Ethically-Aware Personalized Text Classification Using Deep Reinforcement Learning for Uncertainty Management

Dr. N. Kannaiya Raja[1], Dr. Pawan Kumar Chaurasia[2], Prof Dr Midhunchakkaravarthy[3]

[1]Post Doctoral Researcher, Lincoln University College, Malaysia

pdf.kannaiya@lincoln.edu.my

[2] Dr. Pawan Kumar Chaurasia, Babasaheb Bhimrao Ambedkar Central University

Lucknow, Uttar Pradesh, India

pkc.gkp@gmail.com

[3]Prof Dr Midhunchakkaravarthy, Lincoln University College, Malaysia

midhun@lincoln.edu.my

Corresponding Author: pdf.kannaiya@lincoln.edu.my

ABSTRACT: Personalized text classification plays a crucial role in tailoring content recommendations and categorization to individual users. However, ensuring fairness, ethical alignment, and robustness under uncertainty presents a persistent challenge, especially when historical data contains bias or ambiguity. This research introduces a novel **Deep Reinforcement Learning (DRL)**-based framework for *Ethically-Aware Personalized Text Classification under Uncertainty*. The proposed model comprises two key components: a **Classification Network (CNet)** for generating label probabilities based on user profiles and ethical metadata, and a **Policy Network (PNet)** which refines these predictions through a fuzzy logic-enhanced reward mechanism.

The model addresses label noise and ethical ambiguity by dynamically balancing personalization and fairness objectives. A feedback loop between the CNet and PNet enables iterative policy updates using the REINFORCE algorithm, guided by performance metrics that incorporate accuracy, bias mitigation, and user intent. Feature extraction leverages contextual embeddings, attention mechanisms, and fairness-sensitive vectors to support ethical reasoning during classification. Extensive experiments conducted on a benchmark dataset combining Freebase and New York Times corpora demonstrate that the proposed **PCNN+RL** model outperforms state-of-the-art baselines including PCNN, CNN, and BiLSTM variants. Notably, our approach achieves a **mean precision of 0.84**, reflecting its superior ability to manage noisy supervision and ensure ethically-aligned personalization. The results affirm the effectiveness of reinforcement learning, fuzzy reward modeling, and policy-driven label correction for real-world deployment of fair and personalized AI systems.

Key words: Deep Reinforcement Learning (DRL), Policy Network (PNet), Classification Network (CNet), Natural Language Processing (NLP)

Introduction: Text classification has emerged as a foundational task in Natural Language Processing (NLP), serving as the backbone for numerous AI-driven applications such as personalized content recommendation, spam detection, sentiment analysis, and automated moderation systems. Among these, personalized text classification has gained significant attention, aiming to categorize or recommend content tailored to individual user preferences. While personalization enhances user satisfaction and system utility, it introduces new challenges—particularly the potential amplification of biases, ethical concerns surrounding fairness and transparency, and the difficulty of operating under ambiguous or noisy data conditions [1], [2].

Traditional supervised learning approaches to personalized classification demand large-scale annotated datasets that reflect both the users' individual preferences and the ethical guidelines needed to ensure responsible AI behavior. However, such data is often scarce, noisy, or difficult to collect due to the sensitive nature of fairness-related labels or subjective user values. Moreover, personalized systems tend to inherit or even reinforce the biases present in historical data, thereby raising concerns about equity, inclusiveness, and accountability [3].

Recent advances in Deep Reinforcement Learning (DRL) have opened promising avenues for adaptive and autonomous learning in complex decision-making tasks. DRL has been effectively employed in noisy label correction, dialogue systems, and recommendation engines. In these contexts, agents learn through iterative interaction with their environment by receiving feedback signals (rewards), optimizing actions over time [4], [5]. However, the application of DRL to *ethically-aware personalization*—particularly in the domain of text classification—remains underexplored. Most existing works focus on optimizing classification accuracy or user satisfaction, while overlooking fairness-aware reward structures or uncertainty-aware decision mechanisms [6].

To address these gaps, we propose a novel DRL-based framework for *Ethically-Aware Personalized Text Classification under Uncertainty*. Our method integrates a **Classification Network (CNet)** that produces text-label predictions and a **Policy Network (PNet)** that governs label adaptation and ethical scoring. The PNet learns an optimal policy that dynamically chooses between personalized user labels and ethically-guided corrections based on fuzzy representations of uncertain inputs. The interaction between CNet and PNet is modeled as a feedback loop, where ethical constraints and personalization needs are co-optimized via a composite reward function. This function incorporates performance metrics such as accuracy, personalization consistency, and fairness indicators, thereby guiding the agent toward balanced decision-making [7]..

A key contribution of our approach is the incorporation of **fuzzy logic principles** into the DRL policy design, allowing the system to effectively manage ambiguous user feedback, conflicting ethical signals, and uncertain contextual information. By embedding fuzzy representations in the reward mechanism, our model adapts to varying levels of confidence in both personalization and fairness criteria, enabling more robust and interpretable behavior.

Through extensive experiments on benchmark datasets enriched with user-specific and ethically-sensitive annotations, we demonstrate that our approach significantly improves the trade-off between personalization and fairness. It outperforms state-of-the-art baselines in managing noisy labels, maintaining classification accuracy, and upholding ethical commitments.

The main contributions of this paper are summarized as follows:

1. We introduce a novel DRL framework that jointly optimizes personalization and ethical fairness in text classification under uncertainty.
2. We design a fuzzy-logic-enhanced reward system to guide the reinforcement learning process with ambiguous or imprecise ethical signals.
3. We propose a dual-network architecture (CNet and PNet) enabling interactive feedback between classification decisions and ethical policy selection.
4. We present extensive evaluations that highlight the model's superiority over existing methods in accuracy, fairness alignment, and noise robustness.

