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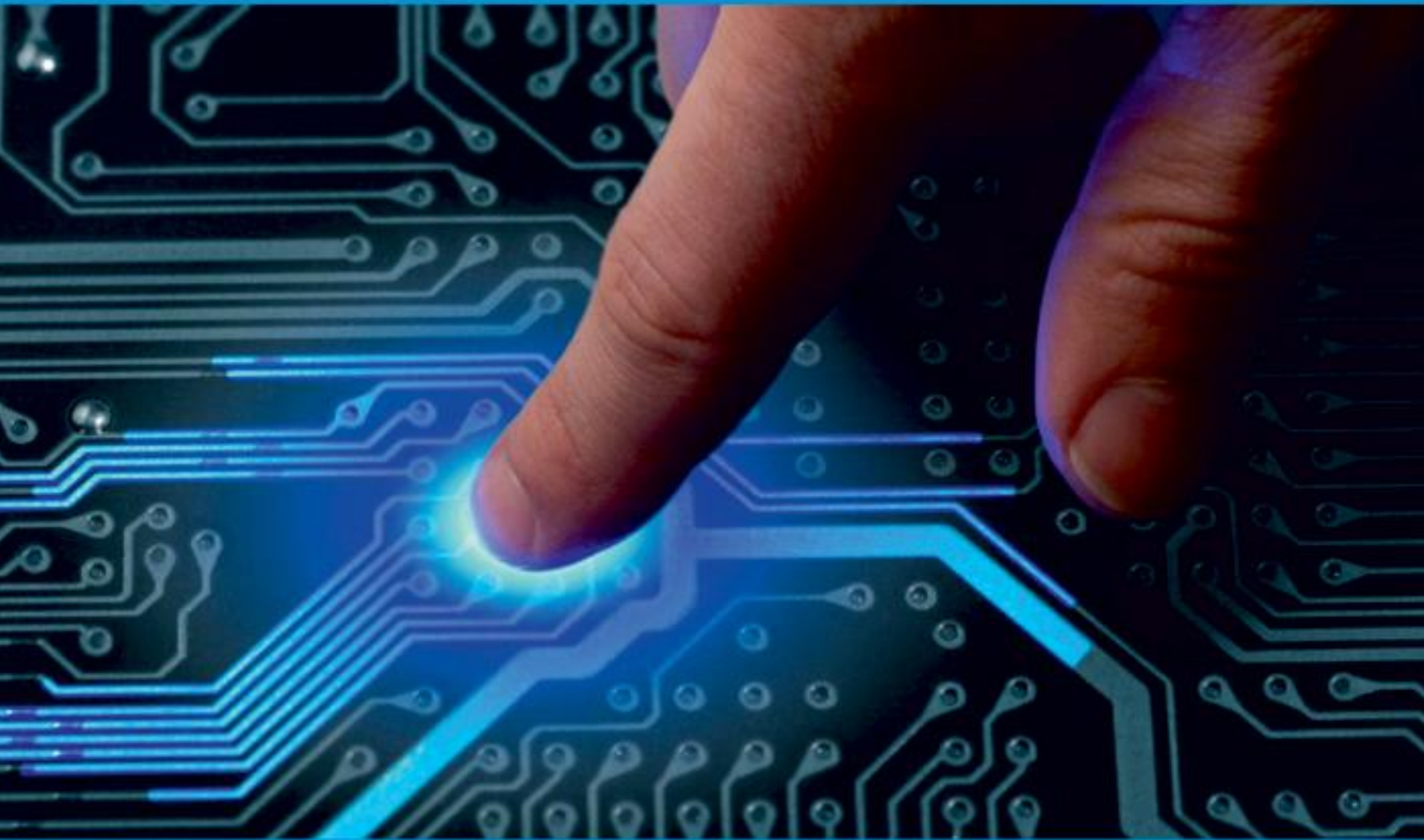

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Simplifying Machine Learning: A Streamlit-Powered Interface for Rapid Model Development with PyCaret

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ABSTRACT: This paper introduces an innovative approach to make machine learning (ML) accessible to everyone through a simpleweb application. As data continues to grow, so does the demand for ML models, but the complexity involved often acts as a barrier. Our solution aims to break down these barriers by enabling users, regardless of their expertise, to easily create ML models using just their datasets. Through a user-friendly interface, individuals can interact with and refine their models effortlessly, democratizingaccess to powerful predictive tools. By employing cutting-edge algorithms and intuitive design, our web app empowers users from various backgrounds to leverage ML for diverse applications. This paper outlines the structure, features, and potential impact of our platform, emphasizing its role in making ML more accessible and usable for all.

KEY WORDS: Automated Machine Learning, PyCaret, Streamlit

I. INTRODUCTION

Acknowledging the pivotal role of streamlined access to machine learning tools in advancing data-driven decision-making, the development of a Streamlit-based browser interface for PyCaret marks a significant stride towards democratizing machine learning model generation. In alignment with the Sustainable Development Goals (SDGs) and their target for universal access to safe drinking water by 2030, the interface aims to ensure accessibility and sustainable management of machine learning resources for all stakeholders. Just as fulfilling the demand for drinking water is a shared responsibility between central and local governments, the task of democratizing access to machine learning models falls on the shoulders of developers, researchers, and practitioners alike. Through the integration of PyCaret within the Streamlit framework, the interface offers a user-friendly platform for generating high-quality machine learning models with ease, akin to the provision of piped water for safe drinking. The importance of focusing efforts on piped water access in Indonesia parallels the necessity of prioritizing user-friendly interfaces for machine learning model generation. As well water faces challenges in quality and quantity, piped water emerges as a relatively less contaminated and more accessible source. Similarly, the achievement of universal access to machine learning tools, represented by the interface, is paramount given its potential to drive innovation, decision-making, and societal progress. Just as the performance of drinking water service providers is assessed against established standards, the efficacy and impact of the Streamlit-based interface for PyCaret are subject to scrutiny. This includes evaluations of usability, performance, and scalability, as well as considerations of user feedback and satisfaction. In essence, the development of the Streamlit-based browser interface for PyCaret mirrors the commitment to ensuring equitable access to essential resources, be it safe drinking water or machine learning capabilities. As such, this project represents a step towards realizing the vision of inclusive and sustainable development through technology.

II. RESEARCH ELABORATION

The Research Elaborations section delves into the methodology and technical implementation of the Streamlit-based browser interface for PyCaret, which enables users to utilize it as a Machine Learning Model Generator. This section elucidates the design choices, functionalities, and integration of PyCaret within the Streamlit framework. The interface

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design focuses on creating an intuitive and user-friendly environment for generating machine learning models using PyCaret. Leveraging the capabilities of Streamlit, the interface offers a clean layout with interactive widgets and components, allowing users to seamlessly navigate through the model generation process. Central to the interface is the integration of PyCaret, a powerful machine learning library, which streamlines the model development workflow. Through PyCaret's simplified APIs and automation capabilities, users can perform tasks such as data preprocessing, model selection, hyper parameter tuning, and model evaluation with minimal code. The functionality of the interface encompasses the entire machine learning pipeline, from data ingestion to model deployment. Users can upload their datasets or connect to external data sources, explore and visualize the data, select the target variable, and choose from a wide range of machine learning algorithms supported by PyCaret. Within the interface, users have the flexibility to configure various aspects of the model generation process, including feature selection, model hyperparameters, cross-validation strategies, and performance metrics.

The interface provides informative tooltips and guidance to assist users in making informed decisions. After generating multiple candidate models, users can evaluate their performance using interactive visualizations and summary statistics presented within the interface. PyCaret's built-in capabilities for model interpretation, values, further enhance the user's understanding of the model's behavior and insights derived from the data.The interface also offers seamless integration with deployment platforms, allowing users to export trained models in various formats (e.g., pickle, PMML) for deployment in production environments. Additionally, users can explore deployment options such as cloud- based services or containerization for scalable and efficient deployment of machine learning models.

Regressors	Classifiers
• Linear Regression Lasso Regression Ridge Regression Elastic Net Regression Lars Regression • Lasso Lars Regression Orthogonal Matching Pursuit Bayesian Ridge • Automatic Relevance Determination Passive Aggressive Regressor Random Sample Consensus • Theil Sen Regressor Huber Regressor Kernel Ridge • Support Vector Regressor K Neighbors Regressor Decision Tree Regressor Random Forest Regressor Extra Trees Regressor Ada Boost Regressor • Gradient Boosting Regressor MLP Regressor • Dummy Regressor	• Logistic Regression • K Neighbors Classifier • Naive Bayes Decision Tree Classifier • SVM Linear Kernel SVM Radial Kernel • Gaussian Process Classifier MLP Classifier Ridge Classifier • Random Forest Classifier Quadratic Discriminant Analysis Ada Boost Classifier • Gradient Boosting Classifier Linear Discriminant Analysis Extra Trees Classifier

Fig 1: List of available algorithms in SwiftML

Throughout the development process, user feedback was solicited and incorporated to enhance the usability and functionality of theinterface. Iterative testing and refinement cycles were conducted to address usability issues, improve performance, and add new features based on user needs and preferences. The Results or Findings section presents the outcomes and insights gleaned from utilizing the Streamlit-based browser interface for PyCaret as a Machine Learning Model Generator. It encompasses the performance of generated models, comparative analyses, and key observations derived from the experimentation process. The section begins by showcasing the performance metrics of the generated machine learning models. Metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC) are reported for each model configuration. Visual representations, including confusion matrices and ROC curves, aid in interpreting the model performance across different evaluation criteria.A comparative analysis is conducted to assess the efficacy of different machine learning algorithms and configurations available through the interface. Models generated using PyCaret's automated approach are compared against baseline models or manually configured models, highlighting any performance improvements or trade-offs achieved through automation.

