Different Learning Methods for Machine-Generated Text Detection

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Abstract

This work introducing various methods (SVM, BiLSTM, and Mistral) for doing the machinetext classification in M4 data, MGTBench for outofdistribution data. It also test their performance in the mixed data inside MixSet as well. Result shows that using RBF kernel in SVM and Attention with BiLSTM can outperform other models in their perspective field, even got 1.0 accuracy in unseen GPT4 data. Meanwhile, using different mixing method will highly affect the detector's results, with the humanize method being the most serious one.

1 Introduction

The advent of generative models, particularly ChatGPT and GPT-4, marks a significant evolution in artificial intelligence, profoundly impacting various fields such as academic writing, story generation, and software development Lee et al. [2023], Pagnoni et al. [2022], Mirsky et al. [2022], Stokel-Walker [2022], Kasneci et al. [2023]. The capabilities of Large Language Models (LLMs) have evolved to produce text nearly indistinguishable from human writing, as evidenced by recent studies Chowdhery et al. [2022]. However, this technological leap brings forth new challenges, notably the difficulty in distinguishing between AI-generated and human-authored texts. This ambiguity raises concerns regarding information quality—given LLMs' dependency on potentially outdated or biased datasets—and the potential for misuse in areas like fake news dissemination and academic dishonesty Yuan et al. [2022], Becker et al. [2023], Zheng et al. [2023].

Current research efforts have focused on developing methods to detect machine-generated content, typically through fine-tuning existing language models with extensive datasets. However, these approaches often overlook the nuanced reality where texts are neither purely machine-generated nor entirely human-written, failing to reflect the complex interactions between AI and human input in real-world applications.

This project aims to bridge this gap by advancing the detection of AI-generated texts while accounting for the hybrid nature of contemporary written content. We propose a novel approach integrating Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Attention mechanisms, targeting the nuanced differences between AI-generated and human texts. This methodology not only seeks to improve detection accuracy across various text lengths and sources but also aims to effectively handle texts that blend AI and human contributions.The significance of this research extends beyond the academic and creative writing spheres, touching on broader societal implications such as ethical standards, copyright laws, and information transparency. By developing more reliable methods to identify AI-generated content, this project contributes to the ongoing discourse on the role of AI in content creation, addressing concerns surrounding authenticity and human creativity in the digital age. Through this endeavor, we aim to provide actionable insights and tools to navigate the evolving landscape of AI-generated content responsibly.

2 Related Work

2.1 Text Classification in Natural Language Processing

Text classification serves as a cornerstone in the field of Natural Language Processing (NLP), essential for tasks ranging from sentiment analysis to fake news detection. Traditionally, this field has relied on machine learning techniques like Naïve Bayes, Decision Trees, and Support Vector Machines (SVMs), utilizing feature extraction methods such as bag-of-words or TF-IDF Li et al. [2015], Gurkhe et al. [2014], Pang et al. [2002]. However, the emergence of Large Language Models (LLMs) like ChatGPT has shifted the paradigm, making the detection of machine-generated text increasingly complex due to their advanced human-like writing styles. This transformation underscores a critical challenge: distinguishing between human and LLM-generated texts, which have become remarkably similar, blurring the lines of authorship Guo et al. [2023], Ma et al. [2023], Muñoz-Ortiz et al. [2023].

2.2 Evolution of Models - LSTM, CNN, and Hybrid Approaches

In the domain of text classification, the introduction of deep neural networks such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) has initiated a paradigm shift from traditional feature extraction methods to more dynamic and intuitive analysis processes. Unlike earlier methods that relied heavily on manual feature engineering, CNNs and RNNs have paved the way for automatic pattern recognition in text, significantly enhancing the efficiency and effectiveness of text classification.

Specifically, CNNs excel in identifying local textual features, providing detailed insights into the structure and composition of the text, while RNNs, especially Long Short-Term Memory networks (LSTMs), are adept at understanding sequence dependencies, capturing the temporal and contextual nuances of written language Giorgi et al..

The convergence of CNNs and RNNs has led to the development of hybrid models that combine the strengths of both architectures, offering a more comprehensive approach to text analysis. This integrated approach significantly improves feature extraction within text sequences, leading to enhanced model accuracy and interpretability Wu and Deng [2022], Wang et al. [2016], Deng et al. [2021], Liu and Guo [2019], Cheng et al. [2020], Bahdanau et al. [2014], Du et al. [2017], SiChen [2019]. Innovations in this area, such as those by G. Wang et al., have introduced methods for embedding label sets into vector spaces, facilitating more effective computation and analysis of text data Wang et al. [2018]. Additionally, the integration of self-attention and label-embedding techniques, as demonstrated by Dong, Y et al. Dong et al. [2019] and Y. Xiao et al. Xiao et al. [2021], further enriches model capabilities, enabling more focused and relevant analyses of textual content.

One notable application of this combined approach is the utilization of CNN and Attention mechanisms as encoders with BiLSTM decoders. This configuration has been effectively applied in scenarios such as stock prediction, showcasing the model's ability to interpret complex sequential data accurately. Similarly, the amalgamation of CNNs and BiLSTMs with interactive Attention mechanisms has proven beneficial in critical areas like fake news detection, underlining the model's proficiency in identifying subtle semantic nuances and patterns within texts.In our project, we intend to further refine this combined model architecture by integrating CNNs with BiLSTMs and embedding strategic attention layers to enhance feature extraction and interpretation. This refined approach is specifically aimed at improving the model's ability to differentiate between texts generated by humans and those produced by LLMs, a task growing ever more challenging with the advancing capabilities of modern language models. By fine-tuning the interaction between these model components and adjusting their configurations, we anticipate not only higher accuracy in text classification but also a deeper insight into the distinguishing characteristics of human versus LLM-generated texts.

2.3 Fine-tuning LLMs for Text Classification

The advent of transformer architectures has introduced a new frontier in NLP, with models like BERT, Roberta, and XLNet setting new benchmarks in text understanding and classification Qiu et al. [2020], Devlin et al. [2019], Liu et al. [2019], Yang et al. [2019], Wang et al. [2019]. These models' finetuning, particularly for tasks like distinguishing LLMgenerated texts, has shown promising results. However, the computational demand of these models poses a significant barrier for individuals with limited resources. Our work seeks to address this by employing a smaller, more efficient model, Mistral-7B, leveraging techniques such as LoRA to enable fine-tuning with reduced resource requirements Jiang et al. [2023].

2.4 Addressing Potential Attacks on Text Classification Models

Despite achieving high performance in identifying machine-generated texts, models remain susceptible to various adversarial attacks that could significantly impair their effectiveness. Recent research highlights that even high-performing models can falter when confronted with specific, subtly altered inputs. For instance, the application of a lightweight paraphrase model to alter the wording and semantic distribution of machine-generated texts has demonstrated potential in undermining zero-shot detection capabilities Sadasivan et al. [2023], Orenstrakh et al. [2023]. This reveals the models' vulnerability to nuanced changes that preserve meaning while altering textual structures.

Further complicating the landscape, Shi et al. Shi et al. [2023] and He et al. He et al. [2023a] have documented the efficacy of permutation strategies in deceiving text detection systems. Techniques such as content cutoff Shen et al. [2020], sequence shuffling Lee et al. [2020], token mutation Liang et al. [2023], and strategic word swapping Shi and Huang [2020] pose significant challenges, indicating that these methods can effectively mask the machine-generated nature of texts, thereby evading detection by otherwise robust models.

In response to these challenges, our project plans to leverage the MixSet dataset Chen [2024], renowned for its incorporation of texts that blend human and machine elements. This dataset serves as a critical resource for simulating real-world applications, where texts often exhibit characteristics of both human and AI contributions. By employing this dataset, we aim to evaluate and enhance the resilience of our models against a range of adversarial tactics. Specifically, we will investigate the model's performance against paraphrased outputs—a common form of attack aiming to 'humanize' machine-generated content. This approach will not only test the models' detection capabilities under manipulated conditions but also contribute to the ongoing discourse on securing AI-driven text analysis tools against emerging threats.

3 Data

This study leverages three primary datasets, each offering unique insights and challenges relevant to distinguishing between AI-generated and human-written texts. Below is a detailed exploration of these datasets:

Dataset creation For the training data, only the English data chosen from the dataset. Regarding the model choice,

For the testing data, several approaches has been done. In the M4 dataset, the testing data is generated by simply splitting test data from the processed data. In the MGTBench dataset, only the data generated by GPT4, ChatGPT and human will be chosen as the test data. While all the data generated from GPT4 from the MixSet data set will be selected as the test set.

M4 Dataset In the M4 dataset Wang et al. [2023] which is for evaluating the machine generated data in multi generator, domain and even languages. However, due to the complexity and the work load dealing with this dataset, only the multi domain and generators be considered. Here is the selected domain and generators loaded in this dataset:

Source/ Domain	Language	Total Human	Parallel Data Human	Davinci003	ChatGPT	Cohere	Dolly-v2	BLOOMz	Total
Wikipedia	English	6,458,670	3,000	3,000	2,995	2,336	2,702	3,000	17,033
Reddit ELI5	English	558,669	3,000	3,000	3,000	3,000	3,000	3,000	18,000
WikiHow	English	31,102	3,000	3,000	3,000	3,000	3,000	3,000	18,000
PeerRead	English	5,798	5,798	2,344	2,344	2,344	2,344	2,344	17,518
arXiv abstract	English	2,219,423	3,000	3,000	3,000	3,000	3,000	3,000	18,000
Baike/Web QA	Chinese	113,313	3,000	3,000	3,000	–	–	–	9,000
RuATD	Russian	75,291	3,000	3,000	3,000	–	–	–	9,000
Urdu-news	Urdu	107,881	3,000	–	3,000	–	–	–	9,000
id_newspapers_2018	Indonesian	499,164	3,000	–	3,000	–	–	–	6,000
Arabic-Wikipedia	Arabic	1,209,042	3,000	–	3,000	–	–	–	6,000
True & Fake News	Bulgarian	94,000	3,000	3,000	3,000	–	–	–	9,000
Total			35,798	23,344	32,339	13,680	14,046	14,344	133,551

Nonetheless, there may have the data imbalanced between the human generated data and machine-generated data as the number of data will be in the ratio of 1 3. In view of this, oversampling to the human generated data is done by multiplying the whole set of the data 3 times to ensure the result number of data is close to the machine-generated data.

