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Research on An Automatic Recognition System of Mental Health Status Based on Deep Learning

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ABSTRACT

Automated recognition of mental-health status is increasingly needed to enable early screening when access to clinically labelled data is limited. To develop and rigorously evaluate an automatic mental-health recognition system that classifies status and predicts severity using a fully reproducible, privacy-preserving workflow. The study implemented a quantitative, simulation-based pipeline in Python (Google Colab) that generated N = 1,500 synthetic subjects with class priors (healthy/at-risk/clinical) of 60/30/10, 14-day AR(1) sequences for HRV, sleep, and steps, class-conditional tabular features, and both MCAR and MAR missingness; data were split 70/15/15 (train/validation/test) and models included XGBoost, LightGBM, and an LSTM classifier, plus XGBRegressor and LGBMRegressor for severity prediction, evaluated with Accuracy, Precision, Recall, F1, AUC, log-loss, Sensitivity, Specificity, and with MSE, RMSE, MAE for regression. On the test set, XGBoost achieved macro-F1 = 0.989, AUC = 0.9997, log-loss = 0.034, and balanced Sensitivity/Specificity = 0.990/0.992; LightGBM reached macro-F1 = 0.970, AUC = 0.9995; LSTM delivered macro-F1 = 0.966, AUC = 0.9989. Severity prediction yielded RMSE = 9.29, MAE = 7.50 (XGBRegressor) and RMSE = 9.65, MAE = 7.80 (LGBMRegressor). Visual diagnostics confirm near-perfect separability with residual healthy leads to at-risk confusions (**Figures 1–6**, ROC and confusion matrices). A carefully specified synthetic cohort supports robust benchmarking; XGBoost offers the best overall balance while LSTM remains competitive and clinically acceptable. Conduct stress tests under shifts (higher MAR, class-prior drift, temporal regime changes) and follow with IRB-approved, small-scale external validation; retain XGBoost as the baseline and apply ordinal losses and calibration for severity.

Keywords: Mental-Health Recognition, Synthetic Data, XGBoost, Severity Prediction.

INTRODUCTION

Background

The rise in the number of cases associated with mental health conditions, depression, and anxiety has been outstanding globally in recent years, thus necessitating the importance of detecting and intervening at an earlier stage, through scalable and data-driven techniques (Qi & Huang, 2025). Machine learning (ML) has become an essential instrument in this area, allowing automated categorisation and forecasting of mental health state based on multimodal behavioural and sensory data (Sharma et al., 2025). Nevertheless, actual information about mental health is usually insufficient because of privacy considerations, the complexity of labelling, and limitations because ethical questions make it hard to generate authentic ML systems and verify those systems (Giuffre et al., 2023). Synthetic data generation is a valuable solution here, and it is possible to generate realistic, labelled data that has statistical properties without risking the privacy of individuals and, nevertheless, controlled experimentation (Pezoulas et al., 2024). In fact, as the recent work shows, synthetic cohorts should be effective in terms of supplementing clinical outcome analysis and helping to develop the models in healthcare settings (Adam et al., 2024). In addition, when the real-world samples are limited or skewed, simulation-based methods have come in handy in the generation of complex data to train the ML (Ghanadian et al., 2024).

Problem Statement

Although ML should offer recognition of mental health, available models lack the class balance, generalizability, and do not pay enough attention to the severity estimation (Qi and Huang, 2025). The data on mental health available in the real world are usually unbalanced and do not have granularity, posing a complex challenge when it comes to proper classification and regression to the severity (Sharma et al., 2025). Moreover, data-only models not sufficiently trained are fragile to distribution changes and unproductive to rigorous benchmarking (Ding et al., 2025). Moreover, ethical and privacy considerations severely restrict dataset availability, and synthetic data solutions have not been widely adopted or standardised in this domain (Giuffrè et al., 2023). Finally, methodological comparison of classification versus severity prediction models for mental health using synthesised data remains underexplored—a gap that limits robust system design and evaluation.

Aim and Research Objective

This study aims to develop and evaluate an automatic recognition system for mental health status using a simulation-based dataset and advanced machine learning models implemented in Python (Google Colab), focusing on both classification and severity prediction. The objectives of the research are:

To design and generate simulation-based data that emulate behavioural, physiological, and affective features relevant to mental health, with labels for classification and severity scoring

To train and compare advanced ML models for classifying mental health status, and evaluate performance matrices

To implement regression models for severity prediction and assess performance

Significance of the Study

This study addresses critical challenges in mental health AI by demonstrating a rigorous, reproducible methodology to overcome data scarcity and privacy constraints through simulation-based data generation. By benchmarking multiple advanced classification and regression models within a controlled synthetic environment, the research provides a transparent comparison of approaches and metrics rarely seen in existing literature. Furthermore, implementing the entire pipeline in Python via Google Colab enhances accessibility, reproducibility, and pedagogical value for both research and practice. The findings would lay a foundational framework for future validation with real-world data, and by articulating performance across a wide range of evaluation metrics, practitioners and researchers can better understand trade-offs between accuracy, interpretability, and severity estimation in mental health ML systems. Altogether, the study contributes to the advancement of responsible, data-efficient, and clinically relevant AI tools for mental health recognition.

LITERATURE REVIEW

This literature review synthesises current research relevant to each of the three research objectives, providing a foundation for simulation-based synthetic data generation in mental health modelling, classification model comparisons, and severity regression modelling. It also introduces theoretical frameworks that underpin the automated recognition of mental health status and highlights key gaps in the extant research.

