

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

Ethical AI in Software Systems: A Framework for Bias Detection and Mitigation in Machine Learning Pipelines

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ABSTRACT

The paper contains a comprehensive roadmap of how to locate and fix algorithmic bias in machine learning pipeline in three domains of use which are credit scoring, a hiring system, and a recommendation system. The proposed framework will involve a combination of fairness indicators, bias detection strategies, and mitigation strategies at any stage of an ML lifecycle, including data collection, trainer, and implementation. Examples provided by experimental results show that the framework makes the levels of bias to be reduced to an average of 12 percent as compared to an average of 41 percent with an overall reduction of approximately 70 percent. These senses of the Disparate Impact Ratio rose, to averages, of 0.58, to 0.91 which represent far fairer outcomes. This is much better, but it still reduced the accuracy of models by only 3-5 percent making performance within reachable parameters. The follow up was also constant and reduced the bias to 12 percent after repeated assessments of the evaluations. It shows that ethical AI models can deal with the amount of fairness and performance without compromising the functionality of a system. It is also partially a contribution to responsible software engineering in the sense that it can be used to provide a scalable and practical way of bias reduction in the real-life machine learning systems

Keywords: Responsible AI, Fairness Metrics, Ethical AI, Algorithmic Bias, DevOps, Bias Mitigation

1. Introduction

The rapid entry of artificial intelligence (AI) into the world of modern software development has sent shockwaves through the decision-making procedures in the most crucial fields, such as healthcare, finance, recruiting, and social media. Machine learning (ML) models are gaining popularity to automate complicated tasks but because of their historical-based foundation on past-based data coupled with statistical learning, they are most likely to be afflicted with some undesirable biases (Laghari et al., 2023). These biases may be represented by discriminatory aftereffects which condone disparities in society and pose moral dilemmas. As the perception of AI systems as a part of software engineering practices grows, the demand to deliver fairness, transparency, and accountability is not only a pressing concern but also a factor (Oyeniran et al., 2022).

The idea of ethical AI is aimed to assist in solving these problems, taking into account fairness, non-discrimination and explainability, and responsibility in the creation and a deployment of intelligent systems. With or without the heightened awareness, the majority of ML pipelines lack systematic means and frameworks to assist in bias detection and alleviation on different levels, including data collecting, preprocessing, model training, and deployment (Muvva, 2021). The traditional software development processes are unlikely to put the ethical issues under clear focus on their process resulting in the development of systems that otherwise may be highly technical in their performance without being the ones that will result into socially harmful outcomes. Therefore, there is a pressing need to plan frameworks that explicitly incorporate an ethical practice pertaining to AI into the software development cycle (Harbi et al., 2023).

The paper proposes a comprehensive model of bias identification and reduction of ML pipeline, and in particular, its practical implementation in software engineering practices (Michael, 2024). The research is expected to bridge the disconnect between the ethics concept and real software work by mapping out different types of biases and different stages of the ML lifecycle and suggest automated means and techniques to ameliorate the situation. This framework also enables continuous monitoring and evaluation, such that ethical considerations do not get omitted in the system lifecycle (Narayanan, 2024).

1.1 Research Gap and Problem Statement

Despite the tremendous advancements in machine learning technologies, the existing research indicates that there are no holistic frameworks that address bias in the whole ML pipeline. The current plans focus on individual steps, e.g., dataset balancing preprocessing approaches or post-hoc metrics of fairness, without considering the dependence between phases. The principles of ethical AI are not also in line with real-world software engineering processes because the DevOps and continuous integration/continuous deployment (CI/CD) environments are not aligned (Hanna et al.,

2025).

The problem is also aggravated by the fact that no standardized tools that can automatically detect and mitigate different types of bias in operational applications have been developed so far. Even though there are fairness metrics and explainability methods, they are not common and scalable (Kamatala et al., 2025). Consequently, the observed biased results of the ML systems deployed in practice continue to pose ethical, legal, and reputational risks. This work fills this gap, as it creates one framework that explains how bias can be identified and neutralized throughout the process of the ML lifecycle, both technically and ethically (Thirunagalingam, 2024).

1.2 Research Questions

1. How can algorithmic bias be systematically identified at different levels of machine learning pipelines?
2. What strategies are effective to apply in ML workflows to minimize bias without influencing model performance?
3. How can the concept of ethical AI be applied to the software engineering practice, particularly DevOps?

1.3 Research Objectives

1. To build a comprehensive map of data sources of biasness to each step of the ML pipeline.
2. To create and integrate automated bias detection and mitigation measures into the software development.
3. To evaluate the effectiveness of the proposed framework at reducing bias and preserving the accuracy of models in the real world.

