e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:02/February-2025 Impact Factor- 8.187 www.irjmets.com

ENHANCING AUTOMATED MACHINE LEARNING THROUGH THE ASSESSMENT OF DATA QUALITY AND QUANTITY

Pavan Kumar Kunisetty[*1], Yerramsetti Sai Sindhu[*2], K Vijay Kumar[*3], G Mahesh Challari[*4]

[*1,3,4]Assistant Professor, Department Of Computer Science And Engineering, Sree Dattha Institute Of Engineering & Science, Hyderabad, India.

[*2]Lecturer, Department Of Computer Science And Engineering, Sree Dattha Institute Of Engineering & Science, Hyderabad, India.

DOI: https://www.doi.org/10.56726/IRJMETS67098

ABSTRACT

This research investigates the symbiotic relationship between data quality, data quantity, and automated machine learning (AutoML), which has become indispensable as machine learning permeates diverse domains. The study aims to elucidate how bolstering data quality and optimizing data quantity influence the efficacy of AutoML pipelines. Through a comprehensive exploration of data quality assessment methods, data augmentation techniques, and their impact on AutoML outcomes, the research introduces a novel framework that seamlessly integrates data preprocessing, quality evaluation, quantity enhancement, and AutoML model selection. This framework not only offers practical guidance to enhance the efficiency of machine learning workflows but also unveils the intricate balance between data quality and quantity, showcasing scenarios where emphasizing one facet could yield superior results. Empirical findings underscore the proposed framework's potential to heighten predictive performance and generalization across tasks, bridging the gap between data quality, quantity, and automated machine learning. This contribution advances the AutoML domain, underscoring the holistic data preparation and model generation approach's significance, providing actionable strategies to augment the overall proficiency of automated machine learning systems sought after by organizations reliant on machine learning-driven decisions.

Keywords: Machine Learning Integration, Automated Machine Learning (Automl), Data Quality, Data Quantity, Model Development And Data Preprocessing.

I. INTRODUCTION

In an era characterized by the widespread integration of machine learning[1,3] into various sectors, the significance of automated machine learning (AutoML) has grown considerably, simplifying the complex task of model[8] development. However, the dependability and performance of AutoML techniques are inherently intertwined with the quality and quantity of the underlying data[1]. This study deeply investigates the intricate interplay between two critical dimensions: the quality and quantity of data, and their profound influence on the effectiveness of AutoML. As machine learning[9] continues its expansion across diverse domains, this research aims to illuminate the dynamic relationship between enhancing data quality and optimizing data quantity within AutoML pipelines.

This research embarks on a comprehensive exploration, delving into different methodologies for assessing data quality and techniques for augmenting data. It meticulously examines their consequences on AutoML outcomes. The primary objective is to unveil the potential gains from improving both data quality and quantity, thereby shaping the efficiency of AutoML processes. A distinct contribution of this study lies in the introduction of an innovative framework, carefully crafted to seamlessly integrate essential components – ranging from data preprocessing and quality assessment to quantity optimization and AutoML model selection[6]. Significantly, this framework goes beyond theoretical concepts, offering practical insights and guidance that resonate with practitioners striving to enhance the effectiveness of their machine learning workflows. However, this study does not solely focus on isolated improvements. It acknowledges the delicate equilibrium between data quality and quantity, showcasing scenarios where prioritizing one aspect over the other could lead to noteworthy enhancements. Empirical findings, drawn from a diverse range of datasets, underscore the framework's potential to enhance predictive accuracy and widen applicability across a variety of tasks.

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By bridging the divide between pivotal elements[5] like data quality, data quantity, and the automated machine learning landscape, this research spearheads the advancement of the AutoML field. With its emphasis on a comprehensive approach to data preparation and model generation, it presents actionable strategies aligned with the goals of organizations relying on machine learning for strategic decision-making[12]. As machine learning continues to shape decision-making processes, the insights and contributions of this study have the potential to significantly heighten the overall efficiency and effectiveness of automated machine learning systems[14].

