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Improved Emotion Detection Framework for Arabic Text using Transformer Models

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Abstract: Emotion detection in text is a challenging task with various applications in natural language processing and psychology. In recent years, there has been increasing interest in developing algorithms for detecting emotions in Arabic text, given the importance of this language and the lack of resources in this domain. This paper proposes the use of transformer-based models for Arabic emotion detection in text. We use the emotone_ar dataset, a resource for the development and evaluation of algorithms and techniques for emotion detection in Arabic. The proposed model is based on transformers for encoding contextual information in text and classify emotions based on this encoded representation. We evaluate the performance of our model on the emotone_ar dataset and compare our results to previous methods for emotion detection. Our model achieves an accuracy of 74.16% and an F1 score of 0.7406 on the test set, outperforming previous methods for emotion detection on this dataset. We also compare our results to the performance of a Naïve Bayes classifier and show that our approach significantly outperforms this baseline. These results demonstrate the effectiveness of transformer-based models for emotion detection in Arabic text and highlight the potential for further improvements in this area.

Keywords: Twitter Emotion detection, Transformer models, Arabic NLP.

Introduction

Emotion detection in Arabic text is an important and growing research area in the field of natural language processing. The ability to accurately identify and classify emotional content in Arabic text can have numerous practical applications, such as improving the effectiveness of social media platforms, enhancing customer service interactions, and aiding in the development of more empathetic and personalized artificial intelligence systems.

Emotion detection in Arabic text is a novel research area within the broader field of natural language processing. While emotion detection has been studied extensively in other languages, the unique features of the Arabic language and the cultural differences of the Arabic-speaking community have presented new challenges and opportunities for research.

For example, the complexity of the Arabic script and the presence of various dialects and language registers have required the development of new algorithms and techniques specifically tailored to the Arabic language. Additionally, the cultural and social norms of the Arabic-speaking community can influence the way emotions are expressed in text, making it important to consider these cultural differences when developing emotion detection models.

However, this research area presents unique challenges due to the complexity of the Arabic language and the limited availability of annotated Arabic datasets.

In addition to its practical applications, emotion detection in Arabic text is also of great interest in the field of social media analysis. Twitter, in particular, is a rich source of data for studying emotions in real-time, as users often express their feelings and opinions on various topics through tweets. However, the use of social media platforms like Twitter also introduces additional challenges for emotion detection in Arabic text. For example, the use of slang, abbreviations, and emoticons can make it difficult for algorithms to accurately identify emotions. Additionally, the presence of multiple dialects and language registers within the Arabic-speaking Twitter community can further complicate the task of emotion detection. Despite these challenges, researchers have made significant strides in developing methods for emotion detection in Arabic text on Twitter, and this research is expected to continue to be an active area of study in the future.

In addition to the challenges posed by the complexity of the Arabic language and cultural differences, the use of social media platforms like Twitter has introduced new challenges and opportunities for emotion detection in Arabic text. For example, the use of slang, abbreviations, and emoticons on social media platforms can make it difficult for algorithms to accurately identify emotions. Additionally, the presence of multiple dialects and language registers within the Arabic-speaking Twitter community can further complicate the task of emotion detection. However, the vast amount of data available on social media platforms also presents a unique opportunity for researchers to study emotions in real-time

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and at a large scale.

This paper makes several contributions to the field of emotion detection in Arabic text. Firstly, we propose the use of transformer-based models for this task, which have shown to be highly effective in other natural language processing tasks. Our model is able to capture contextual information and encode it in a dense vector representation, which is then used for emotion classification. This approach outperforms previous methods for emotion detection in Arabic text, demonstrating the effectiveness of transformer-based models in this domain.

Secondly, we use the emotone_ar dataset, which is a resource specifically designed for emotion detection in Arabic text. The availability of this dataset is a significant contribution in itself, as it provides researchers and practitioners with a standardized and comprehensive resource for the development and evaluation of algorithms and techniques for this task. By using this dataset, we are able to ensure that our results are comparable to those of other researchers, which is essential for advancing the state-of-the-art in emotion detection in Arabic text.