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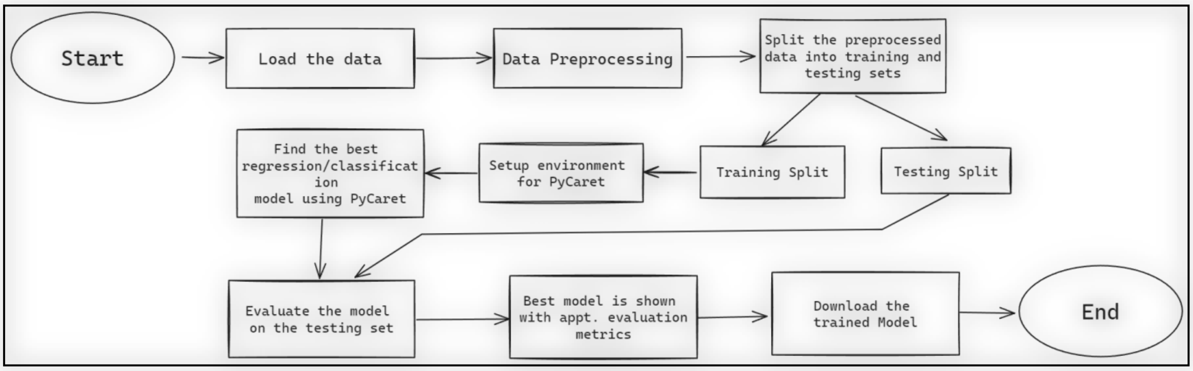

Fig 2: Workflow of the Application

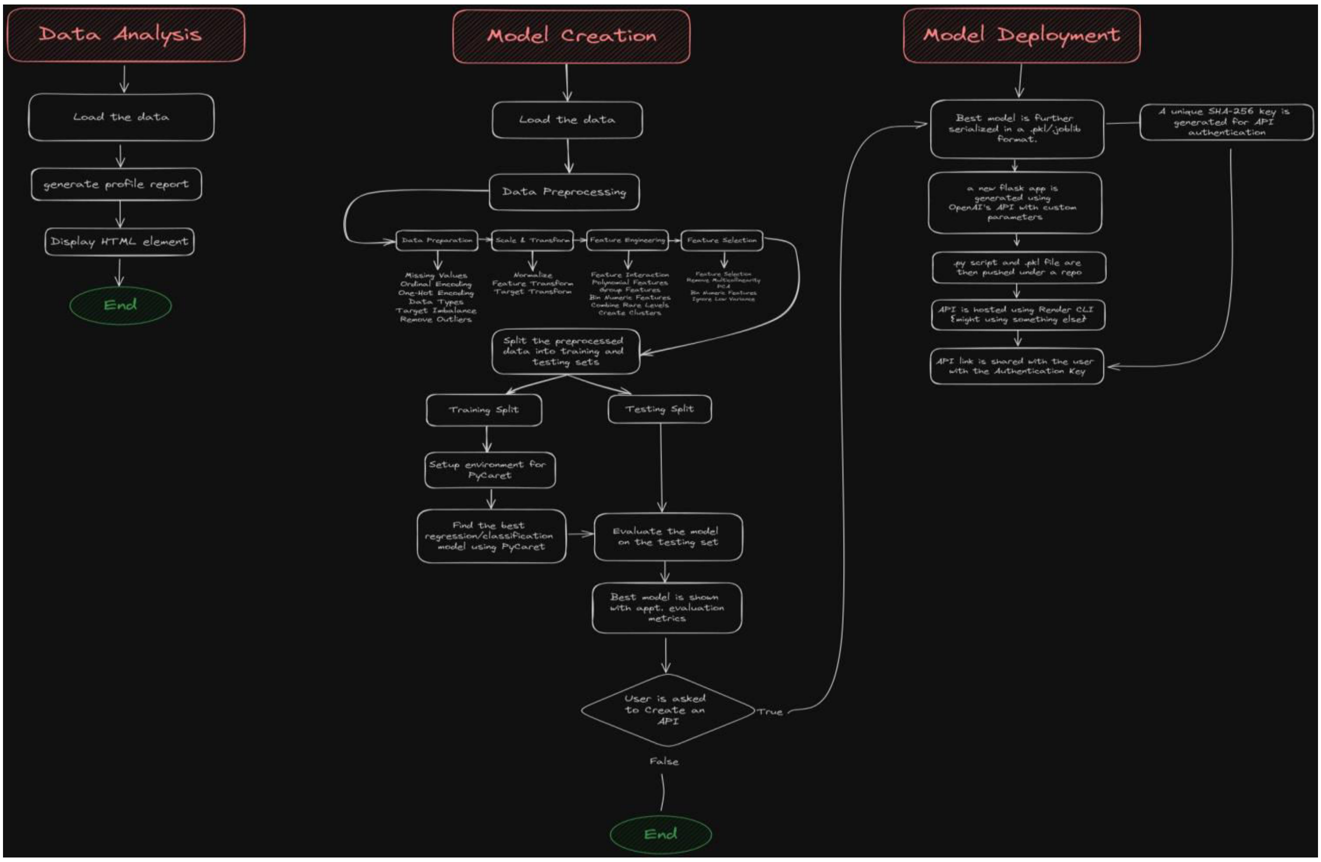

Fig. 3 Flowchart of **Streamlit-Powered Interface for Rapid Model Development with PyCaret**

III. IMPLEMENTATION AND CONTRIBUTION OF A STREAMLIT-POWERED INTERFACE FOR RAPID MODEL DEVELOPMENT

The interface facilitates the exploration of feature importance and interpretability insights derived from the trained machine learning models. Users can examine the contribution of individual features to model predictions, identify influential variables, and gain insights into the underlying patterns driving model behavior. Insights are provided into the model selection and tuning strategies employed within the interface. Performance benchmarks such as execution time are measured across varying dataset sizes and computational environments. Scalability challenges and potential optimizations are discussed to guide future enhancements. User feedback and satisfaction metrics are collected to gauge the usability and effectiveness of the interface. User surveys, interviews, or usability testing sessions capture insights into user experiences, preferences, and pain points encountered during model generation. Feedback is synthesized to

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identify areas for improvement and inform iterative development cycles. Finally, the section may include use case demonstrations or case studies showcasing real-world applications of the interface. Examples of successful model generation and deployment scenarios across diverse domains, such as healthcare, finance, or marketing, illustrate the practical utility and versatility of the interface for solving complex data-driven problems.

3.1 Implementation and Contribution of A Streamlit with PyCaret using Wine Quality

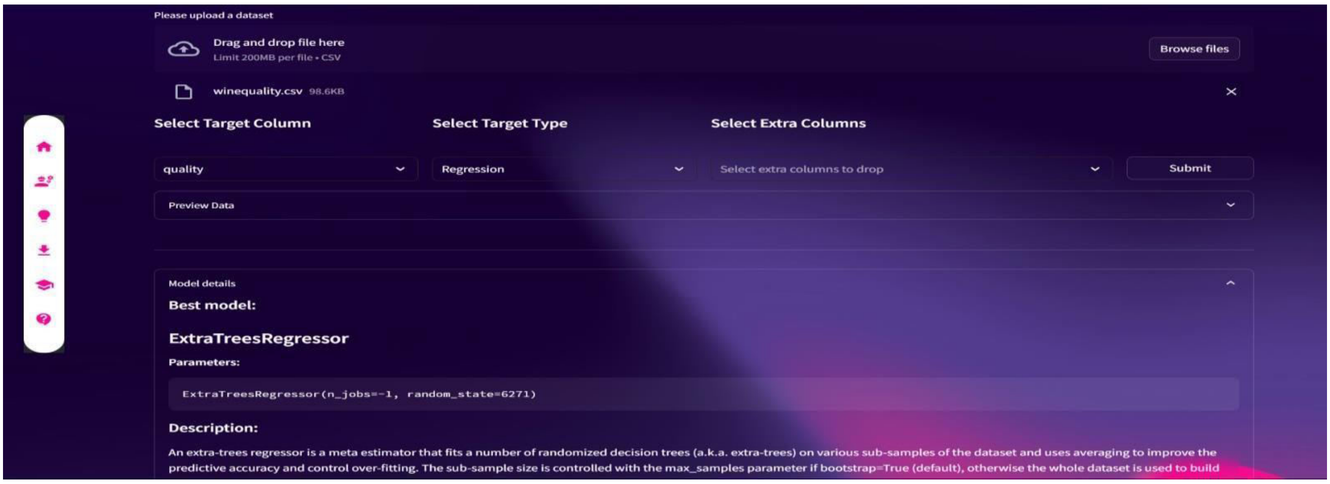

Fig1.

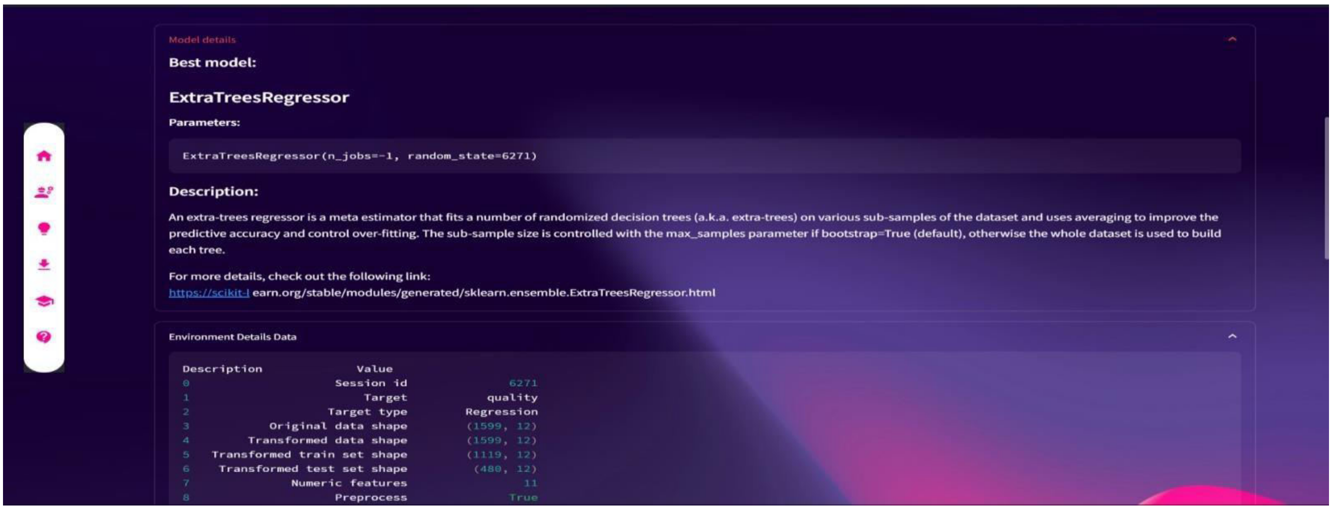

Fig2.

