Faculty Research

A Benchmark Framework for Data Visualization and Explainable AI (XAI)

This white paper provides a summary of an ongoing project.

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Overview

This research introduces a benchmark framework, called EDUMX, designed for machine learning (ML)-based forecasting and XAI tasks, leveraging the Streamlit open-source Python library. The framework offers a comprehensive suite of functionalities, including data loading, feature selection, relationship analysis, data preprocessing, model selection, metric evaluation, training, and real-time monitoring. Users can easily upload data in diverse formats, explore relationships between variables, preprocess data using various techniques, and assess the performance of the ML model using customizable metrics. With its user-friendly interface, this framework offers invaluable insights for forecasting tasks in various domains, catering to the evolving needs of predictive analytics. EDUMX is available for all to use. Please contact mkuzlu@odu.edu if you would like the details to access this tool.

Purpose of the Research

This research aims to develop a benchmark framework called EDUMX designed for machine learning (ML)-based forecasting and XAI tasks, leveraging the Streamlit open-source Python library. The framework offers a comprehensive suite of functionalities, including data loading, feature selection, relationship analysis, data preprocessing, model selection, metric evaluation, training, and real-time monitoring.

Method

In today's world, the need to share and present data science projects interactively is becoming increasingly important. The proposed framework is developed to address this need and provide an interactive web interface using the Streamlit library in Python. Streamlit is a Web application development library, which enables the easy and effective sharing of data science projects [1]. The framework hosts a variety of powerful libraries for data processing and modeling. For instance, Pandas, commonly used for data manipulation and analysis, serve as a fundamental tool, while NumPy is essential for scientific computations and matrix operations. Libraries like Scikit-learn, which encompass machine learning algorithms, form the backbone of our framework. In addition, high-performance prediction models are constructed using libraries, such as XGBoost and LightGBM, particularly beneficial when handling large datasets [2]. To facilitate understanding and interaction with projects through data visualization, the developed framework incorporates libraries such as Matplotlib, Seaborn, and Plotly. A generalized structure of the proposed benchmark framework is given in Figure 1.

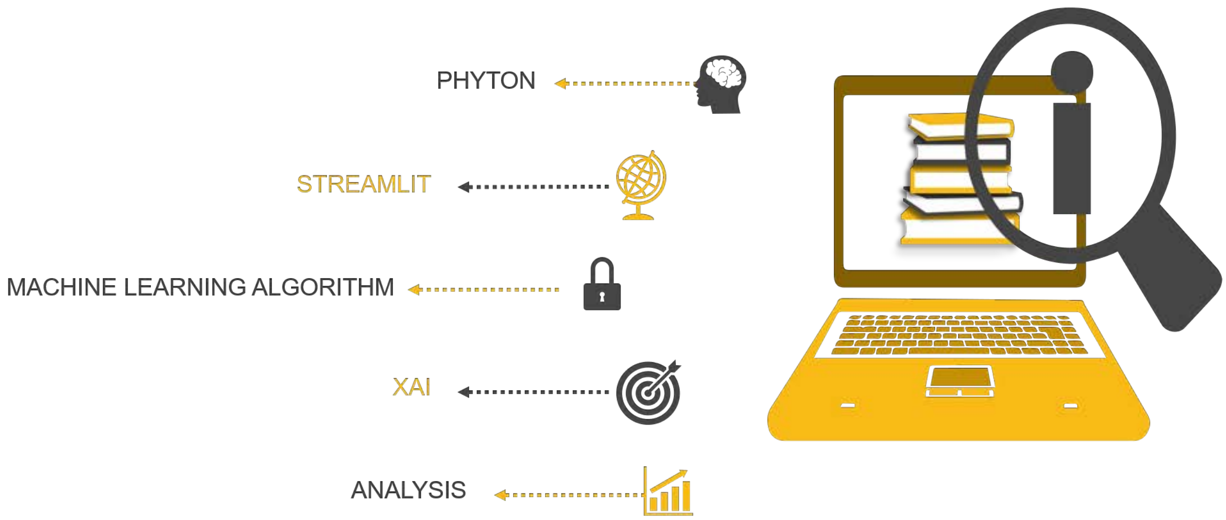

FIGURE 1. General Structure of Proposed Benchmark Framework.

