Comparative Analysis of Stress Detection Techniques Using Machine Learning

Varsha Narayanrao Ikhe
School Of Information Technology, Indira University, Pune, Maharashtra, India

Monali Chaudhari
School Of Information Technology, Indira University, Pune, Maharashtra, India

Santosh Kakade
School Of Information Technology, Indira University, Pune, Maharashtra, India

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Abstract

It is quite common in the modern world to find human beings having the mild or moderate mental stress in diverse circumstances. Meditable degree of stress is healthy to an individual, but excess of stress impacts the mental health of the individual and is a guarantee of suicidal tendencies should the stress remain unattended in the long run. As more and more people experience stress, it becomes imperative to be in a position to recognize it at an early stage and make people understand and fix it before it becomes too late. The archaic means of stress level assessment are by interviewing the person and assessing the facial gestures. When interviewing, the concerns related to stress will be posed in order to gain a clearer insight into the state of the person. When a person is stressed, he or she responds by expressing other facial gestures i.e. the eyebrows are shaped differently, their pupils enlarge or the speed of blinking may vary. Such approaches are not exhaustive because they can overlook stress episodes. Studies in the stress detection field are becoming very fashionable. The limitation that can be improved is the way that the results given by the different methods can be made more accurate.

Non-invasive methods of detecting stress are rather promising. This scientific project suggests the creation of the system to monitor the human mental stress based on the Electroencephalogram (EEG) data, speech data, and audio-visual information. Stress is a psychological state of mind and it makes the electrical activity of the brain to differ with what it should be. Mental stress can be measured using neurological indicators. There are many kinds of electrical exercises which are associated with different states of mind. These indicators can be employed to derive useful information to be used in the initial identification of certain psychological condition. The speech of human beings is the reflection of the state of mind. In this scenario where the data is scarce, Support Vector Machine (SVM) is the most balanced and consistent option to use in detecting stress and mental health across modalities. Ensemble-based or hybrid deep learning models are more robust and they have better performance.

Keywords: Mental Health Detection, Machine Learning, Deep Learning, Depression, Anxiety, Natural Language Processing

1. Introduction

Stress is a debilitating emotional state that is accompanied by a wide variety of alterations on multiple levels, including biochemical, physiological, and behavioral. An emerging area of study, dubbed affective computing, is driven by the goal of developing empathetic machines to better facilitate communication between humans and computers. An emotionally responsive machine would respond to the user's feelings by altering its actions and appearance. It has been defined as "the body's nonspecific reaction to any demand" in the field of medicine. One of the most intriguing feelings is stress [1]. This is because of the health risks associated with stress over the long term, such as headaches, insomnia, and even heart disease [2], [3], [4].

In 2015–16, 37% of all cases of work-related illness in the United Kingdom could be attributed to stress [5]. Automated detection techniques are required for these serious stress-related side effects. An effective stress detection system must take into account the role of the sympathetic nervous system (SNS) in the body's response to stress. The production of stress hormones like cortisol and adrenaline speeds up the reaction, along with other physiological changes like rapid breathing and tense muscular tissue. The body undergoes these physiological modifications to get ready for a physical response (the "fight-or-flight" response).Stress affects people daily. "The body's non-specific reaction to any demand for change" [1] is one definition of stress. Mental health problems like depression and suicidal ideation can develop in people who experience chronic stress and don't get help for it. If stress is identified and treated early, then it is less likely to become chronic and cause permanent damage. Identifying and treating stress while it is still acute or episodic can help reduce its severity and associated risks.

Artificial Intelligence is exactly what its name implies: intelligence that has been programmed by humans to accomplish human tasks. Artificial intelligence is integrated with computer systems to generate AI Systems, which operate as "thinking machines" in the end. General AI systems are capable of intelligent problem-solving. (For instance, an AIpowered stock trading system.) To build an intelligent computer capable of executing certain human tasks, ML(Machine Learning) and DL (deep learning) are commonplace in AI systems. Each component of the AI System is evolving into an autonomous intellect unto itself. Machine learning is an AI discipline that allows machines to gain insight from their past actions and utilize that knowledge to make better choices in the future. Machine Learning makes use of a number of algorithms to iteratively learn, explain, and improve data in order to predict better results. These algorithms employ statistical approaches to identify trends and then act on them. The next phase of machine learning is called deep learning. It includes machine learning as a subset. Deep learning models can predict outcomes independently of any human input. In most circumstances, traditional Machine learning models still require human involvement to achieve the best results. Models built with Deep Learning utilize artificial neural networks (ANNs). This network's architecture was influenced 7 by the biological neural network found in the human brain. It analyses data in a structured way, much like a human would.