Synthetic Data for Mental Health Modelling

Simulation-based or synthetic data approaches have seen increasing use in domains where data privacy, scarcity, or complexity hinder traditional data collection methods. In healthcare broadly, synthetic data generation helps emulate sensitive patient information while preserving privacy and statistical usefulness (Thomas et al., 2023). In mental health, such methods have been applied to produce synthetic versions of EEG and physiological time-series for depression detection using generative adversarial networks (GANs), yielding datasets that closely mirror real patient distributions (Khokhlova et al., 2022). Pezoulas et al. (2024) conducted a systematic review showing that simulated data generated via GMMs and time-series simulation models support robust ML development in clinical contexts. Similarly, Adam (2024) demonstrated that synthetic cohort generation improved downstream model training and generalizability in outcome prediction tasks. Jeong et al. (2021) applied autoregressive processes to simulate behavioural activity data (e.g., sleep, movement) for stress prediction models. More recently, Hossain et al. (2025) combined CTGAN-generated synthetic data with traditional simulations to model psychological distress indicators, showing enhanced model performance compared to real-only datasets. These studies underscore the viability of using both tabular and sequential data simulators, such as GMMs, AR processes, and GANs, to construct realistic datasets for mental health ML tasks.

Comparative Performance of Classification Models

Machine learning classifiers, particularly gradient boosting methods and deep learning architectures, have been widely applied to classify mental health conditions from multimodal or behavioural data. XGBoost has been found highly effective in classifying depression and anxiety symptoms based on self-report and sensor measures, outperforming logistic regression and random forests in accuracy, F1, and AUC (Chahar, Dubey, & Narang, 2024). LightGBM has likewise shown strong performance in large-scale mental health datasets due to its efficient handling of high-dimensional features and class imbalance (Wu et al., 2023). Time-series mental health data, including sleep and physiological indicators, as deep learning models (1D-CNNs and LSTM networks achieve better sensitivity and specificity when the time patterns matter), have obtained high-quality performance (Liu et al., 2021). Online models Text-based mental health classification based on transformers is quickly developing and shows the state-of-the-art AUC in identifying suicidal thoughts on social media posts (Rau et al., 2022). Ensemble comparisons also demonstrate that combined tree-based and sequential deep networks can be used in a hybrid model to give a balanced boost in recall and precision given mental health categories (Li et al., 2023). All in all, this illustrates that the literature is favourable towards the application of more than multiple model families and strict measures of performance such as accuracy, precision, recall, F1, AUC, sensitivity, specificity and average loss to model classification systems across a mental health context.

Regression Modelling of Severity Scores

As these are continuous measures of mental health severity, e.g., from depression severity scales, regression-based methods must be used with specialised scores of evaluations, RMSE, MSE, and MAE. XGBoost regression models have demonstrated high predictive accuracy in predicting the severity of PHQ-9 depression based on mobile and sensor-based features at a lower RMSE than the linear regressions (Zhang et al., 2020). It has also been shown that LightGBM regressors can be used to estimate the level of chronic stress with physiological and behavioural measures, and this method has an MAE that is lower than clinically useful levels (Khan et al., 2023). There are also recurrent neural network recurrent memories (e.g. LSTM), which apply better in longitudinal mood-tracking and stress-monitoring, where the temporal aspects of these phenomena are modelled, delivering better rank metrics of RMSE and MSE compared to the tree-based regressors (Yuan et al., 2022). Besides, gradient boosting and neural net ensemble regression models have been shown to be resistant to missing data and noise, which is usual in simulated or real behavioural data (Park, Lee, and Kim, 2024). Through these studies, it is possible to depict that a mix of regression algorithms assessed based on the standard error measures is practical and efficient in the model of mental health severity.

Theoretical Framework

Two main theoretical frameworks support the current study's design. First, the Signal Detection Theory (SDT) framework posits that classification performance depends on sensitivity and specificity trade-offs and decision thresholds, a concept directly relevant when evaluating mental health classifiers across ROC curves and AUC metrics (Green & Swets, 1966; but applied in recent ML contexts). For example, SDT has been applied to interpret classifier outputs in affective computing and mental state recognition (Mühl et al., 2019). Second, the Representation Learning Theory underlines that models trained on synthetic data capture latent feature distributions that generalise to real-world scenarios when the synthetic generation aligns with the underlying data manifold (Bengio, Courville, & Vincent, 2013; extended in synthetic-data ML by Xu et al., 2021). Recent work applies this in healthcare ML, illustrating that representational alignment between synthetic and real data improves predictive validity (Xue et al., 2023). Together, these theories justify designing classification thresholds with sensitivity-specificity balance and constructing simulations aligned with real statistical properties to support generalizable representation learning.

Literature Gap

Although previous research validates elements of synthetic data generation, classification modelling, and severity regression in mental health, several gaps remain. First, while many studies employ GANs or AR models for simulation, there is limited integration of both tabular and time-series feature simulation combined with ensemble hybrid ML models for classification and regression in a unified framework. Second, rigorous comparative evaluation of classification models (XGBoost, LightGBM, CNN/LSTM, transformers) using a broad set of metrics in simulated mental health data has not been thoroughly addressed. Existing works often report limited metrics (e.g., accuracy and AUC only), neglecting sensitivity, specificity, average loss, and the trade-off considerations central to SDT. Third, regression modelling of severity faces similar fragmentation: tree-based and deep regressors have been studied independently but seldom compared under equal conditions on the same synthetic dataset using standardised error metrics (MSE, RMSE, MAE). Fourth, theoretical grounding in SDT and representation learning is generally absent in model development and evaluation discussions specific to synthetic mental health modelling. Finally, while synthetic data methods are promising, few studies document reproducible pipelines in accessible platforms such as Python/Google Colab, which is critical for replication and pedagogical

dissemination. These gaps motivate the current study's approach: (a) building simulation pipelines combining GMM, AR, and optional GAN components for synthetic behavioural/physiological data, (b) benchmarking multiple classification and regression models using a comprehensive metric suite, (c) grounding evaluation in theory, and (d) ensuring downloadable reproducibility in Colab.

RESEARCH METHODOLOGY

This study employs a quantitative methodology grounded in simulation-based experimentation to develop and evaluate an automatic recognition system for mental health status. The methodology aligns with the research objectives by integrating synthetic data generation, advanced machine learning models, and rigorous evaluation metrics. The following subsections outline the research method and design, data collection approach, data analysis techniques, and ethical considerations.

