Gmail

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Notification of Acceptance of Your Paper ID 4164 for the ECTI DAMT and NCON 2025 International Conference

1 message

ECTI DAMT and NCON 2025 <ectidamtandncon2025@easychair.org> Mon, Dec 30, 2024 at 11:36 AM

To: Pratya Nuankaew <pratya.nu@up.ac.th>

Dear Pratya Nuankaew,

The decision for the paper ID 4164 entitled AI for Healthcare: A Classification Model for Personalized Premenstrual Symptoms and Depressive Crisis Risk Tracking Using Data Analytics and Machine Learning is "Accept with minor revision" and review results are shown below. Please revise and update your camera-ready to the EasyChair system by 15 January 2025. The format of the conference both on Microsoft Word (A4) and Latex is available at https://www.icdamt.org/submission/.

For further preparation, please carefully check the conference's important date at https://www.icdamt.org/call-for-paper/. In addition, it is a condition of paper acceptance that you or the nominated presenting co-author must register for the conference by the registration deadline of 13 January 2025 otherwise, the papers will be removed from the program.

The instructions and registration site are available at https://www.openbadgepay.com/.

For more information, please visit www.icdamt.org. If you have any inquiries, please feel free to contact us.

Best Regards,
ECTI DAMT and NCON 2025 Committee

SUBMISSION: 4164
TITLE: AI for Healthcare: A Classification Model for Personalized Premenstrual Symptoms and Depressive Crisis Risk Tracking Using Data Analytics and Machine Learning

----------------------- REVIEW 1 ---------------------
SUBMISSION: 4164
TITLE: AI for Healthcare: A Classification Model for Personalized Premenstrual Symptoms and Depressive Crisis Risk Tracking Using Data Analytics and Machine Learning
AUTHORS: Pratya Nuankaew, Jidapa Sorat, Jindaporn Intajak, Jirapron Inta and Wongpanya Nuankaew

----------- Overall evaluation -----------
SCORE: 0 (major revision)
----- TEXT:
The authors developed the classified model for stress, anxiety, and depression effects from survey data using several ML techniques.

The submission requires revision to align with established academic standards.

Data Collection:
This section should provide a detailed explanation of how the data was collected, including the sampling design, tools used (e.g., survey forms), and the type of data gathered (continuous or categorical).

- Please clarify the sampling design implemented in this study.
- What is the total population size (N)?
- Based on the "random sampling" method referenced by the authors, how many female students were registered during the 2024 academic year?
- How was the sample size (n) determined from the population?

The authors should relocate Table I to the results section, possibly under the subsection "Context of the Collected Data."

Additionally, the descriptive statistics of the sample data should be presented, specifically highlighting the representation across the 18 educational institutions at the university. Are all faculties within the university included?

Providing this information would substantiate the predictive model's applicability for future analysis involving female students at the University of Phayao.

- Were some data points in Table I initially continuous and subsequently converted into categorical data?
- Were all features utilized in the ML model exclusively as categorical variables? If the data was regrouped, the authors should cite relevant references to justify this categorization.

Research Tools:
Consider renaming this section to "Data Preprocessing" or "Data Manipulation" to reflect its purpose better.

This section should comprehensively outline the dataset preparation steps for ML model training. The authors should include:
- A description of the raw data format.
- Data cleaning and transformation processes (if applicable).
- Any feature engineering conducted.

Furthermore, the final dataset should be described in detail, including:
- The final sample size.
- The outcome variables (labels) and their data types.
- The predictor variables (features) and their data types.

SMOTE should be properly cited, as should any techniques such as Grid Search or Random Search. Note that the last paragraph in this section is redundant and may be omitted.

Modeling:
The CRISP-DM methodology should be cited and introduced at the beginning of the "Materials and Methods" section, possibly after the research scope. As this methodology is central to the study, a brief explanation of its six steps would provide valuable context.

If feasible, include a short description or key characteristics of the ML models utilized.

Model Results and Model Performance:
Tables IV to VI currently share the same title, "Evaluation of the Anxiety Severity Model," which should be corrected for clarity.

Discussion:
This section repeats content from the results section and should instead provide a more comprehensive analysis of the findings. For example:

Why does the SVM model perform best in classifying depression and stress severity, while K-NN outperforms in anxiety severity classification?