EDUMX Framework

This section summarizes the seven main functionalities of EDUMX Benchmark.

- **Data Loading Function**
  This function lets users easily load data in common formats such as CSV and MAT. Users can simply select files through the Streamlit interface, and the detected data is automatically loaded while preserving structural properties and data types. A capture of the data loading block of the benchmark is shown in Figure 2.

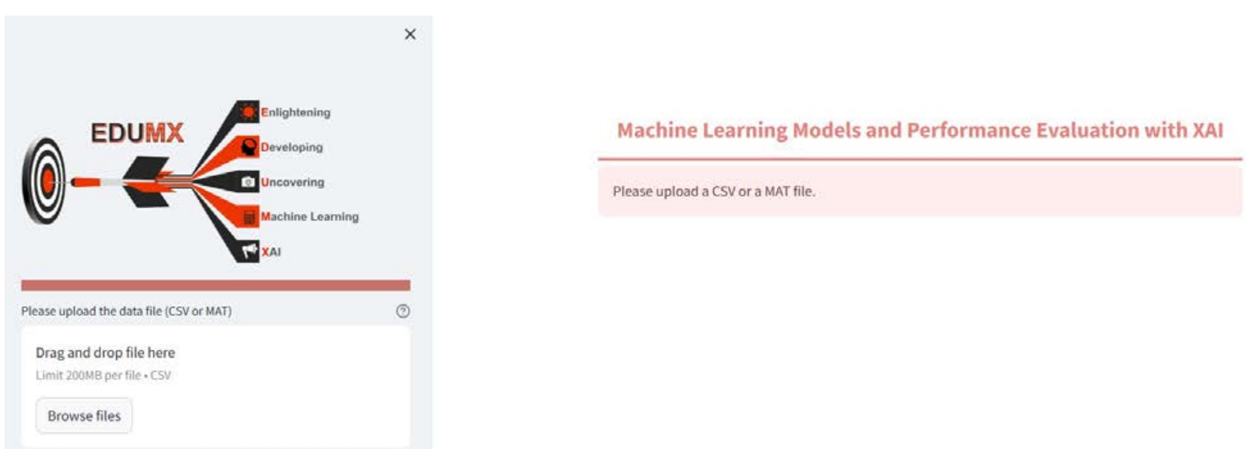

FIGURE 2. A Capture of Data Loading Block of Proposed Benchmark.

- **Feature Selection Function**
  Here you can select important features from the data to be interpreted. A screenshot of the features and the target selection block is shown in Figure 3.

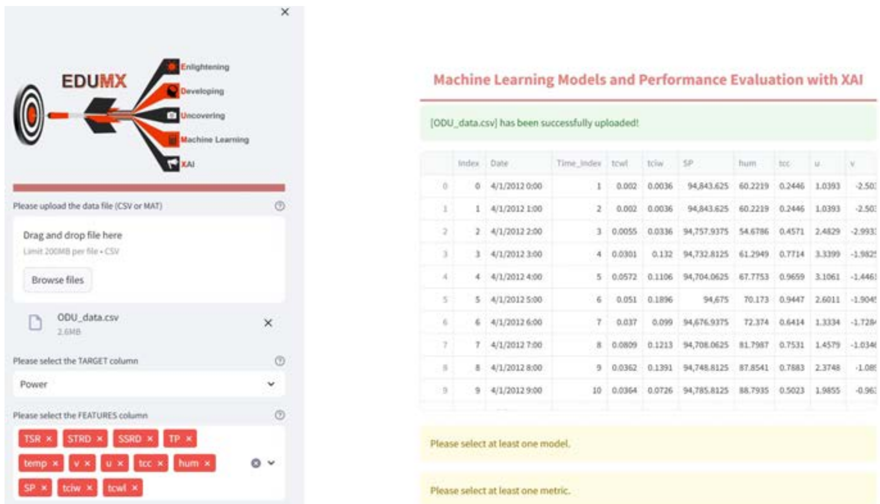

FIGURE 3. Selection of Features and Target.

