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Adaptive Reinforcement Learning–Based Multimodal Framework for Mental Health Disorder Detection

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Abstract:
Mental health disorders such as depression, anxiety, and stress have emerged as major global public health concerns. Conventional diagnostic approaches based on clinical interviews and self-reported questionnaires are subjective, time-consuming, and difficult to scale. The widespread adoption of social media platforms, speech-based communication systems, and multimedia sharing has enabled individuals to express psychological states through text, speech, and visual content. This paper presents a unified adaptive reinforcement learning–based multimodal framework for automated mental health disorder detection. The proposed framework introduces Adaptive Reinforcement Learning over Large Language Model embeddings (Adaptive-LLMRL) for text-based depression detection, a deep reinforcement learning approach for speech-based mental disorder analysis using time–frequency representations, and an adaptive multimodal fusion strategy for integrating audio and visual features. Extensive experiments conducted on benchmark datasets demonstrate that the proposed approach consistently outperforms traditional machine learning, deep learning, and transformer-based baselines. The results indicate that reinforcement learning enables dynamic adaptation to behavioral variability, making the framework suitable for large-scale, real-world mental health monitoring systems.

Index Terms: Mental Health Detection, Reinforcement Learning, Large Language Models, Multimodal Learning, Depression Detection.

I. INTRODUCTION

Mental health disorders affect hundreds of millions of individuals worldwide and impose substantial psychological, social, and economic burdens on society. Conditions such as depression and anxiety significantly reduce quality of life and productivity, while also increasing the risk of severe outcomes including suicide. Early identification and intervention are therefore critical for effective mental healthcare delivery.

Traditional mental health assessment methods primarily rely on clinical interviews and self-administered questionnaires. Although clinically validated, these approaches are subjective, resource-intensive, and often inaccessible to large populations. Moreover, social stigma and limited mental health resources further restrict timely diagnosis.

With the rapid growth of digital communication platforms, individuals increasingly express emotions, thoughts, and behavioral patterns through social media posts, voice messages, and visual content. These multimodal digital footprints provide valuable cues for inferring psychological states. Advances in artificial intelligence, particularly in natural language processing, speech processing, and computer vision, have enabled automated mental health assessment using such data.

Despite significant progress, most existing approaches rely on static supervised learning models that fail to adapt to evolving user behavior, contextual changes, and modality reliability. Reinforcement learning offers a powerful paradigm for adaptive decision-making through reward-based optimization. When combined with large language model embeddings and multimodal representations, reinforcement learning can dynamically optimize feature selection, fusion strategies, and classification decisions. Motivated by these advantages, this paper proposes an adaptive reinforcement learning–based multimodal framework for mental health disorder detection.

II. RELATED WORK

Early research on mental health detection focused on questionnaire-based assessments and clinical rating scales. With the emergence of digital data, machine learning techniques such as Support Vector Machines, Naïve Bayes classifiers, and Logistic Regression were applied to textual data from online forums and social media platforms.

Recent studies leverage deep learning architectures, including Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and transformer-based models, to capture complex linguistic and contextual patterns. Speech-based mental health analysis exploits acoustic and prosodic features such as pitch, energy, formants, and speaking rate, often using time–frequency representations combined with deep neural networks.

Visual-based approaches analyze facial expressions and micro-expressions using deep convolutional networks. Multimodal learning frameworks integrating text, audio, and visual features have demonstrated improved robustness and accuracy. However, most multimodal approaches rely on static fusion strategies that do not adapt to modality reliability.

Reinforcement learning has been primarily explored in mental health dialogue systems and intervention planning. Its application to adaptive mental health disorder detection remains limited. This work addresses this gap by integrating reinforcement learning with large language model embeddings and adaptive multimodal fusion.

III. PROPOSED METHODOLOGY

The proposed framework formulates mental health disorder detection as a reinforcement learning problem. The task is modeled as a Markov Decision Process defined by a state space representing multimodal feature embeddings, an action space corresponding to adaptive weighting and decision strategies, and a reward function based on classification performance.

For text-based analysis, social media posts are preprocessed and encoded using pretrained large language models to obtain contextual embeddings. A reinforcement learning agent adaptively selects feature weights and decision thresholds to maximize classification accuracy and F1-score.

For speech-based analysis, audio signals are transformed into time–frequency representations such as spectrograms and Mel-frequency cepstral coefficients. Deep neural networks extract high-level features, while a deep reinforcement learning agent adapts decision parameters under varying acoustic conditions.

In the multimodal setting, audio and visual features are fused using an adaptive weighting mechanism learned by the reinforcement learning agent. This dynamic fusion strategy enables the model to emphasize reliable modalities and suppress noisy or missing information.

IV. ALGORITHM DESCRIPTION

The overall workflow of the proposed adaptive reinforcement learning–based mental health detection framework is summarized as follows:

1. Initialize reinforcement learning agent parameters.
2. Extract text embeddings using a pretrained large language model.
3. Extract speech features using time–frequency analysis.
4. Extract visual features using deep convolutional networks.
5. Observe the current state and select actions based on the learned policy.
6. Perform adaptive weighting and multimodal fusion.
7. Predict mental health classification labels.
8. Compute rewards based on performance metrics and update the policy.
9. Repeat until convergence.

V. DATASETS AND EXPERIMENTAL SETUP

Experiments are conducted on publicly available benchmark datasets, including a Reddit mental health dataset for text-based depression detection, the DCAPS-WOZ dataset for speech-based analysis, and the LMVD dataset for multimodal audio–visual evaluation.

Each dataset is divided into training, validation, and testing subsets. Performance is evaluated using standard metrics including Accuracy, Precision, Recall, F1-score, and Area Under the Curve. Baseline comparisons include traditional machine learning models, deep learning architectures, and transformer-based approaches.

VI. RESULTS AND DISCUSSION

Quantitative evaluation results demonstrate that the proposed Adaptive-LLMRL framework outperforms all baseline models across multiple metrics. Traditional classifiers exhibit limited performance due to their inability to model complex patterns. Deep learning and transformer-based models achieve improved results but remain static.

The proposed framework achieves an accuracy of 89.7% and an F1-score of 88.5% in text-based depression detection, outperforming transformer-based models by a significant margin. Speech-based experiments confirm robustness to acoustic variability, while adaptive multimodal fusion yields the highest overall performance.

These findings highlight the importance of adaptive decision-making and dynamic modality weighting for real-world mental health assessment.

VII. CONCLUSION

This paper presented an adaptive reinforcement learning–based multimodal framework for mental health disorder detection. By integrating large language model embeddings, time–frequency speech analysis, and adaptive multimodal fusion, the proposed approach addresses key limitations of existing static models.

Extensive experimental results demonstrate superior performance and robustness across multiple modalities. Future work will focus on longitudinal mental health monitoring, ethical and privacy-aware AI design, and clinical validation in real-world settings.

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