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AI-Driven Multimodal Framework for Real-Time Stress Detection and Classification

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Abstract:
This paper presents a comprehensive analysis of existing artificial intelligence (AI) and machine learning (ML) models used for stress detection across diverse domains, including healthcare, occupational environments, education, and human–computer interaction. The review highlights the evolution of computational approaches—from traditional classifiers such as Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), and k-Nearest Neighbors (kNN), to advanced Deep Learning (DL) architectures leveraging CNN, LSTM, GRU, and multimodal fusion techniques. Studies employing physiological, behavioral, and sensor-based data demonstrate the growing capability of AI systems to achieve high accuracy in recognizing stress levels, with several models exceeding 90% accuracy in real-time applications. Additionally, approaches based on Fuzzy Logic and hybrid intelligent systems offer interpretable and low-cost alternatives for stress assessment in practical settings. By synthesizing recent research findings, this chapter identifies strengths, limitations, and performance trends across methodologies, providing essential insights for designing more robust, multimodal, and generalizable stress detection frameworks. The analysis also underscores the increasing relevance of wearable sensing, IoT integration, and multimodal data fusion in advancing next-generation intelligent stress monitoring solutions.

Keywords — Stress, Detection, Artificial Intelligence, Machine Learning.

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I. INTRODUCTION

Stress is a pervasive condition affecting physical health, cognitive performance, and emotional well-being across occupational, academic, and clinical settings. Accurate and timely stress detection enables preventive interventions, personalized care, and safer working environments. This review synthesizes AI and ML approaches for automated stress recognition using physiological, behavioral, and sensor-derived signals.

The paper is organized into thematic sections covering deep learning, support vector machines, decision trees, random forests, k-nearest neighbors, fuzzy logic, and other machine learning approaches. Each section summarizes representative studies, reported accuracy, datasets, and practical implications for real-world deployment.

II. DEEP LEARNING

In order to acquire high level characteristics from data, deep learning—a significant area of machine learning—uses numerous neural processing layers with intricate structures or that comprise multiple nonlinear transformations. In addition to having a vast amount of training data, today's DL algorithms are typically enormous in terms of the quantity of NN layers along with model parameters (Wang et al., 2023).

Rescio et al. (2024) presented a study in which development of a platform is done that employs deep learning techniques to detect worker stress with minimally intrusive multisensory devices. The system is expected to provide real time stress monitoring in the occupational domains through integration of data from different sensors and to make timely actions to prevent the worker from degrading health and productivity. GRU, LSTM and 1D-CNN were the three DL methods that were employed and evaluated in order to fulfil the objective of this study. For the detection of two stress levels, the 1D-CNN performed the best, achieving an accuracy of 95.38 percent, which is an important advancement over earlier results.

Zhang et al. (2022) presented a deep learning framework based mental stress detection system for analyzing multimodal expressions. The combination of data from multiple sources such as physiological signals and behavioral indications is utilized to accurately determine the stress level in individual. This study presented a real-time deep learning architecture for stress detection that combines facial expressions, voice and ECG data. Multiple characteristics from the ECG were extracted in this work using Resnet in 2D-CNN. The outcome indicates that a detection accuracy of 85.1% can be attained by combining multimodality information related to stress.

III. SUPPORT VECTOR MACHINE

Supervised machine learning algorithm for classify and regress tasks uses a Support Vector Machine (SVM). Clearly, it is finding the best hyperplane in the data space that separates data points of different classes with the largest margin between them as shown in Fig. 1. SVM works very well in high dimensional space with its use of kernel functions, making the SVM can use the linear classifier and nonlinear classifier at the same time (Gholami & Fakhari, 2017).

