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A Review of Deep Learning and Machine Learning Methods for Analyzing Covid-19 Stress

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Abstract:- The COVID-19 (C-19) pervasive had impacted negatively on environmental health in a number of nations, with a substantial number of cases and deaths reported to far. C-19 produces not only serious bodily issues, but also a range of psychiatric diseases. In some areas, the spread of C-19 may have an impact on people's stress levels. As a result, monitoring and overviewing the Mental Health (MH) of the populace during emergencies is an important concern. Many researchers have used Machine Learning (ML) and Deep Learning (DL) to detect stress. This survey provides a comparative study on various stress detection (Str-Dec) techniques to understand the drawbacks of those detection frameworks and suggest a new solution to C-19 Str-Dec. A detailed survey on Str-Dec during C-19 epidemic is essential for preserving the psychological well-being for improving their healthy lifestyles. The merits and demerits of these approaches have been analyzed and studied to form a new solution for C-19 Str-Dec.

Keywords:- *Stress classifcation; deep neural network; Mental Health; feature learning; anxiety, insomnia.*

I. INTRODUCTION

In December 2019, distinctive cases of patients with respiratory illness caused by the novel Coronavirus (COVID-19) were known in Wuhan, China, and also the virus' propagation quickly became a worldwide health issue [1]. Despite the actual fact that C-19 may be a novel infectious agent form, it's been joined to diseases starting from the communicable disease to additional serious sicknesses like respiratory illness and Middle East Respiratory Symptoms (MERS) virus. Some of this infective symptoms like fever, chills, tussis, pharyngitis, paresthesia, nausea, vomiting, and diarrhoea.

In additional to its physical effects, COVID-19, will have substantial consequences for people' mental state [2]. During the disease eruption, a wide range of psychiatric impacts were observed at the interpersonal, communal, regional, and global levels. People are more fearful of becoming ill or dying, of feeling powerless, and of being stigmatized by others. The pandemic's harmful impact on public MH, such as Str, will result in physical complications. Immediate treatment of patients in the initial phases of a mental disorder boosts therapeutic procedure efficacy. Health emergencies, such as the C-19 outbreak, generate adjustments in both medical personnel and civilians, and these changes are driven by feelings of fear, panic, despair, or uncertainty [3].

Nervousness and tension in a society have an effect on every people to a massive extent. According to latest survey, folks that are remote or quarantined revel in giant degrees of tension, anger, confusion, and strain. Overall, all of the investigations that have looked into physiological issues during the C-19 epidemic have discovered that affected people exhibit a variety of signs of intellectual trauma, such as emotional turmoil, anxiety, aggravation, temper loss of balance, anxiety, insomnia, attention deficit impulsivity disorder, clamorous pressure disorder, and indignation [4]. As a result, the powerful strain detection approach is critical for an individual's to control their each day sports and healthcare specialists might also additionally offer extra powerful remedy for Str-associated illnesses.

Many studies have been conducted to investigate biological signals extended by detectors that may be coupled to the respective person for strain identification and emotional evaluation [5]. Almost all beyond processes assessed a collection of physiological warnings, which included signals gathered from Electro-Cardio-Gram (ECG), Electro-Dermal-Activity (EDA) and Electro-Myo-Graphy (EMG) detectors. These procedures recognized and categorized sentiments using ML and DL algorithms to investigate physiological signals. In recent years, researchers have developed a variety of devices and in-depth learning procedures to identify Str and its causes.

ML is an Artificial Intelligence (AI) technology that enables organizational systems to learn and develop based on their experiences without having to do it directly. ML algorithms estimate new output values by using past data as input. Many ML research have verified the relationships between various stressors. These studies look at str, Non-stress (N-str), and behavioural stages to extort the relevant data from physiological signals. To categories Str using an Artificial Neural Network (ANN), two feature set structures were designed [6]. A Linear Discriminant Classifier (LDA) based ML method were utilized to discriminate among Str and N-str. Using Strength Spectral Density (SSD) capabilities, a Support Vector Machine (SVM) classifier were utilised [7] to discern among strain stages. In general, the difficulty of those devices learning algorithms is the demand for handcrafted capabilities. When capabilities are misidentified, the accuracy part would be less.

