Research on Business Design Decisions Driven by Machine Learning

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***Abstract*—In the current fast-paced, competitive market, artificial intelligence (AI)-driven decision-making has become an indispensable part, sparking intense interest in industrial machine learning (ML) applications. The demand for experts in requirements analysis far outstrips supply, and one solution is to enhance the user-friendliness of machine learning frameworks. Automated Machine Learning (AutoML) is seen as an attempt to address the issue of expertise shortage by providing fully automated, customized solutions. This study aims to analyze the potential of AutoML in business analytics applications, with the goal of promoting the widespread application of ML. The H2O AutoML framework demonstrated excellent performance, robustness, and reliability by benchmarking against manually tuned stacked ML models on three real datasets. This framework is fast, easy to use, and provides reliable results close to those of professionally tuned ML models. Currently, the capabilities of the H2O AutoML framework can support rapid prototyping, shortening the development and deployment cycle, bridging the gap between the supply and demand of ML experts, and marking a significant step towards fully automated decision-making in business analytics..**

Keywords—Machine Learning, Automated Learning, Business Decision-Making, Business Analytics

I. Introduction

In today's competitive business environment, artificial intelligence (AI) is becoming increasingly important for the survival and development of organizations [1, 2]. The rapid acceleration of globalization and disruptive technologies has led industries to leverage advanced analytics and machine learning-based applications for a competitive edge in the market. Machine learning and AI have evolved into key components of data-driven decision-making, with business analytics playing a crucial role in driving new ways to make informed decisions. This has led to the emergence of interdisciplinary fields that combine multiple disciplines to harness the power of AI for strategic decision-making [3, 4].

AutoML is often lauded for its ability to democratize access to machine learning capabilities, enabling users with limited technical expertise to deploy ML models effectively. Studies have shown that AutoML platforms can significantly reduce the time and effort required to develop predictive models, making ML more accessible to non-experts[5].

Automated machine learning (AutoML) frameworks are vital in the data science toolkit, streamlining the development of ML pipelines by intelligently exploring vast configurations to optimize predictive accuracy, yet they face scalability challenges with large datasets due to increased execution times; SubStrat, an optimization strategy, addresses this by efficiently leveraging genetic algorithms to identify representative data subsets for AutoML, significantly reducing runtimes while maintaining high accuracy, as demonstrated in experiments with Auto-Sklearn and TPOT, achieving an average 79% reduction in runtime with under 2% loss in ML pipeline accuracy[6].

II. Methods and Materials

A. AutoML

In this study, we will delve into the evaluation of hyperparameter optimization and model selection within the H2O AutoML framework, a prominent AutoML solution recognized for its effectiveness in classification and regression tasks. The goal is to utilize automated machine learning tools to streamline the model-building process and enhance predictive analytics capabilities[7, 17].

To begin the evaluation process, we will first identify a set of classification and regression datasets representative of real-world scenarios. These datasets will encompass a range of features and target variables to test the performance of various machine learning models trained within the H2O AutoML framework. Utilizing the H2O AutoML framework, we will conduct a series of experiments on the selected datasets to train and evaluate machine learning models. The framework's hyperparameter optimization capabilities will be employed to fine-tune and optimize the performance of the models. By automating the hyperparameter adjustment process, our aim is to determine the optimal configuration for each model, thereby enhancing their predictive accuracy and generalization capabilities.

The evaluation process will involve training multiple machine learning models on the selected datasets using the H2O AutoML framework. The performance of these models will be assessed using a validation dataset, with metrics such as accuracy, precision, recall, and F1 score used to quantify their effectiveness. Through this comprehensive analysis, we seek to provide insights into the capabilities of AutoML in optimizing hyperparameters and selecting the best-performing models for classification and regression tasks.

In summary, this study aims to promote an understanding of hyperparameter optimization and model selection within the H2O AutoML framework, the efficacy of automated machine learning tools in enhancing predictive analytics capabilities. See Figure 1 below.

