**CHAPTER TWO**

**LITERATURE REVIEW**

**2.0 Introduction**

This chapter looks at related works in this area. It will consider the theoretical framework and key concepts that underpin stress detection, review relevant literature on both traditional and modern approaches, and identify the knowledge and research gaps that emerge from the review.

Stress is a complex biopsychosocial phenomenon, arising when an individual perceives that the demands placed upon them exceed their available resources or coping capacity. Physiologically, it activates the hypothalamic–pituitary–adrenal (HPA) axis, triggering the release of stress hormones such as cortisol, and engages the sympathetic nervous system, which accelerates heart rate, alters respiration patterns, and changes skin conductance. Psychologically, stress manifests as heightened alertness, irritability, or anxiety, while prolonged exposure can result in exhaustion, cognitive impairments, and emotional instability. Social and behavioral impacts include maladaptive coping mechanisms, reduced productivity, and strained relationships. Unmanaged stress has significant health consequences, contributing to cardiovascular disease, hypertension, depression, immune suppression, and other chronic conditions (Kotsiantis et al., 2020). Understanding these multidimensional effects forms the theoretical basis for why accurate, timely detection is critical.

Historically, stress assessment relied on self-report questionnaires, structured or semi-structured clinical interviews, and, in some cases, physiological measurements taken in controlled environments. While these methods long foundational to psychological and medical practice provided valuable insights, they had clear limitations. Self-reports were constrained by recall accuracy, willingness to disclose, and social desirability bias. Clinical interviews required significant resources and were dependent on interviewer skill. Even physiological measures such as blood pressure, cortisol levels, or heart rate offered only discrete snapshots, missing dynamic fluctuations that can occur rapidly, especially in high-pressure contexts (Sano & Picard, 2013).

The last two decades have seen a shift in stress detection, driven by advances in biomedical engineering, wearable sensing, and computational intelligence. Portable, non-invasive biosensors integrated into everyday devices smartwatches, fitness bands, mobile phones—now enable continuous collection of electrodermal activity (EDA), heart rate and heart rate variability (HRV), accelerometry, skin temperature, and even voice-based indicators. These high-frequency, multi-dimensional data streams contain subtle stress signatures that traditional analysis often overlooks. Machine Learning (ML), as a branch of Artificial Intelligence (AI), offers the capacity to uncover these patterns by learning from large datasets. ML can detect deviations from an individual’s baseline with high sensitivity, enabling early detection and proactive management.

Research demonstrates the effectiveness of various ML algorithms in stress detection. Early studies used supervised learning methods like Support Vector Machines (SVM) and Random Forests to classify stress levels in physiological datasets with strong accuracy, even in noisy conditions (Healey & Picard, 2005; Rashid et al., 2022). More recently, deep learning techniques have broadened capabilities: Convolutional Neural Networks (CNNs) excel at extracting spatial features from transformed signals such as spectrograms, while Long Short-Term Memory (LSTM) networks capture temporal dependencies in time-series biosignals (Hasanpoor et al., 2024; Akajari et al., 2023). These methods have been applied successfully in both controlled and real-world contexts, including workplaces, schools, and public health initiatives.

The advantages of ML-based stress detection over traditional methods are significant. They allow continuous, real-time monitoring, empowering timely interventions before stress escalates into more severe health issues. Systems can personalize detection thresholds to reflect individual physiological patterns, increasing relevance and trust (Taylor et al., 2019). Furthermore, cloud-connected ML platforms offer scalability, enabling mental health support for large populations, including underserved regions (Saeb et al., 2015).

Despite these advances, gaps remain. Data quality issues persist due to motion artifacts, inconsistent sensor contact, environmental interference, and device limitations, which can lead to false positives or negatives (Gjoreski et al., 2017). Variability in individual stress responses presents another challenge, requiring adaptive learning mechanisms for accurate detection across diverse users (Taylor et al., 2019). Ethical and privacy concerns are also critical, as continuous monitoring involves sensitive biometric and behavioral data that must be safeguarded in line with regulations such as GDPR and HIPAA (Villani et al., 2018). Moreover, the “black box” nature of some deep learning models limits interpretability, posing barriers to clinical adoption (Holzinger et al., 2017). Finally, translating models from controlled environments to unpredictable real-world conditions often results in reduced accuracy due to environmental noise and contextual variability (Sarker, 2020).