DL has been broadly and successfully hired in a whole lot of domains, which include PC vision, Str and emotion analysis, and so on. Deep Neural Network (DNN) does not require traditional functions, however as an alternative extract functions from raw statistics thru the layers of the NN, ensuing in top notch results which are effective. Many Str-Dec structures primarily based totally on DL strategies had been developed, along with the integrated DL architecture [8], which is used to assess an emotional str by capturing different topological EEG traits. For identifying Str, a unique convolutional recurrent neural classifier was built [9] using multipath sub-networks. To complete the cognitive interpretation of EEG data, a recurrent neural network technique was described [10]. The above-mentioned DL based Str-Dec algorithms have significant limitations, such as the need for huge statistics quantity for practising. Furthermore, deep features produced from DNN are frequently indistinguishable, strongly linked, and have a large feature dimensional space.

In this paper, various Str-Dec methods have been studied and analyzed. After that, a comparative study is conducted based on their advantages, disadvantage and performance metrics. Further, analyzing those drawbacks from the provided literature a new solution can be developed to find effective C-19 Str-Dec methods in future. The remaining section of this article is structured as Section 2 provides the survey on several Str-Dec methods cases during pandemic time. Section 3 presents the comparative their methods and results. Section 4 concludes the survey and suggests the future enhancements.

II. LITERATURE SURVEY

For Str-Dec, two DNN like 1D-CNN and Multi-Layer Perceptron - NN (MLP-NN) were constructed [11]. In this method, the designed network was used to analyse physiologic data acquired by the chest and wrist worn detectors for performing the two-fold tasks like Str-Dec and 3-label emotional classification tasks. Initially, the Str-Dec categorization was binary, with networks discriminating between Str and N-Str circumstances. The next task was 3-class emotive classification, by which the systems discriminated among different backgrounds, Str and N-Str states. However, this method needs be taught and tested on much larger repository with a wide range of human variation.

A modular concurrent EEG-based behavioural training neuro-response system was developed [12] to efficiently determine Str levels in present condition. In this approach, the Mental Str-Dec (MSD) system was designed to distinguish Str and N-Str stages. The developed MSD evaluates conductor placement upon several locations of the skull which selects the location that has the greatest influence on the system's performance. Principle Component Analysis (PCA) attribute depletion was used as a consecutive forward approach to determine an optimal number of fundamental elements and eliminates the attribute dimensionality in order to enhance the performance of the following classifier. On the other hand, this strategy might result in a lesser capacity to recognise Str levels.

Different ML and DL techniques for Str-Dec on people were developed [13] using a heterogeneous database acquired from wearable physiologic and movement sensors. This method was used to assist people in avoiding a range of Str-related health problems. K-Nearest Neighbor, LDA, Random Forest, Decision Tree, Ada Boost, and Kernel SVM-ML approaches were employed to analyse and compare the accuracies of three-class and binary classifications. In addition, a feed forward DL-ANN was used for 3-label tasks and two-fold categorization.

A Str-Dec method was developed [14] by employing ML classifiers to determine the most efficient biological parameters that identify str using one of the most important str databases. The models were trained using physiological data from a chest-worn device, including ECG, EDA, EMG, RESP, and TEMP collected at 700 Hz. The pre-processed dataset was used to extract the statistical feature from the behavioural output. Multiple ML models were trained for Str-Dec using the feature dataset, and their results were compared. However, the dataset was significantly skewed since the procedure includes a variety of conditions that were carried out at different times during the experiment.

The Str-Dec was created [15] by classifying real-time photographs of the user's face with CNN in order to identify the presence of Str indicators. The classification model was created using a transfer learning method and a fine-tuning technique. Two distinct classifier architectures were used with pre-conditioned systems such as VGG16, VGG19, and Inception-ResNet V2. VGG16 was determined in conjunction along with a classifier using a convolutional layer, which would be referred to as a best possibility for categorizing anxious emotions. However, this method's performance on bigger datasets has to be improved.

The Multi-objective Evolutionary Algorithm, MLP and Fuzzy Unordered Rule Induction Algorithm were employed to calculate the depression rate among students [16]. The data was obtained and pre-processed in order to handle lacking content and clean it up with procedures such as replacing in lacking numbers or removing misplaced information rows, smoothing noisy information and resolving report conflicts. The three algorithms were then utilised to calculate statistical performance in order to Str-Dec levels. The participants were adamant about it not filling out the lengthy data report, making it difficult for them to finish the complete cycle.