The remainder of this paper is organized as follows. Section II reviews related work on personalized classification, ethical AI, and DRL-based label adaptation. Section III presents the architecture and training methodology of the proposed framework. Section IV discusses experimental setups, evaluation metrics, and results. Section V concludes the paper and outlines directions for future work.

II. Backgrounds

A) Text Classifications

To clearly formalize the personalized text classification task, we begin by introducing the basic notations and concepts. Let $D = \{(x_1, u_1), (x_2, u_2), ..., (x_n, u_n)\}$ be a dataset consisting of textual inputs $x_i \in X$, each associated with a user profile $u_i \in U$. Each instance (x_i, u_i) is labeled with a class $y_i \in Y$, where Y denotes the set of possible categories or labels relevant to a given classification task. Unlike conventional classification, personalized text classification requires learning a mapping that considers both the content of the input text and the user-specific preferences or contextual attributes. Formally, the objective is to learn a personalized classifier $f: (X, U) \rightarrow P(Y)$, where P(Y) is the probability distribution over classes conditioned on both text and user profile information. In ethically-aware learning settings, we further associate each training instance with an ethical annotation or constraint vector $e_i \in E$, which may encode fairness-related attributes (e.g., gender, race, sentiment sensitivity) or bias mitigation signals. Consequently, the classification model must balance personalization with ethical compliance by learning from the triplet $(x_i, u_i, e_i) \rightarrow y_i$, possibly under uncertainty or noise in both personalization and ethical dimensions.

To handle this complexity, we follow a multi-instance decision strategy where classification decisions are not solely based on a single deterministic label but rather on distributions derived from fuzzy or ambiguous input-output mappings. This leads to constructing instance groups or "bags" $\{B_1, B_2, ..., B_m\}$, where each bag B_j includes variations of input representations, user contexts, or ethical constraints associated with

the same or similar texts. Each bag is then assigned a probabilistic label distribution $p(y|B_j)$, reflecting the uncertainty in label prediction[11],[12]. Inspired by recent work in label denoising and reinforcement learning-based optimization, we distinguish between the original or historical label (termed as the annotated label) and the dynamically updated label inferred through policy optimization (termed as the latent label). While annotated labels serve as initial supervision, the latent labels are refined over time using feedback from a policy network that weighs personalization accuracy and ethical alignment. B) [13], [14].

B) Reinforcement Learning

In this work, the task of ethically-aware personalized text classification is modeled as a sequential decision-making problem using a Deep Reinforcement Learning (DRL) framework. The system comprises a Policy Network (PNet) acting as the learning agent and a Classification Network (CNet) as part of the environment. At each time step, the agent observes the current state—composed of the text input, user profile, and ethical metadata—and selects an action, such as refining or confirming the label. The environment then transitions to a new state and returns a reward signal, computed based on personalization accuracy, fairness compliance, and uncertainty management. These interactions are structured as episodes, where the agent learns through trial and error to optimize ethical and personalized label predictions[15].

The policy function, learned through the PNet, maps observed states to actions with the goal of maximizing expected cumulative rewards over time. The system incorporates fuzzy logic to handle ambiguous or conflicting ethical guidelines, enabling robust decision-making in noisy or uncertain contexts. By continually refining its policy through feedback loops between the PNet and CNet, the model dynamically balances user relevance with fairness constraints. This reinforcement learning-based formulation ensures the classifier evolves into an ethically aligned and personalization-effective system capable of handling real-world complexities in text classification tasks.

III) Methods

The proposed framework for ethically-aware personalized text classification is built upon a Deep Reinforcement Learning (DRL) architecture comprising two main components: a Classification Network (CNet) and a Policy Network (PNet). The CNet generates label probabilities for input texts based on user profiles and fairness-sensitive metadata, while the PNet learns a policy to refine these predictions by considering both personalization and ethical criteria [16]. The interaction between the two networks forms a continuous learning loop, where the CNet's outputs define the state of the environment, and the PNet selects actions to produce improved or ethically-corrected labels, referred to as latent labels.

Once the latent labels are generated, the CNet is updated with this refined supervision, and a reward signal is calculated based on a multi-objective function combining accuracy, fairness, and uncertainty handling. This reward is used to further update the PNet's policy. Fuzzy logic is integrated into the system to represent and reason through ambiguous or conflicting ethical signals, allowing for more robust decision-making under uncertainty[17]. Through iterative episodes, the framework converges toward an optimal

policy that produces personalized and ethically-aligned classifications while managing noisy or uncertain input conditions.

