

Discrete Chaotic Fuzzy Neural Network (DC-FNN) Based Smart Watch Embedded Devices for Sports and Health Monitoring

Xu YUANTAI

Abstract: Improved athletic performance is expected to result from the convergence of semiconductor technology from the wearable device equipped with physiology and its clinical and translation tools. The increasing usage of smart wearable devices has made an impact not only on the lifestyle of the users, but also on biological research and personalized healthcare services. This research optimises the usage of smart watch integrated devices through wireless connection, which sheds light on wearable sensors used in sports medicine. The major objective of this article is to provide a recommended method of using wearable technology for evaluating the efficacy of health and sports monitoring. Any sport at any level may stand to profit from this embedded technology, as might academic research labs, sports medicine practises, and professional sports teams all working toward the same goal of improving player and team performance. As the primary data generated by wearable devices include the heartbeat rate, step count, and energy consumed, researchers have concentrated on associating cardiovascular disorders with these data. A Discrete Chaotic Fuzzy Neural Network (DC-FNN) model was presented to analyse smart watch functionality for use in fitness and health tracking. This study used machine learning algorithm for analyzing the performance of wearing smart watch embedded device among sports players. The study employs discrete chaotic Fuzzy neural network for evaluating the recognition time and efficiency of the embedded device. The Discrete Chaotic Fuzzy Neural Network (DC-FNN) theories focus on the expertise and experience of specialists who understand how sports system works in different parameters. The major elements of the DC-FNN strategy are based mostly on expert expertise. This research work highlights how wearable sensors can help players and trainers keep tabs on athletes' biomechanical and physiological health in real time, preventing or delaying the start of injuries and providing a more accurate picture of how they are doing. Athlete involvement risk is mediated by the interplay between tissue health and training.

Keywords: artificial intelligence; DC-FNN; health monitoring; sensors; smart watch; sports; wireless communication

1 INTRODUCTION

As time goes on, science and technology continue to advance, people's living standards rise, their material needs are met, their access to modern conveniences increases, urban infrastructure improves, the nation's overall power grows, and the rate of growth quickens. Despite constant progress, however, children's and adolescents' physical health has not improved, and teenagers' fitness has worsened and many new issues have emerged [1]. A growing number of individuals are struggling with obesity, as shown by the National Health Survey's findings in recent years. Data also show that college students physical health is deteriorating, that their fitness levels are falling, and that this decline is becoming more noticeable. We need to pay close attention to these issues [2]. Investing in the future of the country's youth is a long-term investment in the country's future. The nation's future strength may be greatly enhanced with the help of the country's youth [3]. Therefore, it is important for a young person with growth potential to work on both improving their quality of life and the level of success they experience. Young people's prospects, progress, and power can only improve via their integration of these factors.

People nowadays enhance their fitness and health by using the Internet, advanced digital systems, and smart, connected devices [4]. Low levels of knowledge about them mean that you may run across circumstances in which individuals are unsure of how to train or which kind of exercise are best for them. Because of this, training does not have a significant impact, and the benefits of exercise cannot be realized. Physical harm may also be caused by training in the dark or by excessive exercise [5]. The core of each piece of equipment and the foundation of each fitness strategy make up the bulk of the sports training system. The primary system is the major component, while the other fitness systems are supplementary, and they are all linked by Internet technology. The final data set may be obtained and compared to previous data by starting at the bottom and working one's way up through the many layers

of the actual situation [6]. Those who are interested in exercising may also be directly affected by the fitness system.