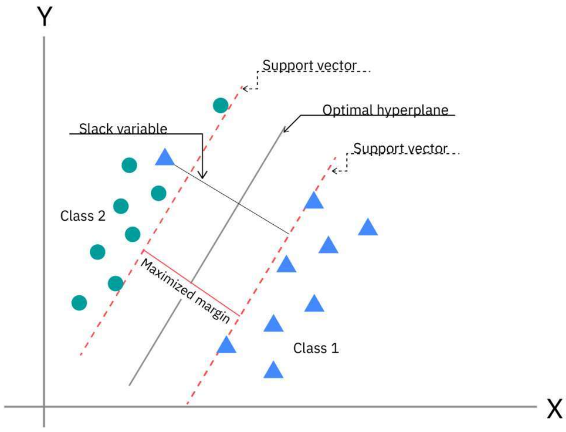

Fig. 1. SVM Model

Verma et al. (2020) developed a ML model to predict stress levels among technical education students. The researchers classify the stress into different levels using physiological and psychological data. The LR and SVM machine learning models are employed for assessing students' stress levels. The dataset for the present research consists of 513 students enrolled in graduation-level engineering programs from several northern Indian colleges. Consequently, the SVM achieved 86.84 percent accuracy, while the LR scored 67 percent. The model's purpose is to predict which students will be exposed to high levels of stress early so that interventions can be made before the problem escalates and affects their academic performance.

Pabreja et al. (2022) collected data through surveys and assessments and implemented various ML approaches for categorizing stress levels among Indian working professionals. LR, Lasso regression, DT regression, RF regressor and SVM regressor model are supervised regression learning methods that have been used. It is aimed to offer perspectives with respect to occupational stress so that organizations can find out ways to boost employees' well-being and productivity. The most accurate results were obtained using SVM Regression which is 91.64 percent.

Jegan, Mathuranjani, & Sherly (2022) examines the measurement of HRV from an ECG signal utilizing the ultra-short term HRV analysis method and the SVM methodology. This paper also uses the MITBIH multi parameter database to import ECG signals and extract time-dependent characteristics for the identification of mental stress in humans. The ultra-short term HRV analysis approach was used to conduct the various tests using 60 segments of the RR interval under both stress as well as normal conditions. Mental stress level can be accurately detected by using an SVM classifier with an RBF kernel. According to the evaluation results, the suggested methods classify mental stress with an accuracy of 91 percent.

IV. DECISION TREE

A supervised ML framework called a decision tree creates a tree-like structure as shown in Fig. 2 by iteratively predicting target variables by dividing data into subsets. The ease of use and interpretability of this make it a popular choice for classification and regression problems (Moslehi, Rabiei, Soltanian, & Mamani, 2022).

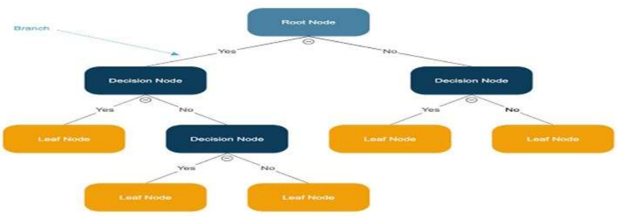

Fig. 2. Decision Tree Model

Zainudin, Hasan, Shamsuddin, & Argawal (2021) identify stress levels using a dataset collected from an IoT sensor that revealed details about a real-life scenario concerning an individual's mental health. Data from sensors like the GSR and ECG were gathered in order to create a pattern for stress detection. Then, DL, SVM, KNN, DT and MLP are used to categorize the dataset. The performance of the data is evaluated using F1-Score, recall, accuracy, and precision. Lastly, out of all the machine learning classifiers, DT performed the best, with an accuracy of 95%.

Delgado-Gallegos et al. (2023) set out to develop a computational and statistical framework algorithm to assess and comprehend the stress levels of healthcare workers in light of the COVID-19 pandemic. Additionally, the authors aimed to consider developing a graphical self-explainable clinical tool that could be utilized as a stress severity predictor. To examine datasets, the C5.0 decision tree method was employed. The final model added a more accurate evaluation to the original stress classification, demonstrating 94% accuracy.