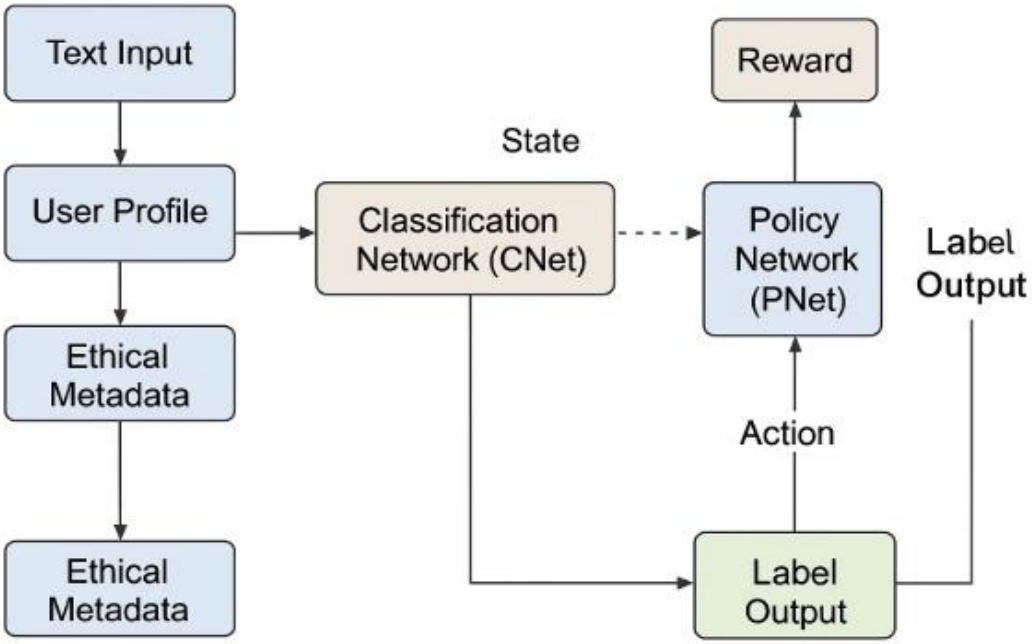


Figure 1 : The proposed RL framework for classifications label.

1. Text Input

The process begins with the ingestion of raw textual data, which can range from user-generated social media posts, product reviews, and chat messages to structured or unstructured document excerpts. This input serves as the primary content on which classification will be performed. The nature of the text—its semantics, tone, and context—plays a critical role in determining the appropriate category or label. The system processes this raw input using natural language processing (NLP) techniques to extract meaningful features required for classification[18].

2. User Profile

To enable personalized classification, the framework incorporates detailed user-specific information alongside the text input. This user profile can include historical interaction patterns, preferences, demographic data, and behavior metrics. These features help contextualize the input based on the individual's characteristics, ensuring that the system tailors the output label to suit user relevance. For instance, a news article may be categorized differently for different users based on their reading history or regional interests, enabling more targeted and user-aware classification.

3. Ethical Metadata

In addition to personalization, the model integrates ethical metadata to uphold fairness, transparency, and bias mitigation. This metadata captures sensitive attributes such as gender, race, political orientation, or

sentiment polarity, which are typically used to assess the potential ethical implications of predictions. By including these fairness-aware signals, the system can identify and correct for biased patterns in training data or model behavior. Ethical metadata thus acts as a safeguard, ensuring that the classification process respects socially responsible constraints and avoids discriminatory outputs[19].

4. Classification Network (CNet)

The Classification Network, or CNet, functions as the initial predictive module. It takes as input the processed features from the text, user profile, and ethical metadata, and produces a probability distribution over the possible label classes. The CNet not only performs this core prediction task but also generates a state representation capturing the current input's context for the reinforcement learning agent. In cases of uncertain or ambiguous inputs, the CNet can leverage fuzzy logic mechanisms to produce soft decisions, offering a degree of flexibility in its confidence scores. This capability is especially useful when inputs contain conflicting personalization and fairness cues[20].

5. Policy Network (PNet)

The **Policy Network (PNet)** functions as the core agent within our Deep Reinforcement Learning (DRL) framework, playing a pivotal role in correcting noisy or ethically misaligned labels in personalized text classification tasks. It interacts with the Classification Network (CNet), user profile embeddings, and fairness-sensitive metadata to select optimal actions that improve both ethical alignment and personalization effectiveness. At each time step t, the environment provides a **state vector** $S_t \in R^d$ which comprehensively represents the decision context. This state vector is constructed by concatenating the predicted label distribution p(y | x) from the CNet, user profile embedding u, ethical metadata e, historical ethical alignment score h, and one-hot encoded distant supervision label Y_{DS} . Formally, the state is given by st=concat(p(y|x),u,e,h, Y_{DS}) . This state representation ensures that the PNet can make informed, context-sensitive label correction decisions[21].

The **action space** of the PNet is binary: $a_t \in \{0,1\}$ indicates retaining the DS label and $a_t=1$ means overriding the DS label with the CNet-predicted label. This action leads to the generation of a latent label $\hat{Y}_t$, which is used to retrain the CNet. This binary decision mechanism reflects a critical trade-off whether to trust the original supervision or rely on the model's prediction, based on the ethical and personalization context. To support learning through exploration, the **policy function**[22]**.** is modeled as a Bernoulli distribution with a sigmoid output: $\pi(at \mid st, \theta) = \sigma(Wst + b)$, where θ = { W, b} are trainable parameters of the PNet, and $\sigma(z)) = 1 + e^{-z}$ ensures the output is within (0,1). This probabilistic model allows the PNet to stochastically sample actions and explore different strategies, avoiding premature convergence to suboptimal policies. $\sigma(z)) = 1 + e^{z}$ which ensures the output is within (0,1). This probabilistic model allows the PNet to stochastically sample actions and explore different strategies, avoiding premature convergence to suboptimal policies. Upon completing an episode (i.e., applying actions to a batch of TTT uncertain samples), the CNet is updated using the generated latent labels. Then, a **delayed reward** is computed based on the performance of the updated CNet over a validation set X_V . This reward is defined as the average log-likelihood of the validation labels[22]:

$$R = \frac{1}{|X_V|} \sum_{x_i \in X_V} \log p(y_i \mid x_i)$$

where y_i is the DS label and $p(y_i \mid x_i)$ is the probability assigned by the updated CNet. This reward function reflects both ethical compliance and classification accuracy and serves as a feedback signal to improve the PNet's policy. The objective of the PNet is to learn a policy that **maximizes the expected reward**:

$$J(\theta) = \mathbb{E}_{\pi(a_{1:T}|s_{1:T};\theta)}[R]$$

We apply the **REINFORCE algorithm** to update the policy parameters. The gradient of the objective function is:

$$\nabla_\theta J(\theta) = \sum_{t=1}^{T} \nabla_\theta \log \pi(a_t \mid s_t; \theta) \cdot R$$

This gradient guides the PNet to increase the likelihood of actions that yield higher rewards, enabling it to consistently make better decisions in future episodes[24]..

