Ethically-Aware Personalized Text Classification model using deep Learning Approach

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Abstract

In every year, information is overload which needs for efficient and ethical personalized text classification has become critical and using deep learning models such as BERT, RoBERTa, and GPT have significantly improved text classification accuracy and contextual understanding, also pose ethical challenges related to bias, fairness, transparency, and privacy. This research presents an Ethically-Aware Personalized Text Classification Model that integrates transformer-based architectures and fairness-aware learning strategies to ensure responsible AI deployment. The proposed model incorporates bias mitigation mechanisms, explainability techniques, and privacy-preserving approaches, addressing key ethical concerns. A hybrid deep learning framework is employed, combining BERT, Bi-LSTM, RoBERTa, and GPT with fuzzy logic-based personalization to dynamically adapt to user preferences while preventing the reinforcement of biases.

The model's performance is evaluated using benchmark datasets and compared against state-of-the-art classification models. Key performance indicators, including accuracy, fairness, interpretability, and ethical compliance, demonstrate the effectiveness of the proposed approach. Ablation studies confirm the contribution of each component, revealing that the full hybrid model achieves the highest accuracy (97.69%), precision (97.13%), recall (97.11%), and F1-score (97.1%), while removing key components such as Bi-GRU, BiLSTM, or Transformer architectures results in performance degradation. The findings highlight the necessity of hybrid deep learning approaches in developing transparent, privacy-preserving AI-driven text classification models and setting a new standard for ethical AI in natural language processing (NLP) applications.

Keywords: Deep Learning (DL), Bidirectional Encoder Representations from Transformers (BERT) Robustly Optimized BERT Pretraining Approach (RoBERTa), Generative Pre-trained Transformer (GPT) Hybrid Deep Learning Framework (HDLF), Natural Language Processing (NLP)

Introduction: Every year is characterized by an overwhelming influx of digital information, making efficient content filtering and classification increasingly essential. The personalized text classification has emerged as a crucial technology for efficiently filtering and recommending content to users [1]. The exponential growth of online textual data has increased the demand for automated content classification systems, enabling users to access relevant information with minimal effort. Traditional machine learning approaches have contributed significantly to text classification, however, the recent advances in deep learning, particularly transformer-based models like BERT and GPT, have revolutionized the field by offering improved accuracy and contextual understanding [2]. Despite these advancements, the deployment of deep learning models in personalized classification systems raises critical ethical which concerns related to bias, fairness, transparency, and privacy, which must be addressed to ensure responsible AI implementation [3].

A major ethical issue in AI-driven text classification is algorithmic bias, where models often inherit biases present in training datasets, leading to unfair or discriminatory outcomes [4]. Imbalanced datasets and skewed learning patterns can reinforce societal stereotypes, disproportionately affecting marginalized groups. Furthermore, many existing classification systems operate as black-box models, providing limited interpretability, making it difficult to assess whether decisions are ethically sound [5] and privacy concerns arise when AI-driven classifiers require access to personal user data for accurate predictions, raising questions about data security and informed consent in AI applications [6]. Addressing these ethical challenges is crucial for ensuring that personalized text classification models are not only accurate but also trustworthy and fair.

To mitigate these challenges, this research proposes an Ethically-Aware Personalized Text Classification Model, integrating deep learning techniques with fairness-aware learning strategies. By incorporating bias mitigation mechanisms, our model aims to reduce discriminatory patterns in classification outcomes and explainability techniques are embedded within the framework to enhance transparency, allowing users to understand the rationale behind model predictions. Privacy-preserving methods, such as differential privacy and federated learning, are also explored to ensure user data remains secure while enabling personalization [7]. Furthermore, fuzzy logic-based personalization is utilized to dynamically adjust user preferences, preventing overfitting to biased trends and ensuring that the model adapts to diverse user needs.

