Stress Detection in Humans through Artificial Intelligence

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Abstract— **Stress has become reason for several illnesses. In addition, chronic stress might involve some psychophysiological conditions. For example, stress increases the possibility of despair, heart attack, and cardiac arrest. smart watches, mobiles, and wristbands have become an essential part of our lives. This elevated the question of whether we can identify and stop stress with mobile phones in addition to wearable sensors. For this, offer a method that benefits in times of need. factors body temperature, respiration rate, blood pressure, and heart rate and -physiological factors such as , , and environmental . A method is defined to five : Normal, Minimum, Intermediate, less-high, and high. deep neural network model for automatic stress recognition. The proposed deep learning method has been trained with 26,000 samples, a 97%. We the performance using Machine Learning containing , Decision Tree, etc. The system results with accuracy of 98%.**

Keywords— deep neural network; machine learning; stress level detection; healthcare; psychophysiological

I. Introduction

Stress is essential to the troubles of people. That upward problem has become an inevitable part of our regular lives. The primary discovery will reduce the harm it causes and stop it from being long-lasting. Scholars have recognized the issue of stress on human health. Stress is defined as a state of mental or emotional anxiety resulting from inevitable or difficult conditions known as a stressor. Many stressors can cause specific anxiety in humans. Stressors release stress hormones in the human body.

Humans establish a lack of variation when exposed to a lot of stressors in place for extended periods of time, which can have significant effects on connections, health, work, and wellness, as well as on nature by triggering psychological failures. Stress in people is classified into eustress, neutered, and distress.

Eustress is defined as upright stress, and a positive kind of stress has an excellent effect on health, motivation, performance, and emotions. Neustress originates from the 'neu', indicating neutral, and is primarily a stress that hinges on the neutral response area. It is a stress that does not cause any particular injury or sadness to the individual, to the extent that it causes distress. Distress is the reverse of eustress in expressions of its expression on a human. This kind of stress has ill effects on a person and is what individuals frequently state when discussing stress. Distress causes hopelessness, sorrow, and despair, or it disrupts the balance of the body.

The unfavorable things of stress are related to harmful physiological reactions that increase blood pressure, heart disease, nervousness, etc. [1] It also reduce workplace efficiency, leading to significant economic impact [2]. Early identification and management of stress is the primary phase in avoiding its harmful effects. Stress can be theorized as a response of the Autonomic Nervous System (ANS) to numerous stimuli such as environmental stimulation, bodily stimulation, etc. The stress response of ANS can be categorized into two kinds: (1) Objective reaction and (2) Subjective reaction. The subjective reaction is the stress perceived through a change in boosted skin conductance, cortisol level, heart rate and sleep pattern etc. Previous studies shown that perceived stress and neutral actions of anxiety are very connected [3].

The gap between job difficulties, abilities, time pressure, and high workload is fundamental factor for workplace stress. Household-connected matters, sicknesses and damages, and expressive issues can be recorded as off-the-office reasons for stress. A current public review disclosed that 52% of European employees have visible emphasis at offices. Predictably, 60 - 70% of European business zone workers are missing out on working times initiated to job-related stress and psychosocial hazards.

There are two categorized of stress: acute plus chronic. The American Psychological Association identified anxiety, pressure from the recent past, and the upcoming reason for acute stress. The possible causes in place of acute stress can

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be detailed as assessment taking, obstacles, or nervousness when meeting the fresh public. Enduring pressures and anxieties calculate the root reasons for chronic stress as an outcome of socioeconomic situations, problems in social connections, or an unfulfilling job. The significance of chronic stress is critical if left unmanaged.

Stress has apparent effects on human wellness. Acute stress's likely signs can be recorded as expressive distress, tension, muscular pain, and digestive issues. Over-arousal-related difficulties are much more noticeable, resulting in arrhythmias, cardiovascular disease, and possible premature demise in those with prior heart disease. Slight impact on physical situations might include back pain, frustrations, stomach, heartburn, raised blood pressure, aches, and a quick heartbeat.