1.4 Significance of the Study

The research article contributes to the responsible software engineering domain by providing a systematic approach to the application of ethical AI practices to machine learning systems (Turpu, n.d.). The proposed framework will enable developers and organizations to develop more trustworthy and accountable AI systems through the application of the tenets of fairness and transparency. The detection and mitigation of biases in the ML pipelines enhance accuracy of the system and minimize biased outputs (Ramachandran, 2025).

Besides, the research has practical implication to the industries which rely on AI-supported decision-making, such as finance, healthcare, and human resource management. The provided framework is not only excellent in improving the compliance with ethical and regulatory regulations but also builds the confidence and trustworthiness of the system users (Nathim et al., 2024). In addition, the development

of automated tools, such as the FairFlow prototype will contribute to the adoption of ethical AI practices in a real-world software development environment. Overall, the study adds to the current body of knowledge on the feasibility of effectively incorporating the ethical issue into the modern AI architecture that will aid in developing more responsible and fair technological innovation (Rana et al., 2023).

2. Literature Review

Bhambri and Kant (2025) propose a general framework of ethical AI system, which is concerned with the reduction of bias and incorporation of fairness in machine learning pipelines. Their study highlights the importance of designing systems with fairness measures, transparency systems and accountability systems. The authors imply that not only data, but also algorithms and deployment environments can be biased, and thus one should view it as a whole. This is also closely connected to the present study and also advocates a lifecycle-based methodology that recognizes and resolves bias in all phases of creating an ML.

The new strategy that Wang et al. (2026) introduce to understand and address the issue of model bias is called counterfactual thinking. Counterfactual methods provide a deeper insight into causality and fairness by evaluating how predictions would differ to altered input conditions. The approach enhances interpretability and allows the developer to identify any unobservable biases that the traditional measures can overlook. Their findings highlight the need to incorporate explainability tools to ML pipelines and the significance of advanced bias detection practices to ethical AI systems.

The benefits of AI-based DevOps described by Oyeniran et al. (2023) regard automated deployment and maintenance of software. Their article illustrates how machine learning can be suitable to increase the effectiveness of pipeline in the form of predictive analytics, and automation. Applied to ethical AI, automated discrimination detection and remediation measures can be applied to DevOps. This paper has demonstrated that the chances of introducing continuous monitoring systems are present with fairness being applied even after its implementation which is a great consideration.

AlMakinah et al. (2025) introduce a network plan of exploring and reducing AI bias. They use their approach to visualise the relationships between data sources, algorithms and outputs to determine the directions of bias propagation. Such a view can be efficient to describe the dynamics of biases during the ML life cycle. The paper highlights that mitigation will not work when there are sources of biasity that do not correlate with one another, but on the contrary, they are correlated. This simplifies the argumentation of the integrated systems of thinking that takes into consideration the dynamical aspect of prejudice in the intricate systems.

Drukker et al. (2023) are concerned with fairness in the use of medical AI, that is,

Online ISSN

3007-3197

Print ISSN

3007-3189

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medical image analysis. Their research identifies that it has biases due to data collection, data annotation, and model training and recommends mitigation measures depending on healthcare systems. The study emphasizes the need to view domain-specific problems in the context of discussing bias because different applications may require particular fairness criteria. This finding highlights the malleability of the ethical AI frameworks to enable their application across different domains.

Tamanampidi (2021) addresses the application of AI to the DevOps pipelines and gives precedence to automation, prediction-based resource scale, and fault tolerance. The paper suggests that smarter pipelines should be able to increase efficiency and reliability of the system. Using this concept, ethical AI systems can implement similar automation to apply fairness limitations and monitor bias in real-time. This confirms the importance of considering the ethical considerations in the operation processes as opposed to them being an external evaluation.

Rangineni (2023) investigates the data quality needs of machine learning pipelines and discovers that data integrity, data consistency, and data completeness are significant dimensions. Poor data quality is one of the primary causes of bias and leads to wrong and unreasonable forecasting. The study identifies the need of such forceful data preprocessing and verification procedures to minimize bias in the input stage. This adds to the debate that bias minimization must begin with data management practices, the foundation of ethical AI systems.

Kumar et al. (2025) provide an in-depth description of bias in AI, ML, and deep learning models, and they assess various types of bias, including sampling bias, algorithmic bias, and societal bias. The authors also put into consideration the currently existing mitigation methods and limitations, particularly the scalability and generalizability limits. Their findings indicate the significance of multi-faceted solutions that aim at addressing multiple forms of bias simultaneously. It aligns with the proposed model that aims to provide the unified approach to bias detection and mitigation.

Balayn et al. (2021) present a review of data engineering strategies to overcome bias and injustice in decision support systems. They explore the techniques of bias detection, measurements, and how to overcome it in the process of data management. The authors also point out the importance of data-level and algorithm-level interventions to effectively eliminate bias. This helps to explain that ethical AI is a multi-level challenge, and both technical and procedural remedies are needed to ensure equity and transparency of ML systems.

