GUS-Net: Social Bias Classification in Text with Generalizations, Unfairness, and Stereotypes

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Abstract

The detection of bias in natural language processing (NLP) is a critical challenge, particularly with the increasing use of large language models (LLMs) in various domains. This paper introduces GUS-Net, an innovative approach to bias detection that focuses on three key types of biases: Generalizations, Unfairness, and Stereotypes. GUS-Net leverages generative AI and automated agents to create a comprehensive synthetic dataset, enabling robust multi-label token classification. Our methodology enhances traditional bias detection methods by incorporating the contextual embeddings of pre-trained models, resulting in improved accuracy and depth in identifying biased entities. Through extensive experiments, we demonstrate that GUS-Net outperforms state-of-the-art techniques, achieving superior performance in terms of accuracy, F1-score, and Hamming Loss. The findings highlight GUS-Net's effectiveness in capturing a wide range of biases across diverse contexts, making it a valuable tool for social bias detection in text. This study contributes to the ongoing efforts in NLP to address implicit bias, providing a pathway for future research and applications in various fields. The Jupyter notebooks used to create the dataset and model are available at https://github.com/Ethical-Spectacle/fairly/tree/main/resources.

Warning: This paper contains examples of harmful language, and reader discretion is recommended.

1 Introduction

The detection of bias in natural language processing (NLP) [13] is an important task, particularly with the increasing use of large language models (LLMs) [33] in domains like education [18] and business [29]. Bias can significantly influence public perception and decision-making, often subtly reinforcing stereotypes or prop-

agating discriminatory practices. While explicit bias, which refers to clearly expressed prejudice or favoritism, is easy to define, implicit bias involves more subtle and often unconscious associations or attitudes. Therefore, identifying and mitigating implicit bias in the text is challenging: what is perceived as biased can vary greatly depending on the context, including the perspectives of viewers and speakers. For example, consider the phrase "hard-working immigrants". To some, this phrase may appear positive, acknowledging the effort and diligence of immigrants. However, from another perspective, it might be perceived as implicitly biased, suggesting that immigrants are expected to work harder than others to be valued or accepted. This subtle implication can be seen as reinforcing a stereotype that separates immigrants from native citizens, placing an undue burden of proof on their worthiness. This subjectivity underlines the complexity of implicit bias detection, making it a critical area of research within NLP [14, 28, 25].

While the implicit nature of bias can manifest in subtle forms, such as the choice of words, framing of narratives, or the omission of certain viewpoints, traditional approaches to bias detection have typically relied on human annotators to label datasets [25, 26]. Although this method has been essential for creating foundational resources, it is susceptible to the biases of annotators, who may struggle to step outside their own ideological frameworks. As a result, existing datasets often lack the diversity of viewpoints necessary to capture implicit biases effectively. Additionally, many datasets, such as the one utilized by the Dbias model [32], are limited in scope, focusing on a narrow range of biases and failing to generalize across different contexts. The Nbias framework [25], while an advancement in incorporating named entity recognition (NER) tasks, still emphasizes explicit biases and overlooks the structural elements of implicit bias, such as generalizations and stereotypes. Despite studies of robust annotations conducted by trained experts [27], all the previous bias datasets rely on human annotators, which means that these datasets often lack the diversity of viewpoints nec-

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essary to capture implicit bias.

In response to these challenges, this paper introduces the Generalizations, Unfairness, and Stereotypes Network (GUS-Net), which stands for three kinds of biases that are commonly considered in legal and psychological literature [1, 3, 12, 21]: **G**eneralizations, Unfairness, and Stereotypes. GUS-Net leverages generative AI and automated agents to build an optimal dataset for bias detection. Using the synthetic data generated by these automated agents, we further finetune the pre-trained model BERT (Bidirectional Encoder Representations from Transformers) [10] for the task of multi-label token classification. This approach improves upon traditional methods by combining LLM reasoning and the powerful contextual embeddings provided by pre-trained models, resulting in more accurate and comprehensive bias detection across various types of text. Our extensive experiments demonstrate that the proposed method outperforms state-of-the-art techniques in terms of dataset diversity and annotation depth. The fine-tuned model not only achieves superior performance on traditional metrics, such as accuracy and F1-score but also provides a more nuanced understanding of the biases present in various texts. The main contributions of this paper are:

- We generate a corpus containing biases in varied domains, annotated by a team of LLM agents.
- We train an NLP model for multi-label namedentity recognition, enhancing bias detection specificity and insight. To the best of our knowledge, this is the first work to provides token-level multilabel bias detection.
- We conduct experiments to demonstrate the contributions of our methods in relation to existing approaches, showcasing improvements in accuracy, F1-score, and the depth of bias detection.