In conclusion, by examining the theoretical foundations of stress detection, critically reviewing existing literature on both traditional and ML-based methods, and identifying the unresolved technical, ethical, and practical challenges, this chapter provides a basis for understanding current capabilities and limitations. The synthesis of these works highlights the knowledge and research gaps that inform the direction of this study and guide the development of more robust, personalized, and ethically sound stress detection systems.

**2.1 Theoretical Concepts**

The development of machine learning–based stress detection systems is anchored in a robust theoretical foundation that blends psychological understanding of human stress with computational principles of predictive modeling. Stress is not merely a physiological occurrence; it is a complex interplay of cognitive, emotional, and environmental factors. Psychological frameworks such as the Cognitive Appraisal Theory provide valuable insight into this interplay, emphasizing that stress responses emerge when individuals perceive a mismatch between external demands and their perceived capacity to cope. This theoretical perspective highlights the fact that physiological responses such as fluctuations in heart rate variability, changes in electrodermal activity, or alterations in skin temperature are deeply influenced by subjective perception, prior experiences, cultural background, and situational context. Consequently, an effective ML-based system must integrate these psychological insights to avoid treating biosignal variations as isolated events and instead interpret them in relation to the broader human experience.

From the computational standpoint, supervised learning theory forms the backbone of most stress detection algorithms. It posits that predictive accuracy improves when a model is exposed to large, well-labeled datasets linking physiological measurements to verified stress states. By iteratively adjusting model parameters through optimization techniques, algorithms such as Support Vector Machines, Random Forests, and Long Short-Term Memory networks learn to capture the subtle, nonlinear patterns in biosignals that may be imperceptible to human observers. This capacity for complex pattern recognition is further enhanced by principles from feature selection theory, which guide researchers in identifying the most discriminative features while filtering out irrelevant or noisy data. This selective focus not only improves model efficiency and generalization but also reduces computational overhead, making real-time analysis more feasible.

Equally significant is the integration of multimodal data fusion theories, which advocate for combining diverse physiological and behavioral signals to improve predictive robustness. In stress detection, this may mean merging data from wearable ECG devices, EDA sensors, accelerometers, and even contextual inputs such as time of day, location, or recent activity patterns. Such integration allows the system to account for potential confounding factors—for example, distinguishing stress-induced heart rate elevation from exercise-related increases—thereby improving reliability. At the same time, incorporating adaptive learning theories enables models to recalibrate continuously based on individual users’ evolving physiological baselines, addressing one of the primary limitations of generic, population-trained algorithms.

The convergence of these psychological and computational principles offers more than just a blueprint for detecting stress; it enables the design of systems that are predictive, personalized, and responsive. When grounded in a theoretical understanding of how humans experience stress and paired with the mathematical rigor of machine learning, these systems have the potential to transition from being passive detectors to proactive companions anticipating stress before it escalates, providing timely interventions, and adapting recommendations to fit an individual’s unique profile. This theoretical integration underscores a paradigm shift in mental health monitoring: one in which human-centered science and artificial intelligence work in synergy to support well-being in both clinical and everyday contexts.

**2.2 Review of Related Works**

Over the years, numerous studies have explored the development and implementation of machine learning–driven stress detection systems, each contributing valuable insights into model design, data acquisition, and system performance. One of the earliest notable works in this field was conducted by Healey and Picard (2005), who applied Support Vector Machines (SVM) to physiological signals such as heart rate (HR), electrodermal activity (EDA), and respiration. Their model demonstrated high accuracy under controlled laboratory conditions, highlighting the promise of ML for stress detection, but its performance was limited by the lack of adaptability to real-world environments and the absence of personalization features. Building on this foundation, Sano and Picard (2013) integrated wearable sensors with ML algorithms to monitor heart rate variability (HRV), skin temperature, EDA, and motion over extended periods. Their system proved effective in long-term tracking, yet struggled to differentiate between stress induced by emotional factors and that caused by physical exertion, underscoring the need for contextual awareness in ML models.

Advancements in real-world applicability were made by Gjoreski et al. (2017), who employed Random Forest classifiers to analyze HRV, EDA, and accelerometer data in naturalistic settings. Their study achieved commendable accuracy outside the laboratory, but also revealed the vulnerability of sensor readings to motion artifacts and noise, which reduced precision during high-activity periods. Addressing the limitations of traditional architectures, Hasanpoor et al. (2022) developed a CNN-MLP hybrid model trained on UBFC-Phys photoplethysmography (PPG) signals, achieving a 96.7% accuracy rate. While their results were impressive, the model’s training in a controlled setting raised concerns about its ability to generalize across diverse environments and user populations. Hasanpoor et al. (2024) further refined this approach by applying a combination of CNN and continuous wavelet transform (CWT) to WESAD PPG data, reaching 93.7% accuracy, though the system remained constrained by its lack of behavioral and contextual input, limiting personalization.