Sharif, Tamang, Fu, Alzahrani, & Alblehai (2025) uses machine learning techniques to investigate the effects of various transit modes on stress levels. The study examines data gathered from 45 people who frequently go to their jobs, with an emphasis on transit, bicycle riding, and cars. Each participant's HR, BP and ECG were recorded for five days in a row using noninvasive wearable sensors. In order to identify levels of stress depending on commuting mode, this study built a number of ML methods. According to the findings, the accuracy of the LDA method was 88 percent, but the accuracy of the LR method was 90.66 percent. At 91.11 percent accuracy, the Boosted Tree method yielded the best results.

V. RANDOM FOREST

Random Forest employs ensemble learning techniques to build several decision trees as displayed in Fig. 3 and produce the mean prediction for regression tasks or the mode of the trees' classifications of the provided data. By combining the outputs of several trees, this enhances overfitting controls and forecast accuracy (Dutta, Paul, & Kumar, 2021).

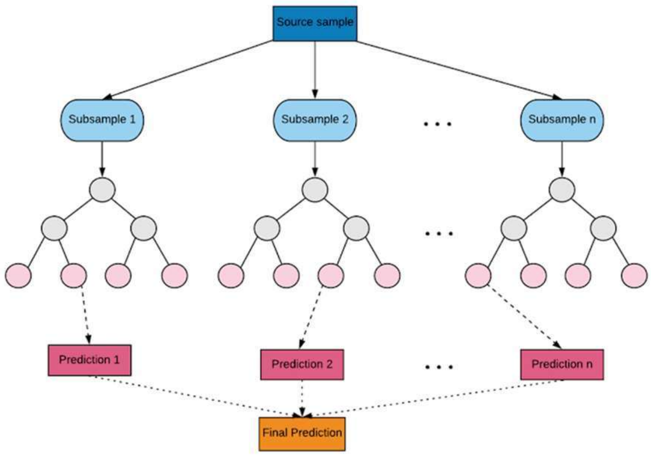

Fig. 3. Random Forest Model

Quadrini, Falcone, & Gerard (2024) provide a thorough overview of the most popular illustrative ML algorithms used in the stress detection domain. This study evaluates different machine learning algorithms for physiological signals from wearable sensors to detect stress. The researchers preprocessed data from 15 subjects using the WESAD dataset and LR, KNN, RF and DT techniques are used. Both binary and multiclass classification scenarios show that the Random Forest model outperforms its alternatives. The accuracy of the RF model is 92% for binary and 70% for multiclass.

Kalai Vani, Savitha, Barkavi, & Eshaswetha (2023) have offered a mechanism that can be used to forecast a student's stress level. The authors created a real-time database and used a set of 48 questions to poll more than 2000 students in order to assess their stress levels and use ML algorithms to treat them early. The survey results are used as input to forecast each student's level of stress. KNN, LR, RF, and DT are among the various ML algorithms that are employed; RF has a highest accuracy rate of 96 percent.

Hossain et al. (2022) predict mental stress using ML and information typically found in a patient's medical file. This approach takes less time and money and needs relatively minimal assistance from physicians. On top of the dataset, 14 distinct ML algorithms were tested in this study. 91% accuracy was attained in this investigation employing RF.

VI. K-NEAREST NEIGHBOR

k-Nearest Neighbors (kNN) is a supervised learning device used for classifying and regression. It takes a data point and classifies it based on the majority class of its k closest neighbours (according to distance calculation such as Euclidean) as presented in Fig. 4. It is so simple and effective that it continues being used in many applications (Halder, Uddin, Uddin, Aryal, & Khraisat, 2024).