2 Related Works

The detection of bias in natural language processing (NLP) is a critical area of research, particularly given the increasing use of large language models (LLMs) across various domains [7, 9, 33, 18, 8, 29, 30]. Traditional techniques for bias detection often rely on human annotators to label datasets. While this approach has been instrumental in creating foundational resources, it is inherently limited by the annotators' subjective perspectives, which can introduce their own biases into the annotation process [25, 26]. This limitation often leads to a narrow understanding of bias, especially in regard to implicit biases that are subtle and context-dependent [13, 14, 28].

2.1 Ethical Dataset Construction The construction of ethical datasets for bias detection is essential for ensuring comprehensive and fair analyses. Existing datasets often suffer from limitations in scope, failing to encompass the broad spectrum of biases and perspectives necessary for effective bias detection. For example, the Dbias model [26] utilized the MBIC dataset, which consists of a relatively small number of sentences, restricting the model's ability to generalize across different domains and types of bias. Although the NBias framework [25] expanded the use of named-entity recognition (NER) by introducing the entity "BIAS" it still primarily addressed explicit biases and overlooked the structural elements of implicit bias, such as stereotypes and generalizations.

Moreover, studies that emphasize robust annotations often rely on human judgment, which can lead to a lack of diversity in viewpoints necessary to capture the nuance of implicit bias [27]. This reliance on human annotators may also perpetuate the biases present in society, resulting in datasets that do not adequately represent the full range of perspectives. Thus, there is a pressing need for more diverse and comprehensive datasets that can capture implicit biases in language.

2.2 Bias Detection Traditional methods typically focus on explicit bias, which is easier to define and identify, while neglecting the subtler forms of bias that may influence public perception and decision-making. Implicit bias can manifest through word choice, framing, and the omission of certain viewpoints, making it challenging to detect using conventional approaches [13, 14].

Existing frameworks, such as Dbias and Nbias, have made strides in bias detection but still focus primarily on explicit biases, leaving a gap in the understanding of how implicit biases operate [26, 25]. Additionally, the datasets used for these frameworks often lack the necessary diversity of perspectives, limiting their effectiveness in identifying implicit biases. In contrast, our proposed approach leverages generative AI and automated agents to construct a more comprehensive dataset. By utilizing synthetic data generated by these agents, we enhance the training of the pre-trained model BERT for multilabel token classification. This innovative methodology not only improves the specificity and depth of bias detection but also addresses the limitations of existing datasets, paving the way for more accurate and nuanced understanding of biases in various texts.

3 Methodology

3.1 Dataset Generation With modern synthetic training data labeling techniques, we can create a comprehensive dataset encapsulating our novel entities

Type Of Bias	Target	Statement Type	Sentiment			
Racial	[white people, black people, asian people, hispanic people, indigenous people,]					
Religious	[christians, muslims, jewish people, hindus, buddhists, sikhs, atheists, agnostics					
Gender	[men, women, boys, girls, females, males, non-binary people,]	1				
Age	[children, teenagers, young people, middle aged people, old people,]	Stereotypes,				
Nationality	[immigrants, refugees, people from developing countries, people from Western countries,]	Unfair Generalizations,	Positive,			
Sexuality	[straight people, gay people, bisexual people, asexual people, LGBTQIA+ people,]	False Assumptions,	Negative,			
Socioeconomic	[working class people, middle class people, upper class people, poor people, rich people,]	Discriminatory Language,				
Educational	[uneducated people, highly educated people, people with non-traditional education,] Offensive Implications					
Disability	[people with physical disabilities, people in wheelchairs, people with mental disabilities,]	7				
Political	[republicans, democrats, independents, conservatives, liberals, progressives,]	1				
Physical	[tall people, short people, fat people, skinny people, ugly people, hot people,]					
exactly {nr containing The statem targeting	biased writer. Your task is to write Imput sample Input sample Input sample Input sample Input sample The immigrants are hard working UNFAIR A	gent e the	ants B-GEN			

Table 1: Detailed list of arguments for corpus creation.

