Human Understanding from Lifelog Data via Mobile Sensors Using a GRU Network with Attention Mechanism

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Introduction

Motivation

Advancements in IoT technology have accelerated human understanding through the collection of lifelog data from smartphones and wearable devices. Traditional methods for analyzing emotions, stress levels, and sleep conditions are resource-intensive and time-consuming, making it difficult to monitor long-term changes. In contrast, time-series analysis techniques, which account for temporal dependencies, allow for continuous monitoring of users' behaviors and physiological changes, enabling more reliable predictions. This study aims to improve the analysis of emotions, stress, and sleep conditions through meaningful feature engineering and time-series forecasting, ultimately enhancing personal health management.

Contribution

- Demonstrated the results of data preprocessing techniques, such as time alignment, handling missing values, and creating derived variables, using actual lifelog data to accurately predict an individual's emotional state, stress level, and sleep quality.
- Developed the Smart Sensor Prediction (SSP) model that precisely models the temporal correlations of sensor data by combining Gated Recurrent Units (GRU) and the Attention mechanism.
- The effectiveness of the proposed model outperformed existing methods in predicting emotions, stress levels, and sleep states using real lifelog data.

Dataset & Preprocessing

	Feature Name								
	mAcc	*mActivity*	*mAmbience*	*mGps*	*mLight*	*mUsageStats*	*wLight*	*wHr*	*wPedo*
Time Unit	1-hour	1-hour	1-hour	1-hour	1-hour	1-hour	1-hour	1-hour	1-hour
Pre-processing	Magnitude Calculation	Reassign numerical values based on activity intensity	Select max probability ambience	Haversine transformation	Average values	Divide by 60000 to convert the time unit to minutes	Average values	Average values	Multicollinearity removal
Missing values	Replace with 0	Replace with Unknown	Replace with None	Replace with 0	Replace with 0	Replace with 0	Replace with 0	Replace with 0	Replace with 0
Derivative variable	mean_x, mean_y, mean_z, magnitude	max_activity	max_ambience_cls	distance	mean_light	app_total_use_time	mean_light	mean_hr	mean_burn

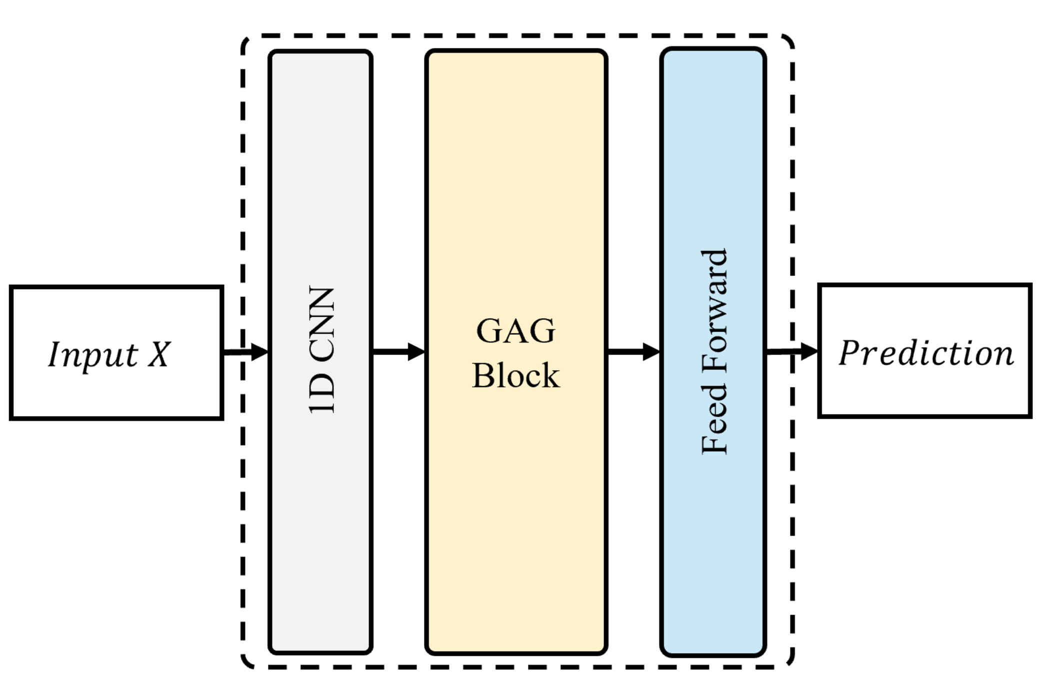
Dataset

- The dataset includes Train, Validation, and Test subsets collected at different times, each with specific sensor limitations: the 2020 Train data (22 participants, 508 days) lacks Galaxy Watch data, while the 2023 Validation and Test data (4 participants) lack sleep sensor data.
- Due to these differences, the Validation data was repurposed for training, with feature engineering applied to enhance the dataset.
- Seven indicators for sleep quality, emotional state, and stress were calculated daily from survey and sensor data and then converted into binary values.