Chronic stress has similar effects to acute stress. Though it 5 causes extra harm near bodily circumstances. It's a significant danger for hypertension, coronary illness, irritable digestive tract syndrome, gastroesophageal reflux disease, common nervousness disorder, and unhappiness.

These health issue contributes to absenteeism and reduce productivity, including 'Presentism' problem can be defined by staff remaining current in their office. Nonetheless, they do not operate with unlimited capacity, which is also appears because of stress. The annual price of nonattendance and presentism has been predicted by 281.61 billion dollars, and the expense of performance damage has been 250.55 billion dollars each year in Europe.

Existing stress detection studies primarily relay on limited data collection using (saliva, cognitive task, TSST, camera, etc). Existing stress studies based on one or two-parameter dataset. During the study, these are not sufficient for accurate Stress Detection. Automatic stress detection methods with multiple features are not presented.

To address this gap, this study proposes five different classifications of stress based on the extent of parameters. A deep learning model is established and tested through datasets with an example size of 4,000 plus 16,000. The training of the process is complete through 80%, while the testing is complete with 20%. The outcomes after the method tested by the training set remained correct in a range of 97% with a loss of 1% or less. The classification model we tested with two algorithms displayed sufficient accuracy. Both models achieved exceeding 98%. The following are the main contributions:

- Detected the stress in humans using multiple attributes. (Heart rate variation, electro-facial activity, EDA, Galvanic skin feedback, Body temperature)
- Evaluated the performance of supervised and unsupervised machine learning algorthims. (K-NN, Random Forest, SVM, Decision Tree, LR)
- Detected the accuracy of combining different signals with models in Stress Detection.

II. LITERATURE REVIEW

Stress is measured through physiological signals, GSR, EDA, and photoplethysmography (PPG). Multi-sensor-based methods work much better than a single sensing unit; stress monitoring gadgets must have many sensors fixed to be fit for correct stress findings. The total number of subjects/features is 13. An edge device is used (Raspberry Pi 3) to detect stress signals. Stress is measured in two classes. Apply a Random forest model to it; the accuracy is 92% [4].

A stress monitoring technique displays stress activity through a smartwatch. Stress is measured through the cognitive task (GSR), RR period, and Body Temperature Level (BTL). Ten young people are used for experimentation. Three-phase tests (rest, test, and final) are taken from the subjects. Twenty-seven attributes connected to GSR, RR, and BT are determined to locate some link relative to the stress state. K-NN classifier applied with one neighbor unit, achieving accuracy of 84.5% [5].

Two signals, i.e., GSR and HR, together with stress-finding systems, are intelligent enough to spot in fewer than 10 seconds. Two main stress tasks, i.e. HV and TP, are performed. Fisher Discriminant Evaluation and a k-NN classifier aim to identify examples of HR and GSR in two classes: stress and not stress [6].

In camera-based detection, physiological measurement is used; Heart Functions, GSR, EMG, and breathing features. They collect behavioral and bodily data. An additional advancement was outside and mind-skilled assessments in self-valuation reports. They displayed that adding physiological and behavior attributes increased classification correctness to about 86% with a Support Vector Machine classifier in two-class classification [7].

The authors established a stress method and also nervousness detection from facial expressions. Mouth movement, Eye movements, head-linked gestures, and HR were measured from the electronic camera. The upstairs said functions and k-Nearest Neighbour, Naive Bayes, Support Vector Machine, and Ada Boost classifiers accomplished 90% accuracy with three classifications, i.e., stressed, neutral, and calm [8].

The Empatica wrist band gathered data on BVP, Electrodermal Activity, ST, Accelerometer, Heart Rate, and IBI. In the laboratory, they videotaped a one-day relaxation model and a psychological math test during the stress stage. Heart Rate, BVP, IBI, electroactivity, and temperature information were obtained. Use entire Machine Learning algorithms in the MATLAB Weka tool kit. Got a 70% accuracy rate with 94% precision [9].

