Contribution of Artificial intelligence to the Promotion of Mental Health

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***Abstract*- Mental stress is a normal and frequent phenomenon in human beings. Earlier stress recognition is critical for avoiding these negative impacts since prolonged stress has an adverse impact on mental health leading to anxiety, loss of sleep, or headache. Making utilize of physiological data gathered from a wearable device, present study attempts to simplify the procedure of psychological stress determination, which helps to distinguish the persons suffering from stress over healthy one. We tested our method using a dataset that was made accessible to the public. The precision of forecasting exact stress state was applied to make comparisons among effectiveness of numerous techniques of artificial intelligence (AI), including Artificial Neural Networks (ANN), Fusions of ANN with Support Vector Machines (SVM), Stack Classifying method, and Radial-basis Function (RF) Networks. The study included 3-class stress categorization method in which, results shown greatest accurate rating of 99.920percent by Stack Classifier, while RF provided the lowest preciseness of 84.462percent. Study outcome infer that the suggested models are efficient in detecting mental stress over time and show that physiological indicators could be highly relevant in identifying mental stress.**

Keywords: Mental health, Artificial neural networking, Stress identification, Machine learning, Artificial intelligence

I. Introduction

Integration of many operations, including as identification, sensing, networking, and processing, is the basis of IoT (Internet of Things). It enables substantial technological breakthroughs and value-added services that tailor how people engage with various " The sudden outbreak of corona virus-pandemic has placed mental well-being of people in deep trouble; these people might experience increased levels of stress, depressed mood, traumatic stress disorder, or indeed suicidal tendencies [1]. Middle East respiratory syndrome breakout in 2015 as well as COVID pandemic have both been the subject of current studies which has revealed a substantial risk of mental disorders [2,3]. Utilizing ideal computing methods to large data is essential for achieving individualized mental health support as a long-term objective. When intensely disturbed persons possess relatively lower stress resilience and other susceptibility traits, like a general inclination for mental discomfort along with poor self-control, their mental health risks are amplified [4]. It is crucial to identify and recognize these people in beginning phases of stressful onset in order to avoid the emergence of more severe long-term psychological issues like traumatic disorder, depression, and suicidal thoughts. Nonetheless, because of existing shortage of biological markers, subjectiveness of humans, and distinctive, personalized traits of ailment that are non-viewable by clinical psychologists, mental disorders are challenging to identify and also harder to forecast [5]. Presently, for psychological illnesses, data-base guidelines are primarily used to classify the clinical features of related problems [6].

In these situations, one of the most major consequences, especially artificial intelligence (AI) and machine learning (ML) are employed which have a capacity of earlier recognition with forecasting of mental health problems, that can lead to long-term psychiatric problems [7-10]. AI is a sort of technology that has been called a "digitalized revolution," with combination of various technological categories [11,12]. Though many well-known societal components are prepared to accept the possibilities of AI, cautiousness is still a common theme in health, particularly in psychology field. Despite apparent issues, AI technologies in medical science are constantly expanding and helping people to manage with stress, despair, as well as other psychological issues as they become more prevalent in clinical practice [13]. While AI technology is increasingly used in healthcare for purposes related to physical wellness, the field of psychological health seems to have been reluctant to accept AI [14,15]. Patient comments and statement records that are subjective and

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qualitative are frequently used as clinical evidence in the psychology field. Nevertheless, AI continues to offer many advantages as a forecasting model in variety of fields [16-18]. AI has the capacity to fundamentally alter diagnosed and addressed mental disorders [19]. The greatest way to completely express a comprehensive mental health of individuals is through their distinct physio-psycho-social makeup [20]. But there exists a limited grasp of the way such social, psychological, and physiological systems connect with one another. Pathogenesis of psychological disorder exhibits significant variety, wherein, the discovery of biomarkers might make it possible to define such conditions more precisely and objectively. Utilizing AI approaches enables the creation of improved pre-diagnostic screening devices as well as risk models to assess a propensity of person or risk of acquiring mental disorder [9].

A technique which has an ability of assessing stress levels from signals produced by a wearable equipment could assist in developing intriguing real-life situations. Psychological stress may play a key role in the development of several ailments. Whenever it relates to the prompt identification of stress, this system is crucial for informing the consumer about raised stress levels, ensuring that they are conscious of stress situation and can avoid future issues. This work intends to utilize the physiological signals that found to be valid predictors of stress-level in psychology [21] and to propose various approaches relevant for the study goal. This stress determining method will be very useful in creating systems that could identify stress as well as undertake precautionary measures or send warnings well in advance so that user could take necessary steps. Investigators may gain from stress determination by getting a more vibrant and complete picture of how technology affects its consumers. Additionally, consumers may benefit from it, since they can incorporate novel apps into their professional and personal lives life based on their degree of stress.

