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Enhancing Depression Prediction via Entropy-Based Behavioral Irregularity and Feature Engineering on Smartphone Sensor Data

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Abstract: Depression has emerged as a major global mental health issue, yet current diagnostic methods largely rely on self-reported questionnaires (such as the PHQ-9), which has the limitation of being based on subjective responses. Against this backdrop, research on objective depression prediction using smartphone sensor data has been actively conducted. Previous research [1] revealed that place diversity entropy showed a significant correlation with depressive symptoms, suggesting that unpredictability(place-based entropy) can be utilized as a mental health indicator. However, the study[1] has limitations in that it only addressed entropy in a single dimension place diversity and did not comprehensively address reflecting the irregularity across the diverse behavioral domains that constitute daily life. Unlike the previous study that was limited to place diversity entropy alone, this study conducts a multidimensional analysis by computing entropy from multiple behavioral indicators, including time-of-day based entropy, screen usage time entropy, physical activity entropy, and light intensity change entropy. Through this, our study seeks to more comprehensively capture patterns of behavioral irregularities associated with depression and to improve prediction accuracy by simultaneously incorporating multiple entropy variables into the model.

Keywords: Entropy, Depression, Prediction, PHQ-9, LSTM

I. INTRODUCTION

Depression is a major global mental health issue that leads not only to a decline in individuals' quality of life but also to social and economic burdens. Sometimes, depression diagnosis relies on self-report questionnaires such as the PHQ-9(Patient Health Questionnaire-9), and this approach has limitations in that it heavily depends on an individual's subjective perception. Accordingly, research on objective depression prediction using smartphone sensor data is actively underway. In particular, the previous study[1] demonstrated that place diversity entropy showed a significant correlation with depressive symptoms, suggesting that the unpredictability of behavior can be utilized as a mental health indicator. However, the study has limitations in that it analyzed only the entropy of a single dimension place diversity and did not sufficiently reflect the various irregularities in behavior that appear in individuals' daily lives.

This paper aims to overcome these limitations by calculating entropy based not only on place diversity entropy but also on various behavioral indicators such as time-based entropy, screen time, physical activity entropy, and light intensity change entropy, and then analyzing them multidimensionally. This approach aims to enhance the accuracy of depression prediction models by simultaneously utilizing multiple entropy variables, thereby providing a more comprehensive understanding of the relationship between behavioral irregularities and mental health.

Meanwhile, the behavioral entropy indicators used in this study inherently exhibit time-series characteristics, as they reflect the irregularity of daily behavioral patterns that change over time rather than representing behavioral traits at a single point in time. In particular, not only the absolute value of entropy but also its temporal pattern of change may be closely related to depressive symptoms.

Additionally, the PHQ-9 score, which is the prediction target of this study, is an indicator with a delayed effect, as it reflects the cumulative outcome of behavioral irregularities and disruptions in daily rhythms over several consecutive days rather than an immediate response to behavioral changes at a specific point in time. Due to these characteristics, simple regression models or traditional machine learning techniques that assume behavioral metrics for each date are independent samples have limitations in fully reflecting the temporal dependence and cumulative effects of behavioral patterns. Therefore, this study determined that a time series modeling approach capable of effectively learning changes in behavioral entropy over consecutive days and their cumulative patterns is necessary, and adopted the LSTM (Long Short-Term Memory) model, which excels at learning temporal dependencies over the long term.

The main contributions of this paper are as follows. First, we proposed a multidimensional entropy measurement method to capture behavioral irregularities across all domains of daily life. Second, we designed a domain knowledge-based composite score reflecting circadian rhythm disruption and nighttime digital overstimulation. Third, we empirically demonstrated that the entropy-based enhanced feature set significantly improves depression prediction performance.

II. RESEARCH METHODS

A. Data Introduction and Characteristics

This study analyzed behavioral patterns associated with depression using smartphone sensor data. Data was collected from adult participants (college students). The collected data includes location information (GPS), physical activity data, digital usage patterns (screen on/off, app usage history), and social interaction data (call and message records). This enabled the quantitative assessment of various behavioral patterns exhibited by participants in their daily lives. The collected data was anonymized by removing personally identifiable information. Analysis of the data characteristics revealed daily and weekly variability in participants' behavioral patterns, which served as a crucial foundation for calculating entropy related to depressive symptoms.