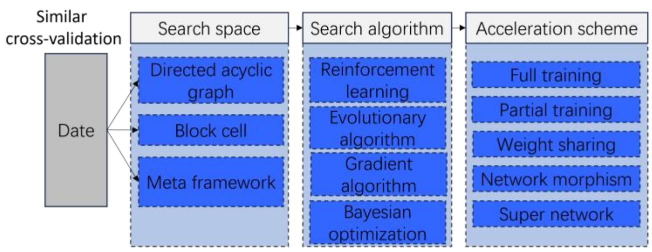

Fig. 1. The H2O AutoML framework trains multiple base learners and subsequently combines these learners with two different meta-learners in the subsequent steps. The technique of designing well-performing models from scratch for a specific dataset, finding network architectures that

perform well for the target task within the search space. The results are automatically ranked according to the chosen evaluation metric.

AutoML frameworks have revolutionized the machine learning model-building process by automatically selecting and optimizing models [9]. H2O has developed a renowned AutoML framework that leverages advanced techniques such as stacked ensembles to create powerful predictive models. During the initial training phase, the framework generates candidate models, such as Generalized Linear Models (GLM), random forests, gradient boosting, and deep learning models. These models are then used to construct two meta-learners through stacking, one that includes all pre-trained candidate models and another that includes the best model from each model family.

Key parameters of the H2O AutoML solution include feature columns (x), response column (y), training_frame, and validation_frame, which specify the datasets used for training and validation. Additionally, parameters such as max_models and max_runtime_secs control the model optimization process, placing limits on the number of models trained and the maximum allowed runtime. Random search is employed as the optimization method, enabling the framework to efficiently explore the hyperparameter space and identify the optimal model configuration.

Studies have shown the effectiveness of AutoML frameworks in enhancing model performance. For instance, Zhu et al. introduced an AutoML framework that utilizes parallel stacking ensemble techniques to improve predictive accuracy[5]. This highlights the potential of ensemble methods in significantly improving model performance, providing a comprehensive review of hyperparameter optimization techniques, emphasizing the importance of adjusting hyperparameters for model generalization. In-depth research on AutoML and hyperparameter optimization has been conducted[18, 19], such as Agrapetidou, Anna, et al., who have explored the application of AutoML in predicting bankruptcy models for banks[20], indicating that JAD and AutoML tools can generally improve the productivity of financial data analysts, prevent methodological statistical errors, and provide models comparable to the latest manual analysis.

In summary, AutoML frameworks developed by H2O provide a systematic and effective approach to machine learning model development. By integrating advanced techniques such as stacked ensembles, researchers can enhance model performance and drive the advancement of the field of automated machine learning.

Algorithm 1 Pseudocode for the Automated Machine Learning (AutoML) process.

Input: Dt (labeled test dataset), D1 (labeled training dataset),
K (number of cross-validation sets), t (time to completion),
M (selection of meta-learner algorithm)

Begin
Step 1: LogisticRegressionClassifier ← TrainClassifier(D1, 'logistic_regression')
Step 2: DeepLearningClassifier ← TrainClassifier(D1, 'deep_learning')
Step 3: GradientEnhancedClassifier ← TrainClassifier(D1, 'gradient_boosting')
Step 4: RandomForestClassifier ← TrainClassifier(D1, 'random_forest')
Step 5: SuperLearner1 ← CreateSuperLearner ([LogisticRegressionClassifier, DeepLearningClassifier, GradientEnhancedClassifier, RandomForestClassifier])
Step 6: BestClassifiers ← SelectBestClassifiersPerCategory(SuperLearner1)
Step 7: SuperLearner2 ← CreateSuperLearner(BestClassifiers)
Step 8: Repeat Steps 1 to 6 until (max_models is reached) or (time limit t is reached)
Step 9: PerformanceMetrics ← EvaluateModels({SuperLearner1, SuperLearner2}, D1, k, 'cross_validation')
Step 10: FinalModel ← SelectModelWithHighestPerformance(PerformanceMetrics, {SuperLearner1, SuperLearner2})
Step 11: HyperparameterTuning(FinalModel, D1, 'grid_search') or HyperparameterTuning(FinalModel, D1, 'random_search')
Step 12: GeneralizationPerformance ← EvaluateModelOnTestSet(FinalModel, Dt)
Step 13: If GeneralizationPerformance is unsatisfactory Then
RetrainFinalModel(FinalModel, D1)
End If
Output: RankedList ← RankModelsAccordingToAccuracy(Dt)
End

Output: A descending list of classifiers created during runtime, ranked according to their accuracy in predicting the test dataset Dt.