The field of study known as "machine learning" examines how computers learn to execute certain tasks by analyzing and mimicking human-designed algorithms and statistical models without being explicitly instructed to do so. There is a niche for it in the study of AI. Algorithms that use machine learning construct a mathematical model from examples of data, known as "training data," so that the machine can make inferences and decisions without being explicitly instructed to do so by the developer.

Building a model in machine learning is meant to help you gain useful insights from data for use in making informed business decisions. Based on your training data, algorithms tell you which result for your target variable is most likely to be accurate. Models form the basis of data analysis. Without statistical models, there would be no way to determine relationships between variables, and without machine learning models, we will not be able to deduce relationships or draw insights from past data. The proficiency and precision of Machine Learning based algorithms have generated significant interest in AI-assisted health monitoring and psychological counseling systems. Services in these domains require an understanding of the user's mental state. Our primary focus is on developing a technique that can determine, among other emotional states, the user's level of stress.Stress detection is a promising area for research, and a careful examination of the literature already available should aid in the design and execution of subsequent studies. Further, they highlighted on evaluation of a variety of studies all focusing on the same area, along with the dataset employed technique, the merits of the method, as well as the potential for further improvement, are outlined.

2. Machine Learning in Stress Identification Literature Review.

2.1. Mental Health Disorders and Stress Vertical.

Stress is a complicated psycho physiologic condition that is marked by systemic changes in biochemical, physiological, and behavioral fields. Medically, it is mostly referred to as the non-specific reaction of the body to any request. Although in acute stress the system of stress response results in increased alertness, chronic stress results in the dysregulation of the system, negatively impacting the mental ability (e.g., memory, concentration), emotional regulation, and mood, which makes individuals susceptible to anxiety and other disorders [2,3]. Affective computing aims at creating systems that are able to identify and react to human affective behavior, such as stress, in order to facilitate more human-computer interaction. Among the fundamental issues of the field, there is the objective and reliable identification of stress, and physiological and behavioral indicators offer important data to this effect.

2.2. Multimodal Data Sources of Stress Detection.

2.2.1. Electroencephalogram (EEG)

The non-invasive recording of the electrical activity in the brain can be performed as an electroencephalogram (EEG), which provides a direct insight into the arousal of the central nervous system related to stress. The changes caused by stress are reflected in spectral features in the power spectral density of the canonical frequency bands (delta, theta, alpha, beta, gamma), thus spectral features are a common basis of classification. EEG has been used to effectively detect EEG stress responses to controlled stimuli, including video viewing [8]. Support vector machines (SVMs) are traditional machine learning models that have been highly utilized to classify stress based on their capacity to work with high-dimensional EEG characteristics and relatively small datasets [9]. Examples of spectral features being used with the classifiers such as SVM, k-NN, and neural networks include research by

Gaikwad and Paithane [9], Lahane and Thirugnanam [10], and Thejaswini et al. [11]. New methods recommend that the full set of features be extracted including temporal, spectral, wavelet and nonlinear dynamism to enhance robustness as observed in models that have been developed on related conditions such as major depressive disorder [18].

2.2.2. Stress Detection on Speech.

Speech provides an inexpensive and non-invasive avenue of detecting stress. The stress has an impact on the autonomic nervous system and the voice characteristics are altered and this includes fundamental frequency (pitch), intensity (loudness), speech rate, jitter, and shimmer. Therefore, acoustic feature is an established technique of identifying stress. Tomba et al. [13] illustrated speech detection through the use of acoustics and the use of classifiers such as SVM and ANN. More complex methods also use Recurrent Neural Networks (RNNs) to predict the temporal characteristics of speech sequences to classify the types of stress [14], or to use wavelet transforms together with neural networks to do better emotional speech recognition [15].

2.2.3. Analysis of Visual and Facial Expression.

Facial expression can be regarded as effective signals of emotional and stress states. The features which are analyzed in video-based systems to determine stress include facial action units, the direction of eye gaze and head movements. The study by Giannakakis et al. [16] aimed at creating a stress and anxiety detection video-based system, which uses the facial cues obtained after the videos are watched and a classifier such as AdaBoost that enables it to perform well.

2.2.4. Multimodal Fusion Approaches.

The incompleteness and noise of any given signal can be a limitation to unimodal approaches. Multimodal fusion combines non-redundant information of various sources (e.g., EEG, speech, video) to form a more complete and strong representation of the users condition, which is usually resulting in higher classification rates and reliability of the system. Seng et al. [17] demonstrated that a rule-based and machine learning system to recognize audio-visual emotions was better than unimodal systems. In the same way, Agrawal and Mishra [19] introduced a fusion-based system that was able to boost performance of emotion recognition systems.