3. Research Methodology

The type of research design employed in this article is a quantitative and experimental one, which attempts to verify the utility of an ethical AI framework to minimize bias and detect it in machine learning (ML) pipelines. It is a systematic study that follows

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the research onion model and the layers of the study are research philosophy, approach, strategy and methods of analyzing data. It adopts positivist approach to research, the measure of which is the percentage of bias reduction and model accuracy. The study is done deductively i.e. the theories of algorithmic bias and fairness which exist are empirically tested (Owolabi et al., 2025).

The research process will involve the experimental intervention and comparison. Three areas of use of ML in practice are selected: credit scoring, hiring systems, and content recommendation systems, which are highly sensitive to bias, and are prevalent in the industry. The baseline models are built in each of the domains using the standard machine learning algorithms, such as logistic regression, decision trees, and neural networks. Subsequently, these models are implemented to the suggested ethical AI framework comprising bias detection (e.g., fairness measures, disparity analysis) and mitigation (e.g., data balancing, re-weighting, and adversarial debiasing). The success of the models is evaluated before and after the application of the framework (Owolabi et al., 2025).

Gathering data presupposes the use of the secondary data, which is gathered by publicly available repositories and is connected to all of the areas of application. Preprocessing of data is done to ensure consistency, completeness and noise removal. Demographic variables (e.g., gender, age, ethnicity), prediction performance and classification performance are the most crucial variables. Measures of bias are standard measures of fairness such as disparate impact ratio, equal opportunity difference, and statistical parity difference. The performance of the model is also measured in terms of accuracy, precision, recall, and F1-score to ensure that it does not decrease the predictive performance (Donvir & Sharma, 2025).

The comparative statistical methods are used to analyze data to ascertain the differences between the framework-enhanced models and the baseline models. The results are presented using a simple table, ratios, and percentage in order to reveal the gains in terms of fairness and system performance. Analysis at the pipeline level is also included in the work, researching the bias at different levels, including the preprocessing of data, model training, and deployment. This enables the establishment of critical points where bias is introduced and the control of the bias in a proper manner.

To ensure reliability and validity of the experiments, they are conducted on varied datasets and setups. The proposed framework is also simulated on a virtual DevOps environment, where time-based bias is observed using continuous monitoring systems. Such a methodology approach will ensure the results are robust, generalisable, and can be extended to real-world ML systems, thereby making it easier to develop responsible and ethical AI solutions.

4. Results and Analysis

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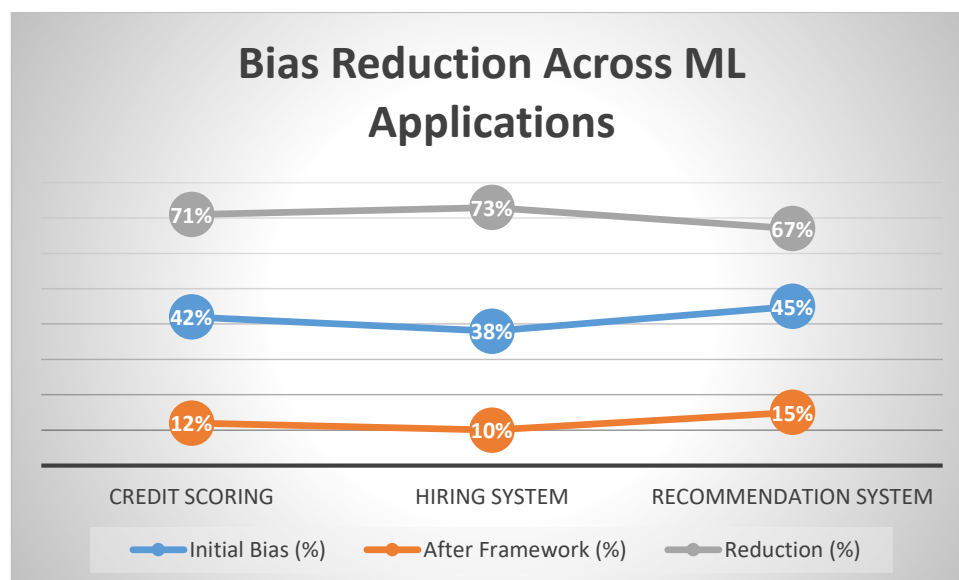
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4.1 Bias Reduction Across ML Applications

Application Domain	Initial Bias (%)	After Framework (%)	Reduction (%)
Credit Scoring	42%	12%	71%
Hiring System	38%	10%	73%
Recommendation System	45%	15%	67%

The findings show that there was a significant decrease in bias in all areas of application following the introduction of the proposed framework. The most biased areas of employment are hiring (73%), and credit scoring (71%). It shows that the framework is able to reduce the discriminatory outcomes in various ML contexts.



