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Random Forest-Based Prediction of Self-Reported Headache Complaint Indicators Among College Students Using Daily Activity and IoT Sensor Data

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Abstract: Headache complaints among college students may be associated with daily activity patterns and environmental conditions. This study aimed to model self-reported headache complaint indicators using daily activity questionnaire data and Internet of Things environmental data without positioning the output as a clinical diagnosis. Environmental data were recorded using BME280, BH1750, and MQ-135 sensors, while daily activity data were collected using a self-report questionnaire. Sensor readings were aggregated by date and integrated with questionnaire responses to form 305 records from 59 respondents. Random Forest was optimized using Randomized Search CV and evaluated against Decision Tree and K-Nearest Neighbors under three feature scenarios Internet of Things features, daily activity features, and combined features. SMOTE was applied only to the training data, and model differences were assessed using the McNemar test and Wilcoxon signed-rank test. Random Forest achieved the highest overall performance in the daily activity questionnaire scenario, with 81.52% accuracy, 84.96% F1-score, and 85.32% mean cross-validation F1-score. In the combined scenario, Random Forest obtained 77.17% accuracy and 81.08% F1-score. Statistical testing showed significant differences only in selected McNemar comparisons, while Wilcoxon tests on cross-validation F1-scores were not significant across all comparisons. Daily activity data were more informative than date-level environmental sensor data in this dataset. The findings should be interpreted as exploratory numerical performance results rather than evidence of clinical causality or universal model superiority.

Keywords: Daily activity, Decision Tree, Feature Importance, Internet of Things, K-Nearest Neighbors, Random Forest, Statistical Significance

INTRODUCTION

Headaches are a common health complaint that can disrupt activities, productivity, concentration, and overall quality of life. These complaints are associated with a range of factors, including biological, psychological, environmental, and lifestyle influences. Among college students, these factors are particularly significant due to demanding academic schedules, irregular sleep patterns, extensive use of electronic devices, and academically related stress, all of which may affect both physical and psychological well-being.

Environmental variables, including temperature, humidity, air pressure, light intensity, and air quality, provide contextual information for observing conditions that may coincide with headache complaints (Alif et al., n.d.), (Muttaqin et al., 2024) In addition to environmental context, daily activity history, such as sleep quality, duration of electronic device use, stress level, fatigue, physical activity, and water consumption, is useful for characterizing respondents' daily conditions (Syofyan et al., n.d.), (Maulidah & Hidayati, 2024), (Khasanah et al., 2025). Therefore, combining environmental context and daily activity data can support an exploratory framework for examining patterns of self-reported headache complaints among college students.

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The development of the Internet of Things (IoT) enables automatic, periodic, and digitally documented recording of environmental conditions (Rivangga et al., 2024). In this study, an ESP32-based IoT device was used in conjunction with BME280 sensors for temperature, humidity, and air pressure, BH1750 for light intensity, MQ-135 for air-quality indicators, and a DS3231 RTC for timekeeping. Environmental data was sent to the Firebase Realtime Database, while daily activity data and headache complaints were collected through a digital questionnaire. The device served as an instrument for recording general environmental data at the observation location, not as a measure of each respondent's personal environmental exposure (Kurnia, 2025), (Inzagi et al., 2025).

It is important to emphasize the limitations of the research design to prevent overinterpretation of the results. Only one IoT device was installed at a single observation location, consequently, the sensor data reflect general daily environmental conditions rather than individual exposure. Because data integration was performed by date, all respondents who submitted questionnaire responses on the same date received identical environmental feature values. Therefore, this study should be regarded as an exploratory investigation that integrates date-level environmental data with daily activity history to model self-reported headache complaint indicators among college students, rather than as a personalized prediction system.

The formation of target labels also requires careful interpretation. In this study, labels were generated from respondents' self-reported scores on a 0-10 headache scale. Scores of 0-3 were classified as no headache complaint indicator, while scores of 4 or higher were classified as a headache complaint indicator. These labels served as an operational binary classification approach and were not considered clinical ground truth because they were not based on a validated pain instrument, standardized anchor descriptions, or medical examination. Accordingly, the term indicator in this article refers to self-reported headache complaints rather than medical diagnoses.