II. Literature Review

According to [22], AI assists in identifying diseases earlier by improving diagnostic methods of diseases. They are known to optimize medicating/therapeutic dosages, and discover new remedies. Rapid pattern analysis of massive datasets is one of key strengths of AI. Most effective applications of pattern determination in healthcare system are in the fields of: radiology, carcinoma diagnosis, and ophthalmology, wherein AI algorithms could evaluate image data for anomalies or subtlety that are practically invisible from eyes as well as from skilled physicians. The utilization of smart technologies to help healthcare decision-making is rising, even though it is uncertain that they will ever entirely replace physicians.

A study by [23] indicated that mood assessment using AI incorporated techniques, like ML (machine learning) and DL (deep learning), can help to identify early indications of depression and raised suicide thoughts, particularly during in COVID crisis. According to the authors, objects or character identification, image detection processes, and examining face changes can help to diagnose possible initial signs of depression.

[24] examined the effectiveness of face expressions, imagery, emotion chatbots, and conversation in social networking sites to identify emotions and psychological well-being. Numerous ML approaches were utilized to distinguish emotional responses from text processing namely Naive-Bayes, SVM, LSTM, RNN, Logistic Regression, etc.; ANN is employed for extraction of features and classifying images in order to determine emotions from face expressions. Study findings concluded that a variety of AI and ML approaches may aid in the identification and study of emotion, and thereby depression, in addition to research-related problems.

A study conducted by [25] explored the use of AI chatbots, particularly in relation to psychological health of post-pandemic era. An intensive literature by authors applied a design scientific method to establish the problem description, define the goals of targeted solutions, and to suggest a well-designed outline for upcoming mental health chatbots. Outcome of study highlighted the importance of taking into account ethical concerns, governance, objective-oriented design, and AI-based technologies while creating novel psychological chatbots.

[26] looked into the effects of AI, who found that mental health is varied by generation and skill level, wherein, less-skilled employees as well as older workers (those over 60 years of age) typically being more favorably impacted. Overtime work and workplace atmosphere have a moderating function in this regard.

Regarding large-scale heart rate prediction, [27] employed CNN on the Wearable Stress and Affect Detection dataset by comparing the results with various traditional ML approaches. Parallel to this, [28] classified bio indicators to several state-of-mind classes by using a various bio signal, and utilized CNN model to categorize blood volume pulse, ECG and EMG.

Through sequentially categorizing distinct emotional states by employing CNN approaches, [21] used a variety of feature-based and CNN models for multiple-targeted affect determination.

III. Methodology

This section provides a concise overview of models which have been assessed in the study

A. Dataset

A dataset which is employed in present study is 'Wearables Stress-effect Detection (WSD)' type- a mode of multiple form, that comprises of 3 emotional conditions namely: pleasure, stress, and neutrality. 15 participants were exposed to various settings for gathering data, in which, the sensor output from wrists and chest wearable devices was continually recorded [21]. Targeted labelling was divided into 3 categories: "Neutral," "Stress," and "Pleasure." By giving them a reading things and table, the neutral condition was observed for 20 min. in an effort to create a neutrality affective status. For amusement criterion, 11 comic videos have been played for 392 secs. to the participants. By compelling every participant to give speech in front of a jury with no prior notice and making them to know that while they would speak in front of an audience, stress was imposed to them. Then, without making any mistakes, they had to keep counting from 2023 to 0 in stages of 17, failing which they had to restart over at 2023. This session took place for five mins.

WSD comprised of data from 2 sources of wearing devices like: a) wrist and b) chest. Study utilized data solely from wearing of chest because of differences in records from wrists one. It had eight variables, namely: body temperature, respiratory rate, electronic design automation, ECG, EMG and 3 axes of acceleration. For analysis, just 10percent of randomly selected samples of particular person was retrieved, because of huge data quantity, comprising about 2.3 mill. entries of information to be examined with. Data was split so that 70percent of dataset was utilized for training, while 30percent was utilized for testing after being adjusted with a mean centered at '0' and a unit std. deviation. All samples were carried out in stratiform to ensure that targeted labelling portions remained identical in the testing as well as training sets.