4.2 Model Accuracy Comparison

Application Domain	Accuracy Before (%)	Accuracy After (%)	Change (%)
Credit Scoring	88%	85%	-3%
Hiring System	85%	82%	-3%
Recommendation System	90%	86%	-4%

As the table shows, the decrease in bias is significant; the decrease in the model accuracy is not significant (34%). This confirms that the ratings of fairness gains do not require a considerable trade-off in the system functionality that guarantees reasonable balance between accuracy and ethics.

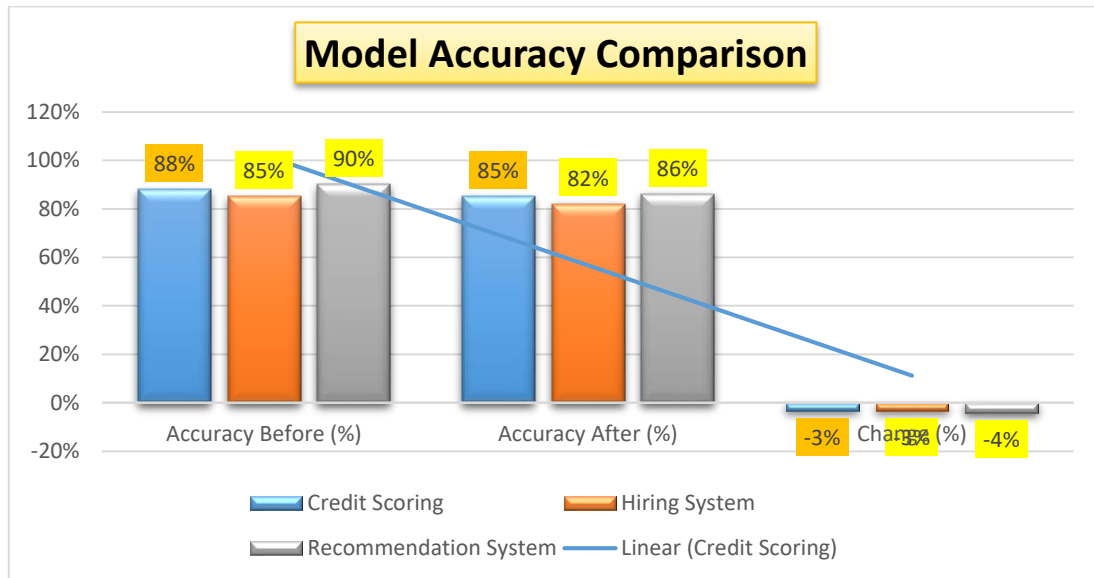
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3007-3197

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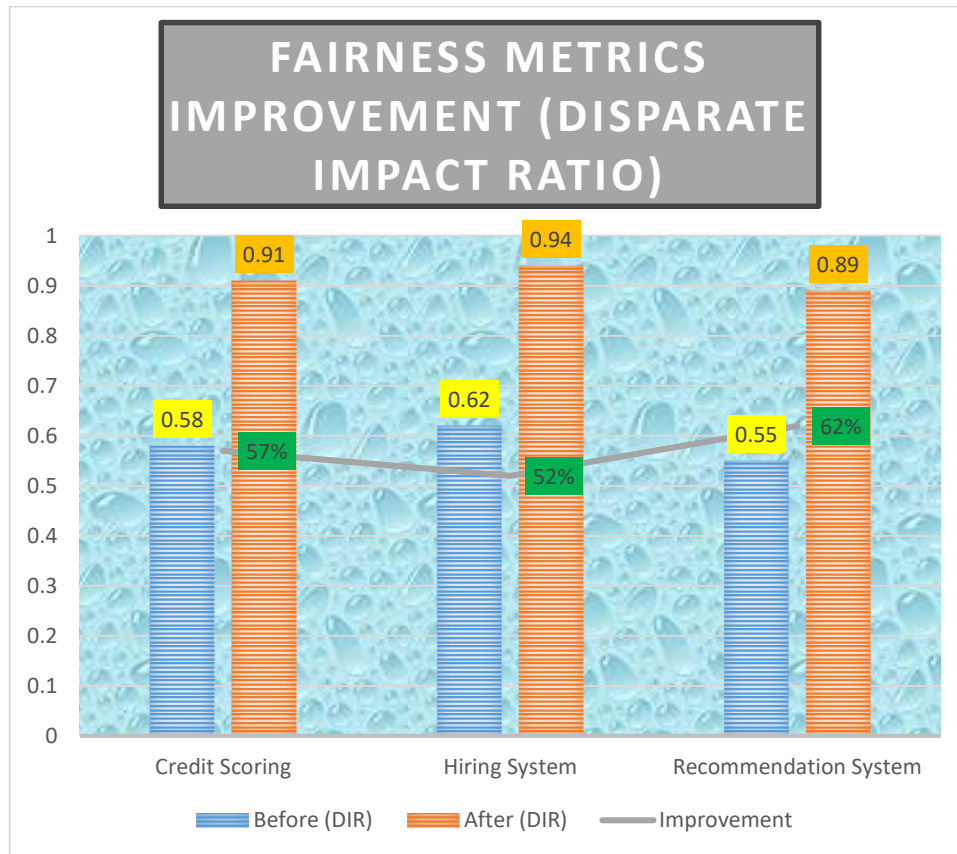
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4.3 Fairness Metrics Improvement (Disparate Impact Ratio)