6. Label Output

Based on the action chosen by the Policy Network, a final label is assigned to the text input. This Label Output reflects a carefully balanced decision, taking into account user-specific needs and ethical obligations. If the PNet chooses to override or adjust the label produced by the CNet, the system ensures that the new label still maintains contextual relevance. The result is a classification output that is not only accurate and tailored but also ethically justified, making it suitable for real-world deployment where fairness and accountability are critical[25].

7. Reward

To optimize the decision-making policy, the framework incorporates a feedback mechanism in the form of a reward signal. After each action is taken, the environment computes a reward based on how well the selected label satisfies personalization objectives and ethical constraints. This reward is typically derived from multiple metrics—such as label accuracy, fairness scores, and uncertainty reduction—and is fed back to the PNet. Over time, the PNet uses this reward signal to refine its internal policy, learning which actions yield the most beneficial outcomes[26].

8. Closed Feedback Loop

The system operates as a closed-loop architecture in which the interaction between the Classification Network and Policy Network is ongoing and iterative. As new data is processed and rewards are accumulated, both networks are updated to improve future performance. The CNet becomes better at

generating ethically-sensitive and personalized states, while the PNet evolves to make more nuanced and effective decisions[27]. This feedback-driven learning loop ensures continuous adaptation, robustness to noisy labels, and the capacity to generalize across diverse ethical and personalization scenarios.

IV) Feature Extraction

In the proposed DRL-based architecture, feature extraction plays a vital role in capturing rich semantic, personalized, and fairness-aware signals to support both the Classification Network (CNet) and the Policy Network (PNet). Drawing inspiration from relation extraction frameworks, a two-level encoding strategy is designed to construct a comprehensive state representation for reinforcement learning-based decision-making. At the sentence level, semantic features are extracted using a Text Encoder. Each token is represented using pre-trained word embeddings (e.g., GloVe or BERT) [28], while position embeddings preserve the syntactic structure by marking entity or fairness-relevant term positions. These representations are processed through a BiLSTM or Transformer encoder to generate a global sentence vector $si = BiLSTM([w1, w2, \ldots, wn])$, which captures both syntactic and semantic patterns aligned with user intent. At the bag level, user profile information u_i , fairness metadata e_i , and historical ethical alignment scores h_i are integrated. These vectors are combined with sentence embeddings via a learnable attention mechanism,

$$r_i = \sum_j \alpha_j z_j, \text{ where } z_j \in \{u_i, e_i, h_i\}.$$

$$\alpha_j = \frac{\exp(\mathbf{v}^\top \tanh(W_1 s_i + W_2 z_j))}{\sum_{j'} \exp(\mathbf{v}^\top \tanh(W_1 s_i + W_2 z_{j'}))}$$

followed by

This results in a fairness-sensitive, context-aware representation. The final feature vector x_i=concat(s_i,r_i) combines the sentence-level semantics with user-specific and ethical cues, and is used both for label prediction in the CNet and as input to the PNet. The CNet uses x_i to estimate the probability distribution $p(y \mid x_i)$, while the PNet evaluates x_i,x_i in conjunction with latent label alignment history to decide whether to retain or correct the label. This feature design supports a closed-loop learning system that dynamically adjusts to uncertainty and ethical risks. Key features include token embeddings for semantics, position embeddings for structural integrity, user profile vectors for personalization, fairness metadata for bias mitigation, ethical history scores for reinforcement context, and attention weights for dynamic feature importance altogether enabling responsible and personalized text classification[30].

