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# Arabic Offensive Language Classification: Leveraging Transformer, LSTM, and SVM

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**Abstract**—Social media platforms have become indispensable parts of our lives, offering avenues to share news, thoughts, and updates, as well as connect with new friends and explore various fields of knowledge. However, these platforms also harbor challenges, as they can inadvertently propagate hate speech and offensive content. Arabic, being the sixth most spoken language globally and widely used in over 22 countries, requires special attention to control and prevent the spread of hate speech. The core objective of this study is to develop an improved Arabic model for classifying offensive content, achieved by merging multiple Arabic hate and offensive datasets, including Iraqi offensive samples. Three distinct strategies were used: support vector machine (SVM), long short-term memory (LSTM), and the AraBERT transformer model. The used models were evaluated using recall, precision, F1-score, and accuracy metrics. Notably, the transformer model consistently outperformed the others across all metrics, showcasing its superior performance. Moreover, each dataset underwent assessment using the three models, consistently revealing the transformer’s heightened efficiency.

**Index Terms**—NLP, Machine learning, Transformer, SVM, offensive language

## I. INTRODUCTION

The Arab countries, home to over 300 million people, encompass one of the largest linguistic gatherings. Situated in the Middle East and North Africa, these countries straddle two continents, Asia and Africa, with significant diasporas residing in Europe and America [1]. Within this rich tapestry, ancient civilizations like Sumerian Iraq and Pharaonic Egypt thrive, coexisting alongside a myriad of diverse regions and cultures [2]. However, such diversity can sometimes give rise to disagreements among inhabitants, with social media platforms amplifying these disputes within the region. Effective content control plays a crucial role in creating a safer online community.

Various techniques are employed to prevent the dissemination of offensive content, with one approach involving manual review by individuals to determine whether a post, comment, or any type of content should be allowed for publication [3]. While this method can be thorough, it may not be practical for large-scale social media networks, as it demands significant effort and requires many users to review all posts. An alternative technique entails compiling a dataset of offensive words and comparing each new post or comment against this list to prevent publication [4]. Although this approach reduces

manual effort, it carries the risk of false positives, potentially blocking posts that contain offensive words without intending harmful content.

In recent decades, the field of information technology has witnessed a remarkable surge in its focus on artificial intelligence [5]. This shift has brought forth a wide array of techniques and algorithms. It all begins with machine learning, which empowers computers to learn and make predictions without explicit programming. Within machine learning, there are multiple approaches, such as Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), among others [6]. Next, we have deep learning, where neural networks are employed to automatically extract intricate patterns from data. Prominent examples include convolutional neural networks (CNN) and recurrent neural networks (RNN) [7], [8]. In the past five years, an exciting new method known as the transformer has emerged. This powerful deep learning architecture has revolutionized natural language processing through its attention mechanism, enabling improved language understanding and generation.

Using neural networks to learn data patterns and understand sentiment contexts makes these techniques a preferred choice for research tasks like classification and text analysis [9]. The following section includes the most recent research related to this work, focusing solely on methods for classifying the Arabic language and not considering other languages.

Nuha Albadi et al in [10] provided the first Arabic religion hate speech dataset, consisting of about 6.6k tweets. They evaluated the dataset using three approaches: Lexicon-based approaches, N-gram-based approaches, and deep learning approaches. The best result was achieved by using deep learning GRU and RNN-based approaches, which achieved an accuracy of 79%.

Hatem Haddad et al in [11] provided the first offensive and hate speech targeting dataset for Tunisia, comprising 6K tweets. The dataset exclusively focuses on Tunisian discourse. The authors used Term Frequency-Inverse Document Frequency (TF-IDF) to extract n-gram features and fed them into two machine learning algorithms: Support Vector Machine (SVM) and Naive Bayes (NB). These algorithms were individually evaluated and achieved high accuracy with a two-class classification by using NB approximately 92%.

Abu Farah et al in [12] developed a multi-task learning architecture based on CNN-BiLSTM for offensive language and hate speech recognition, using the OSACT2020 dataset. The proposed model was evaluated alongside BiLSTM, CNN-BiLSTM, and BERT models. The results showed that the proposed system outperformed the other models, achieving an impressive accuracy of 90.4%.

Duwairi et al in [13]. evaluated three neural network architectures, namely CNN, CNN-LSTM, and BiLSTM-CNN, for detecting hateful content on social media. The authors used the ArHS dataset, comprising approximately 10k tweets annotated with categories such as racism, religious, abusive, and normal. The CNN model achieved the best accuracy, with an impressive score of 81%.