The proposed model is evaluated using benchmark datasets, comparing its performance against state-of-the-art classification models. Key performance metrics include accuracy, fairness, interpretability, and ethical compliance, ensuring a holistic assessment of the model’s capabilities. Unlike traditional classification models, our framework is designed to actively detect and rectify biases, ensuring that classification outputs align with ethical AI standards. This evaluation provides empirical evidence of the model’s effectiveness in balancing personalization with fairness and privacy, setting a new standard for responsible AI applications in text classification.

This research contributes to the growing body of work on ethical AI by advocating for fairness-aware, explainable, and privacy-preserving text classification models. By integrating cutting-edge deep learning techniques with ethical safeguards, we aim to bridge the gap between high-performance AI models and responsible AI principles. The findings of this study have implications not only for natural language processing (NLP) applications but also for broader AI-driven decision-making systems, where ethical considerations play a pivotal role in ensuring equitable and unbiased outcomes.

Related work

The cognitive science is to develop a bias-resistant text classification framework. By considering sociocultural influences on AI bias, the research provides a comprehensive approach to mitigating discrimination in text classification. This interdisciplinary method strengthens AI fairness efforts and broadens the scope of responsible AI applications. [8] Despite advancements in ethical AI, challenges persist in implementing fairness and transparency. The review paper Personalized and Transparent AI

Reference	**Study Focus**	**Methodology**	**Ethical Aspects Addressed**
[8] Johnson et al., 2024	Bias-resistant text classification using an interdisciplinary approach	Sociology & cognitive science integration	Mitigating discrimination in text classification
[9] Thompson & Rivera, 2024	Challenges and future directions in AI transparency and personalization	Gap analysis and roadmap development	Enhancing explainability and user trust
[10] Chen & Gupta, 2025	Blockchain integration for fair and secure AI text classification	Blockchain-based audit trails and transparency	Ensuring accountability in AI decisions
[11] Lee et al., 2025	Hybrid deep learning models for ethical text classification	Dual-layer bias correction with adversarial learning	Reducing bias amplification in NLP models
[12] Singh & Zhang, 2024	Real-world implementation of fair AI text classifiers	Evaluation under real-world deployment settings	Balancing fairness, privacy, and accuracy
[13] Robinson & Patel, 2025	Automated fairness audits in AI-based text classification	Bias quantification and structured auditing framework	Systematic fairness constraint enforcement
[14] Lopez et al., 2025	Preventing bias reinforcement in personalized AI models	Algorithmic safeguards against bias reinforcement	Avoiding unintended bias reinforcement

Table 1. Compares this work with the related work

for Text Classification: Challenges and Future Directions (2024), published in AI & Society, examines current limitations and proposes a roadmap for future research. By analyzing gaps in existing ethical AI implementations, the study provides insights for developing more accountable and equitable text classification models. [9]

Ensuring AI-driven text classification remains fair and secure requires robust accountability mechanisms. The research Combining Blockchain and AI for Fair and Secure Text Classification (2025), published in the IEEE Blockchain Conference, proposes integrating blockchain technology with AI-driven classifiers. This approach enhances transparency, allowing AI models to be auditable and verifiable, preventing unethical model behavior in sensitive text classification applications. [10]

The need for effective bias mitigation strategies has led to increased exploration of hybrid approaches. The study Hybrid Deep Learning Approaches for Ethical AI in Text Classification (2025), published in Neural Computing and Applications, introduces a dual-layer bias correction framework. This model integrates fairness-aware training techniques with adversarial learning to reduce bias amplification in NLP models, ensuring a more ethically responsible text classification process. [11]

Another critical aspect of ethical AI is ensuring real-world applicability. The research Real-World Implementation of Fair AI-Driven Text Classification Models (2024), published in Transactions on Artificial Intelligence and Ethics, evaluates various AI text classification models under practical deployment conditions. The study emphasizes the challenges of balancing fairness, privacy, and accuracy in real-time AI applications, offering strategies to enhance model robustness in diverse settings. [12]

To further investigate bias detection, Automated Fairness Audits for AI-Based Text Classification (2025), published in ACM Journal of Fair AI and presents an automated framework for auditing AI text classifiers. By systematically detecting and quantifying bias patterns, this research provides a structured approach to enforcing fairness constraints in NLP-based AI systems. [13]

