurna, B. (2017). Patient health management system using e-health monitoring architecture. 2017 International Conference on Intelligent Sustainable Systems (ICISS),

Crowell, B., Cug, J., & Michalikova, K. F. (2022). Smart wearable internet of medical things technologies, artificial intelligence-based diagnostic algorithms, and real-time healthcare monitoring systems in COVID-19 detection and treatment. *American Journal of Medical Research*, *9*(1), 17-32.

Doghri, W., Saddoud, A., & Chaari Fourati, L. (2022). Cyber-physical systems for structural health monitoring: sensing technologies and intelligent computing. *The Journal of Supercomputing*, *78*(1), 766-809.

Dorj, U.-O., Lee, M., Choi, J.-y., Lee, Y.-K., & Jeong, G. (2017). The intelligent healthcare data management system using nanosensors. *Journal of Sensors*, *2017*.

El Zouka, H. A., & Hosni, M. M. (2021). Secure IoT communications for smart healthcare monitoring system. *Internet of Things*, *13*, 100036.

Humayun, M., Jhanjhi, N. Z., Almotilag, A., & Almufareh, M. F. (2022). Agent-based medical health monitoring system. *Sensors*, *22*(8), 2820.

Islam, M. M., Rahaman, A., & Islam, M. R. (2020). Development of smart healthcare monitoring system in IoT environment. *SN computer science*, *1*, 1-11.

Kaur, P., Kumar, R., & Kumar, M. (2019). A healthcare monitoring system using random forest and internet of things (IoT). *Multimedia Tools and Applications*, *78*, 19905-19916.

Khatoon, A. (2020). A blockchain-based smart contract system for healthcare management. *Electronics*, *9*(1), 94.

Kondaka, L. S., Thenmozhi, M., Vijayakumar, K., & Kohli, R. (2022). An intensive healthcare monitoring paradigm by using IoT based machine learning strategies. *Multimedia Tools and Applications*, *81*(26), 36891-36905.

Lamonaca, F., Sciammarella, P., Scuro, C., Carni, D., & Olivito, R. (2018). Internet of things for structural health monitoring. 2018 Workshop on Metrology for Industry 4.0 and IoT,

Latchoumi, T., Swathi, R., Vidyasri, P., & Balamurugan, K. (2022). Develop new algorithm to improve safety on WMSN in health disease monitoring. 2022 International Mobile and Embedded Technology Conference (MECON),

Lee, D., & Yoon, S. N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. *International journal of environmental research and public health*, *18*(1), 271.

Mani, N., Singh, A., & Nimmagadda, S. L. (2020). An IoT guided healthcare monitoring system for managing real-time notifications by fog computing services. *Procedia Computer Science*, *167*, 850-859.

Mehta, N., Pandit, A., & Shukla, S. (2019). Transforming healthcare with big data analytics and artificial intelligence: A systematic mapping study. *Journal of biomedical informatics*, *100*, 103311.

Nancy, A. A., Ravindran, D., Raj Vincent, P. D., Srinivasan, K., & Gutierrez Reina, D. (2022). Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. *Electronics*, *11*(15), 2292.

Poongodi, M., Sharma, A., Hamdi, M., Maode, M., & Chilamkurti, N. (2021). Smart healthcare in smart cities: wireless patient monitoring system using IoT. *The Journal of Supercomputing*, 1-26.

Qing, X., Li, W., Wang, Y., & Sun, H. (2019). Piezoelectric transducer-based structural health monitoring for aircraft applications. *Sensors*, *19*(3), 545.

Rajan Jeyaraj, P., & Nadar, E. R. S. (2022). Smart-monitor: Patient monitoring system for IoT-based healthcare system using deep learning. *IETE Journal of Research*, *68*(2), 1435-1442.

Venkatesan, S., Manickavasagam, K., Tengenkai, N., & Vijayalakshmi, N. (2019). Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin. *IET Electric Power Applications*, *13*(9), 1328-1335.

Wu, F., Wu, T., & Yuce, M. R. (2018). An internet-of-things (IoT) network system for connected safety and health monitoring applications. *Sensors*, *19*(1), 21.

Wu, T., Wu, F., Qiu, C., Redoute, J.-M., & Yuce, M. R. (2020). A rigid-flex wearable health monitoring sensor patch for IoT-connected healthcare applications. *IEEE Internet of Things Journal*, *7*(8), 6932-6945.

Yeruva, A. R., Durga, C. V., Gokulavasan, B., Pant, K., Chaturvedi, P., & Srivastava, A. P. (2022). A smart healthcare monitoring system based on fog computing architecture. 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS),

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing*, *115*, 213-237.