In total, there are 85k data combining the training, validation and testing data.

MGTBench MGTBench He et al. [2023b] is another dataset used mainly for the testing propose of testing the performance in out-of-distribution data. In the MGTBench, which also like the the M4 dataset, has multi-domain and multi-generators. Here is the following items selected in this dataset:

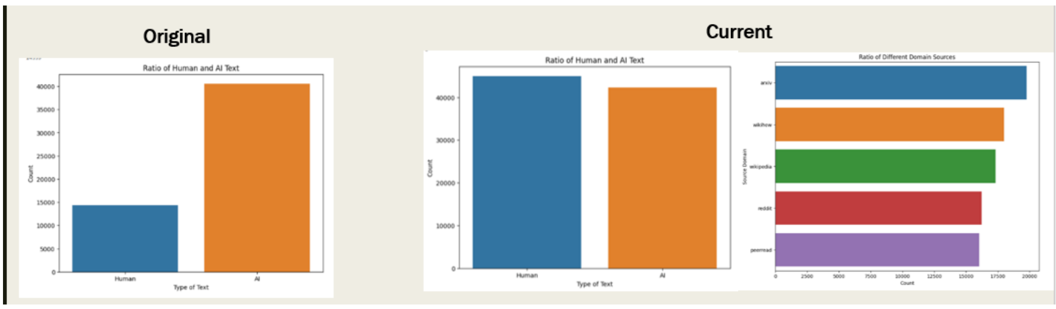


Figure 1: Distribution using old approach and new approach

Table 1: The selected domain and Generator for MGTBench (The italic ones are out-of-distribution)

Domain Used	Generator Used
News	Human
Essay	ChatGPT
Story	*GPT4*

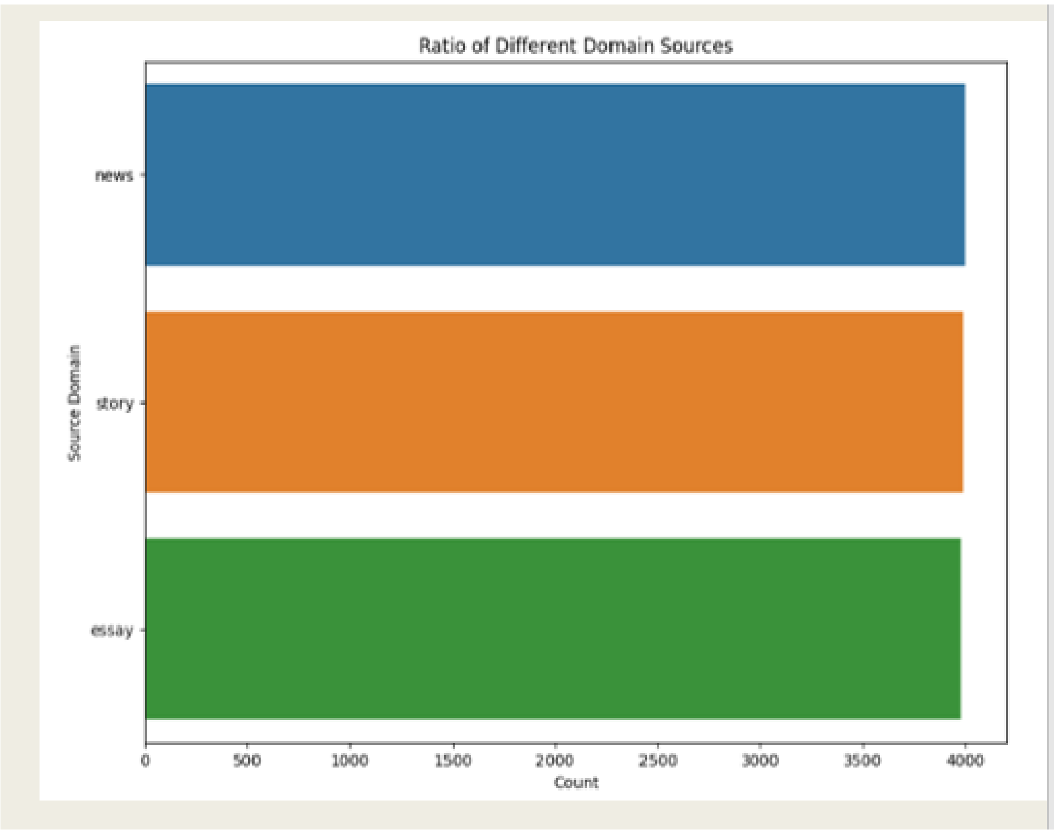


Figure 2: MGTBench Domain Distribution

MixSet MixSet is a dataset of data blending the machinegenerated features and the humanwritten features together. In consist of 4 different mixing methods:

- Polish: The LLM will try to polish the content in sentence level or word level.
- Rewrite: The LLM will extract the key information inside the content and then try to rewrite the whole content.
- Complete: The LLM will read the 1/3 of the original data and tries to complete the remaining 2/3 content.
- Humanize: The LLM will inject the humanwritingfeatures when reconstructing the original machinegenerateddata.

For original data source, it is humanwrittendata in polish, rewrite and complete while the original data source is machinegenerateddata in humanize.

Based on the mixing features inside the dataset, a new classification goal should be set in order make the whole task works. The key idea of it is that "Whether the model will be fooled by LLM and label the result different from original source". Based on that, we can directly set the correction crieta for calculating the accuracy and other metric, table x shows the correction crietas.

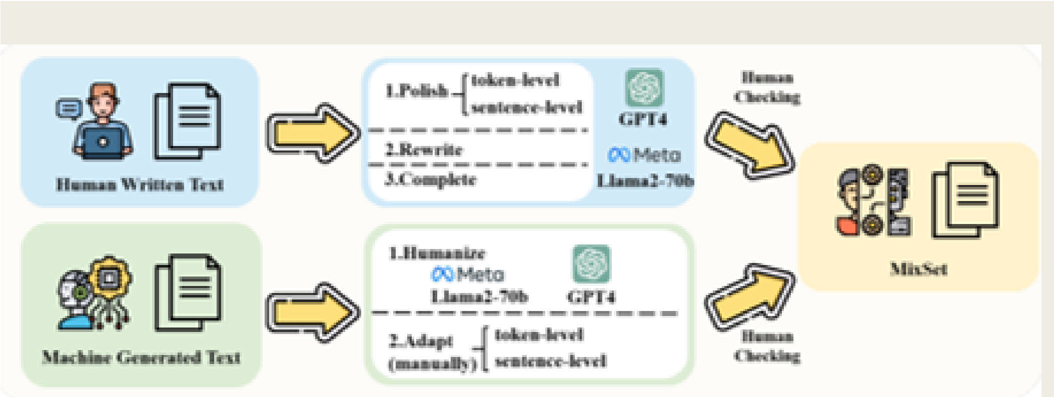


Figure 3: Overview of MixSet

Method	Correct Criteria
Polish	HGT / 0
Rewrite	HGT / 0
Complete	HGT / 0
Humanize	MGT / 1

Figure 4: Label Criteria for MixSet

For the data itself, only the mixed data mixed by GPT4 will be selected and loaded as the testing data. Due to the original dataset size is very small, the loaded test dataset only contain around 750 data.

4 Approach

4.1 Dataset preprocessing

Before loading the datasets for training and testing process, prepare the data from the dataset first. It first needs to remove all the dataset where its language is not English in the dataset. Then, it needs to read different json files and then copy the machine-text or human-text with manually labeling as 0 if it is human-text and 1 if machine-text. After that, we need to clean the data by removing rows with missing values in the 'text' column to ensure data quality. Finally, the result data neeed to be normalized and used for further process.

4.2 Text Processing

For the text processing, we applied standard natural language processing techniques taught in lecture because the feature engineering part will be performed by CNN and Attention in the model. We first tokenized the textual content using a basic English tokenizer for splitting text into words and tokens while removing all the punctuation and stop words then construct a vocabulary with 10000 most frequent tokens to reduce computational complexity and memory requirements. Finally, I encoded the text by replacing the token to index for processing by neural networks with padding and truncation to standardizing the sequences with 200tokens only.

4.3 SVM

4.3.1 General Model Architecture

To task the performance of those traditional machine-learning method for classification of LLM-generated text with human text, I incorporated the SVM for text classification.

Before deploying the model, the preprocessed the data will further employs the TFIDF to converts the text data into a matrix of TFIDF features to enabling the SVM to know the textual features. The TFIDF vectors is set with the maximum length of 1000. After that, the radius basis function will be act as the kernel of SVM and do the classification.