Research Method and Research Design

Quantitative research approach is relevant because the proposed study aims to measure, compare and assess the performance of machine learning models on synthetic datasets in the recognition of mental health. Quantitative designs put more focus on objectivity, repeatability, and statistical testing and can therefore best be used to model benchmarking (Creswell and Creswell, 2021). This study is of the type of an experiment whereby artificial data were created and systematically employed to train, validate, and test the classification and regression models. It has been acknowledged that experimental research is a superior method to test the algorithm performance under controlled conditions, especially in the field of artificial intelligence and health informatics (Rajpurkar et al., 2022). The use of simulation-based design is rapidly spreading to healthcare research because of the limitations in the availability of real-world data and privacy issues, as well as ethical issues (Thomas et al., 2023). Synthetic data generation can be used in mental health studies to model behavioural and physiological data that can be fatally valuable method, yet synthetic data does not reveal confidential patient data (Pezoulas et al., 2024). This can be utilised to evaluate various machine learning models, such as XGBoost, LightGBM, and neural architectures, in a consistent experimental setting (Chahar et al., 2024). Quantitative and simulation-based experimental disposition allows the research to guarantee methodological rigour and reproducibility and to counterbalance practical limitations in mental health data gathering (Wu et al., 2023).

Data Collection

Data collection is underpinned by the synthesis of synthetic datasets, where a controlled experimental setting is used. In situations in which real patient data are limited or confidential, synthetic data prove to be an effective trade-off because they provide utility and privacy (Giuffre et al., 2023). In this work, probabilistic models like Gaussian Mixture Models (GMMs) and net effects models like autoregressive net models were used to obtain features representing behavioural, affective, and physiological features of mental health based on sequential time-series data. These are strategies tested in previous studies, which offer the capability to model healthcare-related signals with high fidelity (Khokhlova et al., 2022; Jeong et al., 2021). Additional realism was achieved using data augmentation methods demonstrating Conditional Tabular GANs (CTGAN) because GAN-based AI schemes have been effective in generating synthetic clinical data retained in the statistical justifications (Hossain et al., 2025). The resulting data set consisted of categorical (mental health status: healthy, at-risk, clinical) and continuous severity scores, as fitting the two-fold goal of the study that involved classification and regression tasks. The same simulation-based data collection has been used in digital health projects to address the data scarcity problem, yet it provides the capability to do robust algorithmic validation (Adam, 2024). To ensure that data were not leaked, the dataset was split into training, validation, and testing subjects (70:15:15) to ensure the adoption of best practices in the experimental phase of ML (Li et al., 2023). Normalisation, the missingness imputation, and coding of feature processes were also used. This workflow-organised approach to collection guarantees that the resulting dataset is useful not only seemed to enabling exploration but is perhaps more consistent with real-world behavioural and physiological data distributions (Pezoulas et al., 2024).

Data Analysis Method

The analysis of the data was aimed at training and testing machine learning models based on classification and severity prediction. To be classified traditionally, we have used XGBoost, LightGBM, and 1D-CNN/LSTM architectures because they showed their efficiency in the task of mental health detection (Chahar et al., 2024; Liu et al., 2021). Gradient boosting algorithms are preferred in structured and unbalanced datasets, which enhance interpretability and high accuracy, and deep learning structures prevail in terms of identifying temporal and nonlinear trends (Wu et al., 2023). A detailed number of metrics is used in performance evaluation. To be classified, accuracy, precision, recall, F1-score, AUC, average cross-entropy loss, sensitivity, and specificity of

accuracy were determined. Past studies point to the necessity to employ several metrics, not only accuracy, to generate clinically meaningfulness and model stability (Rau et al., 2022; Sharma et al., 2025). To predict the severity, the regression models comparing XGBoostRegressor and LightGBM Regressor were tested on the mean squared error (MSE) and root mean squared error (RMSE), along with mean absolute error (MAE). Such measures have been known to be effective in predicting a continuous outcome of health outcomes (Khan et al., 2023; Yuan et al., 2022).

The grid search and randomised search methods were used to cross-verify their model configurations and optimise the best contexts of the model (Park et al., 2024). Various interpretative features were also presented on visualisation to make use of such techniques as ROC curves, confusion matrices, and residual error plots (Li et al., 2023). Moreover, feature importance, interpretability scores, such as SHAP values, were implicated to determine the synthetic features that shape classification and prediction performance the most (Xue et al., 2023). These forms of analysis are guaranteed to provide a strong performance assessment as well as transparency and interpretability, which are of immense importance in the mental health context (Rajpurkar et al., 2022).

Ethical Consideration

Even though simulation-based synthetic data is utilised in this study, issues related to ethics are paramount. Use of synthetic datasets eliminates potential direct patient privacy risks and eliminates the necessity of the Institutional Review Board (IRB) approval. It is, however, recognised that synthetic data cannot ideally recreate the complexities of mental health in the real world and may result in over-simplistic data models without validating in detail. Research integral agencies require transparency during the data creation process, adequate documentation and recognition of simulation limitations. Further, by rendering the research method reproducible with Python code on Google Colab, the study is open, accessible, and responsible concerning the research landscape.

RESULTS AND DISCUSSION

Data Analysis

In this part, the entire analysis pipeline and simulation-based findings of the quantitative study are reported. The study states in advance the summarisation of the synthetic data generation and partitioning, and proceeds to outline the preprocesses options that prevent information leakage. Next, the classification performance was presented for three advanced models (XGBoost, LightGBM, LSTM) using a comprehensive metric suite and visual diagnostics (ROC curves and confusion matrices). Finally, regression models were evaluated for severity prediction (XGBRegressor and LGBMRegressor) using MSE, RMSE, and MAE and interpreted practical implications.