Other studies have emphasized multi-modal and context-aware systems. Rashid et al. (2022) introduced the SELF-CARE framework, integrating ensemble learning with contextual data such as motion, achieving 94.1% accuracy on the WESAD dataset. Despite its robustness, the approach required multiple sensors and complex setup, which could hinder its practicality for everyday use. Expanding on this, Rashid et al. (2023) employed a transformer-based architecture for sensor fusion, combining biometric signals with textual context. This method achieved a comparable accuracy of 94.12%, but demanded high computational resources, posing challenges for deployment on mobile or low-power devices. Akajari et al. (2023) explored a Random Forest model enhanced with contextual daily activity metadata, reaching a 70% F1-score. Although it demonstrated the value of including contextual factors, its performance declined in noisy, dynamic settings and required careful calibration for individual users.

Collectively, these studies reveal a consistent trajectory in the field: from early laboratory-based models toward increasingly complex, context-aware, and multimodal systems. The progression underscores both the potential of ML in stress detection and the persistent challenges particularly in ensuring robustness, personalization, and deployment feasibility in real-world environments. These works provide a critical foundation for further research aimed at bridging the gap between controlled experiments and practical, user-centered stress detection solutions.

**Table 2.2.1: Summary of Related Work**

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| --- | --- | --- | --- | --- | --- |
| AUTHOR(S) | YEAR | METHOD/MODEL | DATA USED | ACCURACY/OUTCOME | KEY LIMITATION |
| Healey & Picard | 2005 | SVM | HR, EDA, Respiration | High accuracy in lab tests | Does not account for real-world conditions; lacks adaptability and personalization. |
| Sano & Picard | 2013 | ML + wearable sensors | HRV, Temp, EDA, motion | Effective long-term tracking | Lacks contextual input; limited in distinguishing physical vs emotional stress. |
| Gjoreski et al. | 2017 | Random Forest | HRV, EDA, Accelerometer | Real-world accurate results | Data noise due to motion; reduced precision during physical activity. |
| Hasanpoor et al. | 2022 | CNN-MLP Hybrid | UBFC-Phys (PPG signals) | 96.7% | Trained in a lab setting; may not generalize to diverse environments or user profiles. |
| Hasanpoor et al. | 2024 | CNN + CWT | WESAD (PPG) | 93.7% | Does not incorporate contextual or behavioral data; lacks personalization. |
| Rashid et al. | 2022 | SELF-CARE + Ensemble Learning | WESAD + context (motion) | 94.1% | Requires multiple sensors; high setup complexity for non-research users. |
| Rashid et al. | 2023 | Transformer + Sensor Fusion | Text + Biometric Signals | 94.12% | High computational demands; challenging to deploy on mobile or low-power devices. |
| Akajari et al. | 2023 | Random Forest + Contextual Data | PPG + daily activity metadata | 70% F1-score | Lower performance in noisy or dynamic settings; requires careful calibration for each user. |

**2.3 Knowledge/Research Gap**

Although machine learning has significantly advanced stress detection, most existing systems rely on wearable devices such as smartwatches or specialized sensors. While effective in controlled settings, these solutions are often inaccessible to individuals without such devices or to those in regions where wearable technology is less common. This creates a major accessibility gap, excluding potential users who could benefit from stress monitoring. Furthermore, many current approaches are designed for automated, continuous sensor input and do not adapt well to real-world variability. They often lack personalization and contextual awareness, making it difficult to distinguish between stress caused by physical exertion and that caused by emotional or cognitive factors.

There is also a shortage of solutions that combine machine learning with a web-based platform capable of accepting manually entered physiological data and self-reported answers. Most current systems require multi-sensor setups or high computational resources, which limits scalability and usability. Few provide an accessible, low-cost, and user-friendly online environment that can deliver accurate, personalized feedback in real time or near real time. This gap highlights the need for a robust web-based stress detection system, integrated with machine learning, that can operate effectively without wearables while maintaining accuracy, adaptability, and accessibility for a wide range of users.