Using a collection of wearable physiological and sociometric sensors, a new ML learning technique for Str-Dec was created [17]. During a Trier Social Str Test (TSST), the data collected from both sensors was analysed and fed into several classifiers that were taught to distinguish between stressful and neutral circumstances. This technology uses wearable sensors to create a system that can accurately measure Str in social situations. Because each participant's reaction to a specific stressor varied so much in this approach, a tailored classifier was learnt for them. This technique, however, was sensitive to outlier datasets.

By monitoring the facial expression dynamics of a person using the Facial Activity Coding System (FACS), a unique multilayer NN-based architecture was built [18] for detecting Depression Anxiety Str Scale (DASS) levels. There are three levels to this approach. The video frames were normalised in the first layer, and the analysed Action Units (AUs) were identified using a multiclass SVMs and an Active Appearance Models (AAM)-based technique. In the second layer, the frequency levels of the chosen AUs for every visual aid were utilised to form an array. The best structure of a Feed- Forward (FF) NN was discovered in the third layer to assess the patterns from the second layer's matrix and forecast the DASS stages for every of the 3- emotive levels. However, performance results were lower compared to existing approaches.

A novel approach based on arbitrary variance based characteristics derived by Empirical Mode Decomposition (EMD) was described [19] to identify Psychological (Psy) - Str using photo-Cardio-Grapy (PCG) output. The Inter-beat Interval (IBI) signal was created using these PCG signals to determine the temporal length of cardiac cycles composed of successive peaks. Intrinsic Mode Functions (IMFs) was created by disintegrating the IBI signal into sub-band signals using EMD. This prediction system was optimised using entropy approaches such as the Bhattacharya space algorithm, Receiver Operating Characteristic (ROC) method, and Wilcoxon method. To classify the collected entropy characteristics were input into a Least-Square (LS) - SVM. However, before being used in homecare and clinical settings, this method must be evaluated on a bigger dataset.

Using an electronic nasal system, a novel non-invasive approach for detecting academic Str was created [20]. Based on the volatile organic chemicals released by the skin, this Str-Dec was developed. Two strategies based on emotional sweating behavior were used to induce a stress response that results in superficial skin sweating in response to sensory stimuli. The first method used the finger's EDA to increase perceived stress, which resulted in a decrease in skin electrical resistance, while the second method used the Volatile Organic Compounds (VOCs) method to determine the VOCs profiles associated with academic Str and their outcomes. This approach, on the other hand, has to be tested on larger samples of Str patients.

Using data from commercial wrist devices, a novel approach for continuous identification of stressful situations was created [21]. This method is made up of 3 ML modules like a base str-Dec which identifies less-range str for every two minutes, an process identifier that consistently accepts customer interest to deliver the context data, and topic-based Str-Dec which utilizes the result of the experimental Str-Dec and the individuals scope to make a complete opinion on every 20 minutes. On the other hand, this approach produces more classification errors.

The EDA and skin conductance acquired by inexpensive wearable sensing devices were combined into a rule-based algorithm to create a Str-Dec system [22]. A system of criteria, balances, and significance value was established for Str-Dec based on an existing approach that used test data. After that, a test procedure was carried out to obtain reports on metabolic reactions to a particular str incident. Finally, the physiological reactions were transformed to stressors by calibrating the algorithm findings. However, this method's testing duration was found to be excessive.

DL was used to test the possibility of [23] using EDA, skin temperature, and pulse rate readings. The behavioural str response was gathered from subjects utilising the wristband and salivary cortisol samples, as well as raw EDA, skin temperature, and heart rate. The Str induction approach known as the TSST protocol was then utilised to detect the Str and N-Str phases using simple and complicated classifiers. However, because this technique relies heavily on small datasets, it must be improved on bigger datasets in order to increase classification performance.

Based on EDA, an automated pre-surgery Str-Dec technique [24] was proposed. A wearable wrist was employed to monitor EDA activity in a non-invasive and unobtrusive manner for Str evaluation. An initial Str-Dec phase was followed by multilevel Str classification in a two-stage system. Subjects' Str levels may be continually monitored and real-time feedback provided through the wearable wrist. This feed-back would operate as a way to fine-tune the Str level, allowing each participant to experience less pre-surgery anxiety. Additionally, this approach has low subjective exertion and appropriateness, both of which will be a important in a therapeutic practice.

