Implementation method of intelligent emotion-aware clothing system based on nanofibre technology

DOI: 10.35530/IT.075.01.202379

LUO QISHU

ABSTRACT – REZUMAT

Implementation method of intelligent emotion-aware clothing system based on nanofibre technology

The creation of smart clothing technologies now has more options because of the merging of fashion design, and wearable technology with nanofibre technology. This study suggests a means for putting a nanofibre-based, intelligent, emotion-aware clothing system into practice. By recognizing and reacting to the wearer's psychological state, the system seeks to improve user convenience and well-being. In this study, a unique, self-sufficient weight-tuned Kohonen neural network (SW-KNN) method is used to categorize emotional states. To determine the wearer's emotional state, we first collect a dataset of signals from the body, including pulse, body temperature, and perspiration production. The dataset is then added to the preprocessing stage, where the raw data is normalized using the min-max method. The important features from the cleaned data are then extracted using the Fast Fourier Transform (FFT). The smart control unit processes the physiological signals that have been acquired. The proposed approach is utilized to categorize the wearer's emotional state, and the white shark optimization (WSO) approach is used to improve the classification accuracy. The control unit has a microchip and wireless connectivity abilities, enabling it to send the devices' connected devices the classified emotional status. The clothing technology can continuously modify its features based on the identified emotional state to enhance the wearer's comfort. The findings of the study stated that the proposed technique has provided accuracy and precision of 97.8% and 98.1% respectively.

Keywords: *smart clothing technology, fashion design, wearable technology, nanofibre technology, emotional state classification, self-sufficient weight-tuned Kohonen neural network (SW-KNN)*

Metodă de implementare a unui sistem inteligent de îmbrăcăminte axat pe inteligenţa emoţională pe baza tehnologiei nanofibrelor

Crearea tehnologiilor inteligente de îmbrăcăminte are acum mai multe opțiuni datorită îmbinării designului de modă, a tehnologiei purtabile cu tehnologia bazată pe nanofibre. Acest studiu sugerează o modalitate de a pune în practică un sistem de îmbrăcăminte inteligent, bazat pe nanofibre și pe inteligenţa emoţională. Prin recunoașterea și reacționarea la starea psihologică a purtătorului, sistemul urmărește să îmbunătățească confortul și bunăstarea utilizatorului. În acest studiu, este utilizată o metodă unică, pe baza rețelei neuronalale Kohonen (SW-KNN) autosuficiente, reglată în funcție de greutate, pentru a clasifica stările emoționale. Pentru a determina starea emoțională a purtătorului, am colectat mai întâi un set de date de semnale de la corp, inclusiv pulsul, temperatura corpului și producția de transpirație. Setul de date este apoi adăugat la etapa de preprocesare, unde datele brute sunt normalizate folosind metoda min-max. Caracteristicile importante din datele curățate sunt apoi extrase folosind transformata Fourier rapidă (FFT). Unitatea de control inteligentă procesează semnalele fiziologice care au fost colectate. Abordarea propusă este utilizată pentru a clasifica starea emoțională a purtătorului, iar abordarea de optimizare White Shark (WSO) este utilizată pentru a îmbunătăți acuratețea clasificării. Unitatea de control este dotată cu un microcip și abilități de conectivitate wireless, permițându-i să trimită dispozitivelor conectate starea emoțională clasificată. Tehnologia de îmbrăcăminte își poate modifica continuu caracteristicile pe baza stării emoționale identificate pentru a spori confortul purtătorului. Concluziile studiului au afirmat că tehnica propusă a oferit acuratețe și precizie de 97,8% și, respectiv, 98,1%.

Cuvinte-cheie: *tehnologie de îmbrăcăminte inteligentă, design de modă, tehnologie purtabilă, tehnologie pe bază de nanofibre, clasificarea stării emoționale, rețea neuronală Kohonen autosuficientă reglată în funcție de greutate (SW-KNN)*

INTRODUCTION

An idea that blends cutting-edge textile components with artificial intelligence (AI) to produce clothes that can detect and respond to the wearer's emotions is known as an intelligent emotion-aware clothing system based on nanofibre technologies. By giving people new opportunities to express themselves and improve their general health, this cutting-edge technology has the potential to completely transform the fashion business. Based on nanofibre technology, develop a smart emotion-aware apparel system [1]. Nanofibre manufacturing includes creating fibres with nanometre-sized diameters, usually fewer than 100 nanometres. These nanofibres have distinctive qualities such as great strength, adaptability, and excellent surface area-to-volume ratios. They may be manufactured from many materials, such as polymers, metallic ones, or ceramics. Nanofibres are perfect for the creation of smart clothing since they can be manufactured to have certain features, such as detecting capacities [2]. The intelligent emotion-aware clothing system makes use of sensors built right into the fabric to identify emotional-related physiological rhythms and impulses. These sensors can be of numerous kinds, such as electrodermal activity (EDA) sensors to measure sweat gland activity, electrocardiography (ECG) sensors for tracking the rhythm of the heart, and even sensors that can recognise fluctuations in the temperature of the body or expressions on the face [3].

An AI algorithm or machine learning model processes the data gathered by these sensors to evaluate the signals and ascertain the wearer's emotional state. This approach takes into consideration variables like conductance of the skin, cardiac variation, and other physiological responses that connect with certain emotions [4, 5]. To effectively identify and understand the wearer's state of mind, the AI model is trained on a sizable collection of physiological data associated with emotions. Different responses from the clothing system are possible depending on the identified emotions. For instance, it may alter its colour, pattern, or texture to visibly reflect the wearer's feelings. A major benefit of smart garment technology is improved comfort and convenience. Imagine clothing that adjusts temperature depending on body heat, weather, and activities. Intelligent sensors and microprocessors manage heat and moisture in these adaptable fabrics to give wearers a personalized experience. Smart clothing may also include responsive lighting, letting customers alter its colour or pattern with a touch or smartphone app.

Additionally, it might produce haptic feedback to produce a soothing or exciting experience, such as soft pressure or vibrations. The system may also communicate with other hardware or software to offer tailored suggestions or interventions based on the emotional state of the user, such as recommending relaxation methods or playing uplifting music [6, 7]. Smart clothing technologies will revolutionize fashion and self-expression beyond comfort. Flexible screens and programmable textiles allow clothes to show dynamic patterns, colours, and pictures. This allows users to change their look and dress for different situations without buying several garments, allowing for infinite creative expression and inventiveness. An intelligent, emotion-aware apparel system has several advantages. It can encourage mental health, facilitate self-expression, and aid people in better understanding and controlling their emotions. It has the potential to improve human relationships and experiences in a variety of fields, including healthcare, sports performance, entertainment, and style. Smart clothing aims to reinvent fashion beyond health. Clothing is a dynamic canvas for self-expression since it may change colours, patterns, and styles. Advanced algorithms and machine learning can assess human preferences and environmental circumstances to recommend outfits that match tastes and the occasion. This blend of aesthetics and technology ushers in a new age of individualized fashion that blurs virtual and real barriers. To generate an all-encompassing emotional experience, the garment system may communicate with outside objects and settings [8, 9]. The wearer's psychological health can be enhanced by immersive settings and coordinated reactions made possible by its connection to smartphones, smart homes, and virtual reality devices. For instance, the garment can produce visual or haptic feedback to amplify good feelings if the user gets a message indicating delight. Security and privacy are top priorities while developing this system. The security of the wearer's private information is a top priority for the intelligent emotion-aware clothing system. It upholds stringent privacy rules, uses encryption to protect private data, and gives the wearer complete discretion over how their emotional information is distributed [10].