- **Relationship Analysis Function**
  This function provides various visualizations to explore the relationships between variables in the data set. Users can interact with various graphs to understand relationships between variables and discover patterns in the dataset. For example, a scatter plot graph visually represents the relationship between two variables, while a heatmap graph represents the relationship between all variables by color coding. Examples of relationship tools graphs are presented in Figure 4.

- **Data Preprocessing Function**
  Data preprocessing involves preparing the dataset before modeling and analysis. Real-world data frequently contains issues, such as missing values, errors, and outliers. The data preprocessing function tackles these errors and inconsistencies. Missing values are estimated and filled. Outliers are identified and corrected. The different features on different scales can affect the model's performance. Therefore, a normalization process is applied to scale all features to the same scale. Different data preprocessing blocks are shown in Figure 5.

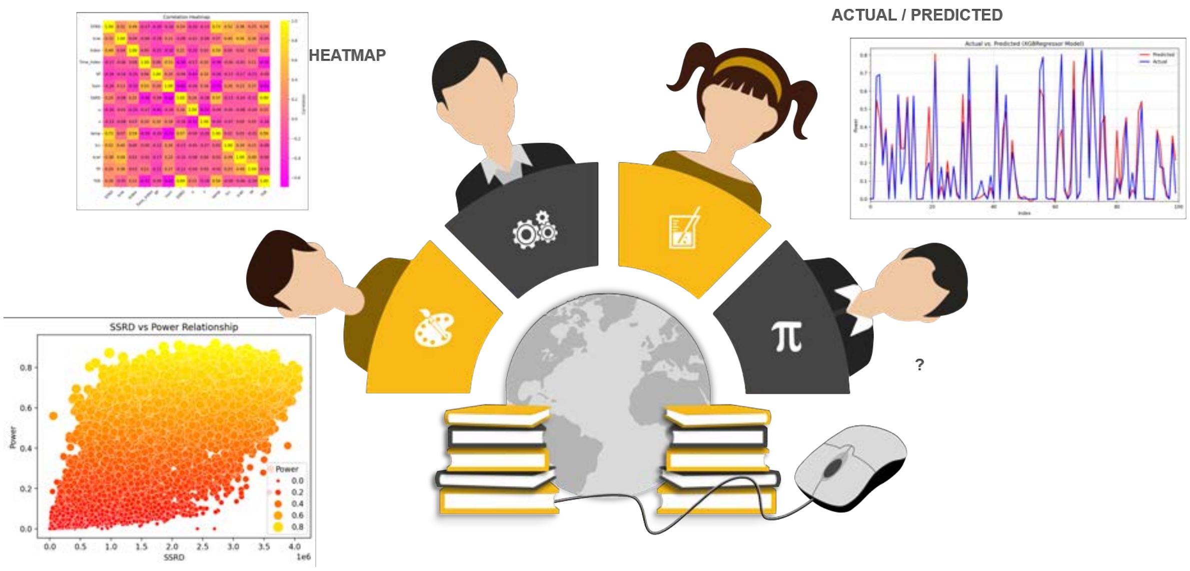

FIGURE 4 Relationship Tools Graph Examples.

