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Original Article

Detection of stress level based on sweat from Gen-Z students using ANN and GA algorithms

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Abstract: In this paper, we aim to contribute to the body of work on the automatic detection of students' stress levels for the long-term goal of technology-based stress management interventions. This study offers a technique for measuring stress levels in Gen-Z students. Sweat pH, temperature, lactate level, skin conductance (GSR), and cortisol level measurements were designed as input parameters. Traditional machine learning techniques for automatic stress recognition have been used in previous research but they sometimes present specific limitations. The emergence of deep learning permits the reveal of underlying patterns in body response, which would otherwise not be easily observed. Therefore, a hybrid artificial neural network with a genetic algorithm (ANN-GA) is also included in the suggested approach as the classifier for determining stress levels. By subjecting a group of Gen-Z students to physical and mental stress stimuli as test subjects, the system was trained and put to the test. To identify student data as low stress, moderate stress, or high stress, psychological tests are administered to 24 students during their semester exams, during class time, in a fun or relaxed mood. The system was developed at a reasonable cost, with little complexity, low power consumption, and no dependence on contact. Being non-invasive and painless, with early detection of stress levels is the major goal of this research project. According to experimental findings, our suggested method achieves a classification accuracy level of 99%, which is comparable to the SVM's 96% success rate. Accuracy was lower for the KNN and SSD (96% and 95%).

Keywords: Stress detection, artificial neural networks, genetic algorithms, normalization, artifact removal, RMSE

Introduction

People in contemporary society are under immense stress due to various factors. As stress is a cause of various diseases and affects longevity, it is vital to keep it under control. Several stress recognition studies have been conducted on physiological signals acquired through wearable devices [1]. Time strain refers to the intellectual or emotional stressors which are uncovered by pressure or tension. Furthermore, on the whole this influences people as they grow from an infant into an adult (adolescent). People are overburdened with adolescent strain from a range of sources, which includes worry about their future, private problems, affections and relationships, and sudden accidents [2]. Human strain can be categorized. Eustress is defined as a very good strain as it motivates a person's performance. Neustress is a form of strain that is innocent and may be ignored. Distress harms the human physiology and is a crucial component in which we focus. Acute and persistent strain are a type of strain [3, 4]. Acute strain refers to a short-time period, of severe degrees of strain, while persistent strain refers to a long-time period of severe degree of strain. People who've been under strain for a prolonged time frame may also have emotional, intellectual, and bodily symptoms. They may also feel overwhelmed, anxious, wound up, fearful, and mentally fatigued, taking time to make decisions, constantly being disturbed, and bodily aches, headaches, sleep problems, feeling worn-out all the time, and over-consumption. They may also showcase behaviors such as smoking more, averting matters or people, and so on, which can occasionally lead to suicidal ideation. Statistics indicate that the rapid growth in strain has turned out to be a main affliction of society, affecting human fitness and life [5, 6].

The psycho-pressure check (PST) is made from (simple) tasks and complicated duties that motivate pressure or misery, in addition to periods of rest. Psychological pressure assesses pressure reactions in scientific practice [7, 8]. Patients with body-related issues inside the context of psychosocial distress are regularly described with psychosomatic symptoms. Before a psychosomatic consultation, those patients have generally surpassed emotions without pathological findings [9]. Patients regularly struggle to recognize the relationship between physiological and psychosocial factors of illness. Stress is related to ailments that have an impact on almost every physiological system, including the cardiovascular, gastrointestinal, and respiratory structures [10]. Much scientific research has experimentally established that stress influences the physiological and mental structures of individuals [11].

In today's environment, stress is a major issue. Investigators, for instance, have stated that a growing number of instances of network violence are linked to rage as a result of unsettling experiences [12-14]. Furthermore, law enforcement officials who do not address pressure and its effects have higher ailments and aggression [15]. Furthermore, pressure has been proven to damage fitness levels and plays a critical function in diseases related to intellectual disorders, which include anxiety and seizures [16]. Because of these harmful influencers of stress, investigators have focused on outcomes and detecting stress as soon as possible. Although the classic blood cortisol tests are the gold standard for calculating stress, there are two main techniques that have been utilized to detect stress noninvasively, also calculating brain waves through implementing EEG electrodes or using biomedical tools to detect physiological bio signals, such as heart rate (HR), blood pressure (BP), and body temperature, and by utilizing sweat sensors to calculate skin conductivity (SC) [17]. In terms of device wearability, although EEG provides accurate readings and valuable information about the brain's a state, its main drawback is that EEG electrodes must be attached to the scalp. Which is detailed and inconvenient [18]. While SC sensors are extensively used in emotion detection systems, they may be regularly used to decide the conductivity of the pores and skin in preference to the electrochemical makeup of perspiration. Importantly, little is thought about the electrochemical additives of sweat, which include the pressure hormones such as cortisol and skin gases.

The temperature sensors [19] are usually categorized as touch or non-touch. In this observation, we modeled a touch temperature sensor [20] that may reveal the distinction in temperature quickly. The accelerometer sensor calculates changes in velocity. It is expressed in meters per square second (m/s^2). Accelerometer sensors are broadly utilized in phones, gaming, trouble solving, fall detection, hobby identification, location recognition, or even human frame movements, with range of steps, going uphill, downhill, etc. Recently, deep learning approaches have made great strides in image processing and natural language processing. This is because they not only automatically extract features from data, but also learn new high-level features based on low-level ones owing to their hierarchical structure [21]. The innovation in this study is the detection of pressure stages is primarily based totally on sweat from the young people in Gen Z, with the use of a hybrid ANN&GA. Gen Z: is the newest generation born between 1997 and 2012. They are currently between 9 and 24 years old. The main contribution of this paper is the use of hybrid ANN&GA to detect stress levels.