Key contribution

The following are the main contributions of this research on the development of smart clothing technologies by combining wearable technology and nanofibre technology.

- The paper presents a nanofibre-based, emotion-aware clothing system. This device detects and responds to the wearer's mental state to increase comfort and well-being. Smart fabrics with sensors and control units can adjust to the wearer's emotional condition.
- The study categorizes emotional states using a self-sufficient weight-tuned Kohonen neural network (SW-KNN). This method analyses the wearer's pulse, body temperature, and perspiration. The SW-KNN analyses and classifies the wearer's emotional state based on data.
- WSO Improves Classification Accuracy: White shark optimization (WSO) improves emotional state classification in the study. White sharks influenced the metaheuristic optimisation algorithm WSO. This method improves emotional state detection and clothing system reactions. The WSO algorithm refines classification, improving the emotion-aware clothing system.

RELATED WORKS

The related works summary is presented in table 1.

MATERIALS AND METHOD

The combination of wearable technology and nanofibre technology has increased the choices for developing smart clothing technologies. This paper makes recommendations for how to implement a nanofibre-based, intelligent, emotion-aware clothing system. Figure 1 depicts the overall methodology.

Dataset

ECG signals are frequently employed for emotion recognition and evaluation because they precisely convey human emotion. To allow real-time user emotion forecasting, the user's emotional representations

Table 1

RELATED WORKS		
Reference	**Objectives**	**Findings**
Hassabo et al. [11]	To improve the performance, functionality, and comfort of sportswear and associated products, the study investigated the developments in nanotechnology and its prospective applications.	Textile nanotechnology technologies like nanomaterials and sensors have increased physicochemical qualities. NPs in textiles improve self-cleaning, UV protection, flame resistance, and antibacterial properties.
Deng and Liu [12]	The research developed a multi-task Using a deep convolutional neural network, customers may participate in design via transferable learning. Learn deep image attributes for picture recovery utilizing client-clicking information. Parameterized programming and neural networks were used to generate garment designs and build wearer-cantered smart outdoor sportswear automatically.	The research produced a new garment design method that lets individuals engage and develop distinctive designs. Visitor-clicking information allows reliable retrieval of images using multi-task deep convolutional neural network learning. Genetic algorithms generate several clothing styles for people. Sensor technology in outdoor sportswear monitors heart rate and microclimate warmth.
Yang et al. [13]	The study created an emotion-aware system using artificial intelligence as well as graphs. The system provides personal emotion identification, smart suggestions, and relationship identification. The research analyses various scenarios to improve the suggested system's efficacy and usability.	The findings indicated that a private machine, smart clothes, cloud terminal, and algorithms might successfully recognize and communicate human feelings, giving significant advantages to consumers.
Moreira et al. [14]	The paper aimed to enhance emotion-aware intelligent algorithms to detect depression following childbirth in pregnant hypertension women. The program analysed biological and socioeconomic information to identify people at risk and create a childbirth health issues reaction strategy.	Mixture predictors predict pregnancy-related psychological illnesses well. The article shows that the method can predict depression after childbirth in pregnant hypertension women. The snippet does not include findings or measurements of performance.
Hu et al. [15]	The work proposed and validated the MULTI-EASE structure to improve user interaction in emotion identification tasks while minimizing end-to-end delay and energy usage. The paper also investigated the MULTI-EASE structure flexible scheduling of tasks.	The study validated the MULTI-EASE structure with a working system. Research findings showed that MULTI-EASE was an effective and durable evaluation of emotions tool. The proposed architecture saves edge computing energy and increases emotional interaction. The study's findings illuminate MULTI-EASE structure flexible planning.
Chen et al. [16]	The paper looked at the network architecture, energy consumption optimization mode, and body area network node design of smart clothing for physiological monitoring. A general review of the requirements and key technologies for body area network transmission of smart apparel is also provided.	The results show that the researchers' internal network-optimized structure for smart clothing satisfies the requirements for safety, dependability, low power consumption, and portability, especially in the area of physiological monitoring. It is also simple to use, portable, and practical.
McDuff et al. [17]	The article described how the platform's audio, visual, and application processing components store and share data for other programs. A tool that encourages creative interfaces between humans and computers was enhancing emotional computing.	The paper's findings described the multisensory emotion and contextual sensor platform's visual, auditory, and computational processor elements. It described how every part helps the overall system record and transmit real-time emotional information. The document explains data storage and communication, allowing other programs to use emotional information for research or API interaction.
Shanmugam and Singh [18]	The purpose of the study was to provide a system that recognizes emotions and includes a personal robot, smart clothing, and a cloud interface. An innovative 'people-centred' method of emotional engagement has been developed.	The data perception and emotion-cognition engines analyse user interactions and environments. The suggested system uses communication, computing, and storage integrated by the artificial intelligence algorithm in the personal robot, smart clothing, and cloud terminal to respond to customer demands.

Table 1 (continuation)