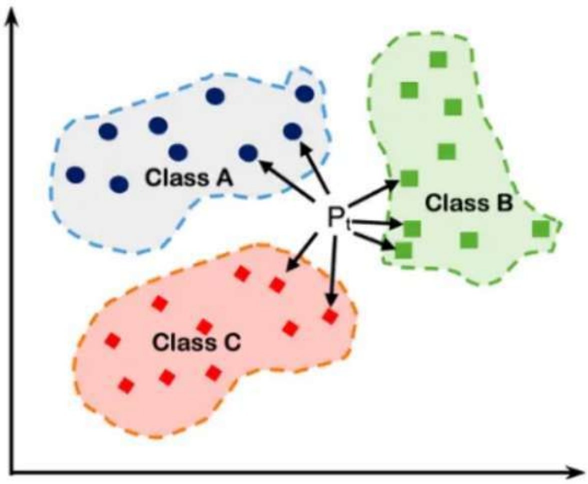

Fig. 4. K-Nearest Neighbor Model

Rahman, Ghosh, Shuvo, & Rahman (2015) investigated mental stress recognition based on EEG signal by using the kNN classifier. Subjects were at different mental workloads, and the mean power of the beta band was used as a feature for EEG data. By classifying the stress only has a maximum accuracy of 91.26%, the kNN classifier outperformed other conventional methods.

Suhas & Phaneendra (2022) leverage ML and IoT techniques to investigate stress in working people. Following appropriate data cleansing and preliminary processing, the authors trained proposed model using a range of ML techniques, including Naive Bayes, DT and KNN. The KNN method produced good results (87.2 percent accuracy) out of the algorithms mentioned above, while the DT produced results of 82.2 percent and the naive bayes algorithm produced the lowest accuracy which is 56.8 percent.

Mohammadi, Fakharzadeh, & Baraeinejad (2022) developed an integrated sensor system for human stress detection utilizing supervised machine learning algorithm. Four signal types—temperature, respiration, EDA and ECG—are analyzed to gather 65 characteristics for a stress detection model. Stress states are distinguished using the K closest neighbor (KNN) algorithm, which produces a 96% classification accuracy.

VII. FUZZY LOGIC

Fuzzy Logic (Fig. 5) is a computational tool for treating the concept of partial truth in which the truth values may lie anywhere within the interval from completely true to completely false. Fuzzy Logic supports reasoning with imprecise or uncertain information that classical binary logic cannot handle.

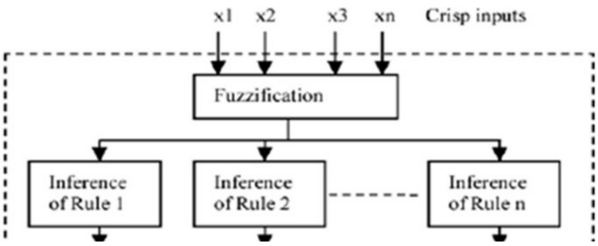

Fig. 5. Fuzzy Logic Model

Cantara & Ceniza (2016) describes a prototype stress sensor that is able to assess stress levels of people at a computer. For collecting physiological data, it relies on self made GSR and HR sensors. These inputs are processed by a Fuzzy Logic algorithm to output stress levels which can be given in real time. With a 72% accuracy rate, the assembled system demonstrated that it could identify stress at a reasonable pace.

Ogunbiyi, Ogunbiyi, & Akanbi (2024) designed a fuzzy logic model for detecting human discomfort. The model processes input data with Fuzzy Logic in order to identify parameters indicative of physical distress. 95.45% at 100 data instances, 96.67% at 40 data instances, 95.24% at 60 data instances, and 94.44% on average were the model's accuracy rates.

Salazar-Ramirez et al. (2018) presented an enhanced fuzzy algorithm for stress detection among individuals. A combination of enhanced fuzzy algorithm and advanced signal processing techniques resulted in better accuracy and reliability for stress detection. The physiological signals used in this work are heart rate, respiratory rate and skin conductance.

VIII. OTHER ML APPROACHES

Reddy, Thota, & Dharun (2018) use ML approaches to examine patterns of stress in employees using data from the 2017 OSMI Mental Health Survey. Following appropriate data cleansing and preliminary processing, variety of ML approaches such as Boosting, Bagging, RF, DT, kNN and LR, to train our model. Among the models used, boosting showed the best accuracy, at 75 percent.