- To propose recognition of stress level from Gen Z student's community based on sweat using ANN and GA algorithms proposed.
- The input data is pre-processed. Here the information of 24 student is taken as input, and then the Min-Max normalization to normalize the image is done.
- Artifact removal is done. Then feature extraction based on Root Mean Square Error (RMSE) is determined.
- Finally, the classification using Hybrid ANN with Genetic Algorithm is determined.

The following is the basic structure of the paper: Section 2 provides a review of related works, and Section 3 explains the proposed stress level detection method. Section 4 explains the overall result and discussion. Section 5 contains the final section.

Literature survey

Ravinder Ahuja and Alisha Banga [22] used four techniques (Random Forest, Nave Bayes, Support Vector Machine, and K-Nearest Neighbor) from the dataset of 206 JIIT Noida college students using sensitivity, specificity, and accuracy criteria. The datasets were not very long, so we used a 10-fold flow validation. We located SVM, out of the four techniques, works well because of its geometric branching mechanism and confined quantity of data. Investigating and inspecting techniques like PSS with greater correct outcomes with a decreased, fee will help human beings' fitness and intellect.

Choi J and Bandodkar AJ [23] have analyzed the most sophisticated systems of this kind, where optimized chemistries, microfluidic designs, and device layouts enable accurate estimation of not only total sweat loss and sweat charge, but also quantitatively measure sweat pH and temperature, as well as chloride, glucose, and lactate concentrations all within physiologically applicable ranges. Color calibration markers built into the images themselves allow for precise announcement through digital picture analysis, suitable for a variety of lighting circumstances. Field testing on healthy volunteers shows the device's full capabilities in sweat biomarkers and temperature analysis, sweat loss/charge calculation, and sweat biomarker analysis, with results that quantitatively match those of standard lab-based total measuring methods.

Disha Sharma and Nitika Kapoor [24] used Naive Baye's, Baye's Net, Logistic Regression, Multilayer Perceptron Random Forest, J48, and R generation to calculate stress. The precision of numerous techniques is measured in the assessment of the use of the Weka tool. According to this investigation, we have completed numerous forms of techniques inclusive of logistic regression, multilayer perceptron, and Baye's net; and we additionally analyzed numerous forms of parameters inclusive of Kappa, statistic, MCC, which implies an absolute error, ROC area, faux positive, actual positive, Recall, and RMSE, and Baye's Net classifier which is well-known for the best accuracy of 88.5965%.

Laavanya Rachakonda and Prabha Sundaravadivel [25] measured iStress as a singular strain detection gadget with video displays unit strain ranges through body temperature, a charge of motion, and sweat resulting from bodily activity. The iStress device has applied the use of a neural community utility with a Mamdani-type fuzzy common sense controller, that measures variables over one hundred fifty times. The accrued data is released and saved inside the cloud, which may resource actual-time tracking of the person's strain stage and for this reason lessen harm. Despite working in actual time, this gadget consumes little energy. The revealing gadget can generate data with 97% accuracy, and it has low gadget complexity, and a slight cost.

Gaballah A and Tiwari A [26] present a context-conscious speech-primarily based strain detection gadget, which has a look at data from one hundred forty-four people who have been tracked in the course of their day for 10 weeks; revealing subjective strain readings that have been amassed on a daily basis. Wearable gadgets measured speech traits in addition to physiological readings which include coronary heart rate. Environment sensors have been used to assess motion in the medical institutions. This demonstrates the importance of context recognition for strain stage detection with the use of a bidirectional LSTM deep neural network. The importance of medical institution areas and circadian rhythm-primarily based contextual cues for strain prediction in particular is important. Overall, it indicates upgrades data as much as 14% while context is brought up with the speech functions alone.

Sharma LD and Bohat VK [27] used a quick length EEG signal, with a singular technique for pressure detection. The desk-bound wavelet rework was used to decompose an EEG signal and extract entropy-primarily based total features. Various supervised device learning algorithms have been used to categorize decided features. Furthermore, different evolutionary stimulated methods have been used to con-

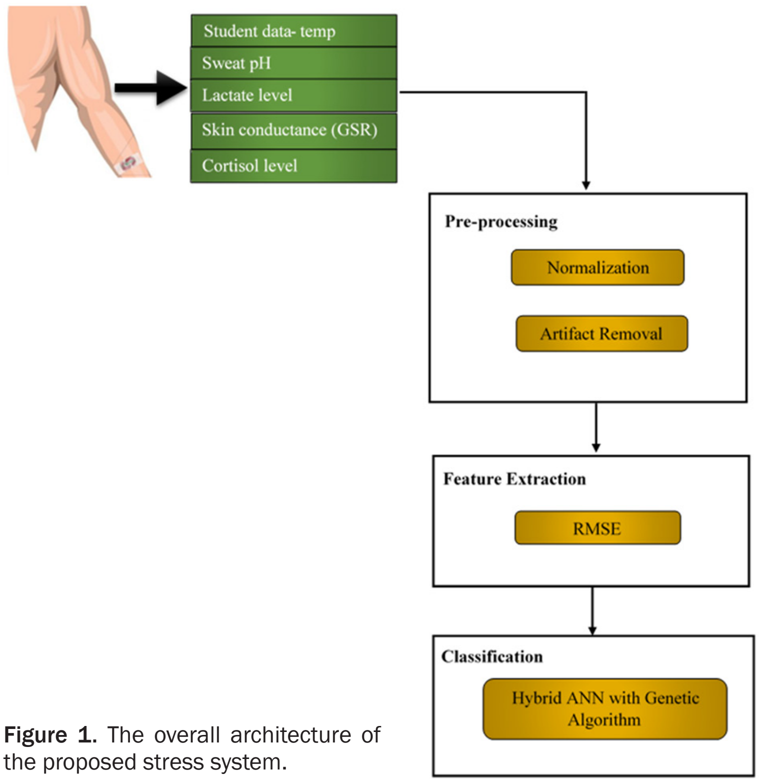

Figure 1. The overall architecture of the proposed stress system.

currently optimize the parameters of guide vector machines (SVM) and carry out function weighting. The accuracy of SVM optimized the usage with optimization rules as high as 97.2559%.