Wassen Aldjanabi et al in [14]. utilized three popular Arabic hate datasets: OSACT-OFF, HSAB, and T-HSAB, to evaluate a proposed system based on MarBERT and ArabBERT. The model achieved an accuracy of 95% with OSACT-OFF, 87% with HSAB, and 80.86% with T-HSAB.

Faisal Yousif in [15] A proposed new dataset consisting of approximately 4k comments, containing categories such as religion, bully, hate speech, and normal, was created. The dataset was evaluated using two proposed RNN architectures: DRNN-2 and DRNN-1, each having different architectures and layers. The system achieved outstanding performance with binary classification accuracy of 99.73%. Table I presents an in-depth overview of the recent relevant studies and datasets focusing on Arabic offensive content.

Based on the previous work, we can draw three main conclusions. First, the largest dataset contains only 10,000 samples, which can be considered relatively small. Second, the high performance achieved with the largest dataset is 90%, while the small dataset achieved an impressive 99.73%, indicating the potential for overfitting with the latter. Third, some datasets are limited to a specific dialect, which means they may not be applicable to other Arabic dialects. The primary objective of this work is to develop a robust and more generalised Arabic model capable of detecting offensive and hateful Arabic content with high accuracy. The model is trained on an extensive and diverse dataset, enabling it to achieve superior performance compared to other existing systems in identifying hateful Arabic content. In the following the main contributions of the paper.

### Contributions

- **Enhanced Arabic Offensive Dataset:** The paper creates a more comprehensive Arabic offensive content dataset by re-labeling multiple existing datasets, resulting in a higher quality resource for classification.
- **Inclusion of Iraqi Dialect:** The dataset is expanded to incorporate Iraqi dialect samples, increasing its diversity and representativeness of Arabic language variations.
- **Model Performance Evaluation:** The paper assesses and compares the effectiveness of machine learning, RNN, and transformer models (ArABERT) for Arabic offensive content classification.

- **Model Performance:** Leveraging AraBERT with the newly processed dataset yields outstanding results, surpassing many recent works in the field.

## II. ARABIC OFFENSIVE CONTENT DATASET

To develop an advanced and high-performance deep learning system, the quantity and quality of the dataset play a crucial role. The aim of this work, as mentioned, is to produce a more general system for Arabic offensive content. We have used different datasets to accommodate different Arabic dialects, and we have relabeled them and combined them into a large signal file. In the following, a brief description of each dataset is used.

- **T-HSAB:** its first hate speech and abusive language in the Arab-Tunisian context. It was proposed at the Arabic Language Processing Conference in Nace, France, in 2019. The dataset was collected from various social media platforms, including YouTube comments, Facebook, and Twitter, and comprises 6,000 samples.
- **OSACT2020:** It is a multilingual Arab offensive dataset comprising three files: a training set, a development set, and a testing set. The dataset contains about 10k samples collected from Twitter, including content from different Arab dialects such as Iraqi, Gulf, Egyptian, Levantine, and Maghrebi. This dataset was used as part of the shared task in the Fourth Workshop on Open-Source Arabic Corpora and Corpora Processing Tools.
- **LHSAB:** It is the first Arabic-Levantine hate speech and abusive dataset proposed at the 3rd Workshop ALW-2019 in Florence, Italy. The dataset was collected from Twitter and comprises many diverse samples from Syrian and Lebanese communities. It contains about 5.8k samples.
- **Let-Mi:** This Dataset was created in 2021, focusing on Arabic-Levantine misogynistic language. The dataset contains 6.6k samples collected from various Lebanese female journalists.

The fourth dataset is classified into two types: first, all samples with hate speech, abuse, and misogynistic language are classified as offensive, while the other dataset samples are classified as normal. The files are then combined into one large dataset with two classes: samples with offensive content labeled as 1, and normal samples labelled as 0. For each sample, any usernames or URLs are removed to protect privacy. We have created a simple program to check the correct labeling of the dataset and to identify any errors in the labeling process (see Figure 1). Additionally, as the authors of this paper are Iraqis, multiple offensive and normal Iraqi samples were added to create a more comprehensive dataset, resulting in a total of 25.3k samples<sup>1</sup>, following this, the dataset was shuffled to eliminate any ordering patterns. This step was taken to enhance the robustness of the dataset and mitigate the risk of overfitting during the splitting process.