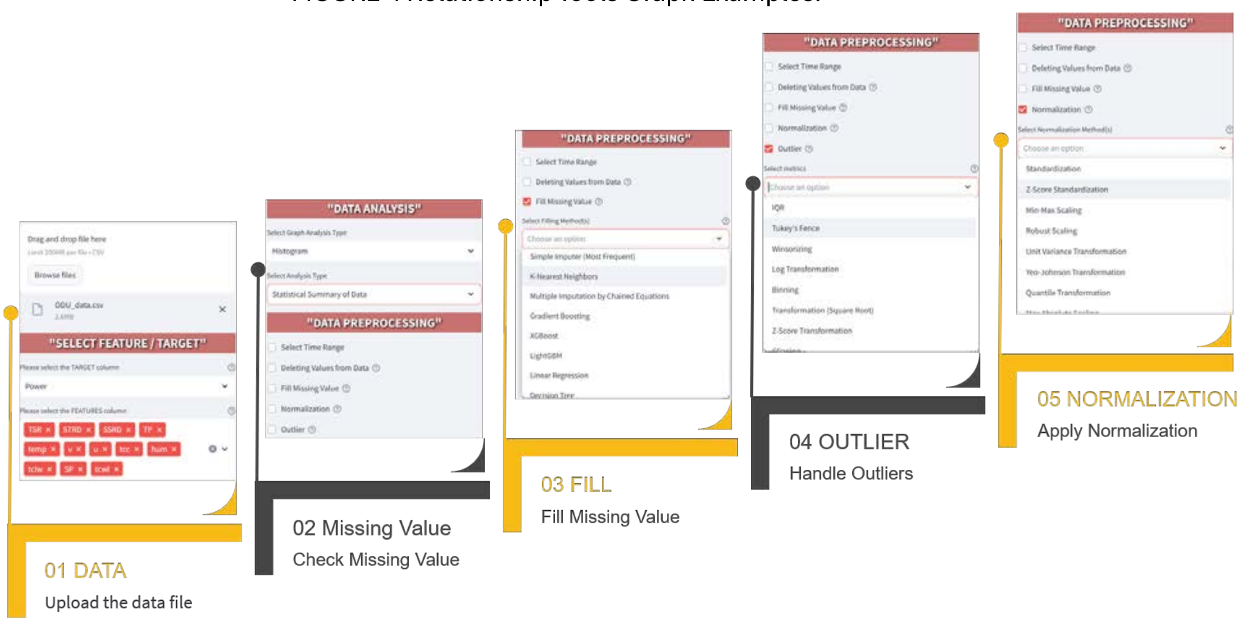

FIGURE 5. Different Data Preprocessing Stages.

- **Model Selection Function**
  This function supports various machine learning algorithms and enables users to select the model that is suitable for different tasks, such as regression, classification, and clustering. When choosing between various models, users can evaluate the advantages, disadvantages, and suitability of each model. A screenshot of the model selection block is shown in Figure 6.

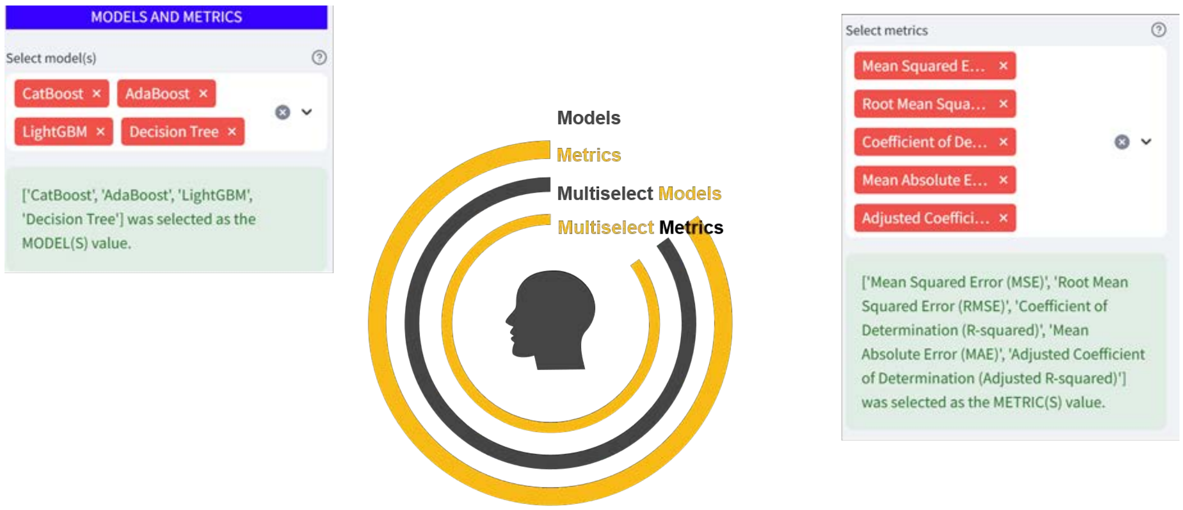

FIGURE 6. Selection of Models and Metrics.