B. Entropy calculation

In this study, multiple entropy metrics were calculated to evaluate the irregularity of individual behavior from various perspectives. Entropy calculation was based on the standard information-theoretic definition. After obtaining the state probability distribution for each behavioral indicator, the following formula was applied. Entropy was calculated based on the probability of occurrence for each behavioral state, according to the information-theoretic definition. In the equation (1), p_i represents the probability that a specific behavioral state i will be observed.

$$H = -\sum_{i=1}^{n} p_i \ln p_i \tag{1}$$

Based on participants' behavioral data, entropy was calculated across multiple behavioral domains to quantify irregularity. Place diversity entropy was calculated by defining different locations as states using participants' location information and computing the probability of visiting each location.

Here, L_n is a set representing the participant's location visit distribution, consisting of elements such as $(r_1, x, y), (r_2, x, y), \ldots (r_n, x, y)$, where each element comprises the proportion r_i spent at that location and the corresponding latitude and longitude coordinates (x_i, y_i). Here, r_i is the visit probability for each location i included in L_i. First, the visit ratios r_i are separated from this set, excluding the location coordinates. Then, $P(L_i)$ is calculated through a normalization process where each r_i is divided by the sum of these values. The resulting

P(Li) represents the relative proportion of time spent at each location. Substituting this probability distribution into the Shannon entropy formula yields the location diversity entropy, which quantitatively indicates how evenly or unevenly participants' location visit patterns are distributed.

$$\boldsymbol{L_n = \{(r_1,\ x,\ y), (r_2,\ x,\ y)\ \ldots,\ (r_n,\ x,\ y)\}} \tag{2}$$

$$\boldsymbol{P(L_i) = \frac{r_i}{\sum_{n=1}^{i} r_n}} \tag{3}$$

Time-based entropy quantifies the temporal regularity of daily activities by dividing the day into daytime and nighttime units, calculating the probability distribution of activity occurrence across these time periods. Screen usage time entropy was calculated by analyzing the duration of the smartphone screen being on, dividing the day into daytime and nighttime units, and basing it on the probability distribution of screen usage. This allows for the assessment of the unpredictability of digital device usage patterns. Physical activity entropy was calculated by utilizing accelerometer sensor data to classify activity levels into day and night, then computing the probability distribution for each state. This allowed us to quantify the irregularity of physical activity patterns. Finally, the illuminance change entropy was calculated by defining indoor/outdoor activities and lighting change states using illuminance sensor values, dividing the units into day and night, and computing the occurrence probability for each state. This allowed us to assess the unpredictability of behavior in response to environmental changes. Thus, entropy excluding that associated with the action domain was calculated by dividing the units into day and night to compute the probability distribution.

C. Feature Creation

In this study, two types of derived scores were generated to more precisely capture nocturnal behavioral patterns that show a high correlation with depression. The features used in this study are designed to reflect the quantity of actions, their variability, and the interactions between actions, respectively, according to their respective roles.

Specifically, raw sensor-based features are quantitative indicators reflecting the intensity and frequency levels of daily and nighttime activities, while entropy metrics quantify the irregularity of behavioral patterns over time. Furthermore, the composite score was designed to reflect interaction patterns where different behavioral signals appear simultaneously. The first score measures the level of circadian rhythm disruption by considering both reduced daytime physical activity and increased smartphone use and light exposure during nighttime hours, with the formula presented in (4). The second score quantifies the level of nighttime digital overstimulation by integrating screen exposure immediately before sleep, duration of nighttime smartphone use, and nighttime light exposure, and its formula is given in (5). At this stage, the weights (w_1, w_2, w_3) for each variable (Z scores) were set based on domain knowledge, drawing from prior studies that reported correlations with depression[2][3][4]. This composite indicator is expected to enhance depression prediction performance by reflecting behavioral coupling patterns that are difficult to capture using single-sensor-based entropy indicators.

$$\boldsymbol{Score\ = w_1 Z(day\_step\_count)\ -\ w_2 Z(night\_phone\_use)\ -\ w_3 Z(night\_light\_exposure)} \tag{4}$$

$$\boldsymbol{Score\ = w_1 Z(sleeptime\_screen\_duration) + w_2 Z(night\_phone\_use\_duration) + w_3 Z(night\_light\_exposure)} \tag{5}$$

III. EXPERIMENT RESULTS

In this study, an LSTM model was used to predict depression scores based on participants' multidimensional behavioral entropy. This is to effectively learn time-series behavioral data that changes over time and to reflect the temporal dependencies between consecutive behavioral patterns.