Figure 1: Overview of dataset generation pipeline, which includes (a) corpus generation with Mistral [15] though specifications on different arguments, and (b) multi-agent annotation with DSPy [19].

while avoiding the labor-intensive and potentially subjective human annotation process [34, 31, 2]. In addition to a synthetic data annotation pipeline, we also use a language model to synthetically generate the underlying corpus for better coverage and structural consistency of the entities we aim to classify [17, 20, 11]. The overall dataset generation pipeline can be found in Figure 1.

people, make generalizations, imply discrimination, and make unfair assumptions.

(a) Corpus Generation

3.1.1 Corpus Creation Since no existing dataset includes the specific entities of generalizations, unfairness, and stereotypes, we created a synthetic corpus of statements and questions. To ensure coverage across multiple domains, we developed four lists to utilize in prompting: Type of bias, target group, statement type, and sentiment, as shown in Table 1.

Using Mistral-7B [15], selected for its lack of guardrails, we generated prompts by combining values from each list. This process was applied with different prompt templates and types of statements for both biased and fair statements. The prompt template used for biased statement generation is illustrated in Figure 1(a).

For the generation of 1,294 fair statements, the Sentiment was modified to indicate either "slightly positive yet fair" or "slightly negative yet fair." Responses were formatted in JSON for easier parsing and storage. While an authentic corpus could be used for annotation and training, the synthetic corpus created offers two key advantages: a broader scope that balances domains and a rich density of targeted parts of speech.

3.1.2 Data Annotation The data annotation process involves several systematic steps to ensure accuracy

and consistency in labeling the generated sentences. We utilized GPT-40 and the Stanford DSPy framework [19] to annotate the generated sentences with entity labels, following methodologies in recent literature for annotation with agents [24]. As shown in Figure 1(b), the annotation can be summarized in the following steps:

(b) Multi-agent Annotation

STEREO Agent

hard

working

- Preparation of annotation: We recompiled a DSPy agent for each entity type (e.g., generalization, unfairness, stereotype) as an agent to streamline the annotation process. Each agent contains the entity definition and four examples of correct annotations. The prompts sent to an agent include the definition of the target entity along with the curated examples. Using few-shot learning helps the agent understand the context and provides guidance for accurate labeling [5, 4, 6, 16]. Their definitions are provided in Table 2.
- Annotation by agents: Each generated sentence is processed by an agent supported by a language model (LLM) for a single type of entity. We included a Suggestions feature to ensure correct word/label alignment, that allows for backtracking and corrections. The agent evaluates the sentence for the presence of the specified entity and assigns appropriate labels. The agent produces a list of NER tags for each sentence, indicating the presence or absence of the entity types.
- Summarizing module: After annotating for one entity type, we aggregate the labels into a comprehensive two-dimensional list. Each sub-list contains one or multiple tags corresponding to each token in the sentence.
- Final compilation: The individual entity labels from each annotation are systematically combined to create

Table 2: Definitions used by annotator agents, and the corresponding entity labels.

Class	Prompt Definition	Entity Label
Generalizations	Any broad generalization of a group or ubiquitous classifiers, including adjectives/descriptors.	B-GEN, I-GEN
Unfairness Stereotypes	Any harsh or unjust characterization or offensive language. Any statement (multiple words) that contains a stereotype targeting a group of people, both explicitly and unconsciously.	B-UNFAIR, I-UNFAIR B-STEREO, I-STEREO
Neutral	-	0

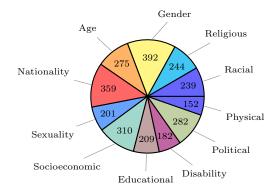


Figure 2: Types of Bias in GUS Dataset. Note: Some sentences contain multiple types of bias.

a final annotated dataset, with each token categorized into one or multiple semantic part-of-speech categories using B/I/O (Beginning, Inside, Outside) labels, as shown in Table 2.