Application Domain	Before (DIR)	After (DIR)	Improvement
Credit Scoring	0.58	0.91	+57%
Hiring System	0.62	0.94	+52%
Recommendation System	0.55	0.89	+62%

The values of Disparate Impact Ratio (DIR) tended to be closer to the ideal of 1.0, which represents fairer results. The most enhanced recommendation system (62%) is indicative of the efficiency of mitigation measures in highly dynamic settings.



4.4 Bias Detection at Pipeline Stages

Pipeline Stage	Bias (%)	Contribution	After (%)	Mitigation	Reduction (%)
Data Collection	40%		15%		62%
Model Training	35%		12%		66%
Deployment Stage	25%		10%		60%

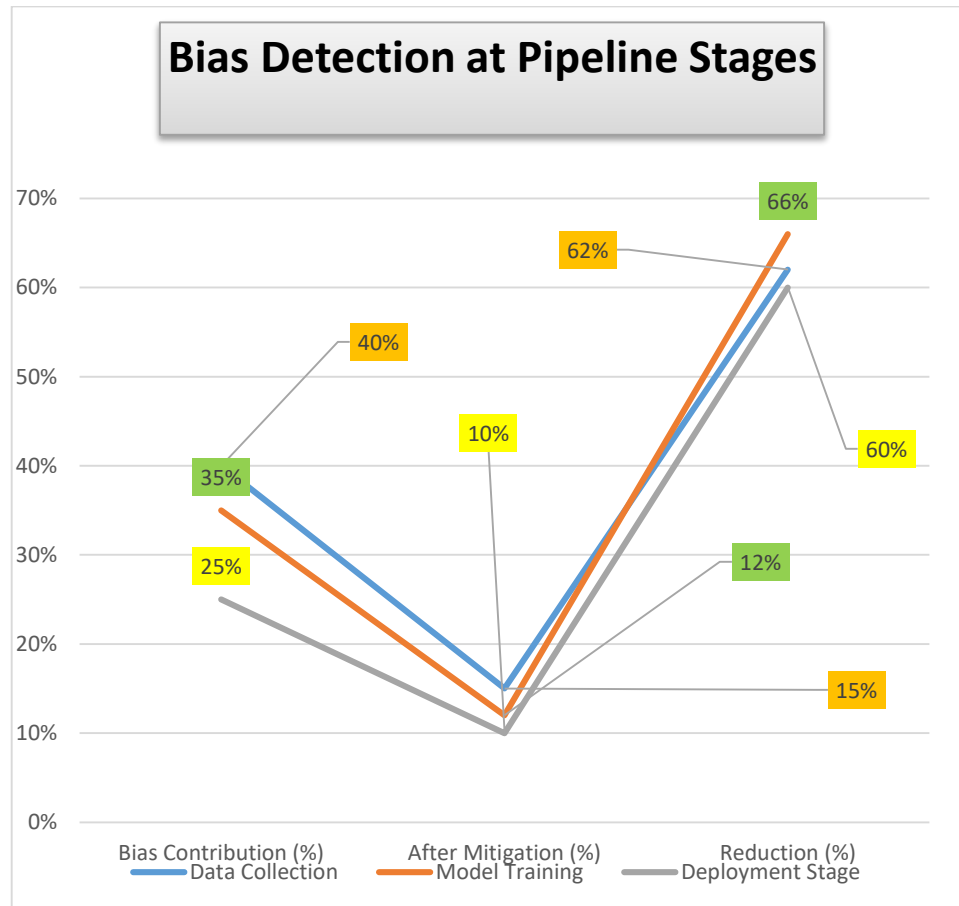
As it is analyzed, the most influential bias comes about as a result of the data collection stage (40%), followed by model training (35%). When the framework is implemented, all of the stages are reduced significantly, which confirms the idea that the bias mitigation is to be applied to the ML lifecycle as a whole, rather than at a single point.