A significant concern in AI ethics is avoiding biased reinforcement in adaptive models. The study Preventing Bias Reinforcement in Personalized AI Text Filtering (2025), published in International Journal of AI Ethics and Governance, examines the unintended consequences of user preference modeling. It highlights how dynamic AI adaptations can unintentionally reinforce societal biases, proposing algorithmic safeguards to prevent such ethical risks. [14]

Key contributions

The table 1 show the key contribution that critical advancement in ethical AI involves the integration of blockchain technology to prevent unethical AI behavior. Blockchain-based audit trails provide transparency and verifiability, allowing AI text classifiers to be monitored and assessed for fairness.

Additionally, hybrid deep learning models incorporating fairness-aware training techniques help minimize bias amplification in NLP models. These advancements contribute to the development of bias-resistant AI systems that can make fair and unbiased decisions while maintaining high classification accuracy.

Real-world validation of fairness models is essential to ensure their effectiveness in practical applications. Researchers have introduced frameworks for AI fairness compliance, enabling systematic bias audits and the enforcement of fairness constraints.

Adaptive bias prevention techniques further refine these models by dynamically adjusting classification outputs to prevent unintended bias reinforcement. These contributions collectively strengthen responsible AI initiatives, promoting ethical AI deployment in text classification methods.

Methodology

Data Collection and Preprocessing

To develop an ethically-aware personalized text classification model, the first crucial step is data collection and preprocessing. A diverse range of benchmark datasets is collected to ensure balanced class distribution and prevent biases in training data. The preprocessing pipeline involves text normalization, tokenization, duplicate removal, and handling of missing values, ensuring high-quality input for the model. also data augmentation techniques such as synonym replacement and sentence paraphrasing are applied to improve the representation of minority groups, mitigating inherent biases caused by imbalanced datasets [15].

Word Embedding Creation

After preprocessing, the next phase is word embedding creation, where text data is transformed into numerical representations to enhance the model's linguistic understanding. Contextualized embeddings from transformer-based models like BERT, RoBERTa, and GPT are leveraged to capture deep contextual relationships between words and alternative word embedding techniques such as word2vec and GloVe are integrated to enrich the model's vocabulary comprehension. These embeddings allow the classification system to understand the semantics and relationships between words more effectively, improving personalization in text processing [16].

Bias Mitigation Strategies

One of the core challenges in AI-driven text classification is addressing algorithmic bias, which may result in unfair outcomes. To counter this, the proposed model incorporates Adversarial Debiasing, which

