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Classification of Mental Health Care Using the ELM, MLP, and CatBoost Stacking Framework

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Abstract

Mental health significantly impacts overall well-being, yet the increasing prevalence of mental health issues presents challenges in their effective classification and treatment. Traditional methods often fail to accurately handle complex, non-linear data, compromising the timeliness and appropriateness of interventions. This study introduces an innovative mental health classification framework, ELM-MLP-CatBoost Stacking, to address these deficiencies. The primary objective is to enhance classification accuracy by integrating three advanced computational techniques: the speed of the Extreme Learning Machine (ELM), the flexibility of the Multi-Layer Perceptron (MLP) for modeling non-linear data, and the predictive refinement of CatBoost as a meta-model. Our methodology involves a stacking approach where ELM and MLP models serve as base learners with CatBoost integrating their outputs to optimize final predictions. Experimental results demonstrate that the ELM-MLP-CatBoost Stacking framework substantially outperforms traditional models, achieving a notable accuracy of 92.76%, an improvement over the MLP's 92.64% and the ELM's 69.59%. This framework enhances the reliability and efficiency of mental health condition classifications and paves the way for further research into advanced diagnostic tools. The novelty of this research lies in the synergistic combination of these models, setting a new standard for accuracy and reliability in mental health diagnostics and establishing a robust foundation for future advancements in the field.

Keywords

Mental health care classification, ELM-MLP-CatBoost Stacking, Extreme Learning Machine (ELM), Multi-Layer Perceptron (MLP), CatBoost.

Introduction

Mental health is a condition in which an individual is able to realize their own abilities, cope with the normal stresses of life, work productively, and contribute to their community (WHO, 2022). Mental health refers to the health of all aspects of a person's development, both physical

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and psychological (Oktary, 2024).Moreover, work stress affects not only the physical health of employees but also their mental health, according to (Xu et al., 2019)With the increasing number of negative impacts from mental health issues, it becomes essential to develop effective methods to classify mental health care and ensure appropriate treatment.

Various types of human diseases have been classified using Extreme Learning Machine (ELM), with applications such as hepatitis classification achieving an average accuracy of 80% (Multazam et al., 2020)and cervical cancer classification reaching 91.76%(Hidayah et al., 2019). ELM offers the advantage of fast training and high accuracy but can be sensitive to noise and requires careful parameter tuning. In mental health classification, the K-Nearest Neighbor (KNN) algorithm demonstrated an accuracy of 83.33% in classifying student stress levels (Ulul Azmi Wafiqi et al., 2024), with the advantage of simplicity but the drawback of computational expense in larger datasets. Wearable devices, used to generate a multimodal dataset for stress detection, achieved an 84.1% accuracy (Montesinos et al., 2019), offering real-time monitoring but relying on the accuracy of sensor data. Meanwhile, a Multilayer Perceptron (MLP) with 2 hidden layers achieved 79% accuracy across multiple metrics (Danil, 2024), with the benefit of modeling complex patterns but the risk of overfitting. Despite these promising results, there remains a need to improve accuracy and develop more robust frameworks for handling larger and more complex datasets.

In response to this need, this study proposes the development of an innovative stacking framework called ELM-MLP-CatBoost Stacking for mental health care classification. This framework leverages the speed of Extreme Learning Machine (ELM) for rapid data processing, the flexibility of Multi-Layer Perceptron (MLP) in modeling complex, non-linear patterns, and the robustness of CatBoost as a meta-model to enhance classification accuracy through advanced boosting techniques. CatBoost has demonstrated superior performance in classification tasks compared to other algorithms, as shown by (Ibrahim et al., 2020) where CatBoost outperformed Random Forest, XGBoost, and Gradient Boost in classifying loan approval and staff promotion. By integrating ELM's fast learning capabilities with MLP's ability to capture intricate data patterns, and utilizing CatBoost's boosting strength as a meta-model, this proposed framework aims to achieve higher accuracy in mental health classification. The novelty of this approach lies in the unique combination of these three powerful algorithms, offering a more reliable and efficient tool for mental health care applications that addresses the limitations of existing methods.