A system is built for perceiving stress from sleep designs. Gather information from Ten Hajj travelers. Both bodily as well as physiological information measurements are obtained. Heart rate variation, ECG, temperature, breathing rate, Galvanic skin response, higher body position sensors, and ACC on the body and arms were databases. After attributes were mined, the SVM, LR, K-NN, and random forest classifiers were applied to the data. Support Vector Machine got the maximum classification accuracy. A 73% classification accuracy was accomplished [10].

Used a breast band through a breathing sensor, accelerometer, and ECG for information gathering. Members are mandatory to fill out fifteen fifteen-question surveys. The SVM classification model was applied. In the Research laboratory analysis, they accomplished 89% recall. On the further, they got 72% accuracy on the rough [11].

Stress increases the probability of despair, stroke, cardiovascular disease, and heart attack. In this situation, an objective extent for classifying the stages of stress, though seeing the human mind can significantly expand the related damaging effects. Stress was assessed through accepting a well-known tentative model based on the Montreal imaging stress task (MIST). The planned ML structure included EEG attribute mining, attribute range (receiver operating characteristic curve, t-test), classification (LR, SVM, and Naïve Bayes classifier), and 10-fold cross-validation. The outcomes presented that offered structure formed 95% precision for 2-level identification of stress and 83% precision for various level identification [12].

In the past, most studies focus on two or three attributes are used for stress detection. Multiple signal data are not collected for stress detection. Most of the work is based on a two-three level classification. A multi-level classification of stress finding is not provided. The present work proposes a five-level stress classification to address this gap.

III. METHODOLOGY

A Deep Neural Network is a kind of artificial neural network generally used for image/object finding and classification. A DNN is a class of neural networks, best usually practical to examine graphic images, character recognition tasks, cancer detection, and biometric authentication. It uses a superior method called convolution. Now, in math, the difficulty is a calculated process of two functions that creates a third function that expresses how the shape of one is improved by the other.

A common type of neural network has an input layer, hidden layers, and an output layer. DNNs are divine by the architecture of the mind. Similarly, a neuron in the brain processes information in the body; artificial neurons in DNNs take inputs, process them, and direct outputs as an outcome. The input layer is where we provide input to the model. The number of neurons in this layer is equivalent to the absolute number of attributes in the information. Deep is 1st layer that prepares feature extraction from an input.

The input layer formerly goes into the hidden layer. Around can be hidden layers depending on the model and the information size. Unlike the number of neurons, each hidden layer can commonly be more significant than the number of functions. The hidden layers take input from the extra layer and give outcomes to another layer. The output from the respective layer is calculated in matrix multiplication of the development of the previous layer with learnable weights of the layer, and after by adding learnable biases computed by the activation function, which creates a non-linear network. The fully connected layer contains weights, preferences, and neurons. It links neurons in one layer to neurons in an extra layer. It is utilized to classify data into various classifications through training.

An activation function in a neural network states [13], [14] how the weighted input calculation is changed into a result from a node or nodes in a network layer. It is also called the transfer function. Common activation functions are Sigmoid, rectified linear unit, Leaky rectified linear unit, Tanh, etc. The fixed linear activation function is a non-direct or direct function that will certainly output the input straight if it is positive or will undoubtedly output nil.

After the hidden layers, data goes into the output layer. The output from the hidden layer is fed into a logistic function, like sigmoid; otherwise, softmax changes the production of individual classes into a possible score of a particular course. The soft-max procedure is utilized as an activation function in the output layer of neural network models that calculate a multinomial probability distribution. That remains, the activation function uses soft-max for multiclass classification difficulties where class connection remains mandatory on more than 2 class labels.

A. Dataset

A Machine Learning Neural Network Model has been accomplished and verified to reduce the calculation complexity and raise the competence. The NSRR (National Sleep Research Resource) stress study dataset has been used in a neural network for testing and training. In this dataset, 5904 subject data were collected between 2000 and 2018. Available to these subjects, raw polysomnography data is gathered. Polysomnography registers your mind waves, the oxygen level in your blood, heart rate and breathing, and eye movements. Polysomnography might be completed at a stress illness unit in a hospital or a center.