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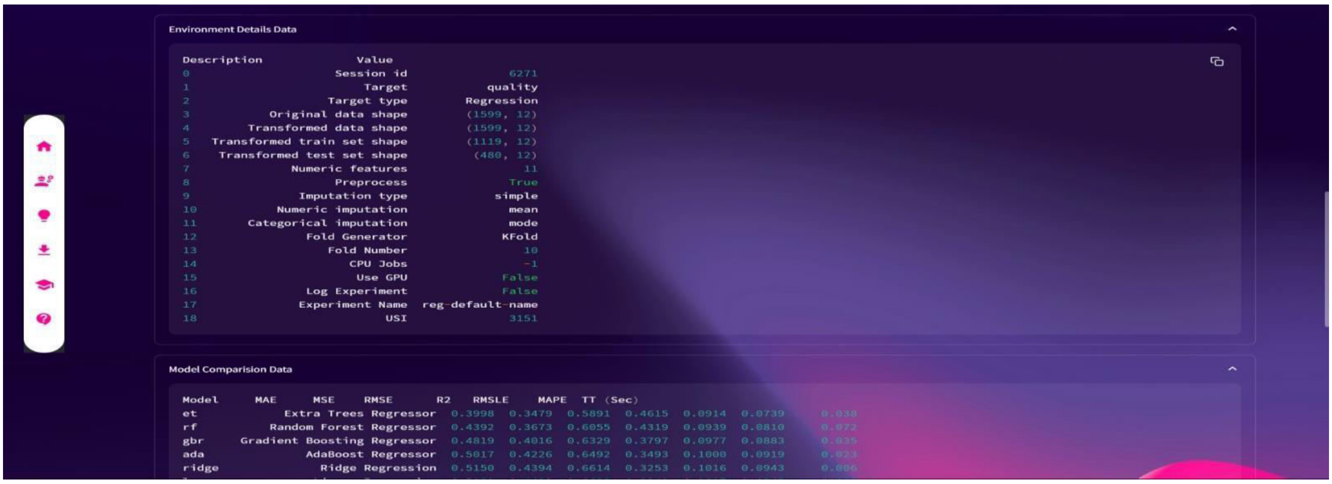

Fig 3.

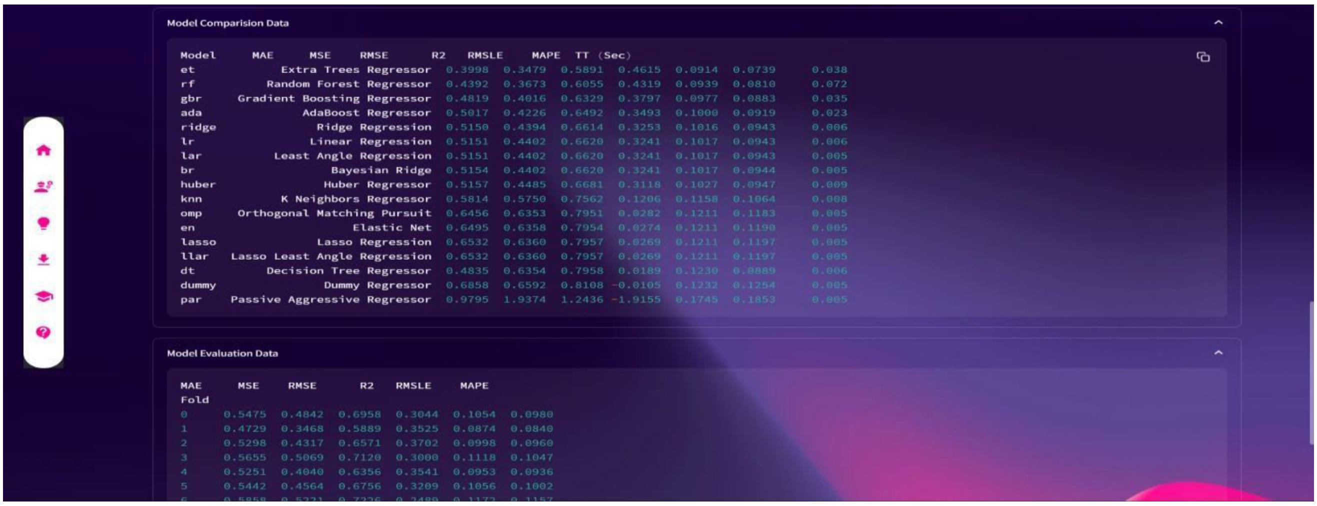

Fig 4.

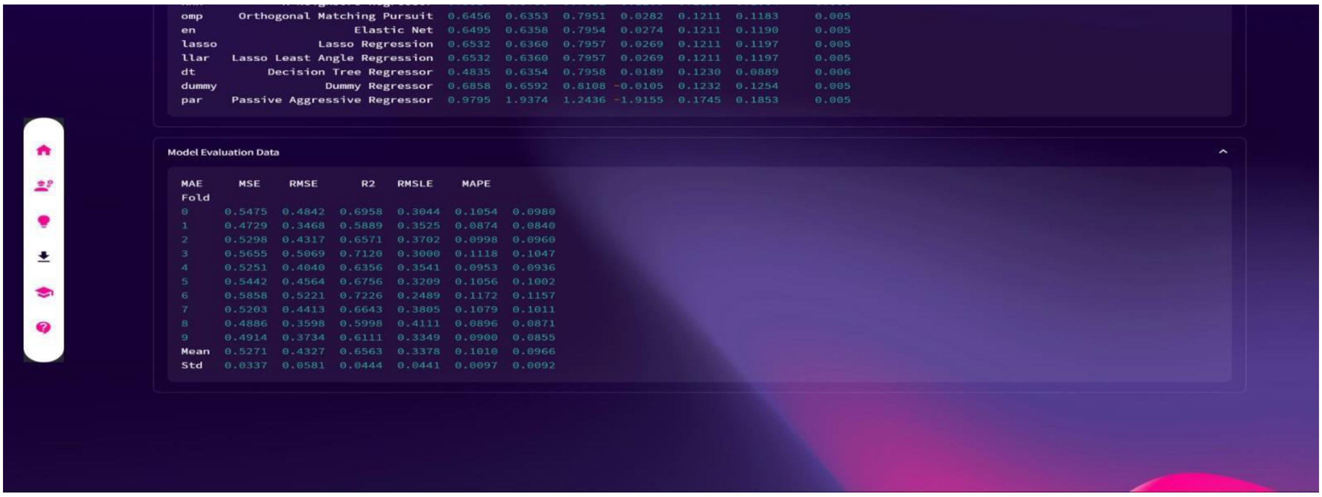

Fig 5.

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Fig 6. The outcomes, depicted in Figures 3, 4, 5, and 6, consist of matrices and graphs that facilitated the identificationof the most effective algorithm by the model.

3. 2 Implementation and Contribution of A Streamlit-Powered Interface for Rapid Model Development with PyCaret using Iris dataset

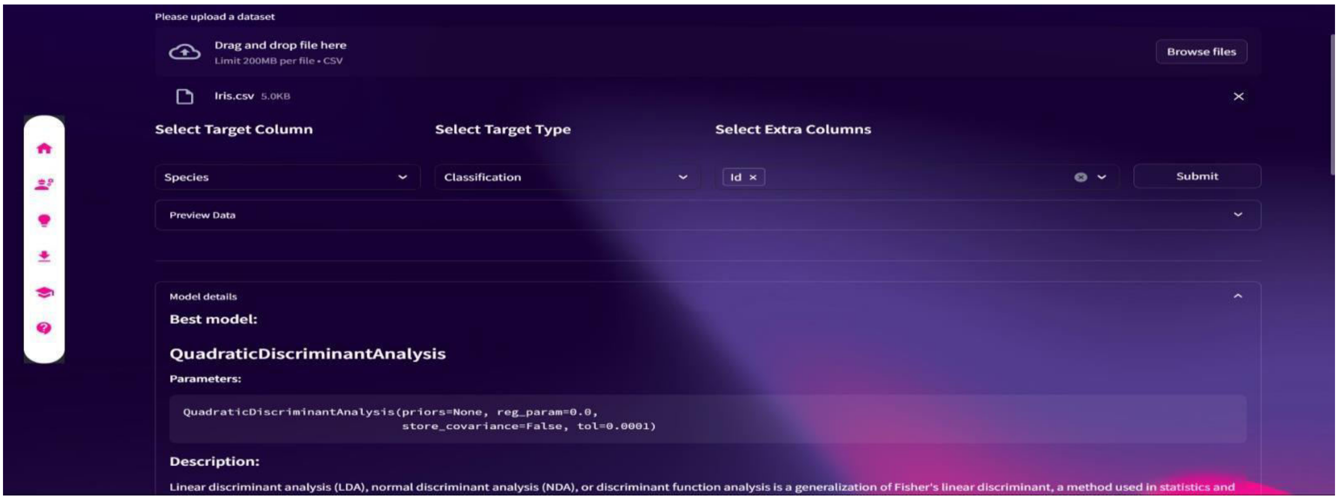

Fig 1.