The collected data were analyzed using a tuned Random Forest algorithm, which is suitable for multivariate classification tasks and provides feature-importance metrics to describe the relative contribution of features in the model (Yennimar et al., 2023), (Gea et al., 2025), (Tamba, 2022). Decision Tree was used as a simple tree-based baseline, while K-Nearest Neighbors was added as an additional distance-based baseline classifier. This broader comparison was used to strengthen model evaluation and reduce overclaiming of Random Forest superiority.

The contribution of this study lies in an exploratory evaluation of daily activity questionnaire features and Internet of Things-based general environmental features for modeling self-reported headache complaint indicators among college students. This study does not aim to establish a clinical diagnostic system or to prove that environmental exposure causes headache complaints. Instead, it evaluates how different feature groups perform under an ablation setting, consisting of sensor features, daily activity questionnaire features, and their combination. The novelty of this study is therefore positioned as an initial comparative analysis of feature-group contribution in a limited observational dataset, rather than as evidence that Internet of Things integration improves predictive performance.

Accordingly, this study aims to record general environmental data using an Internet of Things device, integrate the environmental data with students' daily activity questionnaire data by date, construct operational labels for self-reported headache complaint indicators, evaluate tuned Random Forest performance under three feature scenarios, compare its performance with Decision Tree and K-Nearest Neighbors baselines, apply statistical significance testing, and analyze feature importance as a descriptive measure of model contribution. All findings are interpreted within the limitations of self-reported labels and general environmental sensor data.

LITERATURE REVIEW

Several previous studies have used the Random Forest algorithm for classification and prediction in the health and environmental fields. In the context of health condition prediction based on medical record data, applied Random Forest to predict heart failure and demonstrated that the algorithm has quite good capabilities in classifying health conditions based on clinical data (Tamba, 2022), which is in line with the findings of who implemented Random Forest for stroke diagnosis classification using secondary medical record data and obtained an accuracy of 95% with an AUC value of 0.80 (Ary Prandika Siregar et al., 2023); however, both studies focused entirely on a clinical diagnostic approaches using patient medical parameters without involving environmental data or daily activity data.

In the domain of environmental quality prediction, an Internet of Things and cloud-computing-based system has been developed to predict air quality levels in real time, demonstrating that integration between sensor devices and online platforms can support efficient environmental data collection (Rivangga et al., 2024). Random Forest has also been applied to predict the Air Pollution Standard Index in Jakarta and demonstrated the algorithm's ability to estimate environmental conditions with adequate performance (Roris et al., 2025). However, both studies focused on estimating regional environmental conditions and did not connect the obtained environmental data with individual-level health complaint indicators.

In the integration of Internet of Things and machine learning for health monitoring, Random Forest has been combined with the MAX30102 physiological sensor for early detection of heart health conditions, showing the

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potential of combining sensor data with ensemble learning in an automated monitoring system (Simamora et al., 2025). However, this application was limited to physiological parameters and did not include environmental variables or users' daily activity patterns.

In the context of utilizing behavioral and lifestyle data for health prediction, Showed that daily activity and lifestyle data have the potential to be used as predictors of health conditions through a machine learning approach (Maulidah & Hidayati, 2024). while compared the performance of Decision Tree and Random Forest in predicting hypertension based on medical record data and concluded that Random Forest tends to produce better performance than a single decision tree model ("Prediksi Penyakit Hipertensi Menggunakan Metode Decison Tree Dan Random Forest," 2024). Nevertheless, these studies relied mainly on existing clinical or lifestyle datasets and did not involve direct environmental data collection through sensors. Based on these studies, the integration of general environmental sensor data and daily activity data for modeling self-reported headache complaint indicators in college students remains relatively unexplored and is appropriate for exploratory analysis.

METHOD

This research is a quantitative study with a systems-based experimental approach. Data were obtained from two primary sources: Internet of Things-based environmental sensors and respondents' daily activity questionnaires. All data were processed through data cleansing, sensor data aggregation, date-based integration, operational label formation, feature formation, machine learning modeling, validation, performance evaluation, and feature contribution analysis. The focus of the research was not medical diagnosis but an initial evaluation of self-reported headache complaint indicators.

