INTERNATIONAL UNIVERSITY OF APPLIED SCIENCES

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INVESTIGATING LARGE LANGUAGE MODELS FOR THE DETECTION OF CYBERBULLYING

Vienna, Austria
November 25, 2025

CONTENT

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1

INTRODUCTION

MOTIVATION

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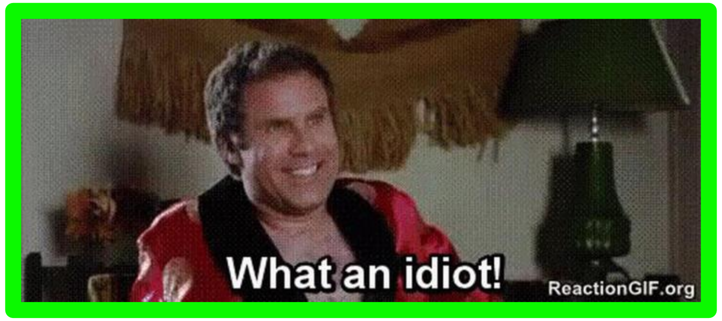

~50% OF TEENAGERS
HAVE EXPERIENCE WITH CYBERBULLYING *(Vogels, 2022)*

MOTIVATION

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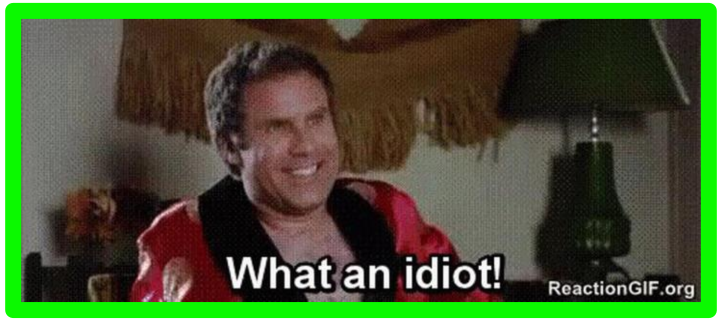
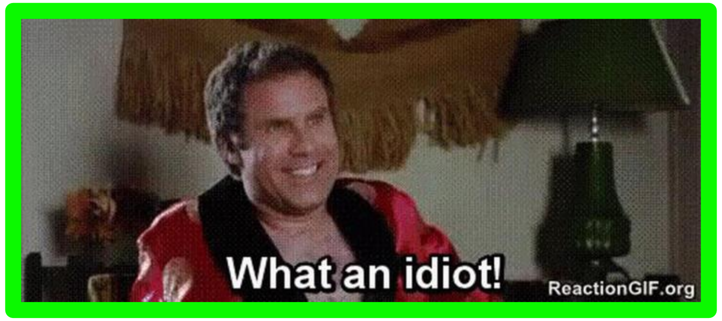


~50% OF TEENAGERS HAVE EXPERIENCE WITH CYBERBULLYING *(Vogels, 2022)*

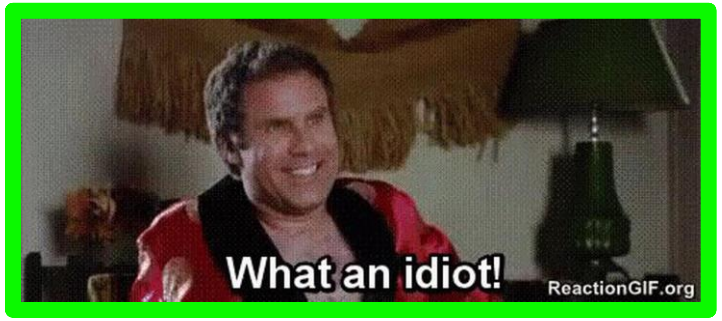
TROUBLE SLEEPING, DIFFICULTY CONCENTRATING, OR FEELINGS OF ANXIETY

MOTIVATION



CYBERBULLYING CAN BE MULTIMODAL! (*Vogels, 2022*)

