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An artificial neural network-based decision support model for early prediction of mathematics learning challenges using the CRISP DM framework

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ABSTRACT

Identifying mathematics learning difficulties remains a challenge for educators due to the subjectivity and inefficiency of conventional methods in capturing psychological factors. To address this limitation, this study proposes an artificial neural network (ANN)-based decision support model developed within the cross-industry standard process for data mining (CRISP-DM) framework. The model integrates 16 academic indicators (quizzes, exams, remedial frequency, online activity) and psychological factors (motivation, anxiety, self-confidence, interest) from 163 student records at SMA Muhammadiyah 16 Jakarta. Synthetic minority over-sampling technique (SMOTE) and focal loss are applied to handle class imbalance and improve reliability. The proposed model achieves 98% accuracy and a 0.97 F1-score in classifying students into three difficulty levels: Easy, moderate, and difficult. These findings demonstrate the model's effectiveness in capturing complex relationships between cognitive and affective features. Unlike prior studies that rely solely on academic performance, this work contributes a robust, comprehensive data-driven framework that enhances multiclass classification for early educational intervention within the Indonesian context.

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1. INTRODUCTION

Mathematics learning difficulties are a major issue frequently experienced by Indonesian high school students. As a core subject essential for developing logical and analytical reasoning, mathematics often contributes significantly to students' low academic achievement [1], [2]. These difficulties arise not only from cognitive limitations but are also closely associated with affective factors such as anxiety, low motivation, and lack of interest in learning mathematics [3]–[5].

In most schools, the identification of learning difficulties still relies on traditional approaches, such as manual teacher observation or test-based evaluations, which are often subjective, time-consuming, and fail to capture psychological dimensions comprehensively [6]–[8]. This limitation delays effective interventions and can even increase students' psychological burden.

Educational psychology research emphasizes that intrinsic motivation fosters persistence, strong interest improves engagement, while anxiety reduces concentration and academic performance [9]–[12].

Students with low motivation often struggle with integral concepts [13], whereas those with high anxiety frequently experience difficulties in solving trigonometric problems [14], [15]. Therefore, psychological indicators such as motivation, interest, and anxiety are essential for understanding students' learning difficulties in mathematics [16]. Likewise, students with low interest tend to be less engaged in learning activities [17].

Most existing academic prediction systems rely solely on quantitative data like test scores and attendance, neglecting psychological factors [18], [19]. This limitation creates a significant gap in understanding the root causes of learning difficulties, as approaches integrating both academic and psychological indicators via a structured data mining framework and artificial neural networks (ANN) remain critically limited, particularly within the Indonesian educational context. To address this need, this study proposes an ANN-based multiclass model to capture complex, nonlinear relationships between these variables, classifying students into easy, moderate, and difficult learning levels [20], [21]. The main contribution of this work is bridging this gap by integrating academic performance with comprehensive psychological dimensions (motivation, anxiety, interest, self-confidence, and parental support). Furthermore, the model applies the cross-industry standard process for data mining (CRISP-DM) framework embedded with synthetic minority over-sampling technique (SMOTE), data augmentation, and focal loss to maximize prediction robustness. To the best of our knowledge, this is one of the first studies in Indonesia to combine these comprehensive factors within an ANN framework for early learning difficulty prediction.

The ANN operates through interconnected neurons that transmit input data and adjust connection weights iteratively using backpropagation and gradient descent algorithms to minimize prediction errors [22]–[24]. Employing nonlinear activation functions such as rectified linear unit (ReLU) and Softmax, ANN effectively captures complex patterns and performs multiclass classification, including grouping students into easy, moderate, and difficult learning levels. Its flexibility in processing various data types, numerical, categorical, and behavioral, enables ANN to combine academic and psychological factors within one analytical model [25].

Although ANN risk overfitting and class imbalance from limited data, this study addresses these challenges using SMOTE, data augmentation, focal loss, early stopping, and learning rate tuning. The research follows the six-stage CRISP-DM framework spanning from business understanding to deployment to guide the predictive modeling process. Unlike prior studies that focus primarily on academic performance [26]–[28], this work integrates both academic and psychological factors within the ANN-CRISP-DM pipeline [28]–[32] for multiclass prediction of mathematics learning difficulties (Easy, Moderate, Difficult). To the best of our knowledge, this is among the first studies in Indonesia to adopt this combined approach for early educational decision support.