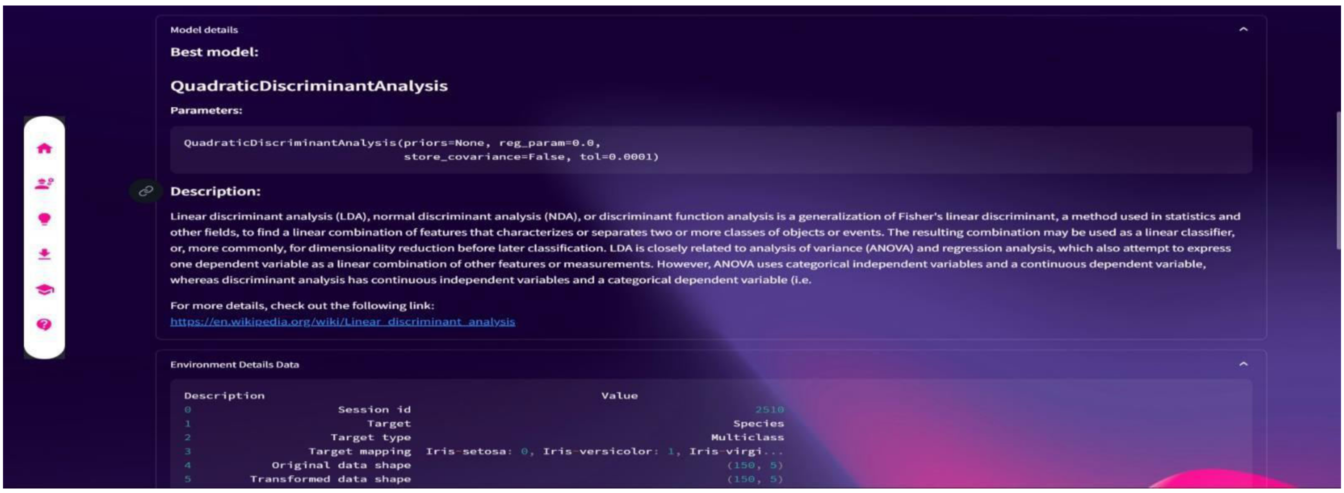

Fig2.

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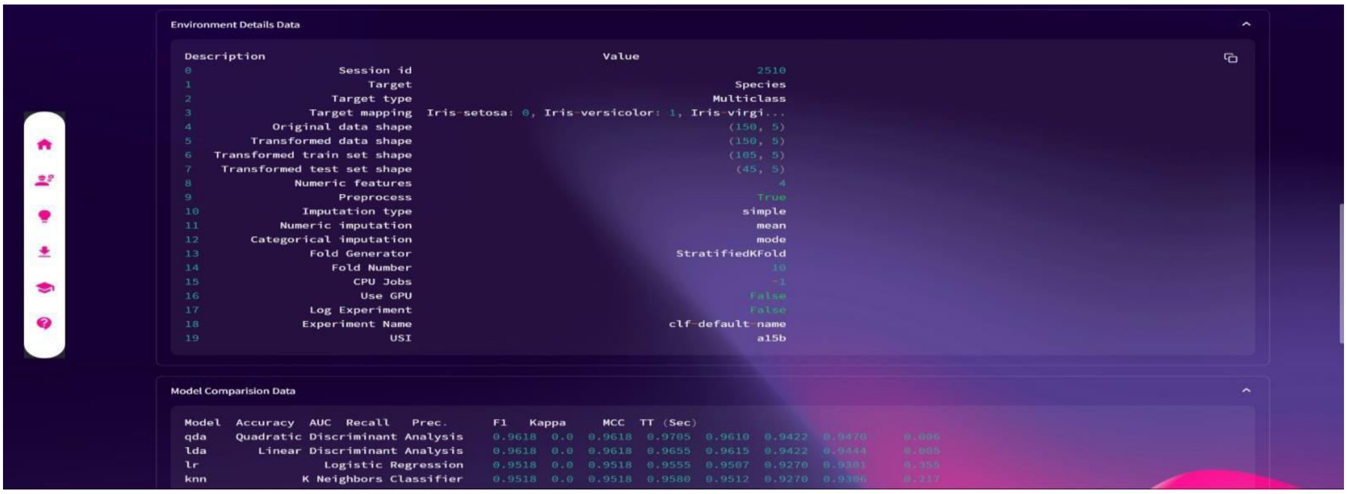
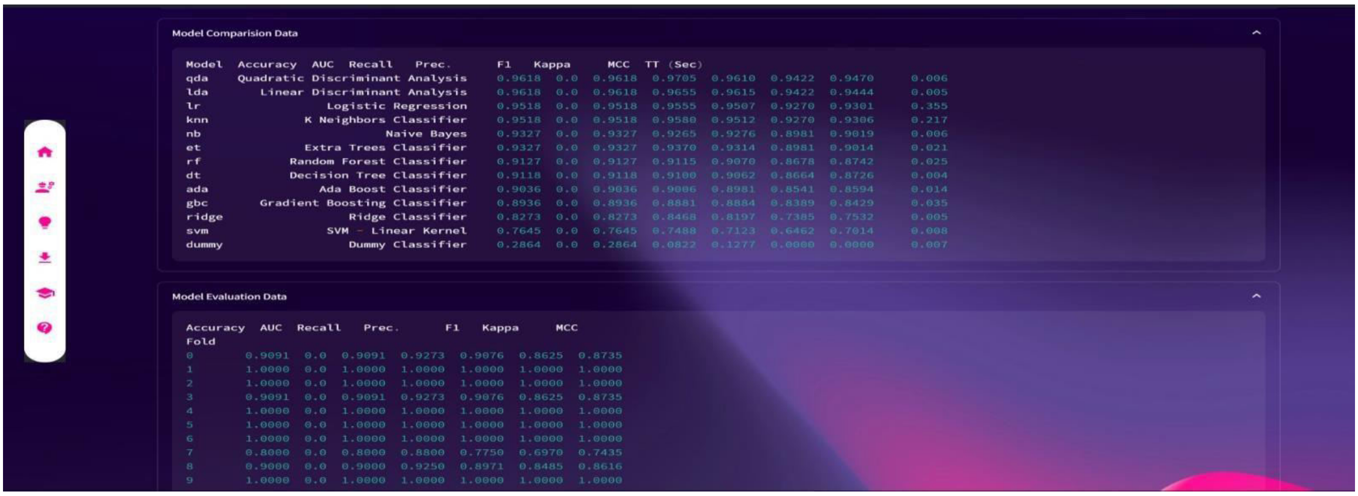


Fig 3.



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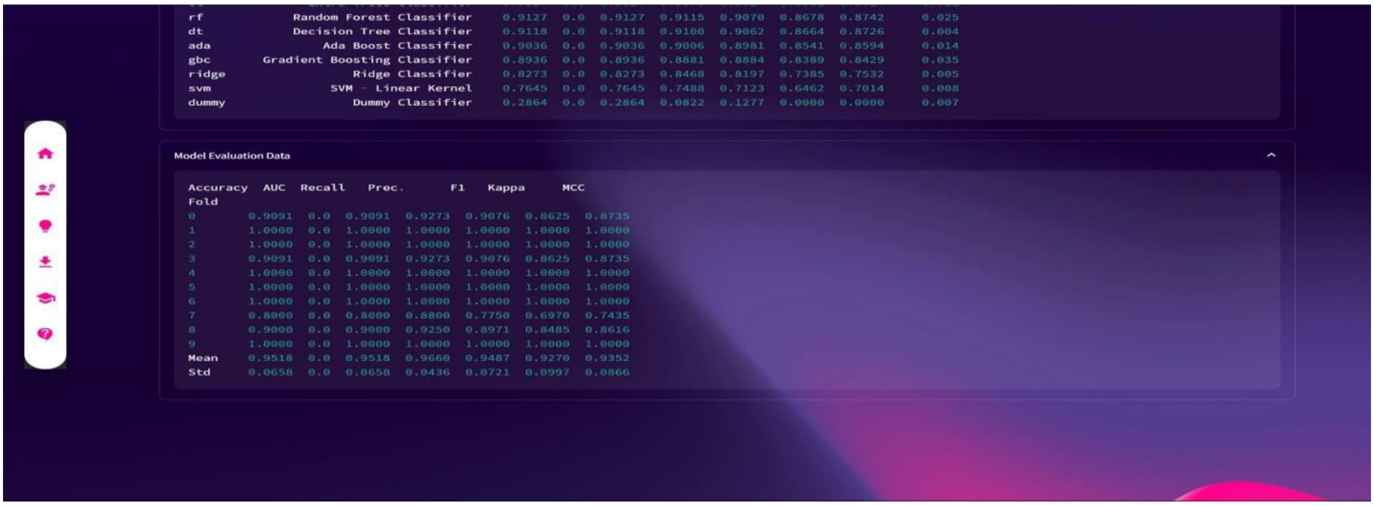

Fig 5.

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3. 3 Implementation and Contribution of A Streamlit-Powered Interface for Rapid Model Development with PyCaret using Sparkling Water Dataset

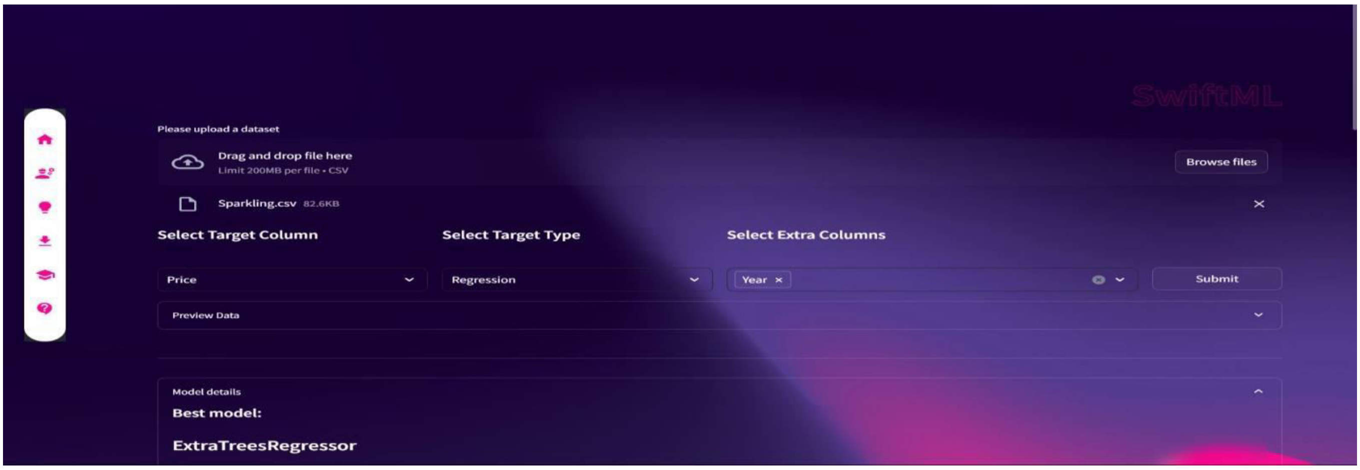

Fig 1.