MOTIVATION



CYBERBULLYING CAN BE MULTIMODAL! *(Vogels, 2022)*

TEXT, IMAGES, VIDEOS

MOTIVATION

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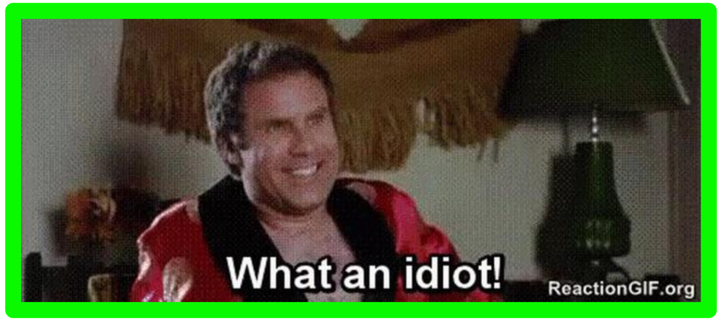
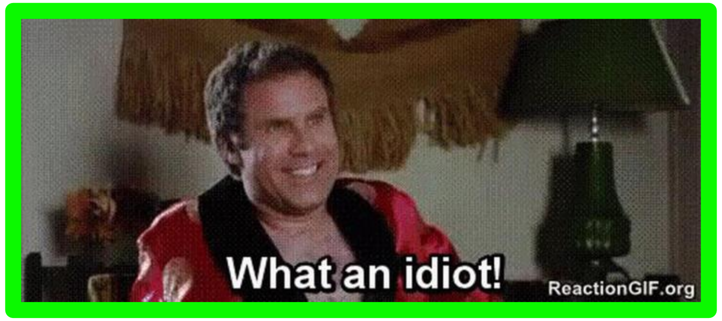


CHALLENGE:
TOO MUCH CONTENT FOR MANUAL DETECTION (*Vogels, 2022*)

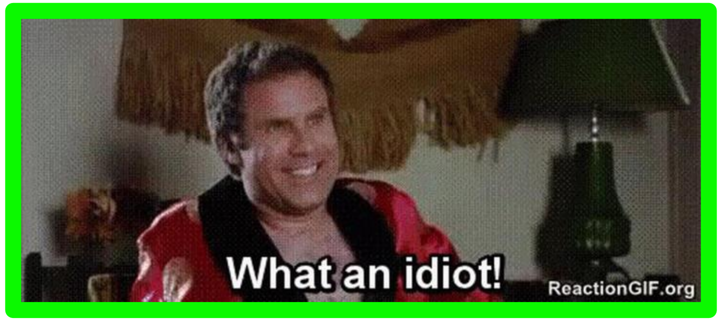
MOTIVATION



CHALLENGE:
TOO MUCH CONTENT FOR MANUAL DETECTION *(Vogels, 2022)*

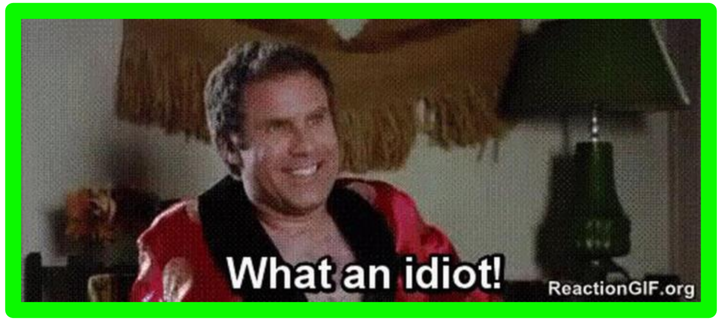
TOO MUCH ONLINE CONTENT TO MANUALLY MONITOR + ADDRESS EVERY CYBERBULLYING POST

MOTIVATION



SOLUTION:
AI TO DETECT CYBERBULLYING AUTOMATICALLY

MOTIVATION



SOLUTION: AI TO DETECT CYBERBULLYING AUTOMATICALLY

AUTOMATICALLY DETECT CYBERBULLYING AND ADDRESS IT MORE EFFECTIVELY AND AT SCALE

2

RELATED WORK

RELATED WORK

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TRADITIONAL +
TRANSFORMERS vs. LLMs

e.g., Nina-Gutiérrez et al. (2024), Shekhar (2024), Ramos at al. (2024)