B. Splitting

Approximately 20,688 samples in the dataset were used for stress detection. In which split as fellow, 80% training set (16688) and 20% testing set (4000). This ensure sufficient for model learning. A portion of training data is further used as validation set. Validation data monitors, overfitting and model generalization. Training is performed in epochs. The batch size of the model to train the dataset is set as 64, as displayed in the Figure. 2 After getting a dataset next step is to analyze the data. To analyze data, use different tools and systems.

C. Preprocessing

Data preprocessing is a crucial step to justify the data is clean, consistent and suitable for training a deep neural network (DNN). The NSRR dataset contains wide term of polysomnography, which include missing, noisy or corrupted values due to sensor errors. Missing or null values in stress signals are corrected using pandas' functions. If the small number of values are missing in feature, they are corrected using mean or median imputation for continuous signals. Outliers caused by sensors error are delete using threshold-based filtering. Apply best techniques to signals for removal of noise.

From raw polysomnography data, the following feature are considered as directly link with stress: (I) Number of times of sleep, (II) Snoring range, (III) Respiratory rate range, (IV) Heart rate range, (V) Oxygen in blood range, (VI) Eye movement rate, (VII) Limb movement rate, and (VIII)

Modification in body temperature. Only relevant and statistically features are retained to reduce complexity and overfitting.

To ensure all feature work equally, applied Min-Max Normalization or Z-score standardization. This scales all features into equal range and improve speed and training stability.

System requirements are the set of procedures for a hardware or software application to run efficiently and proficiently. Failure to see these requirements can result in connection problems or performance problems. In system requirements, use Processor: 2 x 64-bit 2.8 GHz, Ram: 8 GB (or 16 GB), Storage: 400 GB are required for analyzing data. Python libraries that are utilized in Machine Learning [15], [16], [17] are: i) Tensorflow, ii) Numpy, iii) Pandas, iv) Matplotlib, v) Scikit-Learn, etc.

D. Model Details

Stress can be identified as energetic retro, which benefits emerging best health and good via processing repair and body consolidation. In command to observe the feature of sleep, a device suggests actual time physiological signal keeping by seeing factors such as (I) Number of times of sleep, (II) Snoring range, (III) Respiratory rate range, (IV) Heart rate range, (V) Oxygen in blood range, (VI) Eye movement rate, (VII) Limb movement rate, and (VIII) Modification in body temperature. The DNN is implemented using TensorFlow and Kares.

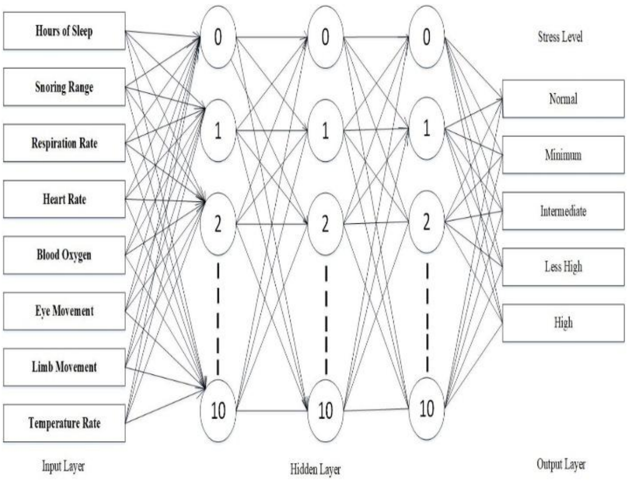

Fig. 1. Deep Neural Network Modal Representation for Stress Detection

Figure 1 represents a Deep Neural Network (DNN) model through a line stack of one input layer, three hidden layers, and one output layer with ten neurons, respectively is utilized to find the connection between physiological factors and stress stages. The number of hidden layers and neurons connected through respectively of each hidden layer are open factors and can be measured casually. The output layer is anywhere the network finishes, and the calculations are set. At the end of the coating, prediction is given for 5 parameters of stress. This parameter defines the level of stress. Everyday Stress, Minimum Stress, Intermediate Stress, Less High Stress, High Stress.