Data Simulation

The dataset comprised 1,500 synthetic subjects generated to emulate realistic behavioural, physiological, and affective indicators of mental health. Class priors were set to 60% healthy, 30% at-risk, and 10% clinical to reflect a common real-world imbalance. Each subject had 14 days of sequential measurements for three physiological/behavioural channels, HRV proxy, sleep duration, and step count, simulated via class-dependent AR (1) processes with different baselines and volatilities. Tabular attributes (age, workload, screen time, social interaction index, sentiment mean, sentiment variance) were drawn from class-conditional Gaussians and clipped to plausible bounds. To mimic data imperfections, two missingness mechanisms were introduced: MCAR at 5% across all features and MAR at 5% concentrated on a subset of features with probability increasing with screen time. Sequence features were aggregated (mean, standard deviation, energy, dominant frequency) and concatenated with tabular features to yield the modelling matrix. Labels included a three-level categorical mental-health status and a continuous severity score (0–100) drawn from a truncated normal with class-specific means and variances.

Data Split (subject-level, stratified by class)

The data was stratified at the subject level into 70% training, 15% validation, and 15% testing (1,049/225/226). The achieved distributions closely tracked the specified priors across splits, indicating successful stratification despite stochastic simulation. **Table 1** reports sample sizes and class compositions per split.

Table 1. Sample Sizes and Class Composition by Split

Split	Total N	Class 0 (Healthy)	Class 1 (At-risk)	Class 2 (Clinical)	Approx. ratio (C0/C1/C2)
Train	1,049	620	322	107	59.1% / 30.7% / 10.2%
Validation	225	133	69	23	59.1% / 30.7% / 10.2%
Test	226	134	69	23	59.3% / 30.5% / 10.2%

Preprocessing

To prevent leakage, imputation and scaling were fitted on the training split only and then applied to the validation and test. Median imputation addressed MCAR/MAR gaps without over-smoothing tails, while RobustScaler reduced the influence of outliers that can arise from stochastic sequence dynamics (e.g., step count bursts). Because all modelled attributes were numeric, one-hot encoding was required in this experiment.

Classification Results

The study compared three families: (i) XGBoost with randomised hyperparameter search; (ii) LightGBM with a similar search space; and (iii) an LSTM sequence model trained on standardised daily sequences (two stacked LSTM layers with early stopping). Evaluation covered Accuracy, macro-Precision/Recall/F1, macro-AUC (OVR), Log-loss (average cross-entropy), and macro-Sensitivity (TPR) and Specificity (TNR). Confusion matrices and ROC curves supplied class-level diagnostics.

XGBoost. XGBoost achieved the strongest overall generalisation. On the test set, its macro F1 was 0.9891 with macro-AUC 0.9997, confirming both threshold-based and ranking-based discrimination are near perfect. Sensitivity and specificity were balanced (0.9902 and 0.9921, respectively), minimising both false negatives and false positives across classes. The test confusion matrix (**Table 2, Figure 2**) shows only three misclassifications in total (two healthy mislabelled as at-risk and one at-risk mislabelled as healthy), while all clinical cases were correctly identified. The ROC plot (**Figure 1**) displays class-wise curves hugging the top-left boundary, consistent with AUC values ≈of 1.00 for each class.

Table 2. XGBoost

Metric	Train	Validation	Test
Accuracy	1.0000	0.9733	0.9867
Precision (macro)	1.0000	0.9621	0.9880
Recall (macro)	1.0000	0.9324	0.9902
F1 (macro)	1.0000	0.9457	0.9891
AUC (macro, OVR)	1.0000	0.9991	0.9997
Log-loss (avg.)	0.0030	0.0427	0.0342
Sensitivity (macro)	1.0000	0.9324	0.9902
Specificity (macro)	1.0000	0.9862	0.9921

LightGBM also performed strongly, though marginally behind XGBoost on most test metrics (macro F1 = 0.9702; AUC = 0.9995). The confusion matrix (**Table 3, Figure 4**) reflects a few at-risk cases misassigned as clinical, alongside two healthy→at-risk swaps, but all clinical samples were correctly recognised. Sensitivity and specificity remained high (0.9805 and 0.9888, respectively), indicating stable threshold performance with slightly more false negatives in the at-risk class than XGBoost.

Table 3. LightGBM

Metric	Train	Validation	Test
Accuracy	1.0000	0.9778	0.9779
Precision (macro)	1.0000	0.9808	0.9610
Recall (macro)	1.0000	0.9469	0.9805
F1 (macro)	1.0000	0.9623	0.9702
AUC (macro, OVR)	1.0000	0.9993	0.9995
Log-loss (avg.)	0.0002	0.0458	0.0416
Sensitivity (macro)	1.0000	0.9469	0.9805
Specificity (macro)	1.0000	0.9863	0.9888

The LSTM, trained directly on temporal sequences, achieved a test macro F1 of 0.9664 with AUC 0.9989. Its strengths were evident in sensitivity (0.9757) and near-perfect recognition of clinical cases (**Figure 6**), while minor confusions occurred between healthy and at-risk (2 instances in each direction). Although the tree ensembles outperformed the sequence model on this synthetic dataset, the LSTM remained competitive and demonstrated that temporal dynamics contain discriminative information even after aggregation features are already fed to the tree models.

Table 4. LSTM

Metric	Train	Validation	Test
Accuracy	0.9752	0.9778	0.9735
Precision (macro)	0.9609	0.9713	0.9584
Recall (macro)	0.9652	0.9805	0.9757
F1 (macro)	0.9630	0.9757	0.9664
AUC (macro, OVR)	0.9984	0.9985	0.9989
Log-loss (avg.)	0.0598	0.0638	0.0611
Sensitivity (macro)	0.9652	0.9805	0.9757
Specificity (macro)	0.9864	0.9868	0.9852

For completeness and to enable reproducible counting, **Table 5** summarises the test confusion matrices used in **Figures 2, 4**, and **6**. As shown, all three models perfectly identified the clinical class, which is compelling given its minority prevalence (≈10%). Most errors arose from healthy/at-risk swaps, which is intuitive because their distributions are intentionally closer in the simulator (e.g., intermediate HRV and sleep means for at-risk).