The input sequence for the LSTM was constructed based on the participant's daily data. Specifically, after arranging the daily aggregated behavioral and entropy metrics in chronological order, a sliding window of a fixed length was applied to generate a single input sequence from the data spanning consecutive n days. This enables the model to learn not only behavioral characteristics at a single point in time, but also continuous behavioral changes and cumulative patterns. In this study, the window size was set to 7 days to adequately reflect these temporal cumulative effects.

In this study, to verify the impact of feature engineering on the predictive performance for depression (PHQ-9), models were designed using four configurations: basic features (A), basic features + entropy (B), basic features + feature engineering (C), and all features (D). Model A is the baseline using only 22 raw features. Model B adds 4 entropy-based behavioral diversity metrics to verify the impact of behavioral irregularities. Model C introduces two composite scores to reflect interactions between metrics. Model D integrates all characteristics to form a maximum information-based comprehensive model.

The MSE (Mean Squared Error)-based loss learning curve in Fig. 1 was visualized based on the average of results obtained through repeated training using 5-fold cross validation. All four models showed stable convergence as the epoch increased. Model D (all features) showed the best results in terms of initial convergence speed and final loss value, Next, Model B (including entropy) rapidly reduced loss compared to the baseline and achieved learning stability. In contrast, Model A maintained the highest loss level and exhibited the lowest predictive performance, indicating that using only the original features makes it difficult to adequately explain the temporal changes in depressive psychological states. These results suggest that the addition of entropy and composite variables substantially contributes to improving model performance, and that utilizing all variables in model construction yields the most robust predictive capability.

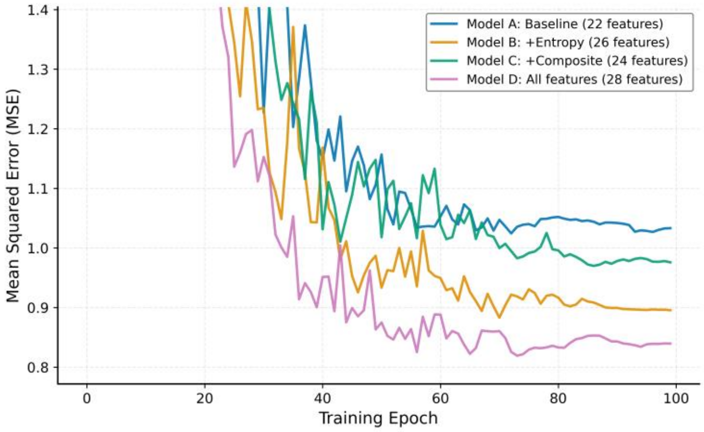

Fig. 1 MSE-based loss comparison graph

Furthermore, the fact that Model D demonstrated the most stable learning curve and superior generalization performance across all metrics empirically demonstrates that the integration of multidimensional behavioral indicators is a key factor in depression prediction models. This implies that extended features incorporating change patterns, volatility, and interaction information reflect mental health status more accurately than simple usage-based features. In particular, entropy-based indicators have been confirmed as a key characteristic that effectively explains behavioral deviations not captured by existing models, as they can quantify the irregularity of daily activities and emotional fluctuations.

This performance difference is also clearly evident in the MSE and R^2 comparison bar graphs shown in Fig. 2 and Fig. 3. Model D, which included all 28 features, achieved the highest predictive accuracy among the four models, recording the lowest MSE (0.832) and the highest R^2 (0.9015). In contrast, Model A, which used only the basic features, showed the highest error and the lowest explanatory power, demonstrating the limitations of a baseline model.