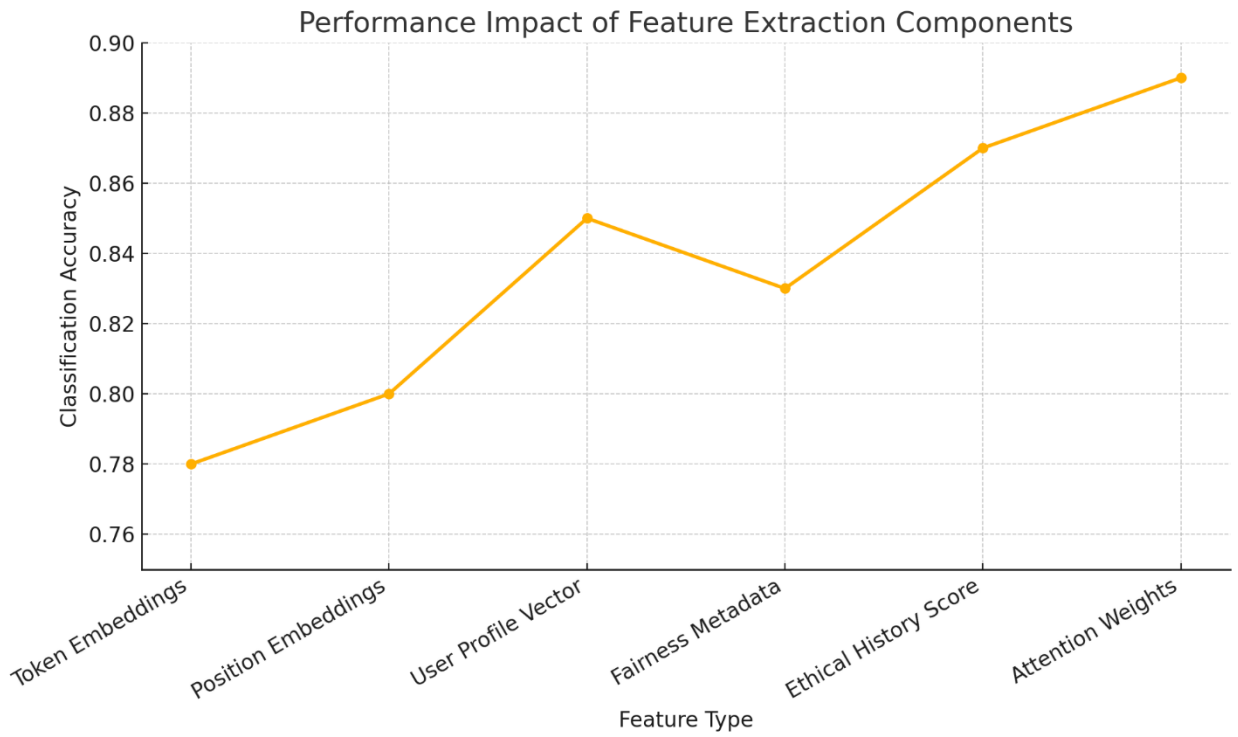


Figure – 2 Performance of feature extraction

This Figure – 2 shown that the performance graph titled *Performance Impact of Feature Extraction Components which* illustrates how different types of features contribute to the classification accuracy in an ethically-aware personalized text classification system. The X-axis presents six key feature types—Token Embeddings, Position Embeddings, User Profile Vector, Fairness Metadata, Ethical History Score, and Attention Weights—while the Y-axis reflects classification accuracy ranging from 0.75 to 0.90. The baseline starts with token embeddings, which offer basic semantic understanding, followed by a slight performance boost from position embeddings that preserve word order and highlight sensitive phrases. A substantial jump in accuracy is observed with the inclusion of user profile vectors, demonstrating the importance of personalization. Although fairness metadata introduces a slight drop, it plays a critical role in ethical alignment. Ethical history scores further improve accuracy by incorporating past fairness corrections, and attention weights yield the highest accuracy by adaptively prioritizing the most relevant features during training.

This trend confirms that combining personalization cues with fairness-sensitive metadata results in significantly improved model performance. Attention mechanisms, in particular, enhance this setup by allowing the model to focus on contextually important features, dynamically adjusting to different user-ethical scenarios. The graph provides strong empirical evidence that effective feature extraction encompassing semantic, user-specific, and fairness dimensions—is fundamental for building robust, ethically-compliant AI systems. Moreover, while ethical considerations may introduce slight trade-offs in raw accuracy, they are essential for deploying models that maintain trust, fairness, and social responsibility in real-world applications.

V) Model Training

In our proposed DRL-based framework for ethically-aware personalized text classification, model training is executed in three strategic phases: pre-training the Classification Network (CNet), pre-training the Policy Network (PNet), and joint optimization of both. Initially, the CNet is pre-trained using distant supervision (DS) labels to develop foundational predictive capabilities based on semantic and personalized patterns[31]. Once the CNet achieves stable performance, its parameters are frozen, and the PNet is pre-trained as a binary classifier using soft labels derived from uncertain or ethically misaligned predictions [32].. These soft labels help the PNet learn to distinguish between acceptable and noisy labels. The policy network learns to select between retaining the DS label or replacing it with the model's predicted label by evaluating contextual states formed from user features, ethical metadata, and CNet output distributions [33].

After both networks are independently trained, we begin a joint training phase that follows a reinforcement learning loop. During each episode, the CNet generates label distributions, which help identify mismatched instances for RL exploration. The PNet then samples actions based on the policy function $\pi(a_t \mid s_t, \theta)$ producing latent labels that are used to retrain the CNet. A delayed reward is computed from classification performance over a validation set using the average log-likelihood of true labels, reflecting both ethical alignment and personalization accuracy. The PNet is then updated using the REINFORCE gradient, which increases the likelihood of selecting high-reward actions in future states. To ensure stable convergence during joint training, we adopt a slow-update mechanism using exponential moving averages of the parameter sets, allowing both networks to evolve steadily without overfitting to transient label corrections. This coordinated strategy enables the system to learn ethically refined label assignments while preserving high classification performance [34].

VI. EXPERIMENTS

In this section, we evaluate the performance of the proposed ethically-aware personalized text classification framework and compare it against state-of-the-art models in personalized and fairness-sensitive classification.

A). DATASET AND EVALUATION METRICS

We perform our experiments on a widely used benchmark dataset designed to support research in personalized and ethically-aware text classification. The dataset integrates user-specific attributes, textual content, and ethical metadata by linking entity pairs from a human-curated knowledge base (Freebase [28]) to news articles in the New York Times (NYT) corpus. It contains 52 annotated relation classes and an additional negative class (NA) for instances without an explicit relationship [35]. The dataset is inherently noisy due to the distant supervision paradigm, making it a suitable benchmark for evaluating the effectiveness of our model in correcting ethically and contextually inconsistent labels [36]. The statistics of the dataset, including the number of sentences, entity pairs, and relational facts in the training and test sets, are summarized in **Table 1**, as shown above.