The proposed web-based system targets performance benchmarks of at least 85% accuracy, 80% recall, and 0.80 F1-score to enable early intervention. ANN is specifically selected for its superior ability to model complex, nonlinear relationships within heterogeneous educational data, outperforming traditional methods like decision trees (DT) and support vector machines (SVM) in capturing interactions between cognitive and affective factors.

2. METHOD

This study adopts a machine learning approach using an ANN to predict students' mathematics learning difficulty levels based on academic and psychological indicators. The ANN model classifies students into three categories: Easy, moderate, and difficult, serving as an early warning system to support timely educational interventions. The overall methodology, including data collection, model training, and evaluation, is illustrated in Figures 1 and 2.

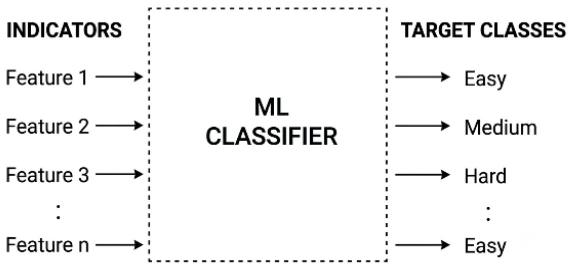

Figure 1. Conceptual method

During training, data from SMA Muhammadiyah 16 Jakarta-comprising academic variables and psychological factors from a validated 5-point Likert questionnaire-was preprocessed using normalization, categorical encoding, and SMOTE, The ANN model was developed via TensorFlow/Keras [31] using ReLU activation [32], dropout regularization, and the Adam optimizer with tuned hyperparameters. For evaluation, 30% of the dataset was reserved as testing data to measure accuracy, precision, recall, and F1-score. The complete list of input attributes is summarized in Table 1.

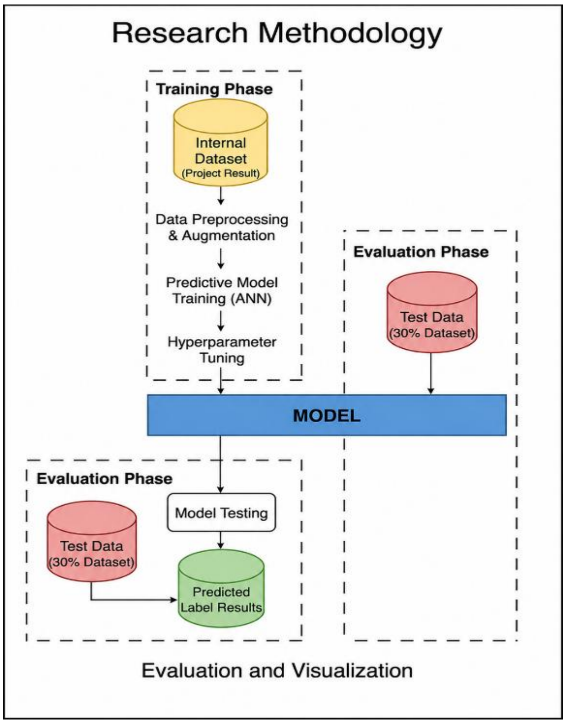

Figure 2. Research method

Table 1. Input variables

No	Variable	Description
1	Age	Student's age
2	Latest Mathematics Quiz Score	Score obtained from the most recent quiz
3	Mathematics Semester Exam Score	Final exam result in mathematics
4	Mathematics Assignment Score	Average score of mathematics assignments
5	Number of Mathematics Remedial Sessions	Frequency of remedial participation
6	Average Score of Other Subjects	Overall academic achievement across subjects
7	Motivation	Level of enthusiasm and drive to learn mathematics
8	Anxiety	Level of anxiety during problem-solving
9	Interest	Interest and curiosity toward mathematics
10	Self Confidence	Confidence in completing mathematical tasks
11	Parental Support	Family encouragement in academic learning
12	Study Duration	Average time spent studying mathematics per day
13	Online Platform Access Frequency	Number of times accessing online learning platforms weekly
14	Online Study Time	Total duration accessing online materials per day
15	Task Submission	Consistency in submitting assignments on time
16	Classroom Participation	Activeness in classroom discussions and group activities