Reference	Objectives	Findings
Peng et al. [19]	The purpose of the study is to contribute to this subject by examining the relevant literature. They suggested a three-tiered structure that encompasses the fundamentals of emotion analysis, various technologies and models, concerns about privacy, and implementation settings.	They examine the significance of integrating emotional intelligence into urban design and emphasize the potential of various technologies to contribute to an increase in the well-being of the populace. In general, this framework offers a complete method for examining feelings and their interactions with new technology in an urban setting.
Miao et al. [20]	The article investigates a technique for the automated development of clothing styles and designs parameterized code for use with the said approach. Compared to image feature representation based on image recognition training on artificially labelled datasets, the image and text feature representations developed in this study better reflect genuine user demands.	The research uses parametric binary coding to develop suit-style pieces using interactive genetic algorithms automated design approach. The interactive genetic algorithm based on the usual style optimizes garment inheritance and benignly evolves suit design depending on user assessment.
Chen et al. [21]	The article suggested a small portion of that market was smart apparel. Companies may maximize smart clothing's capability by engaging both device owners for personal data insights and big data analysis for commercial use, unlike personal wearable gadgets.	In these platforms collect large amounts of data from corporate systems and external sources, use powerful machine learning algorithms for rigorous, predictive, and continuous analysis, and provide actionable insights for mission-critical business imperatives.
Dang and Zhao [22]	This article introduced smart fibres and smart textiles and described their functionality and main categories. The article also covered smart fibre and textile usage across industries. It also emphasizes these new textile techniques' infinite growth and potential for profit.	This article covered smart fabrics and materials. It discusses form memory, colour-changing, intelligent heat leadership, impermeable and moisture-permeable, cleans themselves, and digitally stored smart fabrics. It also explores intelligent fibres and textiles' use in medical care, military protection, entertainment, sports, and clothing. These novel textile innovations have great potential for sale, as the paper underlines.
Hu et al. [23]	The research creates sensor-based smart apparel for home and ambulatory health monitoring during menopause. Initially, a survey analyses biological data to identify menopausal transition symptoms and target body locations for sensor placement on clothes.	The results show that this smart clothing monitoring system can accurately measure skin temperature and relative humidity and calculate the frequency, duration, and intensity of hot flashes in different body areas, as reported by subjects.
Krishna et al. [24]	The research polled people to discover smart clothing adoption barriers. Thus, perceived hazards and unavailability of smart garments, new items, have raised innovation resistance.	As a consequence of this, it has been proven that the fashion-forwardness of customers plays a role in boosting innovation resistance to inexpensive smart apparel. It is possible to conclude that customers who place a higher priority on maintaining their image face the additional pressure of having to make frequent purchases of somewhat pricey trendy clothing to stay on trend.
Ahsan et al.[25]	The structure provided requirements for design, detectors, and textile materials for smart apparel, particularly pants. The goal also involved seamlessly incorporating detectors into garments and developing a system for gathering data, manufacturing, and making choices approach to medical diagnosis and prediction.	The framework's specs for design, detector connection methods, and smart garment components are shown. Examples show how to apply the structure. Addressed were the problems of promoting smart clothing and its promise for medical athletics, sports, and style.

based on a previous ECG dataset are created in the cloud, and their accessibility is tested on a testbed. In addition, 20 volunteers – 8 men and 12 women, ranging in age from 22 to 29 – were enlisted for the study's conduct and assessment, and their ECG signals were labelled with five emotional states: normal, joyful, furious, fearful, and sad. For independent feature extraction, the entire set of ECG data is split into a training set (60 percent) and a testing set (40 percent).

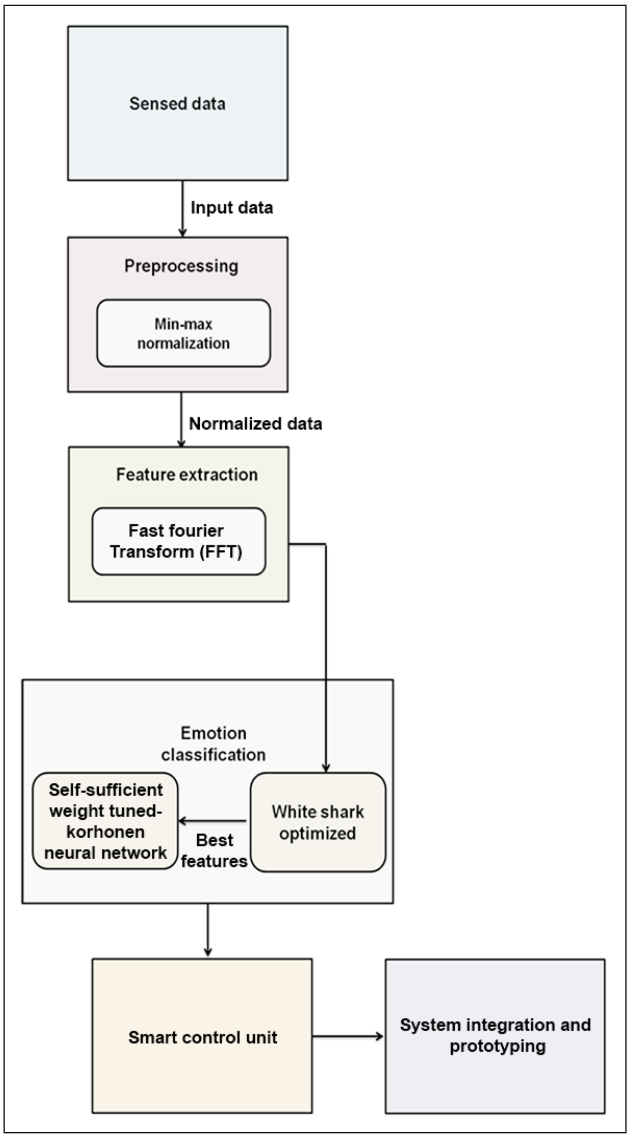

Fig. 1. Proposed model

Data preprocessing

Min-max normalization

A common tool for data preprocessing, used by the majority of data mining systems, is normalization. To normalize a dataset, scale each attribute's values such that they all lie inside a small specified range, say, 0.0 to 1.0. Preprocess data from children to estimate the risk of malnutrition using the min-max normalization strategy. With this technique, the features or outputs are scaled from one set of values to another. The characteristics are often rescaled to fall between [0, 1] and [–1, 1] or anywhere in between. A formula for linear interpretation is often used to do the rescaling in (equation 1), such as:

$$y' = \frac{y - min_E}{max_E - min_E}(new\_max_E - new\_min_E) + + new\_min_E \quad (1)$$

where max_E is the attribute's highest value, min_E – its lowest value, and $(new\_max_E - new\_min_E) = 0$. When $max_E - min_E = 0$, it means that the value for that feature in the data is always the same. When the min-max normalization is used, each feature will stay the same as long as it is in the new range of values.

Feature extraction

Fast Fourier transform

The Discrete Fourier Transform (DFT) of a sequence can be calculated effectively using the FFT technique. Using the discrete Fourier transform (DFT), an impulse in the time domain can be computationally converted into a comparable signal in the domain of frequencies. The FFT approach makes the DFT substantially faster for large input sizes by reducing the complexity of computation from $O(n^2)$ to $O(n \log n)$.

The following is the equation for the DFT of a sequence of length N, $x[n]$:

$$X[k] = \sum n = 0 \ to \ N - 1 \, x[n] * exp\left(\frac{-j2pink}{N}\right) \quad (2)$$

where $X[k]$ stands for the frequency element at index k in the frequency domain, j is the imaginary unit $\sqrt{-1}$, pi is the number pi, or roughly 3.14159, and $exp()$ stands for the exponential function.

The input sequence is broken down into smaller subproblems by the FFT method, which then combines the answers to get the final DFT. One of the most used FFT algorithms, the Cooley-Tukey algorithm, is described in general terms as follows:

Step 1: The DFT is simply the value of the input sequence if the length of the input sequence N is 1; thus, return it.

Step 2: Divide the input sequence into two smaller sequences, each of length $N/2$, if N is more than 1. Let's give them the names X_{even} and X_{odd} to stand for the original sequence's even- and odd-indexed components, accordingly.

