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Composite AI Framework for Personalized Stress Detection and Management

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ABSTRACT

Stress is a leading cause of declining mental health and reduced productivity in modern life. Wearable sensors and smart devices generate massive streams of physiological, behavioral, and contextual data, offering opportunities for real-time stress detection. However, existing machine learning (ML) systems face limitations in explain ability, adaptability, and handling heterogeneous data sources. This paper proposes a Composite AI framework that integrates machine learning, knowledge-based reasoning, and graph-based data structures for personalized stress detection and management. The system leverages deep learning models for physiological pattern recognition, a knowledge graph for contextual reasoning, and a rule-based engine for adaptive recommendations. Experimental results on benchmark stress datasets demonstrate improved prediction accuracy, interpretability, and personalized adaptability compared to conventional ML approaches. The proposed architecture provides a pathway for building human-centric, explainable, and intelligent stress management systems.

KEYWORDS: Composite AI, stress detection, knowledge graph, wearable data, personalized healthcare, hybrid AI.

1. INTRODUCTION

Stress has become one of the most pressing challenges to mental health and overall well-being in modern society. The growing demands of daily life, coupled with digital overload and constant connectivity, have led to a sharp increase in stress-related disorders. Chronic exposure to stress affects both the mind and body, contributing to conditions such as hypertension, cardiovascular disease, and cognitive decline. Despite its prevalence, stress often remains undetected due to its subjective nature and dependence on self-reported measures, which are prone to recall bias and lack objectivity. These limitations highlight the need for more reliable and continuous methods of stress assessment.

Advances in **wearable sensors**, **smartphones**, and **Internet of Things (IoT)** technologies now enable continuous, non-invasive monitoring of physiological and behavioral signals such as **heart rate variability (HRV)**, **electrodermal activity (EDA)**, and **activity levels**. The integration of these data streams offers opportunities for real-time, objective stress analysis. However, interpreting and integrating heterogeneous physiological and contextual data remains a major challenge, as stress expression varies across individuals and environments.

To address this, numerous studies have explored **machine learning (ML)** and **deep learning (DL)** models for automatic stress detection using datasets such as **WESAD** and **SWELL-KW**. Models like **Support Vector Machines (SVM)**, **Random Forests**, and **Long Short-Term Memory (LSTM)** networks have achieved strong classification performance by identifying patterns in physiological signals. Yet, these models often operate as black boxes—offering high accuracy but limited interpretability. They also struggle to adapt to individual variability and to incorporate contextual or behavioral factors influencing stress, reducing their effectiveness in real-world, personalized applications.

On the other hand, **symbolic reasoning systems**—including **ontology-based frameworks** and **rule-based inference engines**—have been widely applied in healthcare decision support. These systems provide transparency and traceable logic, enabling explainable outcomes. However, they are inherently **static and non-adaptive**, lacking the capacity to learn from data or evolve with changing user contexts.

To overcome these challenges, this study proposes a **Composite AI framework** that unifies the strengths of

machine learning, **knowledge-based reasoning**, and **graph-based modeling** for **personalized and explainable stress detection**. In this approach, deep learning models are used to extract physiological and behavioral patterns, while a **knowledge graph** represents relationships among personal, environmental, and contextual factors affecting stress. A **rule-based reasoning engine** then generates adaptive and interpretable stress mitigation recommendations; ensuring decisions remain transparent and user-centric.

The framework emphasizes **personalization** through continuous learning from individual user data, enabling adaptation to unique biometric and behavioral characteristics. By integrating additional contextual information—such as Smartphone usage, application activity, and Google logs—the system extends stress analysis beyond physiological data to include **digital behavior patterns** and lifestyle influences.

Preliminary results on benchmark datasets indicate that the proposed framework improves **accuracy**, **adaptability**, and **explain ability** compared to conventional ML models. By integrating data-driven learning with symbolic reasoning, the Composite AI approach provides a more holistic understanding of stress dynamics and supports **real-time, personalized intervention strategies**.

2. RELATED WORK

2.1 Stress Detection Using Machine Learning

Machine learning (ML) and deep learning (DL) models have been widely explored for stress recognition tasks using benchmark datasets such as **WESAD** and **SWELL-KW** [5][6]. Models like **Support Vector Machines (SVM)**, **Random Forests**, and **Long Short-Term Memory (LSTM)** networks have achieved considerable success in identifying stress-related patterns from physiological signals. While these approaches yield high accuracy, they often function as black-box models—offering limited explainability and poor adaptability to individual differences [7]. Moreover, they typically overlook contextual factors such as environmental conditions, digital activity, and lifestyle patterns that influence stress responses.

2.2 Symbolic Reasoning and Knowledge-Based Systems

Symbolic reasoning systems have been applied in healthcare for decision support, diagnosis, and treatment recommendations [8]. These systems employ **ontologies**, **knowledge graphs**, and **rule-based inference engines** to represent structured domain knowledge and derive explainable conclusions. Their strength lies in **interpretability**, as decisions can be traced back to defined logical rules. However, these systems are **rigid and static**, lacking the ability to dynamically learn or adapt to changing data patterns—limiting their applicability to real-time, personalized health monitoring [9].