B. *Experimental Design*

The primary objective of this empirical study is to benchmark the H2O AutoML framework against manually trained ensemble super learners, thereby testing its performance, robustness, and reliability on real datasets from the domains of credit risk, insurance claims, and marketing.

1) *Datasets*

The focus of this study is to conduct a comprehensive experimental analysis using three publicly available datasets from machine learning repositories or Kaggle, aimed at evaluating the performance of classification algorithms. The datasets consist of features used as predictors to determine the classification categories related to defaulting customers, insurance claims, and successful marketing campaigns. The datasets used include 35,000 observations and 15 features, with each feature capturing unique characteristics of the data. These features are crucial for predicting classification outcomes related to defaulting customers, insurance claims, and successful marketing activities. The first dataset includes information about the age of customers, the second dataset centers on the initiation of insurance claims, and the third dataset focuses on the impact of marketing efforts on sales. Each dataset contains a binary response column indicating the occurrence or absence of a specific event. Highlighting the applicability and effectiveness of classification algorithms, Table 1 provides a detailed summary of key points extracted from the datasets used in this study.

TABLE I. DESCRIPTION OF DATASETS

Case Study				
Age_group	***Person_income***	***loan_int_rate***	***loan_amnt***	***loan_percent_income***
21	9600	11.14	1000	0.1
22	59000	16.02	35000	0.59
23	65500	15.23	35000	0.53
24	54400	14.27	35000	0.55
25	9600	12.87	5500	0.57

1 The “Credit Risk” dataset can be accessed here: https://www.kaggle.com/datasets/laotse/credit-risk-dataset
2 The “Insurance Claims” dataset can be accessed here: https://www.kaggle.com/datasets/thedevastator/prediction-of-insurance-charges-using-age-gender
3 The Marketing/Sales dataset can be accessed here: https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

a) *Age_group:*

The Credit Risk Dataset from the credit risk domain contains rich information on credit card customer payment behavior and demographic characteristics. With observations ranging from 21 to 25 years old, the dataset is well-balanced with 14,548 "positive" observations, indicating non-default, and 895 "negative" observations indicating default. The dataset consists of 15 features, and the response column displays binary default or non-default information. Some key features present in the dataset include historical payment information, such as payment amounts and dates, as well as demographic information, such as gender, age, marital status, and level of education. The dataset provides a comprehensive view of credit card customers in Southeast Asia and offers valuable insights into the factors affecting credit risk. Analyzing this dataset can help financial institutions effectively assess and manage credit risk.

b) Person_income

This study utilizes a dataset of 198,100 observations to investigate the complex relationship between policyholder characteristics and their claim status. The dataset contains 57 detailed features, including policyholder demographic data, coverage details, and historical claim information, including a key response column indicating the claim status of each policyholder. Through a comprehensive analysis of these features, this study aims to enhance predictive modeling in the insurance industry, providing valuable insights for risk assessment, claim management, and customer segmentation strategies.

c) Loan_amnt

The third dataset focuses on marketing and sales in the financial services sector, providing extensive customer information related to direct marketing activities. The dataset consists of 111,500 observations, including 1,000 failed observations and 110,500 successful observations, where success is defined as resulting in a conversion or final sale. Each observation in the dataset is composed of 16 features, covering various aspects of customer behavior and marketing campaign engagement. The dataset also has a response column displaying binary outcomes, indicating whether the marketing campaign led to a successful conversion or sale. This dataset is highly valuable for analyzing the effectiveness of marketing strategies and determining the key factors for successful customer engagement in the financial services sector. By leveraging this dataset, businesses can optimize their marketing campaigns, enhance their sales efforts, and drive conversion and revenue growth.