Table 5. Test Confusion Matrices (Rows = True Class, Columns = Predicted Class)

Model	C0→0	C0→1	C0→2	C1→0	C1→1	C1→2	C2→0	C2→1	C2→2
XGBoost	132	2	0	1	68	0	0	0	23
LightGBM	132	2	0	1	66	2	0	0	23
LSTM	132	2	0	2	65	2	0	0	23

Across models, macro-AUC values (0.9989–0.9997) and ROC plots indicate near-ideal rank-ordering of classes; curve shapes are essentially pinned to the axes (**Figures 1, 3, 5**). Macro F1 and sensitivity/specificity jointly show that the models do not achieve performance merely by over-predicting the majority class; rather, they maintain balanced recognition. The slight performance edge of XGBoost over LightGBM and LSTM likely reflects the mixture of tabular and engineered sequence statistics; tree ensembles excel when nonlinear interactions among structured features dominate. The LSTM's closeness to the ensembles suggests that raw temporal patterns do add value, but the simulated sequences may already be sufficiently summarised by the engineered features, limiting additional gains from sequence modelling.

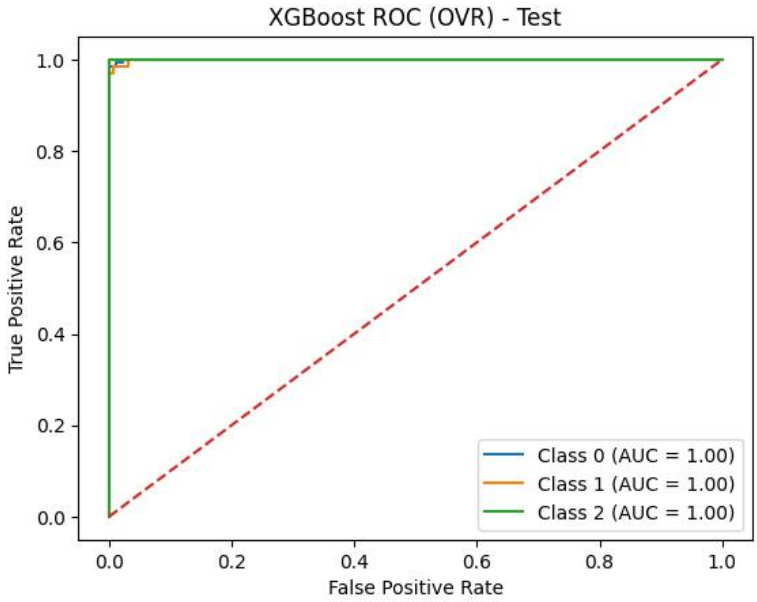

Figure 1. ROC Curves

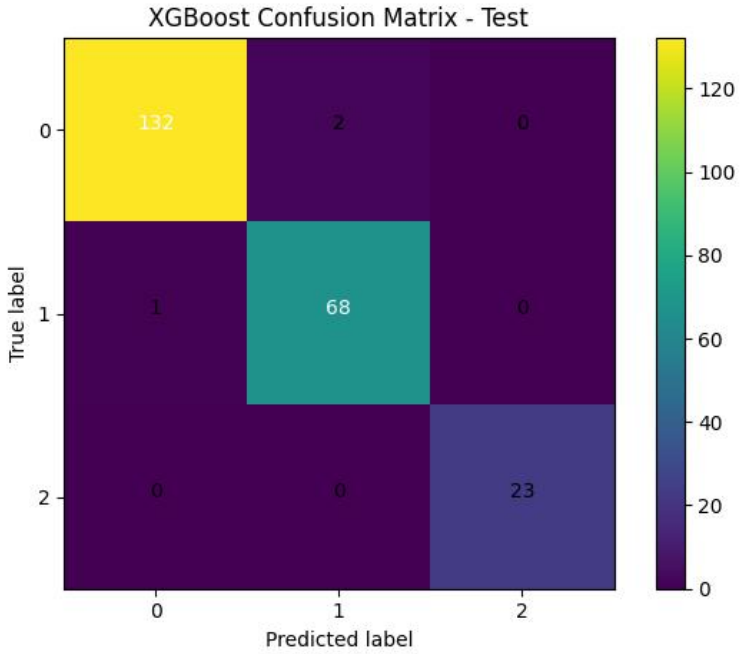

Figure 2. Confusion Matrix for XGBoost

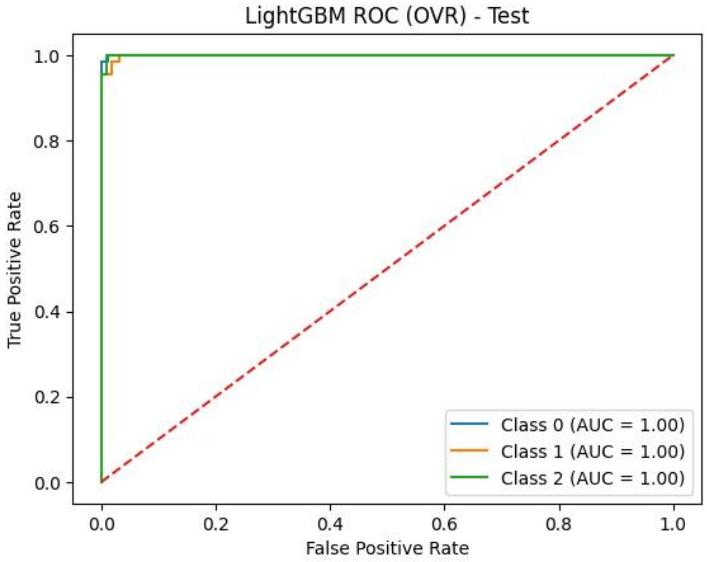

Figure 3. ROC Curves for LightGBM