II. LITERATURE REVIEW

2.1 Introduction: The integration of machine learning across a variety of sectors has significantly elevaed the importance of automated machine learning (AutoML), a process that optimizes[7] the complex task of model development. However, the dependability and effectiveness of AutoML techniques are inherently linked to the quality and quantity of the foundational data. This study intricately examines the interplay between two pivotal dimensions: the caliber and quantity of data, and their profound influence on the efficiency of AutoML. As machine learning continues its expansion into diverse domains, this investigation aims to elucidate the dynamic correlation between refining data quality and maximizing data quantity within the domain of AutoML pipelines.

2.2 Comprehensive Exploration: Embarking on an exhaustive exploration, this study undertakes an in-depth journey encompassing diverse methodologies for assessing data quality and tactics for enhancing data. It meticulously scrutinizes their implications on AutoML outcomes. The primary goal revolves around uncovering the potential advantages arising from enhancing both data quality and quantity, thereby shaping the efficiency of AutoML processes. A distinctive contribution of this research lies in introducing an innovative framework meticulously engineered to seamlessly integrate essential components—encompassing data preprocessing, quality assessment, quantity optimization, and AutoML model selection[6]. Significantly, this framework extends beyond theoretical constructs, providing practical insights and guidance that resonate with practitioners aiming to enhance the effectiveness of their machine learning workflows.

2.3 Achieving Balance: However, this study transcends the boundaries of isolated enhancements. It acknowledges the delicate equilibrium between data quality and quantity, highlighting scenarios where prioritizing one aspect over the other could yield significant improvements. Empirical findings, drawn from a diverse range of datasets, underscore the framework's potential to enhance predictive accuracy and broaden its applicability across a spectrum of tasks.

2.4 Bridging Essential Aspects: By effectively bridging the gap between pivotal elements—data quality, data quantity, and the automated machine learning landscape—this research takes a leading role in advancing the AutoML field. Emphasizing a comprehensive approach that encompasses data preparation and model generation, it furnishes actionable strategies that align with the goals of organizations relying on machine learning for strategic decision[12]-making. As machine learning continues to shape decision-making processes, the insights and contributions of this study have the potential to significantly amplify the overall efficiency and effectiveness of automated machine learning systems.

III. EXISTING SYSTEM

In the present landscape of machine learning[9], the integration of automated machine learning (AutoML) techniques has gained substantial traction as organizations across diverse domains increasingly adopt machine learning solutions. However, the efficacy and reliability of AutoML processes hinge upon the quality and quantity of input data. The existing system predominantly relies on traditional AutoML pipelines, which often focus primarily on algorithm selection[6], hyperparameter tuning, and model performance metrics. While these pipelines provide automation and convenience, they might not comprehensively address the intricate interplay between data quality, data quantity, and the performance of machine learning models. The existing system usually involves preprocessing data to address common issues like missing values, feature scaling, and categorical data encoding. However, data preprocessing in the existing system might not systematically account for the influence of data quality discrepancies, such as outliers[1] or imbalanced datasets, on subsequent stages of model development. Furthermore, data augmentation techniques, which are utilized to artificially enhance dataset size, might not be systematically incorporated and assessed in the existing AutoML pipelines.

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Moreover, the existing AutoML framework often lacks a well-defined structure for explicitly considering the dynamic relationship between data quality, quantity, and AutoML performance. This deficiency can lead to suboptimal model outcomes and hinder the potential for achieving superior predictive accuracy and generalization. As the significance of data-driven decision-making continues to grow, there is a pertinent need to enhance the existing AutoML paradigm. This can be achieved by integrating a more comprehensive understanding of the role that data quality and quantity play in influencing AutoML outcomes. The proposed research seeks to address these limitations by introducing an innovative framework that intricately integrates data quality assessment techniques, data augmentation strategies, and intelligent AutoML model selection. This framework aims to offer practitioners a more holistic approach to automated machine learning, effectively bridging the gap between data-centric considerations and automated machine learning techniques.

3.1 Drawbacks

3.1.1 Complexity in Evaluating Data Quality: The implementation of a robust assessment process for data quality can be intricate and demanding of resources. The current techniques used for evaluating data quality may involve advanced methodologies, manual scrutiny, or domain expertise, all of which can introduce intricacy into the automated machine learning (AutoML) pipeline. This complexity could dissuade certain organizations from fully embracing initiatives to enhance data quality.