2) Preprocessing

Several preprocessing steps were necessary before running the experiment:

a) Random undersampling

Dataset imbalance presents significant challenges in the field of predictive modeling, especially in datasets where the ratio of positive to negative observations exceeds 90:10. Imbalance can distort the predictive accuracy of classifiers, attributing success more to differences in data distribution rather than actual model performance. To correct these imbalances, techniques such as random undersampling can be employed to reduce the abundance of the majority class observations, achieving a more balanced state. While undersampling can lead to the loss of information, this trade-off is generally acceptable in benchmarking exercises where the primary goal is to compare the performance of an automated machine learning (AutoML) system with manually optimized super learners. Conversely, oversampling certain classes to address imbalance issues can be considered, but this strategy may increase the size of the dataset and prolong training time, especially in already information-rich datasets. Striking a balance between dataset distribution and predictive accuracy is crucial for robust and reliable predictive modeling outcomes.

b) Encoding

A key preprocessing step in the fields of artificial intelligence and machine learning is the encoding of categorical data into numerical representations to facilitate model training and evaluation. This transformation is necessary because AI and ML models typically operate on numerical input variables. To convert categorical data into a numerical format, techniques such as one-hot encoding or ordinal encoding are commonly used. One-hot encoding involves creating binary columns for each distinct category of a feature, while ordinal encoding is used when the categories display a predefined ordering. Notably, the H2O platform provides a parameter setting called "one_hot_explicit," which generates N+1 new columns for a categorical feature with N levels, effectively converting categorical data into a numerical format suitable for model training and analysis. These encoding methods play a critical role in enhancing the interpretability and performance of AI and ML models, ensuring that the data structure is appropriate for predictive modeling tasks.

c) Training

In the context of machine learning model development, the choice of data split ratio is key to ensuring model robustness. Here, an 80:20 data split strategy is employed, where 80% of the dataset is allocated for training purposes, and the remaining 20% is used for testing, as a standard practice to assess the generalization capability of the trained classifier. This division allows for the evaluation of the model's performance on unseen data, thereby measuring its ability to make accurate predictions on new observations. Additionally, a similar cross-validation setup is essential for integrating the base learners into the meta-learner. During the model training process, cross-validation techniques further divide the 80% training data subset into different training and validation sets. This iterative process helps fine-tune model parameters, optimize predictive accuracy, and validate the model's performance across multiple iterations, enhancing the reliability and robustness of machine learning algorithms.

3) Setup and Evaluation

In the domain of automated machine learning, the H2O AutoML framework emerges as a potent tool, leveraging a diverse array of base classifiers, including Generalized Linear Models (LR), Random Forests, Gradient Boosting Machines, and Deep Feedforward Neural Networks [17]. The ensemble of these classifiers forms the backbone of the AutoML solution, collectively contributing to the model training process and enhancing predictive capabilities across various domains. Following the individual training of these base models, an ensemble approach, such as stacking, amalgamates the pre-trained candidate models into a super learner. The purpose of this strategic fusion is to automatically identify the optimal model based on specified evaluation metrics, thereby improving predictive accuracy and simplifying the model selection process.

To assess the efficacy of this framework, a comparative study was conducted, replicating the internal workings of the H2O AutoML mechanism by manually training base models and subsequently aggregating them into manually stacked super learners. This comparative analysis involved evaluating two meta-learners, one generated by the automated workflow of H2O AutoML, and the other manually orchestrated and fine-tuned. To measure the performance and robustness of these two approaches, a comprehensive assessment was conducted using four key metrics: Area Under the Curve (AUC), Accuracy, F-score, and Recall. These metrics provide a multifaceted evaluation of model performance, revealing the effectiveness of both automated and manual model-building processes and highlighting the strengths and limitations of each method in terms of predictive accuracy and generalization capabilities.

4) Software

The seamless integration of preprocessing, model fitting, and evaluation within RStudio signifies a significant advancement in statistical programming and machine learning research. RStudio, a comprehensive Integrated Development Environment (IDE) [21] tailored for the R programming language, is a crucial tool in the fields of data science and machine learning. Notably, R, as the primary language for data exploration, modeling, and prototyping in computational statistics, has been widely adopted in both research and practical application domains. In the context of this study, the AutoML framework and base models, including Random Forest, Gradient Boosting Machines, and Deep Learning, were constructed using the H2O package in R[22].