Is this outcome consistent with the distribution of samples across the five severity levels presented in Table III?

Additional aspects that merit discussion include the impact of sample size and resampling techniques (e.g., oversampling and undersampling). The use of SMOTE, which creates synthetic samples by interpolating between points and their K-nearest neighbors, may increase the risk of overfitting and should be evaluated in this context.

Questions:

- Given that SMOTE addresses class imbalance, why are additional metrics beyond accuracy necessary, particularly when there is no inherent bias toward majority or minority classes?

Suggestions:

- Use abbreviations for healthcare terms and ML model names after their first mention in the text.
- The authors should perform preliminary data analysis or exploratory data analysis (EDA) to derive insights and obtain critical findings that could support or lead to the study's results and discussion.

----------------------- REVIEW 2 ---------------------
SUBMISSION: 4164
TITLE: AI for Healthcare: A Classification Model for Personalized Premenstrual Symptoms and Depressive Crisis Risk Tracking Using Data Analytics and Machine Learning
AUTHORS: Pratya Nuankaew, Jidapa Sorat, Jindaporn Intajak, Jirapron Inta and Wongpanya Nuankaew

----------- Overall evaluation -----------

SCORE: 1 (minor revision)
----- TEXT:
The research work is interesting and could provide a strong impact. However, the classification is unclear. There should be details regarding the features (how many and what are they?) and the labels (how to get the labels?) used in classification.

----------------------- REVIEW 3 ---------------------
SUBMISSION: 4164
TITLE: AI for Healthcare: A Classification Model for Personalized Premenstrual Symptoms and Depressive Crisis Risk Tracking Using Data Analytics and Machine Learning
AUTHORS: Pratya Nuankaew, Jidapa Sorat, Jindaporn Intajak, Jirapron Inta and Wongpanya Nuankaew

----------- Overall evaluation -----------
SCORE: 2 (accept)
----- TEXT:
Contributions
The paper proposes a machine learning-based classification model aimed at tracking and predicting premenstrual symptoms and depressive crises. Utilizing six machine learning techniques (Decision Trees, K-Nearest Neighbors, Logistic Regression, Naïve Bayes, Random Forests, and Support Vector Machines), the study evaluates their performance using a dataset from 282 female students. It aims to address the critical need for personalized healthcare solutions in managing Premenstrual Syndrome (PMS) and related mental health issues. The research contributes to healthcare by identifying effective predictive models and providing actionable insights for future applications, such as mobile health tools.

Strengths
Focus on Personalized Healthcare: The study addresses a relevant issue in women's health, emphasizing the need for personalized risk assessment and early intervention for PMS and depressive crises.
Comprehensive Methodology: The use of multiple machine learning techniques with detailed evaluation metrics (accuracy, precision, recall, F1-score, and time) strengthens the reliability of the findings.
Real-World Application: The proposed models are well-suited for deployment in mobile health applications, providing a pathway for practical use in healthcare.
Effective Handling of Imbalanced Data: The application of SMOTE (Synthetic Minority Oversampling Technique) to address class imbalances enhances the robustness of the models.
Weaknesses
Limited Dataset: The dataset is relatively small (282 participants) and geographically restricted, which may limit the generalizability of the findings.
Model Scope: While the study explores six models, it omits other advanced techniques such as ensemble methods or deep learning, which could potentially improve performance.
Lack of External Validation: The models are not validated using external datasets, raising questions about their robustness in diverse contexts.
Insufficient Analysis of Psychological Context: The study does not delve deeply into the psychological and behavioral factors influencing PMS and depression, which could add depth to the findings.
Suggestions for Improvement
Expand Dataset: Include a larger and more diverse sample to improve the generalizability of the findings and ensure the robustness of the models across different populations.
Explore Advanced Techniques: Investigate additional machine learning techniques, such as ensemble methods or deep learning models, to potentially enhance prediction accuracy.
Conduct External Validation: Test the developed models on external datasets to evaluate their robustness and applicability in different settings.
Integrate Behavioral Insights: Incorporate a deeper analysis of psychological and behavioral factors influencing PMS and depressive crises to provide a more comprehensive perspective.
Assess Model Scalability: Include a discussion on the scalability and computational feasibility of the models in real-world applications, especially in resource-constrained settings.