B. *Artificial Neural Network (ANN)*

ANN is a controlled learning system influenced by biology that resembles biological neurons [28]. Biologically in neurons, the electrical impulses are acquired by dendrites from other neuronal axons. Contrarily, in ANN, this function is carried out by numeric value that are recorded from layers of input to output when crossing by one or more layers of hidden one. Constituents of latter layers could be thought as a self-learned feature space of artificial network. A weight summation of constituents for layer '*l*' is determined before being crossed through an activating function to plot from one layer '*l*' to '*l*+1'. The choice of precise no. of hidden neurons as well as layers is not supported by any theory. To find the best hyperparameters besides, to reduce variance and bias, utilization of hit and trial strategy could be made. Coping with non-linear information requires the use of at least one hidden layer. Figure. 3.1 depicts the conceptual design of an ANN algorithm.

Whenever regression needs to be done, only one neuron is employed in output layer. For categorization, the no. of input layer neurons is determined by the no. of variables or forecasters in dataset, while the no. of targeted factors determines the no. of neurons in output layer. Activation functions (AF) are essential for capturing non-linear data, without of which, the link among input and output would be limited to a linear eqn. with a large no. of parameters, irrespective of how many hidden layers are present [29].

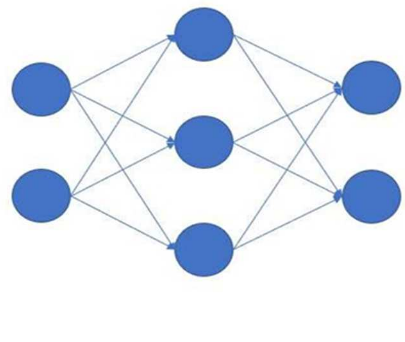

Figure 1. ANN design

Rectified Linear Unit (RLU) and activation function (AF) SoftMax (S. Max) have both been utilized in present experiment. The piece - wise RLU function, indicated by R(x), which generates '0' for a non-positive value and restores similar for positive input values. Contrasting to sigmoid and tanh AF, RLU converges more rapidly. S. Max, represented with s(x), is utilized by providing classes-specific probabilities since it sums all output values to one, making it simple to compute class-specific probabilities. The formulae for RLU and S. Max AF are as follows, considering K to be the no. of classes and x to be input:

$$R(x) = \max \{0, x\} \tag{1}$$

$$S(x)i = \frac{e^{xi}}{\sum_{i=0}^{K-1} e^{xi}} \tag{2}$$

Generally, ANN has an optimizing issue. We used micro batches to train ANN by applying stochastic gradient descent. The gradients of loss function (LF) w.r.t. weights are computed through backpropagation using the Chain rule of derivatives. This is accomplished by utilizing cross-entropy LF, a most typical categorization issue. LF will be of extremely higher value if we are confident/likely to forecast the wrong class, whereas, it will have a relatively low value if probably, we are confident to forecast the right class [30,31]. To discover optimal response, gradient descent iteratively updates weights in the path of diminishing loss.

$$L\,(Y, Y^{\wedge}) = -\sum_{i=0}^{k-1} \quad Y_i \, log \, log \, (Y_i^{\wedge}) \tag{3}$$

In above formula, Y_i is the binary true value of i^{th} class and $Y_i^{\wedge}$ is the forecasted category-wise probabilities for that class. An aggregate of those loss of mini batch is the value which is put into gradient descent. Although normalizing data prior passing to an ANN is usually preferable, there is a possibility that variation will be introduced while backpropagation [32]. Hence, in order to regulate the variability prior sending it to activation, batch normalizing process is applied wherein, 2 novel parameters namely mean and variance are learned during ANN training by utilizing current batch.

$$W_j = \gamma_j \left[\frac{Wj - \mu j}{\sqrt{\sigma j}} \right] + \beta j \tag{4}$$

For the purpose of ANN training with a single hidden layer and thirty-two neurons, we employed Keras architecture with TensorFlow as the backing. SoftMax is used for activating the output layer and RLU is used for activating hidden layer. The 4096-batch size had been chosen, and ANN was trained for twenty times.

C. Fusion of ANN with Support Vector Machine (SVM)

SVM is an approach whose hyperplane borderline functioning divides the classes by a maximal margin [33]. Determining the deciding border with certain breadth among different classes is preferred to just determining the plane that separates the classes [34]. Rather than using a Gaussian kernel, a linear kernel was utilized in the study, owing to the magnitude of dataset. ANN model with prior-training as described previously was employed initially and the values of hided layers were put into linear-kernel SVM. However, we trained a single SVM model rather than employing multiple SVM with various kernels for every feature spacing subgroup. Figure. 3.2 depicts the schematic of hybrid algorithm.