<sup>1</sup>[https://github.com/AREEG94FAHAD/Arab\\_Offensive\\_dataset](https://github.com/AREEG94FAHAD/Arab_Offensive_dataset)

Table I  
OVERVIEW OF THE RECENT RELEVANT STUDIES AND DATASETS

Ref	Name	Size	Dialect	Method	Accuracy
[10]	AraHate	6.6k	Multiple	Lexicon N-gram GRU-RNN	79%
[11]	T-HSAB	6k	Tunisia	NB SVM	92%
[12]	L-HSAB	5.8k	Levantine	NB SVM	90%
[13]	OSACT2020	10k	Multiple	MT CNN-BiLSTM	90.04%
[14]	OSACT2020	10k	Multiple	CNN CNN-LSTM BiLSTM-CNN	81%
[16]	Let-Mi	5.2k	Levantine	NB SVM	89%
[14]	L-HSAB OSACT2020 T-HSAB	5.8k 10k 6k	Multiple	MarBert AraBert	95% 87% 80.68%
[15]	4k	None	Multiple	DRNN-1 DRNN-2	99.73%



Figure 1. A data labelling simple program designed to check the correctness of data samples. The interface displays the actual label and row index to track progress. It includes three buttons: one for changing the label to "offensive," another for changing it to "normal," and a "save" button to save the new version to a CSV file.

### III. OFFENSIVE ARABIC MODELS

After preprocessing the dataset, we partitioned it into 80% for training and 20% for testing. The training data was then fed into the models, as illustrated in Figure 2. We employed three distinct models for classifying offensive Arabic text. The initial model utilized was a Support Vector Machine (SVM) based on the chi-square method. The second model employed was a Long Short-Term Memory (LSTM), and the third model chosen was the AraBERT transformer model. Subsequent sections will delve into the implementation details of each model.

#### A. Support Vector Machine based Chi-Square model

The Support Vector Machine is a powerful supervised machine learning algorithm used for completing classification tasks, particularly for text and image classification [17]. SVM aims to find a hyperplane that effectively separates the data points of different classes. This hyperplane can take the form of a linear or nonlinear plane depending on the nature of the

dataset. Since the machine learning algorithm only accepts numerical data for processing, we used the Term Frequency-Inverse Document Frequency (TF-IDF) for this purpose which is also used to measure the importance of words in a dataset sample relative to all dataset samples [18]. TF-IDF converts each feature into a numerical value based on its appearance in each sample and the entire dataset. This approach assigns higher weights to the most impactful features. To compute TF-IDF for each feature, we first calculated the TF of each feature in each sample, as shown in Equation 1.

$$TF = \frac{N_i}{N_t} \quad (1)$$

Where  $N_i$  represents the number of word occurrences in a dataset sample, while  $N_t$  represents the total number of features in a sample. Next, we computed the IDF for each feature in the dataset, as shown in Equation 2. Here,  $N$  is the total number of dataset samples, and  $N_x$  is the number

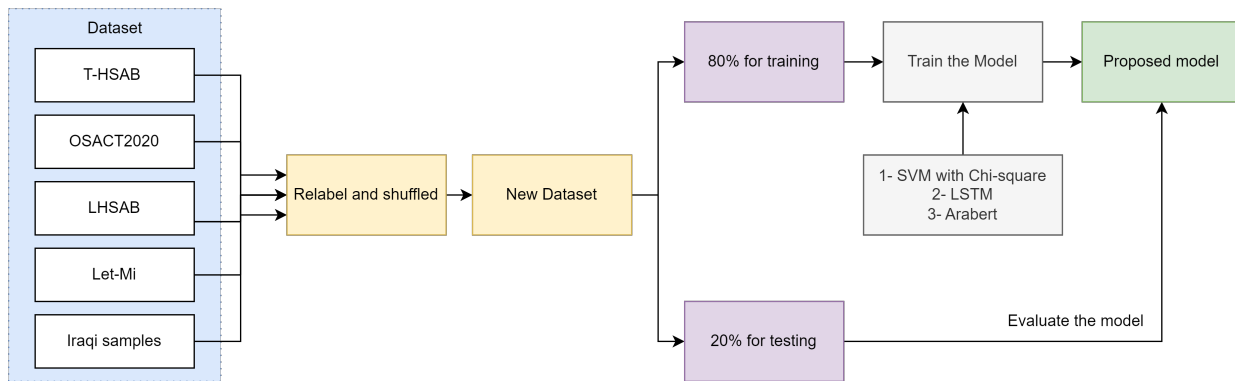


Figure 2. The proposed model architecture

of samples containing the feature. Finally, the TF-IDF was computed using Equation 3.