The research was conducted within a university environment where the Internet of Things device was installed. The device was placed in an academic activity area to ensure that the collected environmental data were relevant to the general observation area. The device used an ESP32 microcontroller integrated with a BME280 sensor to measure temperature, humidity, and air pressure; a BH1750 sensor for light intensity; an MQ-135 sensor for relative air-quality indicators; and a DS3231 RTC for timekeeping. The MQ-135 sensor was used as a relative raw-reading indicator and was not converted into AQI or specific gas concentrations.

Sensor readings were taken periodically and recorded using timestamps. Sensor data was sent to the Firebase Realtime Database and then backed up in CSV format via Google Sheets and local storage. The time-series sensor data, originally in the form of periodic readings, was aggregated into daily summaries. This aggregation was performed to obtain the average, maximum, and minimum values for each environmental variable. Environmental change features were then created, including delta_temperature, delta_humidity, delta_pressure, delta_light, and delta_air.

Data on students' activity and headache complaints were collected using a Google Form completed once daily in the evening, between 8:00 PM and 10:00 PM. The questionnaire included daily activity level, duration of electronic device use, sleep duration, sleep quality, water consumption, stress level, fatigue, activity environment, and headache severity. Each respondent was assigned a code to maintain anonymity and to allow calculation of the number of unique respondents and the distribution of responses per respondent.

Environmental data were collected using a single Internet of Things device installed at one observation location within the university environment. Sensor readings were aggregated into daily summaries and then merged with questionnaire data by date. Consequently, all respondents who submitted questionnaire responses on the same date received identical environmental feature values. Therefore, the sensor variables in this study represent general daily environmental conditions at the observation location and should not be interpreted as individual environmental exposure.

The target label was constructed from respondents' self-reported headache scores on a 0-10 scale. Scores from 0 to 3 were coded as no headache complaint indicator, while scores of 4 or higher were coded as a headache complaint indicator. This threshold was used only as an operational binary classification rule for machine learning evaluation. The labels were not derived from clinical diagnosis, validated pain instruments, or medical examination. Therefore, the output of the model represents self-reported headache complaint indicators rather than clinical headache risk or medical ground truth.

The preprocessing stage included normalizing column names, removing duplicate data, removing records with missing values, selecting records with paired sensor data and completed questionnaires, converting data types, encoding categorical data, generating binary labels, and generating daily delta features. Age and gender were not used as primary features because the study focused on daily activities and the general environment. The final dataset was then split into training and testing sets in a 70:30 ratio. SMOTE was applied only to the training data to address class imbalance without introducing data leakage, while the testing data retained its original distribution (Muhammad Alfathan Harriz, 2025).

The modeling features were divided into three scenarios: sensor features only, activity questionnaire features only, and a combination of both. The sensor scenario contained delta_temperature, delta_humidity, delta_pressure, delta_light, and delta_air. The activity questionnaire scenario contained activity, device usage, sleep, sleep quality,

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drinking water, stress, fatigue, and activity environment. The combined scenario contained all features from both groups. Random Forest was used as the main classifier, Decision Tree was used as a simple tree-based baseline, and K-Nearest Neighbors was used as an additional distance-based baseline.

Random Forest hyperparameter tuning was performed using RandomizedSearchCV on the training data. The tuned parameters included n_estimators, max_depth, min_samples_split, min_samples_leaf, and max_features. Decision Tree was configured with max_depth=10, class_weight=balanced, and random_state=42. K-Nearest Neighbors was configured with n_neighbors=5, distance weighting, and Euclidean distance; StandardScaler was applied before KNN because the algorithm is sensitive to feature scale. These models were evaluated under identical feature scenarios to support a fair comparison.

The environmental change feature was calculated using Equation (1), where the delta for each sensor variable is obtained by subtracting the daily minimum from the daily maximum. In this equation, x represents the daily sensor variable, x_max the daily maximum, and x_min the daily minimum. The binary classification label is shown in Equation (2), with s representing the respondent's self-reported headache score.

$$\Delta_x = x_{max} - x_{min} \quad (1)$$
$$y = 0, if\ 0 \ \leq s \ \leq 3; 1, if\ s \geq 4 \quad (2)$$

Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, and 5-fold stratified cross-validation. The F1-score was used as an important indicator because the label distribution was not completely balanced. In addition, statistical significance testing was performed to avoid overclaiming model superiority. The McNemar test was used to compare paired predictions on the holdout testing set, while the Wilcoxon signed-rank test was used to compare cross-validation accuracy and F1-scores across the same folds (Rainio et al., 2024). Feature importance in Random Forest was used descriptively and was not interpreted as causal evidence.