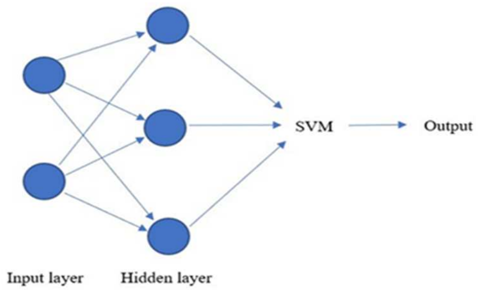

Figure 2. Fusional ANN-SVM

Through training this hybrid approach using ANN-learned features, the benefits of SVM could be utilized. In order to make finalized forecasts, we employed Keras architecture by initially passing inputting layer to hided one, that has thirty-two neurons, and then employing similar hided layer unit as input for SVM, that has been done utilizing sci-kit learning module.

D. Stack Classifier

A study by [34] implemented KNN (k = nine), Linear Discriminating Analyzer, DT, AdaBoost, and R-forest Classifiers [21]. Rather than polling or aggregating the outcomes, we created an ensemble of such methods and passed the outputs of every model to an ANN as finalized predictor. A supervised ML algorithm - KNN could be applied for classification and regression issues. Based on the distance between data point and nearby group, this method predicts the category to which data point relates [35]. Since it makes reference to the training set rather than modelling a function, this method seems to be an illustration of a "lazy learner." K-NN falls within the category of non-parameterized techniques [36].

Another supervised ML approach is linear discriminant analysis (LDA), that finds the strongest linear combination of factors (predictive) to effectively distinguish between 2 targeted categories. Primary goal of this model is to reduce the dimensions of a higher-dimensional space by projecting its attributes onto a space of lesser-dimension [37]. It generates a decisional plane that optimizes between-class variability and reduces variability of within - classes. LDA relies on Bayes theory, which presumes that data points of every class remain regularly dispersed.

AdaBoost is a stimulating method that seeks to strengthen a group of weaker classifiers. The weight summation of outputs from previous learning algorithms serves as finalized output of classifier [38]. It has been revealed that efficiency of Decision tree (DT) on binary classifying issues is improved with AdaBoost [39]. The method is receptive to anomalies and noise data. A tree-based approach is a DT, which is structurally comprised of an internal node, branches, as well as leaf node. It will stand in for a feature, a decision rule, and an output, accordingly. A root node of DT is its highest node [40]. Depending on attribute value, algorithm learns to categorize. DT divides the training data set recursively till every section is made up entirely of samples from a single class [41]. A series of fundamental tests, each of which evaluates a numerical value vs a threshold value, are effectively incorporated by DT.

A series of randomized DT are created by RF Classifier, an ensemble approach, using sampling from training dataset that have been randomly chosen. The votes from various DT are then combined to forecast finalized class [42]. Every DT in RF is made using a randomized subset of characteristics. Initially, class-wise probability was determined after each single model had been trained. The input of this ANN has fifteen units because there are five models and three categories, as illustrated in Figure. 3.3. For ANN training and to reduce cross-entropy LF, stochastic gradient descent involving micro-batches was used. For output layer, SoftMax AF was employed.

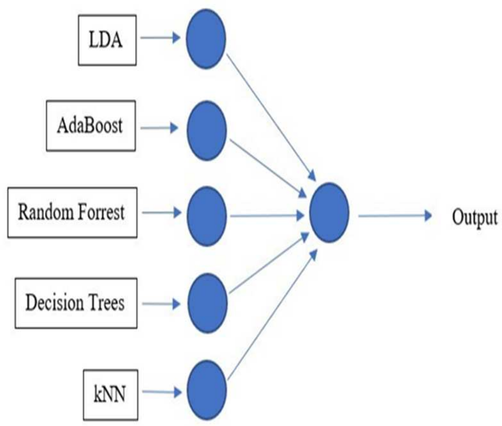

Figure 3. Stack Classifier

E. Radial-basis Function (RF)

RF system consists of solitude hidden layer, in which each of predictions are located in input layer, similar to that of ANN [43]. In RF, the Radial-based functioning that serves as an AF, receives the calculated descriptive length among input as well as a hided node [44]. This layer produces a dispersion with a means and a std. deviation as its output. When input is located at center, the activation increases; however, it decreases when input is further apart. Such activations are weighted summed for output layer to get class-wise probabilities needed for categorization.

$$h(\,x/\,l) = //\,x - \,l\,//_2 \tag{5}$$

$$G(x) = \frac{e^{2^{\frac{-1(x-\mu)2}{\sigma 2}}}}{\sigma\sqrt{2\pi}} \tag{6}$$

These values of hidden nodes, that become contrasted with input vector, are chosen at randomly from training data set. The no. of samples to be taken will rely upon that hidden neurons we select. A cluster technique such as K-Means (K-Me) may be used to choose these nodes at random or to determine the center of every cluster. K-Me. was employed to locate the centers (represented by l). For output layer, S. Max AF was employed. Following our earlier methodology, RF networking was trained by utilizing Gradient Descent with thirty-two hidden units. In Figure. 3.4, RF network is shown schematically.