4.3.2 Comparable Baselines

The model will be comparable with the same SVMs, but with different kernels which are linear, sigmoid and polynomic to understand how well each variant perform across the same text sources.

4.4 BiLSTM-Attention series models

The following sections will introduce all the curcial elements for that series of model and showcase the key different in their architectures.

4.4.1 Embedding Layer

The first layer is the embedding layer, after loading the preprocessed text, it will map each token to a high-dimensional vector using one-hot encoding to put them into dense representations to capture semantic properties such similar vectors for later layers to understand the content.

4.4.2 1D Convolution Layer

After converting to the word vectors, it will be applied into 1D CNN model to extract a representative and effective feature by performing a one-dimensional convolution operation with various filters in different sizes. Using various filters over the sequence data, the 1D CNN can capture hierarchical features inside the long sequence and passes the filtered information to the next layer. By applying more than one convolutional layers, the 1D CNN model deepens the feature extraction process. Tus a higher level of features makes the prediction task more robust and discriminative,

Assume the input text is with dimension d, those vectors will form an input matrix with dimensions corresponding to the sequence length and vector size which is L x d. Then, the matrix can be processed by the multi-channel convolutional layer that employs kernels of varying size in 2, 3, and

4 words to capture different local textual features. Those kernels will focus on different n-gram combinations while the global ax pooling reduces the feature map into condensed representation.

Assume the input from the embedding layer is with dimension d, those vectors will form an input matrix with dimensions corresponding to the sequence length and vector size which is L x d. Then the matrix can be processed by the multi-channel convolution layer that employs kernels of varying size in 2, 3, and 4 words to produce different feature map lengths in order to capture different local textual features. Those kernels will focus on different n-gram combinations while the global max pooling reduces the feature map into condensed representation. Then the Rcetified Linear Unit (ReLU) is used as the activation function for introducing the non-linearity into the model as well.

4.4.3 Attention mechanism

In general, for classifying the content if it is machine-generated or not, not all the parts of that content contribute equally to decide the final prediction. Some must be more important than others. In view of this, the utilization of the attention mechanism is performed to emphasize the most important parameters during prediction. In this series of models, the attention mechanism can be performed in either two places: After 1D CNN and before Bi-LSTM and after Bi-LSTM, we will call it Pre-LSTM attention and Post-LSTM Attention.

Pre-LSTM Attention After generating the feature maps using CNN layers, attention mechanism is used to aim to weigh the importance of different n-gram features extracted by the CNN layers before they are processed by the LSTM which can focus on more relevant features extracted from the convolutional layers. It does so by computing a weight sum of the features based on the attention weights, resulting in an attended feature vector which represents a focused summary of the most relevant features.

Post-LSTM Attention The Post-LSTM attention is applied to focus on local text features before sequence processing, the Post-LSTM Attention assesses the importance of different parts of the text after considering its full context. This attention step assigns weights to each position in the BiLSTM's output sequence, identifying which parts are most relevant for the classification decision. Using it can emphasize the most informative parts of the texts given from the output of BiLSTM layer to make the final classification decision. The result will finally input to the fully connected layer to give the binary classification of human (0) or machine-text (1).

4.4.4 Bi-direction LSTM

The Bi-directional LSTM network is a two-way stacked LSTM network with forward and backward LSTM features. This layer can be able to capture the long-term dependencies within sequence data with the additional information the feature sequences. The layer is using bi-directional version of LSTM to capture the context from both sides due to the fact that the meaning or choice of wording should be depend form both sides not just words before it. It can thus offer a more complete understanding of each word within its surrounding context.

4.4.5 Comparing Baselines

There are the following models used in the experiment, Bi-LSTM, Attention-Bi-LSTM, CNNBiLSTM, CNNBiLSTM-BiAttention and CNNBiLSTMAttention. The following table is the comparism between them:

- Ordinary version of BiLSTM: Using BiLSTM directly in extracting the sequential dependencies of the sequences for classification - Attention with BiLSTM: Attention is appended after BiLSTM for further focusing the important features in the result produced in BiLSTM - CNN with BiLSTM: CNN is performed in feature extraction before doing the classification with BiLSTM - CNNBiLSTM-Attention: A similar approach to the proposed model but removing the attention layer between CNN and BiLSTM to test the effectiveness of that layer - CNNBiLSTM-BiAttention: The model with all the layers including the pre-LSTM Attention and post-LSTM Attention.

Table 2: Comparison of Model Architectures

Layer (Specification)	BiLSTM	Att-BiLSTM	CNN-BiLSTM	CNNBiLSTM-Att	CNNBiLSTM-DouAtt
Embedding	vocab_size dim=128	vocab_size dim=128	vocab_size dim=128	vocab_size dim=128	vocab_size dim=128
CNN	-	-	filters=100 kernels=[2,3,4]	filters=100 kernels=[2,3,4]	filters=100 kernels=[2,3,4]
Pre-LSTM Att	-	-	-	-	heads=4 depth=per_head
Bi-LSTM	hidden=256 layers=2	hidden=256 layers=2	hidden=256 layers=2	hidden=256 layers=2	hidden=256 layers=2
Post-LSTM Att	-	heads=4 depth=per_head	-	heads=4 depth=per_head	heads=4 depth=per_head
Dense Output	classes=1	classes=1	classes=1	classes=1	classes=1

4.5 Mistral 7B

Another model going to be used is Mistral 7B, according to their paper released, this model completely outperforms Llama 2 13B, the popular model in LLM field on all benchmarks, and even outperforms Llama 34B on many benchmarks, showing the small LLM's ability is comparable with large ones with proper settings. In the project, the Mistral-7B's variant which is block-wise model-update Filtering and Bit-centering (BNB) is used for enhancing the model efficiency and memory usage. Moreover, the quantized 4bits Face [2024a] version would be used for reducing the model's size and can be trainable even in T4 GPU.

In the project, it will use 'FastLanguageModel' from UnSLoth AI [2024] library for downloading the model and setting the maximum sequence for up to 2048 tokens. Meanwhile, LoRA would be used to train only 4% of its parameters with gradient accumulation and precision training. After the data loaded, rather applying standard natural language processing techniques like what I did in SVM and LSTM model, the Supervised Fine-Tuning method would be performed where the text data and their labels will be structured as a suitable prompt format for the model retraining on the Machine-text classification task. Finally, it will incorporate with Peft Face [2024b] and SFTTrainer Face [2024c] for doing the model training.

5 Experiment

5.1 Text Processing

For the text processing, we applied standard natural language processing techniques taught in lecture because the feature engineering part will be performed by CNN and Attention in the model. We first tokenized the textual content using a basic English tokenizer for splitting text into words and tokens while removing all the punctuation and stop words then construct a vocabulary with 10000 most frequent tokens to reduce computational complexity and memory requirements. Finally, I encoded the text by replacing the token to index for processing by neural networks with padding and truncation to standardizing the sequences with 200 tokens only.

5.2 Training augment

After prepossessing the text, we will perform the training process for each models.

BiLSTM series For BiLSTM series models, TF-IDF features to enabling the SVM to know the textual features. The TF-IDF vectors is set with the maximum length of 1000. After that, the radius basis function will be act as the kernel of SVM and do the classification.

For all models, they will all trained in 8 epochs to ensure the fairless.

Mistral7B Here are the setting for each part when training with Mistral-7B model:

```
model, tokenizer = FastLanguageModel.from_pretrained(
        model_name = "unsloth/mistral-7b-bnb-4bit", # Choose ANY! eg teknium/OpenHermes-2.5-Mistral-7B
        max_seq_length = max_seq_length,
        dtype = dtype,
        load_in_4bit = load_in_4bit,
        # token = "hf_...", # use one if using gated models like meta-llama/Llama-2-7b-hf
)
```

Figure 5: Enter Caption

```
model = FastLanguageModel.get_peft_model(
        model,
        r = 8, # Choose any number > 0 ! Suggested 8, 16, 32, 64, 128
        target_modules = ["q_proj", "k_proj", "v_proj", "o_proj",
                          "gate_proj", "up_proj", "down_proj",],
        lora_alpha = 32,
        lora_dropout = 0, # Supports any, but = 0 is optimized
        bias = 'lora_only',    # Supports any, but = "none" is optimized
        use_gradient_checkpointing = True,
        random_state = 3407,
        use_rslora = True,  # We support rank stabilized LoRA
        loftq_config = None, # And LoftQ
)
```

Figure 6: Lora and Peft setting

5.2.1 Loss Function

Since with the nature of the M4 dataset, the data is in the form of 1 human written text with several machinegenerated text from various models over certain topic, loading it will inevitably have the imbalanced data issue. Even though oversampling is done to human data, it may introducing another bias of the distribution in generator's aspect view, leading those models learning towards the majority class only. In view of this, for the loss function used, rather than the traditional Binary classification loss, the Focal Loss [46] will be used as the loss function.