Table 1. Research Method Design Summary

Component	Information
Types of research	Quantitative with a systems-based experimental approach
Data source	IoT sensors and daily activity questionnaire
Sensor device	BME280, BH1750, MQ-135, RTC DS3231, ESP32
Data storage	Firebase Realtime Database, Google Sheet, local CSV
Prediction target	Self-report-based headache complaint indicators
Main model	Random Forest Classifier
Comparison model	Decision Tree Classifier and K-Nearest Neighbors
Data ratio	Training 70% and testing 30%
Hyperparameter tuning	RandomizedSearchCV for Random Forest
Statistical testing	McNemar test and Wilcoxon signed-rank test

Table 2. Modeling Feature Scenario

Feature Group	Variables
IoT Sensors	delta_temperature, delta_humidity, delta_pressure, delta_light, delta_air
Activity questionnaire	activity, device_usage, sleep, sleep_quality, drinking_water, stress, fatigue, activity environment
Combined	All IoT sensor features and all activity questionnaire features

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RESULT

This section presents the research results, starting with data collection, sensor validation, preprocessing, Random Forest model testing, an ablation study, comparison with Decision Tree and KNN, cross-validation, statistical significance testing, feature importance, and sensor range analysis. The results demonstrate the process of integrating Internet of Things sensor data and students' daily activity data, and evaluate the dataset's initial potential for modeling self-reported headache complaint indicators.

Data Collection Results and Sensor Stability

The data used in this study come from environmental data recorded by IoT sensors and daily student activity data collected through a digital questionnaire. Sensor data includes temperature, humidity, air pressure, light intensity, and air quality indicators. Questionnaire data includes daily activity, electronic device usage, sleep, sleep quality, water consumption, stress, fatigue, activity environment, and headache levels. After data cleaning, duplicate removal, complete data selection, and date-based merging, a final dataset of 305 records from 59 unique respondents was obtained.

Each record represents a single respondent on a specific date, paired with daily environmental data for that date. The number of unique respondents and the distribution of records per respondent were examined to ensure that the dataset was not dominated by a single respondent. Most respondents had seven records, while others had only one. The largest respondent contributed 2.3% of the total data, so the dataset composition was not concentrated in a single individual.

Table 3. Final Dataset Summary

Information	Mark
Training	213
Testing	92
Final record count	305
Data source	IoT sensors and questionnaires
Prediction target	Headache complaint indicators

Table 4. Summary of Respondent Data Structure

Information	Mark
Number of records	305
Number of unique respondents	59
Respondent with 7 records	41
Respondent with 1 record	18
Most respondents record percentage	2.3%

Sensor validation was performed to ensure that the environmental data obtained were within reasonable bounds before being used in modeling. Temperature and humidity readings from the IoT sensor were compared with an HTC-2 digital hygrometer. The readings were relatively close to those of the comparison device. Differences in readings can be influenced by the device's sensitivity, sensor position, ventilation, and microenvironmental conditions around the device. The MQ-135 sensor is only used as a relative indicator of changes in air quality, not as an absolute AQI value.

A stability check of the sensor data was also conducted during the observation period. Sensor data was collected between 9:00 AM and 9:00 PM to represent environmental conditions during students' daily activities. The results showed that the sensor data comprised 998 records, of which 995 occurred between 9:00 AM and 9:00 PM. The sensor data covered 7 observation dates with an average of 142.14 records per date. The minimum number of records per date was 135, and the maximum was 144, indicating that the sensor data collection was quite stable throughout the study period.