H2O is an open-source machine learning platform developed in Java, offering a multitude of predictive modeling functionalities and unique performance advantages by facilitating the transition from traditional laptop/desktop environments to large-scale distributed systems. This enhanced scalability not only improves model efficiency but also enables seamless handling of extensive datasets, a critical asset in modern data-intensive research environments. The integration of H2O into RStudio through a REST API further emphasizes the platform's interoperability and versatility, providing researchers and practitioners with a powerful and flexible toolkit for simplifying model development and evaluation within the R environment.

III. NUMERICAL RESULTS

In the field of machine learning, the quest for the best predictive performance is eternal. To this end, our experiment delves into how a manually tuned stacked integrated learner compares to the H2O AutoML solution. By delving into three different real-world cases, including credit risk assessment, insurance claims prediction, and marketing analysis, we tried to uncover the true efficacy of these methods.

The H2O AutoML solution is compared to the artificially optimized super learner, and the optimal approach to the H2O AutoML solution is continuously discovered using four key evaluation metrics: area under the curve (AUC), accuracy, f score, and Recall.

The experimental structure is as follows:

The first step involved the careful training of three baseline models: Random Forest, Gradient Boosting Machine, and Deep Learning. To adjust the hyperparameter settings of the base models, traditional methods such as grid search and random search within predefined parameter ranges, as well as manual tuning, were employed during the training process. Table 2 presents the numerical results for each dataset's base classifiers. Gradient Boosting achieved the highest overall performance, followed by Random Forest. Deep Learning scored the lowest in performance. This was consistent across all three datasets.

TABLE II. NUMERICAL ANALYSIS OF LOAN RISK OPTIMIZATION

Case Study	Method	AUC	Accuracy	F-score	Recall
Compare_models	CatBoost Classifier	0.9432	0.9372	0.8337	0.7268
	Random Forest	0.9268	0.9322	0.8199	0.7127
	Gradient Boosting	0.9246	0.9282	0.8092	0.7028
	SVM - Linear Kernel	0	0.7114	0.3448	0.4288
Evaluate_model	CatBoost Classifier	0.948	0.9388	0.8406	0.7393
	Random Forest	0.9288	0.9319	0.8203	0.7124
	Gradient Boosting	0.9271	0.9274	0.8086	0.7033
	SVM - Linear Kernel	0	0.6887	0.2824	0.3736
Predict_model	CatBoost Classifier	0.9488	0.9388	0.8406	0.7393

In the second step, candidate models were combined with the so-called super learner through an ensemble method known as stacking, which has been proven to provide asymptotically optimal improvements on a set of base classifiers. For each case study, super learners were created using all three base models (RF, GBM, DL). All three combinations of the stacking ensemble's baseline models were tested, and in all three case studies, the best performance was achieved using RF, GBM, and DL as inputs to the super learner. This is not always the case.

TABLE III. COMPARISON OF BENCHMARK MODELS IN LOAN RISK ANALYSIS

model	score_test	score_val	pred_time_test	pred_time_val	fit_time	stack_level
WeightedEnsemble_L2	0.935918	0.931471	0.137792	0.077305	16.102642	2
CatBoost	0.935743	0.929725	0.017009	0.017721	9.904861	1
LightGBMLarge	0.935045	0.928852	0.028564	0.016615	4.18175	1
RandomForestEntr	0.929806	0.924051	0.347751	0.158012	14.002217	1
NeuralNetFastAI	0.929632	0.92536	0.140897	0.058506	37.681989	1

In the final step, the stacked super learners created in the second step were benchmarked against the H2O AutoML solution to evaluate its performance, robustness, and reliability. Table 3 presents the final comparison between the H2O AutoML solution and the trained super learners.

Recent research comparing stacked super learners and AutoML models on different datasets has found that the Area Under the Curve (AUC) of stacked super learners is consistently superior to that of AutoML models. Stacked ensembles not only show superior results in terms of AUC but also outperform AutoML solutions in most cases.