$$y\,(Z) = \sum_{k=0}^{M}(\omega i z i \;+\; \omega o) \qquad (1)$$

Where Z = z1, z2,..., zn is the n-dimensional input, y is the reply of the neuron, ωi are weighted for individual information, and ωo is a constant bias.

With the help of a Support Vector Machine, the device is planned as a classification model to expect one of the o classes since r inputs. In the device, the neurons at the three hidden layers remain 10, 20, and 10, respectively. The number of neurons in the output layer links accurately to the number of stress kind classifications. This generates a clear input by way of a set in Equation (2). Which formerly applies to activation functions to create the output? The Rectified Linear Function is utilized as an activation function for hidden layers. The outcome layer uses the softmax function. The estimates at the output layer are created using the set in Equation (2). Once the model is skilled and fed through an unlabeled sample, it produces five predictions by the outcome layer.

$$Fj \;=\; E\left((C)j, m \cdot (z)i \;+\; (d)j, m\right) \qquad (2)$$

Wherever (C)j, m is the weight matrix, (d)j, m the bias, and E is the Rectified Linear Unit activation function.

The output layer prepares the classification and estimation of the input sensor data into a stress kind utilizing the softmax function:

$$q \;=\; softmax(\omega \cdot z \;+\; n), \qquad (3)$$

Where ω, q, and n represent weight, predictor function, and bias for stress detection. For some neural network models, the loss factor remains to enhance the model.

We gather data from smart watches, smart bands, head and wrist bands, etc. We collect data from different psychological signals like heart rate (electrocardiogram signal), respiratory rate (capnogram), skin conductance (electrodermal activity or EDA signal), and muscle current (electromyography signal). After getting data, set boundary conditions on all calls for obtaining the required sensor data. Data is found after the boundary condition, and we choose a valuable parameter for stress detection. The parameter we found checks whether the specification meets our requirements or not. If the parameter requirement is met, apply the DNN model. If the parameter requirement is unmet, return to the boundary condition. After getting parameters, a DNN with a fully connected layer model is applied. Applying DNN, the parameters pass through one input layer, three hidden layers, and one output layer. All this model process, we get different stress values. These stress values are not classified. We use a support vector classifier (SVC) to classify stress matters into specific ranges. After getting degrees, the SVC classifies the data into five classes of stress detection.

The procedure of assisting the algorithm study in command to create improved calculations is identified as training, for the preparation loop feeds the datasets near the model in epochs. The training epoch means the number of times the model should learn from the training set of the dataset.

IV. RESULTS AND DISCUSSION

DNN with a fully connected layer architecture develop, the result goes to the output layer after data is passed through the hidden layer. The procedure of helping the algorithm learn to create improved calculations is recognized as training, is carried out by iteratively feeding the dataset to the model over multiple epochs. One epoch represents a complete forward and backward pass of the entire training dataset through the network.

Table 1 shown the performance of the predictive DNN model across different epochs. As the numbers of epoch increases, the model describes a consistent reduction in loss and an improvement in accuracy.

TABLE I. PERFORMANCE OF PREDICTIVE DNN MODEL

Epoch	Loss	Accuracy
75	0.385	95.66
85	0.289	97.33
90	0.195	97.90

The declining loss values confirm the difference between predictive and actual output decrease as training progresses, while increasing accuracy improve classification capabilities.

