A Comprehensive Review of Machine Learning Techniques for Stress Detection: Challenges and Future Directions

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Abstract. *Stress detection has emerged as a vital area of research due to its widespread impact on human health, behavior, and productivity. This paper presents a comprehensive investigation into the role of machine learning (ML) techniques in detecting and classifying stress using physiological, psychological, textual, and behavioral datasets. Stress, although a natural physiological and emotional response, can lead to serious health consequences if prolonged or unmanaged. Various factors such as personal characteristics, workplace dynamics, psychological disposition, and interpersonal relationships contribute to stress. Additionally, the exponential increase in the usage of technology has led to conditions like techno-anxiety and techno stress, further exacerbating stress levels. The study reviews and categorizes multiple ML approaches, including Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN), Bayesian classifiers, Hidden Markov Models (HMM), and Fuzzy logic techniques, highlighting their methodologies, dataset types, performance accuracies, and limitations. A summary table of current literature provides insights into the strengths and weaknesses of each approach. Furthermore, the paper discusses the challenges associated with stress detection such as inter-individual variability, real-time computation constraints, model interpretability, data quality issues, and ethical considerations. This research aims to support the development of more reliable, interpretable, and ethical stress detection systems that are scalable across real-world environments and diverse populations.*

Keywords: - Stress Detection, Machine Learning, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees.

Introduction

Stress is a feeling of physical or mental tension or anxiety that a per- son comes across in case of unavoidable circumstances or any thought which makes one restless, angry and frustrated [1]. It is the body's reaction to any change it experiences which a person expresses in the form of physical, mental or emotional responses. In simple terms, an individual feels stressed when the expectations forecasted and reality struck are distant making one restless and tensed. Stress can be positive, that is stress keeps a person active, boosted and ready for any peril [2]. On the other hand, stress can have an overall negative impact on an individual if the stressors (viz. stress-related factors) persist for longer durations without relaxation or waiting causing a breakdown [3]. We very well understand that stress cannot be uprooted at a stance but we can at least identify and address various factors which cause stress in people coming from different occupational areas. Therefore, getting through the stressors is very important to develop an effective stress management plan accordingly. There are several reasons why stress is normally caused to humans. Some of them are financial obligations that people face in life, emotional stress, and workplace/career-related. Students go through academic stress, while traumatized individuals face PTSD, and post-traumatic stress [4]. People find it difficult to cope in the face of changes in the status quo, uncertainty, loss of close ones, illness or physical health issues, etc..Stress is a normal reaction for any human being, their reaction has both positive and negative effects in everyone's life. Automatic stress detection is becoming a frequently investigated problem in human-computer interface models, as the demand for communication between humans and intelligent systems grows. So, while measuring hormone levels can detect stress, it is not a practical way for detecting stress in human-machine interactions [5].

However, there are several difficulties in monitoring stress. One researcher has identified three topics that make it difficult to monitor stress of the people. The first one is that stress is a subjective condition. While a stimulus triggers stress in one person, it may not in another person. The second one is the difficulty of defining the ground truth. For this reason, monitoring of physiological data is performed or the self-assessment method is used. The last one is that stress cannot be directly monitored [6]. While physiological data can be monitored directly by sensors, behavioral and affective data cannot be directly monitored.

Factors Affecting Stress

The stressors included in this category are the ones that lead to stress to people directly or indirectly independent of the occupational backgrounds from which they come. In other words, the factors included here are common to all individuals and have the same impact on them [7].

Personal Factors- These factors include age, gender, education, race, occupation and nationality which are major drivers of stress. Such factors affect the individual’s performance to an extent and also hamper their morals. Though these factors have no genetic races but still they help in shaping human beings. These factors contribute to social exclusion, violence and discrimination among various groups of people.

Work-Related Factors- It entails any work or work environment or work issue events that affect a working professional’s throughput and productivity. Some of the factors include job role, job status, experience and personal-work balance. These factors play an important role in job satisfaction. When these functions act as a motivator, they result in creativity and satisfaction and consequently remove boredom. But when they function negatively, they lead to low job satisfaction and aggression.

Psychological Factors- These relate to an individual’s attitude, motive and belief toward his life. Psychological stressors depict how a person will react or respond when faced with an uncertain event or episode which in turn is the cause of stress. Two of the most vital factors are state anxiety and depression. These factors lead people to shrink their network and isolate themselves up and stop doing lots of activities they enjoy.