Specifically, when analyzing the credit risk case study, insurance dataset, and marketing case study, performance differences were observed in terms of accuracy, F-score, and Recall. While AutoML performed slightly better in the marketing case study, with some improvement in accuracy and F-score, manually adjusted stacked ensembles demonstrated better performance across all three case studies compared to the AutoML solution.

These findings highlight the potential of stacked ensembles as a powerful tool in machine learning, showcasing their superior capabilities over AutoML solutions in various practical applications.

IV. Discussion

The empirical study conducted a thorough benchmarking of the H2O AutoML framework against manually trained ensemble super learners, utilizing three distinct real-world datasets from the credit risk, insurance claims, and marketing domains. The aim was to scrutinize the performance, robustness, and reliability of AutoML in practical scenarios.

The "Credit Risk Dataset" from Kaggle, featuring credit card customer data, provided a comprehensive view of customer payment behavior and demographic characteristics, with a focus on credit risk assessment. The "Insurance Claims Dataset" offered insights into customer behavior and factors contributing to insurance charges, with detailed information about insurance customers. Lastly, the "Marketing/Sales Dataset" from the UCI Machine Learning Repository centered on the impact of marketing efforts on sales, with customer information related to direct marketing activities.

Preprocessing steps, including random undersampling to address dataset imbalance and encoding of categorical data, were crucial for model training and evaluation. The 80:20 data split strategy, with cross-validation, ensured the robustness of the models developed.

The experimental setup in RStudio, leveraging the H2O package, allowed for the construction and evaluation of various base models, including Generalized Linear Models, Random Forests, Gradient Boosting Machines, and Deep Learning models. These models were then integrated into super learners through stacking, aiming to identify the optimal model configuration.

Numerical results from the study revealed that while the H2O AutoML solution showed competitive performance, manually adjusted stacked ensembles demonstrated superior results across all case studies in terms of AUC, Accuracy, F-score, and Recall. Notably, in the marketing case study, AutoML showed slight improvements in accuracy and F-score, yet overall, the manually tuned models outperformed the AutoML solution.

The study concludes that although AutoML frameworks like H2O provide a valuable tool for rapid prototyping and ease the expertise shortage, their performance may not surpass that of carefully crafted, manually tuned models. The findings underscore the importance of considering both automated and manual approaches in model development, depending on the specific requirements and constraints of the business environment.

V. Conclusion

The development of the digital world economy has ushered in a new era of demand for expertise in the fields of machine learning and artificial intelligence (AI), leading to skill shortages that hinder the widespread adoption of AI and machine learning methods in the field of business analytics. This talent scarcity poses a significant challenge for organizations seeking to leverage the transformative potential of AI and machine learning technologies in their decision-making processes.

To address these challenges, the emergence of Automated Machine Learning (AutoML) frameworks, such as H2O AutoML, is considered a promising solution that can alleviate the prevalent talent shortage and accelerate the development of predictive analytics pipelines. Although the capabilities of current AutoML frameworks may not yet reach the pinnacle of predictive accuracy achievable through meticulous manual model tuning, research indicates that AutoML remains a powerful and valuable tool in the arsenal of machine learning practitioners.

In the prototyping phase, AutoML serves as a foundational platform for machine learning experts, simplifying the development and deployment cycle of machine learning projects. By providing a simplified interface and automating various aspects of the model selection and training process, AutoML enhances the accessibility of machine learning models to non-specialist users, bridging the gap between technical complexity and user-friendly interfaces.

Furthermore, integrating AutoML into the machine learning workflow is a crucial step towards building a complete end-to-end decision engine in business analytics. By automating key elements of the decision pipeline, AutoML paves the way for organizations to harness the power of data-driven insights and actionable outcomes, propelling them towards more informed and effective decision-making processes.

In conclusion, the use of AutoML frameworks exemplifies a pivotal advancement in the democratization of machine learning capabilities, providing organizations with a pathway to address the challenges posed by talent shortages and accelerate their journey towards establishing comprehensive decision engines in the realm of business analytics..