Focal Loss Lin et al. [2017] is designed to modulate the contribution of each example to the loss based on the classification error. The key idea is to focus training more on hardtoclassify examples and reduce the relative loss for well-classified instances. It is an extension of standard Cross-Entropy Loss and we can enhance the sensitivity of the models towards minority classes and improve the overall balance in performance across different classes.

```python
from trl import SFTTrainer
from transformers import TrainingArguments

trainer = SFTTrainer(
        model = model,
        tokenizer = tokenizer,
        train_dataset = train_data,
        eval_dataset = val_data,
        dataset_text_field = "formatted_text",
        max_seq_length = max_seq_length,
        args = TrainingArguments(
                output_dir = "outputs",
                per_device_train_batch_size = 8,
                gradient_accumulation_steps = 8,
                warmup_steps = 5,
                max_steps = 60,
                learning_rate = 2e-4,
                fp16 = not torch.cuda.is_bf16_supported(),
                bf16 = torch.cuda.is_bf16_supported(),
                logging_steps = 1,
                optim = "adamw_8bit",
                weight_decay = 0.01,
                lr_scheduler_type = "linear",
                seed = 3407
        ),
)

```

Figure 7: SFTTrainer Setting

5.3 Training Log

5.3.1 SVM

Since using SVM is just directly calling the build-in function to train the model and return the analysis results, there are no training log inside SVM. However, regarding the time needed, training SVM with that much training dataset will be extremely time-consuming process. For the training time, it took around 4 hours to train and evaluate one kernel. While it can be shortened into 1.5 hours if reducing the training dataset size.

5.3.2 BiLSTM series

The following and the training log containing the training and validation loss while with the training and validation accuracies in the training process.

Here is the training log for each model:

```
Epoch [1/8], Train Loss: 0.0658, Train Accuracy: 0.5769, Val Loss: 0.0618, Val Accuracy: 0.6853
Epoch [2/8], Train Loss: 0.0521, Train Accuracy: 0.7256, Val Loss: 0.0450, Val Accuracy: 0.7946
Epoch [3/8], Train Loss: 0.0333, Train Accuracy: 0.8503, Val Loss: 0.0281, Val Accuracy: 0.8641
Epoch [4/8], Train Loss: 0.0197, Train Accuracy: 0.9214, Val Loss: 0.0242, Val Accuracy: 0.9306
Epoch [5/8], Train Loss: 0.0131, Train Accuracy: 0.9514, Val Loss: 0.0185, Val Accuracy: 0.9372
Epoch [6/8], Train Loss: 0.0095, Train Accuracy: 0.9660, Val Loss: 0.0251, Val Accuracy: 0.9074
Epoch [7/8], Train Loss: 0.0068, Train Accuracy: 0.9759, Val Loss: 0.0229, Val Accuracy: 0.9320
Epoch 00008: reducing learning rate of group 0 to 1.0000e-04.
Epoch [8/8], Train Loss: 0.0075, Train Accuracy: 0.9718, Val Loss: 0.0238, Val Accuracy: 0.9422
```

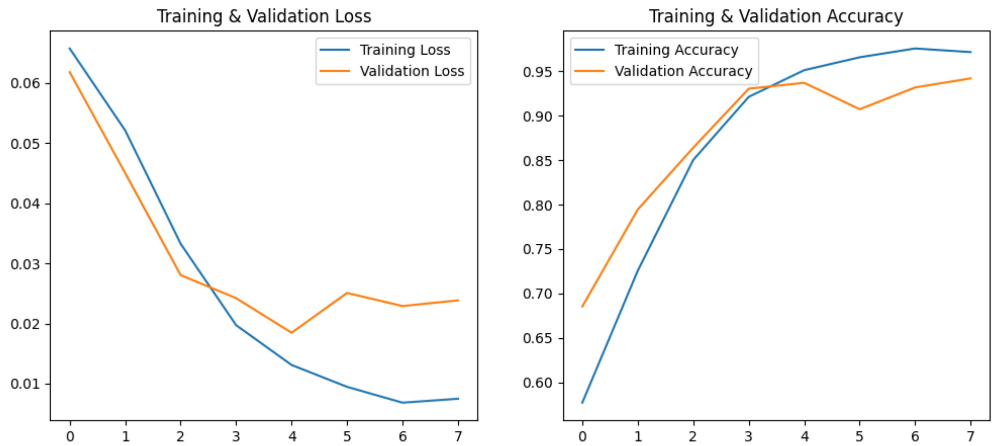


Figure 8: Training Log for BiLSTM

```
Epoch [1/8], Train Loss: 0.0580, Train Accuracy: 0.6547, Val Loss: 0.0399, Val Accuracy: 0.8293
Epoch [2/8], Train Loss: 0.0316, Train Accuracy: 0.8594, Val Loss: 0.0253, Val Accuracy: 0.8857
Epoch [3/8], Train Loss: 0.0199, Train Accuracy: 0.9174, Val Loss: 0.0202, Val Accuracy: 0.9181
Epoch [4/8], Train Loss: 0.0139, Train Accuracy: 0.9466, Val Loss: 0.0182, Val Accuracy: 0.9384
Epoch [5/8], Train Loss: 0.0103, Train Accuracy: 0.9610, Val Loss: 0.0182, Val Accuracy: 0.9350
Epoch [6/8], Train Loss: 0.0075, Train Accuracy: 0.9719, Val Loss: 0.0207, Val Accuracy: 0.9299
Epoch 00007: reducing learning rate of group 0 to 1.0000e-04.
Epoch [7/8], Train Loss: 0.0062, Train Accuracy: 0.9772, Val Loss: 0.0201, Val Accuracy: 0.9500
Epoch [8/8], Train Loss: 0.0030, Train Accuracy: 0.9896, Val Loss: 0.0250, Val Accuracy: 0.9513
```

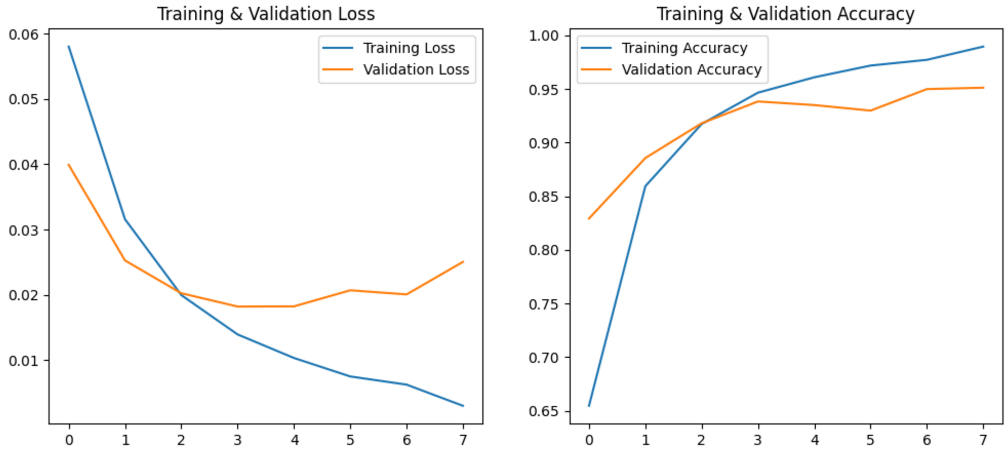


Figure 9: Training Log for CNNBiLSTM

```
Epoch [1/8], Train Loss: 0.0387, Train Accuracy: 0.7975, Val Loss: 0.0270, Val Accuracy: 0.8732
Epoch [2/8], Train Loss: 0.0192, Train Accuracy: 0.9202, Val Loss: 0.0198, Val Accuracy: 0.9039
Epoch [3/8], Train Loss: 0.0123, Train Accuracy: 0.9510, Val Loss: 0.0163, Val Accuracy: 0.9477
Epoch [4/8], Train Loss: 0.0083, Train Accuracy: 0.9681, Val Loss: 0.0191, Val Accuracy: 0.9530
Epoch [5/8], Train Loss: 0.0058, Train Accuracy: 0.9787, Val Loss: 0.0195, Val Accuracy: 0.9357
Epoch 00006: reducing learning rate of group 0 to 1.0000e-04.
Epoch [6/8], Train Loss: 0.0042, Train Accuracy: 0.9846, Val Loss: 0.0197, Val Accuracy: 0.9520
Epoch [7/8], Train Loss: 0.0013, Train Accuracy: 0.9959, Val Loss: 0.0249, Val Accuracy: 0.9561
Epoch [8/8], Train Loss: 0.0006, Train Accuracy: 0.9984, Val Loss: 0.0320, Val Accuracy: 0.9587
```