Step 3: Apply the FFT procedure to each and then recursively compute the DFT of X_{even} and X_{odd}.

$$X_{even} = FFT(x_{even}) \quad (3)$$

$$X_{odd} = FFT(x_{odd}) \quad (4)$$

Step 4: To get the final DFT of the initial sequence, combine the findings from the DFT of X_{even} and X_{odd}. In this phase, the DFT of X_{odd} is multiplied by the necessary twiddle factors and added to the DFT of X_{even}.

For $k = 0$ to $N/2 - 1$:

$$X[k] = X_{even}[k] + W_N k * X_{odd}[k] \quad (5)$$

$$X\left[k + \frac{N}{2}\right] = X_{even}[k] - W_N k * X_{odd}[k] \quad (6)$$

where $W_N k = exp\left(\frac{-j2pink}{N}\right)$ is the twiddle factor.

Step 5: The resulting DFT sequence is returned as $X[k]$.

Kohonen neural network (SW-KNN)

An artificial neural network design that was modelled after the way neurons are arranged in the visual cortex of the human brain is called a Kohonen neural network. This architecture is also known as a self-organizing map (SOM). It has widespread use in the fields of high-dimensional data clustering, visualization, and dimensionality reduction. The most important job of the network is to convert the high-dimensional input data into a lower-dimensional grid while maintaining the topological connections between the data points. This makes it possible for the network to discover hidden patterns and structures within the complicated information. Competitive learning characterizes the Kohonen neural network. The input layer accepts data, while the output layer is frequently grid-arranged. Each output layer neuron matches a grid node. The network changes its weights (synaptic strengths) to fit input data during training. The general architecture of KNN is shown in figure 2.

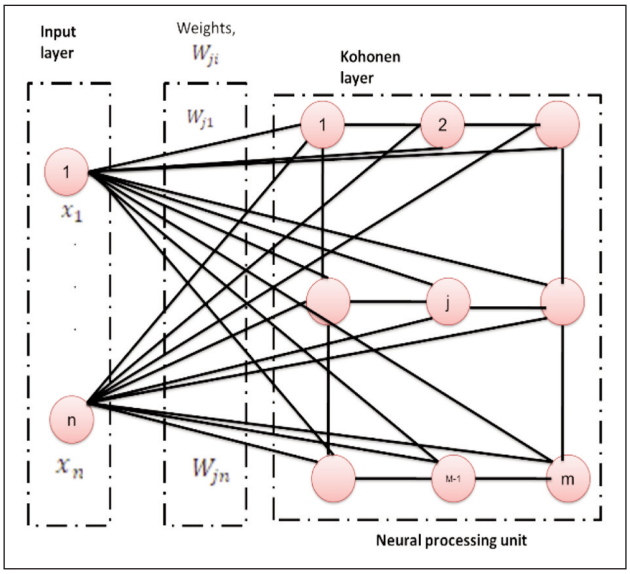

Fig. 2. General architecture of KNN

KNN training algorithm:
Step 1: Give the first input (x), a weight matrix (w) with random initialization, and a learning rate (α).
Step 2: Euclidean distances should be calculated for each output layer.

$$c(i) = \sum_{j\neq 1}^{M} (w_j - x_{old})^2 \qquad (7)$$

Step 3: the neuron (j) with the least distance value should be located.
Step 4: Specifically alter the winner neuron's weights.

$$x_{ji}(new) = x_{ji}(old) + [w_j - x_{ji}(old)] \qquad (8)$$

Step 5: Steps 2 through 4 should be repeated with the new set of weights.
Step 6: The process should be repeated 100–200 times for each iteration.

Modified Self-sufficient Weight-tunedKohonen neural network (SW-KNN) I

Since the SW-KNN is an unsupervised network, it has a lower accuracy level than the BPN. The training algorithm has undergone several changes to improve Accuracy. New weight values in SW-KNNs heavily rely on activation. Therefore, new weight values in this upgraded SW-KNN won't rely on old weight values. The proposed architecture of KNN is shown in figure 3.

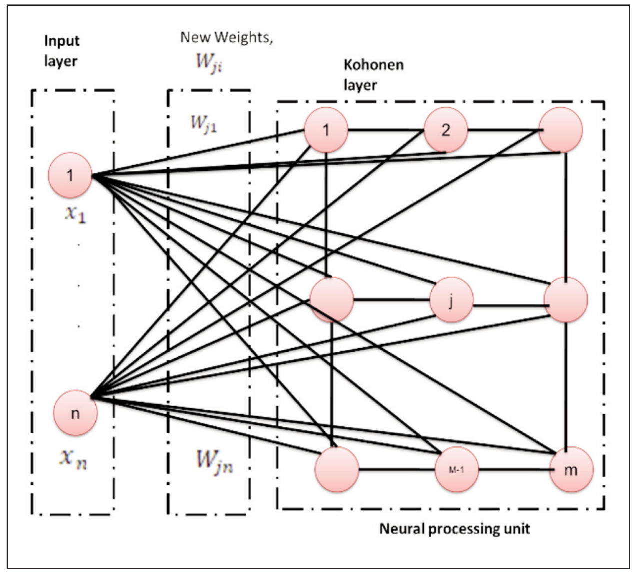

Fig. 3. Proposed architecture of KNN

Training algorithm of Modified SW-KNN I:
Step 1: First input (x), a weight matrix (w) with starting values chosen at random, and a learning rate (α) should be provided.
Step 2: Each output layer's Euclidean distance should be known.

$$c(i) = \sum_{j\neq 1}^{M} (w_j - x_{old})^2 \qquad (9)$$

Step 3: It is important to identify the neuron (j) whose distance value is the smallest.
Step 4: Specifically alter the winner neuron's weights

$$\Delta x_{ji} = 2 \propto w_j + \propto \qquad (10)$$

Step 5: With the new set of weights, repeat steps 2 through 4 again.
Step 6: Repeat the algorithm a certain number of times. (150).

This work uses an alpha value of 0.6. The procedure of weight correction is distinct from the traditional system. The distinction between the inputs and the old weights has no bearing on the weight modification procedure in the suggested method. The efficiency of the typical system is subpar since this gap can never be zero. The suggested way gets around this.

Modified Self-sufficient Weight-tunedKohonen neural network (SW-KNN) II

A few further adjustments are made to the modified SW-KNN II to improve Accuracy compared to the original SW-KNN. This network's accuracy level is greater than that of the standard Kohonen and lower than that of the modified SW-KNN II.

Application algorithm of Improved SW-KNN II:
Step 1: The weight matrix (w) with a randomly initialized first input (x), and learning rate (α) should be provided.
Step 2: Each output layer's Euclidean distance should be known.

$$c(i) = \sum_{j\neq 1}^{M} (w_j - x_{old})^2 \qquad (11)$$

Step 3: It is important to identify the neuron (j) whose distance value is smallest.

Step 4: Specifically alter the winner neuron's weights.

$$\Delta x_{ji} = 2 \propto w_j - \propto^2 \tag{12}$$

Step 5: Repeat the process using the updated weights.

Step 6: For a set number of repetitions, repeat the process. (150)

This work uses an alpha value of 0.6.