People nowadays place less and less value on their bodily wellbeing. There has not been widespread dissemination of information on how individuals may utilize the Internet, advanced digital systems, and smart technology to enhance their health [7]. A number of problems exist as well, including a widespread lack of understanding. This platform uses a Bluetooth technology to transmit signals between fitness equipment and connected devices, enabling users to engage in exercise, enjoy media, and learn new knowledge. The equipment automatically syncs with a user's mobile device or computer and transmits data such as workout duration and calorie burn [8]. Finally, consumers will be presented with more tailored and precise fitness and nutrition recommendations that take into account their unique body and circumstances. Further research has led to the successful construction of a series of network intelligent digital collecting systems, with the majority of these systems finding use in fitness centers [9]. It has a human body and mind perceiving system, a data-collecting network system, a data-gathering system, and an application system for analyzing the data. The perception system's primary role is to assess a person's physical fitness and the amount of force that their body can withstand. After collecting consumer data, the network system processes it, sends it to the appropriate server, and finally delivers the sorted data to the appropriate employees. The application's primary purpose is to collect and save information. The literary work poses a pressing issue that calls for immediate attention. Users are disinterested and fitness centers are empty [10]. The cutting-edge technology included into the newly fashioned exercise machines may first validate the user's identification before offering a custom workout setting. With the integration of virtual reality, the new system provides a more satisfying experience for its users. Avoiding the drawback of inadequate communication with users, the system can

capture the data and outcomes of people's activity in real time, making fitness equipment more individualized and digitized [11]. Treadmills are a popular piece of equipment among users. The technology integrates perception and embedded technology into treadmills, allowing for the verification of user identities, the collection of statistics both during and after exercise, a more reasonable division of labor between fitness equipment, fitness enthusiasts, and fitness trainers, and improved communication among all parties to increase efficiency, variety, and accuracy [12]. There are two basic categories of information involved in the gathering and sending of fitness-related exercise data: exercise outcomes and exercise apparatus information. Data on heart rate is a vital metric for reflecting the impact of exercise on practitioners, particularly aerobic exercise [14]. At the same time, it is important to correlate the heart rate data with the tools actually used during exercise. It is important to delve deeply into the differences between the heart rate changes brought on by aerobic exercise and the heart rate changes brought on by strength training [15]. The subject's heart rate was collected using a heart rate sensor, and the exercise machine's characteristics were gleaned using radio frequency identification technology in this study.

1.1 Use of Smart Watch Embedded Device in Sports

Strength training is a great way to boost your health, but it is important to keep your heart rate up as you work out so you do not hurt yourself. Name, gender, age, height, and weight may all be gleaned from the practitioner's smart device, and using that data and their resting heart rate, a maximal heart rate can be determined [16]. There are four distinct "heart rate zones" that may be used to categorize exercise intensity based on the effects each zone has on the body. During the warm-up phase, your heart rate should be between 50% and 60% of your maximum. The goal of this phase of exercise is to enhance bodily function and avoid damage, hence the intensity is minimal. The fat-burning heart rate zone is defined as being between 60%-70% of one's maximal heart rate. The exercises at this point are more strenuous than the warm-up. Exercise's fat-burning benefits are maximized at moderate intensities. Those looking to trim their waistlines will benefit greatly from this phase. The heart rate zone during the endurance portion of a workout is between 70% and 80% of one's maximal heart rate [17]. Cardiovascular and respiratory fitness are greatly aided by exercise at this level, despite its increased intensity compared to the fat-burning level and shorter duration. Therefore, those who need to boost their cardiopulmonary function should focus on this stage. During the strength training phase, your heart rate should be at least 80% of your maximum. At this point in the workout, the intensity is at its peak, the muscular load is at its greatest, and tiredness sets in quickly. Therefore, this phase is excellent for those who want to bulk up their muscles and develop more power and stamina. The user's heart rate is monitored during exercise, and the data is collected over the Internet. The examination of the system is then performed in light of the requirements of the users [18]. Fat loss users should aim for a heart rate between 60% and 80% of their maximum whereas muscle-building users should aim for a heart rate of 80% or higher (strength exercise stage). Furthermore, keeping track of your heart rate while physical activity may boost the effectiveness of

your workout, lessen the likelihood of injury, and bring a more scientific and professional air to your routine.