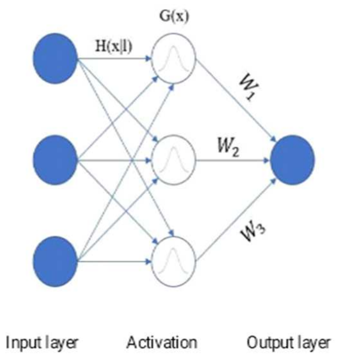

Figure 4. Radial-basis functioning system

IV. Analysis And Findings

ANN, fusion of ANN and SVM, Stack Classifying, and RF are the approaches known to be assessed in this study as shown in Figure 4.1. The effectiveness of each model was assessed using its precision to predict proper targeted label from the testing dataset. Accurateness has been the primary parameter employed by all prior articles on WSD to assess the effectiveness of their categorization systems. Table 4.1 displays the outcomes of models employed in this study.

TABLE I. Output of overall models

Models	Preciseness (in percentage)
ANN	90.580
Stack Classifier	99.921
ANN -SVM	91.482
Radial-basis Function (RF)	84.462

It is clear that Stack Classifying method achieved the highest precision of 99.921percent from all models. Further, RBF network was of higher computational-cost because in addition to backpropagation, K - me. strategy needed to be used for locating the centers of various clusters. RF networking has the lengthier training time with poorest accuracy (84.462percent) among all models as studied in this research. The suggested ANNSVM performed somewhat better than ANN, demonstrating that utilizing learnt attributes across hidden layers for a fusional ANNSVM system was successful in boosting model efficacy of investigation. The preciseness is raised from 90.580 to 91.482percent, indicating that ANN fusion with SVM can more accurately categorize around 6,200 additional data points. Fig.4.1 compares each of the evaluated models, while, Table 4.2 displays the stacking classifier's confusion matrix.

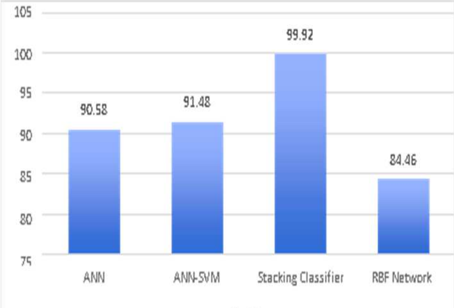

Figure 5. Comparability of all tested models

TABLE II. Stack Classifying Confusion Matrix

	Forecast neutrality	Forecast pleasure	Forecast stress
Real neutrality	369,761	11	59
Real pleasure	30116868	116,868	177
Real stress	88	132	209,066

V. Conclusion

Taking advantage of physiological information gathered from wearables, this research aims to illustrate how DNN and tree-based ML models can be used to create resilient and effective approaches for stress determination with the help of signal-data collection. In this study, we present 4 distinct NN models for neutrality, stressful, and pleasure classes of stress on the publicly accessible WSD dataset. The strategies used in this research include ANN, ANNSVM fusion, Stack Classifying method, and RF network. We developed a fusion of previously unutilized ANN-SVM, RF Networking and Stack Classifying method for WSD. With a classifying accuracy of 99.92percent, Stack approach yielded most remarkable outputs, while RF system provided outcomes with an accuracy of 84.46percent.

Numerous AI algorithms possess the potential to determine mental stress. To combat chronic stress onset, AI models may be employed for developing a continual tracking wearable equipment, that can identify stress level of an individual and send out warnings if it remains elevated for an extended period of time. Considering each person, irrespective of whether he is a learner or job holding person, managing the stress is vital. The information from a wearable device may be utilized by our suggested categorization algorithms to produce a reasonable forecast.

Rather than employing structured surveys in future, additional research could be accomplished by considering the personal reports of respondents in which, WSD dataset features might be used as a referral. Moreover, AI strategies may be created to accurately categorize the various effect levels (such as less, medium and higher stress) in optimal way. The physiological data could be integrated with other various techniques, such as audio records and facial signs, to produce a novel dataset for determining stress more accurately, because it contains almost all the features needed to cause stress in humans.

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