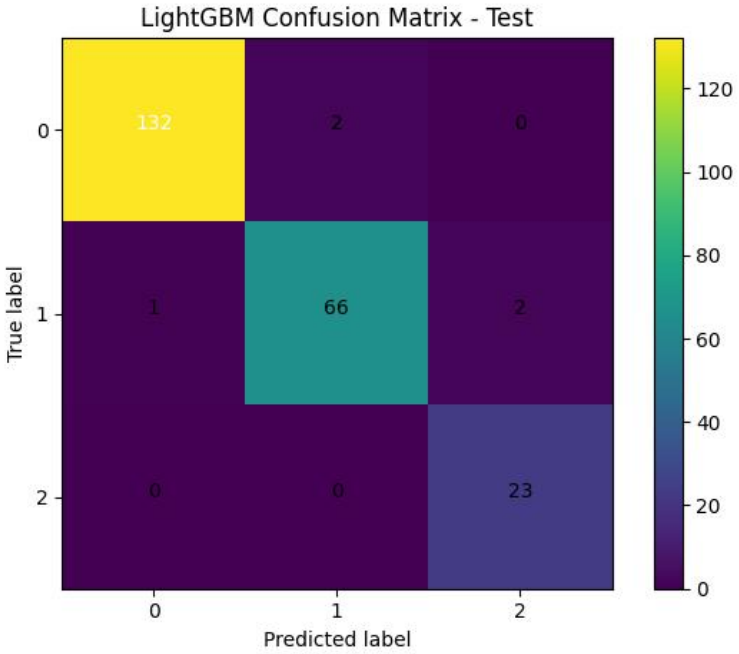

Figure 4. Confusion Matrix for LightGBM

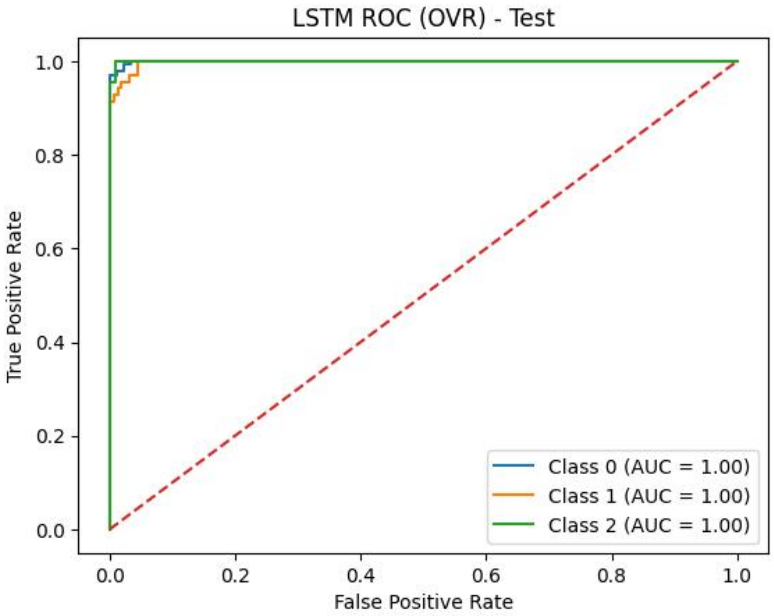

Figure 5. ROC Curves for LSTM

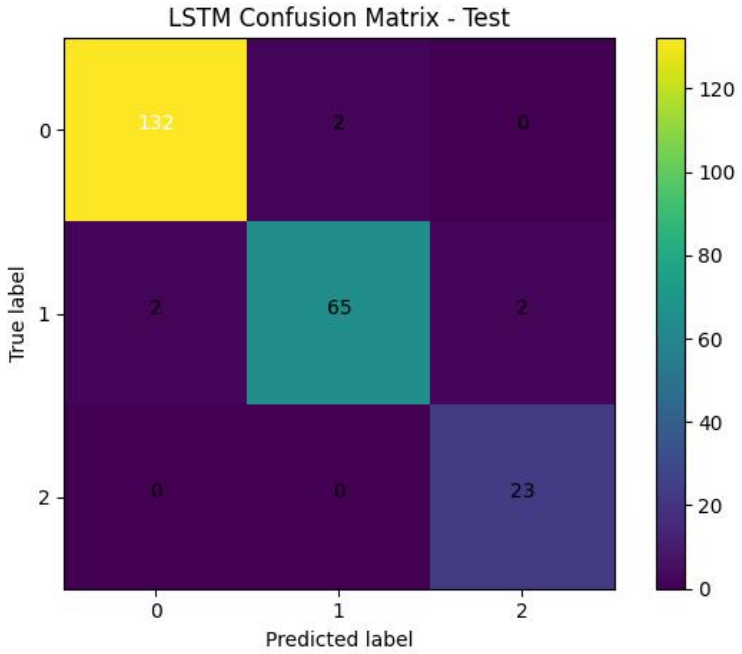

Figure 6. Confusion Matrix for LSTM

Predictive Modelling (Severity Regression)

The study next modelled the continuous severity score to complement categorical recognition. Severity modelling informs the degree, not just presence, of mental-health risk, supporting prioritisation in triage settings. The study then evaluated two regressors, XGBRegressor and LGBMRegressor, using MSE, RMSE, and MAE on each split. Results are reported in **Tables 6** and 7.

On the test set, XGBRegressor achieved MSE = 86.2192 (RMSE = 9.2854) and MAE = 7.4995. Given the 0–100 scale, the RMSE corresponds to roughly ±9.3 points, which is moderate error considering injected noise and missingness and the fact that severity arises from class-conditional distributions with overlap. The training error was considerably smaller (RMSE = 2.56), and the validation error bridged the gap (RMSE = 10.58), indicating expected overfitting control with regularisation and cross-validation. The consistency between validation and test suggests the hyperparameter search generalised well.