White Shark Optimization (WSO)

This section provides a full explanation of the mathematical equations that were created to describe the behaviours of hunting with white sharks to solve the OPF problem. This entails hunting down and killing prey.

WSO's initialization

In the accompanying two-dimensional matrix, which displays a populace of n where shark optimization in an area with d examine domain dimensions, the position of each pole suggests a possible answer to the difficulties that have been identified:

$$x = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_c^1 \\ x_1^2 & x_2^2 & \cdots & x_c^2 \\ \cdots & \cdots & \cdots & \cdots \\ x_1^m & x_2^m & \cdots & x_c^m \end{bmatrix} \tag{13}$$

where d indicates the quantity of choice varying for a particular assignment, and w shows the precise position of every shark in the search region.

Movement Speed Toward Prey

Equation 14 shows how a white shark can locate its target by detecting a pause in the movement of the waves.

$$v_{l+1}^j = \mu [v_l^j + o1(x_{h\,best_l} - x_l^j) \times d_1 + o2(x_{best}^{u_l^j} - x_l^j) \times d_2 \tag{14}$$

The new speed vector of the i^{th} shark is indicated by u_{l+1}^j and the integers $i = 1, 2, \ldots, n =$ index of sizes. Equation 15 indicates that u^i is the i^{th} index vector of sharks reaching the ideal position:

$$u = [m \times rand\ (1,m)] + 1 \tag{15}$$

where $rand$ (1,m) is a collection of randomly generated numbers with a range of [0, 1]:

$$o_1 = o_{max} + (o_{max} - o_{min}) \times f^{-(4k/k)^2} \tag{16}$$

$$o_2 = o_{min} + (o_{max} - o_{min}) \times f^{-(4k/k)^2} \tag{17}$$

where o_{min} and o_{max} stand for the beginning and ending speeds for white shark motion, and = *current,* and K = *maximum* repetitions. The values of o_{min} and o_{max} were determined to be 0.5 and 1.5, accordingly, after a careful study.

$$\alpha = \frac{2}{\left|2 - \tau - \sqrt{\tau^2 - 4\tau}\right|} \tag{18}$$

τ denotes the acceleration factor, which was determined through thorough research to be 4.125.

Generally moving in the direction of the best opportunity

In this context, the conduct of white sharks as they approach prey was described using the position update mechanism provided in equation 19.

$$x_{l+1}^j = \begin{cases} x_l^j, \rightarrow \oplus x_0 + v.b + k.a; & rand < nu \\ x_l^j + \dfrac{v_l^j}{f}; & rand \geq nu \end{cases} \tag{19}$$

b and a are defined as binary vectors, accordingly, in equations (20) and (21):

$$b = thm\,(x_l^j - v) > 0 \tag{20}$$

$$a = thm\,(x_l^j - v) < 0 \tag{21}$$

$$x_0 = \oplus (b, a) \tag{22}$$

where $\oplus$ equation (22), the result of a bitwise xor, is used to represent the result. Equations 22 and 23, respectively, describe the white shark's propensity for wavy motion and how often it strikes prey.

$$e = e_{min} + \frac{e_{max} - e_{min}}{e_{max} + e_{min}} \tag{23}$$

$$nu = \frac{1}{a_0 + f^{(1/2 - l)/b_1}} \tag{24}$$

where the control exploration and exploitation locations are determined by the constants a_0 and b_1.

Aiming to go towards the path of the shark

Sharks may hold their ground in front of the nearest target, the most beneficial competitor. Equation 25 illustrates the expression for these phenomena.

$$x_{l=1}^{\prime j} = x_{h\,best_l} + q_1 \vec{C}_x\, thm\,(q_2 - 0.5)\, q_3 < T_t \tag{25}$$

To change the searching path, $thm\,(q_2 - 0.5)$ yields 1 or –1, and q_1, q_2, and q_3 are all rand values. $x_{l=1}^{\prime j}$ = the position of the improved shark. No, in the range [0, 1], equation 26 states that Dw = length for both the target and the shark. Equation 27 calls for the parameter T_t to represent the strength of white sharks:

$$\vec{C}_x = \left| rand \times (x_{hbest} - x_l^j) \right| \tag{26}$$

$$T_t = \left| 1 - f^{(-b_2 \times l/l)} \right| \tag{27}$$

where the location factor b_2 controls the amount of exploitation and exploration.

Behaviour in Fish Schools

White shark fish school behaviour was defined using the equation shown below:

$$x_{l=1}^j = \frac{x_l^j + x_{l+1}^{\prime j}}{2 \times rand} \tag{28}$$

where and stands for a [0, 1]-dimensional random number with a uniform distribution equation 27, which shows that the sharks can alter based on the best shark that has arrived at the optimal place, which is extremely close to the goal, to determine its position, shows that the sharks can. Sharks' last resting place is typically near their prey in the search area. Fish behaviour, shark motion to the largest shark, and enhanced global and local search skills are indicators of WSO interaction.

WSO execution and evaluation

White sharks constantly work to get closer to the overall ideal solution when evaluating functions. White sharks are more likely to discover the best solution by leveraging and investigating the study area around the space, which explains why. This ability is achieved by using the location of the superior sharks and their victims. Sharks may, therefore, constantly scout out possible prey-rich areas and contribute to them. The main operations of Algorithm 1's algorithm can be utilized to summarize WSO's pseudo code.

Algorithm 1: WSO's pseudo code

1. Initialize the Parameter of the Problem,
2. Initialize the parameter of WSO
3. Randomly generate the initial positions of WSO
4. Initialize the velocity of the initial population
5. Evaluate the position of the initial population
6. While(l<L)do
7. Update the parameters u, o_1, o_2, m, b, a, x_0, e, x_u, and T_t using equations 15–18, 20–24 and 27, respectively
8. For $j = q$ to m do
9. $v_{l+1}^j = \mu[v_l^j + o1\left(x_{hbest_l} - x_l^j\right) \times d_1 +$
   $+ o2\left(x_{best}^{u_l^j} - x_l^j\right) \times d_2$
10. End for
11. For $j = 1$ to m do
12. If $rand < nu$ then
13. $x_l^j, \rightarrow \oplus x_0 + v.b + k.a;\ rand < nu$
14. Else
15. $x_{l+1}^j = x_l^j + \frac{v_l^j}{f}$
16. Endif
17. End for
18. For $j = 1$ to m do
19. If rand $\leq T_t$
20. $\left|rand \times (x_{hbest} - x_l^j)\right|$
21. If $j = 1$ then
22. $x_{l=1}^j = x_{hbest_l} + q_1 \vec{C}_x thm(q_2 - 0.5)$
23. Else
24. $x'^j_{l=1} = x_{hbest_l} + q_1 \vec{C}_x thm(q_2 - 0.5)$
25. $x_{l=1}^j = \frac{x_l^j + x'^j_{l+1}}{2 \times rand}$
26. End if
27. Endif
28. End for
29. Make the necessary adjustments to the positions of the white sharks that go over the barrier.
30. Examine and bring the new positions up to date.
31. $l = l + 1$
32. end while
33. Return the best outcome you've so far found

RESULT AND DISCUSSION

In this section, we analyse the following metrics: Accuracy (%), Precision (%), Recall (%), and F1-score (%), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Existing approaches include such as and Deep Convolutional Neural Networks (D-CNN) [15], Convolutional Neural Networks–Long Short-Term Memory (CNN-LSTM) [20].