The trend toward remote monitoring, real-time, and rapid identification of diseases has prompted the emergence of a new area of study: remote healthcare. The term "remote healthcare," which encompasses a wide range of practices (telehealth, mobile health), describes the use of technology to track patients outside of institutionalized medical treatment [19]. Among the many advantages of remote patient monitoring are the following: the ability to detect illnesses early and in real-time; preventing untimely deaths and worsening illness, ability to administer patients and reduce number of hospitalization and enhancement in effective healthcare services through the wireless communication technology [20]. Patients with chronic conditions, those with mobility challenges or other disabilities, those recovering from surgery, newborns, and the elderly are all potential beneficiaries of remote patient monitoring. Because of the nature of their illnesses, all of these patients benefit from constant monitoring. The goal of quality healthcare is to restore patients to as normal and pleasant a life as possible. Most studies adhere to the concept of letting patients have the freedom to go about their daily lives in their own homes or other personal settings, rather than being confined to an expensive hospital room [21]. In order to back up this idea, many technological methods are being developed. New apps for remote health monitoring allow older individuals to go about their day without assistance. These programs make it possible for the user to stand while doing things like reading or watching TV, or even while sleeping, with no disruption. Wearable sensors will have little impact on the events. Smart wristwatches are equipped with sensors. For victims of unexpected injuries, the only time they are under remote monitoring might be in the ambulance on the way to the hospital. However, there has been an emphasis on ensuring a safe trip to the hospital, and remote monitoring aids in the prompt implementation of medical measures for really serious patients [22]. Doctors are able to keep an eye on their patients, noting any changes or providing advice to the paramedics who are on the scene as needed.

The end-terminal at the hospital, the data processing system, the data collecting system, and the communication network are the foundations of a remote monitoring system. The many sensors or devices that make up a data collecting system have the capacity to wirelessly transmit data. There is a possibility that cameras and cellphones may replace medical sensors in the near future because modern studies have focused on contactless approaches, in which no physical contact is made between the patient and the equipment [23]. One prevalent use of such sensors in non-contact techniques is the usage of Wireless Sensor Networks (WSN). One may further classify these systems into PANs, BANs, and WBANs, or wireless Body Area Networks (BAN). A data processing system consists of a processing unit/circuitry and a data receiving and transmission system. Any hospital-based computer, database, specialized device, or even the doctor's own smartphone might serve as the hospital's terminal [24]. A healthcare provider who is also linked to the system via the underlying communication network may access the processed data and draw conclusions from the collected data. Depending on the severity of the problem, the patient may be instructed to seek medical attention at a hospital, take precautionary measures, or take medication [25]. There is a wide variety in the technology, capacities, and

procedures of the various remote health monitoring systems.

2 PROPOSED SYSTEM

Through the implementation of health surveillance programmes for the early identification of adverse health consequences, players health monitoring aims to guarantee that the safeguards in place to protect players from dangers are successful. However, there are a number of reasons why medial monitoring is not ideal. The first is the extra expense of the diagnostic tests for the players. The emotional energy that is expended on falsely good results is the second factor. False-positive findings will eventually be identified, and the player will be notified. In fact, there are numerous different technologies that make up artificial intelligence. In order to figure out how well the players of that specific sport are doing in terms of their health, this article used artificial intelligence with wireless communication and sensor techniques. In order to accomplish healthy management and preserve a relationship between the players and trainers, the system will regularly assess and monitor the players' health using AI intelligence technology and inform the player of the results. Health monitoring plays a significant role in the daily activities of the players of any sports. In the traditional system it is highly difficult to monitor the health manually. These difficulties are overcome by the implementation or utilization of recent trending technologies. Some of the notable technologies for monitoring the health of the players include Artificial Intelligence, wireless sensor networks, smart devices and so on. This research focuses on the utilization of smart watches which are treated as embedded devices utilised for health monitoring of sports players. Individual sports have their own uniqueness and hence an unique embedded device can be designed to optimize the functionalities.