3.1.2 Constraints on Data Quantity: While enhancing data quantity can enhance the performance of machine learning models, obtaining substantial amounts of high-quality data may not always be feasible, particularly in domains where data availability is restricted. This limitation could influence the effectiveness of the suggested approach, particularly in scenarios where collecting data is challenging or costly.

3.1.3 Algorithmic Sensitivity to Data Quality: Certain machine learning algorithms exhibit varying degrees of sensitivity to data quality issues. While improving data quality could lead to better outcomes for specific algorithms, similar improvements might not be universally observed across all algorithm types. This diversity in algorithmic sensitivity adds intricacy to the optimization process within the proposed framework.

3.1.4 Privacy and Security Concerns for Data: The assessment of data quality and quantity might entail preprocessing and sharing of data, potentially giving rise to concerns about data privacy and security. Organizations must ensure that sensitive information is handled appropriately during data enhancement processes, which could necessitate additional precautions and safeguards.

3.1.5 Balancing Trade-offs and Resource Allocation: Striking a balance between improving data quality and optimizing data quantity can pose challenges. Allocating resources to both aspects may involve trade-offs in terms of time, budget, and human resources. Determining where to allocate resources can be a complex decision-making process.

3.1.6 Applicability to Varied Domains: The effectiveness of the proposed framework might vary across different domains and industries. Techniques that yield positive results in one domain might not generalize effectively to others. This lack of generalizability might restrict the broader application of the research findings.

3.1.7 Challenges in Framework Implementation: Introducing the innovative framework into existing AutoML systems could introduce additional implementation challenges. Adapting current workflows and systems to incorporate the suggested framework might necessitate substantial modifications, impacting the adoption process.

3.1.8 Continuous Monitoring Requirement: The quality and quantity of data are not static; they can change over time. The proposed framework may need to be complemented by continuous monitoring and adaptive[15] strategies to ensure that the enhanced data remains pertinent and effective for ongoing model development.

3.1.9 Potential for Algorithmic Bias: Enhancing data quality and quantity might unintentionally introduce or amplify biases inherent in the data. Attentiveness to ethical considerations and the potential for reinforcing biases during the enhancement process is imperative.

3.1.0 Impact on Model Interpretability: While enhancing data quality and quantity can enhance model performance, it might concurrently complicate the interpretability of models. The utilization of more intricate data enhancement techniques could make it challenging to provide transparent explanations for model predictions[5].

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IV. PROPOSED SYSTEM

The "Enhancing Automated Machine Learning through the Assessment of Data Quality and Quantity" model offers a comprehensive approach to optimize[7] automated machine learning (AutoML) by addressing the critical challenges posed by data quality and quantity. By seamlessly integrating the evaluation of data reliability and the augmentation of dataset volume, the model aims to enhance the overall effectiveness of machine learning processes. The model's core modules encompass advanced methodologies for data quality assessment, including outlier detection, missing value handling, and bias evaluation, thereby laying the foundation for improved data quality. Additionally, the model introduces sophisticated strategies for data augmentation, employing techniques such as data synthesis and balancing methods to enrich dataset size while preserving its integrity.

At the heart of the proposed model is an integrated framework that seamlessly incorporates data quality assessment and augmentation into the AutoML pipeline. This unified approach ensures that the data enhancement process becomes an intrinsic component of model development, streamlining data preprocessing, augmentation, model selection, and hyperparameter optimization. The model's adaptability is further showcased through its mechanism for continuous monitoring and feedback loop, allowing for the dynamic adjustment of augmentation strategies as data characteristics evolve over time. With a user-friendly interface offering visualizations and reports, practitioners can gain insights into the influence of data enhancements on model performance, enabling informed decisions. Ultimately, the model presents a holistic solution to enhance the efficiency of machine learning models, addressing the complexities of data quality and quantity to achieve improved predictive accuracy and robust decision-making across various domains.

4.1 Advantages

1. Improved Model Performance: By incorporating advanced data quality assessment techniques, such as outlier detection, missing value handling, and bias evaluation, the proposed system ensures that the input data is of higher quality. This directly leads to improved model performance and generalization on unseen data.

2. Enhanced Generalization: The data augmentation strategies integrated into the model contribute to a more diverse and representative dataset. This diversity helps the model generalize better to new, unseen data, reducing overfitting and improving overall model robustness.