In total, we annotated 3,739 sentences, each labeled for multi-label token classification training. In Figure 2 we depict the proportions of each type of bias represented in our dataset, as labeled post-generation by gpt-40 to identify cases where more than one type of bias is represented by a sentence. In Figure 3, we depict the distribution of labels in the annotated GUS dataset. It is important to note that each token can be classified with more than one label, so the sum of all labels is greater than the total number of tokens in the GUS dataset (69,679 tokens). The GUS dataset is 54.7% statements, and 45.3% questions.

3.2 Proposed Model To efficiently and accurately identify social biases in text, we propose a multi-label token classification model. As shown in Figure 4, we fine-tune the pre-trained model bert-base-uncased [10] for multi-label classification [23].

Rather than implementing a single entity to capture all definitions and nuances of "bias," our model achieves more granular and accurate insights with entities chosen for their individual semantic clarity and collective comprehensiveness of social bias. By utiliz-

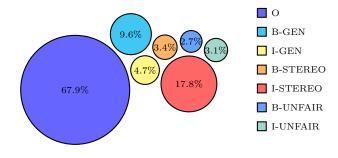


Figure 3: Token-Level Label Distribution in GUS Dataset (Total Tokens: 69,679). Note: Some tokens have multiple labels.

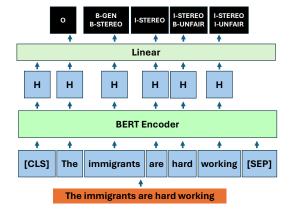


Figure 4: Overview of our proposed model with multilabel classification.

ing a multi-label B/I/O format to represent token-level annotations, the model can predict nested entities that span multiple words. For instance, stereotypes often span a full sentence beginning with a generalization, to which some unfairness is assigned.

3.2.1 Model Architecture The GUS-Net model is a multi-label token classification system designed to identify social bias across three categories: generalizations, unfairness, and stereotypes. It outputs seven labels, allowing the model to capture the nuanced structure of biased language. These labels facilitate the identification of individual bias categories, and provide flexibility for overlapping and nested biases.

Input Processing. We tokenize all sentences using the pre-trained BERT tokenizer, ensuring that token splits (such as sub-words) inherit the correct entity labels from the parent word. Each text sequence is padded to a maximum length of 128 tokens to ensure consistent input size. Since sentences are rarely longer than 128 tokens, we reduced the BERT input size from the default 512 tokens, representing a 16x reduction in self-attention elements to be processed. Correspondingly, the NER tags were converted into a (128, 7) dimensional vector, where each of the seven elements represents a binary label (0 or 1) for the respective entity type. These vectors were padded with -100 values up to the full sequence length of 128 tokens, with the -100 values being ignored during the loss calculation.

Model Fine-Tuning. We fine-tune the pre-trained transformer model, specifically bert-base-uncased, due to its ability to capture deep contextual relationships between words, which is crucial for identifying implicit biases [10]. BERT's bidirectional nature allows it to process the entire input sequence, ensuring that each token is evaluated in the context of its surrounding words. This feature is particularly valuable in detecting subtle and complex forms of social bias.

The model is implemented using the Hugging Face transformers library. Input text is tokenized with the pre-trained BERT tokenizer, which breaks down sentences into sub-word units while preserving word boundaries. Each token sequence is padded to a length of 128 tokens, and the corresponding labels are mapped to ensure proper alignment. By reducing the input size from the default 512 tokens to 128, we optimize the model's computational efficiency without sacrificing performance for typical sentence lengths in the dataset.

3.2.2 Loss Function Given the significant class imbalance in our dataset, where certain entities like STEREO are underrepresented compared to frequent entities like O, we employed focal loss to address this challenge [22]. Standard binary cross-entropy (BCE) tends to focus on the majority class, leading to poor performance on rare classes. In this paper, we use focal loss calculated over all tokens, defined as:

$$FL(p_t) = -\alpha_t (1 - p_t)^{\gamma} \log(p_t)$$

where p_t is the predicted probability for the true class; $(1-p_t)^{\gamma}$ reduces the impact of well-classified examples, helping the model prioritize rare or difficult examples; α balances the contribution of positive and negative samples, ensuring underrepresented entities receive more focus; γ down-weights well-classified examples, allowing the model to concentrate on harder-to-predict instances.