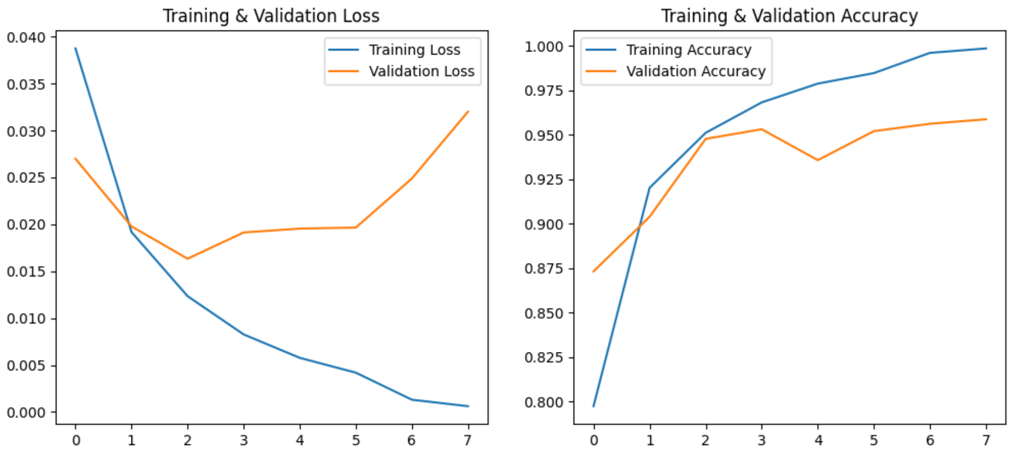


Figure 10: Training Log for Attention BiLSTM

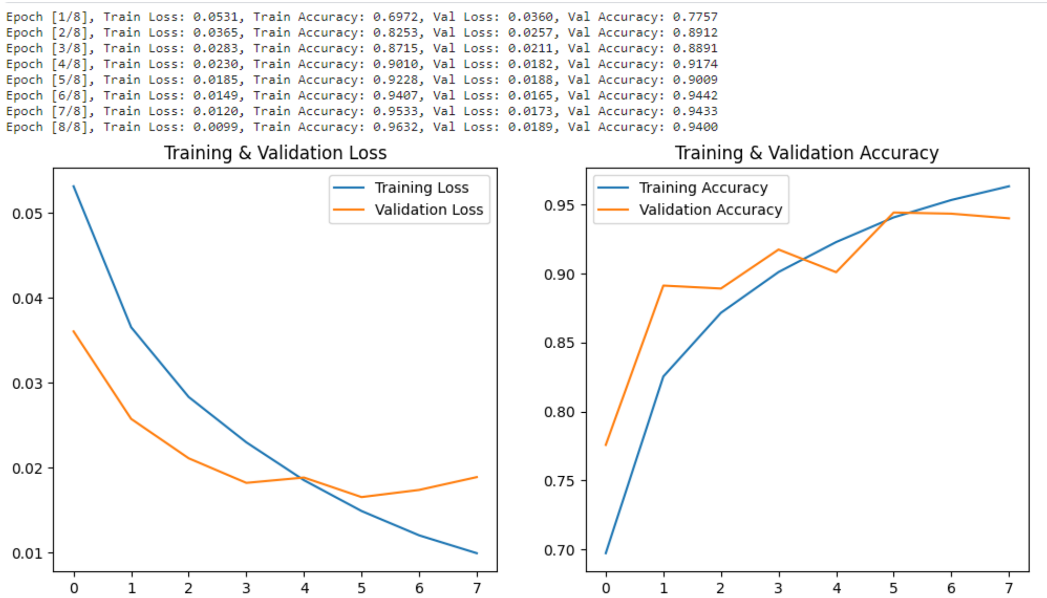


Figure 11: Training Log for CNNBiLSTMAttention

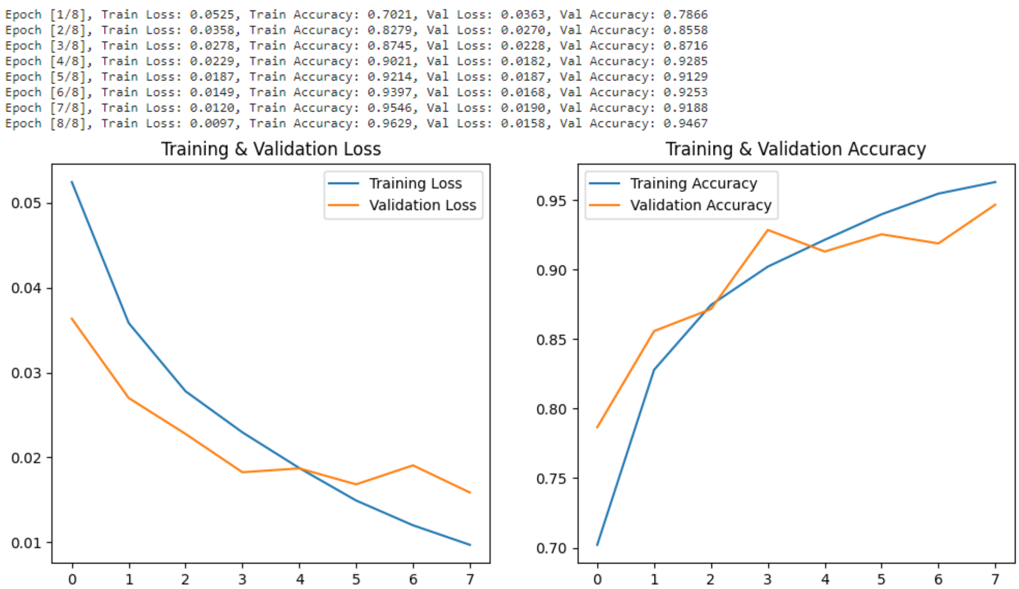


Figure 12: Training Log for CNNBiLSTMDouAttention

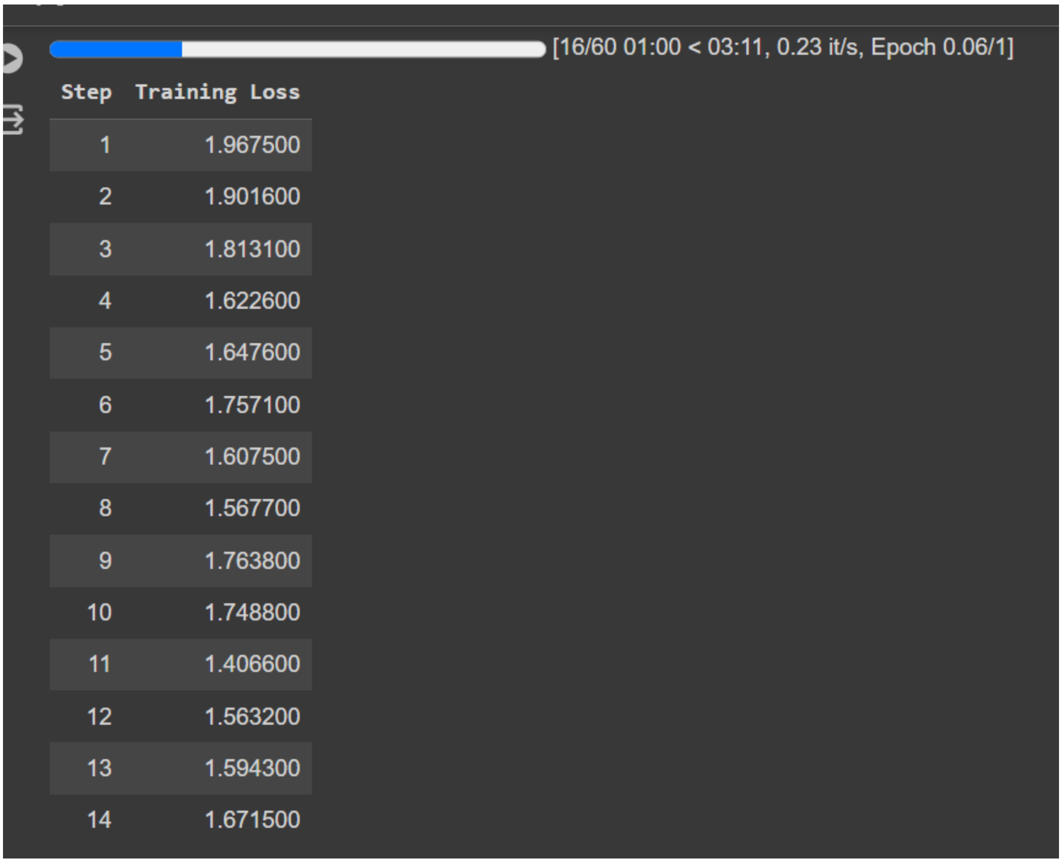
5.3.3 Mistral-7B

[!htbp] In the SFTTrainer, it alreay show the training loss inside each epoch.

5.4 Evaluation Metrics

In the testing process, I will record the model different metrics like the accuracy, F1 score, recall and the auc for knowing the overall performance of the model.

Meanwhile, a domain-specific metric and the generator-specific metric will be recorded to understand the model's power in different source of the domain. Moreover, the data of its performance of


[16/60 01:00 < 03:11, 0.23 it/s, Epoch 0.06/1]

Step	Training Loss
1	1.967500
2	1.901600
3	1.813100
4	1.622600
5	1.647600
6	1.757100
7	1.607500
8	1.567700
9	1.763800
10	1.748800
11	1.406600
12	1.563200
13	1.594300
14	1.671500

Figure 13: Training Log for Mistral-7B

identifying the text generating from different model will also be recorded to know the performance over it, especially on the human-text.

Regarding the MixSet dataset, rather than directly getting the domain-specific or generator-specific metric, the mixingmethod's specific metric will just directly applied to see the model's performance in different mixing methods.