Sections of this paper are divided into methodology, results and discussion, and conclusions and recommendations. In the methodology section, the research strategies employed are outlined, including data collection methods, data processing, and framework design. Following this, the results and discussion section addresses the findings from the experiments conducted, which are analyzed in depth to obtain broader insights. In the concluding section, conclusions and suggestions, the outcomes of this study are presented along with recommendations for future research.

Methodology

The methodology used is experimental and focuses on mental health classification using a framework that combines ELM, MLP, and CatBoost Stacking. Below is an explanation of the experimental stages:

Data Collection and Preprocessing

The mental health classification process commences on August 23 and concludes on September 7. It begins with the loading of a CSV dataset from Kaggle, which encompasses a variety of features pertinent to mental health care classification. The initial step involves data preprocessing, where the dataset is imported using the pandas library. Categorical variables within the dataset are then transformed into a numeric format using the LabelEncoder to facilitate model processing. Subsequently, the data is normalized using the StandardScaler, with the exception of the target column 'treatment', to ensure all features maintain a consistent scale.

Data Splitting

After data preprocessing, the dataset is split into two subsets: a training set and a testing set. This split allocates 80% of the data to the training set and the remaining 20% to the testing set. In this split, the 'treatment' column serves as the target variable, while the other features are used as input for the classification model. This process ensures that the model is trained and tested with representative data, allowing for an accurate evaluation of its performance in classifying mental health care.

ELM (Extreme Learning Machine) Model

The Extreme Learning Machine (EML) has a learning process where the types of learning include batch, sequential, and incremental learning, according to (Nguyen et al., 2023). The EML model is initialized with 50 neurons in the hidden layer and uses a sigmoid activation function, which transforms inputs into outputs in the range of 0 to 1, suitable for binary classification problems. EML is trained quickly as the weights of the neurons in the hidden layer are chosen randomly, and the weights of the output layer are computed analytically, without the need for lengthy iterations. Predictions from the EML are then combined with outputs from other models in a stacking framework to enhance the accuracy of mental health classification.

MLP (Multi-Layer Perceptron) Model

The Multi-Layer Perceptron (MLP) is structured using Keras's Sequential class, beginning with an input layer tailored to the training data's features and includes two hidden layers with 64 and 32 neurons respectively, both utilizing the ReLU activation function. It features an output layer with a sigmoid function for binary classification. (Wang et al., 2022) note that MLP's performance is at least on par with transformer models. The MLP is trained for up to 50 epochs, with early stopping and a validation split of 0.2, using the binary_crossentropy loss function and the Adam optimizer, focusing on accuracy. After training, it assesses performance on both training and test data.

Data Preparation for Prediction Merging

The process of merging predictions from two machine learning models, ELM and MLP, for both training and testing data. Predictions from these models are horizontally concatenated using the np.stack function, resulting in new features named X_train_combined and X_test_combined. These combined features are then used as inputs for a meta-model, aiming to integrate the strengths of both models to enhance overall classification accuracy.

CatBoost Model

The CatBoost model functions as a meta-model in this classification framework. At the same time, it shows that if we have similar size ensembles we could expect CatBoost and LightGBM to be competitors for the fastest method, while XGBoost is significantly slower than both of them (Dorogush et al., 2018) .This model is trained using the combined predictions from the ELM and MLP models, which are merged to form a new feature set (X_train_combined). The CatBoostClassifier is initialized with 100 iterations, a learning rate of 0.1, and a depth of 3, with verbose output disabled. The model is then trained using the combined training data (X_train_combined) and the target variable (y_train). As a meta-model, CatBoost integrates the strengths of the ELM and MLP models to enhance classification accuracy, providing a robust approach to handling the complexities of mental health classification data.