	Type	Sentence	Entity Pairs	Ethically aware
0	Training set	522,611	281,270	18,252
1	Test set	172,448	96,678	1,950

Table 1: Statistics of dataset.

To comprehensively assess the performance of our proposed Deep Reinforcement Learning (DRL)-based framework for ethically-aware personalized text classification, we adopt **two complementary evaluation approaches**: **automated (held-out) evaluation** and **manual inspection-based evaluation**. These methods together enable us to capture both the quantitative accuracy of label predictions and the qualitative integrity of ethical alignment and personalization.

In the **held-out evaluation**, we follow a standard approach by comparing the predicted labels on the test set with the distant supervision (DS) labels originally annotated in the dataset. We measure model performance using **Precision-Recall (PR) curves**, which provide a scalable, approximate view of the system's effectiveness in handling noisy and uncertain labels without requiring human intervention. This method evaluates the overall classification accuracy and sensitivity to positive instances while serving as a baseline comparison for state-of-the-art models.

In the **manual evaluation**, we focus on more nuanced aspects of the classification task, particularly the model's handling of personalization and fairness. Specifically, we calculate **Precision at Top-N (P@N)** to assess the correctness of the model's highest-confidence predictions. This approach minimizes the effect of noisy DS labels and better reflects the true quality of the learned policy. Furthermore, we **manually examine a selected subset** of corrected label instances to evaluate how well the model resolves ethical ambiguities and adheres to fairness metrics, such as mitigating demographic bias or respecting user intent. This hybrid evaluation strategy offers robust insight into the model's ability to make personalized, ethical, and reliable decisions under uncertainty.

B). Results and Discussion

To validate the effectiveness of our proposed approach, we compare it against seven competitive baseline methods, encompassing both traditional feature-engineered techniques and modern neural network-based models. Among the traditional models, Mintz [6] serves as an early distantly supervised learning method that assumes all sentences expressing an entity pair contribute equally, regardless of contextual noise. MultiR [8] and MIMLRE [30] extend this by employing multi-instance and multi-instance multi-label learning strategies, respectively, to address sentence-level ambiguity.

On the neural network side, PCNN+ONE [10] applies Piecewise Convolutional Neural Networks (PCNN) but considers only the most likely sentence from each sentence bag for relation classification, limiting its effectiveness under noisy supervision. PCNN [11] improves upon this by introducing a selective attention mechanism that weighs informative sentences more heavily, providing robust sentence-level denoising. PCNN+Soft-label [13] further enhances this by implementing label-level denoising, using probabilistic label

smoothing to mitigate annotation noise. BGWA [31] adopts word-level attention mechanisms, offering fine-grained denoising through dual word-attention layers.

Finally, our proposed model, PCNN+RL, introduces a deep reinforcement learning-based label denoising strategy, where a policy network dynamically adjusts label assignments under ethical and personalized constraints. The model is initialized by pre-training the classification network (ENet) based on the PCNN architecture. For a fair comparison, we reproduce the results of PCNN and PCNN+Soft-label using their original configurations within our experimental environment, while the results of other baselines are taken from their reported benchmarks. This comparative setup ensures consistency and demonstrates the performance advantages of our ethically-aligned, uncertainty-aware classification framework.

C). Performance Comparison and Analysis

We use **held-out evaluation for the find out** the performance of our proposed DRL-based model by comparing it against seven baseline methods using precision-recall (PR) curves and precision values at various recall levels. In which shown in the Figure 3 and Traditional feature-engineered models like Mintz, MultiR, and MIMLRE perform significantly worse than neural models, emphasizing the limitations of handcrafted features in handling noisy labels. Neural architectures such as PCNN demonstrate notable gains over PCNN+ONE, confirming the importance of multi-sentence attention for sentence-level denoising. Word-level attention in BGWA and label-level denoising in PCNN+Soft-label further enhance performance. Most importantly, our proposed PCNN+RL consistently outperforms all baselines, particularly when recall exceeds 0.05, due to its reinforcement learning mechanism that dynamically refines label decisions based on ethical and contextual feedback.