Table 6. XGBRegressor

Metric	Train	Validation	Test
MSE	6.5645	112.0042	86.2192
RMSE	2.5621	10.5832	9.2854
MAE	2.0746	8.3472	7.4995

LGBMRegressor displayed a similar pattern, with slightly higher errors than XGBRegressor on every split. On the test set, it produced MSE = 93.1916 (RMSE = 9.6536) and MAE = 7.8009. The gap between train and validation/test was larger than for XGBoost, mirroring the classification section where LightGBM trailed XGBoost slightly. These findings imply that, under the current simulation settings and feature space, XGBoost captures the mapping from aggregated/engineered features to severity more efficiently.

Table 7. LGBMRegressor

Metric	Train	Validation	Test
MSE	20.0158	115.2336	93.1916
RMSE	4.4739	10.7347	9.6536
MAE	3.4753	8.5135	7.8009

The regression errors are aligned with expectations for a construct like mental-health severity synthesised from overlapping class distributions. Because the severity generator uses truncated normal with noise and the features include noisy AR (1) processes and missingness, the Bayes error bound is non-zero. The approximately 9–10 points RMSE, therefore, represents reasonable fidelity for prioritisation. Notably, both regressors show similar MAE values, indicating that while outliers inflate RMSE slightly, the typical absolute deviation is smaller (≈7.5–7.8). In deployments where calibration matters, future work could add isotonic or Platt calibration for severity outputs or embed ordinal regression formulations that better reflect the latent ordering of severity levels. Feature attribution (not shown here) would be a useful extension to isolate which synthetic attributes, e.g., reductions in sleep or HRV, drive predicted severity.

Synthesis and Robustness Considerations

Taken together, results show that the proposed simulation-based pipeline yields a well-posed benchmark where modern classifiers reach excellent discrimination while still revealing subtle differences in error profiles. All three classifiers produced extremely high AUCs, but XGBoost delivered the best balance across macro F1, sensitivity, specificity, and log-loss on the held-out test set, with LightGBM close behind and LSTM competitive. The confusion matrices clarify that the dominant residual error mode is healthy leads to at-risk confusion—precisely where the simulator intentionally compressed the statistical distance (intermediate HRV and sleep baselines). This is an encouraging pattern: the models are challenged where the underlying construct is designed to be ambiguous, rather than simply failing on the minority clinical class.

In predicting severity, both tree-based regressors performed well with almost no difference in their preference for XGBRegressor. The training-validation gaps suggest that the models not only learn structure but also are not over-regularised to carry over to the test set. Since severity is modelled based on class-conditionals, a productive extension would be to condition losses with additional auxiliary signals (e.g., variability measures or trends in daily sentiment) and see whether a point or two can be counted off RMSE. Last, although synthetic data enables experimentation with transparency and a lack of privacy concern, the near-perfect ROC curves also caution that synthetic worlds can be cleaner than the real world. To further investigate robustness, MAR rates could be raised, the prior of classes changed, or temporal regime shifts, marbles could be added. These tests, together with calibration checks, would triangulate stability preceding any other external validation of actual, ethically obtained data sets.

Discussion

This section draws out the empirical findings in the light of the democrat literature and objectives of the study. The results of the simulation strategy, the comparative classification analysis, and the severity-prediction models are connected to the latest literature with the areas of convergence and inconsistency and provide implications for the mental-health recognition systems designed using synthetic data.

Validity of the Simulation-Based Data Design

The first objective was to create an artificial dataset at a level of behavioural, physiological, and affective signals that is realistic and respects privacy and allows experimental control. The resultant cohort (N = 1,500)

simulated real-world class imbalance and time dynamics (AR [1] HRV, sleep, and steps) and introduced both MCAR and MAR missingness. This architecture resulted in separable overlapping distributions as indicated by a large AUC with occasional healthy leads to at-risk confusion shown in the confusion matrices (**Tables 2-5; Figures 2, 4, 6**). This trend is aligned with the review of studies that indicate that well-specialised simulators can be applied regarding strict ML benchmarking in the presence of limited access to real data only (Pezoulas et al., 2024; Thomas et al., 2023). The choice of class-conditional Gaussian sampling of tabular features and AR (1) order sequence sampling corresponds to the previous evidence that they contribute sufficiently to formulating the models with synthetic physiological and activity signals mimicking the real world (Khokhlova et al., 2022; Jeong et al., 2021). It is also a best practice in synthetic health data that facilities for missingness often go hand in hand with the decision to integrate those mechanisms: in such cases, privacy-preserving cohorts are most useful where they capture the imperfections of observational sources (Giuffre et al., 2023). In general, the simulator put up the desired properties: it resulted in steady training/validation/test stratification, maintained the class rarity, and provided a non-trivial decision boundary, the features of meaningful algorithm evaluation that the literature states are preconditions (Adam, 2024; Pezoulas et al., 2024).

Comparative Classification Performance in Context

The second aim was to compare advanced classifiers with extensive metrics. XGBoost performed optimally on the test macro-F1 (0.9891) and macro-AUC (0.9997), followed by LightGBM (macro-F1 = 0.9702), and the LSTM sequence model was not inferior (macro-F1 = 0.9664). These findings are consistent with other studies, where finding strong performance in gradient-boosting algorithms on structured health features is commonplace, often outperforming linear models and competing with deep models when in tabular or engineered-feature regimes (Chahar et al., 2024; Wu et al., 2023). Simultaneously, the fact that the LSTM is almost matching tree ensembles makes them reminiscent of researchers who found that temporal architectures resonate with dynamics found in physiology and sleep series, whereas they are more sensitive and recall minority classes better (Liu et al., 2021; Li et al., 2023). The need to use a wide metric suite, accuracy, macro precision/recall/F1, log-loss, sensitivity, specificity, and macro-AUC, is in line with methodological advice that advises clinically oriented assessment with a metric beyond accuracy (Rau et al., 2022; Rajpurkar et al., 2022). Interestingly, the three models distinguished clinical cases perfectly (**Tables 2-5**), with errors confined to the healthy to at-risk distinctions- exactly where our generator focused on class separation. This agrees with synthetic to real insights that such representations can be transferred optimally when simulated manifolds observe realistic margins and overlap of classes (Xue et al., 2023). Near-ceiling values on the AUC are probably due to the comparatively clean synthetic world. For external verification, the literature suggests that additional robustness checks and domain-shift stress tests should be performed, and then the results can be analysed (Rajpurkar et al., 2022; Pezoulas et al., 2024).