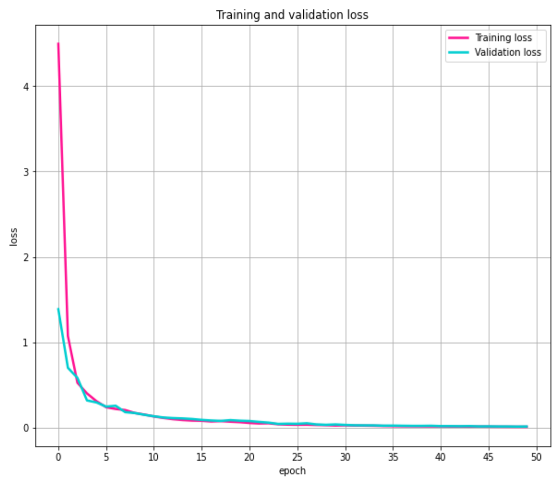

Fig. 2. Training Validation

Figure 2 shows the relationship between epoch count and validation loss. The loss function that matches object and predicted outcome values, the decline in loss after successful epochs indicates that model is generalize well and does not suffer from overfitting. Accuracy is computed as the relation between the amounts of accurate predictions to the total number of predictions. In Table 2, accuracy will increase, and loss will decrease after every epoch.

Performance metrics for any model's calculation are accuracy, precision, recall, and F1-score. TensorFlow gives built-in support for these metrics using function such as tf.metrics.Accuracy, tf.metrics.Precision and tf.metrics.Recall. Additionally, overall accuracy and confidence interval (CI) are computed using Equations (4) and (5):

$$\alpha = \frac{(TP+TN)}{(TP+TN+FP+FN)} X\ 100\% \quad (4)$$

$$CI = error \pm z\sqrt{\frac{(error).(1-error))}{n}} \quad (5)$$

Wherever n is the trial extent, the error is the confidence mistake, and z is the critical value after the normal distribution.

The DNN model achieve a mean cross-validation accuracy of 96-98% with low variance, shown that the model performs consistent across different subset of data. This confirms that the high accuracy reported is not due to overfitting or data imbalance, but show predictive results.

To further validate effectiveness of DNN, machine learning classifier were applied on same dataset. A Support Vector Classifier (SVM) and Decision Tree classifier (DT) to classify data to check performance and the evaluation matrix. The data is classified into different classes. Calculate the model's performance using accuracy, precision, and the F1-score of individually of each type individually, along with their weighted and macro average.

TABLE II. CLASSIFICATION REPORT OF SVM STRESS DETECTION

Classes	Precision	Recall	F1-score
Normal Stress	0.98	0.96	0.98
Minimum Stress	0.90	0.98	0.95
Intermediate Stress	0.98	0.95	0.98
Less High Stress	0.97	0.98	0.95
High Stress	0.98	0.97	0.96

Table II shows the model's performance with accuracy, precision, recall, and f1-score for each class. In the classification report of the support vector machine classifier, every stress class calculates precision, recall, and F1-score. The overall accuracy of the support vector classifier is 98%. And the micro average of each type in the support vector classifier is 98. And weighted average of each class is precision 99, recall 98, and f1-score 98. Figure 3, the confusion matrix, shows the result of actual and predicted classes.

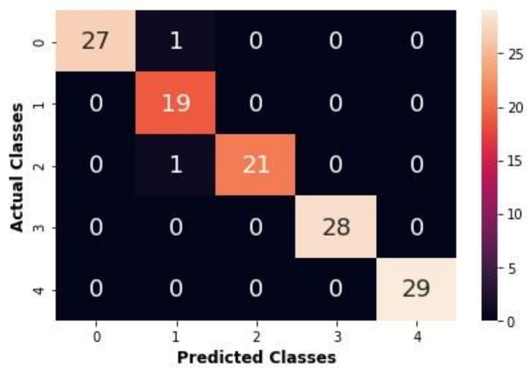

Fig. 3. Confusion Matrix SVM

TABLE III. CLASSIFICATION REPORT OF DECISION TREE

Classes	Precision	Recall	F1-score
Normal Stress	0.99	0.98	0.99
Minimum Stress	0.95	0.96	0.97
Intermediate Stress	0.99	0.95	0.98
Less High Stress	0.98	0.97	0.99
High Stress	0.95	0.98	0.93

Table 3 shows the model's performance with accuracy, precision, recall, and f1-score for each class. In the classification report of the decision tree classifier, every stress class calculates precision, recall, and F1-score. The overall accuracy of the decision tree classifier is 99. And the micro average of each type in the decision tree classifier is 99. And weighted average of each class is precision 98, recall 98, and f1-score 99. Figure 4, the confusion matrix, shows the result of actual and predicted classes.