RESEARCH ON CYBERBULLYING WITH LLMS LIMITED

RELATED WORK

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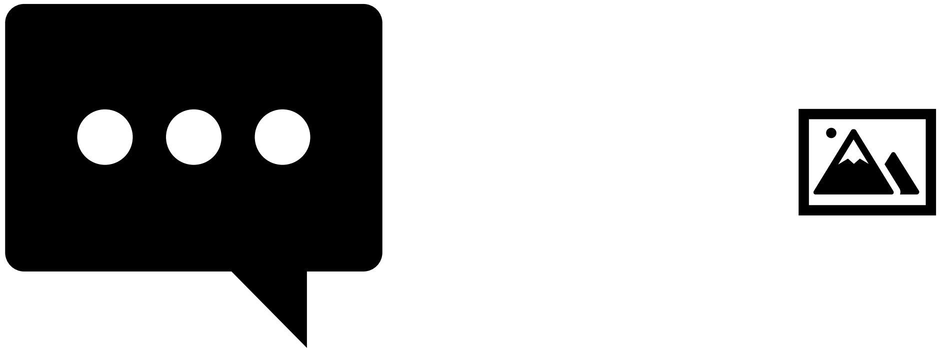
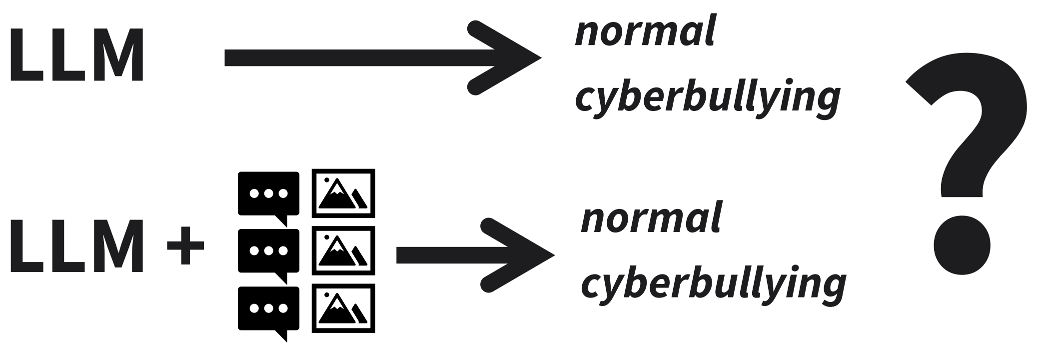


e.g., Batani et al. (2022), Islam et al. (2020), Raj et al. (2021), Alkomah et al. (2022), Atoum (2020), Van Bruwaene et al. (2020)

TEXT FEATURES ARE MORE INVESTIGATED

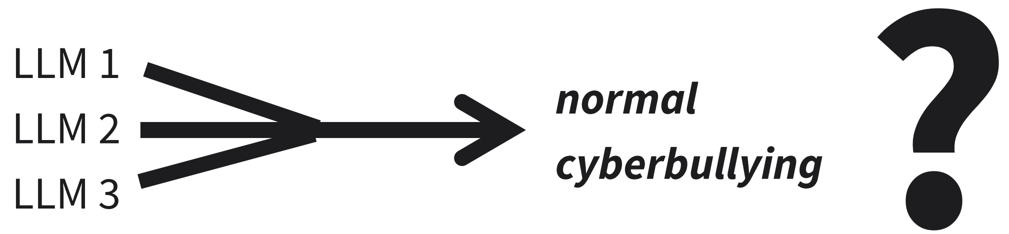
RELATED WORK



e.g., Bauer et al. (2024), Bucciarelli at al. (2024)

ZERO-SHOT VS. FEW-SHOT
ONLY FOR SENTIMENT ANALYSIS

RELATED WORK



e.g., Gomez et al. (2019), Mahlangu & Tu (2019), Yadav et al. (2020), Mahat (2021), Roy et al. (2020), Bharti et al. (2021)

LLM COMBINATION REMAIN UNEXPLORED

3

EXPERIMENTAL SETUP

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EXPERIMENTAL SETUP: LLMS

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Model	Provider	Context Window	Max Images	API Access
GPT-4o	OpenAI	128k	16	Paid
GPT-4o mini	OpenAI	128k	16	Paid
Gemini Flash-1.5	Google	1,000k	3	Free
Claude 3.5 Sonnet	Anthropic	200k	8	Paid
Pixtral-12b	Mistral	n.a.	8	Free

EXPERIMENTAL SETUP: LLMS

INTERNATIONAL UNIVERSITY OF APPLIED SCIENCES

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Claude 3.5 Sonnet	Anthropic	200k	8	Paid
Pixtral-12b	Mistral	n.a.	8	Free

TEXT + IMAGE, PRIORITIZED FREE ACCESS

EXPERIMENTAL SETUP: PROMPT FOR ZERO-SHOT

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You are an AI assistant tasked with identifying cyberbullying in social media posts.