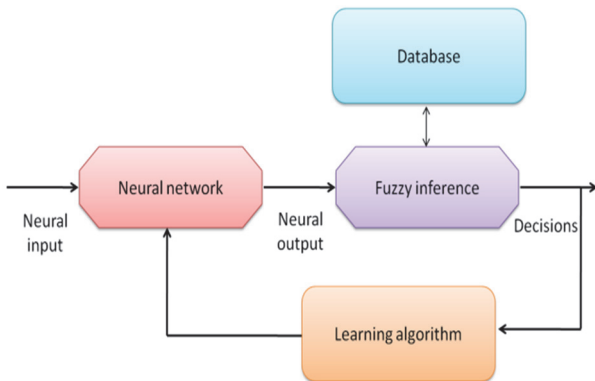


Figure 1 Model of Fuzzy Neural Network

This study used machine learning algorithm for analyzing the performance of wearing smart watch embedded device among sports players. The study employs discrete chaotic Fuzzy neural network for evaluating the recognition time and efficiency of the embedded device. The Discrete Chaotic Fuzzy Neural Network (DC-FNN) theories focus on the expertise and experience of specialists who understand how sports system works in different parameters. The major elements of the DC-FNN strategy are based mostly on expert

expertise. Fig. 1 depicts the model of Fuzzy Neural Network.

$$b_{qc} = \frac{b_{qc} - \min_p a_{pc}}{\max_p a_{pc} - \min_p a_{pc}}, \tag{1}$$

To restore the information to its previous form

$$a_{qc} = \cup(b_{qc}) = b_{qc} \left(\max_p a_{pc} - \min_p a_{pc} \right) + \min_p a_{pc}, \tag{2}$$

The following is how these data are routed through the FNN. The following operations are done first from the input layer to the hidden state:

$$\tilde{I}_{ql}^s = \sum_{c=1}^C \left(\tilde{H}_{cl}^s b_{qc} \right), \tag{3}$$

$$\tilde{n}_{ql}^s = \tilde{I}_{ql}^s (-) \tilde{\theta}_l^s = \left(I_{ql1}^s - \theta_{l3}^s, I_{ql2}^s - \theta_{l2}^s, I_{ql3}^s - \theta_{l1}^s \right), \tag{4}$$

$$\tilde{s}_{ql}^s = \frac{1}{1 + e^{-\tilde{n}_{ql}^s}}, \tag{5}$$

where h_{el}^s is the relationship weight among effort node c and hidden-layer node l ; $l = 1 \sim L$ θ_l^s .

On the output node, the concealed layer's inputs are gathered. The performance of wearing embedded smart watch can be evaluated by using the equation below.

$$\tilde{I}_j^k = \sum_{l=1}^L \left(\tilde{h}_l^k (\times) \tilde{s}_{ql}^s \right), \tag{6}$$

And then the network output $z_q = z_{q1}, z_{q2}, z_{q3}$ is evaluated as

$$Z_j = \frac{1}{1 + e^{-\tilde{I}_j^k}}, \tag{7}$$

where

$$\tilde{n}_Q^Z = \tilde{I}_Q^Z (-) \tilde{\theta}^Z, \tag{8}$$

All variables and parameters in the suggested method are expressed as DC-FNN or are estimated by them. DC-FNN with a single convolutional whereby all hyperparameters can be fuzzy and complex transition functions are used. We want to hypothetically maximize the quantities of fuzzy parameters without having to solve the Neuro-Linguistic Programming (NLP) issue while ensuring that all calculation is included in the fuzzy forecasts. Rather than fuzzifying all variables at once, this study uses an autonomous fuzzification strategy, in which each parameter is fuzzified separately. This research is significant because it is a necessary step in building an

exact DC-FNN, as it sets the groundwork for constructing a precise deep DC-FNN with numerous.

Athletes' current internal and external workloads can be monitored with the use of wearable and IoT technology. Still, more information on the athlete's internal burden is needed if we are going to be able to fine-tune training and boost performance. To give just one example, the ability to non-invasively and continuously monitor physiological biomarkers like saliva or sweat allows for the possibility of optimal hydration modification, boosting the athlete's overall performance. In addition, there are novel avenues for exploration in sports activity detection and tracking made possible by the employment of such technology.