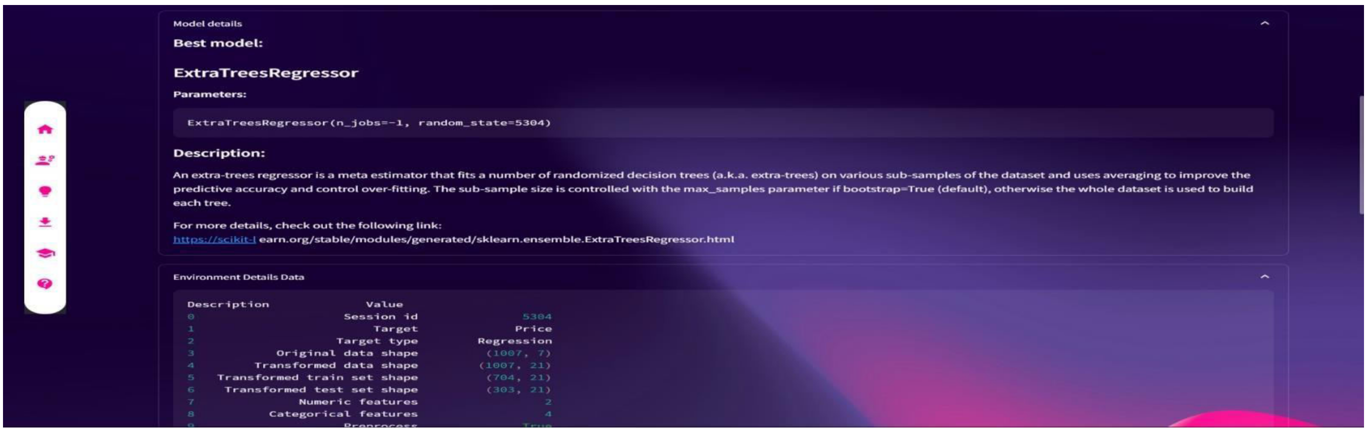

Fig2.

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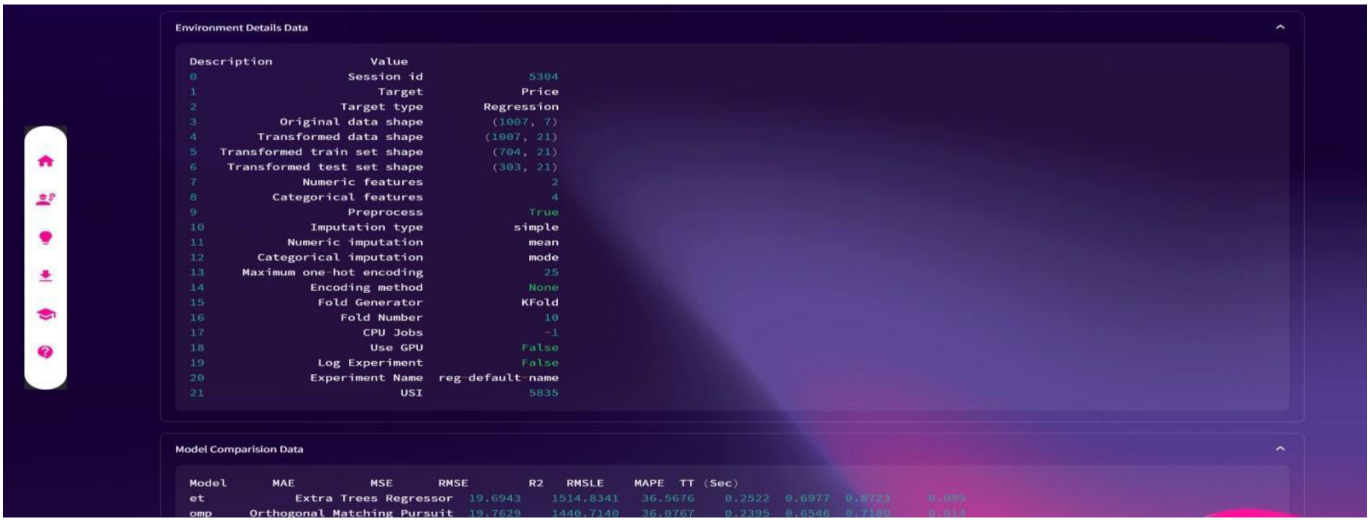

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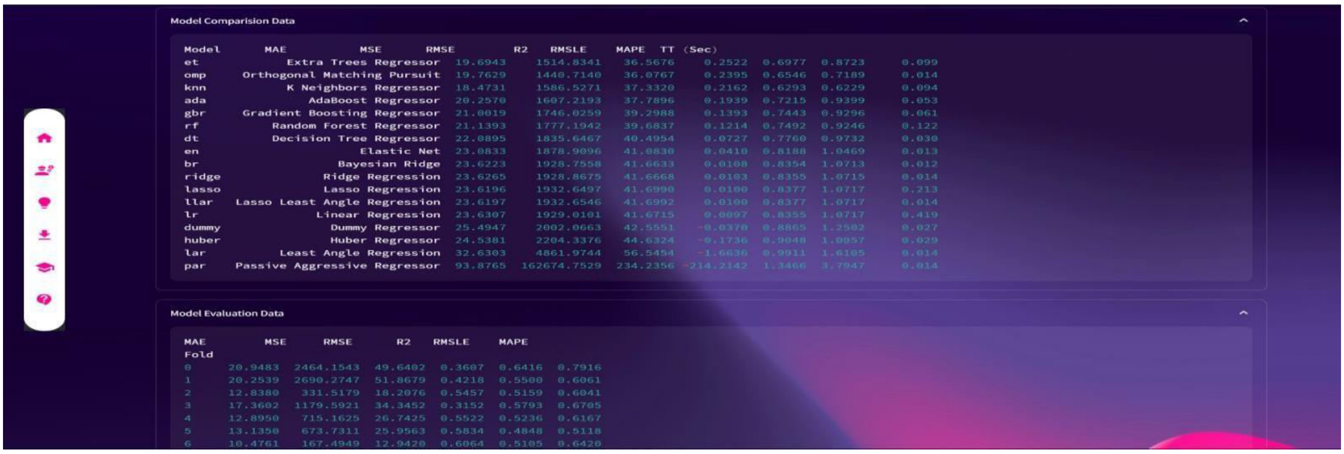

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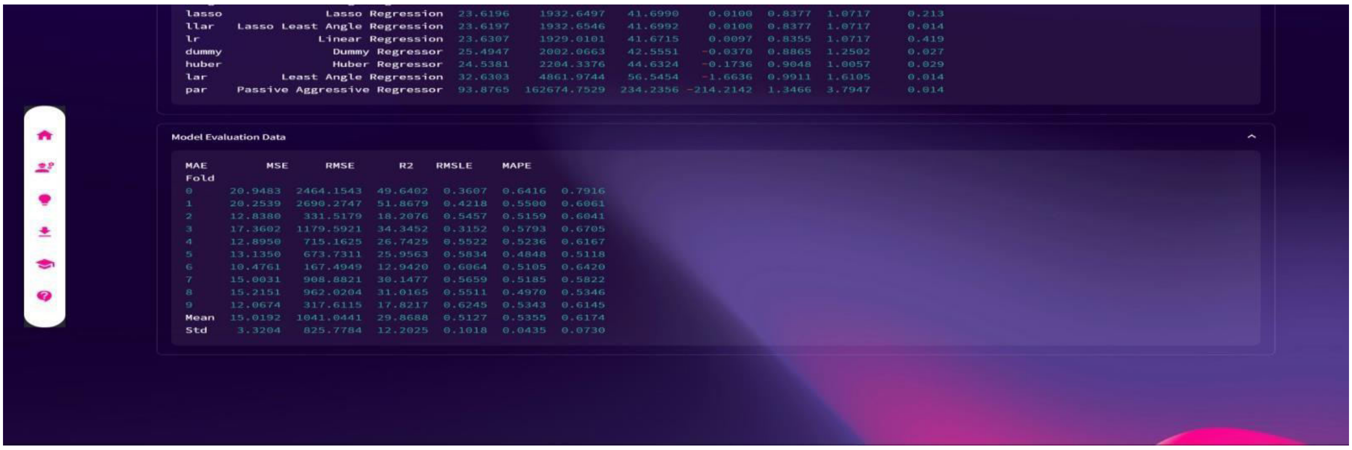

Fig 5.

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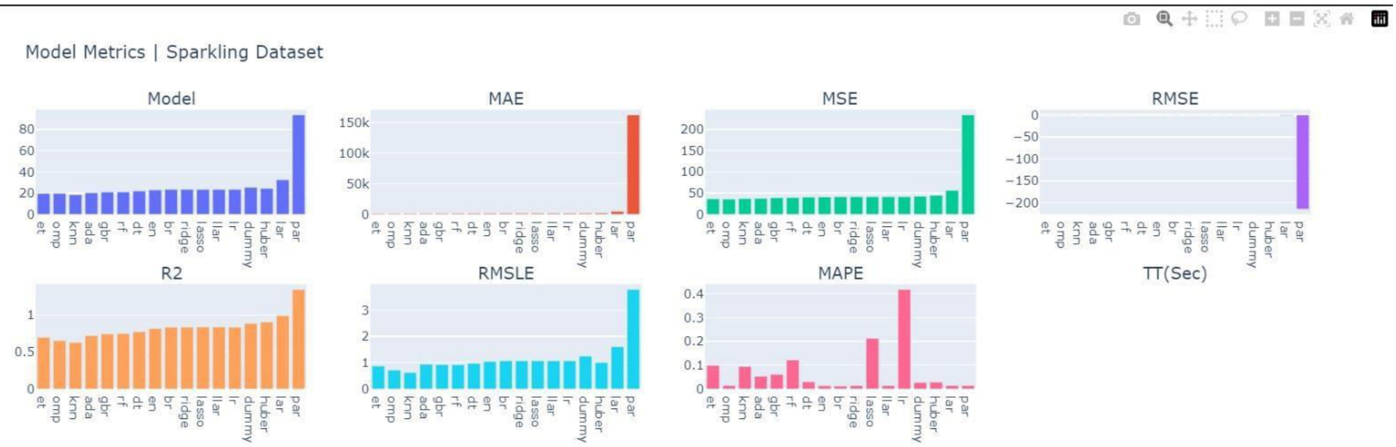

Fig 6. The outcomes, depicted in Figures 3, 4, 5, and 6, consist of matrices and graphs that facilitated the identificationof the most effective algorithm by the model.