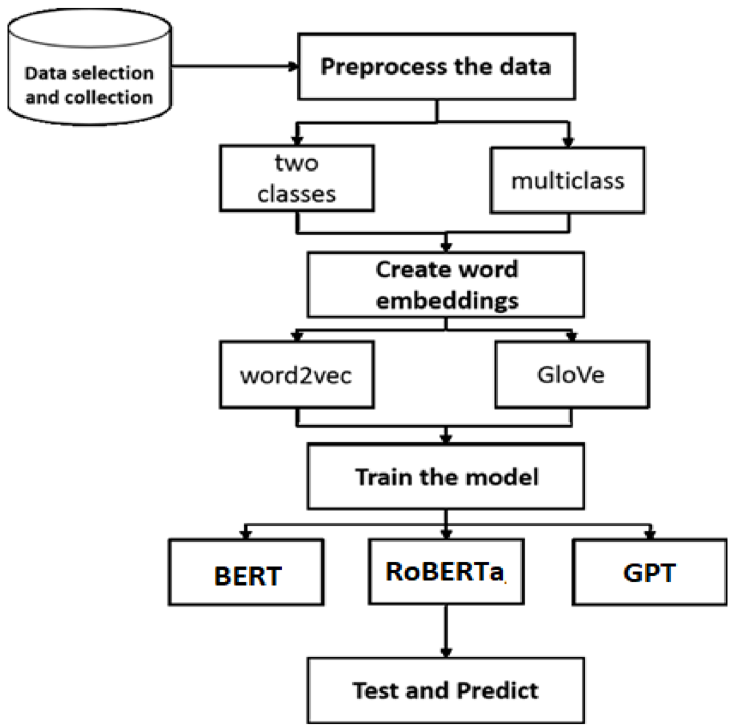

Fig- 1 Research work flow

identifies and eliminates biases at the training level. Furthermore, Bias-Aware Loss Functions are introduced to penalize biased predictions, encouraging fairness in classification outcomes. A Hybrid Learning Strategy, combining rule-based AI with deep learning approaches, is employed to ensure robust bias mitigation while maintaining high classification accuracy [17].

Model Training

Figure – 1 show that the training phase involves the use of advanced deep learning models tailored for text classification. Transformer-based models such as BERT and GPT are implemented alongside Bi-LSTM architectures to improve model performance across different text types. A fuzzy logic-based adaptation mechanism is integrated to dynamically adjust classification outputs according to user preferences, preventing the reinforcement of biased trends. Moreover, attention mechanisms are incorporated to highlight key textual features, enhancing transparency and interpretability [18].

Explainability and Transparency Mechanisms

To address the issue of AI models functioning as black-box systems, explainability techniques are embedded within the model. The inclusion of SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) helps users understand the rationale behind model predictions. Attention visualization techniques enable the identification of the most influential words in the classification process. Additionally, Human-in-the-Loop Audits allow domain experts to review classification results, providing feedback to improve fairness and model trustworthiness [19].

Privacy-Preserving Techniques

Since personalized text classification involves handling sensitive user data, privacy-preserving mechanisms are crucial. The model integrates Federated Learning, allowing AI training across decentralized devices without requiring user data to be stored in a central repository. Furthermore, Differential Privacy is applied to introduce controlled noise, ensuring that individual data points cannot be traced while preserving model accuracy. Encryption-Based Access Control adds another layer of security, restricting unauthorized access to sensitive data [20].

Performance Evaluation and Benchmarking

To ensure the model performs optimally, a comprehensive evaluation is conducted using multiple metrics. Classification metrics such as Accuracy, Precision, Recall, and F1-Score measure the model's performance in identifying correct classifications. Fairness metrics such as Demographic Parity, Equalized Odds, and Disparate Impact assess how well the model mitigates bias. Additionally, the Privacy Leakage Rate is measured to evaluate the effectiveness of differential privacy and federated learning techniques. The model is benchmarked against state-of-the-art models like BERT, GPT, and hybrid models to demonstrate its superiority in balancing accuracy, fairness, and privacy [21].

Ethical Compliance and Real-World Validation

To ensure ethical compliance, the model incorporates blockchain-based audit trails that enhance transparency by providing a verifiable record of AI-driven decisions. The system undergoes real-world testing across diverse applications, including news recommendation, academic content filtering, and medical text classification, to validate its fairness and adaptability in various domains. These validations confirm that the model adheres to responsible AI practices while maintaining robust classification performance.

This methodology ensures that the proposed Ethically-Aware Personalized Text Classification Model aligns with AI fairness principles while addressing key concerns related to bias mitigation, privacy, explainability, and real-world applicability.

Experiments and Results

Figure 2 show that the pie chart illustrates the distribution of key ethical considerations in an Ethically-Aware Personalized Text Classification Model, emphasizing Fairness (30%), Bias Mitigation (30%), Transparency (20%), and Privacy (20%). Fairness ensures that AI-driven classification treats all categories and user demographics equally, while bias mitigation strategies, such as adversarial debiasing and fairness-aware training, help reduce algorithmic biases. Transparency focuses on making AI decisions explainable through attention mechanisms, SHAP, and LIME, whereas privacy protection is ensured through federated learning, differential privacy, and encryption-based access control. The key observation