2.3. Machine Learning Methods of Stress Detection.

One typical pipeline in ML-based stress detection is to acquire the signal, preprocess (e.g., noise, normalization), extract features, train the model, and evaluate it. The modality-specific feature engineering involves spectral, temporal and nonlinear features of EEG studies; the focus of speech analysis is on prosodic and spectral acoustic features; and the focus of video analysis on geometric or appearance-based face features.The type of data determines the choice of the classifier. SVMs and Random Forests are still common with structured and feature-engineered data, namely on smaller datasets [9]. Deep learning systems such as Convolutional Neural Networks (CNNs) to learn spatial / spectral patterns and RNNs / LSTMs to learn temporal sequences have become more popular because of their capacity to learn hierarchical representations directly off raw or low level processed data [14, 15]. Multimodal fusion methods, which can be classified into early (feature level) and late (decision level) fusion methods are essential in fusing data streams of different modalities [17, 19].

3. Comparison and Analysis of Stress Detection Literature.

Table 1 provides a summary of major studies, pointing to the development of classical classifiers on individual modalities to neural network and multimodal-based classifiers.

Table 1: Summary of Selected Stress Detection Studies

Ref.	Key Algorithm(s) Used	Data Modality	Primary Outcome
[6]	SVM, k-NN	EEG	Effective stress level classification
[9]	SVM	EEG	Improved stress recognition accuracy
[10]	k-NN, Shallow Neural Network, Decision Tree	EEG	Multi-class emotion & stress recognition; NN superior
[11]	Rule-based + ML	EEG	Stress level classification
[13]	SVM, Artificial Neural Network (ANN)	Speech	Demonstrated speech-based stress detection
[14]	Recurrent Neural Network (RNN)	Speech	Effective classification of stress types
[15]	Wavelet Transform + Neural	Speech	Emotional speech

	Network		recognition
[16]	AdaBoost	Facial Video	Reliable video-based stress/anxiety detection
[18]	Comprehensive ML Framework	EEG	High accuracy in mental disorder classification
[19]	Fusion-based ML	Multimodal (e.g., Audio-Visual)	Robust, improved emotion recognition performance

4. Discussion

4.1. Datasets, Evaluation Protocols Limitations.

The development of effective stress detecting systems is limited by the inconsistency of the datasets and the evaluation. Many research rely on opportunistic social media data or lab-controlled datasets of produced stress (e.g., using the Trier Social Stress Test), which may be ecologically flawed or lack clinical foundations. Largely-scaled longitudinal, multimodal datasets with clinically-annotated and collected data in real-world conditions are particularly scarce.

The methodologies of evaluation differ widely, and random division of data, as well as subject-independent cross-validation are used in some studies. The latter is essential in generalizability evaluation, although it is less frequently reported. Because of this variety and the widespread lack of conventional benchmarking techniques, it is difficult to compare studies directly, and claims of algorithmic superiority are nearly always context-specific or inappropriate.

4.2. Deployment Problems in the Real World.

There are significant challenges with the translation of the laboratory-validated models into practical applications:

Physiological and behavioral data are very sensitive and their ethical and privacy concerns are high. Implementation of this kind of systems must follow the regulations of data protection measures (e.g., GDPR, HIPAA) and user consent regime.

- Bias and Fairness: Non-representative datasets may cause demographic, cultural, or linguistic bias in models trained on such datasets, which results in unfair performance differences between the population subgroups.
- Interpretability and Clinical Utility: Due to the black-box quality of most deep learning models, clinicians do not trust them or are not ready to use them. Having explainable AI (XAI) mechanisms is also crucial to make these systems functional as plausible decision support members, but not obscure diagnostic robots.

Hardware and Usability: Systems need to be enclosed in wearable or mobile environments capable of constant monitoring with the least obtrusions posing a challenge to sensor quality, power consumption as well as user comfort.

5. Future Research Directions

The future efforts should focus on:

1) Developing and using standardized, open-source benchmark datasets with sufficient multimodal data and a more diverse range of participants;
2) Adopting standardized, rigorous assessment procedures with a stronger emphasis on subject-independent validation;
3) Creating lightweight models that can be easily deployed on an edge device;
4) Developing ethical and explainable artificial intelligence systems that can be more fair, transparent, and clinically relevant; and
5) Longitudinal in-situ studies to assess the efficacy in the real world beyond

6. Conclusion

This review has provided an overview of machine learning strategies in identifying stress with multimodal data EEG, speech and visual input. As shown in the literature, the traditional ML models and the deep learning architectures have a lot of potential in the detection of the stress patterns, automatically. The field is however fragmented through different datasets, different evaluation techniques and a tendency to concentrate on offline accuracy, rather than solutions to be deployed. The efficacy of the models is very specific, and no one single algorithm can be considered as a universal one. Next-generation studies are needed to close the gap between laboratory performance and practical use of these technologies to realize the potential of these technologies in the scalable mental health screening and intervention approach. This requires a concerted effort on solid benchmarking, interdisciplinary cooperation and a steady and principled stance on the ethical, privacy, and equity issues involved in the implementation of affective computing systems.

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