3. 4 Implementation and Contribution of A Streamlit-Powered Interface for Rapid Model Development with PyCaret using Diabetes Dataset

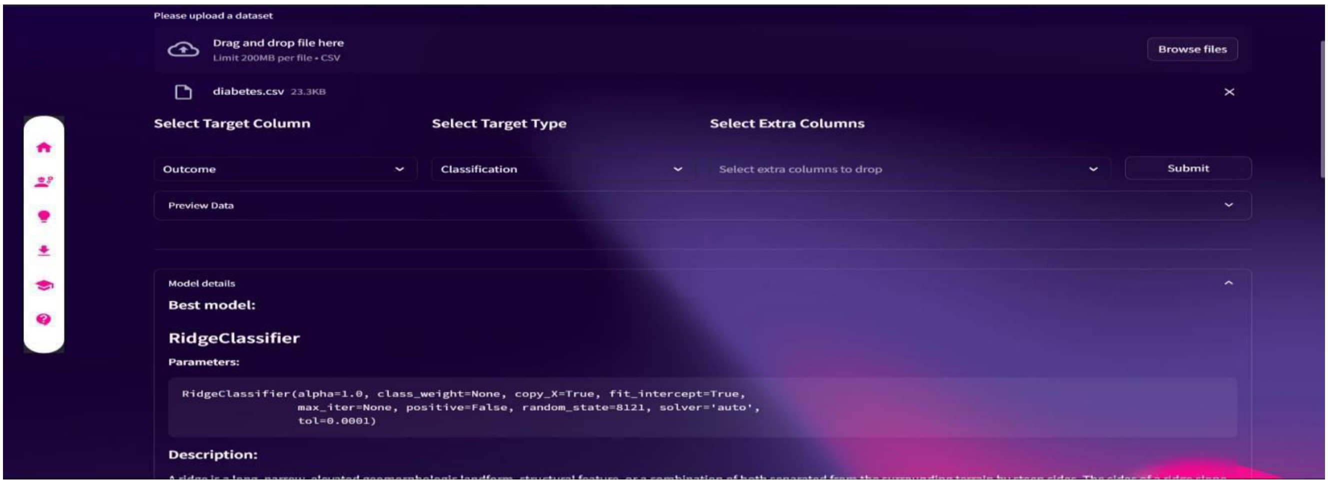

Fig 1.

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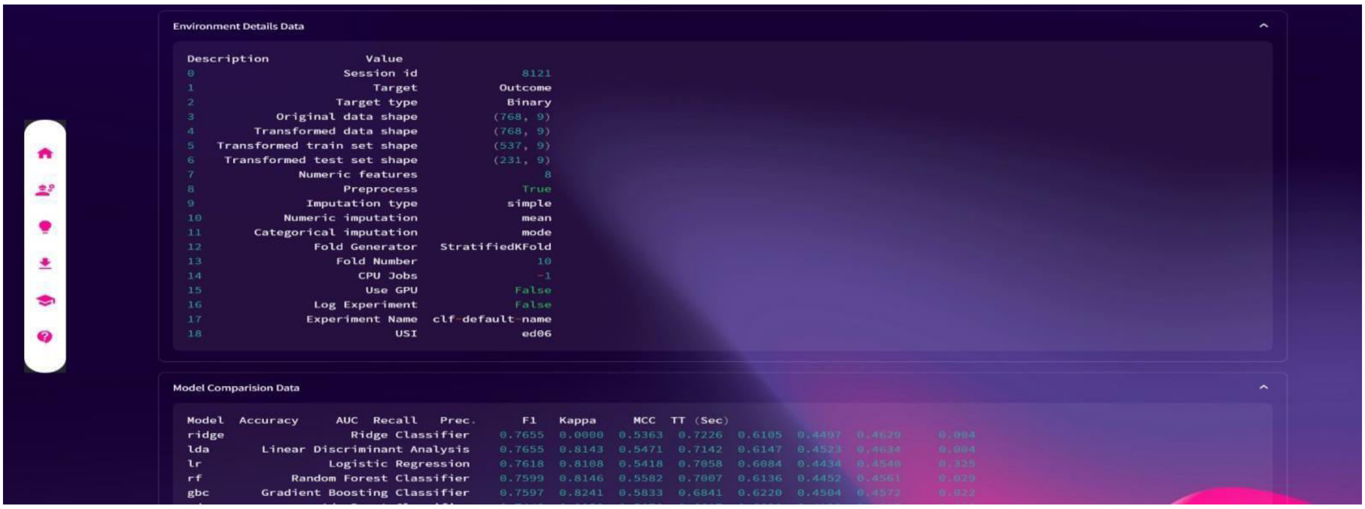

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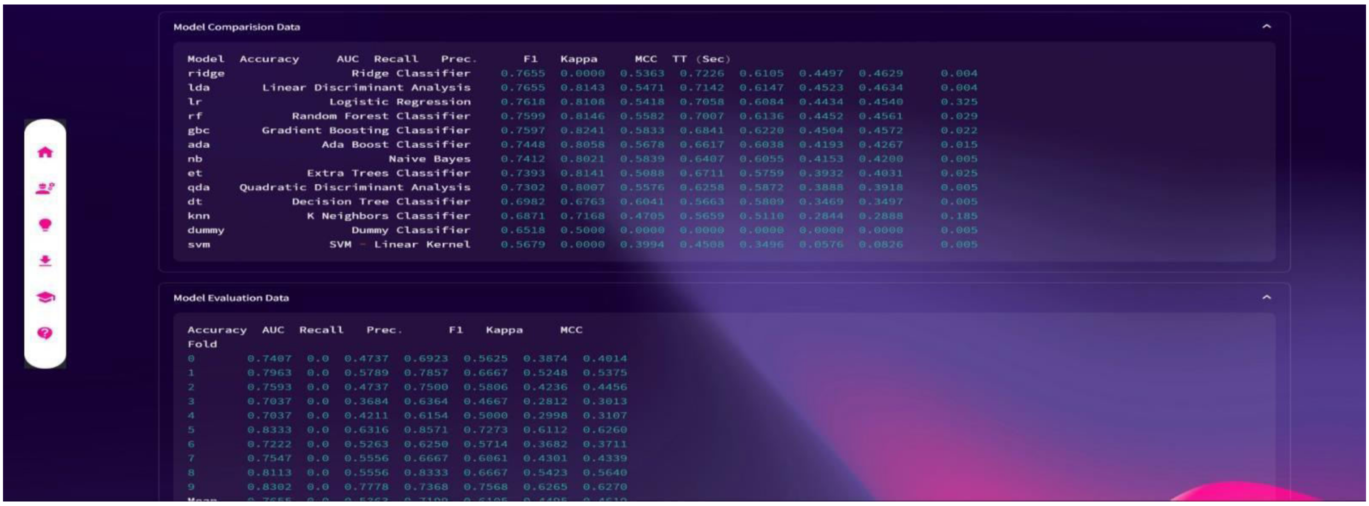

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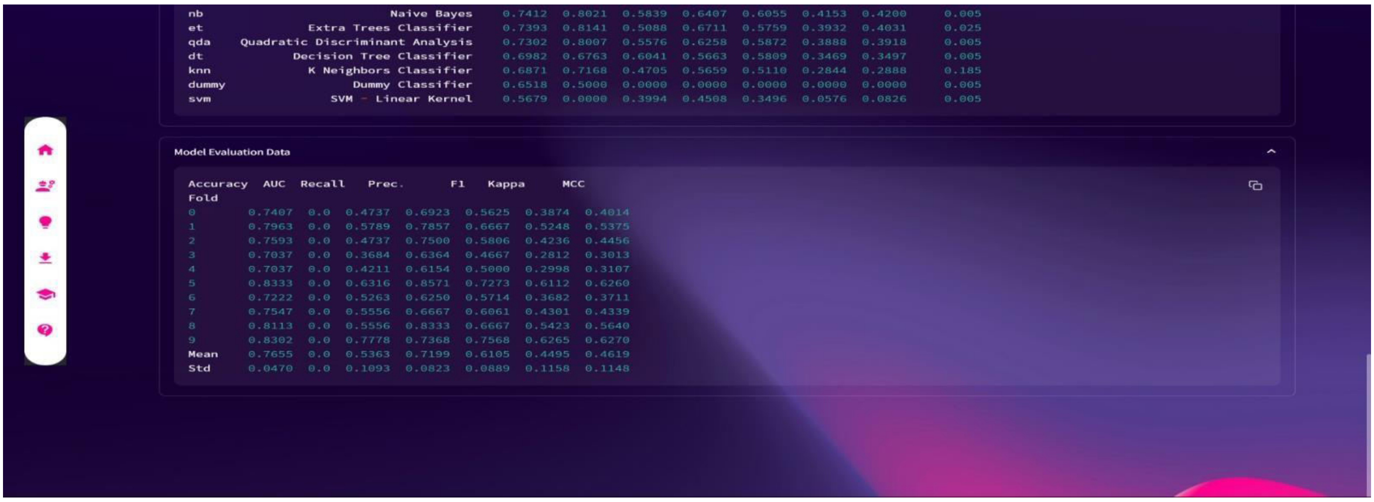