In a retrospective study, the ANN or GA-based algorithm is used to measure the stress level with a low accuracy rate. Our prospective study is a hybrid artificial neural network with a genetic algorithm (ANN-GA) that is included to improve the accuracy rate.

Proposed methodology

With the use of body temperature, acceleration, sweat rate, sweat pH, and lactic acid level measurements, a novel stress detection system is proposed in this methodology to track students' levels of stress. Smart Stress detection systems are implemented utilizing neural network technology and a comparison of hybrid ANN-GA. The target locations must be cleansed and dried with deionized water as soon as the person starts to perspire. We applied sterile patches on the forehead, upper chest, right scapula, left scapula, right posterior mid-forearm, and left posterior mid-forearm. The patches were removed immediately before the subjects start to sweat heavily before they begin their demanding activity. The patches are then cleaned of sweat. The LAQUA twin Na+ and pH sensors are used to measure a small sample of the sweat solution that has been extracted. We cleaned the sensor with tap water and patted it dry with a paper towel to display samples once more. The proposed block diagram is given in **Figure 1**.

Input data

Here the information of 24 student's details is taken as input. We are going to further expand our research study with the information from these students. Based on the input, students' Psychological test is taken during their semester examination, during class hours, in a fun/relaxed state as well as cortisol sensor monitors for the student's temperature, pH, lactate level, skin conductance (GSR), and cortisol level. Based on this preprocessing it is explained in detail as follows.

Preprocessing

In this stage of preprocessing; students' psychological test is taken during their semester examination, during class hours, in a fun/relaxed state. Based on the sensor's data-student temperature, pH, lactate level, skin conductance (GSR), and cortisol levels are identified, and GSR, as well as cortisol sensor artifacts, are removed in the stage of preprocessing.

We carried out record cleaning, with integration to fill in missing values, and elimination of redundant records. The pre-processing section prepares the dataset for manipulation and it's considered a critical strength to address student records. The everyday pre-processing stepladders comprise at least one of the accompanying processes: (a) Filtering extracts student information from the dataset if the delta (max-min) isn't always precisely a specific value or the look at (max/min) isn't always precisely a specific value. (b) We set the threshold in addition to lesser threshold values. If any articulation value is lesser than the decreased threshold it is set to the decreased threshold values. If any articulation value is large then the better threshold is situated as the better threshold. (c) A psychological look at is taken for each student's temperature, pH, lactate level, skin conductance (GSR), and cortisol levels. (d) Data normalization is applied to eliminate methodical deviations amongst samples that are carried out so each pupil's record has an average of 0 in addition to a variant of one. (e) Artifact elimination does away with artifacts of GSR and cortisol sensors [37].

Normalization: Normalization is the linear transformation of the student's data to fit within a specific range. In this case, Min-max normalization is used to standardize student data, which linearly transforms the data. The accompanying condition is frequently used to perform Min-Max normalization.

$$SY = \frac{SY - SY_{\min}}{SY_{\max} - SY_{\min}} \tag{1}$$

Where, SY_{min} and SY_{max} are the Min and Max values in SY, and SY is the set of values in the dataset.

Artifact removal: In this stage, GSR and cortisol sensor artifacts are removed based on blind source separation (BSS). The BSS method employs several unsupervised learning algorithms that do not require prior knowledge or additional reference channels. The following is a general description of the BSS methodology. Let Z be observed signals obtained from students' psychological test which is taken during their semester examination, during class hours, fun/relaxed state. Here the sensor data sensors student temperature, pH, lactate level, skin conductance (GSR), and cortisol level. Let T serve as the signal's source as well, containing both the original signals and artifacts. An unknown matrix B linearly combines these source signals:

$$Z=BT \tag{2}$$

Obtain the signals that were seen. The BSS algorithm is a reversed version:

$$V=XZ \tag{3}$$

Where V is the estimation of sources and X is the reverse mixing of Z. Then components representing the artifacts are removed from students' data. After the stage of preprocessing, the student data are moved to the next phase of feature extraction which is explained in detail as follows.

Feature extraction

Following the removal of artifacts, the student's data is passed on to the feature extraction stage. The extraction of features is an important stage in classification. For classification purposes, the beneficial features of the artifact-removed data are extracted from the input data. It is difficult to extract a useful feature from artifact removal data. There are numerous feature extraction methods available. We extract RMSE features from data in this work.

Feature extraction based on root mean square error (RMSE): RMSE defines the standard deviation of the residuals (prediction errors). Residuals are a measure of how far away statistical components are from the regression line, and RMSE is a measure of how dispersed those residuals are. In other words, it shows how evenly distributed the statistics are along the good fit line. RMSE is frequently employed in student mental test evaluation to confirm results. The formula is:

$$RMSE = \sqrt{\overline{f - O}} \tag{4}$$

Where $f \rightarrow$ predicts (normal values or anonymous results), $O \rightarrow$ values found (identified results). The bar above the squared differences is the mean (similar to $\bar{x}$). The same formula can be written in slightly different notation as follows.

$$RMSE_{fo} = \left[\sum_{i=1}^{N} (S_{fi} - S_{oi})^2 / N\right]^{1/2} \tag{5}$$

Where $\sum \rightarrow$ Summation, $(S_{fi}\text{-}S_{oi})^2 \rightarrow$ dissimilarities and adjusted, $N \rightarrow$ sample size. A shortcut to finding the root mean square error is:

$$RMSError = \sqrt{1 - r^2 SD_y} \tag{6}$$

Where SD_y is the standard deviation of y.

