

# Darubini: A social media hate speech detector

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To develop an application for detecting political hate speech propagated over social media platforms in Kenya.

- Social media has permeated our lives.
- Control of communication over social media is difficult to achieve or enforce:
  - different legislative environments.
  - extreme fast flow and dynamism of information.
- Social media is a global megaphone for hate [1] – Mr. António Guterres, Secretary-General of UN.
- Hate Speech is a trigger of violence and precursor to atrocity crimes, genocide and suffering.

# Examples of atrocities linked to Hate Speech

- 1 Crises in Tigray – Ethiopia; Guinea; and Sri Lanka [2],
- 2 Kenya's 2007- 2008 political post-election violence [3],
- 3 Sino phobic hate during COVID – 19 pandemic [4],
- 4 Shaheen Bagh protests in New Delhi [5],
- 5 Xenophobic tensions in South Africa [6],
- 6 The Holocaust [16],
- 7 The 1994 genocide in Rwanda [16],
- 8 The Srebrenica genocide in Bosnia and Herzegovina [16],
- 9 The Cambodian genocide [16], and
- 10 The Rohingya refugee crisis in Myanmar [16].



**Detecting Hate Speech is important!**

- **Hate speech** is content defined by its action i.e., generally spreading hatred or *inciting violence*, or *threatening people's freedom, dignity and safety* **by any means**, and by **its target** – which must be *a protected group*, or an *individual targeted* for belonging to such a group and not for his/her individual characteristics [7].
- Hate speech can be propagated on social media through: *text messages, pictures, videos, emoji, or emoticons*.
- Hate speech could be obfuscated through: *intentional misspelling* [8], *hiding hate text messages in images*, and using *hate sarcasm* with images [9].

# Challenges of dealing with hate speech on social media

- 1 Produced easily at low cost,
- 2 Produced 'anonymously',
- 3 Distributed quickly to diverse audience,
- 4 Relative permanence of online content – can regain popularity.



**Hate speech detection and control deserves research attention!**

To develop “Darubini”, an application for detecting political hate speech that is propagated over social media platforms in Kenya.

- Darubini is a Swahili word for a telescope i.e., an optical instrument for observing distant astronomical objects like stars.
- Searching for hate-speech over social media platforms is synonymous to searching for new heavenly objects among the many stars in sky.

# Specific Objectives

By the end of this work, the project was expected to be able to:

- ① Develop a model for detecting political hate speech that is propagated over social media platforms in Kenya.
- ② Deploy the developed model as a web application for monitoring social media discourses.
- ③ Flag out hateful messages propagating through social media platforms.
- ④ Establish original authors of the flagged hateful messages (only for a special class of users).
- ⑤ Visualize severity of hate speech in given geographical locations.

# Gaps in contemporary hate-speech detection models

- ① Training dataset challenges:
  - Over-dependency on English language training datasets [17], [18] – excluding other languages;
  - Use of small sizes of training datasets [19], [20] and [21];
  - Data bias – poor data collection methods, data annotation challenges, and absence of contextual information [22], [23].
- ② Generalizability challenges of models [24]; and
- ③ Limited inclusion of relevant stakeholders in the war against hate-speech [25].

# Schema for the method

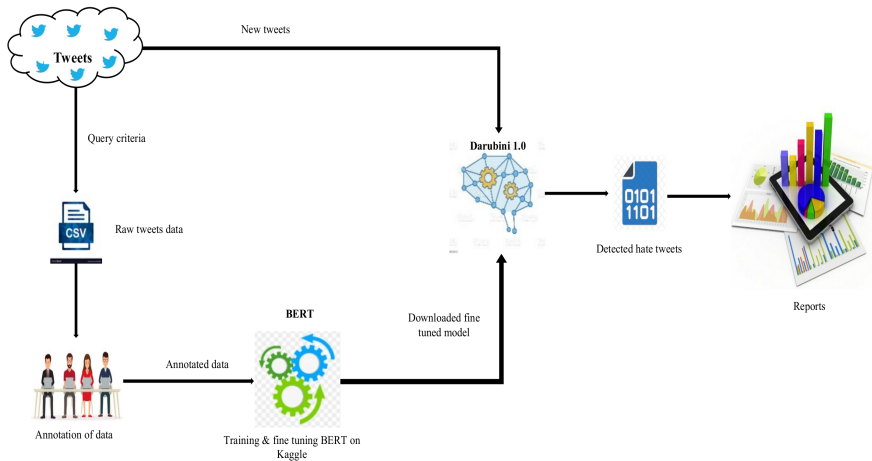


Figure 1: Schema for the method.

- BERT (**B**idirectional **E**ncoder **R**epresentations from **T**ransformers) model [26] fine tuned to classify text data (*Offensive, Hate Speech, Neither*) .
- **Why BERT?**
  - ❶ It alleviates the unidirectionality constraint of standard language models [26],
  - ❷ It understands contextual relationships across long sentences [27],
  - ❸ It is superior in hate-speech detection [27 – 31].