The performance of a classification model can be evaluated using various statistical metrics, one of which is Accuracy. A comparison of the Accuracy of the recommended method with the Accuracy of the traditional method is presented in figure 4 and table 2, respectively. D-CNN and CNN-LSTM had values of 89.6 percent and 90.5 percent, respectively, when tested against the existing methods; however, the technique that was recommended (SW-KNN) has a value of 97.9 percent. The performance of the method that we have proposed as a direct consequence of this factor is significantly improved.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (29)$$

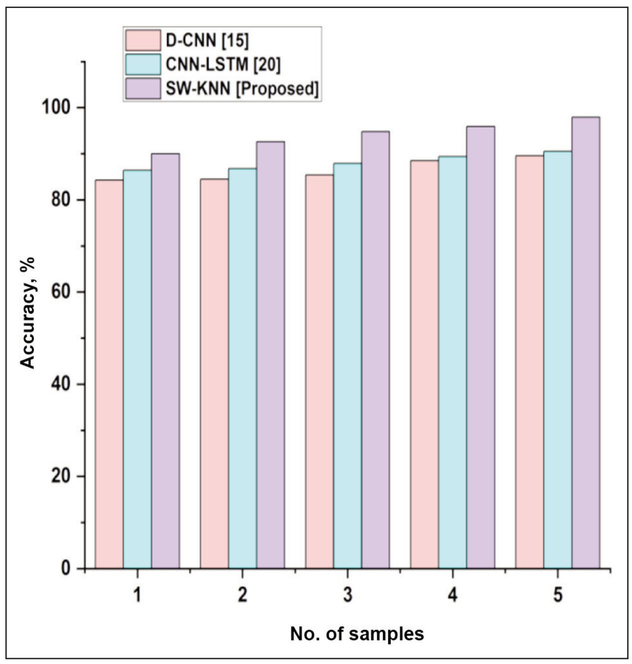

Fig. 4. Result of accuracy

Table 2

RESULT OF ACCURACY			
No. of samples	**Accuracy (%)**		
	D-CNN [15]	**CNN-LSTM [20]**	**SW-KNN [Proposed]**
1	84.3	86.4	90
2	84.5	86.8	92.6
3	85.4	87.9	94.8
4	88.5	89.4	95.9
5	89.6	90.5	97.9

A statistical parameter called precision is used to assess a classification model's performance, particularly in binary classification problems. Out of all occurrences projected as positive, including both true positives and false positives, it calculates the percentage of accurately predicted positive instances (true positives). Figure 5 and table 3 show a contrast between the precision of the recommended method and the precision of the conventional method. When compared to the well-known approaches, D-CNN and CNN-LSTM scored 89.4% and 92.6 percent, respectively; however, the strategy that was suggested (SW-KNN) scored 98.1 percent. As a direct result of this factor, the solution we have suggested performs substantially better.

$$Precision = \frac{TP}{TP+FP} \qquad (30)$$

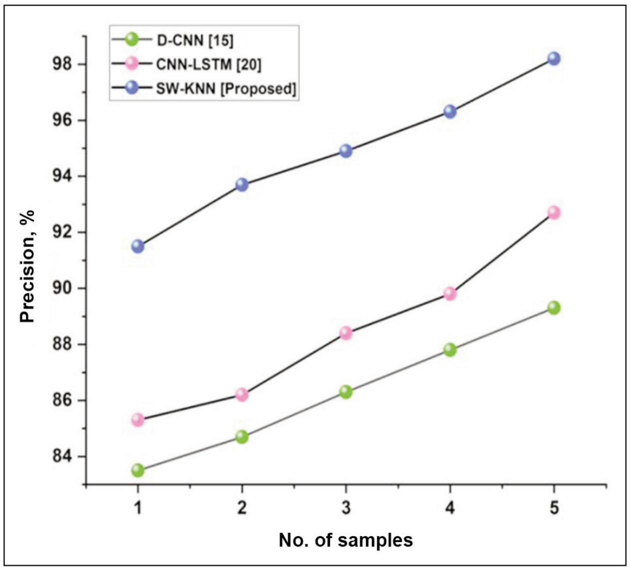

Fig. 5. Result of precision

Table 3

RESULT OF PRECISION			
No. of samples	Precision (%)		
	D-CNN [15]	CNN-LSTM [20]	SW-KNN [Proposed]
1	83.6	85.2	91.4
2	84.8	86.2	93.6
3	86.2	88.3	94.8
4	87.9	89.9	96.2
5	89.4	92.6	98.1

A statistical parameter called recall, often referred to as sensitivity or true positive rate, is used to assess a classification model's performance, particularly in binary classification problems. Out of all actual positive instances, it calculates the percentage of accurately anticipated positive instances (true positives). The recall of the recommended approach and the recall of the conventional way are contrasted in figure 6 and table 4. D-CNN and CNN-LSTM scored 88.4% and 90.1 percent in comparison to the existing methods; however, the proposed method (SW-KNN) scored 97.1 percent. This factor directly contributes to the significantly superior performance of the approach we have proposed.

$$Recall = \frac{TP}{TP+FP} \qquad (31)$$

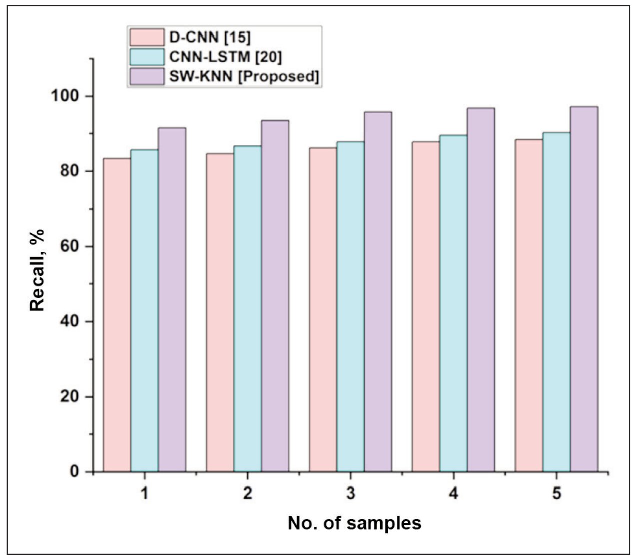

Fig. 6. Result of recall

Table 4

RESULT OF RECALL			
No. of samples	Recall (%)		
	D-CNN [15]	CNN-LSTM [20]	SW-KNN [Proposed]
1	83.3	85.9	91.4
2	84.8	86.9	93.4
3	86.3	87.8	95.9
4	87.8	89.4	96.9
5	88.4	90.1	97.1