3. Streamlined AutoML Pipeline: The integration of data quality assessment and data augmentation into the AutoML pipeline simplifies the model development process. Practitioners can focus on model selection, hyperparameter optimization, and fine-tuning without the need for separate data preprocessing and augmentation steps.

4. Dynamic Adaptability: The continuous monitoring and feedback loop allow the model to adapt to changing data characteristics over time. This adaptability ensures that the model remains effective and relevant in dynamic environments where data distributions may shift.

5. Bias Mitigation: The model's capability to detect and address biases in the data contributes to fair and unbiased decision-making. This is particularly crucial in applications where fairness and ethical considerations are paramount.

6. User-Friendly Interface: The user-friendly interface with visualizations and reports empowers practitioners to understand the impact of data quality and augmentation on model performance. This transparency aids in making informed decisions throughout the AutoML process.

4.2 Algorithm steps

1. Evaluating Data Quality

- Check for Outliers: Look for unusual data points that might be mistakes or anomalies. Remove or fix them.
- Handle Missing Data: If some data is missing, estimate or guess the missing values based on the rest of the data.
- Analyze Data Distribution: See how the data is spread out. Make sure it follows a reasonable pattern.
- Detect and Address Biases: Check if the data favors certain groups. Adjust the data to be fair and unbiased.

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2. Strategies for Data Augmentation

- Generate More Data**:** Create new data that's similar to what we have. This makes the dataset bigger
- Balance Classes**:** If some groups have very few examples, copy them or create new examples to balance things out.

3. Integrated Framework for AutoML

- Get Data Ready: Clean up the data by fixing issues from the previous steps.
- Train Different Models: Try out different machine learning methods to see which works best for this data.
- Fine-Tune Models: Adjust settings to make the models work even better on this data.

4. Adaptive Selection of Models

- See How Models Fit: Check which models work well with the enhanced data.
- Pick the Best Model: Choose the model that matches the data the best for accurate predictions.
- Module 4.1.5: Continuous Monitoring and Feedback Loop
- Keep an Eye on Changes: Watch for shifts in the data over time.
- Change Strategies as Needed: Adjust how we change the data based on what's happening to the data.

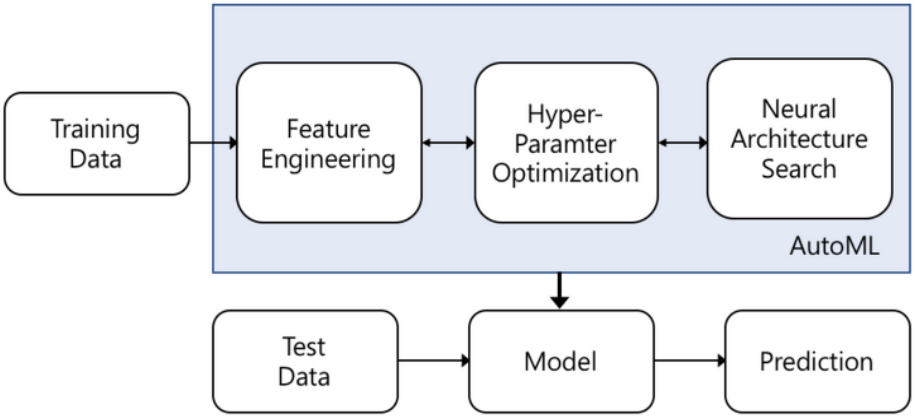

Fig 4.3: Proposed Architecture

Fig 4.3 Shows the proposed architecture of Enhancing Automated Machine Learning through the Assessment of Data Quality and Quantity