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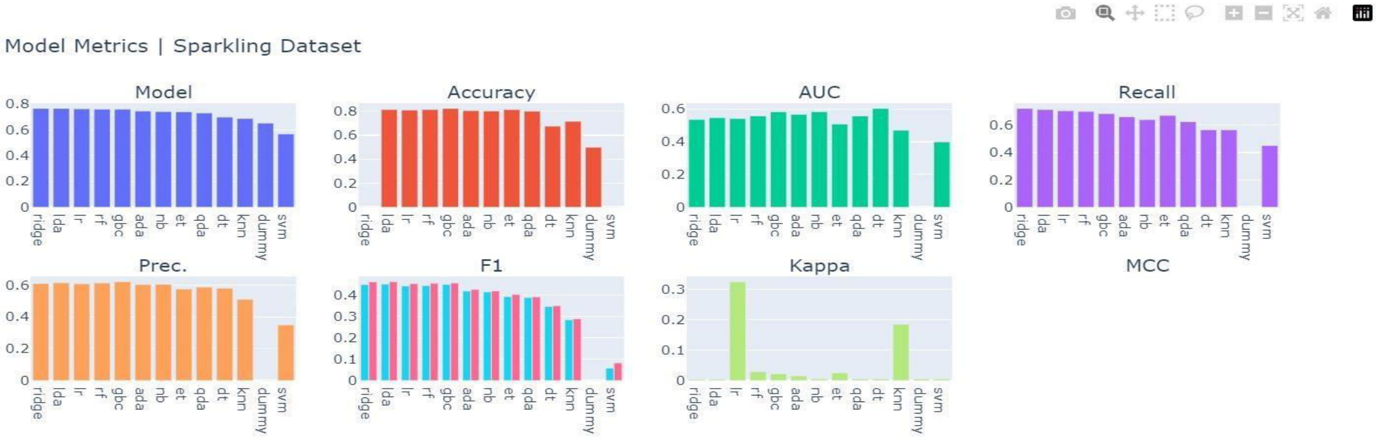

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3. 5 Implementation and Contribution of A Streamlit-Powered Interface for Rapid Model Development with PyCaret using Online Food Dataset

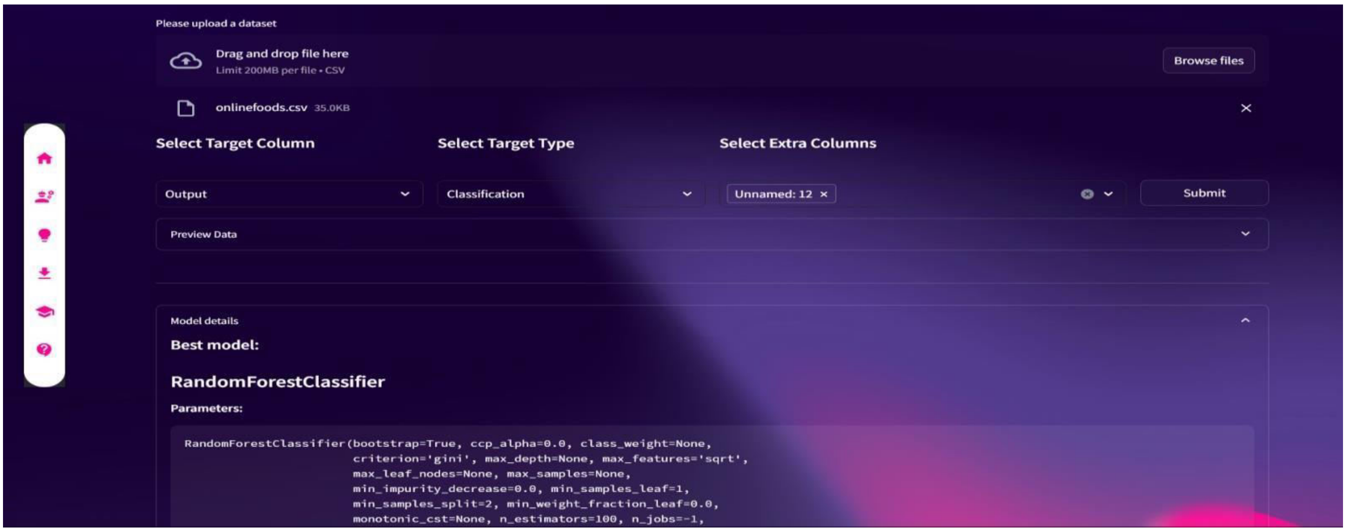

Fig 1.

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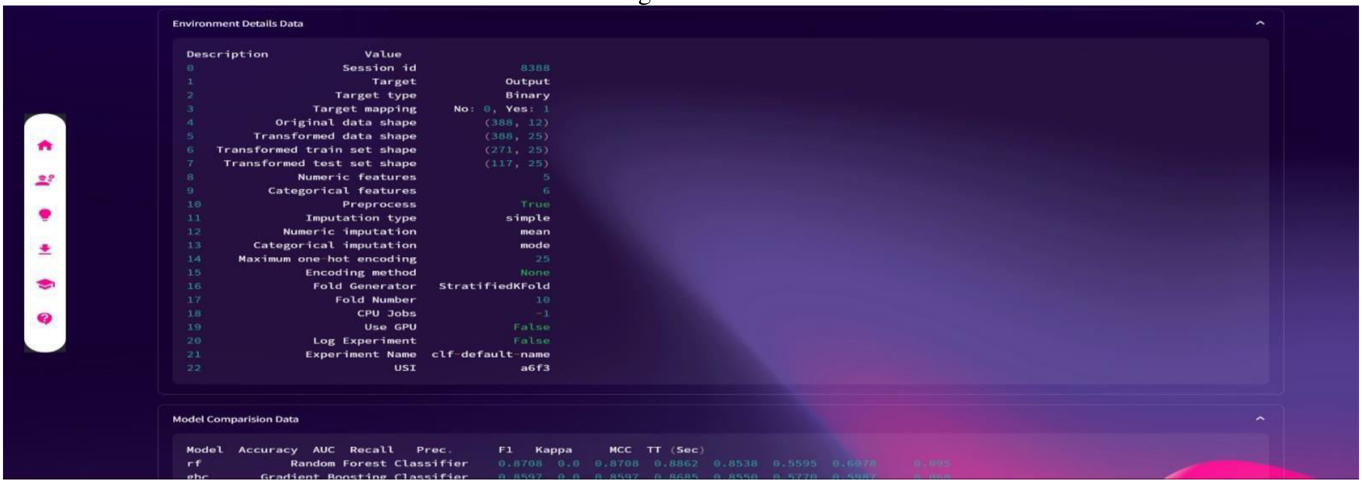
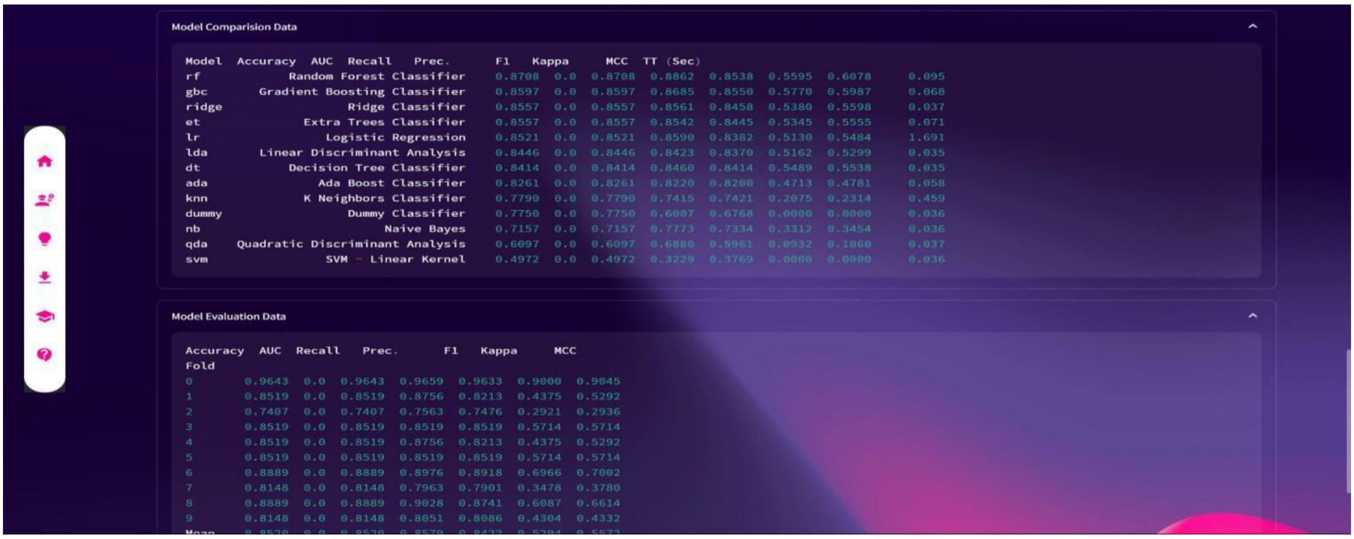

Environment Details Data

	Description	Value
0	Session id	8388
1	Target	Output
2	Target type	Binary
3	Target mapping	No: 0, Yes: 1
4	Original data shape	(388, 12)
5	Transformed data shape	(388, 25)
6	Transformed train set shape	(271, 25)
7	Transformed test set shape	(117, 25)
8	Numeric features	5
9	Categorical features	6
10	Preprocess	True
11	Imputation type	simple
12	Numeric imputation	mean
13	Categorical imputation	mode
14	Maximum one-hot encoding	25
15	Encoding method	None
16	Fold Generator	StratifiedKFold
17	Fold Number	10
18	CPU Jobs	-1
19	Use GPU	False
20	Log Experiment	False
21	Experiment Name	clf-default-name
22	USI	a6f3

Model Comparision Data

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
rf	Random Forest Classifier	0.8708	0.0	0.8708	0.8862	0.8538	0.5595	0.6078	0.095

Fig 3.