Table 5. Summary of Sensor Data Stability

Information	Mark
Total number of sensor records	998
Number of sensor records at 09.00-21.00	995
Number of sensor observation dates	7
Average sensor records per date	142.14

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Minimum sensor record per date	135
Maximum sensor records per date	144
Sensor observation clock	09.00-21.00

Data Preprocessing Results

Preprocessing was performed to ensure that the dataset was formatted appropriately for machine learning. This stage included normalizing column names, removing unused columns, converting data types, encoding categorical data, generating operational labels, and generating environmental change features. Labels were generated from a self-reported headache scale, with scores of 0-3 indicating no headache complaint indicator and scores of 4 or higher indicating a headache complaint indicator. Because the labels were derived from self-reports, they are interpreted as indicators of headache complaints rather than clinical diagnoses.

The label distribution indicates that the number of records with headache complaint indicators exceeded the number of records without complaint indicators. The dataset consisted of 123 records without complaint indicators and 182 records with complaint indicators. This imbalance was the reason for using class_weight=balanced in the model and applying SMOTE to the training data. SMOTE was not applied to the testing data to ensure that evaluation remained based on the original distribution and to prevent data leakage.

Table 6. Self-Reported Headache Complaint Indicator Label Categories

Headache Score	Label	Description
0-3	0	No headache complaint indicator
>=4	1	Headache complaint indicator

Table 7. Distribution of Dataset Labels

Label	Description	Number of Records
0	No headache complaint indicator	123
1	Headache complaint indicator	182

Environmental features were generated as daily deltas, namely the difference between the daily maximum and minimum values. Delta features were used to represent daily changes in general environmental conditions at the sensor location. Because sensor data were merged with questionnaire data by date, all respondents on the same date received the same sensor feature values. Therefore, delta features cannot be interpreted as each respondent's individual environmental exposure.

Table 8. Environmental Change Features

Feature	Formula	Description
delta_temperature	temperature_max - temperature_min	Daily temperature change
delta_humidity	humidity_max - humidity_min	Daily humidity change
delta_pressure	pressure_max - pressure_min	Daily air pressure change
delta_light	light_max - light_min	Daily light-intensity change
delta_air	air_quality_max - air_quality_min	Daily relative air-quality indicator change from MQ-135

Ablation Study Results and Model Comparison

Random Forest was used as the main model, while Decision Tree and KNN were used as baseline models. Model comparison was conducted under equivalent feature scenarios, and the results were supported by statistical significance testing.

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Table 9. Ablation Study Results and Model Comparison

Scenario	RF Accuracy	RF F1-score	DT Accuracy	DT F1-score	KNN Accuracy	KNN F1-score
IoT sensors	56,52%	62,26%	56,52%	62,26%	56.52%	65.52%
Activity questionnaire	81,52%	84,96%	76,09%	80,70%	70.65%	76.11%
Combined sensor + questionnaire	77.17%	81.08%	60,87%	65,38%	66.30%	70.48%

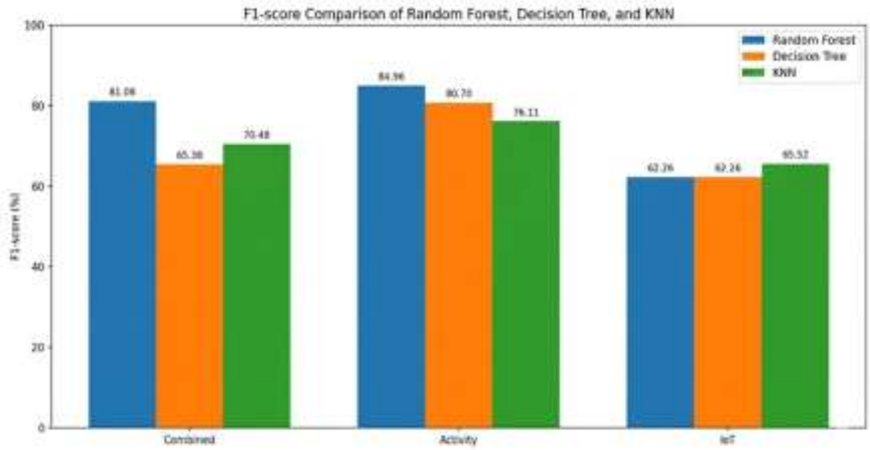

Fig 1. Comparison of the F1-Score of Random Forest, Decision Tree, and K-Nearest Neighbors

The ablation results show that Random Forest with daily activity questionnaire features achieved the highest overall performance, with an accuracy of 81.52% and an F1-score of 84.96%. The environmental sensor-only scenario produced low performance across all models; KNN achieved the highest F1-score in this scenario at 65.52%, while Random Forest and Decision Tree both obtained 62.26%. In the combined feature scenario, Random Forest achieved 77.17% accuracy and an F1-score of 81.08%, outperforming Decision Tree and KNN. These findings indicate that, in this dataset, daily activity questionnaire features were more informative than date-level environmental sensor features.