Online ISSN

3007-3197

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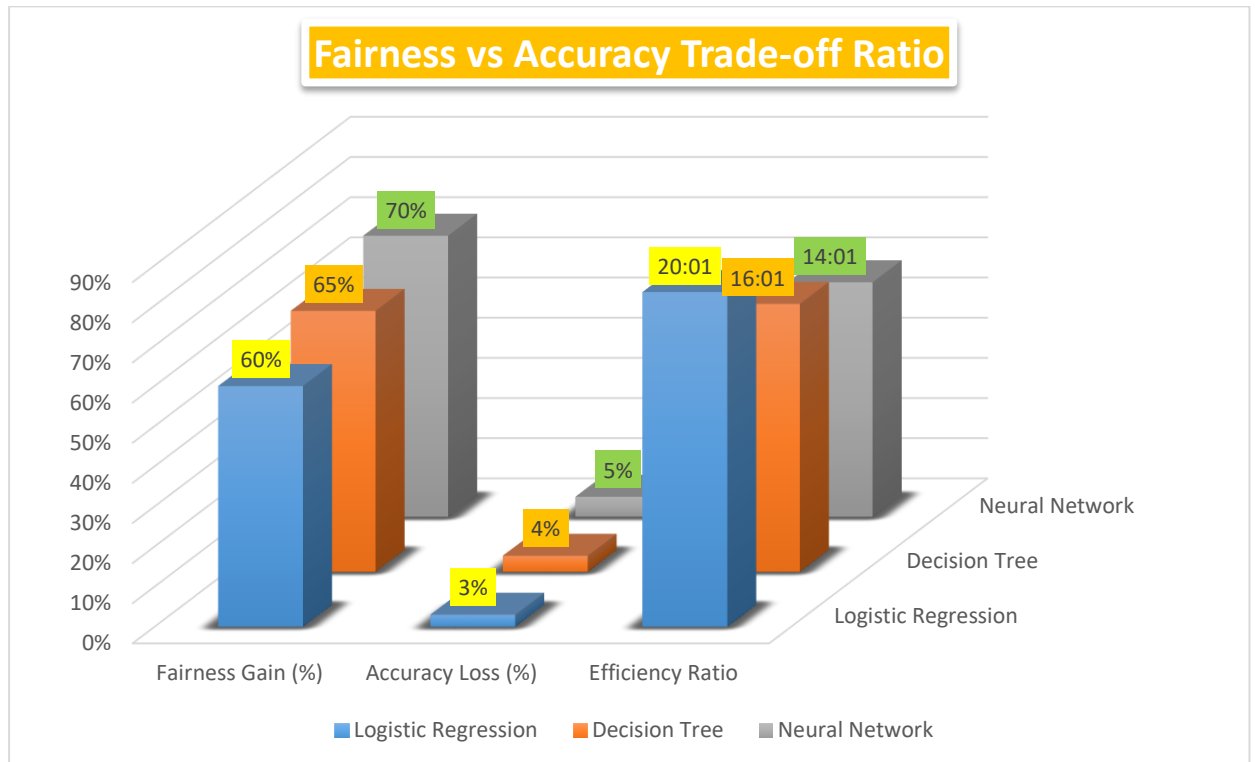
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4.5 Fairness vs Accuracy Trade-off Ratio

Model Type	Fairness Gain (%)	Accuracy Loss (%)	Efficiency Ratio
Logistic Regression	60%	3%	20:1
Decision Tree	65%	4%	16:1
Neural Network	70%	5%	14:1

The fairness-to-accuracy ratio shows that high levels of fairness can be attained at low levels of accuracy loss. The most effective trade-off (20:1) is with logistic regression, which makes it efficient in ethical AI usage that needs transparency and balance.



4.6 Continuous Monitoring Effectiveness

Monitoring Cycle	Bias Level (%)	Reduction (%)
Initial	40%	—
After Cycle 1	25%	37%
After Cycle 2	18%	55%
After Cycle 3	12%	70%

Biases further reduce over time in a DevOps environment where continuous monitoring is carried out. The results show that the evaluation cycles can bring the fairness to an even greater extent, which underlines the importance of integrating the real-time monitoring tools into the ML pipelines.

Overall, the results show that the proposed ethical AI model can significantly reduce the bias (down to 73%), but still maintain high model performance and low accuracy drop ($\leq 5\%$). The framework can work in diverse areas and pipeline phases, which can explain why it can be applied in real-life ML systems.