A statistical metric used to assess a classification model's performance, particularly in binary classification problems, is the F1 score. It provides a fair evaluation of the model's efficacy by combining precision and recall into a single measure. Figure 7 and table 5 compare the F1-Score of the suggested method with the F1-Score of the traditional method.
Comparatively to the well-known approaches, D-CNN and CNN-LSTM scored 88.9% and 89.8%, respectively; however, the proposed method (SW-KNN) scored 98.5 percent. This component directly contributes to our suggested method performing much better.

$$F1 - Score = 2 \times \frac{Precision * recall}{Precision + recall} \qquad (32)$$

Root Mean Square Error is referred to as RMSE. The average difference between a model's predicted values and the actual values is a frequently used metric

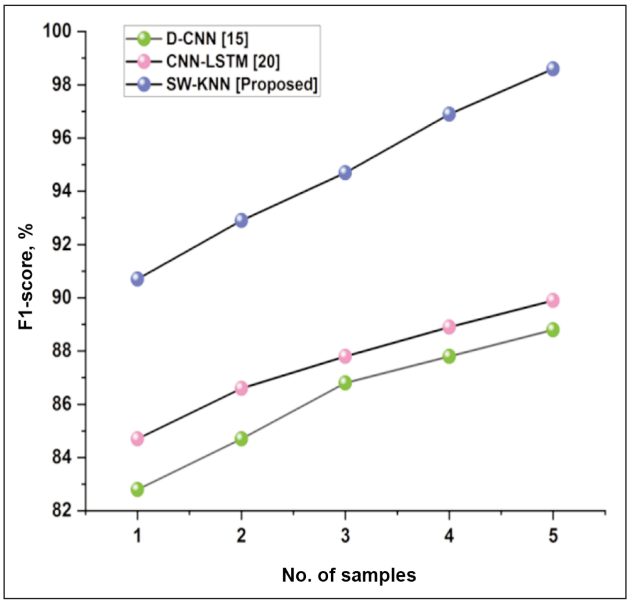

Fig. 7. Result of F1-Score

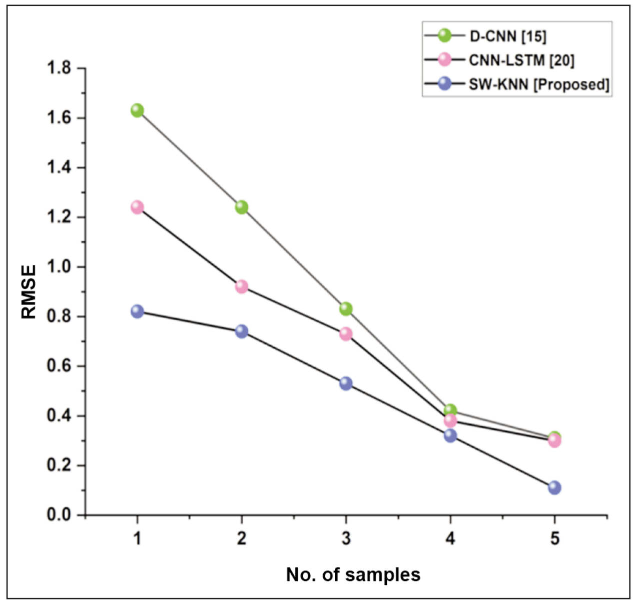

Fig. 8. Result of RMSE

Table 5

RESULT OF F1-SCORE

No. of samples	F1-Score (%)		
	D-CNN [15]	CNN-LSTM [20]	SW-KNN [Proposed]
1	82.9	84.8	90.6
2	84.8	86.8	92.8
3	86.8	87.9	94.6
4	87.9	88.9	96.8
5	88.9	89.8	98.5

Table 6

RESULT OF RMSE

No. of samples	RMSE (%)		
	D-CNN [15]	CNN-LSTM [20]	SW-KNN [Proposed]
1	1.63	1.24	0.82
2	1.24	0.92	0.74
3	0.83	0.73	0.53
4	0.42	0.38	0.32
5	0.31	0.3	0.11

in regression tasks. The performance of models that predict continuous numerical values can be assessed with the use of RMSE. Figure 8 and table 6 show a comparison of the RMSE between the recommended and conventional approaches. In contrast, the suggested methods SW-KNN, D-CNN and CNN-LSTM all achieve RMSE values of 0.31, 0.3, and 0.11, respectively. The SW-KNN algorithms that have been suggested have a lower RMSE value than the existing methods. It demonstrates that the suggested approach is more successful.

$$RMSE = \sqrt{1/n * sum(predicted_i - actual_i)^2} \quad (33)$$

Mean Absolute Error is referred to as MAE. The average absolute deviation between a model's predicted values and the actual values is a regularly used metric in regression tasks. MAE is especially helpful for assessing how well models work when they predict continuous numerical values. A comparison of the MAE between the suggested and traditional procedures is shown in figure 9 and table 7. SW-KNN, D-CNN and CNN-LSTM, on the other hand, all produce MAE values of 0.2, 0.31, and 0.3, respectively, when used as indicated techniques. The recommended SW-KNN algorithms have a lower MAE value than the current techniques. It proves that the suggested strategy is more effective.

$$MAE = \left(\frac{1}{n}\right) * sum(|predicted_i - actual_i|) \quad (34)$$

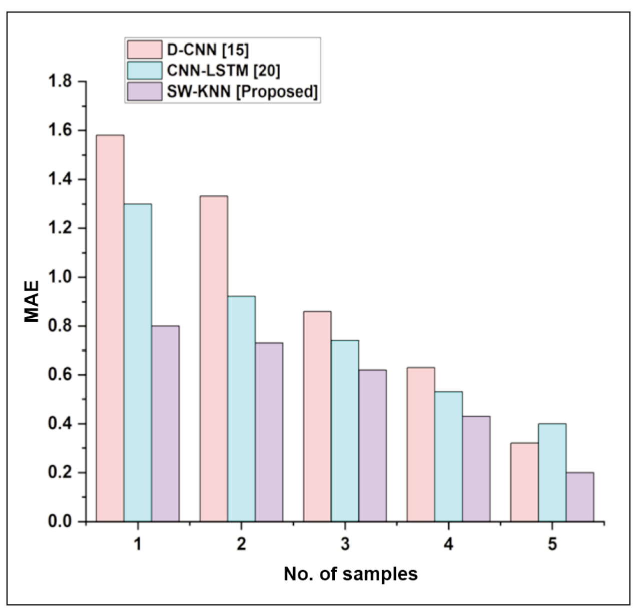

Fig. 9. Result of MAE

Table 7

RESULT OF MAE			
No. of samples	**MAE (%)**		
	D-CNN [15]	**CNN-LSTM [20]**	**SW-KNN [Proposed]**
1	1.59	1.29	0.9
2	1.32	0.91	0.72
3	0.85	0.73	0.61
4	0.62	0.52	0.42
5	0.31	0.3	0.2