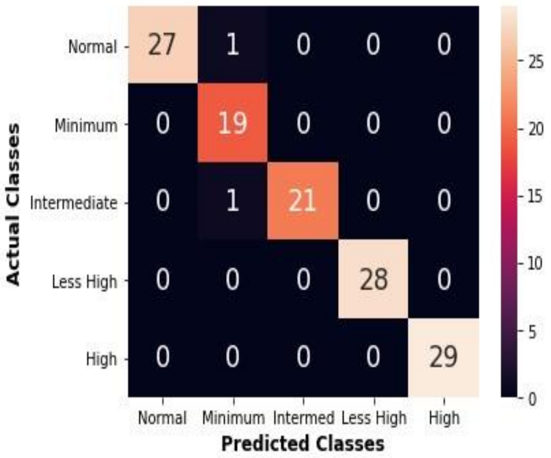

Fig. 4. Confusion Matrix of DT

TABLE IV. COMPARISON OF MACHINE LEARNING CLASSIFIER STRESS DETECTION

Sr #	Classifier	Precision	Recall	Accuracy
1	SVM	0.98	0.98	0.98
2	DT	0.99	0.98	0.99

Achieving high accuracy (97–98%) is mainly weighty for real-world stress-detection systems. In real applications such as mental-health monitoring, workplace wellness programs, and healthcare decision support, even small classification errors can lead to incorrect stress calculation and delayed interference. High precision confirms fewer false alarms, while high recall guarantees that stressed individuals are correctly identified. The solid F1-scores indicate a balanced trade-off between precision and recall, making the proposed model reliable, scalable, and suitable for deployment in real-time stress monitoring environments.

Overall, the experimental results, validation analysis, and comparison with traditional classifiers prove that the proposed DNN-based approach offers strong, accurate, and practical stress-classification performance.

TABLE V. OVERALL DATA CLASSIFICATION RESULT FOR STRESS DETECTION

Examples	Parameter
Sample 0 Calculation	Everyday Stress (0.6%)
Sample 1 Calculation	Minimum Stress (0.8%)
Sample 2 Calculation	Intermediate Stress (55.8%)
Sample 3 Calculation	Less High Stress (30.7%)
Sample 4 Calculation	High Stress (10.8%)

Lastly, the loss and accuracy of the model are experiential to remain at about <1% and >97%. To explore stress finding and calculation, a tool on the customer is used to procedure the physiological signal data. Although the Dataset since NSRR has 20,689 example collections, the execution was done using Tensor Flow through 16000 examples of data used for training and 4688 standards used for testing. The correctness and cost of the models are about 97% and 1%. Through the achieved accuracy, the entire amount of Accurate Precision & Recall is measured. Calculations were made using Eqn. (3). Through this, the numbers of improper Calculations originate via deducting the accurate calculations from the calculations made. Therefore, the Confidence Interval (CI), which stands for the possibility of the noticed result dropping in different stress-level classifications, is experimental using Eqn. (4).

Alongside the overhead stated metrics, time and space complexity are used to calculate the model's performance. Through an estimated correctness of 97% and CI, the time necessary to complete the process in the model is around three minutes, through a bandwidth of 16000 data examples. Concerning computational time complexity, the neural network used is O (n4), where n is the absolute number of neurons in the model, and the space complexity is O (n). The stress calculation is done by compiling the perceived stress levels every 10 minutes and relating the detected stress levels.