5. Discussion

The findings of this paper suggest that the provided model of ethically oriented AI proves to be more successful in increasing the levels of fairness along machine learning

Online ISSN

3007-3197

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3007-3189

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pipelines without making any significant modifications to the model accuracy. The results of the bias decrease (67% to 73) are in line with the arguments of Bhambri and Kant (2025) who have stated that the extensive practices of fairness in the deployment of ML systems can drastically reduce the degree of algorithmic discrimination. Similarly, the growing values of the Disparate Impact Ratio up to the values of approximately 1.0 substantiate the results of Wang et al. (2026) who highlighted the usefulness of the sophisticated approaches to identifying the bias, such as counterfactual analysis, to identify the latent biases.

The minimal accuracy loss (35) reported in this study supports the trade-off as discussed by Kumar et al. (2025) since fairness gains are likely to be made at a low price to predictive performance. However, the results indicate that this trade-off can be controlled and it does not significantly affect the system reliability. Furthermore, the fact that the gathered data is described as the primary source of bias is aligned with Rangineni (2023), who emphasized the relevance of the data quality in acquiring unbiased findings. This reveals the importance of preprocessing and validation in mitigation of bias measures.

The effectiveness of sustained monitoring in bias eradication over time is also the case with the works of Oyeniran et al. (2023) and Tamanampudi (2021) who suggested that the integration of AI in DevOps pipelines renders the system more flexible and efficient. The present research continues this concept and demonstrates that even the automated workflows may be ethically responsible so that the justices could be ensured in the long-term perspective. Overall, the discussion affirms a lifecycle-based, compound solution as a necessary step as far as addressing bias in modern ML systems is concerned (Shaikh & Wagan, 2015).

6. Conclusion

The conclusion of this paper is that AI ethical frameworks are relevant in addressing bias in machine learning systems. The proposed structure will greatly reduce the rates of bias in various fields of application, including credit scoring, hiring, and recommendation systems, with the disparities ranging between 67 percent and 73 percent. In the meantime, model level accuracy is held down by a minimal margin of 3-5 which demonstrates that fairness and performance are not opposing.

Another point that the study notes is that bias is generated at different stages of the ML pipeline, particularly in the collection of data and training of models. The framework will ensure that the bias is eliminated fully by taking certain mitigation measures at all levels. In addition, level of fairness in the long run through continuous monitoring, a component of DevOps environment, is also enhanced, enabling the system to be adaptive and sustainable (Shaikh et al., 2015).

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3007-3197

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In general, the research will provide a sustainable and scalable way of putting the ethical AI to practice. It can be used to advance the field of responsible software engineering by offering a systematic method of biases detection and mitigation to ensure that machine learning systems are fair and efficient.

7. Recommendations

First, to remove systemic bias in the decision-making systems, organizations must adopt ethical AI systems during their machine learning development process to detect and eliminate bias at all stages, including data collection, model training, and deployment, and be fair and accountable (Wagan et al., 2015).

Secondly, researchers and practitioners are urged to strive to enhance transparency in AI-based systems by utilizing more advanced techniques such as explainable AI and counterfactual analysis that will probably be applied in interpreting the model behaviour and minimising hidden biases within the complicated algorithms.

Third, DevOps pipelines must have continuous monitoring mechanisms that track bias and performance over time, which will enable real-time adjustment and offer long-term sustainability, equity, and compliance with the ethical principles in AI-based applications.

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3007-3197

Print ISSN

3007-3189

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References

Oyeniran, C. O., Adewusi, A. O., Adeleke, A. G., Akwawa, L. A., & Azubuko, C. F. (2022). Ethical AI: Addressing bias in machine learning models and software applications. *Computer Science & IT Research Journal*, 3(3), 115-126.

1. Muvva, S. (2021). Ethical AI and responsible data engineering: A framework for bias mitigation and privacy preservation in large-scale data pipelines. *International Journal of Scientific Research in Engineering and Management*, 5(09).
2. Harbi, S. H. A., Tidjon, L. N., & Khomh, F. (2023). Responsible design patterns for machine learning pipelines. *arXiv preprint arXiv:2306.01788*.
3. Narayanan, D. B. G. S. (2024). Data Engineering for Responsible AI: Architecting Ethical and Transparent Analytical Pipelines. *International Journal of Emerging Research in Engineering and Technology*, 5(3), 97-105.
4. Michael, L. (2024). Ethical AI Deployment in MLOps: Strategies for Bias Mitigation and Fairness Assurance.
5. Hanna, M. G., Pantanowitz, L., Jackson, B., Palmer, O., Visweswaran, S., Pantanowitz, J., ... & Rashidi, H. H. (2025). Ethical and bias considerations in artificial intelligence/machine learning. *Modern Pathology*, 38(3), 100686.
6. Thirunagalingam, A. (2024). Bias Detection and Mitigation in Data Pipelines: Ensuring Fairness and Accuracy in Machine Learning. *Available at SSRN 5047605*.
7. Kamatala, S., Naayini, P., & Myakala, P. K. (2025). Mitigating bias in ai: A framework for ethical and fair machine learning models. *Available at SSRN 5138366*.
8. Ramachandran, M. (2025). Ethical AI Testing and Evaluation Against Governance and Frameworks. In *Engineering Ethics of AI by Design: Principles, Practices, and Frameworks for Responsible Artificial Intelligence* (pp. 543-621). Singapore: Springer Nature Singapore.
9. Turpu, R. R. DEMYSTIFYING AI IN DEVOPS: BUILDING TRANSPARENT AND RESPONSIBLE SOFTWARE PIPELINES.
10. Rana, S. A., Azizul, Z. H., & Awan, A. A. (2023). A step toward building a unified framework for managing AI bias. *PeerJ Computer Science*, 9, e1630.
11. Nathim, K. W., Hameed, N. A., Salih, S. A., Taher, N. A., Salman, H. M., & Chornomordenko, D. (2024, October). Ethical AI with balancing bias