Dataset to be available

A. The "Credit Risk" dataset can be accessed here:

https://www.kaggle.com/datasets/laotse/credit-risk-dataset

B. The "Insurance Claims" dataset can be accessed here:

https://www.kaggle.com/datasets/thedevastator/prediction-of-insurance-charges-using-age-gender

C. The Marketing/Sales dataset can be accessed here:

https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

REFERENCES

[1] Bergdahl, J., et al., Self-determination and attitudes toward artificial intelligence: Cross-national and longitudinal perspectives. Telematics and Informatics, 2023. 82: p. 102013.

[2] Clayton, P.R. and J. Clopton, Business curriculum redesign: Integrating data analytics. Journal of Education for Business, 2019. 94(1): p. 57-63.

[3] Ashmore, R., R. Calinescu, and C. Paterson, Assuring the Machine Learning Lifecycle: Desiderata, Methods, and Challenges. ACM Comput. Surv., 2021. 54(5): p. Article 111.

[4] Silva, F.A.R., Analytical Intelligence in Processes: Data Science for Business. IEEE Latin America Transactions, 2018. 16(8): p. 2240-2247.

[5] Zhu, X., et al., Automated machine learning with dynamic ensemble selection. Applied Intelligence, 2023. 53(20): p. 23596-23612.

[6] Lazebnik, T., A. Somech, and A.I. Weinberg, SubStrat: A Subset-Based Strategy for Faster AutoML. ArXiv, 2022. abs/2206.03070.

[7] Truong, A.T., et al., Towards Automated Machine Learning: Evaluation and Comparison of AutoML Approaches and Tools. 2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI), 2019: p. 1471-1479.

[8] Zöller, M.-A., et al., XAutoML: A Visual Analytics Tool for Understanding and Validating Automated Machine Learning. ACM Trans. Interact. Intell. Syst., 2023. 13(4): p. Article 28.

[9] El Rajab, M., L. Yang, and A. Shami, Zero-touch networks: Towards next-generation network automation. Computer Networks, 2024. 243: p. 110294.

[10] Brown, O., et al., Theory-Driven Perspectives on Generative Artificial Intelligence in Business and Management. British Journal of Management, 2024. 35(1): p. 3-23.

[11] Mathrani, S., A. Mathrani, and D. Viehland, Using enterprise systems to realize digital business strategies. Journal of Enterprise Information Management, 2013. 26(4): p. 363-386.

[12] Alotaibi, N.S., et al., Secure Enhancement for MQTT Protocol Using Distributed Machine Learning Framework. Sensors, 2024. 24(5): p. 1638.

[13] Huang, L., et al., Enhancing computer image recognition with improved image algorithms. Scientific Reports, 2024. 14(1): p. 13709.

[14] Kwon, H., Dual-Targeted Textfooler Attack on Text Classification Systems. IEEE Access, 2023. 11: p. 15164-15173.

[15] Kwon, H. and S. Lee, Friend-guard adversarial noise designed for electroencephalogram-based brain–computer interface spellers. Neurocomputing, 2022. 506: p. 184-195.

[16] Canhoto, A.I. and F. Clear, Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. Business Horizons, 2020. 63(2): p. 183-193.

[17] Lazebnik, T., A. Somech, and A.I. Weinberg, SubStrat: A Subset-Based Optimization Strategy for Faster AutoML. Proc. VLDB Endow., 2022. 16(4): p. 772–780.

[18] Park, H., et al., HyperTendril: Visual Analytics for User-Driven Hyperparameter Optimization of Deep Neural Networks. IEEE Transactions on Visualization and Computer Graphics, 2021. 27(2): p. 1407-1416.

[19] Poulakis, Y., C. Doulkeridis, and D. Kyriazis, A Survey on AutoML Methods and Systems for Clustering. ACM Trans. Knowl. Discov. Data, 2024. 18(5): p. Article 120.

[20] Agrapetidou, A., et al., An AutoML application to forecasting bank failures. Applied Economics Letters, 2021. 28(1): p. 5-9.

[21] Bruelheide, H., et al., Implementing the formal language of the vegetation classification expert systems (ESy) in the statistical computing environment R. Applied Vegetation Science, 2021. 24(1): p. e12562.

[22] Tomas Fryda, E.L., Navdeep Gill et al. , *h2o: R Interface for the 'H2O' Scalable Machine Learning Platform.* Retrieved November 2024. **22**.