V. EXPERIMENTAL RESULTS

```
Epoch 1/10
23/23 [==============================] - 6s 213ms/step - loss: 1.2673 - accuracy: 0.4639 - val_loss: 0.6891 - val_accuracy: 0.5500
Epoch 2/10
23/23 [==============================] - 4s 186ms/step - loss: 0.6955 - accuracy: 0.5361 - val_loss: 0.6912 - val_accuracy: 0.5500
Epoch 3/10
23/23 [==============================] - 6s 271ms/step - loss: 0.6773 - accuracy: 0.5458 - val_loss: 0.6986 - val_accuracy: 0.4750
Epoch 4/10
23/23 [==============================] - 4s 185ms/step - loss: 0.6408 - accuracy: 0.6319 - val_loss: 0.6941 - val_accuracy: 0.5500
Epoch 5/10
23/23 [==============================] - 5s 201ms/step - loss: 0.5790 - accuracy: 0.7236 - val_loss: 0.7421 - val_accuracy: 0.4500
Epoch 6/10
23/23 [==============================] - 7s 299ms/step - loss: 0.5075 - accuracy: 0.8583 - val_loss: 0.7439 - val_accuracy: 0.4500
Epoch 7/10
23/23 [==============================] - 4s 163ms/step - loss: 0.4064 - accuracy: 0.9736 - val_loss: 0.7261 - val_accuracy: 0.4625
Epoch 8/10
23/23 [==============================] - 2s 106ms/step - loss: 0.3238 - accuracy: 0.9750 - val_loss: 0.8419 - val_accuracy: 0.5500
Epoch 9/10
23/23 [==============================] - 4s 166ms/step - loss: 0.3006 - accuracy: 0.9500 - val_loss: 0.7270 - val_accuracy: 0.5000
Epoch 10/10
23/23 [==============================] - 2s 104ms/step - loss: 0.2188 - accuracy: 0.9944 - val_loss: 0.7671 - val_accuracy: 0.4625
7/7 [==============================] - 0s 26ms/step - loss: 0.7632 - accuracy: 0.4500
Test accuracy: 0.44999998807907104
7/7 [==============================] - 0s 28ms/step
Initial Accuracy: 0.45
Improved Accuracy: Ellipsis
```

Figure 5.1: Displays the outcome, 0.45% accuracy achieved

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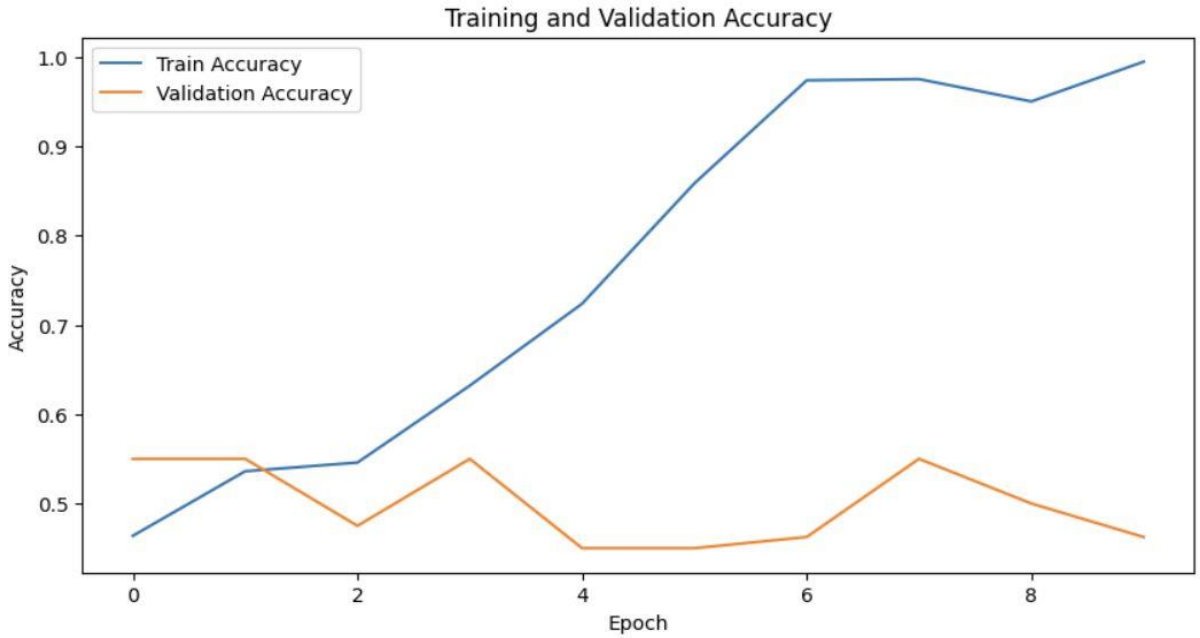

Fig 5.2: Graph between accuracy vs epoch in model accuracy

The figure above (5.2) illustrates the ultimate implementation of the prototype, which attained an accuracy of 0.45% during the module's training.