The output variable classifies mathematics learning difficulty into three target classes (Table 2) based on the average of daily quizzes, semester exams, and assignments. During training, the ANN model maps complex relationships between 16 input variables and these difficulty levels, integrating Batch Normalization for faster convergence and focal loss for class imbalance. Evaluation via confusion matrices and epoch-wise accuracy trends proves the model successfully identifies learning difficulties by balancing academic and psychological factors. This framework establishes the foundation for a web-based decision support system enabling early diagnoses and targeted interventions.

Table 2. Output variable classification

Class	Score Range	Description
Difficult	< 60	Students experience significant difficulty in understanding mathematical concepts.
Moderate	60–79	Students show moderate comprehension but still require improvement.
Easy	≥ 80	Students demonstrate good mastery of mathematical materials.

3. RESULTS AND DISCUSSION

This section presents the findings of the study, including data exploration results, ANN model evaluation, and predictive analysis related to the classification of students' mathematics learning difficulty levels. The data exploration stage provides an overview of the dataset's structure and distribution, as well as the relationship between academic and psychological indicators and the categorized levels of learning difficulty.

3.1. Dataset overview

The preprocessed dataset consists of 120 student records with a target variable distributed into three classes: Moderate (46.67%), Easy (29.17%), and Difficult (24.17%), indicating a manageable class imbalance. Descriptive statistics reveal that the mean assignment score (82.67 ± 13.43) is notably higher than the semester exam (62.76 ± 18.00) and daily test (66.55 ± 18.71) scores, while remedial frequency shows high variability (9.13 ± 22.77). Students perform better in non-mathematics subjects, as shown by the high average score of other courses (79.37 ± 13.80). Although several psychological variables were excluded during integration due to incomplete responses, the final dataset effectively captures heterogeneous academic performance patterns, making it highly suitable for robust multiclass classification modeling.

3.2. Data exploration

Data exploration reveals that most students fall into the moderate learning challenge category (scores 60–79), with semester exams and remedial frequency strongly influencing difficulty levels. Input distributions vary, showing normally distributed daily quizzes alongside unevenly dispersed study times and diverse psychological readiness (motivation and anxiety). Distinct topic-specific patterns emerge: high anxiety hampers trigonometry performance (especially in word problems), weak antiderivative comprehension hinders calculus/integrals, complex equations disrupt algebra, and low visualization limits solid geometry. Ultimately, these findings confirm a critical interrelationship where strong motivation and confidence enable consistent problem-solving, while psychological factors heavily dictate academic mathematical difficulties across specific topics.

3.3. Model development and training

The classification model in this study uses a multilayer ANN consisting of dense, batch normalization, and dropout layers to reduce overfitting. The model was trained using data from SMA Muhammadiyah 16 Jakarta, with a 70:30 train–test split. To address class imbalance, data augmentation and the SMOTE were applied before training.

These techniques generated 50 synthetic samples, increasing the dataset from 113 to 163 records and improving class balance from a dominant Moderate class (53 samples) to a more balanced distribution of 83 Moderate, 43 Easy, and 37 Difficult samples according Table 3.

Table 3. Class distribution before and after augmentation

Category	Before Augmentation	After Augmentation
Easy	33	43
Moderate	53	83
Difficult	27	37

After preprocessing, the ANN model was trained for a maximum of 150 epochs to ensure sufficient learning. However, convergence was observed around the 15th epoch, and relatively stable performance was achieved after approximately 40 epochs, with no substantial improvement thereafter. Several learning rates and batch sizes were tested to identify the most effective configuration. The optimal parameters were found to be a learning rate of 0.001 and a batch size of 8, producing stable learning curves and satisfactory generalization on the validation set. The Focal Loss function was used to address residual class imbalance during training.