Interpersonal Factors- These incorporate the relationship among people i.e. the kind of relationship that one maintains with peers and colleagues in offices or say teachers and students in schools or universities.

These include emotional and mental harassment or mistreatment and also the troubles caused by their family members, friends and seniors. Taking these factors in a positive way, having good peers can help increase ones performance, whereas, having peers who push others in a negative situation lead to reduction in one's performance.

Impact of Increased Usage of Technology on Stress

Modern communication technologies have made our lives easier, ex- changes that would take weeks to happen before can now happen within minutes or seconds on the other side of the world. But they have also increased the rate at which they move. Modern technology has gained such a presence in our lives that it' easy to become addicted to its use to the point it starts impacting our lives in many ways [8]. This research would look at how technology has impacted our lives and contributed to an increase in an individual's overall stress levels. First of all, users of information and communication technology aka ICT have been documented to experience stress, worry, and tension as a consequence of the technology use as shown in figure 1**.**

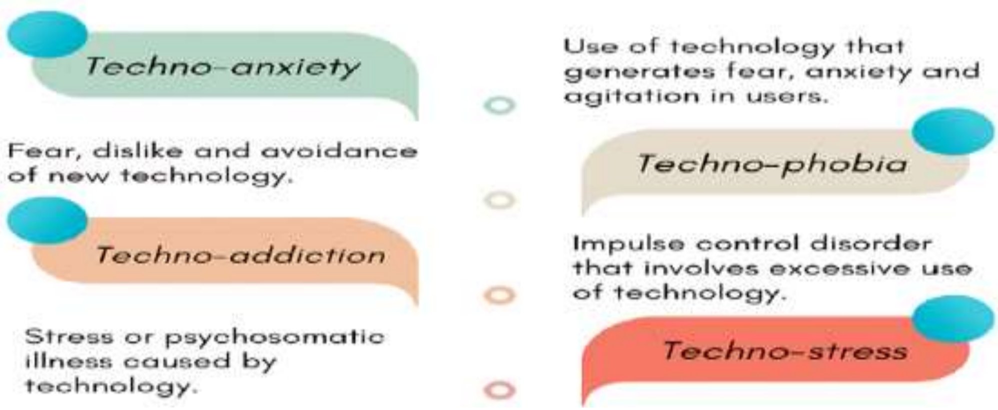

Figure 1: Types of stress in technology use.

This is a condition known as techno anxiety. Secondly, users can also experience psychological effects which could lead to decreased confidence levels. Such circumstances can lead to emotions of helplessness and discomfort, as well as an aversion to or fear of using computers, a condition known as technophobia Thirdly, using ICTs excessively can lead to a condition known as techno-addiction [9]. And lastly, Techno-stress is a condition of the modern times of adaptation due to the inability of coping with new computing technology in a productive outcome and healthy manner.

Stress Detection Methods

Machine learning is a system of computer algorithms that can learn from examples on their own without being explicitly coded by anyone and automatically improve their performance through experience. Using these techniques, it is convenient to develop extremely difficult or expensive systems. Machine learning is divided into supervised, unsupervised, semi-supervised, and reinforcement learning [10]. All the literature discussed here uses either supervised or unsupervised learning.

Supervised learning- Supervised learning is an approach where a computer algorithm is trained on input data that has been labelled for a particular output. The various algorithms generate a function for mapping inputs to desired outputs. It is based on training and good at both classification and regression problems. In the classification problem, the learner is required to learn a function which maps a vector into one of the numerous classes by observing numerous input-output examples of function.

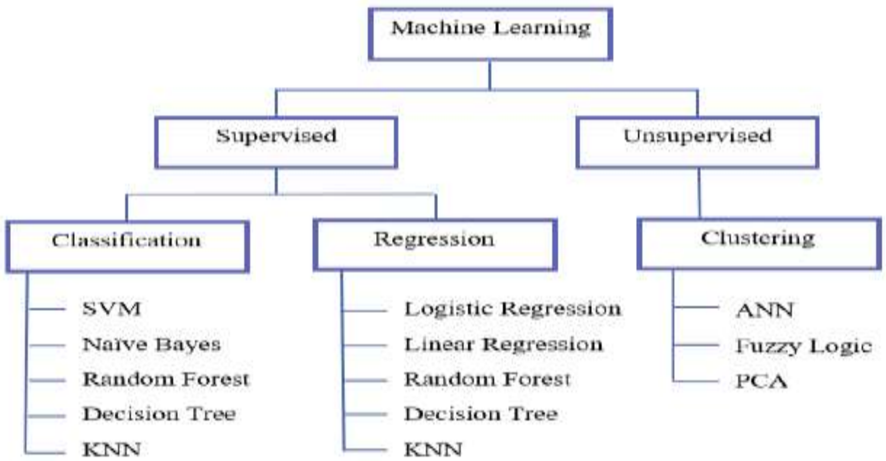

Figure 2: Machine learning techniques.