- **Metric Evaluation Function**
  This method employs diverse metrics to evaluate the effectiveness of the chosen model. For instance, metrics like mean squared error and mean absolute error are applicable for assessing regression problems. These metrics propose the consistency of the model's predictions compared to the actual values. A screenshot of ML models and metrics selection block is shown in Figure 6.

- **Training and Real-Time Monitoring Function**
  This function enables the selected model to be trained on training data and its performance to be monitored in real-time. Model training is the process of applying the selected algorithm to a specific dataset and adjusting its parameters to understand the relationships between the data and make predictions. This monitoring provides valuable feedback on which features the model is learning better, helping it learn faster and more efficiently. Additionally, it helps identify and correct issues such as overfitting and underfitting, leading to more accurate predictions. This also allows for better management of the training process and optimization of the model's performance.

- **Hyperparameter Tuning**
  Hyperparameters include learning rate, number of epochs, batch size, and network depth, which are parameters used in the training process of a model affecting its learning style and performance. While empirical methods are one approach to finding the best hyperparameter settings, they can be time-consuming and challenging. To overcome this challenge, the hyperparameter tuning function automates the process by testing various hyperparameter combinations. This enables users to efficiently determine the optimal set of hyperparameters, leading to improved model performance. This function ensures that the model achieves optimal performance, facilitating more accurate and consistent results. It also provides a user-friendly tool suitable for individuals of all levels, thus improving the efficiency of the model training process. A capture of hyperparameter tuning is shown in Figure 7.

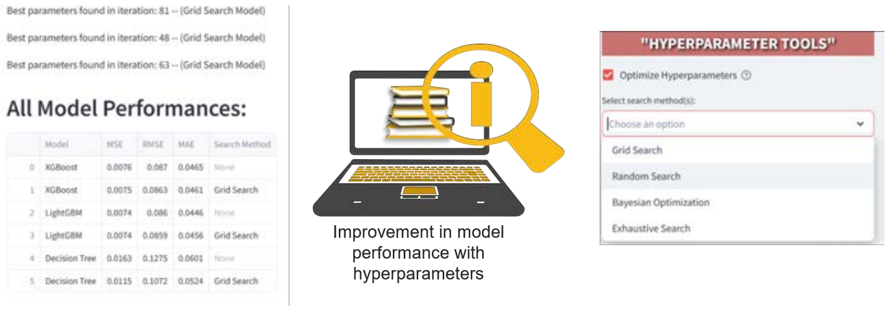

FIGURE 7. Hyperparameters Tuning.

- **Explainable Artificial Intelligence (XAI)**
  XAI refers to a set of techniques and methods used to understand and explain the decisions made by artificial intelligence algorithms. XAI techniques enable AI models to move away from being "black boxes" and become more transparent and reliable. While advanced AI models can perform well on complex data structures, it is important to understand their decision-making processes and ensure their reliability. Among the techniques that can be used in this framework are Permutation Feature Importance (PFI), Local Interpretable Model-Agnostic Explanations (LIME), and SHapley Additive exPlanations (SHAP). XAI is an important toolkit, especially in areas where critical decisions are made, for improving the reliability and usability of artificial intelligence models. Example graphs of LIME and SHAP XAI methods are given in Figure 8.