3 RESULTS AND DISCUSSION

The existing methods such as Deep generative Bayesian optimization (D-BO) [26], Internet of Things (IoT) [27] and Smartphone Sensors (S-S) are used to assess the proposed method (DC-FNN). The parameters such as cost efficiency, processing time, encryption time, decryption time, energy consumption and precision are obtained. Tab. 1 represents the outcomes of cost efficiency, processing time and encryption time for existing and proposed methods.

Table 1 Outcomes of cost efficiency, processing time and encryption time

	Cost efficiency / %	Processing time / s	Encryption time / s
D-BO	79	95	90
IoT	86	92	82
S-S	74	85	75
DC-FNN [Proposed]	95	74	60

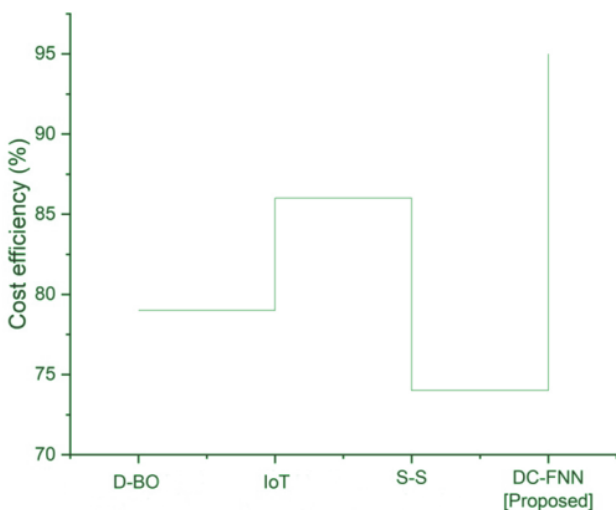


Figure 2 Cost efficiency

When a piece of technology is reworked to function more efficiently, it saves money over the long run. By reducing procurement expenses and enhancing overall efficiency, the company hopes to improve its bottom line. The proposed method (DC-FNN) has a higher in cost efficiency and lower in existing methods (D-BO, IoT, S-S). Fig. 2 depicts the cost efficiency for existing and proposed methodologies.

It is significant to enhance production by reducing the processing time, which they defined as "the time it takes to execute a particular task.

$$(N - 1)P1 + (N - 2)P2 + \dots + PN - 1, \tag{9}$$

Fig. 3 indicates the processing time for proposed and existing methods. The proposed methods have lower processing time when compared to the existing methods.

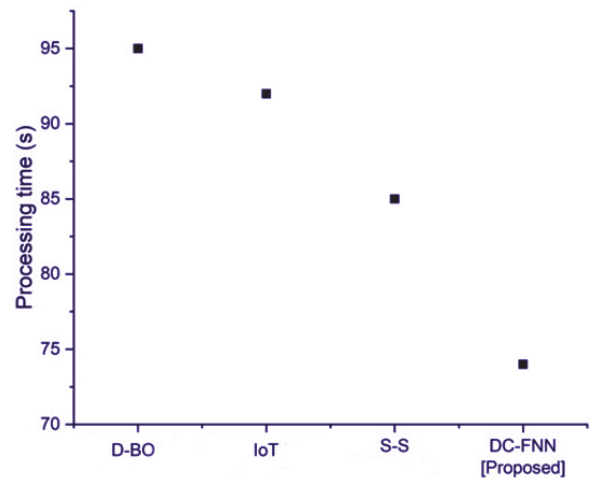


Figure 3 Processing time

A security strategy is offered as a solution to the problem of private data leakage. It is challenging to provide security and safeguard privacy in smart devices due to the open nature of wireless communication between them. Existing studies mostly seek to improve smart watch extension functionality and stop motion sensor data leakage. Other than a PIN, the Bluetooth protocol does not provide any other means of authentication. In addition, the fine-grained access control is not considered by the current cloud-untrusted solution in the Internet of Things. Not only that, but private information is easily accessible by the cloud. When compared to other computing devices, certain smart watches are relatively lightweight IoT devices. Therefore, the smart wearable gadgets cannot use the encryption methods that are too complicated. As a result, we must address the problem of implementing a reliable security system for smart wearable gadgets. The time it takes to encrypt a set of media files is discussed and displayed on an "encryption time" graph. Time is counted in seconds. The time required to encrypt some media data is proportional to the size of the media content file used as input.