V. CONCLUSION

The offered process can be included in a structure that benefits persons overwhelmed by stressful conditions. Such a structure can outline nerve-wracking actions, offer healthiness information, and detect stress. The proposed technique gathers and examines eight physiological signal data near calculated pressure and teaches the handler the aids of intelligent sleeping. Five different classifications of stress based on the extent of parameters are offered in this work. The differences in the parameters are well described, along with the relationship of the pressure with the measured parameters. The system is trained, and the outputs are made as a result. A deep learning method is established and tested through datasets with an example size of 4,000 plus 16,000. The training of the process is complete through 80% of the example size, while the testing is complete with 20% of the example size. The outcomes after the method was tested by the training set remained correct in a range of 97% with a loss of 1% or less. The classification model we tested with two algorithms displayed sufficient accuracy. Both models exceeded 98%.

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References

[1] Picard, R.W., Automating the recognition of stress and emotion: From lab to real-world impact. IEEE MultiMedia, 2016. 23(3): p. 3-7.

[2] Picard, R.W., Affective Computing. 1997, MIT Press, Cambridge, Massachusetts.

[3] Picard, R.W. Affective computing for HCI. In HCI (1). 1999.

[4] Nath, R.K., et al., Machine learning based solutions for real-time stress monitoring. IEEE Consumer Electronics Magazine, 2020. 9(5): p. 34-41.

[5] Ciabattoni, L., et al. Real-time mental stress detection based on a smartwatch. in 2017 IEEE International Conference on Consumer Electronics (ICCE). 2017. IEEE.

[6] De Santos Sierra, A., et al. Two stress detection schemes based on physiological signals for real-time applications. in 2010 Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing. 2010. IEEE.

[7] Aigrain, J., et al., Multimodal stress detection from multiple assessments. IEEE Transactions on Affective Computing, 2016. 9(4): p. 491-506.

[8] Giannakakis, G., et al., Stress and anxiety detection using facial cues from videos. Biomedical Signal Processing and Control, 2017. 31: p. 89-101.

[9] Gjoreski, M., et al., Monitoring stress with a wrist device using context. Journal of Biomedical Informatics, 2017. 73: p. 159-170.

[10] Muaremi, A., et al. Monitoring the impact of stress on the sleep patterns of pilgrims using wearable sensors. in the IEEE-EMBS international conference on biomedical and health informatics (BHI). 2014. IEEE.

[11] Hovsepian, K., et al. cStress: towards a gold standard for continuous stress assessment in the mobile environment. in Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing. 2015.

[12] Subhani, A.R., et al., Machine learning framework for the detection of mental stress at multiple levels. IEEE Access, 2017. 5: p. 13545-13556.

[13] Rashid, J., Qaisar, B. S., Faheem, M., Akram, A., Amin, R. U., & Hamid, M. (2024). Mouth and oral disease classification using InceptionResNetV2 method. Multimedia Tools and Applications, 83(11), 33903-33921.

[14] Qaisar, B. S., Shahid, M. A., Ashraf, S., Adnan, M., Azeem, M. M., Ali, M., & Nauman, M. (2025). Automated Trauma Detection by Using Machine Learning. Volume, 10, 2129-2135.

[15] Qaisar, B. S. (2025). Canker and Cold Sore Classification Using Xeception Technique. Journal of Machine Learning and Deep Learning (JMLDL), 2(01).

[16] Azeem, M. M., Mehdi, S. A., & Shahid, M. A. (2025). Garbage Detection Using Deep Learning Methods. Journal of Innovative Science and Research Technology, 10(9), 608-618.

[17] Inam Ul Haq; Ahmad Ali; Bilal Shabbir Qaisar; Hafiz Muhammad Adnan; Mubasher Hussain; Muhammad Nauman.“Steganography Techniques for Medical Images: A Recommender Paper.” " Volume. 8 Issue. 9, September - 2023 International Journal of Innovative Science and Research Technology (IJISRT), www.ijisrt.com. ISSN - 2456 2165, PP :- 79-87. https://doi.org/10.5281/zenodo.8340603