Model Evaluation

After training the CatBoost model using the combined predictions from the ELM and MLP models, The next step is to make predictions based on the combined test data (X_test_combined). The resulting predictions are then compared with the actual labels (y_test) to calculate the model's accuracy using the accuracy_score function. The CatBoost model is evaluated with this test data, and the classification accuracy is computed to demonstrate the effectiveness of the ELM-MLP-CatBoost Stacking framework in classifying mental health care. The accuracy results are printed to show the effectiveness of the ELM-MLP-CatBoost Stacking framework in mental health care classification.

Results and Discussion

Based on the methodological process that has been conducted, we obtained the experimental results of the classification framework with the ELM-MLP-CatBoost Stacking model, which are presented in the following table:

Table 1. Classification Meta Model Report

Algorithm	Testing Accuracy
Extreme Learning Machine (ELM)	69.59 %
Multi-Layer Perceptron (MLP)	92.64 %
ELM and MLP Using Stacking CatBoost	**92.76 %**

Following the method logical process we conducted, we obtained experimental results from the classification framework using the ELM-MLP-CatBoost Stacking model. These results are presented in the table below, indicating improvement in accuracy compared to previous methods. The Extreme Learning Machine (ELM) achieved a testing accuracy of 69.59%, which, while respectable, is considerably lower than the other methods tested. The Multi-Layer Perceptron (MLP) enhanced the accuracy, reaching 92.64%. The combination of ELM and MLP, utilizing CatBoost for stacking, slightly improved upon the MLP alone, achieving a top accuracy of 92.76%. This incremental enhancement highlights the efficacy of integrating these models in a stacked arrangement to refine predictive performance.

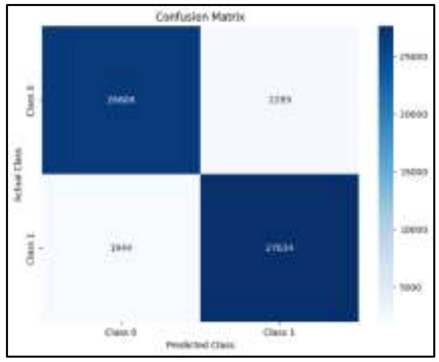

Figure 1. Confusion Matrix

The test results graph in Figure 1. provides a clear visualization of the model's classification results for the two different classes. The model demonstrates high precision for both classes, with approximately 90.89% for Class 1 and 94.51% for Class 0. Additionally, the recall for this model is also quite high, with 94.89% for Class 1 and 90.25% for Class 0.

The novelty of this research lies in the application of a stacking technique that involves the ELM and MLP models with CatBoost, an approach that has not been widely used in classification within the context of mental healthcare. With the integration we introduced, the model was able to produce more accurate predictions compared to using each model separately. Compared to similar studies, such as the one conducted by (Multazam et al., 2020), which applied ELM to hepatitis disease and achieved an average accuracy of 80%, and the application of ELM to cervical cancer by (Hidayah et al., 2019) , which resulted in an accuracy of 91.76%, the ELM-MLP-CatBoost Stacking model shows an accuracy improvement. This improvement is attributed to the unique combination of machine learning techniques used, which optimizes predictive strength through a complex ensemble process.

Conclusion

This research successfully demonstrates the effectiveness of the ELM-MLP-CatBoost Stacking framework in addressing the challenges of mental health classification. The integration of the Extreme Learning Machine, Multi-Layer Perceptron, and CatBoost into a single stacked model classification accuracy and reliability, as evidenced by the experimental results. The ELM, while providing a base accuracy of 69.59%, is substantially augmented by the MLP's capability to model non-linear data, achieving a 92.64% accuracy rate. The use of CatBoost as a meta-model to integrate ELM and MLP further refines these results, culminating in an accuracy of 92.76%. This innovative approach not only outperforms traditional classification methods but also contributes substantially to the field of mental health care by providing a more accurate, reliable, and efficient means of diagnosing mental health conditions. It is recommended to try other methods and more advanced classification techniques to better handle the complexities of mental health and produce more accurate results, improving the accuracy of future research.

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