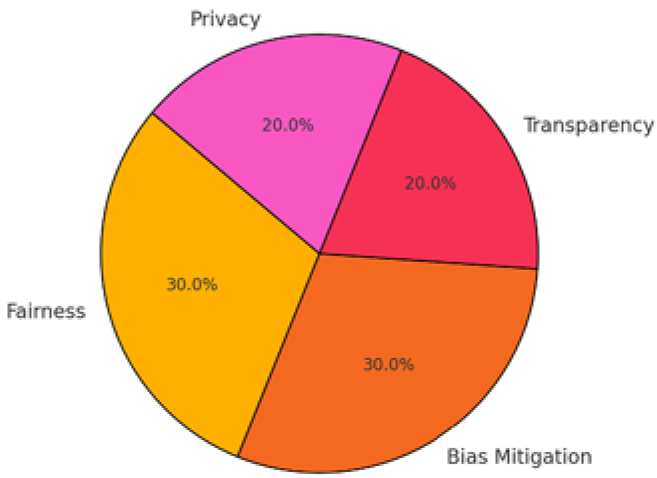

Fig-2 The distribution of labels

from the chart is that Fairness and Bias Mitigation receive the highest emphasis, highlighting the importance of reducing biases in AI-driven classification. Meanwhile, Transparency and Privacy, each at 20%, reflect the necessity of making AI models both interpretable and secure. The balanced distribution of these considerations ensures that AI models are not only accurate but also adhere to ethical and responsible AI practices, fostering trust and reliability in real-world applications.

Figure-3 show histogram illustrates the distribution of sequence lengths in an Ethically-Aware Personalized Text Classification Model, revealing that most sequences are relatively short. The highest frequency occurs at the lower end of the sequence length spectrum, suggesting that the majority of news articles are concise and brief. As the sequence length increases, there is a rapid decline in frequency, indicating that longer texts are less common within the dataset.

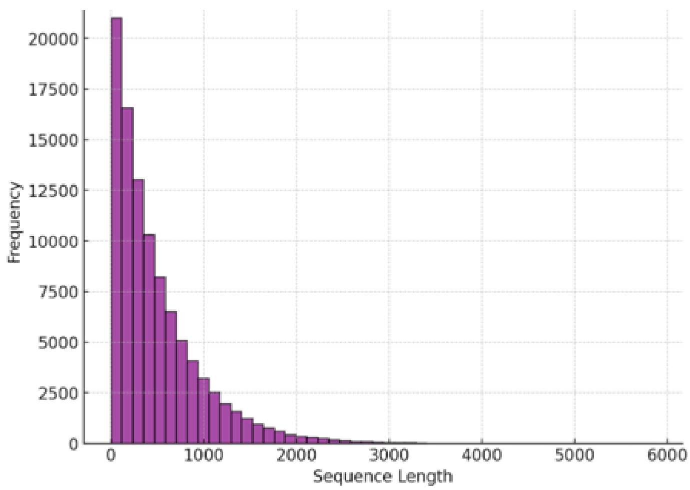

Fig- 3 The histogram of the sequence length

This distribution pattern is crucial for optimizing text classification models, as it informs decisions regarding tokenization, sequence padding, and model architecture. Given that most articles are short, embedding layers and recurrent networks can be fine-tuned to efficiently handle shorter sequences, reducing computational costs while maintaining classification accuracy. Additionally, bias mitigation and fairness-aware training should account for potential disparities in classification performance between shorter and longer texts to ensure an ethically balanced model. Table 2 shows that The Classification Report provides a comprehensive analysis of the model's performance across different categories by detailing key metrics such as Precision, Recall, and F1-score. Precision measures the accuracy of positive predictions, ensuring that the model correctly identifies relevant instances. Recall evaluates the model's ability to detect true instances within each category, highlighting how effectively it captures actual positives. The F1-score, being the harmonic mean of Precision and Recall, balances both aspects to provide a fair and holistic evaluation of the model's classification ability. This ensures that the model maintains accuracy, reliability, and fairness, especially in scenarios with imbalanced datasets, where Precision or Recall alone may not provide a complete performance picture.