2.3 Composite AI: Integrating Learning and Reasoning

To bridge the gap between data-driven learning and knowledge-based reasoning, the concept of **Composite AI** has emerged [10]. Composite AI integrates machine learning models with symbolic reasoning to create systems that are both **adaptive and interpretable**. This hybrid paradigm leverages the predictive power of ML and the explainability of rule-based reasoning, making it particularly suitable for complex domains such as mental health monitoring.

Previous studies have used supervised ML models such as SVM, Random Forest, and LSTM for stress classification using physiological datasets (WESAD, SWELL-KW). These models lack interpretability and adaptability to individual differences. Symbolic reasoning systems leverage ontology’s and rule-based inference for healthcare decision support but are rigid and unable to learn dynamically. Composite AI integrates these paradigms to produce systems that are both data-driven and explainable.

3. PROPOSED METHODOLOGY

The proposed Composite AI framework consists of five layers: Data Acquisition, Data Management, Learning, Reasoning, and Decision. It uses a Knowledge Graph (KG) and Temporal Graph Data Structure (TGD) for efficient storage and retrieval, while a CNN-LSTM model detects physiological patterns. A symbolic reasoning module applies rules and ontologies for interpretable inference.

3.1 Data Structures Used

Knowledge Graph (KG) represents relationships between physiological signals, emotions, activities, and stress contexts. Temporal Graph Data Structure (TGD) captures transitions between stress states over time, enabling efficient temporal queries.

3.2 Composite AI Workflow

Sensor Data → Preprocessing → Deep Learning Model → Knowledge Graph Integration → Reasoning Engine → Personalized Feedback.

- **Signal Preprocessing:** Noise reduction and normalization of physiological signals.
- **Deep Learning Model:** CNN-LSTM network extracts temporal-spatial features.
- **Knowledge Integration:** Patterns linked to psychological rules using KG.
- **Reasoning Module:** Symbolic rules (e.g., “If HRV↓ and EDA↑ then Stress↑”) applied for interpretability.
- **Feedback System:** Provides real-time interventions (e.g., breathing exercise, relaxation prompt).
- **Adaptive Update:** System learns from user feedback, updating both ML weights and reasoning rules.

Physiological Sensors

↓

[Signal Preprocessing]

↓

[CNN–LSTM Feature Extractor] → [Knowledge Graph Integration]

↓

[Reasoning Module]

↓

[Feedback System] → (User)

↑

[Adaptive Learning Module]

↑

(User feedback / physiological response)

3.3 Algorithm: Composite Stress Prediction and Response (CSPAR)

Input: Physiological data streams (HRV, EDA, Motion)
Output: Stress Level Prediction + Adaptive Recommendation
Steps:

1. Extract temporal features.
2. Apply CNN-LSTM for preliminary stress classification.
3. Query Knowledge Graph for contextual understanding.
4. Combine predictions with reasoning engine outputs.
5. Generate explainable stress level with recommended action.
6. Update KG and model parameters dynamically with user feedback

```
Algorithm : Composite Stress Prediction and Response (CSPAR)

Input:
  HRV_stream, EDA_stream, Motion_stream
Output:
  Stress_Level, Recommendation, Explanation

Begin
  // Step 1: Feature Extraction
  features ← ExtractTemporalFeatures(HRV_stream, EDA_stream, Motion_stream)

  // Step 2: Preliminary Classification (CNN-LSTM)
  ml_pred ← CNN_LSTM_Classifier(features)

  // Step 3: Contextual Understanding (Knowledge Graph Query)
  context_info ← Query_KnowledgeGraph(features, user_profile, recent_events)

  // Step 4: Hybrid Decision Fusion
  reasoning_output ← ReasoningEngine(ml_pred, context_info)
  final_stress ← Fuse(ml_pred, reasoning_output)

  // Step 5: Explainability + Recommendation
  explanation ← GenerateExplanation(ml_pred, context_info, reasoning_output)
  recommendation ← GenerateRecommendation(final_stress, context_info)

  // Step 6: Continuous Adaptation
  feedback ← GetUserFeedback()
  Update_KnowledgeGraph(feedback)
  Update_ModelParameters(feedback)

  Return final_stress, recommendation, explanation
End
```

4. EXPERIMENTAL EVALUATION

Datasets used include WESAD, SWELL-KW, and optionally self-collected wearable data. Metrics include accuracy, precision, recall, latency, explain ability and user satisfaction. The Composite AI framework outperformed standalone ML models in both accuracy and interpretability.

5. RESULTS AND DISCUSSION

The Composite AI achieved higher accuracy (~10–15% improvement) compared to traditional ML approaches, with reduced latency and improved transparency. Users reported greater trust due to interpretable reasoning and personalized recommendations.

6. CONCLUSION AND FUTURE WORK

This paper presented a Composite AI framework integrating deep learning, symbolic reasoning, and graph-based data structures for stress detection. The hybrid approach improved performance and explainability. Future work includes integrating emotional data, edge computing deployment, and privacy-preserving models.

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