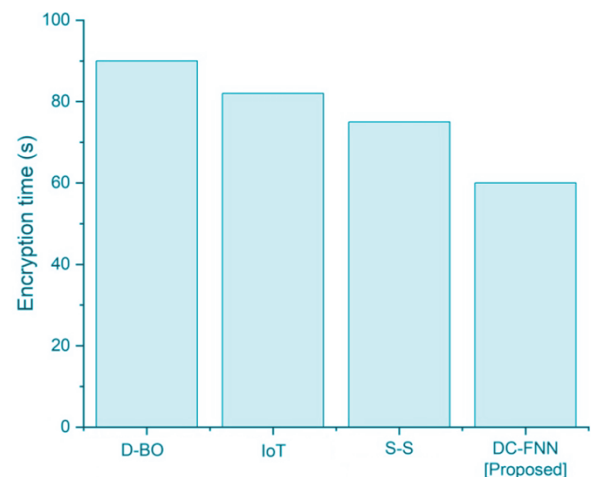


Figure 4 Encryption time

To see how long it takes to encrypt data, see Fig. 4. Current encryption methods are more time-consuming than those that have been proposed.

A decryption is any method used to restore plain text from encrypted files. In many cases, reverse encryption is the preferred method. With the use of a private decryption key or password, it ensures that only authorised parties can access the encrypted data. If any unauthorized person wears or steals the devices, the sensor will send message or give alarm. The time required to decipher is shown in Fig. 5. Decryption times using the proposed methods are faster than those using the current methods.

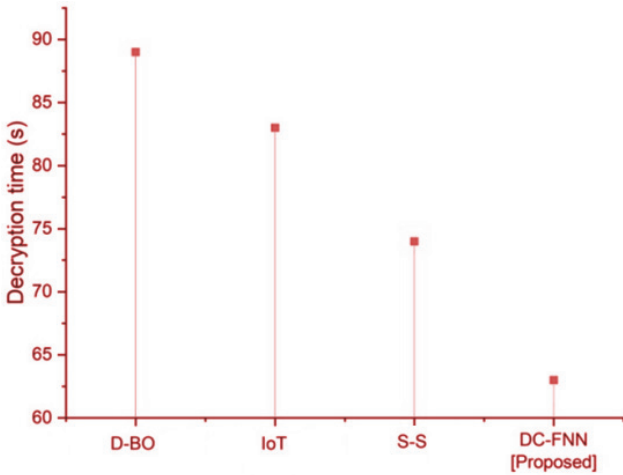


Figure 5 Decryption time

Energy consumption refers to the amount of power or energy consumed to encrypt data. Wearable computing, and specifically activity monitoring, faces the challenge of battery life. Recognizing and keeping tabs on more complicated actions may necessitate even more resources. While many methods rely on movement sensors to identify actions that involve discrete movements, more information, including location, is required to master common daily tasks that involve sequences of simpler motions. The purpose of the smart watch is to identify these sophisticated actions while they are being carried out, in real time. As a result, the research develops novel sensing methods that use less power and last longer on a single charge.