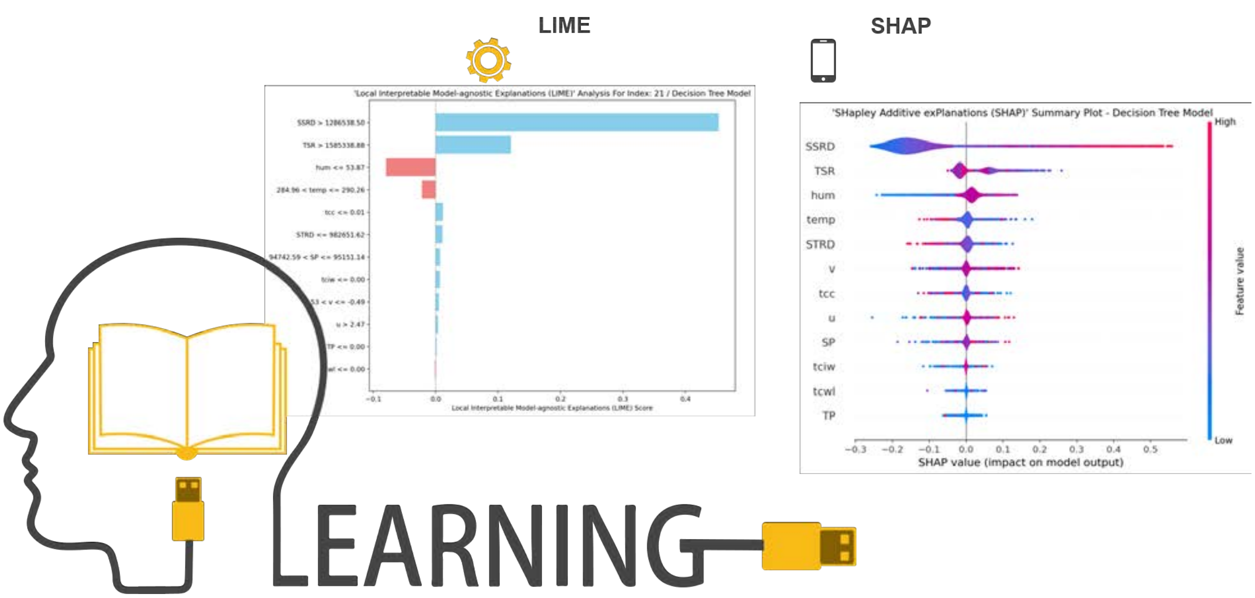

FIGURE 8. XAI (Explainable Artificial Intelligence).

Findings and Discussion

The EDUMX Framework has been structured to meet the specific needs of the educational sector. The findings and results from reviews and practical tests can be summarized as follows:

- **Increased Access to Educational Materials:** The integration of the Streamlit interface offers a simpler and more interactive experience for students and faculty working with complex datasets.
- **Integration of Data Analysis Tools in Education:** The use of libraries that deepen data analysis is crucial for teaching students data manipulation, analytical thinking, and modeling techniques in a practical manner.
- **Advanced Data Visualization:** Utilizing visualization libraries allows students and academics to analyze and present data more effectively. As a result, the interpretation of complex data and class discussions become more understandable.
- **Simplification of Modeling and Evaluation:** EDUMX facilitates processes from data loading to model training and evaluation, helping students reinforce their theoretical knowledge of machine learning and artificial intelligence with practical applications.
- **Transparency with XAI:** The application of XAI techniques like PFI, SHAP, and LIME enables students to better understand model decisions and grasp the ethical and social dimensions of these models.
- **Interdisciplinary Applications:** The framework's flexible structure can be adapted to meet the specific needs of students and faculty from different disciplines. This adaptability enables the use of EDUMX across a broad academic spectrum.

Conclusions

The EDUMX framework enables users across various sectors to analyze different datasets and training models efficiently and effectively, guiding their decision-making processes. It represents a significant advancement in the integration of machine learning and explainable artificial intelligence (AI) within the educational sector. Leveraging the user-friendly features of the Streamlit library, along with robust data manipulation and visualization tools, EDUMX aims to enhance learning and teaching experiences in the disciplines of data science and artificial intelligence. Its flexibility, customizability, and rapid performance assist users in making better decisions and more accurate predictions.

References

1. Khorasani M, Abdou M, Hernández Fernández J. Getting Started with Streamlit: 1–30; Berkeley, CA: Apress . 2022
2. Bentéjac C, Csörgő A, Martínez-Muñoz G. A comparative analysis of gradient boosting algorithms. Artificial Intelligence Review 2021; 54: 1937–1967.