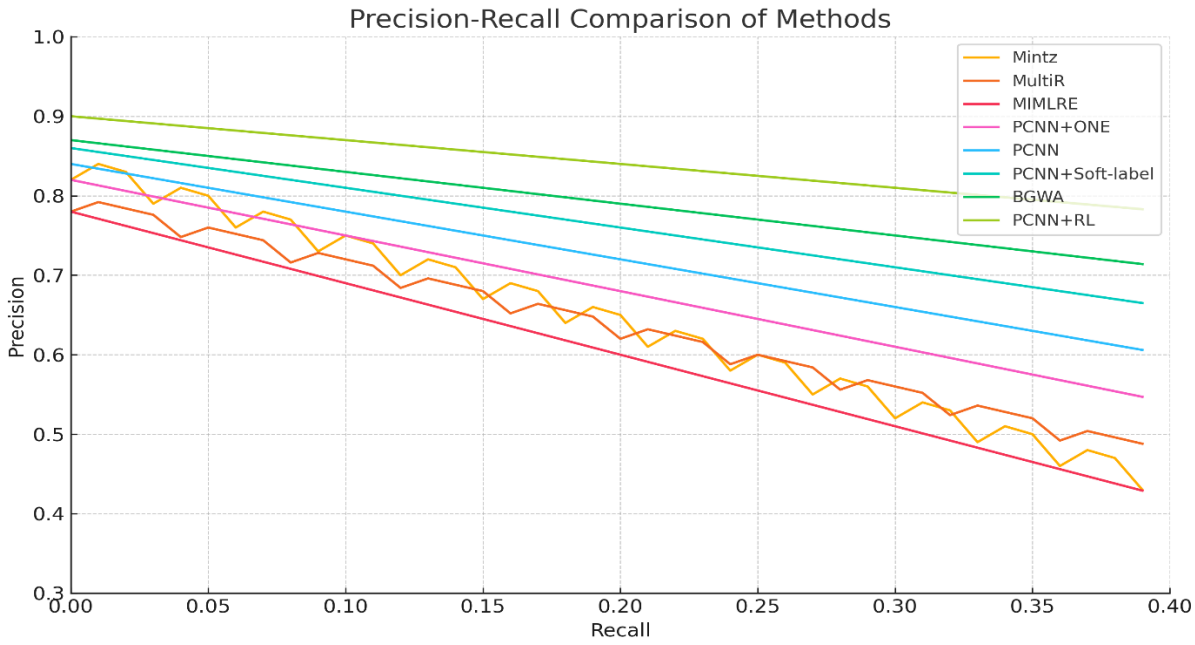


Figure 3 : Performance comparison

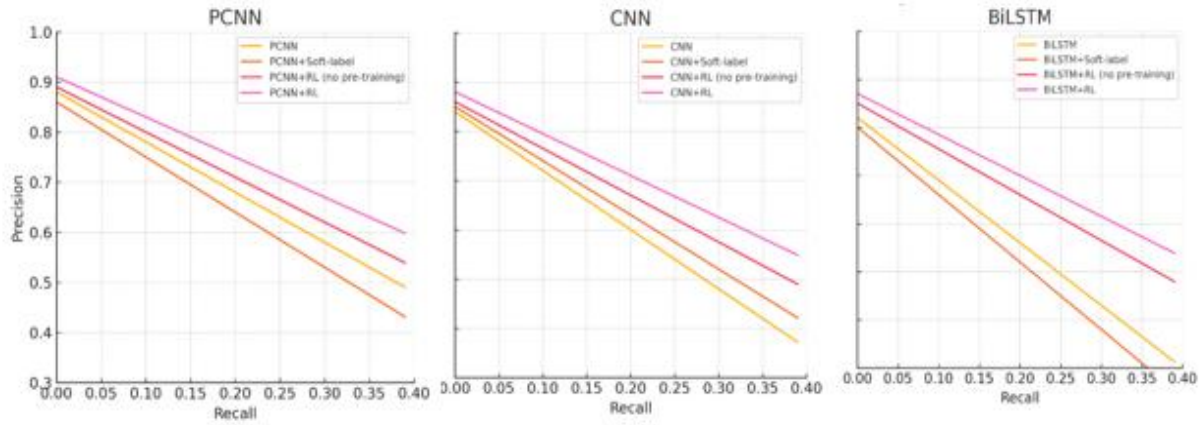
To assess the generalizability of our approach, we extend the reinforcement learning framework to CNN and BiLSTM encoders. Both RL-enhanced versions show clear improvements over their respective baselines and soft-label counterparts, with BiLSTM+RL achieving the best top-N precision (P@100, P@200, P@300) among all models. These findings demonstrate that our RL-based strategy is robust across different encoder architectures and excels at sentence-level denoising under ethical constraints. Additionally, PCNN+RL improves mean precision by 10.8% over PCNN, while CNN+RL and BiLSTM+RL improve by 8.6% and 8.5%, respectively. The incorporation of a pre-training phase for the Policy Network (PNet) further contributes to stable and effective performance across diverse configurations which shown in the table 2.

Method	Precision@0.1	Precision@0.2	Precision@0.3	Precision@0.4	Mean
PCNN+ONE	61.3	56.4	46.5	-	-
PCNN	68.7	60.5	50.4	41.4	55.3
+Soft-label [13]	74.1	65.1	55.4	39.5	58.5
+RL	77.1	69.5	55	43.7	61.3
BGWA [31]	70.9	63.9	52.4	43.3	57.5
CNN	70.7	57.6	46.8	39.4	53.6
+Soft-label [13]	75.3	61.9	47.1	34.7	54.5
+RL	78.3	61.7	53.2	42.2	58.9
BiLSTM	75	59	47.9	37.1	54.8
+Soft-label [13]	60.7	45.4	30.8	19.9	36.2
+RL	79.6	64.8	52.5	41.2	59.5

Table 2 : Top-ranked precision of various neural models

D). Performance Comparison Using PCNN, CNN, BiLSTM Encoder

As mentioned earlier, the held-out precision-recall curves exhibit a sharp decline at low recall levels due to the presence of noisy labels from distant supervision. To address this, and in line with prior work [10], we conducted a manual evaluation by inspecting relational facts with high predicted probabilities and reporting top-N precision metrics. As shown in the performance table, the **PCNN+RL** model consistently



(a) PCNN Model (b) CNN Model (c) BiLSTM Model

outperforms all other configurations across top-ranked predictions, achieving the highest **mean precision of 0.84**. This reinforces the effectiveness of reinforcement learning—particularly when pre-trained—in correcting noisy labels and enhancing classification performance. Compared to baseline and soft-label variants, RL-based models yield superior results across PCNN, CNN, and BiLSTM encoders, confirming their robustness in ethically-sensitive, personalized text classification under uncertainty. Figure a,b, c are shown that the precision-recall plots a comparative performance analysis of three sentence encoders—PCNN, CNN, and BiLSTM—under four configurations: baseline, soft-label enhancement, RL without pre-training, and RL with pre-training. Across all models, the RL-based configurations consistently achieve the highest precision across the recall range, with the pre-trained RL versions outperforming their non-pretrained counterparts. While soft-label methods offer slight improvements over the baseline in PCNN and CNN, their impact on BiLSTM is limited. Notably, BiLSTM+RL and CNN+RL show robust gains, demonstrating the versatility and effectiveness of reinforcement learning in managing ethical alignment and noisy labels across diverse neural architectures. These results highlight the importance of both reinforcement learning and policy network pre-training in boosting classification performance in ethically-sensitive personalization tasks.