Model performance improved substantially after data augmentation and balancing. Without these enhancements, the model achieved an accuracy of only 68.33%, but with the inclusion of SMOTE and augmentation, accuracy rose to 98.00%, as shown in Table 4.

Table 4. Model accuracy comparison

Method	Accuracy
ANN (without SMOTE)	68.33%
ANN + Augmentation + SMOTE	98.00%

Although the model achieved 98% accuracy, the relatively small dataset (n=163) may lead to optimistic performance estimation and potential overfitting risk. Therefore, the results should be interpreted cautiously and require further validation using larger, more diverse, and multi-institutional datasets. The learning progress of the ANN model is illustrated in Figures 3 and 4, which present the training and validation accuracy and loss curves across epochs.

As shown in Figure 3, both training and validation accuracy increased in the early epochs and then stabilized. Training accuracy rose from about 0.43 to 0.85–0.91, while validation accuracy improved from 0.80 to 0.84-0.95, indicating effective learning and consistent generalization on unseen data.

Figure 4 shows a similar trend in loss reduction. Training loss decreased from 0.21 to 0.02–0.04, while validation loss declined from 0.10 to around 0.02. The most significant improvement occurred in the early epochs (before epoch 15), after which both curves stabilized, indicating model convergence.

Despite achieving a high accuracy of 98%, caution is needed due to the limited dataset size. However, the close alignment between training and validation curves suggests that the model does not suffer from severe overfitting, supported by regularization effects such as dropout.

Nevertheless, since the dataset originates from a single institution with 163 records (after augmentation), external validation with larger and more diverse data is required to ensure stronger generalization.

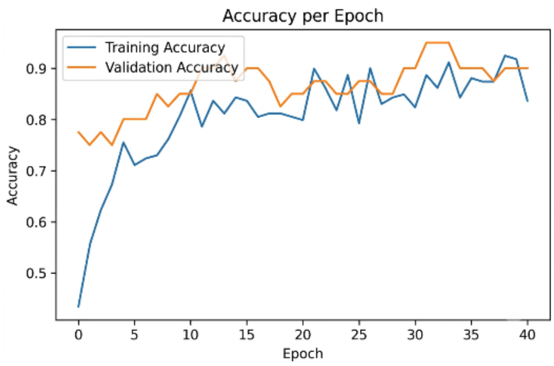

Figure 3. Training and validation accuracy across epochs

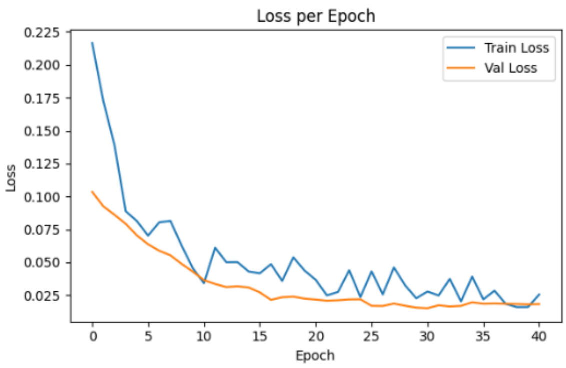

Figure 4. Training and validation loss across epochs

3.4. Model evaluation and performance

Model performance was further evaluated using precision, recall, and F1 score metrics for each category. The results, summarized in Table 5, show that the ANN achieved near-perfect classification accuracy across all classes.

Table 5. ANN model performance evaluation per class

Category	Precision	Recall	F1 score	Data Count
Easy	1.00	1.00	1.00	17
Moderate	0.94	1.00	0.97	17
Difficult	1.00	0.94	0.97	16
Overall Accuracy			0.98	50

As visualized in Figures 5 and 6, the proposed model achieved strong multiclass performance with 98% overall accuracy. The Easy and Difficult classes reached near-perfect scores, while the Moderate class achieved an F1-score of 0.97. This balanced capability was supported by a balanced testing dataset (17 Easy, 17 Moderate, 16 Difficult) that minimized class bias. To ensure a fair comparison, all baseline models were trained under identical preprocessing conditions, including feature scaling and SMOTE. These findings confirm the model's effectiveness, though further validation on larger, more diverse datasets is required.