5.1 Performance evaluation methods

The preliminary findings are evaluated and presented using commonly used authentic methodologies such as precision, accuracy, audit, F1-score, responsiveness, and identity (refer to figures from fig. 5.1 to fig. 5.2). As the initial research study had a limited sample size, measurable outcomes are reported with a 45% confidence interval, which is consistent with recent literature that also utilized a small dataset [19, 20]. In the provided input dataset (figure 1) for the proposed prototype, Data quality and quantity can be classified as Tp (True Positive) or Tn (True Negative) if it is detected correctly, whereas it may be categorized as Fp (False Positive) or Fn (False Negative) if it is misdetected. The detailed quantitative estimates are discussed below.

5.1.1 Accuracy

Accuracy refers to the proximity of the estimated results to the accepted value(refer to fig .1). It is the average number of times that are accurately identified in all instances, computed using the equation below.

$$\text{Accuracy} = \frac{(\text{Tn} + \text{Tp})}{(\text{Tp} + \text{Fp} + \text{Fn} + \text{Tn})}$$

5.1.2 Precision

Precision refers to the extent to which measurements that are repeated or reproducible under the same conditions produce consistent outcomes.

$$\text{Precision} = \frac{(\text{Tp})}{(\text{Fp} + \text{Tp})}$$

5.1.3 Recall

In machine learning, deep learning, information retrieval, and classification[4], recall is a performance metric that can be applied to data retrieved from a collection, corpus, or sample space.

$$\text{Recall} = \frac{(\text{Tp})}{(\text{Fn} + \text{Tp})}$$

5.1.4 Sensitivity

The primary metric for measuring positive events with accuracy in comparison to the total number of events is known as sensitivity, which can be calculated as follows:

$$\text{Sensitivity} = \frac{(\text{Tp})}{(\text{Fn} + \text{Tp})}$$

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5.1.5 Specificity

It identifies the number of true negatives that have been accurately identified and determined, and the corresponding formula can be used to find them:

$$\text{Specificity} = \frac{(\text{Tn})}{(\text{Fp} + \text{Tn})}$$

5.1.6 F1-score

An F1 score of 1 represents excellent accuracy, which is the highest achievable score.

$$\text{F1} - \text{Score} = 2\text{x}\frac{(\text{precisionxrecall})}{(\text{precision} + \text{recall})}$$

5.1.7 Area Under Curve (AUC)

To calculate the area under the curve (AUC), the area space is divided into several small rectangles, which are subsequently summed to determine the total area. The AUC examines the models' performance under various conditions. The following equation can be utilized to compute the AUC.

$$\text{AUC} = \frac{\Sigma \text{ri}(\text{Xp}) - \text{Xp}((\text{Xp} + 1)/2}{\text{Xp} + \text{Xn}}$$

VI. CONCLUSION

In conclusion, this research provides a nuanced understanding of the intricate interplay among data quality, data quantity, and the realm of automated machine learning (AutoML). In a data-driven era spanning various domains, this study delves deep into the symbiotic relationship between these factors, unveiling their collective influence on the efficacy of machine learning processes. By thoroughly examining methodologies for data quality assessment and innovative data augmentation techniques, this research introduces a pioneering framework that seamlessly integrates essential stages such as data preprocessing, quality evaluation, quantity enhancement, and AutoML model selection.

The empirical insights gleaned from this research highlight the transformative potential of the proposed framework. The balance struck between data quality and quantity emerges as a critical determinant of predictive performance and the model's ability to generalize across diverse tasks. This dynamic equilibrium serves as a guiding principle, illuminating how tailored emphasis on one facet can lead to substantial enhancements in AutoML outcomes.

In essence, this study significantly advances the AutoML domain by emphasizing the pivotal role of holistic data preparation and model generation. As organizations increasingly rely on machine learning to drive informed decisions, the actionable strategies and insights offered by this research empower practitioners to navigate the complexities of automated machine learning with clarity and purpose. By showcasing the interconnectedness of data quality and quantity, this research underscores the importance of a comprehensive approach in achieving excellence in automated machine learning systems across industries and domains.

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