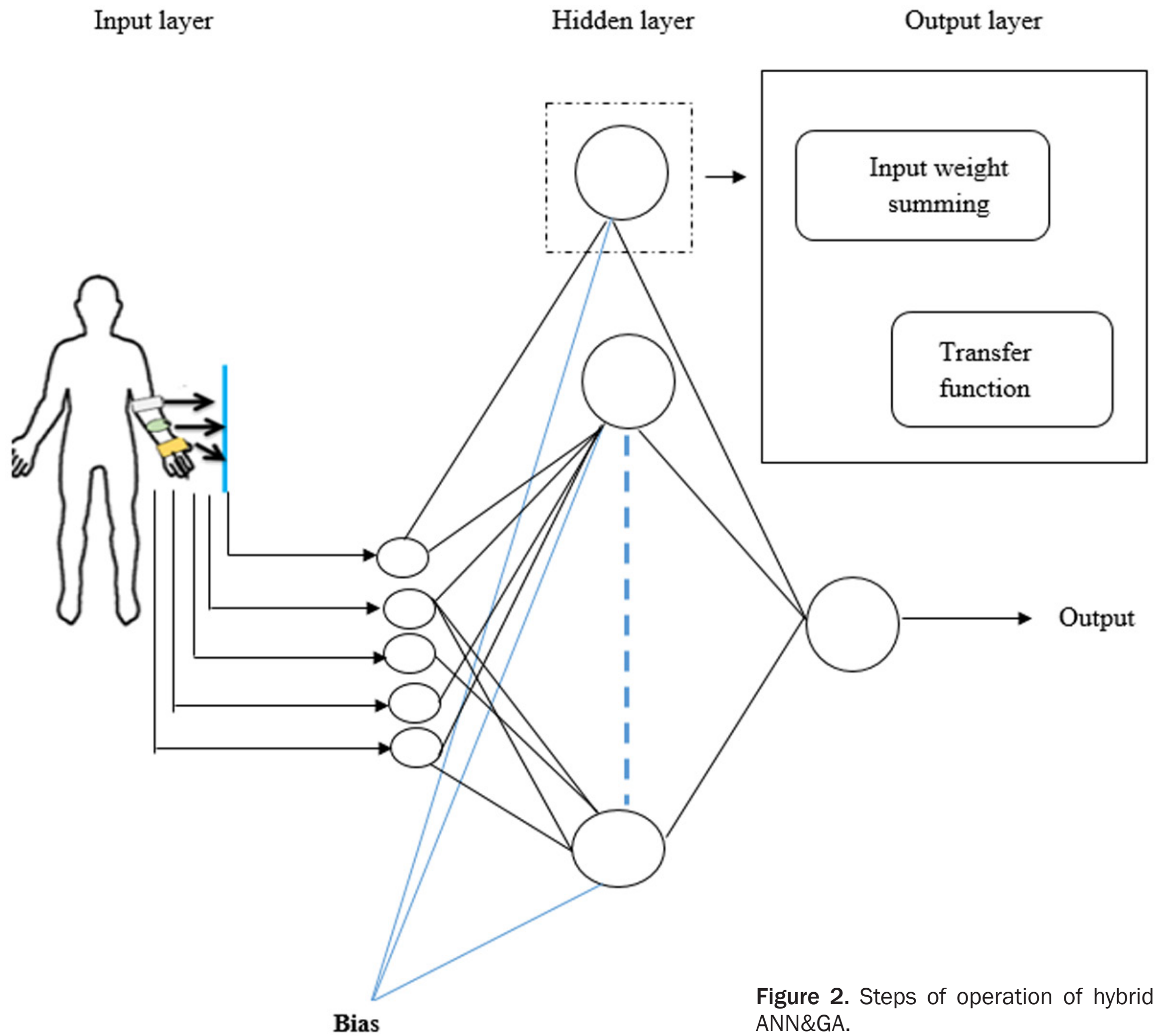

Figure 2. Steps of operation of hybrid ANN&GA.

Classification using hybrid ANN with genetic algorithm

Because ANN has numerous drawbacks, inclusive of a lengthy education time, undesirable convergence to the neighborhood instead of worldwide ultimate solutions, and a huge wide variety of parameters, tries have been made to mitigate a number of those drawbacks via way of means of combining ANN with any other set of rules that can deal with a selected problem. GA is a set of rules that has often been blended with ANN. To find a good neural community architecture by using GA to improve weighted connections. A hybrid ANN-GA version that uses an example to reduce the dimensionality of the data. To determine density correlation, GA was used to identify rigid weights for connections to each node in an ANN model. To categorize the strain stage while optimizing weight and bias, a hybrid ANN and GA approach has been proposed. Our explanation for combining ANN and GA was that it might be preferable to use, first, a small number of strong subsets of entering variables that can be imported, and second, a few entering variables for each technical indicator that is based entirely on exceptional beyond periods. Processing the astronomically different subsets of the variables might take a lot of computation time, but GA took care of that. The fundamental ideas behind GA are to create an exploratory population of students' test answers (search solutions), then use choice and recombination operators to create a new, more potent population to eventually include the fittest test (ultimate population). Here are the five steps of an ANN and GA hybrid intelligence operation.

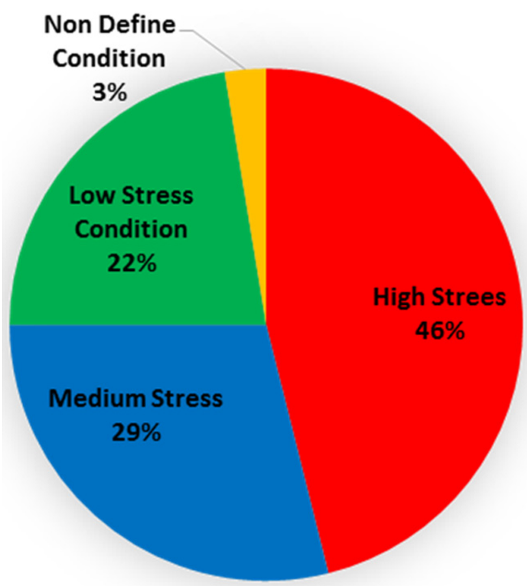

Figure 3. Results obtained from PST.