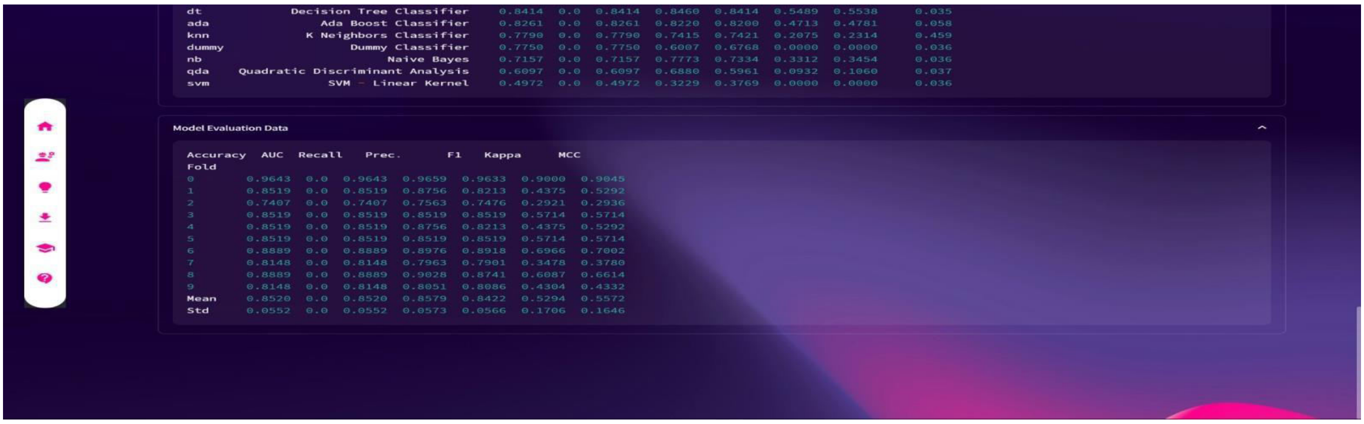

Model Comparision Data

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
rf	Random Forest Classifier	0.8708	0.0	0.8708	0.8862	0.8538	0.5595	0.6078	0.095
gbc	Gradient Boosting Classifier	0.8597	0.0	0.8597	0.8685	0.8550	0.5770	0.5987	0.068
ridge	Ridge Classifier	0.8557	0.0	0.8557	0.8561	0.8458	0.5380	0.5598	0.037
et	Extra Trees Classifier	0.8557	0.0	0.8557	0.8542	0.8445	0.5345	0.5555	0.071
lr	Logistic Regression	0.8521	0.0	0.8521	0.8590	0.8382	0.5130	0.5484	1.691
lda	Linear Discriminant Analysis	0.8446	0.0	0.8446	0.8423	0.8370	0.5162	0.5299	0.035
dt	Decision Tree Classifier	0.8414	0.0	0.8414	0.8460	0.8414	0.5489	0.5538	0.035
ada	Ada Boost Classifier	0.8261	0.0	0.8261	0.8220	0.8200	0.4713	0.4781	0.058
knn	K Neighbors Classifier	0.7790	0.0	0.7790	0.7415	0.7421	0.2075	0.2314	0.459
dummy	Dummy Classifier	0.7750	0.0	0.7750	0.6007	0.6768	0.0000	0.0000	0.036
nb	Naive Bayes	0.7157	0.0	0.7157	0.7773	0.7334	0.3312	0.3454	0.036
qda	Quadratic Discriminant Analysis	0.6097	0.0	0.6097	0.6880	0.5961	0.0932	0.1060	0.037
svm	SVM - Linear Kernel	0.4972	0.0	0.4972	0.3229	0.3769	0.0000	0.0000	0.036

Model Evaluation Data

Fold	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.9643	0.0	0.9643	0.9659	0.9633	0.9000	0.9045
1	0.8519	0.0	0.8519	0.8756	0.8213	0.4375	0.5292
2	0.7407	0.0	0.7407	0.7563	0.7476	0.2921	0.2936
3	0.8519	0.0	0.8519	0.8519	0.8519	0.5714	0.5714
4	0.8519	0.0	0.8519	0.8756	0.8213	0.4375	0.5292
5	0.8519	0.0	0.8519	0.8519	0.8519	0.5714	0.5714
6	0.8889	0.0	0.8889	0.8976	0.8918	0.6966	0.7002
7	0.8148	0.0	0.8148	0.7963	0.7901	0.3478	0.3780
8	0.8889	0.0	0.8889	0.9028	0.8741	0.6087	0.6614
9	0.8148	0.0	0.8148	0.8051	0.8086	0.4304	0.4332

Fig 4.



	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
dt	Decision Tree Classifier	0.8414	0.0	0.8414	0.8460	0.8414	0.5489	0.5538	0.035
ada	Ada Boost Classifier	0.8261	0.0	0.8261	0.8220	0.8200	0.4713	0.4781	0.058
knn	K Neighbors Classifier	0.7790	0.0	0.7790	0.7415	0.7421	0.2075	0.2314	0.459
dummy	Dummy Classifier	0.7750	0.0	0.7750	0.6007	0.6768	0.0000	0.0000	0.036
nb	Naive Bayes	0.7157	0.0	0.7157	0.7773	0.7334	0.3312	0.3454	0.036
qda	Quadratic Discriminant Analysis	0.6097	0.0	0.6097	0.6880	0.5961	0.0932	0.1060	0.037
svm	SVM - Linear Kernel	0.4972	0.0	0.4972	0.3229	0.3769	0.0000	0.0000	0.036

Model Evaluation Data

Fold	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.9643	0.0	0.9643	0.9659	0.9633	0.9000	0.9045
1	0.8519	0.0	0.8519	0.8756	0.8213	0.4375	0.5292
2	0.7407	0.0	0.7407	0.7563	0.7476	0.2921	0.2936
3	0.8519	0.0	0.8519	0.8519	0.8519	0.5714	0.5714
4	0.8519	0.0	0.8519	0.8756	0.8213	0.4375	0.5292
5	0.8519	0.0	0.8519	0.8519	0.8519	0.5714	0.5714
6	0.8889	0.0	0.8889	0.8976	0.8918	0.6966	0.7002
7	0.8148	0.0	0.8148	0.7963	0.7901	0.3478	0.3780
8	0.8889	0.0	0.8889	0.9028	0.8741	0.6087	0.6614
9	0.8148	0.0	0.8148	0.8051	0.8086	0.4304	0.4332
Mean	0.8520	0.0	0.8520	0.8579	0.8422	0.5294	0.5572
Std	0.0552	0.0	0.0552	0.0573	0.0566	0.1706	0.1646

Fig 5.

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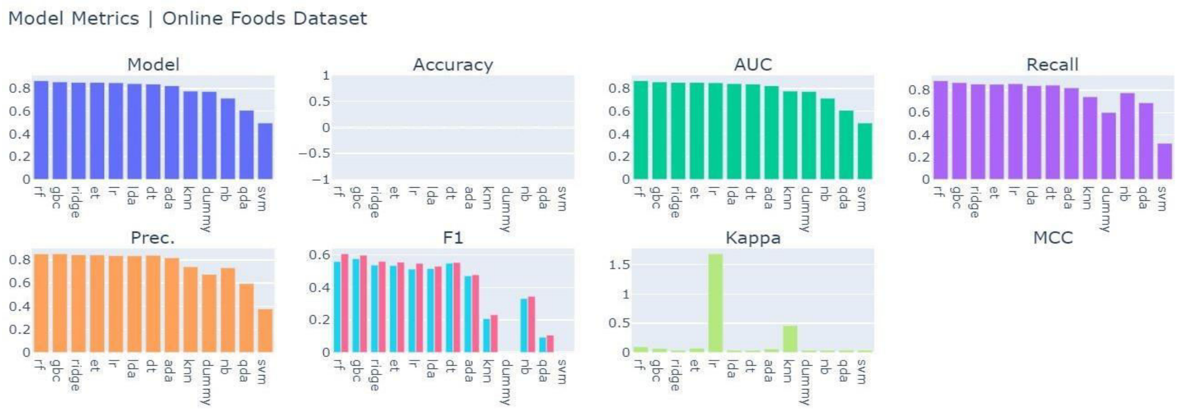

Fig 6. The outcomes, depicted in Figures 3, 4, 5, and 6, consist of matrices and graphs that facilitated the identification of themost effective algorithm by the model.

IV. CONCLUSION AND FINDINGS OF THE RESEARCH WORK

The Conclusions section synthesizes the key findings and implications drawn from the utilization of the Streamlit-based browser interface for PyCaret as a Machine Learning Model Generator. It encapsulates the significance of the research endeavor, highlightscontributions to the field, and outlines future directions for research and development. The section begins by summarizing the main findings and insights derived from the experimentation and analysis conducted using the interface. This includes a succinct overview of model performance, comparative analyses, feature importance insights, and user feedback. The interface represents a significant contribution to the field of machine learning model development by democratizing access to advanced machine learning techniques and automation capabilities. By integrating PyCaret within the Streamlit framework, the interface empowers users with a user-friendly and intuitive tool for generating high-quality machine learning models with minimal coding effort. The implications of the interface extend beyond academic research to practical applications in industry and academia. Practitioners can leverage the interface to expedite the model development process, accelerate decision-making, and unlock actionable insights from data. Researchers can utilize the interface as a platform for exploring new methodologies, conducting comparative studies, and advancing the state-of-the-art in machine learning automation.

While the interface offers valuable capabilities for model generation and evaluation, it is not without limitations. Future iterations ofthe interface may seek to address scalability challenges, enhance support for specialized machine learning tasks or algorithms, and improve usability based on user feedback. Additionally, ongoing research efforts may focus on expanding the interface's capabilities for model deployment, interpretability, and collaboration among users. In conclusion, the Streamlit-based browser interface for PyCaret represents a promising tool for democratizing machine learning and accelerating innovation in data-driven decision-making. Researchers, practitioners, and developers are encouraged to explore the interface, contribute to its development, and leverage its capabilities to solve complex real-world problems. The authors express gratitude to all individuals and organizations who contributed to the development and evaluation of the interface, including collaborators, beta testers, and open-source contributors. Their support and feedback were instrumental in shaping the interface and advancing the field of machine learning model development.

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