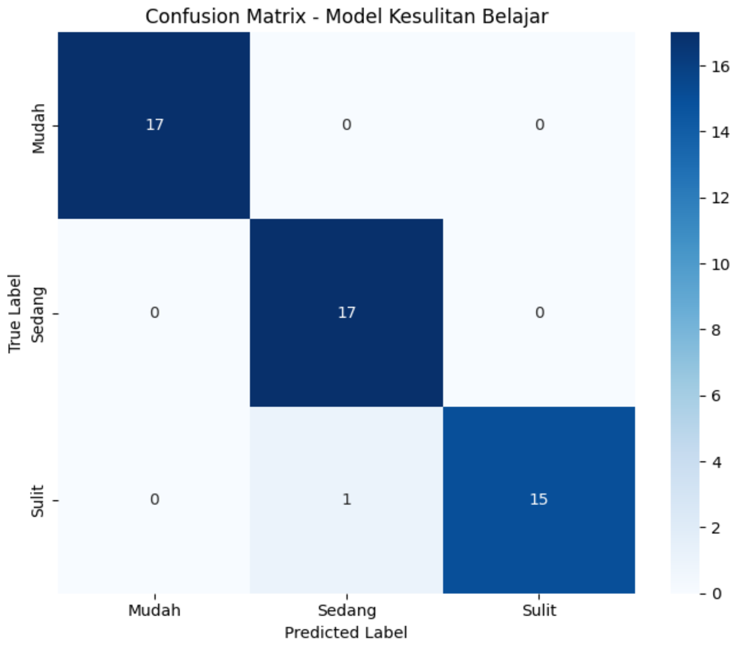

Figure 5. Confusion matrix of the ANN classification results

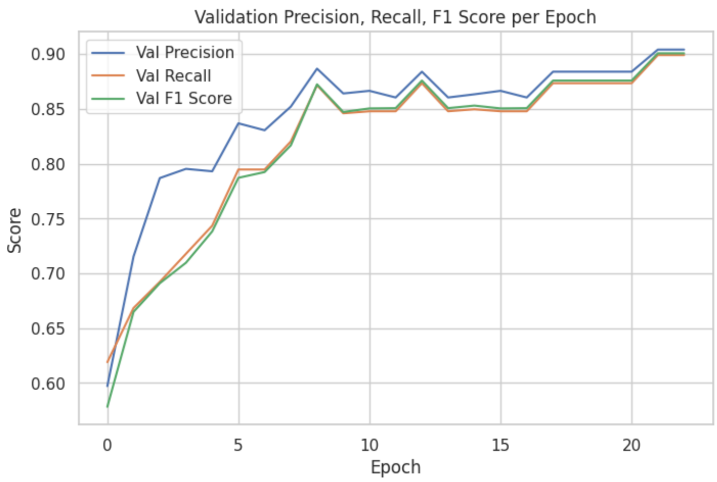

Figure 6. Validation precision, recall, and F1 score across epochs

Table 6. Performance comparison of machine learning models

Model	Accuracy	F1-score
Decision tree	0.875	0.8759
SVM	0.875	0.8707
Random forest	0.925	0.9255
ANN	0.98	0.97

To evaluate model robustness and generalization, a 5-fold stratified cross-validation was performed. The results are reported as mean ± standard deviation, with accuracy of 0.9167 ± 0.0589, F1-score of 0.9179 ± 0.0603, precision of 0.9165 ± 0.0607, and recall of 0.9250 ± 0.0571. These results indicate consistent performance across data folds and reduced overfitting risk compared to a single train-test split.

In contrast, the single train-test split shows that the ANN achieved a peak performance of 0.98 accuracy and 0.97 F1-score, representing its best-case performance, while cross-validation provides a more reliable estimate of generalization ability.

Based on Table 6, the ANN outperformed all baseline models in accuracy and F1-score, confirming its ability to capture complex nonlinear relationships in the data. Random forest (RF) showed competitive performance as the strongest traditional model, while DT and SVM performed lower, indicating limited ability to model complex feature interactions.