Unsupervised learning- In these learning, models are not supervised using a training dataset. The models find the hidden patterns themselves and understand from given data. The task of unsupervised learning is to automatically develop a classification lab find the fundamental structure of the dataset and group that data according to similarities and finally signify that dataset in a compressed format. Figure 2 shows how the different techniques were categorized based on these criteria.

Machine Learning Techniques for Stress Detection

Various software programs, tools and packages are available for analysing physiological and physical signals. Most of the tools and applications are not specifically designed for primary measures of stress but they suffice for general data exploration. Exploring signal data is beneficial because it enables selection of appropriate computational techniques to model stress. It also allows detection of noisy, corrupted or missing signal data, which is useful in the process of preparing data before computational stress models are developed. This section focuses on computational modelling techniques used for stress.

Bayesian classification- Bayesian classifiers [11] can predict class membership probabilities for given samples. Such classifiers are based on Bayes' theorem and have been used to calculate posterior probabilities stress states. Naive Bayesian classifiers have been used to classify stress, which assumes classes are independent. A maximum posterior (MAP) decision rule was used to classify features from physical measures to stress classes: “Stress” and “Normal”. Alternatively, Bayesian belief networks or Bayesian Networks (BN) can be used when classes have dependencies. A BN can be represented by a directed acyclic graph or conditional probability tables to show joint conditional probabilities for attributes or variables. Nodes in the graph depict variables and arcs portray causality. A simple architecture of Bayesian classification is shown in figure 3.

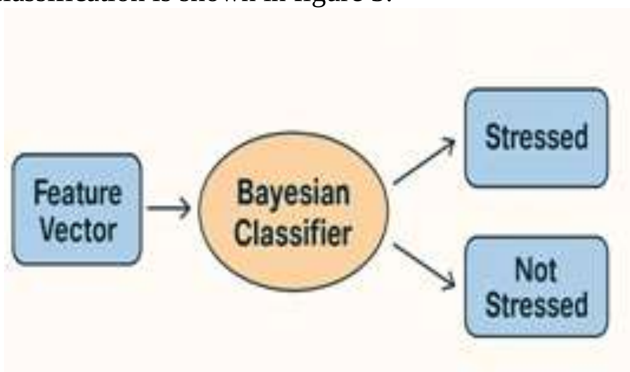

Figure 3: Architecture of Bayesian classification for stress detection.

Decision trees- Decision tree [12] classifiers, based on a divide-and-conquer approach, have been used in stress classification. The structure of a decision tree is like a flowchart. Each internal node represents some criteria or test to divide the input space into regions, each branch denotes an outcome of the test, and each terminal node or leaf represents a target class. Algorithms have been established to generate decision tree. Unknown samples are classified by starting at the root of the tree and moving the sample towards the leaf after testing the sample against the criteria at the internal nodes in the path. Decision trees have been used to classify stress based on characteristics in physiological measures (e.g. EEG) and combinations of primary measures (e.g. combination of BVP, GSR, PD and ST. A simple architecture of Decision trees is shown in figure 4.

Figure 4: Structure of a Random Forest.

Artificial neural networks- Artificial neural networks (ANNs) [13] are inspired by biological neural networks with characteristics for learning and reacting, making them a common technique in classification problems in health systems and an upcoming approach for stress research. Stress models based on ANN are at the early stages of research and have produced promising results. It has been claimed that an ANN is better at recognising stress than humans from voice recordings and this result contributes to motivation for further research with ANN for stress. Multi-layered perceptrons, a type of ANN with multiple hidden layers, have been used for stress classification. A RANN based on labelled voice data for experiment participants playing a video game has been developed. Utterances were recorded when participants answered questions while playing the video game. A simple architecture of ANN is shown in figure 5.