Your task is to analyze the following post and determine if it is *normal* or *offensive*. *offensive* posts are those that demean, mock, discriminate against, or insult a person or group of people. *normal* posts do not contain *offensive* content.

Based solely on the content provided, classify the post as either *normal* or *offensive*. Respond with just one word: either *normal* or *offensive*.

Post: [TEXT and/or IMAGE]

ZERO-SHOT

EXPERIMENTAL SETUP: PROMPT FOR FEW-SHOT

You are an AI assistant tasked with identifying cyberbullying in social media posts.

Your task is to analyze the following post and determine if it is *normal* or *offensive*. *offensive* posts are those that demean, mock, discriminate against, or insult a person or group of people. *normal* posts do not contain *offensive* content.

Below are examples of posts and their classifications:
Example 1 (*normal*): [TEXT and/or IMAGE]
Example 2 (*offensive*): [TEXT and/or IMAGE]
[Examples 3-6 follow the same pattern]

Now, analyze the following post and determine if it is *normal* or *offensive*. Respond with just one word: either *normal* or *offensive*.

Post: [TEXT and/or IMAGE]

FEW-SHOT

EXPERIMENTAL SETUP: DATA

506 posts

(*Toraman et al., 2022*)

6 few-shot
- 3 *normal*
- 3 *offensive*

500 test
- 250 *normal*
- 250 *offensive*

EXPERIMENTAL SETUP: METRIC + MODALITIES

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F1 SCORE

Text-only

Image-only

Text + Image

4

RESULTS

RESULTS: ZERO-SHOT

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Content	Model	F1 (%)
Text-only	Claude Sonnet 3.5	82.52
	Gemini Flash 1.5	**85.64**
	GPT-4o mini	85.17
	GPT-4o	77.06
	Pixtral-12b	84.39

RESULTS: ZERO-SHOT

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STRONG TEXT COMPREHENSION CAPABILITIES

RESULTS: ZERO-SHOT

Content	Model	F1 (%)
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	Gemini Flash 1.5	**85.64**
	GPT-4o mini	85.17
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	Pixtral-12b	84.39
Image-only	Claude Sonnet 3.5	43.32
	Gemini Flash 1.5	42.81
	GPT-4o mini	47.26
	GPT-4o	45.78
	Pixtral-12b	**50.51**

RESULTS: ZERO-SHOT

INTERNATIONAL UNIVERSITY OF APPLIED SCIENCES

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	Pixtral-12b	**50.51**

< 50%

RANDOM F1 = 50%

RESULTS: ZERO-SHOT

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	Pixtral-12b	**50.51**

< 50%

RANDOM F1 = 50%

FUNDAMENTAL LIMITATION IN VISUAL PROCESSING

RESULTS: ZERO-SHOT

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	GPT-4o	45.78
	Pixtral-12b	$\boxed{\textbf{50.51}}$

< 50%

RANDOM F1 = 50%

HUMAN F1 = 65%

DIFFICULT FOR LLMS AND FOR HUMANS

RESULTS: ZERO-SHOT

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Text-only	Claude Sonnet 3.5	82.52
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	GPT-4o	45.78
	Pixtral-12b	**50.51**
Text + Image	Claude Sonnet 3.5	79.74
	Gemini Flash 1.5	77.15
	GPT-4o mini	79.48
	GPT-4o	**81.89**
	Pixtral-12b	72.88

RESULTS: ZERO-SHOT

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	GPT-4o	**81.89**
	Pixtral-12b	72.88

Ø 82.96%

Ø 78.22%

RESULTS: ZERO-SHOT

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	Pixtral-12b	72.88

Ø 82.96%

Ø 78.22%

IMAGES OFTEN DO NOT PROVIDE ADDITIONAL VALUABLE INFORMATION

RESULTS: FEW-SHOT

Content	Model	F1 (%)	F1 (%)
Text-only	Claude Sonnet 3.5	82.52	73.17
	Gemini Flash 1.5	**85.64**	54.74
	GPT-4o mini	85.17	66.00
	GPT-4o	77.06	**78.12**
	Pixtral-12b	84.39	75.51
Image-only	Claude Sonnet 3.5	43.32	49.06
	Gemini Flash 1.5	42.81	41.66
	GPT-4o mini	47.26	49.34
	GPT-4o	45.78	**51.35**
	Pixtral-12b	**50.51**	36.08
Text + Image	Claude Sonnet 3.5	79.74	70.64
	Gemini Flash 1.5	77.15	62.15
	GPT-4o mini	79.48	70.18
	GPT-4o	**81.89**	**78.33**
	Pixtral-12b	72.88	70.58