3.5. Feature analysis

Based on the ANN model's feature importance (Figure 7), academic performance variables emerge as the dominant predictors of mathematics learning difficulties compared to weaker behavioral and demographic factors. Continuous and summative assessments hold the highest influence, led by the last math daily test score (0.302) and the math semester exam score (0.278), followed moderately by the math assignment score (0.114) which reflects formative consistency. In contrast, the average score of other subjects (0.067) exerts only a secondary academic influence. Among non-academic features, age (0.051) provides a minor developmental contribution, while the number of math remedials taken (0.031) has the lowest importance. Ultimately, these findings confirm that the model primarily relies on structured academic performance patterns to classify learning difficulty levels.

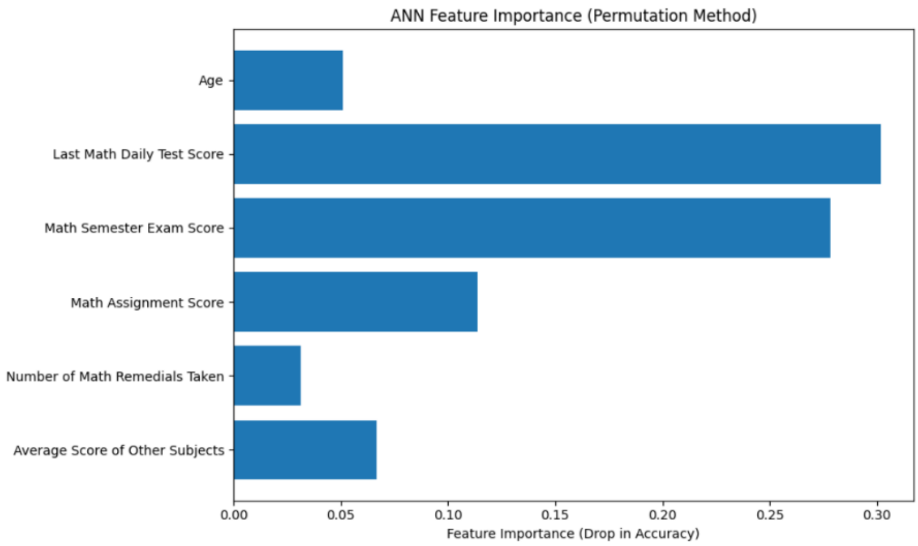

Figure 7. Feature importance

3.6. Practical implications

This study contributes to the development of machine learning–based decision support systems in education by demonstrating the effectiveness of ANN in predicting students' learning difficulties using academic and psychological data. The proposed model enables early identification of at-risk students, supporting timely interventions and reducing reliance on subjective assessment methods. It can also assist educational authorities in mapping learning difficulties at a broader scale, although its application should consider data privacy, model validity, and ethical use.

3.7. Strengths and limitations

This study presents a systematic ANN-based framework integrating academic and psychological data; however, its findings are limited by a relatively small, single-institution dataset and potential bias from self-reported information.

4. CONCLUSION

This study developed an ANN-based model within the CRISP-DM framework to predict mathematics learning difficulties, achieving 98% accuracy with balanced performance across all levels. Results indicate that academic indicators are the most influential predictors, supporting effective early detection. However, the study is limited by a relatively small dataset from a single institution and potential self-reporting bias in psychological data. Future research should expand the dataset across multiple schools and compare alternative machine learning approaches to enhance model generalization for real-world educational applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Harry Dhika	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓		
Surajiyo		✓	✓		✓	✓								
Lasia Agustina				✓	✓			✓	✓	✓	✓		✓	
Abdul Muchlis	✓				✓		✓	✓						

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

ETHICAL APPROVAL

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DATA AVAILABILITY

The datasets used in this study, including academic records, psychological data, questionnaire responses, and field data from SMA Muhammadiyah 16 Jakarta, are securely stored by the research team and are not publicly available due to privacy and ethical considerations. However, they may be obtained from the corresponding author upon reasonable request, subject to institutional and ethical approval.

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