CONCLUSION

Emotional states are categorized using a novel, self-sufficient weight-tuned Kohonen neural network (SW-KNN) technique. We first gather a dataset of bodily signals, such as pulse, body temperature, and sweat production, to ascertain the wearer's emotional state. The dataset is subsequently included in the preparation stage, where the min-max approach is used to normalize the raw data. The Fast Fourier Transform (FFT) is then used to extract the significant features from the cleaned data. For the proposed method's performance, we were able to obtain values for Accuracy (97.8%), Precision (98.1%), Recall (97.1%), F1-Score (98.5%), RMSE (0.12), and MAE (0.20). The proposed method was compared to the one that is currently being used, and the results of the experiments showed that the proposed strategy was more effective. Using physiological information to classify emotions limits the study's sophisticated emotion-aware clothing system. Physiological signs like pulse, body temperature, and perspiration can reveal a person's emotional state, but they may not convey its complete complexity and nuances. Incorporating multi-modal data fusion techniques into the intelligent emotion-aware clothing system to increase emotion recognition is one of the potential future applications for this technology.

REFERENCES

[1] Muhammad, G., Alshehri, F., Karray, F., El Saddik, A., Alsulaiman, M., Falk, T.H., *A comprehensive survey on multimodal medical signals fusion for smart healthcare systems*, In: Information Fusion, 2021, 76, 355–375

[2] Chen, M., Qian, Y., Hao, Y., Li, Y., Song, J., *Data-driven computing and caching in 5G networks: Architecture and delay analysis*, In: IEEE Wireless Communications, 2018, 25, 1, 70–75

[3] Zheng, J., Zhang, Q., Xu, S., Peng, H., Wu, Q., *Cognition-based context-aware cloud computing for intelligent robotic systems in mobile education*, In: IEEE Access, 2018, 6, 49103–49111

[4] Qian, Y., Lu, J., Miao, Y., Ji, W., Jin, R., Song, E., *AIEM: AI-enabled affective experience management*, In: Future Generation Computer Systems, 2018, 89, 438–445

[5] Song, J., Liu, M., Wu, G., Lu, W., Li, Y., Song, E., *Emotion Communications Driven by Big Data Cloud, Smart Clothing, and Robotics,* In: 12th EAI International Conference on Testbeds and Research Infrastructures for the Development of Networks & Communities, 2018, 34–41

[6] Saranya, P., Asha, P., *Survey on big data analytics in health care,* In: 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT), IEEE, 2019, 46–51

[7] Chen, M., Yang, J., Hao, Y., Mao, S., Hwang, K., *A 5G cognitive system for healthcare,* In: Big Data and Cognitive Computing, 2017, 1, 1, 2

[8] Zhou, P., Hossain, M.S., Zong, X., Muhammad, G., Amin, S.U., Humar, I., *Multi-task emotion communication system with dynamic resource allocations*, In: Information Fusion, 2019, 52, 167–174

[9] Mbunge, E., Muchemwa, B., *Towards emotive sensory Web in virtual health care: Trends, technologies, challenges, and ethical issues*, In: Sensors International, 2022, 3, 100134

[10] Rumiantcev, M., Khriyenko, O., *Emotion-based music recommendation system,* In: Proceedings of Conference of Open Innovations Association FRUCT. Fruct Oy, 2020

[11] Hassabo, A.G., Zayed, M., Bakr, M., Abd-Elaziz, E., Othman, H.A., *Applications of Supercritical Carbon Dioxide in Textile Finishing: A Review*, In: Journal of Textiles, Coloration, and Polymer Science, 2022, 19, 2, 179–187

[12] Deng, H., Liu, M., *Personalized smart clothing design based on multi-modal visual data detection*. Computational intelligence and neuroscience, 2022

[13] Yang, J., Wang, R., Guan, X., Hassan, M.M., Almogren, A., Alsanad, A., *AI-enabled emotion-aware robot: The fusion of smart clothing, edge clouds, and robotics*, In: Future Generation Computer Systems, 2020, 102, 701–709

[14] Moreira, M.W., Rodrigues, J.J., Kumar, N., Saleem, K., Illin, I.V., *Postpartum depression prediction through pregnancy data analysis for emotion-aware smart systems*, In: Information Fusion, 2019, 47, 23–31

[15] Hu, L., Li, W., Yang, J., Fortino, G., Chen, M., *A sustainable multi-modal multi-layer emotion-aware service at the edge*, In: IEEE Transactions on Sustainable Computing, 2019, 7, 2, 324–333

[16] Chen, M., Yang, J., Zhu, X., Wang, X., Liu, M., Song, J., *Smart home 2.0: Innovative smart home system powered by botanical IoT and emotion detection*, In: Mobile Networks and Applications, 2017, 22, 1159–1169

[17] McDuff, D., Rowan, K., Choudhury, P., Wolk, J., Pham, T., Czerwinski, M., *A multi-modal emotion-sensing platform for building emotion-aware applications*, 2019, arXiv preprint arXiv:1903.12133

[18] Shanmugam, M., Singh, M., *Analysis of emotion-aware healthcare and Google Cloud messaging*, In: 2017 International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), IEEE, 2017, 667–670

[19] Peng, Y., Peng, L., Zhou, P., Yang, J., Rahman, S.M.M., Almogren, A., *Exploiting energy-efficient emotion-aware mobile computing*, In: Mobile Networks and Applications, 2017, 22, 1192–1203

[20] Miao, Y., Wu, G., Liu, C., Hossain, M.S., Muhammad, G., *Green cognitive body sensor network: architecture, energy harvesting, and smart clothing-based applications,* In: IEEE Sensors Journal, 2018, 19, 19, 8371–8378

[21] Chen, M., Ma, Y., Li, Y., Wu, D., Zhang, Y., Youn, C.H., *Wearable 2.0: Enabling human-cloud integration in next-generation healthcare systems*, In: IEEE Communications Magazine, 2017, 55, 1, 54–61

[22] Dang, T., Zhao, M., *The application of smart fibres and smart textiles*, In: Journal of Physics: Conference Series, IOP Publishing, 2021, 1790, 1, 012084

[23] Hu, L., Yang, J., Chen, M., Qian, Y., Rodrigues, J.J., *SCAI-SVSC: Smart clothing for effective interaction with a sustainable vital sign collection*, In: Future Generation Computer Systems, 2018, 86, 329–338

[24] Krishna, K.V., Rao, M.V., Murthy, G.V., *Secured System Design for Big Data Application in Emotion-Aware Healthcare*, 2017

[25] Ahsan, M., Teay, S.H., Sayem, A.S.M., Albarbar, A., *Smart clothing framework for health monitoring applications*, In: Signals, 2022, 3, 1, 113–145

Author:

LUO QISHU

Guangdong Industry Polytechnic, Guangzhou, Guangdong-510000, China

Corresponding author:

LUO QISHU
e-mail: luoqishu2023@163.com, QishuLuo202306@outlook.com