- Collected data from Twitter using Twitter API V2 [12] – No longer available.
- Period of collection – 1st January 2017 to 31st May 2022
- Query search criteria
  - hate words by National Cohesion and Integration Commission (NCIC) as political[13] – *sipangwingwi*.
  - political figures and political parties.
- Focus – text data:
  - most hate speech messages on social media are constructed through texts [14]
  - text models tend to outperform multi-modal models in detecting hate speech [15].
- Training data – 9247 records,
- Deployment Data – 135728 records (expected to continuously increase....).

SHENG' TERMS				
Commonly Used Hate Term	Translation	Target Community	User Community	Meaning
<b>Kama noma, noma. Kama mbaya, mbaya</b>	If it is bad, then it is bad.	Political aspirants and perceived supporters of the less dominant political party in an area	Political aspirants and supporters of the dominant political party in an area	This statement is perceived by communities that if an opposing political party plays foul, then party supporters should unleash the severest form of counterattack.
<b>Hatupangwingwi</b>	No one can arrange us	Specific families & communities that have been in power for long particularly the Luo, and Kikuyu.	Political aspirants from families/ communities that have not been at the center of power in the past	This statement is used to underscore the fact that some families/ communities have been at the periphery of national leadership and influence for so long and they no longer want to remain out.
<b>Operation Linda Kura</b>	Secure the vote	Political aspirants and supporters of the less dominant political party in an area	Political aspirants and supporters of the dominant political party in an area	This statement is perceived as a rallying call by the political party to ensure that there will be rigging and voters should

Figure 2: Sheng' terms.

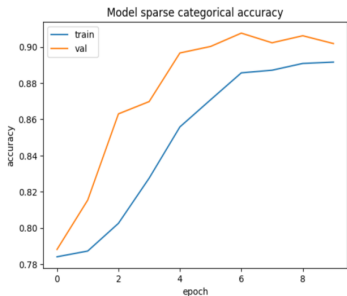
- **Demo of Darubini**

# Results: Performances of fine-tuned BERT models

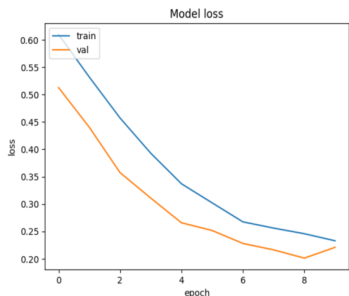
Hyper-parameters	Model_A	Model_B	Model_C	Model_D
Learning_rate	5.00E-05	5.00E-05	3.00E-05	3.00E-05
epochs	15	5	5	10
Batch_size	32	32	32	32
Validation_split	0.1	0.1	0.1	0.1
Dropout_rate	0.1	0.1	0.1	0.1
Attention_heads	12	12	12	12
Hidden_size	768	768	768	768
Number_of_layers	12	12	12	12
loss	0.6375	0.6373	0.2921	<b>0.2209</b>
Sparse_categorical_accuracy	0.7867	0.7867	0.8600	<b>0.9018</b>
Test_accuracy	0.79000	0.78673	0.85797	<b>0.90180</b>

Figure 3: Summary of performance of models for given hyper-parameters.

# Results: accuracy & loss



(a) Accuracy against number of epochs.



(b) Loss against number of epochs.

Figure 4: Accuracy and loss for Model\_D.

# Results: Comparizon of models

Author	Best performing Technique	Metrics for measuring model performance
Gomez et al. [9]	LSTM + Glove embeddings	F-Score = 0.703, AUC = 0.732, Accuracy=68.4%
Ong [32]	BiLSTM-CNN	F1-Score=0.75
Badjatiya et al. [33]	LSTM, LSTM+Random Embedding+Gradient, Boosted Decision Trees	Precision = 0.930, Recall=0.930, F1=0.930
Dorris et al. [34]	LSTM	Accuracy 90.82%
Ndenga [35]	GradientBoostedTrees with embeddings	Accuracy = 98.86%, Recall=0.9587, Precision=0.9831, AUC =0.9984
This research (Model_D)	BERT (Bidirectional Encoder Representations from Transformers)	Accuracy = 90.18%, Recall=0.8997, Precision=0.9023, AUC =0.99038

Figure 5: Performance comparisons of hate-speech detection models.

- The purpose of this research was to propose a model for detecting political hate speech in Kenya propagated through social media platforms.
- The BERT model has exhibited a comparatively good performance for a hate-speech detection according to the contemporary state-of-the-art.
- Therefore, this model can be utilized for detecting hate speech on social media platforms.

This study has made three contributions;

- 1 Developed a new model for detecting hate-speech and shared it on Kaggle<sup>1</sup>.
- 2 Packaged the model and hosted it as Darubini: A social media hate-speech detector<sup>2</sup> – registered by Kenya Industrial Property Institute (KIPI) as a utility model – registration number **KE/U/2024/2346 (22) 16/01/2024**.
- 3 Created a new annotated raining dataset for training hate-speech detection models and shared it Kaggle.

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<sup>1</sup><https://www.kaggle.com/malangalanga/darubini-bert-model>

<sup>2</sup><https://darubini-hatespeech-detector.streamlit.app/>

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Thank You.  
Questions?