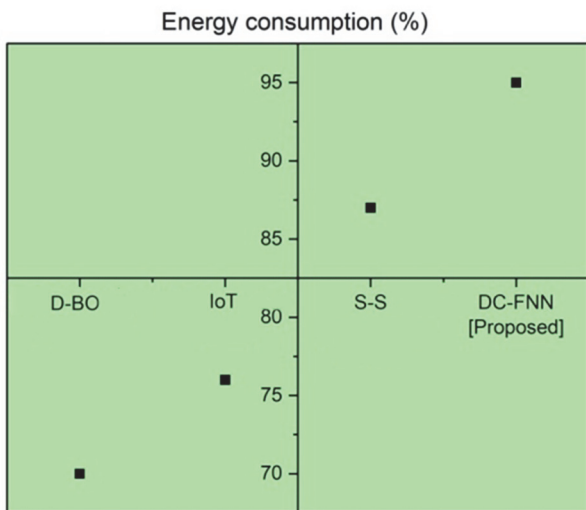


Figure 6 Energy consumption

Fig. 6 depicts Energy consumption. Energy consumption is higher in proposed and lower in existing methods.

The ratio of positive cases to all instances that were predicted to be positive is known as precision. The formula below may be used to compute it:

$$Precision = \frac{TP}{TP + FP}, \tag{10}$$

Fig. 7 depicts the Comparative evaluation of precision in Suggested and Traditional Methods. Precision for proposed is high when compared to the existing methods. With the help of wireless communication network, the players can wear embedded devices for health monitoring. Tab. 2 represents the outcomes of decryption time, energy consumption and precision for existing and proposed methods.

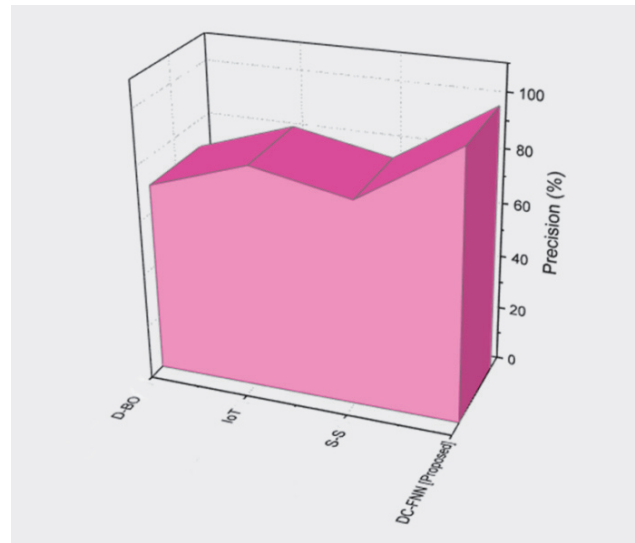


Figure 7 Precision

Table 2 Outcomes of decryption time, energy consumption and precision

	Decryption time / s	Energy consumption / %	Precision / %
D-BO	89	70	70
IoT	83	76	82
S-S	74	87	75
DC-FNN [Proposed]	63	95	98

The study highlights how wearable sensors can help players and trainers keep tabs on athletes' biomechanical and physiological health in real time, preventing or delaying the start of injuries and providing a more accurate picture of how they're doing. Athlete involvement risk is mediated by the interplay between tissue health and training.

4 CONCLUSION

This research focuses on the utilization of smart watches which are treated as embedded devices utilised for health monitoring of sports players. Individual sports have their own uniqueness and hence a unique embedded device can be designed to optimize the functionalities. This study used machine learning algorithm for analyzing the

performance of wearing smart watch embedded device among sports player. The study employs discrete chaotic Fuzzy neural network for evaluating the recognition time and efficiency of the embedded device. The Discrete Chaotic Fuzzy Neural Network (DC-FNN) theories focus on the expertise and experience of specialists who understand how sports system works in different parameters. The major elements of the DC-FNN strategy are based mostly on expert expertise model for analysing the performance of smart watch in the sports and health monitoring.

In the future wearable technologies are required to overcome the current challenges including data security and privacy through improved regulation mechanisms.

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Contact information:

Xu YUANTAI

Huami (Nanjing) Information Technology Co.,
Ltd. (Zepp Health), Nanjing 210019, Jiangsu, China
E-mail: xuyuantai.huami@gmail.com