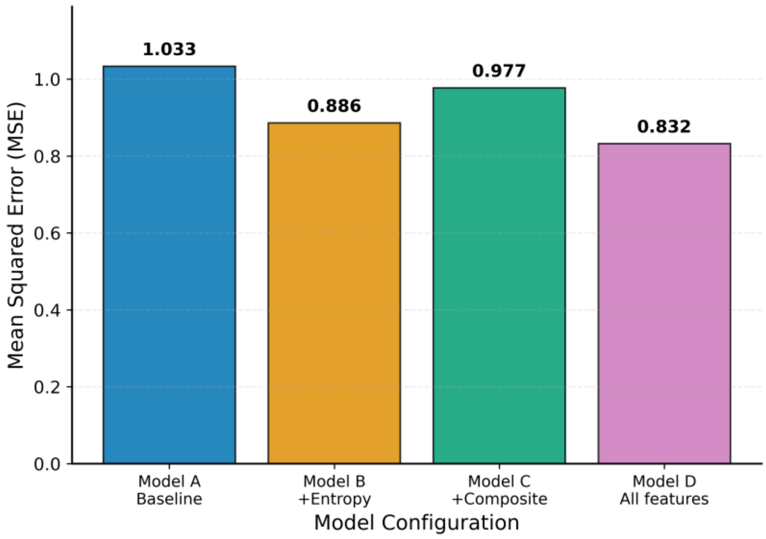

Fig. 2 MSE Comparison

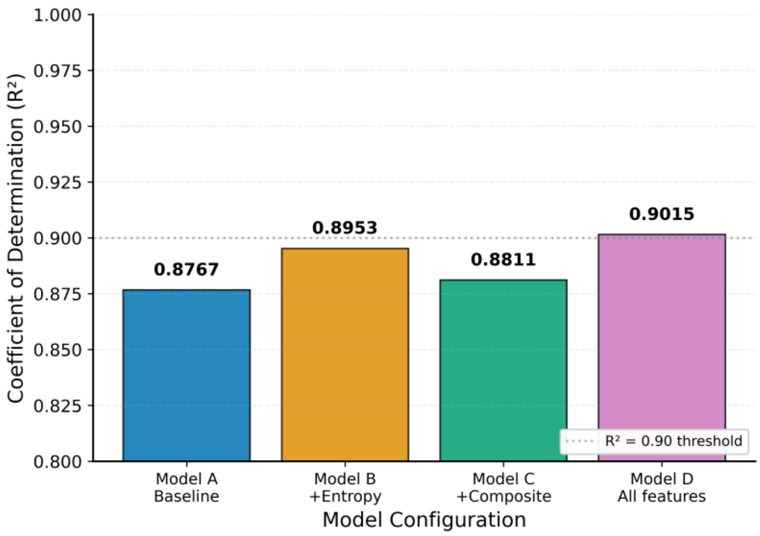

Fig. 3 R^2 Comparison

IV. CONCLUSION

This study aimed to predict depression (PHQ-9) scores using smartphone-based lifelog data, constructing an LSTM-based time series model that applied various behavioral entropies and feature engineering. In particular, comparing four models with different input variable configurations revealed that models incorporating both entropy metrics and domain knowledge-based composite features demonstrated superior predictive performance compared to models utilizing only basic features. The comprehensive model integrating all features showed the most stable and effective results. This confirmed that feature expansion including irregularities in behavior, pattern changes, and interaction information and entropy calculation substantially contributed to improving depression prediction performance.

Nevertheless, this study has several limitations. First, this study utilized a sample primarily composed of college students, and consequently, there are limitations to generalizing the findings to the general population with diverse age groups and lifestyle patterns. Second, since the behavioral characteristics analysis treated daytime and nighttime as discrete time intervals, it may not have fully reflected individual differences in sleep duration or the continuous changes in daily rhythms. Third, the PHQ-9 score used to measure depression levels is based on a self-report questionnaire, making it difficult to completely exclude the influence of respondents' subjective perceptions or response biases.

Despite these limitations, this study suggests that non-invasive mental health analysis is possible using only smartphone sensor data, demonstrating its potential as a framework for modeling and analyzing depression risk based on continuous, everyday behavioral observation. Furthermore, the proposed analytical framework can be extended to various mental health domains such as sleep disorders, anxiety, and stress. It is anticipated that this framework can contribute to research on preventive mental health management and the development of personalized analytical approaches, particularly when combined with long-term data collection, explainable AI (XAI)-based interpretation, and integration with clinical indicators.

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