Table 1. 24 student temperature value

Student	Temperature
1	98.180
2	98.380
3	90.560
4	92.660
5	80.3
6	85.7
7	99.98
8	100
9	90
10	90.07
11	96.93
12	97
13	80
14	80.1
15	80.2
16	99.7
17	99.26
18	98
19	98.92
20	99.6
21	90
22	88.1
23	85
24	83

● Produce a population of removed artifacts, which are bit strings of randomly generated binary values. This is step 1 (population initiation). For the population sizes, we used 60 and 24 artifact-removed data points.

● The second step, or decoding, entails determining which input variables will be chosen by decoding student data (bit strings).

● To forecast the SET24 index for the following day, perform Step 3 (ANN). The model we used had the same input parameters as those that were reported.

● The prediction accuracy of each ANN data set with artifacts removed is used as the fitness value for GA in Step 4 (fitness evaluation).

● Decide whether to continue or end the loop in step 5 (the stopping criterion). Less than 24 students met the cutoff point. **Figure 2** displays each step in full.

○ Fitness evaluation: We used accuracy to determine Non-invasive, painless, and early detection of the student's level, as well as classify the stress level and measure the performance of the prediction model. Fitness values in GA were taken as the accuracy values that can be calculated below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

○ Where TP is a true positive, FP is a false positive, TN is a true negative, and FN is a false negative.

Dataset collection

The data was carried from the 24 Gen-Z students and divided the data into 5 parameters such as the student's temperature, pH, lactate level, skin conductance (GSR), and cortisol level. Sweat pH can change significantly among individuals and characteristically ranges from approximately 0 to 7. Sweat temperature can vary from 90 to 100 among these 24 Gen-Z students. Sweat acceleration also differs within this student from 0-200. Sweat lactate level can change significantly among individuals and typically ranges from approximately 0-31. The average range of sweat [Na+] is between 10 and 100 mmol/L, though individual differences can be quite large. Despite variations in sweating rate, is significantly lower and less variable than these other variables.

Table 2. 24 student sweat pH value

Student	Sweat pH level	Volt (mV)
1	4.5	200
2	4.2	220
3	5.5	170
4	5.7	180
5	6.2	110
6	6.6	95
7	6.5	90
8	5.8	181
9	5.5	170
10	5.6	170
11	6.2	110
12	5	190
13	6.3	115
14	7	50
15	6.2	110
16	4.6	210
17	3.4	250
18	0	0
19	4.7	220
20	4.4	200
21	7	50
22	7.6	10
23	7.1	51
24	6.8	70

Table 3. 24 student lactate level mmol/L

Student	Lactate level mmol/L
1	18.5060
2	19.8460
3	5.9840
4	9.6740
5	0.15
6	2.85
7	30.566
8	30.7
9	5
10	5.123
11	17.177
12	17.29
13	0
14	0.05
15	0.1
16	28.69
17	25.742
18	17.3
19	23.464
20	28.02
21	5
22	4.05
23	2.5
24	1.5

Here, the student's data are collected from Basic stress analysis done by PPT - Psycho stress test (PST). The range of the sensor values of 4 divided parameters is displayed in **Figure 3**.

Here, the analysis was done for 60 students. Student performance data means data relating to the student stress level, including student temp, pH, lactate level, skin conductance (GSR), and cortisol level.

Student data - temp

Temperature sensors are generally labeled as both touch or non-touch. In this study, we designed a touch temperature sensor that could music the fee of change in frame temperature. In this study, virtual temperature sensors just like the TSYS03 hardware used may be beneficial in a kind of healthcare application. It is the small length and excessive accuracy that provides crucial temperature facts in several clinical applications. The TSYS03 offers facts in a direct virtual layout and combines a temperature-sensing detail with an A-to-D converter, amplifier, and interface circuitry that permits direct connection to an I2C bus. The TSYS03 is a miniature virtual temperature sensor that offers manufacturing unit calibrated, exceedingly accurate temperature facts in **Table 1**.

Sweat pH

Sweat is typically a clear biofluid with low tonicity and a slightly acidic nature, with a mean pH of 6.3, making it more acidic than blood. When the body is dehydrated, the concentration of sodium in sweat increases, as indicated by a higher pH value in **Table 2**. A balanced pH is also important for skin health; skin conditions such as dermatitis and acne can occur if the student's skin is too acidic or alkaline.

Lactate level

Lactate stages inside the blood need to be between 0.5 and 1 mmol/L. **Table 3** defines