A Two-phased Str-Dec Network (TSDNet) was presented [25] for Str-Dec. TSDNet learns visual feelings and action patterns for str identification by combining a attention function of facial expression based variational pooling system with an action-level frame. To better comprehend Str-related face traits, researchers used state-space average pooling with various kernel widths. The findings of feature and action-level detectors were integrated using a channel weighted aggregator with local and global attention. However, the detection accuracy was inadequate when compared to previous techniques.

Through video-recorded face signals, a ML framework [26] was constructed for the identification and evaluation of different emotional states. Using various external and internal stresses, the experimental methods were designed to create scientific deviation in emotional levels like anxiety, moderate, and relaxed. In each experimental phase, attribute extraction processes were used for selecting the massive characteristics, processed by categorization algorithms that discriminated among emotions and lateral levels with connection to a relaxed stage. Using self-reports and a grading modification, the relationship between visual appearance and an individual's observed level of str was explored. However, the amount of time spent for facial recording was excessive, which might have influenced the performance outcomes.

DNN and tree-based ML models were shown to have the potential to build resilient and robust algorithms for Str-Dec using physiological information obtained from wearable devices [27]. This technique would help to distinguish a str individual from a typical one by automating the mental Str-Dec procedure using biological reports collected from a wearable systems. To compute the accuracy of forecasting proper Str state, a hybrid of ANN-SVM, Stacking Classifier, and RBF system was created. However, this model has to be refined to better define the many levels of Str that are affected, such as low, moderate, and severe Str.

For detecting mental Str states, a DNN with hierarchical learning capabilities was built [28]. Utilizing multivariate time-series data, powerful representations of attributes with generalization strengths were generated using carpus related and chest-based locator bio-transitions. For explicating the data correlation, a model-level fusion technique was designed as various sub-networks to operate over features that learn individually for every source class and it is combined with compatible depiction. However, the computational complexity of this strategy was found to be substantial.

The CNN- Bi-directional Long Short-Term Memory (BiLSTM) technique for Str-Dec was used to build the attention mechanism [29]. Different attention mechanisms, such as Convolutional Block Attention Module (CBAM), Non-Local (N-L) NN and Dual Attention Network (DA-NET), were introduced to the CNN and BiLSTM layers individually in this technique. The goal of this whole network was to see how successful the attention mechanism was in detecting Psy-Str from ECG data. However, in order to predict the data, this model required a lengthy training period.

In the context of User eXperience (UX) analysis, an unique paradigm was established [30] to examine the efficacy of Wearable Str And Emotion Detection (WESAD). The EDA and WESAD skin temperature signals were then utilized to train various ML classifiers as well as a basic feed-forward ANN with continuous variables and entity embedding's. WESAD characteristics were fed into three ML algorithms like Cubic (C) -SVM, Linear (L)-SVM, and Quadric (Q)-SVM, as well as a DL model aimed at distinguishing the two emotive states (Str vs. N-Str). In contrast, this methodology necessitates the collection of a huge dataset in order to produce efficient results.

III. COMPARTIVE ANALYSIS

In this section, some Str-Dec methods are compared with their merits, demerits and performance are compared to detect the Str and other mental issues to reduce C-19 pandemic Str analysis. The table 1 provides observational studies of Str-Dec approaches with their performance metrics.