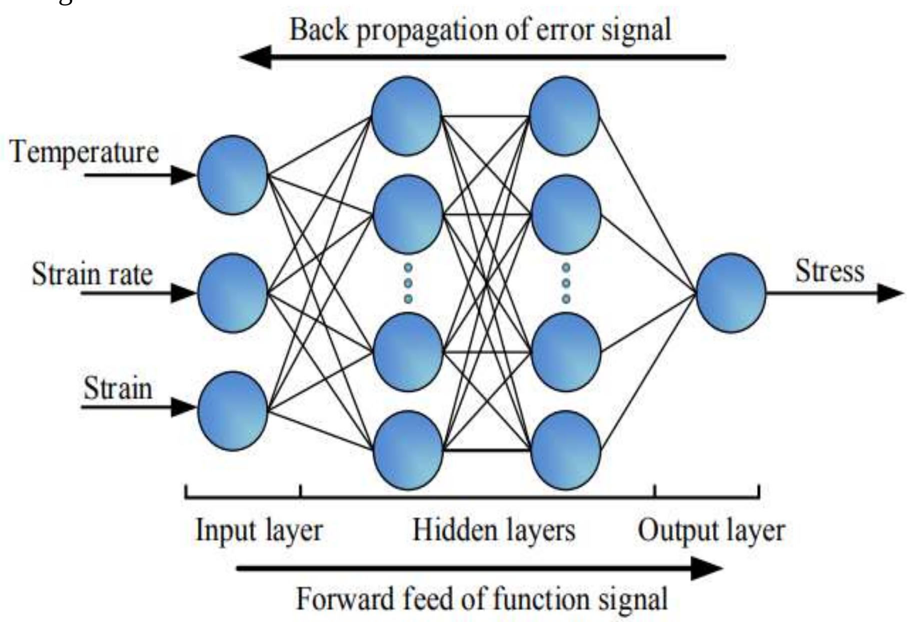

Figure 5: ANN in Stress Detection.

Support vector machines- Stress models have been developed using support vector machines (SVMs) [14]. It can be used for classifying linear and nonlinear primary measures. A SVM transforms training data to a higher dimension, in which a linear separating hyper-plane is determined. An appropriate non-linear mapping can separate two classes of data with a hyper-plane provided that the data has been transformed to a satisfactorily high dimension. Training samples, or support vectors, and margins, which are defined by support vectors, are used to determine a hyperplane. SVMs have been used to predict stress states using BVP, GSR, PD and ST data. It was claimed that their SVM algorithm was not dependent on experiment subjects. SVM has been used to model emotions based on EEG data. A simple architecture of SVM is shown in figure 6.

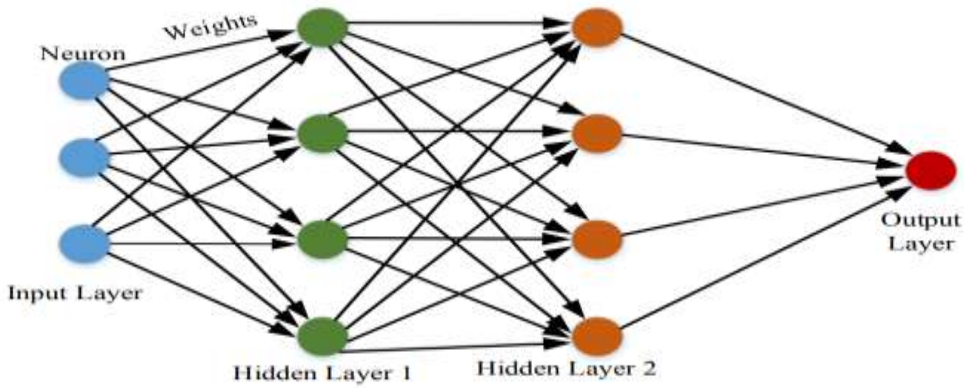

Figure 6: A simplified Architecture of SVM.

Hidden Markov models- The Markov property [15] is a time-domain process with conditional probability density of the current event depending on the ith most recent event, given all the past and present events. A Markov chain is the simplest form of a Markov model. It models the state of a system with a random variable, which varies with time, where a state is dependent on prior states. The system of a Markov chain is fully observable. On the other hand, a hidden Markov model (HMM) is a type of a Markov chain but, as its name suggests, it is partially observable. Only the sequence of observations can be seen in HMMs. HMMs are a double stochastic process with a Markov chain that has a finite number of states and a set of functions that corresponds to each state. The process is in one state in the system at a time and produces a symbol that is dependent upon a random function for that state. A simple architecture of hidden Markov models is shown in figure 7.