Arya, Anju, & Azuana Ramli (2024) focuses on assessing stress levels among students by employing supervised machine learning techniques and Artificial Neural Networks (ANNs). ANN, MLP, DT, NB, KNN, LR, XGB, Extra Tree, Light GBM, CatBoost, AB, SB, RF, and SVM are some of the machine learning and deep learning models that are proposed in this paper. SVM achieved the least performance in tests at 85.45%, while the Naive Bayes model reached 90%.

Pankajavalli, Karthick, & Sakthivel (2021) propose a classification system for stress prediction based on ANFIS-FWGWO. The suggested ML architecture leverages sensor integrated keyboard input to forecast computer users' stress levels. The findings obtained indicate that, with an accuracy of 94% for the characteristics chosen by the LASSO algorithm, the ANFIS-FWGWO classification method performs better than the current approaches.

Huysmans et al. (2018) investigates the possibilities of stress detection using SOM. The ECG and SC of the test participants were recorded. The SOM's structure was then constructed using a training set of ECG and SC characteristics. SOM areas with comparable features were grouped using a Gaussian Mixture Model. It is observed that the developed model had an overall performance of 79 percent.

A. *Comparative Discussion*

Across reviewed studies, deep learning and ensemble tree methods frequently achieve the highest reported accuracies on multimodal wearable datasets, while SVM remains competitive on smaller structured feature sets. kNN and fuzzy logic offer interpretable and low-complexity options suitable for edge deployment. Multimodal fusion consistently outperforms single-sensor pipelines, though at increased computational and annotation cost.

Common limitations include small sample sizes, laboratory-only recordings, limited demographic diversity, and lack of cross-dataset validation. Future systems should prioritize explainability, privacy-preserving inference, and standardized benchmarking on public stress datasets such as WESAD.

B. Evaluation Metrics and Datasets

Stress detection studies commonly report accuracy, precision, recall, F1-score, and area under the ROC curve. Physiological datasets such as WESAD, SWELL, and DEAP provide labeled stress and affect states collected from wearable sensors under controlled and semi-controlled protocols. Survey-based occupational datasets complement sensor studies by capturing self-reported stress and contextual factors such as workload, sleep, and social support.

Cross-validation and subject-independent testing are essential to assess generalization, yet many published models are evaluated only on random splits within the same cohort. Reporting calibration error, inference latency, and model size alongside accuracy supports fair comparison between deep learning and classical ML baselines for deployment on mobile and wearable hardware.

C. Wearable and IoT Integration

Wearable devices enable continuous acquisition of ECG, GSR, accelerometry, and skin temperature without disrupting daily activities. IoT architectures aggregate sensor streams at the edge or cloud for batch inference and dashboard visualization. Studies integrating smartphones, chest bands, and smartwatches demonstrate that multimodal wearable fusion improves robustness to sensor noise and motion artifacts compared with single-modality pipelines.

Real-time stress analytics require low-latency preprocessing, efficient model serving, and secure transmission of sensitive health data. Edge deployment of lightweight classifiers such as kNN or fuzzy rule engines complements cloud-based deep models for hierarchical monitoring in occupational health programs.

IX. CONCLUSION

This paper highlights that a wide range of AI and ML techniques such as DL, SVM, DT, RF, kNN, and FL have been effectively utilized for stress detection across diverse domains. Most studies demonstrate high accuracy, proving that AI-driven stress assessment is reliable, scalable, and capable of handling multimodal physiological and behavioural data.

X. FUTURE SCOPE

Future research can explore hybrid and explainable AI models, integration of multimodal real-time wearable sensors, and personalized stress analytics. Improved datasets, cross-population validation, and deployment-ready intelligent systems will further enhance the accuracy, transparency, and practical usability of AI-based stress detection solutions.

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