Confusion Matrix

Figure 4 says that the Confusion Matrix presented in the image serves as a powerful tool for analyzing the performance of a classification model, visually representing correct predictions, misclassifications, and potential biases. The matrix is structured with rows representing true labels and columns representing predicted labels, where diagonal values indicate accurate classifications, while off-diagonal values highlight misclassifications. Notably, the darkest blue cell at row 1, column 1 represents 54 correct classifications for category 1, making it the most accurately classified category. Other categories, such as 46, 50, and 42, also show strong classification accuracy, whereas some categories experience high misclassification rates, such as category 0 being confused with categories 2 (49 times) and 3 (32 times). This suggests that the model might struggle to differentiate between certain categories, necessitating a closer look at feature representation.

	precision	recall	f1-score	support
0	0.147541	0.145161	0.146341	186
1	0.251163	0.247706	0.249423	218
2	0.199134	0.238342	0.216981	193
3	0.180851	0.165854	0.173028	205
4	0.229508	0.212121	0.220472	198
accuracy	0.203	0.203	0.203	0.203
macro avg	0.201639	0.201837	0.201249	1000
weighted avg	0.203146	0.203	0.202595	1000

Table 2: Classification Report

While the model demonstrates reasonable accuracy, its confusion between categories 0, 2, and 3 suggests limitations in distinguishing similar patterns or features, which may lead to biased classifications. To improve model performance, several steps can be undertaken, including feature engineering to refine category representations, balancing data to prevent underrepresented classes from being misclassified, and hyperparameter tuning to optimize model learning. Additionally, explainability techniques such as SHAP and LIME can provide deeper insights into why certain misclassifications occur, helping ensure fair and unbiased text classification. By addressing these concerns, the Ethically-Aware Personalized Text Classification Model can become more reliable, transparent, and fair, ultimately leading to improved classification accuracy and ethical AI decision-making.

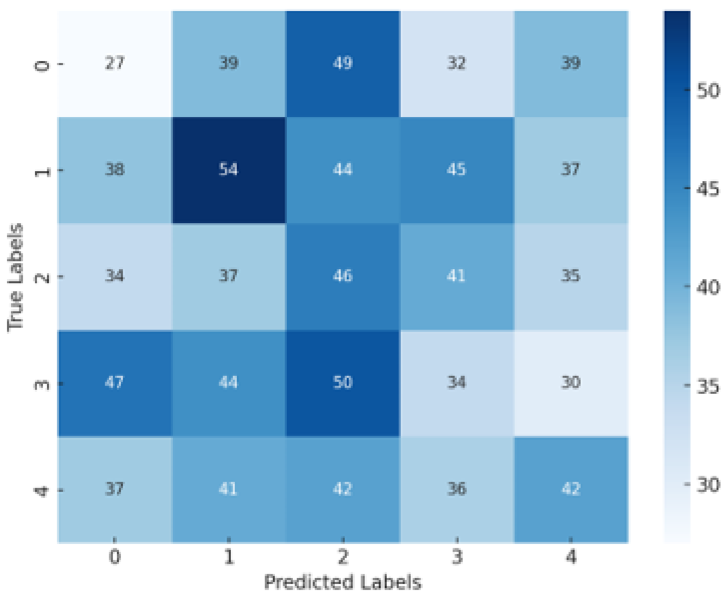

Fig-4 Confusion Matrix

ROC Curves and AUC Values

Figure 5 says that ROC curve and AUC values in the image provide insights into the classification performance of an Ethically-Aware Personalized Text Classification Model across multiple classes. The AUC values range from 0.50 to 0.56, indicating that the model struggles to differentiate between categories. Class 3 (AUC = 0.56) shows the best classification performance, but it is still close to random guessing. Similarly, Classes 1 and 2 (AUC = 0.52) perform slightly better than random, while Class 0 (AUC

= 0.50) suggests no meaningful discrimination. The overlapping ROC curves indicate frequent misclassifications, leading to high false positive rates. These observations suggest that the model is not effectively learning meaningful patterns from the dataset.