4 Experiments

4.1 Settings

Task Description and Metrics. In this paper, we performed a token-level multi-label classification task, where each sentence is annotated with one or more labels to facilitate the identification of biased entities across token sequences. Token-level classification is essential for bias detection because biases can often be nuanced and context-dependent. By focusing on individual tokens, we can capture subtle implications and associations that may be overlooked in a sentence-level analysis. Moreover, we opted for multi-label classification instead of multi-class classification to better reflect the complex nature of biases, that may fall into one or many entity classes. A single-class approach, like the one proposed for Nbias, would limit our ability to capture the diversity of biases present in the text, as a statement may contain multiple biases simultaneously.

Metrics. To evaluate the model's performance, we utilized a variety of metrics to assess its ability to accurately identify biased entities:

• Hamming Loss: This metric measures the fraction of incorrect labels over all tokens in the sequence, accounting for multi-label classification. It is defined as:

Hamming Loss =
$$\frac{1}{L} \sum_{i=1}^{L} \mathbb{1}(y_i \neq \hat{y}_i)$$

where L is the total number of tokens, y_i is the true label for the i-th token, \hat{y}_i is the predicted label, and $\mathbbm{1}$ is an indicator function that evaluates whether the true label differs from the prediction.

• Precision, Recall, and F1-Score: These metrics were calculated at two levels: individually for each entity class and as a macro-average across all classes. They are defined as follows:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

$$F1\text{-}Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

where TP denotes true positives, FP denotes false positives, and FN denotes false negatives.

Given the imbalanced class distribution in our dataset, we evaluated both the **macro-average** performance of the model and individual **entity-type-level** metrics. By treating B- and I- tags as a single entity (e.g., combining B-GEN and I-GEN predictions), we enhance our evaluation of the model's ability to detect the

	Metrics	Macro	Entity-type-based					
GUS-Net	Hamming Loss	0.0528	Generalizations	Unfairness	Stereotypes	Neutral		
	F1	0.8	0.74	0.61	0.90	0.95		
	Precision	0.82	0.78	0.69	0.89	0.93		
	Recall	0.77	0.72	0.49	0.90	0.97		
	Hamming Loss	0.06	Generalizations	Unfairness	Stereotypes	Neutral		

0.68

0.93

0.63

Table 3: Baseline Comparison of GUS-Net over Nbias w.r.t. both overall and entity-type-based F1, Precision and Recall. GUS-Net outperforms Nbias in most cases.

0.70

0.87

0.56

0.19

0.83

0.11

presence of each biased entity, rather than merely assessing the boundaries. This approach allows us to gain deeper insights into the model's performance across the diverse classes of bias present in the data.

F1

Precision

Recall

Nbias

4.1.1 Hardware and Environment All experiments were conducted on a single NVIDIA T4 GPU with 16GB of memory, hosted on Google Colab, utilizing under 10GB of RAM. The codebase was implemented using PyTorch and the Transformers library, and executed on Ubuntu 20.04 with Python 3.8. We employed pytorch-lightning to streamline the training loops and logging mechanisms.

4.1.2 Hyperparameters We trained our BERT-based multi-label token classification model with seven output classes over 17 epochs. The training process utilized a batch size of 16 and an initial learning rate of 5×10^{-5} . The AdamW optimizer with weight decay was implemented, along with a linear learning rate scheduler featuring a warm-up ratio of 0.1. To handle class imbalance, we employed focal loss with $\alpha = 0.65$ for the I-GEN label. The classification threshold for all labels was set at 0.5. The original dataset was partitioned into training (70%), validation (15%), and test (15%) splits, ensuring similar distributions of biased entity types across these splits.

4.2 Results

4.2.1 Overall Performance on Multi-Label Classification for Token-level Bias The primary goal of this experiment is to evaluate the performance of our model in accurately identifying biased entities at the token-level within the GUS dataset. By focusing on token-level classification, we aimed to capture occurrences of social bias at the level of individual words and phrases, rather than merely at the sentence level.