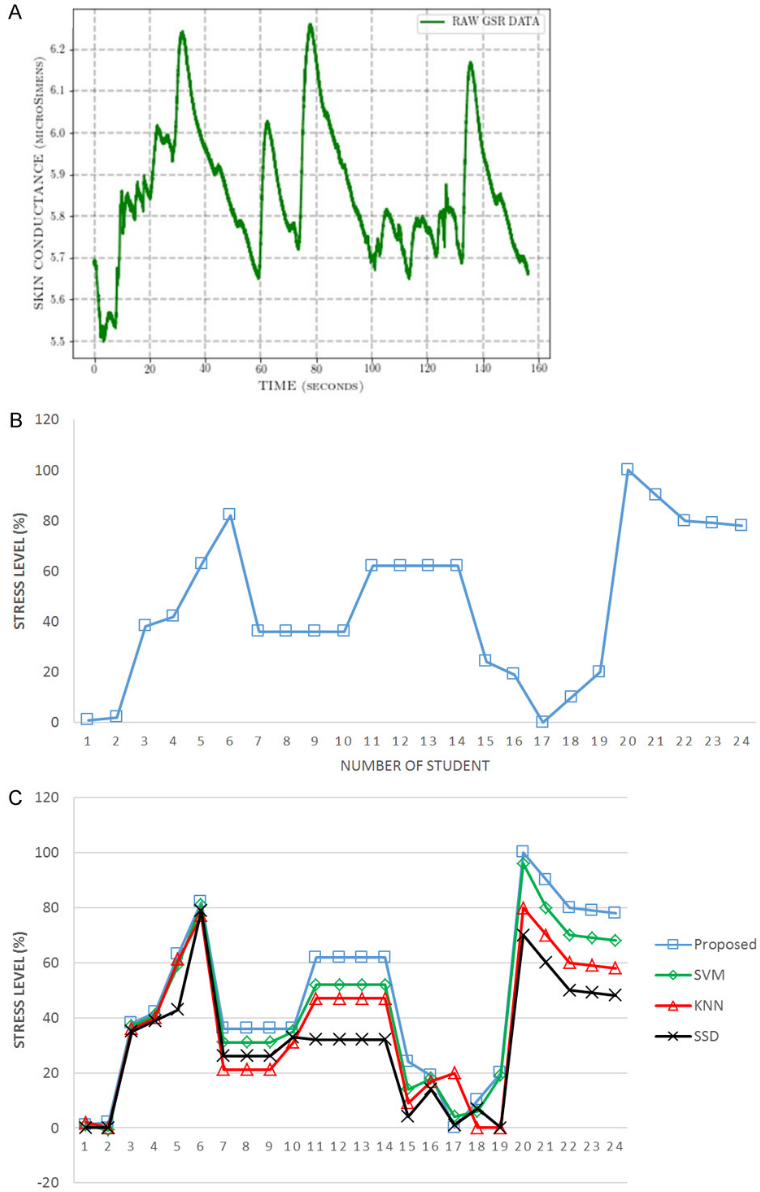

Figure 4. A. Skin conductance (GSR) to measure sweat gland activity. B. Students' stress level in (%) using ANN-GA. C. A comparative analysis of student stress level of the proposed method with existing methods.

hyperlactatemia as a persistent, slight to fairly elevated (2-four mmol/L) lactate stage without metabolic acidosis. This is feasible with good enough tissue perfusion and oxygenation. This test determines the awareness of lactic acid, additionally called lactate, in your blood. Lactic acid is a substance produced through muscular tissues, and red blood cells, which ship oxygen from the lungs to the of the body. Lactic acid levels inside the blood are typically low.

Skin conductance (GSR)

We can use a GSR sensor to determine sweat gland activity, that is related to emotional arousal. We use the electrical homes of the pores and skin to calculate GSR. The pores and skin conductance reaction also referred to as the electrodermal reaction (and in older terminology as "galvanic pores and skin reaction"), is the phenomenon wherein the pores and skin briefly become a higher conductor of energy in reaction to physiologically arousing outside or inner stimuli, as shown in **Figure 4**.

Cortisol level

Cortisol ranges inside the bloodstream fluctuate during the day in sync with the circadian rhythm. Cortisol ranges, for example, are lowest at midnight, start to push upward in the early morning, peak rapidly after awakening, and step by-step decline for the day. Cortisol is a crucial stress hormone as it turns on numerous metabolic pathways, consisting of anti-inflammatory and anti-stress pathways through regulating blood glucose ranges. Cortisol, on the other hand, will have a poor effect on the immune system by affecting T-cell multiplication, lowering bone formation, which causes osteoporosis and probably inflicts many other persistent diseases. Salivary cortisol correlates thoroughly with unfastened cortisol in the blood, due to the identical passive diffusion via salivary cells as unfastened cortisol.

Results

Students' stress level in (%)

This proposed system is an ANN with a GA strain-detecting device for an individual to

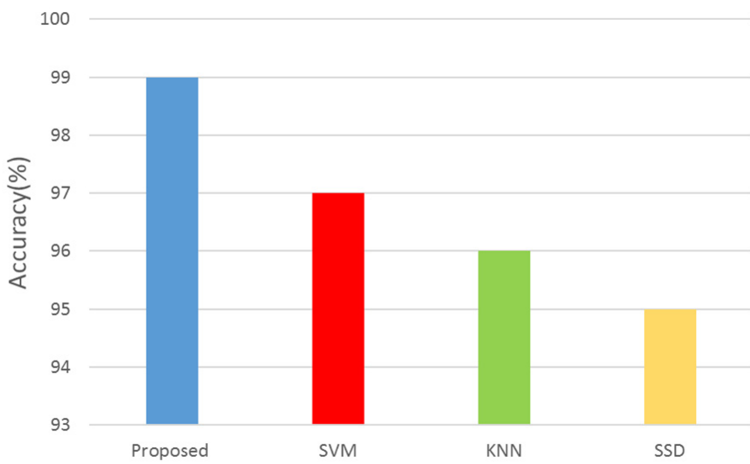

Figure 5. Evaluation of the proposed method's accuracy with that of existing methods.

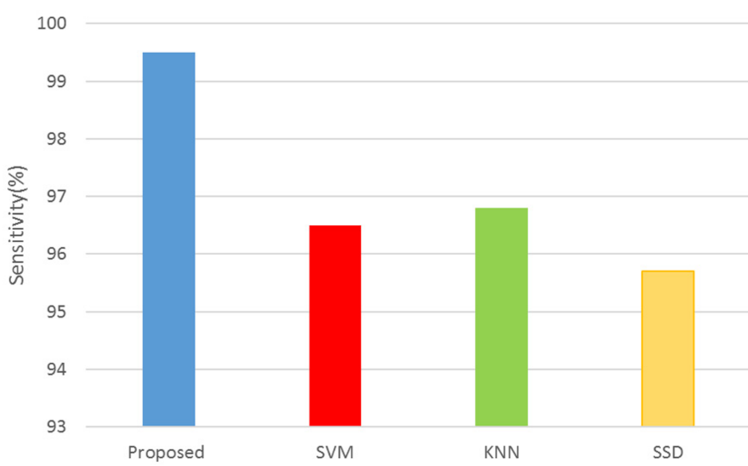

Figure 6. Evaluation of the proposed method's sensitivity with that of existing methods.