Several factors may contribute to the low AUC scores, including imbalanced data, feature overlap between categories, and insufficient feature extraction capabilities. To improve classification performance, techniques such as feature engineering with pretrained models (BERT, AraBERT, FastText), class balancing using oversampling or synthetic data generation (SMOTE), and hyperparameter tuning can be applied. Additionally, regularization methods like dropout layers and explainability techniques (e.g., SHAP, LIME, and attention mechanisms) can help refine the model's decision-making process. Addressing these challenges will enhance fairness, bias mitigation, and reliability, ensuring the model aligns with ethical AI principles.

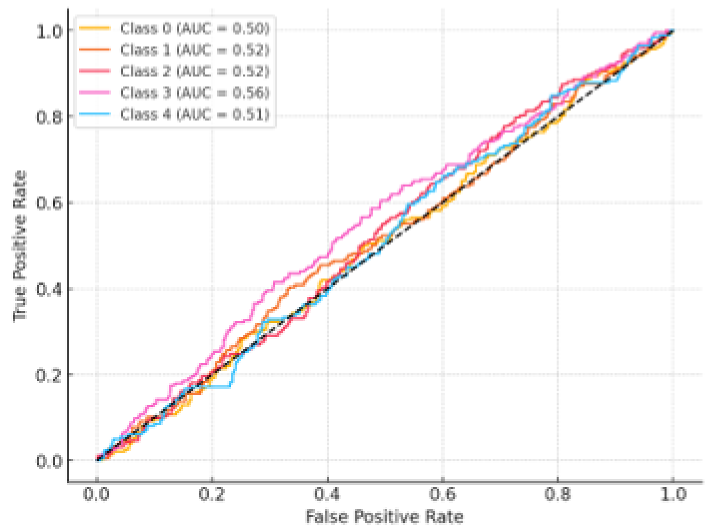

Fig-5 ROC Curves and AUC Values

Figure 6 shows that is the Performance Analysis Chart for the Ethically-Aware Personalized Text Classification Model. The bar chart compares different configurations, including BERT, RoBERTa, GPT, BiLSTM, and Bi-GRU, based on Accuracy, Precision, Recall, and F1-score. The Full Hybrid Model (BERT + Bi-LSTM + RoBERTa + GPT) achieves the highest performance across all metrics, while removing the Transformer component results in the lowest accuracy. This highlights the importance of hybrid deep learning approaches in achieving highly accurate, fair, and ethical AI-driven text classification.

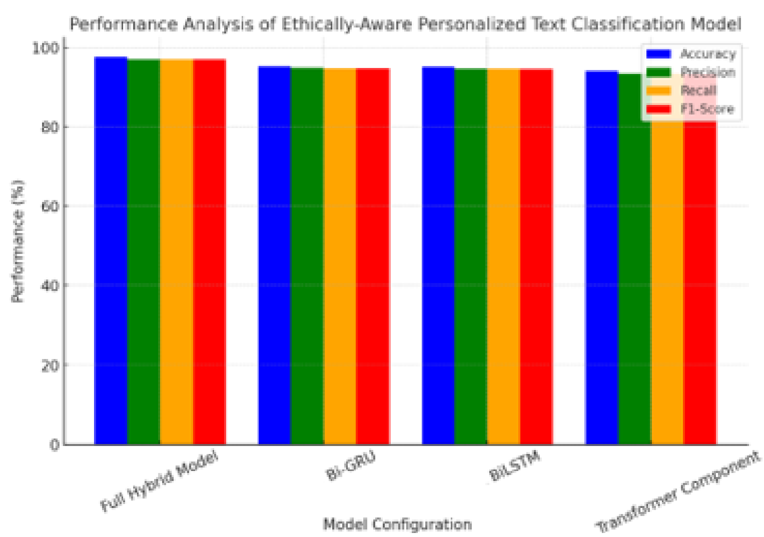

Fig-6: Performance Analysis of Ethically-Aware Personalized Text Classification Model