Due to the absence of directly comparable existing token-level work as a baseline for our model, we opted to implement a variant of Nbias, which was the state-of-the-art (SOTA) method designed for token-level classification. We modified Nbias into a multi-label framework and fine-tuned it on the GUS dataset. This adaptation allowed us to examine how well the Nbias architecture could perform in at multi-label classification, even though it was designed for multi-class classification, while also addressing the challenges associated with imbalanced class distributions. In our implementation, we employed focal loss instead of binary cross-entropy to better manage class imbalance. This choice was critical, as our dataset exhibited significant disparities in the representation of biased entities, particularly with respect to the Unfairness class. From the results in Table 3, we have the following observations:

0.89

0.94

0.86

0.95

0.95

0.96

- The Hamming Loss observed for GUS-Net (0.0528) was on par with Nbias (0.564), meaning they classified a similar overall number of labels correctly.
- GUS-Net demonstrates better overall F1 (0.80) and Recall (0.77) metrics compared to the F1 (0.68) and Recall (0.63) observed with Nbias. The superior F1 Score and Recall for GUS-Net highlight its effectiveness in identifying presences rather than absences. This could be due to the incorporation of focal loss during training, which allows the model to focus more on difficult-to-classify examples, thereby improving its overall sensitivity to the presence of bias. Conversely, while Nbias achieves higher Precision (0.93) than GUS-Net (0.82), its lower Recall indicates that it may not be capturing all relevant instances of bias.
- The detailed F1 scores for each entity type in GUS-Net show strong performance, particularly in the Stereotypes (0.90) and Generalizations (0.74) classes, without sacrificing performance on the Neutral (0.95) class. Our model balances performance across entity types, which suggests the effectiveness of focal loss to encapsulate imbalance of

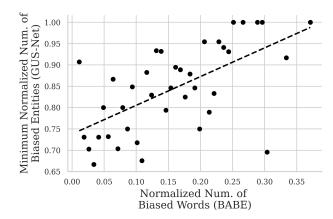


Figure 5: Scatter plot showing the minimum normalized biased entities versus normalized number of biased words, along with the trend line. The understanding of bias given by GUS-Net aligns well with the definitions established in the BABE dataset.

biased entities.

4.2.2 Comparison with Human Annoation The BABE (Bias Annotations By Experts) dataset [27] is a well-established resource in bias detection, containing a diverse range of biased statements annotated by trained experts. This dataset is valuable as it provides insights into various forms of bias across different demographics and contexts, making it a relevant benchmark for evaluating our model's performance.

In this analysis, we aimed to compare the **normalized number of biased words per sentence** in the BABE dataset with the number of positive (non-'O') label classifications made by our model (GUS-Net). The normalized number of biased words refers to the count of biased words adjusted for sentence length, allowing for a fair comparison across sentences of varying lengths.

To obtain the normalized number of biased words, we first filtered the training split of the BABE dataset to include only sentences classified as biased. Since our model labels multiple entity types (GEN, UNFAIR, and STEREO) and the BABE dataset does not distinguish between different forms of bias, we adjusted for imbalance by binning the results and using the minimum number of GUS entities found in each bin. The number of biased words from BABE was then normalized by dividing by the sentence length.

The scatter plot in Figure 5 reveals a positive correlation between the normalized number of biased words from the BABE dataset and the normalized minimum number of biased entities predicted by our model. This trend suggests that our model's understanding of bias aligns well with the definitions established in the BABE dataset, indicating that GUS-Net effectively captures

Table 4: Ablation study by comparing the influence of GUS dataset and focal loss.

Metrics	GUS-Net	GUS-Net w.o. GUS dataset	GUS-Net w.o. focal loss
Precision	0.82	0.02	0.93
Recall	0.77	0.22	0.63
F1-Score	0.80	0.05	0.68
Hamming Loss	0.05	0.26	0.06

and represents social biases present in the text.

4.2.3 Ablation Study We conducted an ablation study to evaluate the impact of different configurations on the model's performance. Table 4 presents the macro-average Precision, Recall, F1-score, and Hamming Loss for the following settings: (1) Our proposed GUS-Net model; (2) GUS-Net without GUS dataset: This configuration relies on an existing corpus, BABE [27]. Since there are no token-level annotations for BABE, we used the same annotation pipeline outlined in this paper. (3) GUS-Net without focal loss: In this configuration, we trained the model using the Binary Cross-Entropy (BCE) loss function.