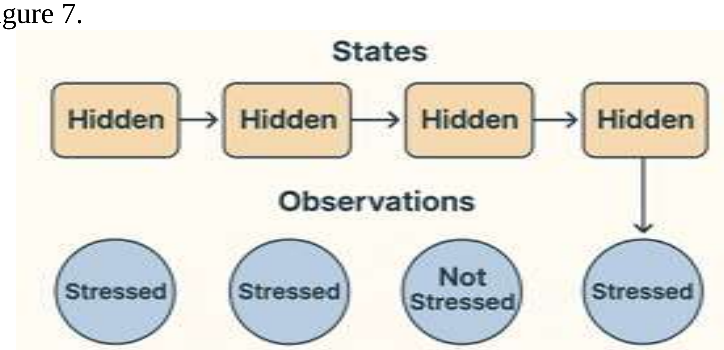

Figure 7: Aarchitecture of Hidden Markov models for stress detection.

Fuzzy techniques- Fuzzy-based techniques [15], in particular fuzzy clustering have been used to measure stress. A fuzzy technique has used HR to model workload, which is somewhat related to stress. In addition, fuzzy filters could be used to filter out uncertainties in physiological measures of stress. A nonlinear fuzzy filter for reducing random variations has been developed for heart rate signals. Fuzzy clustering, a hybrid of fuzzy and clustering techniques, has been used to determine stress based on HRV as a primary measure. Unlike traditional clustering where data elements belong to at most one cluster, fuzzy clustering generates data clusters such that data elements can belong to more than one cluster with different membership degrees. Each data element has a set of membership level values. A simple architecture of Fuzzy techniques is shown in figure 8.

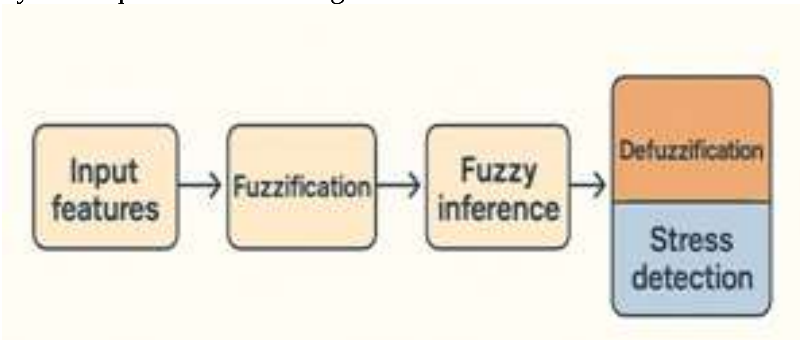

Figure 8: Architecture of Fuzzy techniques for Stress Detection.

Literature Survey

A summary of the literature based on methodology, performance measures, and limitations is presented in Table 1.

Table 1: Summary of the Stress Detection Methods Including Limitation.

Reference	Methodology	ML Model	Dataset Types	Accuracy/Precision Level	Limitations
[1] Singh et al. (2023)	Review of ML techniques for stress detection	Various ML algorithms	N/A	N/A	Lack of empirical data; general overview
[2] Acharrjya& Saha	Stress prediction using ML algorithms	Decision Trees, SVM	Simulated datasets	N/A	Limited real-world application
[3] Nath et al. (2020)	Real-time stress monitoring solutions	Random Forest, SVM	Sensor data	85% accuracy	Dependency on sensor accuracy
[4] Hanchate et al. (2023)	Machine learning for stress detection	Logistic Regression, SVM	Physiological signals	90% accuracy	Small sample size
[5] Sreenivasu et al. (2024)	NLP and ML for stress detection over interactions	LSTM, Random Forest	Social media text	N/A	Requires extensive data preprocessing
[6] Rachakonda et al. (2018)	IoMT sensor-based stress level detection	DNN, SVM	IoMT sensor data	N/A	Limited scalability; Sensor limitations;

					potential data privacy issues
[7] Kagan et al.	Sentiment analysis for PTSD signals	NLP techniques	Textual data	N/A	Focus on PTSD may limit broader applicability
[8] Kaushik (2023)	AI-powered stress detection	Various ML models	Mixed datasets	N/A	General report; lacks specific validation
[9] Chappidi& Anitha (2022)	Survey of ML for emotion recognition	ANN, SVM	Speech data	N/A	Broad focus; may lack depth in specific areas
[10] Rachakonda et al. (2019)	DNN-integrated edge device for stress detection	DNN	IoMT Sensor data	92% accuracy	Complex model; requires high computational power; Hardware dependency
[11] Li & Liu (2020)	Deep neural networks for stress detection	DNN	Medical data	88% accuracy	Limited to medical data; may not generalize well
[12] Arya et al. (2024)	Predicting student stress using supervised ML	ANN, SVM	Student survey data	85% accuracy	Sample bias; limited demographic representation
[13] Singh et al. (2023)	Stress detection using physiological signalsbreathing rate, skin conductance, heart rate.	SVM, Random Forest, Logistic Regression	Physiological data collected during routine daily activities	89% accuracy	No mention of data imbalance handling or real-time application validation
[14] M.S. Kalas et al. (2017)	Eye movement analysis under cognitive and physical tasks with ANN validation in office setup.	Artificial Neural Network (ANN)	Eye movement data from 8 participants doing various office and physical tasks	ANN showed potential (accuracy not numerically stated)	Small sample size; limited generalization; focused on eye movements only