Confusion Matrix and Cross-Validation Results

Table 10. Confusion Matrix Activity Questionnaire Model

Actual/Predicted	No Indicator	Indicator
No Indicator	27	10
Indicator	7	48

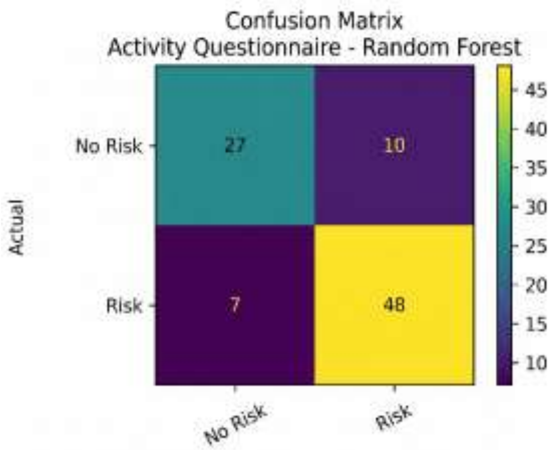

Fig 2. Confusion Matrix Activity Questionnaire Random Forest

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The confusion matrix of the daily activity questionnaire model shows that 27 records were correctly classified as no headache complaint indicator and 48 records were correctly classified as headache complaint indicator. The model produced 17 misclassifications, consisting of 10 false positives and 7 false negatives. In the context of self-reported complaint indicator modeling, false negatives should be interpreted carefully because they represent records with reported complaint indicators that were predicted as no complaint indicators.

Table 11. Random Forest Cross-Validation Results

Feature Scenario	Mean CV Accuracy	Mean CV F1-score
IoT sensors	54.43%	58.58%
Activity questionnaire	82,30%	85,32%
Combined sensor + questionnaire	78.03%	81.62%

The 5-fold cross-validation results show that Random Forest using activity questionnaire features obtained the highest mean cross-validation F1-score of 85.32%. In the combined scenario, Random Forest obtained a mean cross-validation F1-score of 81.62%, while Decision Tree and KNN obtained 78.23% and 72.07%, respectively. In the sensor-only scenario, all models showed relatively low cross-validation performance, confirming that date-level sensor features alone were less informative than activity questionnaire features.

Table 12. Statistical Significance Test Results

Feature Scenario	Comparison	McNemar p-value	Wilcoxon CV F1 p-value	Interpretation
IoT sensors	RF vs Decision Tree	1.0000	1.0000	Not significant
IoT sensors	RF vs KNN	1.0000	0.8125	Not significant
Activity questionnaire	RF vs Decision Tree	0.1797	0.0625	Not significant
Activity questionnaire	RF vs KNN	0.0063	0.1875	Significant by McNemar only
Combined sensor + questionnaire	RF vs Decision Tree	0.0026	0.0625	Significant by McNemar only
Combined sensor + questionnaire	RF vs KNN	0.0525	0.0625	Not significant

The statistical tests show that Random Forest was significantly different from KNN in the activity questionnaire scenario based on the McNemar test ($p=0.0063$), and significantly different from Decision Tree in the combined scenario based on the McNemar test ($p=0.0026$). However, the Wilcoxon signed-rank tests on cross-validation F1-scores did not show statistically significant differences at the 0.05 level across all comparisons. Therefore, Random Forest is interpreted as having the strongest numerical performance in the main feature scenarios, but not as universally superior across all statistical comparisons.

Feature Importance Results

Feature importance was used to describe the relative contribution of each feature in the Random Forest data-splitting process. The feature importance value indicates how much a feature contributed to model separation within the dataset. It does not directly indicate a cause-and-effect relationship with headache complaints. The global feature importance results show that daily activity variables contributed more dominantly than Internet of Things sensor variables.