5.5 Results

5.5.1 SVM

Table 3: SVM Domain Specific performance In M4 Dataset

Model	wikihow	arxiv	wikipedia	peerread	reddit
Linear	0.87	0.77	0.89	0.92	0.86
Poly	0.90	0.82	0.91	**0.97**	0.89
RBF	**0.91**	**0.84**	**0.93**	0.96	**0.91**
Sigmoid	0.83	0.73	0.85	0.84	0.82

Table 4: SVM Generator Specific performance in M4 Dataset

Model	human	cohere	chatGPT	davinci
Linear	0.91	0.84	0.95	0.86
Poly	0.94	0.91	**1.00**	0.90
RBF	**0.96**	0.90	0.99	**0.91**
Sigmoid	0.85	0.79	0.91	0.82

Table 5: Performance Matrix in M4 dataset

Model	Accuracy	Precision	Recall	F1	AUC
Linear	0.86	0.86	0.86	0.86	0.93
Poly	0.90	0.90	0.90	0.90	**0.97**
RBF	**0.91**	**0.91**	**0.91**	**0.91**	**0.97**
Sigmoid	0.81	0.81	0.81	0.81	0.89

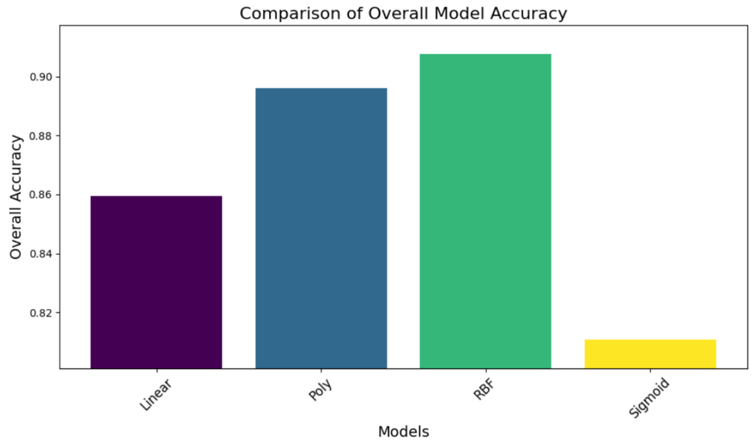


Figure 14: The SVM accuracy of different models in M4 dataset

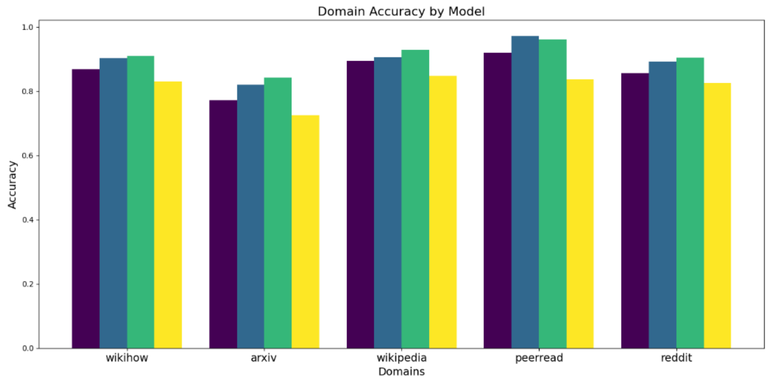


Figure 15: The SVM domain specific accuracy in M4 dataset

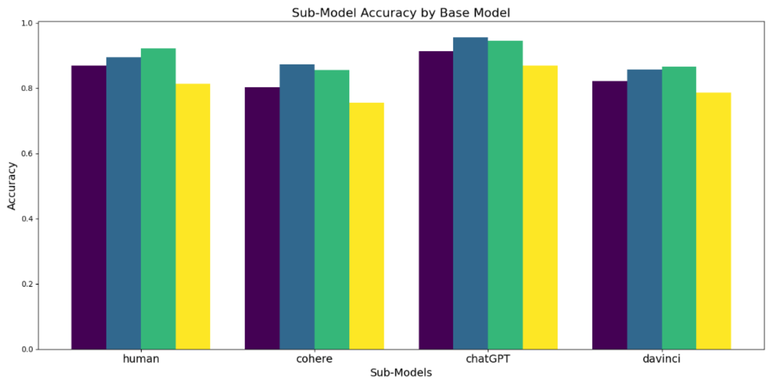


Figure 16: The SVM generator specific accuracy in M4 dataset

Table 6: SVM domain specific performance in MGTBench dataset

Model	story	essay	news
Linear	0.77	**0.69**	0.84
Poly	0.78	0.63	**0.89**
RBF	**0.79**	0.68	**0.89**
Sigmoid	0.75	0.67	0.82

Table 7: SVM generator specific performance in MGTBench dataset

Model	human	GPT4	chatGPT
Linear	0.79	0.94	0.90
Poly	0.72	**1.00**	**0.97**
RBF	**0.79**	0.97	0.94
Sigmoid	0.77	0.90	0.87

Table 8: SVM performance matrix in MGTBench dataset

Model	Accuracy	Precision	Recall	F1	AUC
Linear	0.77	0.77	0.77	0.77	0.85
Poly	0.77	0.78	0.77	0.76	0.83
RBF	**0.79**	**0.79**	**0.79**	**0.78**	**0.87**
Sigmoid	0.75	0.75	0.75	0.75	0.83

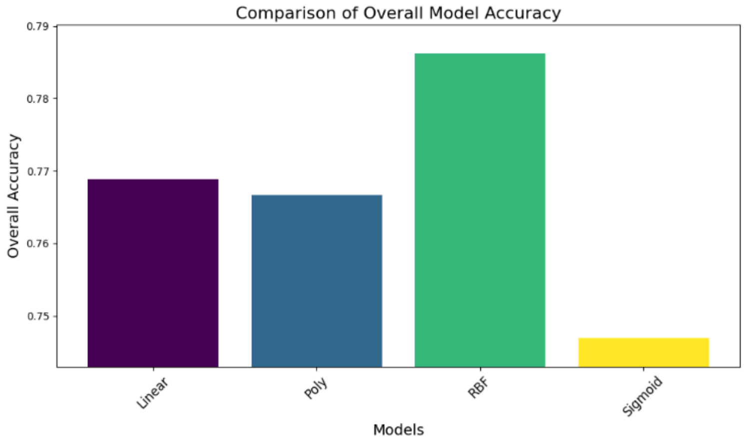


Figure 17: The SVM accuracy of different models in MGTBench dataset

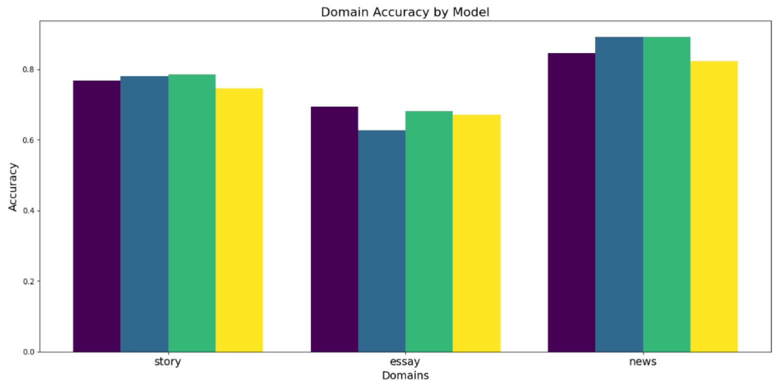


Figure 18: The SVM domain specific accuracy in MGTBench dataset

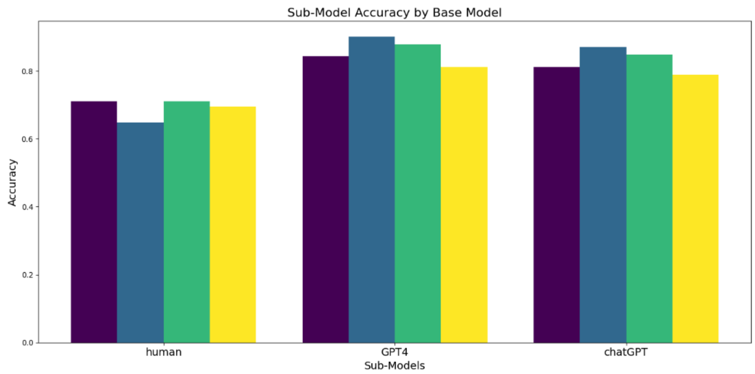


Figure 19: The SVM generator specific accuracy in MGTBench dataset

Table 9: The SVM mixing method accruacy in MixSet

Model	Humanize	Complete	Rewrite	Polish
Linear	**0.64**	**0.02**	0.04	0.06
Poly	0.56	0.02	0.04	0.06
RBF	**0.64**	**0.02**	0.01	0.02
Sigmoid	0.59	0.03	**0.06**	**0.09**

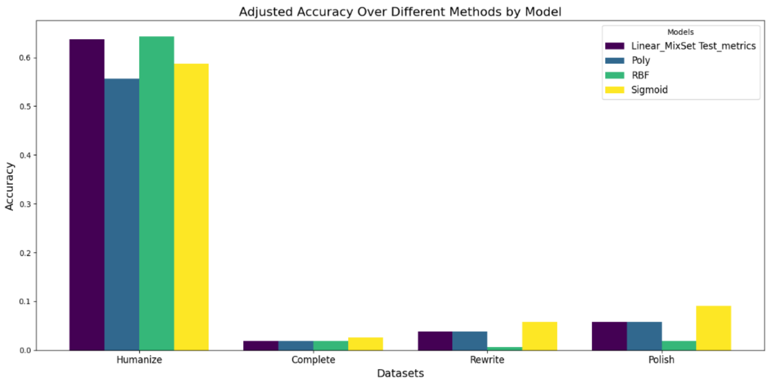


Figure 20: The SVM Mixing method accuracy in MixSet dataset

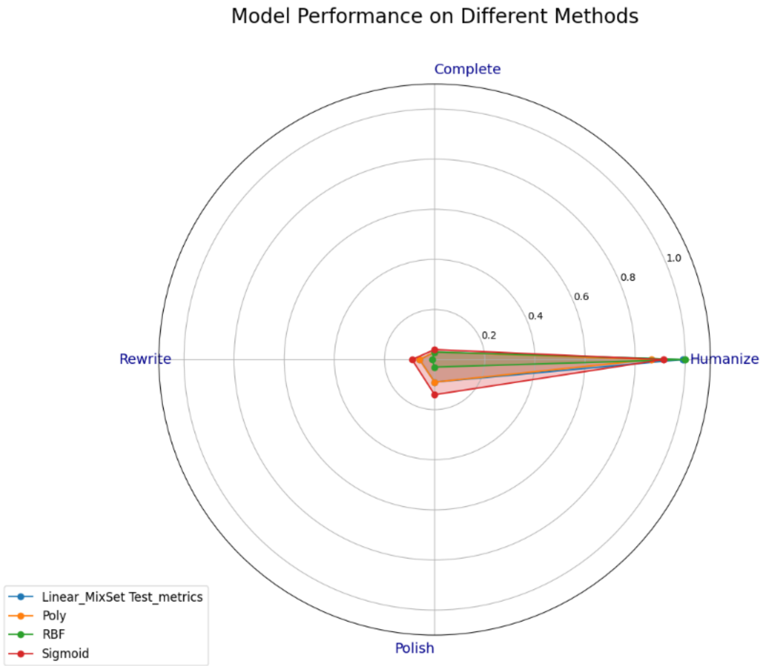


Figure 21: The SVM radar chart in MixSet dataset

5.5.2 BiLSTM series

For BiLSTM series result, they will also compared with SVM with Poly kernel as the baseline.