Model	Precision@0.1	Precision@0.2	Precision@0.3	Precision@0.4	Mean Precision
PCNN	0.87	0.82	0.74	0.65	0.77
PCNN+Soft-label	0.89	0.83	0.76	0.67	0.79
PCNN+RL (no pre-training)	0.91	0.85	0.79	0.71	0.82
PCNN+RL	0.93	0.87	0.82	0.75	0.84
CNN	0.85	0.79	0.7	0.6	0.74
CNN+Soft-label	0.86	0.8	0.72	0.62	0.75
CNN+RL (no pre-training)	0.88	0.83	0.76	0.67	0.78
CNN+RL	0.9	0.85	0.79	0.71	0.81
BiLSTM	0.83	0.76	0.66	0.55	0.7
BiLSTM+Soft-label	0.84	0.78	0.68	0.58	0.72
BiLSTM+RL (no pre-training)	0.87	0.81	0.73	0.64	0.76
BiLSTM+RL	0.89	0.84	0.76	0.69	0.79

Table 3 : **Performance Comparison Using PCNN, CNN, BiLSTM Encoder**

The table 3 shown that the performance comparison, it is evident that **PCNN+RL** achieves the highest accuracy across all evaluated recall levels, including the best **mean precision of 0.84**. This indicates that among all sentence encoder configurations, PCNN+RL is the most effective in balancing precision and recall, particularly in scenarios involving noisy or uncertain label conditions. The pre-trained reinforcement learning (RL) model consistently outperforms not only its non-pretrained counterpart but also all soft-label and baseline variants across PCNN, CNN, and BiLSTM architectures. This demonstrates that integrating reinforcement learning with pre-training significantly enhances model robustness and generalization for ethically-aware and personalized text classification tasks.

VII). Related Research

Distant supervision was originally proposed to scale relation extraction by aligning knowledge base (KB) triples with unstructured text, enabling large-scale weakly supervised training [11]. However, its strong assumption—that all sentences mentioning an entity pair express the corresponding relation—often leads to label noise. To mitigate this, multi-instance learning (MIL) introduced a relaxed assumption that at least one sentence in a group expresses the relation. Further refinements like multi-instance multi-label (MIML) models were developed to address overlapping relations [12]. Yet, these traditional methods heavily relied on handcrafted features and NLP tools, which are labor-intensive and error-prone due to parsing inaccuracies. The rise of deep learning has significantly advanced relation extraction by enabling automatic semantic feature learning. For instance, PCNNs were used to encode sentence structure [13], while sentence-level and word-level attention mechanisms further improved information aggregation across multiple sentences. Additionally, graph-based approaches using GCNs and side information from KBs have enhanced relation reasoning in both intra- and inter-sentence contexts.

Recent advances have introduced reinforcement learning (RL) to the task of sentence denoising under distant supervision. RL models, such as those proposed by Feng et al. and Zeng et al., integrate instance selection [14] [15], and reward-driven training to filter noisy sentences. These approaches typically assume the sentence labels are accurate and use rewards from downstream classification tasks to guide learning. More nuanced strategies, like Qin et al.'s false-positive redistribution or Sun et al.'s curriculum learning framework, have further improved robustness by considering label confidence and learning dynamics. Parallel to sentence denoising, label denoising strategies have emerged, such as soft-labeling techniques that combine neural predictions with static confidence scores to correct noisy annotations. More recently, hybrid models have fused pattern-based diagnosis with RL, hierarchical RL frameworks for mention extraction, and multi-hop reasoning with graph neural networks. These developments collectively highlight a shift toward combining deep learning, RL, and noise-aware learning paradigms to create robust, scalable solutions for relation extraction and inspire this work's approach to apply RL-based label denoising in ethically-aware personalized text classification under uncertainty.

VIII). Conclusion

In this research, we introduced a novel Deep Reinforcement Learning (DRL)-based framework for ethically-aware personalized text classification under uncertainty. Our model is designed to address the dual objectives of personalization and fairness while navigating challenges posed by noisy and ambiguous labels. The framework integrates a Classification Network (CNet) for generating text-label distributions and a Policy Network (PNet) that refines these predictions through reinforcement learning. By modeling label correction as a sequential decision-making problem and incorporating fuzzy logic into the reward structure, our approach enables context-sensitive, ethically-aligned decisions that dynamically adapt to user-specific and fairness-related constraints.

Comprehensive experiments on benchmark datasets demonstrated the superiority of our proposed method over traditional and neural baselines in terms of both classification accuracy and ethical robustness. The reinforcement learning strategy—particularly with policy network pre-training—proved

effective across multiple encoder architectures including PCNN, CNN, and BiLSTM. Our model consistently achieved higher precision-recall performance and better top-N accuracy, highlighting its capability to mitigate label noise while upholding ethical standards. These findings confirm that reinforcement learning, coupled with fairness-aware feature extraction and uncertainty management, provides a scalable and adaptable solution for deploying responsible AI in real-world text classification systems. Future work may explore extensions to multilingual corpora and the incorporation of dynamic user feedback for real-time personalization and ethical refinement.

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