RESULTS: FEW-SHOT

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Content	Model	F1 (%)	F1 (%)
Text-only	Claude Sonnet 3.5	82.52	73.17
	Gemini Flash 1.5	**85.64**	54.74
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	Pixtral-12b	72.88	70.58

FEW-SHOT DID NOT CONSISTENTLY IMPROVE F1 OVER ZERO-SHOT

RESULTS: FEW-SHOT

Content	Model	F1 (%)
Text-only	Claude Sonnet 3.5	82.52
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	GPT-4o	**81.89**
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Ø 82.96%

F1 (%)
73.17
54.74
66.00
78.12
75.51

Ø 69.50%

RESULTS: FEW-SHOT

INTERNATIONAL UNIVERSITY OF APPLIED SCIENCES

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Ø 82.96%

F1 (%)
73.17
54.74
66.00
78.12
75.51

Ø 69.50%

RESULTS: FEW-SHOT

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	GPT-4o mini	79.48	
	GPT-4o	**81.89**	
	Pixtral-12b	72.88	

Ø 45.93%

Ø 45.49%

RESULTS: FEW-SHOT

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Ø 45.93%

F1 (%)
73.17
54.74
66.00
78.12
75.51
49.06
41.66
49.34
51.35
36.08

Ø 45.49%

RANDOM F1 = 50%

HUMAN F1 = 65%

RESULTS: FEW-SHOT

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	GPT-4o	**81.89**	**78.33**
	Pixtral-12b	72.88	70.58

Ø 69.50%

Ø 78.22%

Ø 70.37%

RESULTS: FEW-SHOT

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Ø 69.50%

Ø 78.22%

Ø 70.37%

INTERPRETATION: ZERO-SHOT VS. FEW-SHOT

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Content	Model	F1 (%)	F1 (%)
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INTERPRETATION: ZERO-SHOT VS. FEW-SHOT

‘KNOWLEDGE PRIORS’ EFFECT: PRE-TRAINED OVER FEW-SHOT

(Chochlakis et al., 2024)

	GPT-4o	77.06	**78.12**
	Pixtral-12b	84.39	75.51
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	Gemini Flash 1.5	42.81	41.66
	GPT-4o mini	47.26	49.34
	GPT-4o	45.78	**51.35**
	Pixtral-12b	**50.51**	36.08
Text + Image	Claude Sonnet 3.5	79.74	70.64
	Gemini Flash 1.5	77.15	62.15
	GPT-4o mini	79.48	70.18
	GPT-4o	**81.89**	**78.33**
	Pixtral-12b	72.88	70.58

INTERPRETATION: ZERO-SHOT VS. FEW-SHOT

‘KNOWLEDGE PRIORS’ EFFECT: PRE-TRAINED OVER FEW-SHOT

(Chochlakis et al., 2024)

FEW-SHOT EXAMPLES MAY NOT BE REPRESENTATIVE ENOUGH

	GPT-4o	77.06	**78.12**
	GPT-4o	45.78	**51.35**
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OVERFITTING: LLMS MAY BE TOO SENSITIVE TO EXAMPLES

RESULTS: LLM FUSION WITH MAJORITY VOTING

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Method	Content	All 5	Top 3	Best
zero-shot	Text	84.77	**87.59**	85.64
	Image	43.90	46.38	50.51
	Text + Image	81.95	81.43	81.89

RESULTS: LLM FUSION WITH MAJORITY VOTING

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few-shot	Text	71.73	77.13	78.12
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global top 3	Cross-method & modality		$\boxed{83.47}$	**85.64**

GEMINI FLASH 1.5 WITH ZERO-SHOT + TEXT: 85.64%

GPT-4O MINI WITH ZERO-SHOT + TEXT: 85.17%

GPT-4O MINI WITH ZERO-SHOT + TEXT+IMAGE: 85.89%

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MAJORITY VOTING NOT A UNIVERSAL SOLUTION

6

CONCLUSION AND FUTURE WORK

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Conclusion

- **LLMs perform very well on text-based cyberbullying detection**
  - ➔ achieving up to 85.64% F1 in zero-shot settings,
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Future Work

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- **Combine LLMs with specialized vision models**
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- **Fine-tune LLMs on cyberbullying data**
  ➔ Improve performance for both text and multimodal inputs through task-specific adaptation

THANK YOU

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