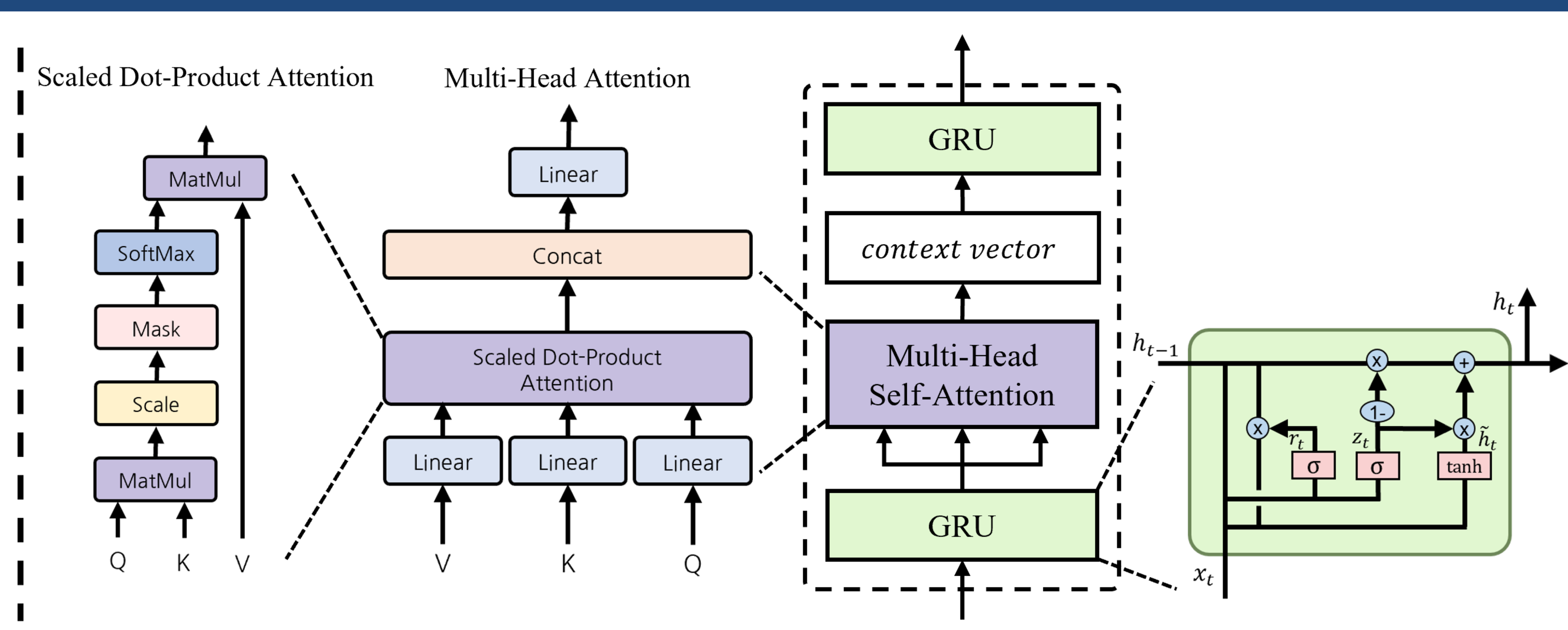
Preprocess

- **mAcc**: Added directional averages and Signal Vector Magnitude for behavior insights.
- **mActivity:** Used hourly max intensity as physical state indicator.
- **mAmbience:** Added dominant auditory environment per hour for psychological impact.
- **mGps:** Calculated hourly travel distance for fatigue assessment.
- **mLight:** Averaged light intensity to track eye strain.
- **mUsageStats:** Summed app usage time per hour for eye strain relevance.
- **wLight:** Averaged light intensity like mLight.
- **wHr:** Added hourly average heart rate; ECG excluded for quality.
- **wPedo:** Remove correlated variables to avoid multicollinearity, keeping meaningful averages.

Method



(a) Framework of SSP Model



(b) GAG Block

Training Loss

We use Binary Cross-Entropy (BCE) to measures the discrepancy between predicted probabilities and actual labels to optimize:

$$BCE(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}(y_i \cdot log(\hat{y}_i) + (1-y_i)\cdot log(1-\hat{y}_i))$$

Performance Measure

The performance was evaluated by calculating the total F1-score, which aggregates weighted F1-scores form individual components:

$$F1\text{-score macro} = 2 \times \frac{Precision \times Recall}{Precision + Recall},\ Total\ F1-Score = \textstyle\sum_{i=1}^{3} w_i Q_i + \sum_{i=1}^{4} w_i S_i$$

Result & Conclusion

Metric	Explanation	Values
Q1	Overall sleep quality as perceived by a participant immediately after waking up	0: below average, 1: above average
Q2	The emotional state of a participant just before sleep	0: below average, 1: above average
Q3	Stress levels experienced by a participant just before sleep	0: **above** average, 1: **below** average
S1	Total sleep time (TST)	0: below average, 1: above average
S2	Sleep efficiency (SE)	0: below average, 1: above average
S3	Sleep onset latency (SOL, SL)	0: below average, 1: above average
S4	Wake after sleep onset (WASO)	0: below average, 1: above average

Architecture	Method	Total F1-Score
	Base	5.6628938
MLP	**+ 1D CNN**	5.7464249
	+ MSA	5.3760444
	Base	5.319269
GRU	**+ 1D CNN**	5.3987669
	+ MSA SSP(Ours)	**5.9636025**

Conclusion

In conclusion, our study provides compelling evidence for the significant impact of model architecture on healthcare time series data processing. The proposed SSP model, combining GRU and self-attention, achieved superior performance with a Total F1-score of 5.96, outperforming MLP-based models. The integration of 1D CNN and self-attention further improved the ability to capture both local patterns and global correlations in physiological data. This research advances healthcare analytics and supports the development of more effective, personalized health management systems, contributing to a more proactive and precise approach to patient care.

* Total F1-Score = $\sum_{i=1}^{3} w_i Q_i + \sum_{i=1}^{4} w_i S_i$