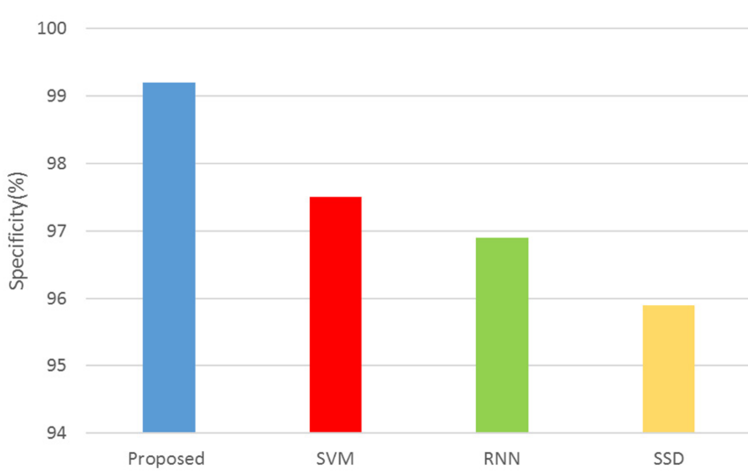

Figure 7. Evaluation of the proposed method's specificity with that of existing methods.

ascertain the level of strain on the human body and prevent them from experiencing the worst fitness issues. The evaluation of strain degree using ANN-GA algorithms developed by the Gen-Z student community is shown in **Figure 4**. We have established that sweat-derived algorithms ANN and GA are reliable tools for determining strain levels. To obtain higher accuracy, our method looks at how to collect useful data from ANN-GA applied hierarchical GA. The proposed system has the benefits of being time-efficient, increasing productivity, and improving accuracy. We may say that our method achieves a higher recognition rate when compared to previous stress detection systems that just use ANN-GA parameters. We compared the performance of our algorithm to that of three conventional algorithms, SVM and KNN, as well as SSD because the performance of a given algorithm depends on several variables, including the type of stressor, the number of subjects, the techniques used, and so on. Even though our method's reported accuracy was lower, a comparison of its performance on the same dataset showed that it greatly outperformed both the algorithm for stress detection that employs ANN features and the algorithm that utilizes GA features.

Accuracy

Accuracy is defined as the proportion of true outcomes true positive or true negative in a population. It evaluates how accurately data is classified. The equation is used to calculate accuracy (7).

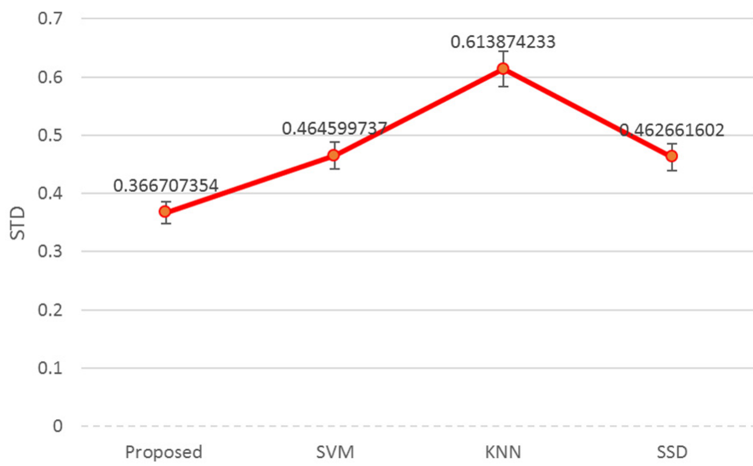

Figure 8. Evaluation of the proposed method's STD with that of existing methods.

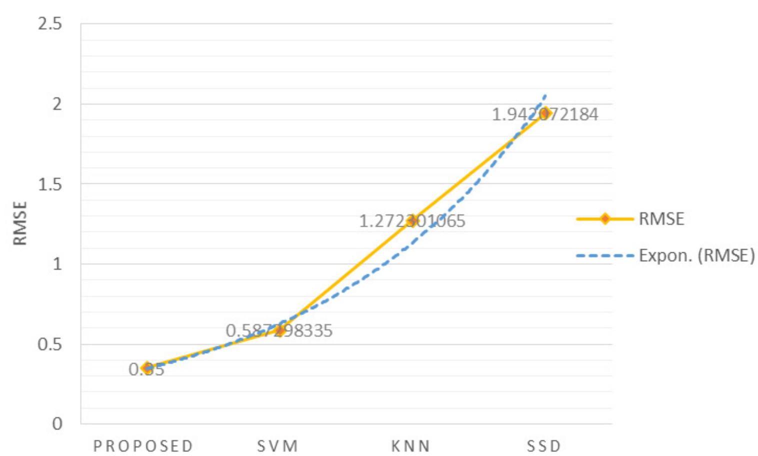

Figure 9. Evaluation of the proposed method's RMSE with that of existing methods.

Sensitivity=TP/(TP+FN) (8)

Figure 6 illustrates the proposed method's analytical classification execution. The proposed method's highest sensitivity can reach 99.5% and 96.5%, respectively. While the least sensitivity is KNN at 96.8% and SSD at 95.7%. The results confirm the proposed technique's suitability and efficacy.

Specificity

Specificity is the number of true negatives that a classification experiment correctly estimates. It proves how outstanding the experiment is at describing conventional data. The equation is used to calculate specificity (9).

Specificity=TN/(TN+FP) (9)

Figure 7 illustrates the proposed method's analytical classification execution. The most extreme specificity of the proposed technique is up to 99.2% and 97.5%, respectively, while the least specificity is KNN at 96.9% and SSD at 95.9%. The findings support the proposed technique's efficiency and suitability.