Ref No.	Methods Used	Merits	Demerits	Performance Metrics
11	1D CNN and a MLP-NN	When compared to other traditional approaches, this method has a high classification performance for detecting Str.	It would need to be developed and evaluated on significantly greater datasets containing a diverse spectrum of human groups.	(i) Using Deep CNN accuracy rates for binary Str-Dec 99.80% and 3-class emotional classification and 99.55% (ii) For deep MLP, the accuracy rates are resulted for binary Str = 99.65% and 3-class emotional classification = 98.38%
12	EEG-based behavioural training neuro-response system and PCA	The real-time EEG-based intellectual Str-Dec system was maintained by this system, which was more transportable and easier to begin.	Lower capability to detect the Str and its level.	Accuracy for Str-Dec = 99.9%; Accuracy for Non- Str-Dec = 99.26%;
13	ML and DL techniques	By establishing the subject independent, this approach has been modified and outperforms on data from formerly unidentified individuals.	Requires high processing time if neural network is large.	Accuracy for three-fold classification = 84.32% ; Accuracy Two-fold classification for Str-Dec = 95.21%,.
14	ML classifiers	Even on an unseen participants, the model would perform better.	Obtained dataset was highly imbalanced for the data classification.	For binary Str-Dec F1-scores = 83.34%; Accuracy = 84.17% For three class emotional classification F1-scores = 65.73%; Accuracy = 67.56%.
15	CNN and Transfer Learning System	Although this method was congential, it did need the use of a digicam to track the person's facial gestures.	Performances on larger datasets were slightly slow.	Accuracy rate = 92.1%
16	MLP, Multi-objective Evolutionary Algorithm and Fuzzy Unordered Rule Induction Algorithm	It provides an efficient performance even on larger datasets.	Participant's responses were low in this method.	For Str level detection, the accuracy rate of MLP = 90.90%; Multi-objective = 92.76% Evolutionary Algorithm and Fuzzy Unordered Rule

				Induction Algorithm = 92.95%
17	ML Approach	This method correctly labels the test samples with high accuracy.	This method was sensitive to outlier datasets.	Using AdaBoost classifier, the resulted accuracy = 0.94%; precision = 0.94 Recall = 0.96
18	FF-NN based architecture, FACS and AAM	It has lowest prediction time	Low performance accuracy	Accuracy rate for Depression = 87.71% Anxiety = 82.13% Str = 93.21%
19	EMD and LS-SVM	It is a quick procedure that may be used for real-time psychological evaluations of Str-Dec	Testing on larger datasets needs to be improved.	Accuracy = 96.67%
20	Electronic Nose System	This method has broad range of possibilities to use in different detection areas.	Low results on larger patients samples.	For Str-Dec, 96% success rate is achieved for E-nose signals and 100% with the GSR signals
21	An activity-recognition classifier, a basic Str-Dec, and a Topic related Str-Dec	The model was unique with less computational complexity.	Results in more classification errors.	Accuracy = 92%
22	Rule-based algorithm	It was more efficient to be used in real time application for Str and other physiological detection	High testing time	Accuracy = 84%
23	DL and Str induction method	Less computational complexity	This method majorly depends on smaller datasets.	Accuracy rate for Str-Dec = 96%
24	Automatic pre-surgery Str-Dec scheme	This approach requires less subject effort and is inconspicuous, both of which were critical in a therapeutic context.	Compared to existing works, Low performance classification was resulted.	Classification accuracy = 85.06%
25	Video-based Two-levelled Str-Dec Network	Less training time	Low detection accuracy was achieved when compared to existing works.	Accuracy = 85.42% F1-Score = 85.28% Precision = 85.32% Recall = 85.53%.
26	ML framework	This method has good classification compared to other methods.	The performance results was lower due to the high facial recording time	Using AdaBoost classifier, the resulted accuracy = 91.68%
27	DNN and Tree-based ML models	Using inputs from a wearable indicators , this approach detects a practical forecast.	More computational time in training the data.	For Str-Dec, classification accuracy = 99.92%
28	DNN and Model-level fusion strategy	Takes less time to train the data.	High computational complexity	Performance accuracy = 87.7% F-score = 83%
29	CNN-BiLSTM, CBAM, N-LNN, DA-NET	Better generalization ability	High training time	Accuracy = 0.860 Specificity = 0.924
30	ML classifiers and a simple feed forward DL-ANN	This approach maximizes the practicality detections and maintains high levels accuracy	Requires large dataset collection	Accuracy = 97.4%

Table 1: Comparison of Str-Dec methods

IV. CONCLUSION

Despite the lack of studies to date, it is evident that the C-19 epidemic has compelled a complex and multifaceted response from MH and allied specialists and also physiological problems like anxiety and other severe behavior will be discussed at different stages by the regular populace, medical care trainers and an affected citizen. This paper provides a various Str-Dec methods in which the ideas and concept can be taken as instances in future for detecting the C-19 Str analysis. The above comparison will provide better understanding on those limitations which can be rectified in the new implementation of C-19 Str-Dec methods effectively in future findings.

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