[15] Castro Gracia JA et al. (2022)	low-cost BAN system capturing multiple physiological signals with BLE-based communication.	Signal-based edge-computing system (no ML model trained)	Multi-sensor dataset with EEG, ECG, BR, EDA, ST captured by 4 wearable devices	SNR: ECG - 9.8 dB, EDA - 61.6 dB (No ML accuracy given)	Preliminary stage; no full-scale ML model used; experiment only for feasibility testing

Challenges and Limitations in Stress Detection

While the field of stress detection using machine learning and deep learning has made significant strides, several challenges still impede its broader application and real-time efficacy. These challenges, stemming from data complexities to model interpretability, must be addressed for stress detection systems to become reliable and widely applicable in practical environments.

Data Variability- One of the primary challenges in stress detection is the variability of stress responses across individuals. Stress manifests uniquely in each person, influenced by a multitude of factors such as genetic predisposition, environmental conditions, psychological state, and coping mechanisms. As a result, physiological signals like heart rate, skin conductance, and EEG patterns, which are commonly used for detecting stress, vary significantly from one individual to another. This variability makes it difficult to create universal models capable of detecting stress in a consistent and reliable manner across different populations.

Real-Time Detection and Computational Complexity

Real-time stress detection is a key application in scenarios such as workplace monitoring, health monitoring, or even in personal wearables. However, many machine learning and deep learning models struggle with real-time deployment due to their computational demands. Models that rely on large volumes of data—such as high-dimensional physiological signals or video data for facial expression analysis—often require substantial processing power and memory, making them difficult to run on resource.

Interpretability and Trust- Deep learning models, particularly complex architectures like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), often function as black boxes. While they can achieve high accuracy in stress detection tasks, understanding why a model classifies a particular instance as stressed or relaxed remains difficult. This lack of interpretability poses a significant challenge, especially in applications where trust and transparency are essential, such as in healthcare or workplace monitoring. ***Data Quality and Labeling-*** Another significant challenge in stress detection is the quality and labeling of data. Many stress detection models rely on large, labeled datasets to train and validate their performance. However, obtaining high- quality labeled data for stress detection can be difficult and expensive. Labeling stress data typically requires manual annotation, which involves experts or even participants themselves identifying whether they are stressed or relaxed at different time points.

Ethical Concerns and Privacy Issues -Finally, the deployment of stress detection systems, particularly in real-time applications or wearable devices, raises significant ethical concerns and privacy issues. Continuous monitoring of an individual's physiological and behavioural signals can lead to invasions of privacy if not handled correctly. Users may feel uncomfortable or even violated if their stress levels are constantly monitored without proper consent or if the data is used inappropriately.

Conclusion

Stress detection using machine learning techniques holds significant promise in advancing human-computer interaction, healthcare monitoring, and occupational well-being. The review illustrates that while several ML models have demonstrated notable accuracy in detecting stress across varied data modalities, practical implementation is hindered by core challenges. These include high inter-personal variability in stress responses, computational complexity in real-time systems, lack of interpretability in deep learning models, subjective and inconsistent data labeling, and ethical concerns around privacy and consent. Despite promising results—such as accuracy rates surpassing 85% in models using physiological and social media data—many studies remain confined to controlled or small-scale environments. A critical finding is the underutilization of hybrid models and context-aware systems which can adapt dynamically to individual behavior and environmental factors. Future research should focus on standardizing datasets, enhancing transparency in model decision-making, and developing lightweight, edge-computable architectures to facilitate real-time deployment. Moreover, robust data governance frameworks are essential to ensure user trust, safeguard privacy, and ethically manage stress-related insights. Overall, this work emphasizes the necessity of interdisciplinary collaboration to build intelligent, transparent, and responsible stress detection systems for widespread societal benefit.

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