Table 13. Feature Importance of the Combined Random Forest Model

Variable	Importance Value
fatigue	0.244188
stress	0.208506
drinking_water	0.109594
activity	0.068734
device_usage	0.050947

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delta_light	0.043184
activity_environment_indoor_ac	0.041065
delta_air	0.040276
delta_pressure	0.037534
sleep_quality	0.036666
delta_humidity	0.035682
sleep	0.030076

Table 14. Total Contribution of Feature Groups

Feature Group	Total Importance
Internet of Things sensors	0.186019
Daily activity	0.813981

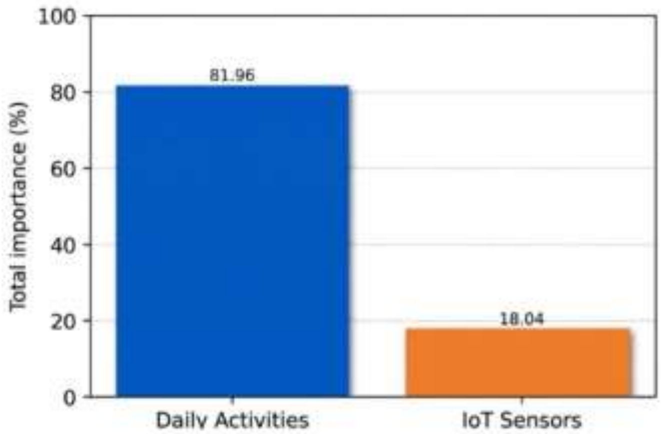

Fig 3. Total Contribution of IoT Sensor Features and Activity Questionnaire

The feature importance results show that daily activity features contributed 81.40% of total feature importance, while environmental sensor features contributed 18.60%. These values do not indicate causal effects. They only show how frequently and effectively the features contributed to model separation within this dataset. Therefore, fatigue, stress, drinking water, activity level, device usage, and sleep-related variables should be interpreted as informative variables for the model, not as proven causes of headache complaints.

Analysis Sensor Range and Discussion

The sensor range analysis was conducted only as an exploratory description of environmental patterns in the dataset. Several ranges of delta_air, delta_pressure, and delta_light showed relatively high proportions of headache complaint indicators. However, these results cannot be interpreted as environmental thresholds for headache complaints. The MQ-135 values were still relative sensor readings and were not calibrated into AQI or specific gas concentrations. Moreover, because the same sensor values were assigned to all respondents on the same date, the sensor range analysis does not represent individual exposure and cannot support causal conclusions.

Table 15. Sensor Range with High Complaint-Indicator Percentage

Sensor Variable	Value Range	Indicator Percentage
delta_light	1882-2494	68.18%
delta_air	106-194	72.73%
delta_pressure	4.18-4.75	69.23%
humidity_mean	64.02-67.65	65.15%

In general, the ablation study results showed that daily activity data were more informative than date-level environmental data from Internet of Things sensors. Random Forest with activity questionnaire features produced the highest overall numerical performance, whereas sensor-only models showed weak performance. The combined model improved over Decision Tree and KNN in the holdout test but remained lower than the activity-only

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Random Forest model. This indicates that the addition of sensor features did not provide sufficient additional information under the current data design.

DISCUSSIONS

The discussion focuses on interpreting model testing results from the ablation study, comparing Random Forest with Decision Tree and KNN, interpreting statistical significance testing, and analyzing feature contributions. The discussion emphasizes model performance, daily activity variables, environmental sensor contribution, and research limitations in modeling self-reported headache complaint indicators.

Discussion of Model

The ablation study results showed that Random Forest with activity questionnaire features achieved the best overall numerical performance, with an accuracy of 81.52% and an F1-score of 84.96%. In the combined scenario, Random Forest achieved 77.17% accuracy and an F1-score of 81.08%, outperforming Decision Tree and KNN. However, the statistical significance results indicate that Random Forest superiority should be interpreted cautiously because not all pairwise comparisons were significant across both McNemar and Wilcoxon tests.