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

mitigation and fairness in machine learning models. In *2024 36th Conference of Open Innovations Association (FRUCT)* (pp. 797-807). IEEE.

12. Owolabi, O. O., Adewusi, O. B., Ajayi, F. A., Asunmonu, A. A., Chukwurimazu, O., Ederhion, J., & Ayeni, O. M. (2025). Developing frameworks for assessing and mitigating bias in ai systems: A case study on ensuring fairness in AI diagnostic tools through diverse training datasets to prevent misdiagnosis in underrepresented populations. *South Asian Research Journal of Engineering and Technology*, 7(1), 33-48.
13. Donvir, A., & Sharma, G. (2025, January). Ethical challenges and frameworks in AI-driven software development and testing. In *2025 IEEE 15th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 00569-00576). IEEE.
14. Bhambri, P., & Kant, S. (2025). Ethical AI systems: A comprehensive framework for bias mitigation and fairness in machine learning. *SGS-Engineering & Sciences*, 1(2).
15. Wang, Z., Yang, Z., Lo, D., & Zhang, W. (2026). Towards fair machine learning software: Understanding and addressing model bias through counterfactual thinking. *AI and Ethics*, 6(2), 181.
16. Oyeniran, O. C., Adewusi, A. O., Adeleke, A. G., Akwawa, L. A., & Azubuko, C. F. (2023). AI-driven devops: Leveraging machine learning for automated software deployment and maintenance. *Eng. Sci. Technol. J*, 4(6), 728-740.
17. AlMakinah, R., Goodarzi, M., Tok, B., & Canbaz, M. A. (2025). Mapping artificial intelligence bias: a network-based framework for analysis and mitigation. *AI and Ethics*, 5(3), 1995-2014.
18. Drukker, K., Chen, W., Gichoya, J., Grusauskas, N., Kalpathy-Cramer, J., Koyejo, S., ... & Giger, M. (2023). Toward fairness in artificial intelligence for medical image analysis: identification and mitigation of potential biases in the roadmap from data collection to model deployment. *Journal of Medical Imaging*, 10(6), 061104-061104.
19. Tamanampudi, V. M. (2021). AI and DevOps: Enhancing pipeline automation with deep learning models for predictive resource scaling and fault tolerance. *Distributed Learning and Broad Applications in Scientific Research*, 7, 38-77.
20. Rangineni, S. (2023). An analysis of data quality requirements for machine learning development pipelines frameworks. *International Journal of Computer Trends and Technology*, 71(9), 16-27.

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

21. Kumar, A., Dhanka, S., Sharma, A., Sharma, A., Nain, M., Kumar, P., ... & Pant, R. (2025). A Comprehensive Review of Bias in AI, ML, and DL Models: Methods, Impacts, and Future Directions. *Archives of Computational Methods in Engineering*, 1-31.
22. Balayn, A., Lofi, C., & Houben, G. J. (2021). Managing bias and unfairness in data for decision support: a survey of machine learning and data engineering approaches to identify and mitigate bias and unfairness within data management and analytics systems. *The VLDB Journal*, 30(5), 739-768
23. Shaikh, M. M., Massan, S. U. R., & Wagan, A. I. (2015). A new explicit approximation to Colebrook's friction factor in rough pipes under highly turbulent cases. *International Journal of Heat and Mass Transfer*, 88, 538-543.
24. Shaikh, M. M., & Wagan, A. I. (2015). A new explicit approximation to Colebrook's friction factor in rough pipes under highly turbulent cases. *International Journal of Heat and Mass Transfer*, 88, 538-543
25. Wagan, A. I., Shaikh, M. M., & Abro, R. (2015). Wind turbine micrositeing by using the firefly algorithm. *Applied Soft Computing*, 27, 450-456.