$$IDF = \log \left( \frac{N}{N_x} \right) \quad (2)$$

$$TF - IDF = TF \times IDF \quad (3)$$

After computing the TF-IDF values and converting each dataset sample into a vector representation, we advanced to the implementation of the Chi-squared method. The primary objective is to discern and preserve the utmost significant features, discarding those with lesser influence. This crucial manoeuvre empowers our approach to precisely highlight the most distinguishing attributes for each class, effectively guiding the model's focus towards the most relevant information. As a result, the performance of the method is enhanced, and the dimensionality of the feature space is reduced, leading to efficient computational processing. To compute the chi-square for each feature in the dataset, we need to first compute the number of occurrences of each feature in each class, denoted as  $N_{w,c}$ . Then, calculate the number of samples in each class, denoted as  $N_c$ , and the total number of occurrences of each feature, denoted as  $N_w$ . These values will be used to compute the expected frequency ( $EF$ ) in each class, as shown in Equation 4. Subsequently, the Chi-Square value for each feature can be computed using Equation 5.

$$EF_{w,c} = \frac{N_w \cdot N_c}{N} \quad (4)$$

$$X^2 = \frac{(N_{w,c} - EF_{w,c})^2}{EF_{w,c}} \quad (5)$$

The TF-IDF values of the features are multiplied by the corresponding Chi-square values across all dataset samples. The unselected features are disregarded, and the resulting new vector is fed into the SVM model for classification.

### B. Long Sort Term Memory

Long Short-Term Memory (LSTM) is a recurrent neural network architecture that excels at capturing sequential patterns in data [19]. It is extensively used in tasks involving

sequences, such as sentence comprehension, text classification, and various Natural Language Processing (NLP) tasks. There are multiple LSTM architectures designed to accommodate different data and task requirements. For instance, the 'many-to-many' architecture is employed in tasks like machine translation, while the 'one-to-many' architecture is suitable for tasks like paragraph generation. In this work, we leverage the 'many-to-one' LSTM architecture. Since the dataset used comprises samples the objective is to classify them into one specific feature.

The system architecture of the LSTM is show in Figure 2. The model architecture is a Sequential neural network tailored for binary classification tasks. Its core components consist of an Embedding layer that transforms word indices into 256-dimensional dense vectors, enhancing the representation of text data. To combat overfitting, a 1D Spatial Dropout layer with a dropout rate of 0.2 is strategically positioned. The heart of the architecture comprises four LSTM layers, each progressively extracting intricate patterns: a 512-unit LSTM layer with dropout of 0.2 and recurrent dropout of 0.2, followed by a 256-unit LSTM layer with dropout of 0.21 and recurrent dropout of 0.32, then a 128-unit LSTM layer with dropout of 0.22 and recurrent dropout of 0.34, and lastly a 100-unit LSTM layer with dropout of 0.12 and recurrent dropout of 0.32. Culminating the architecture is a Dense layer equipped with a sigmoid activation function.

### C. Transformer model (AraBert V2)

Transformer is a revolutionary neural network technology for sequence-to-sequence tasks that is proposed in [20]. The main idea of the Transformer is based on the attention method, which allows each feature in the sequence to attend to all other features simultaneously. which is to process all features in a dataset sample simultaneously rather than sequentially as in RNN. The Transformer has proven to be highly efficient for tasks like machine translation, text generation, and more.

BERT, an advancement built upon the Transformer architecture, introduced a groundbreaking approach to language modeling [21]. Developed by Google AI, BERT employs bidirectional training by processing text in both directions during pre-training. This innovation enables BERT to capture deep

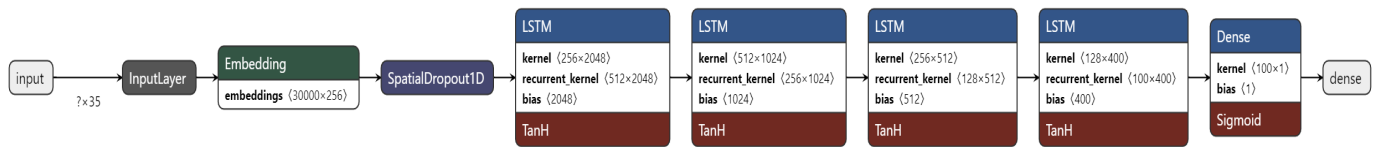


Figure 3. LSTM model architecture

contextual relationships between words, leading to improved language understanding. BERT’s pre-trained embeddings can be fine-tuned for various NLP tasks.