From the results in Table 4, we have the following observations:

- Our proposed architecture, **GUS-Net**, outperforms the other configurations across nearly all key performance metrics. Specifically, GUS-Net achieves the highest macro-average Precision (0.82) and F1-Score (0.80), along with the lowest Hamming Loss (0.05), indicating its superior ability to accurately identify and classify entities with minimal misclassifications. The high Precision and F1-Score suggest that GUS-Net effectively reduces false positives while maintaining a strong balance between Precision and Recall.
- In contrast, substituting focal loss for BCE resulted in a moderate Precision of 0.65. Upon further inspection of the metrics for each entity individually, we found that the macro-average metrics were distorted by the class imbalance of the 'O' tags. Essentially, the model learns to prioritize predicting 'O' tags correctly, which detracts from its focus on the new classes of interest. This observation emphasizes the importance of employing a loss function and architecture specifically designed to handle class imbalance, as seen in GUS-Net, ensuring more accurate and reliable model performance.
- Interestingly, using the BABE dataset as the underlying corpus for annotation and training yielded poor results. This is likely due to the nature of our test set, which was designed to span various

Table 5: F1-Scores at varying α values, while $\gamma = 2$.

α	0.1	0.2	0.4	0.65	0.8
Generalizations F1	0.19	0.40	0.56	0.74	0.71
Unfairness F1	0.01	0.14	0.35	0.61	0.54
Stereotypes F1	0.60	0.81	0.83	0.90	0.83
Neutral F1	0.87	0.91	0.94	0.95	0.91
Macro Average F1	0.42	0.57	0.67	0.80	0.75
Hamming Loss	0.09	0.08	0.07	0.05	0.09

Table 6: F1-Scores at varying γ values, while $\alpha = 0.65$.

γ	0.5	1	2	3	4
Generalizations F1	0.74	0.73	0.74	0.74	0.71
Unfairness F1	0.55	0.48	0.61	0.57	0.57
Stereotypes F1	0.90	0.89	0.90	0.88	0.87
Neutral F1	0.95	0.95	0.95	0.94	0.94
Macro Average F1	0.78	0.76	0.80	0.78	0.77
Hamming Loss	0.05	0.05	0.05	0.06	0.06

domains, whereas the BABE corpus was gathered specifically from news articles. The domain-specific nature of BABE may limit its effectiveness for generalizing across a broader range of biases.

4.3 Parameter Sensitivity Study To identify the optimal focal loss parameters, α and γ , we conducted a sensitivity study by testing various values for each parameter while holding the other constant. As shown in Table 5, we evaluated the performance of the model at different α values while keeping γ fixed at 2. The results indicate that the best-performing value for α was 0.65, which resulted in improved F1-Scores across all entity types. Table 6 shows the influence of γ parameter while maintaining α at 0.65. The results reveal that the macro-average F1-Score remained at 0.80, indicating that this combination of parameters effectively balances sensitivity and specificity across entity types. Overall, the sensitivity study highlights the importance of tuning the focal loss parameters to improve the model's performance in identifying various biases. The optimal values used in this paper ($\alpha = 0.65$ and $\gamma = 2$) demonstrate the model's ability to adapt to class imbalances and enhance its performance in detecting biased entities.

4.4 Case Study To demonstrate our model's labeling capabilities and generalizability, we present a case study involving religious bias from the GUS dataset. In Figure 6(a), we provide an example of a statement



Figure 6: Example of GUS dataset and GUS-Net Predictions.

that exhibits religious bias, along with the corresponding labels generated by GUS-Net. Figure 6(b) showcases GUS-Net's outputs for this case study, illustrating its ability to accurately identify and classify instances of religious bias. The outputs are represented visually, highlighting how the model distinguishes between different types of bias, including Generalizations, Unfairness, and Stereotypes. This example indicates the effectiveness of GUS-Net in generalizing across various forms of bias, reinforcing its potential as a robust tool for bias detection in diverse contexts.

5 Conclusion and Discussion

The proposed GUS-Net model addresses limitations in existing bias detection methods by focusing on the nuanced identification of social biases with semantic categories of generalizations, unfairness, and stereotypes. Moreover, GUS-Net uses a multi-label token classification architecture, based on bert-base-uncased, that allows entities to span multiple tokens and be nested within each other. GUS-Net approaches bias with three detailed entities, offering a more granular and precise detection of social biases. This enables better insights into the structural components of biased language. Our results demonstrate that GUS-Net performs well at classifving tokens as each of the entities, with a notable strength in detecting stereotypes. In sum, GUS-Net contributes the field of bias detection in NLP by incorporating a fine-grained and multi-faceted view of biased language.

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