The McNemar test showed significant differences for Random Forest versus KNN in the activity questionnaire scenario and for Random Forest versus Decision Tree in the combined scenario. Nevertheless, the Wilcoxon signed-rank test on cross-validation F1-scores did not indicate statistically significant differences at the 0.05 level across all model comparisons. Therefore, this study reports Random Forest as the model with the strongest numerical performance in the main feature scenarios, not as a model with universal statistical superiority.

This performance decline indicates that the addition of sensor features did not improve model performance. This likely occurred because sensor features were date-level variables and had the same value for all respondents on the same date, thus not representing individual variation in environmental exposure. Therefore, the combined model results cannot be interpreted as evidence that Internet of Things sensors strengthen individual prediction. Rather, they indicate that the sensor contribution remained limited in this study's data design.

The addition of sensor features to the combined scenario may have introduced limited additional information because the features lacked individual variation among respondents on the same date. Thus, the lower performance of the combined model compared with the activity questionnaire model is an important finding: in this research design, general environmental sensor features did not provide sufficiently strong additional information beyond daily activity variables.

Discussion of Activity Factors

Feature importance indicates that fatigue, stress, drinking water, activity level, and sleep quality were among the most informative variables for the model. These variables are related to students' physical condition, daily activity load, water consumption pattern, and rest quality. Therefore, in this dataset, daily activity variables had a stronger predictive relationship with self-reported headache complaint indicators than date-level environmental sensor variables. This relationship is predictive within the dataset and should not be interpreted as causal evidence.

Discussion of IoT Sensor Factors

The Internet of Things sensor feature group had a total importance of 18.60% in the combined model, but its interpretation is limited. Sensor data came from a single device at a single location and were aggregated by date, so all respondents on the same date received identical sensor values. Therefore, these results do not prove that personal environmental exposure affects respondents' headache complaints. They only indicate limited contextual patterns of the general daily environment within the dataset.

Discussion of Sensor Value Range

Sensor range analysis showed that several ranges of environmental change values had relatively high proportions of headache complaint indicators, including delta_air 106-194, delta_pressure 4.18-4.75, and delta_light 1882-2494. However, these results cannot be interpreted as general thresholds for headache complaints. The analysis is exploratory because the MQ-135 values are relative sensor readings and have not been calibrated into AQI or specific gas concentrations. Furthermore, the sensor values used were identical for respondents on the same date. Therefore, the sensor range analysis only provides an initial overview of general environmental data trends and not evidence of individual exposure or clinical causality.

Research Limitations

This study has several limitations. First, the target labels were generated from self-reported headache scores and were not based on clinical diagnosis or validated pain instruments. Second, the dataset consisted of 305 records from 59 respondents, so the findings remain preliminary and cannot be generalized broadly. Third, the environmental sensor data represented one observation location and were not measured at the individual level.

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Fourth, MQ-135 readings were used as relative air-quality indicators and were not converted into AQI or specific gas concentrations. Fifth, the model comparison was expanded by adding KNN and hyperparameter tuning for Random Forest, but the Wilcoxon tests did not show significant differences across all comparisons; therefore, model superiority should be interpreted cautiously. Future studies should use validated headache assessment instruments, larger datasets, individual or wearable sensors, calibrated environmental measurements, broader baseline models, and more extensive nested hyperparameter tuning.

CONCLUSION

This study evaluated the use of daily activity questionnaire data and Internet of Things-based general environmental data for modeling self-reported headache complaint indicators among college students. The final dataset consisted of 305 records from 59 respondents. Random Forest was compared with Decision Tree and KNN under sensor-only, activity-only, and combined feature scenarios. The activity questionnaire scenario produced the highest overall performance, with Random Forest achieving 81.52% accuracy, 84.96% F1-score, and 85.32% mean cross-validation F1-score. In the combined scenario, Random Forest achieved 77.17% accuracy and 81.08% F1-score. Statistical testing showed that several holdout-test differences were significant based on the McNemar test, but the Wilcoxon signed-rank test did not indicate significant differences in cross-validation F1-scores across all comparisons. Therefore, the findings should be interpreted as exploratory numerical evidence rather than definitive statistical proof of universal Random Forest superiority. Feature importance analysis showed that daily activity features contributed 81.40% of total importance, while environmental sensor features contributed 18.60%. Overall, daily activity data were more informative than date-level environmental sensor data in this dataset.

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