Figure 5 illustrates the analytical classification execution of the proposed method; the analysis results show that our proposed method outperforms the current SVM, KNN, and SSD classifiers. The proposed technique's most extreme accuracy is up to 99% and 98%, while the least accuracy is KNN at 95% and SSD at 94%. The results confirm the proposed technique's efficacy and worth.

Sensitivity

The number of true positives effectively determined by a classification experiment is referred to as sensitivity. It demonstrates how well the experiment describes the data. The equation is used to calculate sensitivity (8) [36].

Standard deviation (STD)

The STD is similar to the average deviation, with the exception that the averaging is done with a patch rather than the pixel.

$$\tilde{\sigma}^2 = \frac{1}{n-1}\sum_{i=0}^{n-1}(s_i - \mu) \quad (10)$$

The proposed method's explanatory STD performance is shown in **Figure 8**, and the analysis's findings demonstrate that it outperforms the SVM, KNN, and SSD classifiers that are currently in use. According to **Figure 8**, the proposed scheme has the least STD of up to 0.36 and 0.37, while the most extreme STD is SVM 0.46 and KNN 0.69.

Table 4. Confusion matrix tables of proposed with existing methods

A. Proposed					
Accuracy		Predicted			
		Low	Moderate	High	Rejected
Actual	Low	14	0	0	10
	Moderate	1	12	4	0
	High	0	2	22	0
	Rejected	0	0	0	24
B. SVM					
Accuracy		Predicted			
		Low	Moderate	High	Rejected
Actual	Low	12	2	0	10
	Moderate	1	13	4	1
	High	1	2	21	0
	Rejected	1	1	0	22
C. SSD					
Accuracy		Predicted			
		Low	Moderate	High	Rejected
Actual	Low	10	4	0	10
	Moderate	0	14	6	4
	High	2	2	20	0
	Rejected	0	2	1	20
D. KNN					
Accuracy		Predicted			
		Low	Moderate	High	Rejected
Actual	Low	10	0	4	10
	Moderate	4	14	6	0
	High	1	3	21	0
	Rejected	0	4	0	20

Root mean square error (RMSE)

The root mean square error (RMSE) is used to determine a slight deviation in the insights. The proposed scheme has the potential to help RMSE. The RMSE is calculated using the formula.

$$RMSE' = sqrt\left\lfloor m\,(obt_{res} - orj_{.res})^2 \right\rfloor \quad (11)$$

Here, obt_{res}→ calculated the result of the testing process, $orj_{.res}$→ original outcome, and m is the mean value. **Figure 9** illustrates the proposed system's performance investigation graph in terms of RMSE.

The examination result of **Figure 9** shows that our proposed method outperforms the existing SVM, KNN, and SSD classifiers. In comparison to these existing techniques, our methodology produces better results.

Comparative analysis

Table 5 includes a comparison of the specific implementation with related work as well as the respective accuracy of the test on various dataset groups based on machine learning approaches. The experimental results of the proposed system were first compared [28-35] using comparative evaluation.

Discussion

Sweat pH can change significantly among individuals and characteristically ranges from approximately 0 to 7. Sweat temperature can vary from 90 to 100 among these 24 Gen-Z students. Sweat acceleration also differs within this student from 0-200. Sweat lactate level can change significantly among individuals and typically ranges from approximately 0-31. The average range of sweat [Na+] is between 10 and 100 mmol/L, though individual differences can be quite large. Despite variations in sweating rate, is significantly lower and less variable than these other variables.

Confusion matrix

A confusion distribution is a tool for illustrating how well a classification method works even on a small sample of test data where the true value is computed. The terminology used to describe the confusion matrix can be perplexing, even though it is straightforward to understand. A confusion matrix is constructed according to the desired accuracy. **Table 4** depicts the confusion matrix tables and their respective values. Based on the following conditions, confusion matrices are generated.

- TP: The values of the stress level accuracy were as expected and positive.

- FP: The values for the stress level accuracy were predicted as positive when they were negative.

- FN: Although incorrectly predicted as negative, the stress level accuracy values were positive.

Performance analysis

The proposed method's efficiency is assessed through the use of performance measures. To analyze our proposed technique for efficient categorization of stress, to calculate several

Table 5. Comparative analysis based on deep learning approach

Author	Year	Methodology	Accuracy %	Processing Cost System	Energy Consumed	System Complexity
[28]	2018	ANN-SLDS	74%	Edge (at the sensors)	Moderate	Moderate
[29]	2018	EGI	90.2%	Edge (at the sensors)	Moderate	Moderate
[30]	2019	SA-KNN	85.7%	Edge (at the sensors)	High	Complex
[31]	2018	RMSD	90.1%	Edge (at the sensors)	Moderate	High complexity
[32]	2019	RSL-WS	80.0%	Edge (at the sensors)	Moderate	Complex
[33]	2021	K-NN	83.0%	Edge (at the sensors)	Moderate	Moderate
[34]	2019	MSD	86.2%	Edge (at the sensors)	High	Complex
[35]	2022	SSD	91.5%	Edge (at the sensors)	Low	Complex
Proposed	-	ANN-GA	99%	Edge (at the sensors)	Low	Less complex

assessment metric values. Three metrics, Student stress level in (%), Accuracy, Sensitivity, Specificity, Standard Deviation (STD), and RMSE, are used to evaluate the value of our methodology compared with existing SVM [27], and KNN [33] as well as SSD [35]. The equations below show how to demonstrate these assessment indicators.

Conclusion

A hybrid ANN-GA application for sweat detection in the Gen-Z student community has been implemented. This application's consumer electronics implementation makes use of sweat pH level, temperature, lactate level, skin conductance (GSR), and cortisol level. After that, the detected stress value is compared to ANN-GA. In a comparison of its performance on the same data, it generated significantly better results than the ANN-based algorithm and probably slightly better results than the GA-based algorithm for stress detection. The system was also created at a low cost, with minimal complexity, low power consumption, and no user interaction necessary.

Disclosure of conflict of interest

None.

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