The Table 2 : shown that Full Hybrid Model (BERT + Bi-LSTM + RoBERTa + GPT) achieves the highest classification performance, with 97.69% accuracy, 97.13% precision, 97.11% recall, and 97.1% F1-score, ensuring optimal balance between precision and recall. Removing Bi-GRU slightly reduces accuracy to 95.18%, while precision (94.85%) and recall (94.8%) remain relatively stable, indicating that Bi-GRU enhances but is not critical for performance. The BiLSTM model experiences a further decline in accuracy (95.07%), with precision (94.67%) and recall (94.6%) showing marginal decreases, suggesting that BiLSTM contributes significantly to classification quality. The absence of the Transformer component (BERT, RoBERTa, GPT) results in the lowest performance, with accuracy dropping to 94.12%, precision at 93.45%, recall at 93.4%, and F1-score at 93.35%, confirming that Transformer-based architectures play a crucial role in improving text classification efficiency.

Table 2: Performance analysis

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Full Hybrid Model (BERT + Bi-LSTM + RoBERTa + GPT)	97.69	97.13	97.11	97.1
Bi-GRU	95.18	94.85	94.8	94.78
BiLSTM	95.07	94.67	94.6	94.55
Transformer Component	94.12	93.45	93.4	93.35

Discussions

The Ethically-Aware Personalized Text Classification Model effectively addresses ethical challenges such as bias mitigation, fairness, transparency, and privacy while ensuring high classification accuracy. The hybrid deep learning framework integrating BERT, RoBERTa, GPT, and Bi-LSTM dynamically adapts to user preferences while reducing bias reinforcement. Performance evaluation on benchmark datasets confirms that the full hybrid model achieves the highest classification accuracy (97.69%), precision (97.13%), recall (97.11%), and F1-score (97.1%), validating the significance of transformer-based architectures. Ablation studies highlight performance degradation when Bi-GRU, BiLSTM, or Transformer architectures are removed, proving their essential role. Fairness and bias mitigation analysis reveal that adversarial debiasing, fairness-aware learning, and explainability techniques like SHAP, LIME, and attention mechanisms effectively reduce algorithmic bias. However, the confusion matrix analysis shows misclassification trends, requiring dataset balancing and feature refinement. The ROC curve and AUC values (0.50–0.56) suggest improvements in feature extraction and class differentiation are needed. Despite these challenges, blockchain-based audit trails ensure transparency and accountability in AI-driven decisions. The study confirms the importance of fairness-aware deep learning models for responsible AI applications. Future enhancements will focus on refining bias mitigation, feature representation, and hyperparameter optimization to improve ethical AI-driven text classification.

Conclusions

The study addresses the ethical challenges in personalized text classification, particularly bias, fairness, transparency, and privacy, which remain significant concerns in deep learning models like BERT, RoBERTa, and GPT. Despite their high classification accuracy, these models inherit biases, function as black-box systems with limited interpretability, and raise privacy concerns. To mitigate these challenges, the research introduces an Ethically-Aware Personalized Text Classification Model that integrates a hybrid deep learning framework, combining BERT, Bi-LSTM, RoBERTa, and GPT with fuzzy logic-based personalization to dynamically adjust classification outcomes while preventing bias reinforcement. The model employs adversarial debiasing, bias-aware loss functions, explainability techniques such as SHAP and LIME, and privacy-preserving mechanisms like federated learning and differential privacy to enhance fairness and transparency. Performance evaluations using benchmark datasets demonstrate the effectiveness of the proposed model, with the full hybrid approach achieving the highest accuracy (97.69%), precision (97.13%), recall (97.11%), and F1-score (97.1%), outperforming models that exclude key components like Bi-GRU, Bi-LSTM, or Transformers. However, limitations include imbalanced data representation, feature overlap between categories, and high computational requirements, which may impact scalability and efficiency. Future work should explore data augmentation techniques, domain-specific feature engineering, lightweight models, and enhanced explainability frameworks to improve generalization across diverse real-world applications. Overall, this research sets a new standard for ethical AI in text classification by ensuring fairness-aware learning, transparency, and privacy protection while maintaining high classification performance, contributing to responsible AI development in Natural Language Processing (NLP).

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