In this work, we used the AraBERT model. AraBERT is a specialized variant of BERT designed for Arabic text processing. Developed in [22], AraBERT leverages BERT’s bidirectional architecture to understand the nuances of the Arabic language context. Similar to BERT, AraBERT is pre-trained on a large Arabic text corpus using a masked language modeling objective. We have tuned the ArabBert for our task classification, and we use it to classify offensive Arabic content. The AraBERT model version utilized in this study is AraBERT V2. This version offers notable improvements, including enhanced preprocessing of punctuation and numbers. Moreover, AraBERT V2 benefits from a substantially larger training dataset compared to its predecessor, with an expansion of over 3.5 times.

#### IV. EXPERIMENTAL EVALUATION AND COMPARATIVE ANALYSIS

The datasets utilized, including THSAB, LHSAB, Let-Mi, and OSACT2020, underwent a thorough evaluation employing established classification metrics: Recall, Precision, F1-score, and accuracy. Our assessment encompassed three approaches highlighted in Section 3: SVM, LSTM, and AraBert.

To ensure a comprehensive evaluation, we explored various hyperparameters—distinct learning rates for each dataset, diverse batch sizes, and variations in the number of features (MF) alongside the integration of chi-square features. The dataset division adhered to an 80-20 split, dedicating 80% for training and reserving 20% for robust testing. methodology utilized for assessing the datasets considered earlier. the performance results are shown in Table 2.

#### V. DISCUSSION

In this section, we delve into a comprehensive discussion of our results. As showcased in Table 2, a clear trend emerges: the utilization of transformer techniques demonstrates superior performance across all datasets. Notably, the transformer approach outperforms both machine learning methods such as SVM and recurrent techniques like LSTM. This observation holds true for all performance metrics assessed. This significant enhancement can be attributed to our employment of AraBERT v2, a transformer model fine-tuned on substantial datasets including the expansive Wikibida Arabic corpus. This abundance of training data empowers the system with an inherent linguistic adaptability, yielding weight distributions that are finely attuned to the nuances of Arabic language.

An additional distinguishing feature lies in the architecture itself. The Bidirectional structure of BERT facilitates training on both contextual sides, fostering a deeper understanding compared to the unidirectional approach taken by LSTM or the feature-based strategy of SVM. Furthermore, AraBERT’s training regimen encompasses the OSACT202 dataset, a key component of this study. This implies that AraBERT is already acquainted with offensive language constructs, thereby endowing it with a foundational knowledge base.

The results also demonstrate that LSTM outperforms SVM in terms of F1-score and Recall. LSTM’s strength lies in its ability to thoroughly comprehend and analyze the content and contextual information of each word, facilitating a more nuanced understanding of feature relationships compared to SVM. This nuanced understanding results in LSTM excelling at identifying false negatives, a crucial aspect of the recall metric.

#### VI. CONCLUSION

The main goal of this study is to create a more versatile model for categorizing offensive Arabic content. To achieve this, multiple datasets were collected, processed, and expanded with additional samples. The effectiveness of the model was then assessed using three different approaches: SVM, LSTM, and AraBERT. The results show the significant impact of leveraging transformer-based models, which possess the ability to capture intricate patterns and nuances in the Arabic language context. AraBert V2, being fine-tuned on a large Arabic text corpus, exhibited remarkable adaptability and linguistic understanding.

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Table II  
RESULTS FOR DIFFERENT DATASETS AND METHODS

Dataset	Method	LR	BS	Chi-Square	Recall (%)	Precision (%)	F1-Score (%)	Accuracy (%)
T-HSAB	SVM	-	-	8k	55.87	91.63	69.42	81.57
	LSTM	48e-4	18	-	80	80	80	81
	AraBert	8e-6	8	-	98.88	99.32	99.10	99.34
OSACT202	Ref	-	-	-	-	-	-	-
	SVM	-	-	4.9k	64.38	86	73.66	90.80
	LSTM	2e-4	30k	-	89	88	88	88.64
LHSAB	AraBert	8e-6	8	-	99.28	100	99.64	99.86
	SVM	-	-	11k	56.83	86.53	68.60	83.40
	LSTM	5e-4	28	-	82	82	80	82
Let-Mi	AraBert	8e-6	8	-	99.69	9848	99.08	99.49
	SVM	-	-	4.2k	80.06	92.37	86.01	87.30
	LSTM	5e-4	32	-	82.1	84.50	83.3	83.5
New Dataset	AraBert	8e-6	8	-	99	98	99	99
	SVM	-	-	27.3k	64	85.37	73.33	86.50
	LSTM	5e-4	32	-	82	83	81.3	83.5
	AraBert	8e-6	8	-	97	98	98	99

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