Table 10: Domain Specific performance In M4 Dataset

Model	WikiHow	ArXiv	Wikipedia	PeerRead	Reddit
BiLSTMAttention	**0.96**	**0.95**	**0.94**	**0.99**	**0.96**
BiLSTM	0.95	0.94	0.93	0.99	0.95
CNNBiLSTMDouAttention	0.94	0.92	0.92	0.99	0.95
CNNBiLSTM	0.95	0.94	0.93	0.99	0.95
CNNBiLSTMAttention	0.93	0.90	0.89	0.98	0.93
SVM	0.83	0.73	0.85	0.84	0.82

Table 11: Generator specific performance in M4 dataset

Model	human	cohere	chatGPT	davinci
BiLSTMAttention	0.99	0.93	**0.99**	**0.92**
BiLSTM	0.99	0.91	0.98	0.90
CNNBiLstmDouAttention	0.99	0.90	0.98	0.87
CNNBiLSTM	0.99	0.91	**0.99**	0.89
CNNBiLSTMAttention	**1.00**	0.83	0.96	0.82
SVM	0.82	0.77	0.88	0.80

Table 12: Performance Matrix in M4 dataset

Model	Accuracy	Precision	Recall	F1	AUC
BiLSTMAttention	**0.96**	**0.96**	**0.96**	**0.96**	**0.96**
BiLSTM	0.95	0.95	0.95	0.95	0.95
CNNBiLstmDouAttention	0.94	0.95	0.94	0.94	0.94
CNNBiLSTM	0.95	0.95	0.95	0.95	0.95
CNNBiLSTMAttention	0.93	0.93	0.93	0.93	0.93
SVM	0.81	0.81	0.81	0.81	0.89

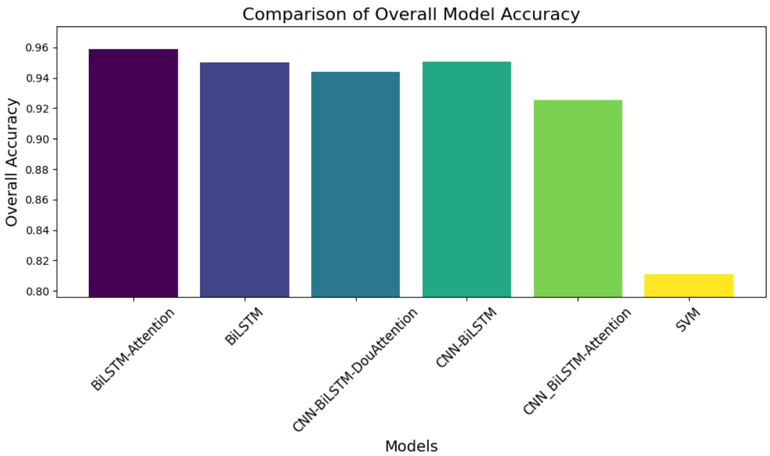


Figure 22: The accuracy of different models in M4 dataset

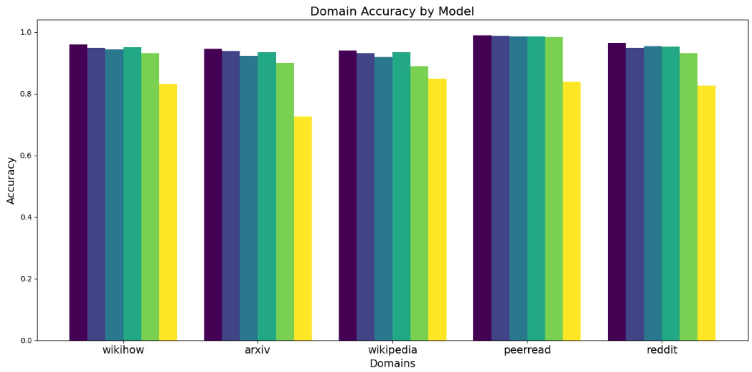


Figure 23: The domain specific accuracy in M4 dataset

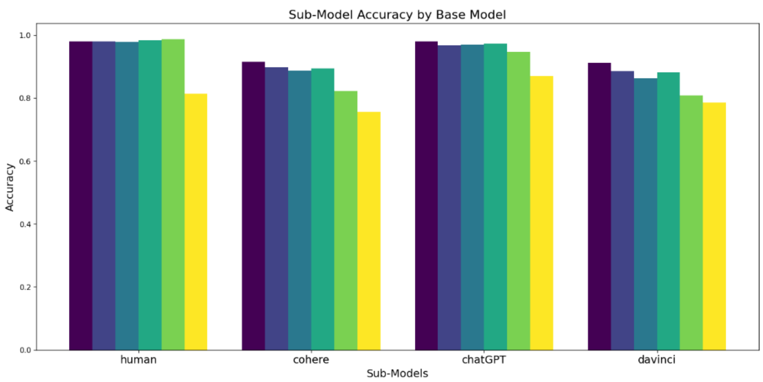


Figure 24: The generator specific accuracy in M4 dataset

Here are the results in MGTBench:

Table 13: Domain Specific performance in MGTBench

Model	story	essay	news
BiLSTMAttention	**0.81**	0.65	**0.87**
BiLSTM	0.77	0.67	**0.87**
CNNBiLstmDouAttention	0.78	0.69	0.83
CNNBiLSTMAttention	0.77	**0.73**	0.83
CNNBiLSTM	0.76	0.68	0.86
SVM	0.75	0.67	0.82

Table 14: Generator specific performance in MGTBench

Model	human	GPT4	chatGPT
BiLSTMAttention	0.77	**1.00**	**0.95**
BiLSTM	0.80	0.97	0.89
CNNBiLstmDouAttention	0.83	0.93	0.87
CNNBiLSTMAttention	**0.89**	0.89	0.82
CNNBiLSTM	0.82	0.94	0.87
SVM	0.78	0.91	0.89

Table 15: Performance Matrix in MGTBench

Model	Accuracy	Precision	Recall	F1	AUC
BiLSTMAttention	**0.78**	**0.79**	**0.78**	**0.78**	**0.78**
BiLSTM	0.77	0.77	0.77	0.77	0.77
CNNBiLstmDouAttention	0.77	0.77	0.77	0.77	0.77
CNNBiLSTMAttention	**0.78**	0.78	**0.78**	**0.78**	**0.78**
CNNBiLSTM	0.77	0.77	0.77	0.77	0.77
SVM	0.75	0.75	0.75	0.75	0.83

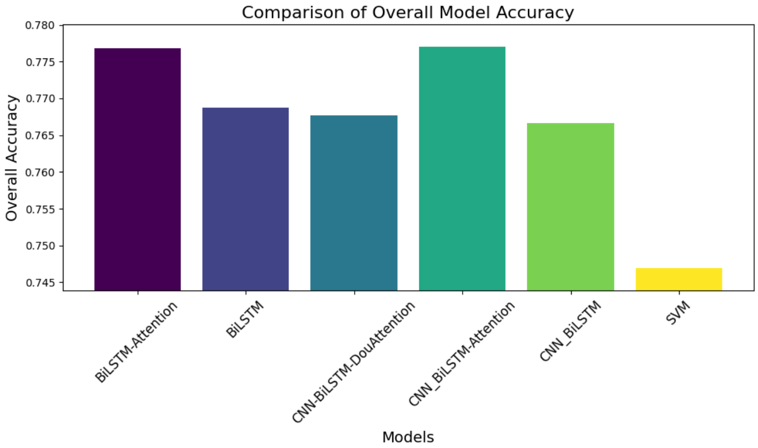


Figure 25: The accuracy of different models in MGTBench dataset

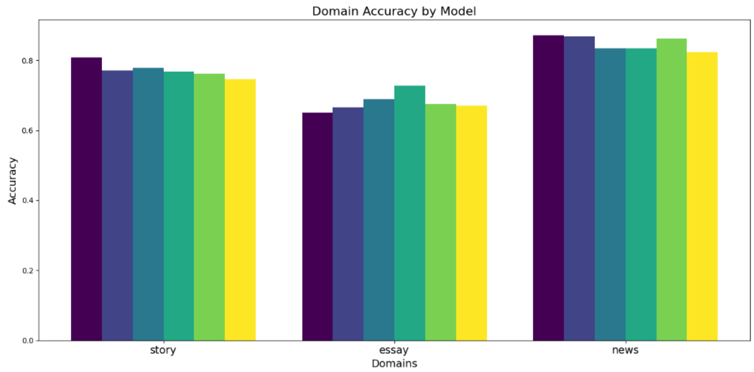


Figure 26: The domain specific accuracy in MGTBench dataset

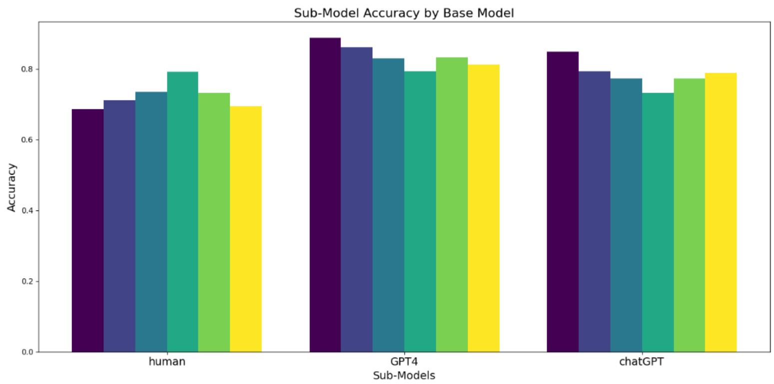


Figure 27: The generator specific accuracy in MGTBench dataset

Here is the result in MixSet:

Table 16: Mixing Method performance in Mixset

Model	Humanize	Complete	Rewrite	Polish
BiLSTMAttention	0.01	0.41	0.36	0.36
BiLSTM	0.01	**0.92**	**0.87**	0.91
CNNBiLSTMDouAttention	0.01	0.85	0.83	0.88
CNNBiLSTMAttention	0.01	0.90	0.86	**0.92**
CNN_BiLSTM	0.06	0.81	0.68	0.81
SVM	**0.56**	0.03	0.01	0.03

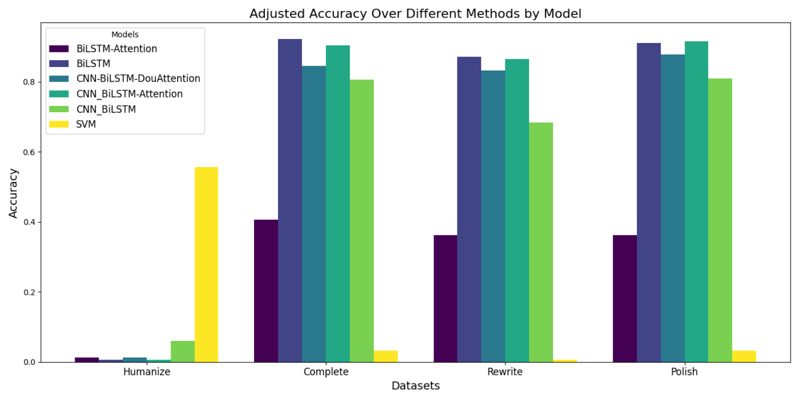


Figure 28: The Mixing method accuracy in MixSet dataset

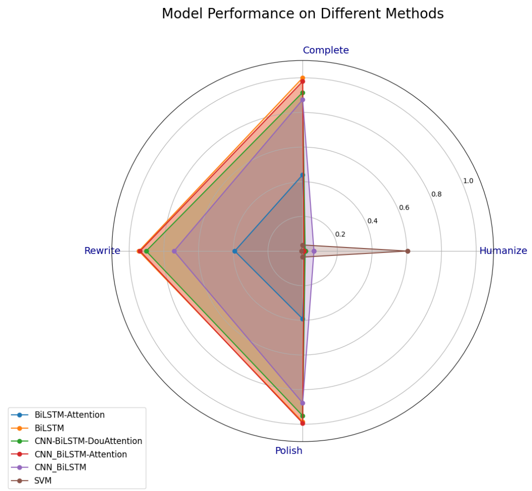


Figure 29: The radar chart in MixSet dataset

5.5.3 Mistral

Table 17: Mistral Overall Performance on the M4 Dataset

Metric	Value
Accuracy	0.6747
F1 Score	0.7429
Precision	0.6044
Recall	0.9636
AUC	0.6816
False Positives	5376

Table 18: Mistral Accuracy by Domain in M4 Dataset

Domain	Accuracy
Arxiv	0.5571
Peerread	0.9172
Reddit	0.7925
Wikihow	0.6123
Wikipedia	0.5218

Table 19: Mistral Accuracy by Model in M4 Dataset

Model	Accuracy
ChatGPT	0.9512
Cohere	0.9492
Davinci	0.9888
Human	0.3995

Table 20: Mistral Overall Performance on the MGTBench Dataset

Metric	Value
Accuracy	0.5473
F1 Score	0.6862
Precision	0.5243
Recall	0.9930
AUC	0.5486
False Positives	5374

Table 21: Mistral Accuracy by Domain in MGTBench Dataset

Domain	Accuracy
Essay	0.5322
News	0.5813
Story	0.5285

Table 22: Mistral Accuracy by Model in MGTBench Dataset

Model	Accuracy
GPT4	0.9885
ChatGPT	0.9973
Human	0.1043

Table 23: Mistral Accuracy by Dataset in MixSet

Dataset	Accuracy
Complete	0.00129
Humanize	1.0000
Polish	0.0581
Rewrite	0.0387

5.6 Analysis

5.6.1 SVM Kernel Compasison

In the section 5.5.1, it is obvious that RBF kernel and Poly kernel are both outperform the other 2 kernels in different testing dataset. For example, the RBF kernel gets the all the highest scores in table 5 and table 8. Meanwhile, even though Poly kernel is slightly worser than RBF kernel is various field, it is shown to be better when dealing with the machine-generated data. For example, the poly kernel outperforms the RBF kernel in Cohere and ChatGPT in table 4, and ChatGPT and GPT4 in table 7, showing that using poly kernel can indeed get a better detector in detecting the machine-generated text.

However, when dealing with the mixed data in table 9 and 21, they all performed really poorly where they just get nearly 0 accuracy in 3 out of 4 mixing methods. Regarding the humanize method, the accuracy are just around 0.6, showing that they are not extracting the features well, they are just doing some random guessing.

5.6.2 BiLSTM series

M4 Dataset For the M4 dataset, 12 shows that across BiLSTM series models and SVM model, BiLSTM series models can outperform the SVM model, it is because of the model complexity and how effectively the LSTM, CNN and Attention capturing the key features inside the original content for better classification.

Across the BiLSTM series models in table 12, the BiLSTMAttention outperform all other models in the table, (reason).

Regarding the domain specific analysis in table 10, there has a gap across each domain, they perform nearly perfect in PeerRead data while a bit worser in Wiki data as well.

For the generator specific analysis in table 11, there also have a gap between two groups of generators. They perform relatively well in human or ChatGPT data. But regarding the cohere and davinci data, they cannot classify nearly perfectly like the other group does.

MGTBench In the MGTBench, similar result show in table 15 where BiLSTMAttention outperform all other models again and SVM perform the worse inside all models. However, inside the table, it can show a significant drop in different slots inside the table, from above 0.9 to only around 0.8, showing that the models cannot classify well compared to the testing data splitted from the original M4 dataset.

Regarding the outofdistribution data, in 13. they all perform very decent on story field, while relatively bad in the essay field (reason). Surprising, the accuracy of detecting GPT4 generated data which is not seen in the original training data is extremely high across the BiLSTM series models. Some like BiLSTMAttention can even got perfect score in GPT4 data. This is because (reason)

Nonetheless, regarding the human written data in 14, those models perform worser inside this dataset, which contribute the main reason of the drop in table 4. Those model just more easily mislabel the HWT into MGT, this may be becuase of the human choice when building up the dataset is different, where they would have different writing style and wording choice which may not be seen from the original training set as well.

MixSet In the data mixing the machinegenerated features, the BiLSTM series models can perform decent in 3 out of 4 mixing methods except the humanize method in table 16 and 29, some can even have around 0.92 accuracy. However, SVM performed very poorly in this dataset, it got around 0% accuracy in those mixing methods. In humanize, it's results is just like doing random guessing, showing that SVM is not good at classifyin the features inside a mixed data while the remaining ones can do so by extracting the key features inside the mixed data and do the correct identification.

Comparing to the mixing methods, there has a huge drop of performance in the humanize mixing methods, where all the BiLSTM series getting nearly 0% in that field, showing that thinge GPT4 is doing deep reconstructing of the original data while successfully inject different human features well inside the original MGT content, making those models thinks that the result is human written.

5.6.3 Mistral-7B

In Mistral-7B, it gets an extremely bad accuracy in both the M4 dataset and MGTBench case in table 17 and 20 which is even lower than using SVM only. However, the recall rate is comparable than the BiLSTM series model. Showing that in Mistral-7B model, it labels nearly perfect in machine-generated text but almost wrongly in human-written-text, which is because of over fitting to the machine-text data.

In the Mixset dataset in table 23, similar result happens where it got extremely poor in those mixing methods except the humanize like how SVM performed. Nonetheless, it got perfect score in humanize mixing method. It may be due to the fact that it is overly biased into the machine-generated text side instead of correctly identify the features inside the content.

6 Conclusion

In conclusion, this project has successfully implemented various methods for detecting the machine-generated text in different datasets, domains, and generators. Those methods, some can successfully detect the outofdistribution data like the data generated by GPT4 too. Nonetheless, those methods encounters some issue where they would mislabel the humanwrittentext into machinegeneratedtext which is not well accepted in some field like academic plagiarism detectors. In view of using LLM for mixing the text, it shows that using GPT4 to humanize the original machinegenerated data can indeed successfully fool other models, which would introduce some potential problem in those detectors.

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