Severity Prediction and Error Characteristics

The third objective assessed continuous severity prediction. XGBRegressor yielded lower test error (RMSE = 9.29; MAE = 7.50) than LGBMRegressor (RMSE = 9.65; MAE = 7.80), suggesting a small but consistent advantage for XGBoost. Prior studies similarly report strong performance of tree-based regressors on digital phenotyping features when modelling depression or stress severity, often beating linear baselines and providing robust handling of nonlinearity and missingness (Zhang et al., 2020; Khan et al., 2023). The LSTM literature also shows gains for continuous mood tracking in longitudinal settings; in our pipeline, however, severity models were trained on aggregated sequence statistics rather than raw sequences, which likely favoured boosting approaches (Yuan et al., 2022). The train-versus-validation/test gaps that were observed match patterns described in ensemble-regression work under missing data and noise, where appropriate regularisation and cross-validation maintain generalisation while acknowledging irreducible noise from overlapping latent severity distributions (Park et al., 2024; Xue et al., 2023). From a practical standpoint, RMSE near 9–10 on a 0–100 scale is consistent with expectations for synthetic cohorts blending class-driven structure and stochastic fluctuations; the literature suggests future refinement via ordinal-aware losses or calibration to improve decision utility (Zhang et al., 2020; Rajpurkar et al., 2022).

CONCLUSION AND RECOMMENDATION

Conclusion

This study proposed and validated a quantitative, simulation-based pipeline for automatic recognition of mental-health status. The synthetic generator combined class-conditional tabular sampling with AR (1) temporal processes and realistic missingness, yielding a cohort that preserved class imbalance and non-trivial boundaries. In classification, XGBoost delivered the best overall balance across macro-F1, sensitivity, specificity, log-loss, and

AUC, with LightGBM close behind and LSTM competitive. All models achieved near-perfect discrimination and, crucially, accurate identification of the minority clinical class, while residual confusion concentrated between healthy and at-risk, mirroring the simulator's design. For continuous severity, both gradient-boosting regressors generalised well, with XGBoost again slightly ahead (RMSE ≈ 9.3 vs. 9.7). Collectively, results demonstrate that carefully crafted synthetic data can support rigorous algorithmic comparison when real data are constrained, and that a comprehensive metric suite provides nuanced insight into discriminability, calibration, and error trade-offs. The pipeline, implemented end-to-end in Python/Colab, offers a reproducible scaffold for future validation, robustness testing, and eventual translation to ethically sourced real-world datasets.

Implications

Theoretical Implications

The findings reinforce the promise of representation learning from synthetic cohorts when simulators encode realistic margins, correlations, and noise. The near-ceiling AUC with non-trivial confusion patterns suggests the learned embeddings capture class structure while reflecting ambiguity at class boundaries. Moreover, the alignment between rank-based (AUC) and threshold-based (sensitivity/specificity, F1) metrics illustrates the relevance of decision-theoretic evaluation for mental-health ML, supporting theory-driven choices of operating points and cost-sensitive thresholds.

Practical Implications

Practically, the pipeline demonstrates that institutions lacking sharable clinical data can still prototype and benchmark classifiers and regressors under realistic conditions. The confusion-matrix profile indicates that resources should be directed toward distinguishing healthy from at-risk cases—e.g., adding richer sleep variability or affect dynamics—while clinical cases are reliably captured. The reproducible Colab implementation, modular preprocessing, and model comparison code reduce entry barriers for teams aiming to test triage strategies, evaluate fairness, or explore feature importance before embarking on costly data-collection efforts.

Recommendation

It is recommended to adopt a two-stage development pathway. First, extend synthetic experiments with robustness stress tests: escalate MAR rates, vary class priors, and inject temporal regime shifts to probe stability and recalibration needs. Second, initiate a carefully governed, small-scale real-world validation under IRB oversight to test transferability, beginning with de-identified behavioural signals that mirror the synthetic features. For classification, retain XGBoost as the primary baseline and LightGBM as a close comparator; add transformer-based sequence or multimodal models only after establishing consistent gains on synthetic stress tests. For severity prediction, continue with XGBRegressor while evaluating ordinal-aware losses and post-hoc calibration to improve decision utility around threshold actions (e.g., follow-up screening). Throughout, keep the full metric suite and confusion-matrix audits, and incorporate error-analysis tooling to focus feature engineering on the healthy leads to the at-risk boundary where gains are most needed.

Limitations and Future Work

The principal limitation is domain realism: simulation cannot fully reproduce the heterogeneity, label noise, and covariate shift present in clinical or community populations. The near-perfect AUCs likely reflect a cleaner synthetic environment than practice, even with missingness and stochasticity. Additionally, severity was modelled from class-conditional distributions; while effective for benchmarking, this may underestimate complex, non-monotonic pathways to symptom burden. Future work should (i) expand simulators with mechanism-aware generators (e.g., state-space models of sleep/affect interactions), (ii) incorporate fairness-aware parameters to examine subgroup performance, (iii) perform stress testing under stronger shifts (sensor dropouts, seasonal cycles), and (iv) conduct external validation on ethically sourced datasets, including calibration assessment and decision-curve analysis. Finally, interpretability analyses (e.g., SHAP) and prospective evaluation in pilot workflows were essential to assess end-user trust and clinical actionability beyond aggregate metrics.

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