The novel aspect of this paper is the application of fine-tuning a pre-trained transformer model to the task of emotion detection in Arabic text, using the emotone_ar dataset (Al-Khatib and El-Beltagy, 2018). To the best of our knowledge, this is the first study to use this specific fine-tuning approach and dataset for this task. The results demonstrate the effectiveness of the proposed method, achieving strong performance in comparison to the benchmark models, including the Complement Naive Bayes classifier, with an overall accuracy of 74.16%, F-measure of 0.7406.

The motivation of this research lies in the growing need for natural language processing techniques that can effectively analyze and understand the sentiments and emotions expressed in Arabic text. The proposed method provides a novel and effective approach for this task, and the emotone_ar dataset can be used as a valuable resource for future research in this area. Additionally, the results of this study have the potential to be applied to various applications such as social media analysis, sentiment analysis, and opinion mining in Arabic language.

In this paper, we propose the use of transformers for Arabic emotion detection in text. Specifically, we propose the use of a transformer-based model to encode the contextual information in text and classify emotions based on this encoded representation. The emotone_ar [16] dataset as a resource for the development and evaluation of algorithms and techniques for emotion detection in Arabic. We evaluate the performance of our model on the emotone_ar [16] dataset and compare our results to previous methods for emotion detection.

In Section 2, we provide an overview of related work in the field of emotion detection in text, including previous methods and their limitations. In Section 3, we describe the dataset used for the training and evaluation of our model, including the preprocessing steps. Section 4 presents the proposed model in detail, including the architecture and training process. In Section 5, we conduct experiments to evaluate the performance of our model and compare it to previous approaches. We find that our model outperforms previous methods in terms of accuracy and efficiency.

Finally, in Section 6, we conclude the paper and outline potential directions for future research. Our work highlights the potential of transformer-based models for emotion detection in text and suggests that this approach has the potential to be applied to a variety of other NLP tasks.

2 Related works

Text categorization problem is investigated using transformers, BERT (Bidirectional Encoder Representations from Transformers) [1], which pre-trains a deep bidirectional transformer model on large-scale corpora and fine-tunes it for downstream tasks such as text classification. Similarly, GPT (Generative Pre-trained Transformer) for language modeling, which has also been adapted for various NLP tasks such as text classification and sentiment analysis [2]. In a recent work [3], Huang et al. a dual-path transformer architecture for text classification, which combines both word-level and sentence-level representations for better performance.

Another work tried solving sentiment analysis using transformers [4], proposed a multi-task learning framework, which jointly learns sentiment analysis and emotion recognition tasks. They utilized a transformer-based model and achieved promising results on benchmark datasets. A dual-attention mechanism for sentiment analysis using transformers, which utilizes both word-level and sentence-level attention for better performance [5]. Our proposed approach for emotion detection in Arabic text can be seen as an extension of these works, where we focus specifically on the task of emotion detection in Arabic text and utilize a transformer-based model for better performance.

Emotion detection in Arabic text has received considerable attention in recent years due to its potential applications in various domains such as social media analysis, customer service, and healthcare. Emotion detection is defined as the process of identifying and classifying emotional states from textual data. It is a challenging task due to the inherent complexity of natural language and the cultural nuances of different languages. Despite the increasing demand for emotion detection in Arabic text, the development of effective algorithms and techniques has been hampered by the lack of annotated datasets [6].

The importance of emotion detection in Arabic text can be observed in the context of social media platforms. Social media has become a ubiquitous means of communication, and its usage has increased exponentially in the Arab world [7]. Social media platforms are a rich source of data that can be used to understand the emotional states of users. Emotion detection in Arabic text can help social media platforms to monitor and analyze the emotional responses of users towards various events and topics. This information can be used to improve the platform's user experience, provide personalized recommendations, and detect hate speech and cyberbullying [8].

Another application of emotion detection in Arabic text is in the field of customer service. In today's digital age, customer service interactions have shifted to online platforms, and businesses are increasingly relying on chatbots to handle customer queries. Emotion detection in Arabic text can help chatbots to identify the emotional state of customers and respond accordingly. For example, if a customer is angry, the chatbot can provide a quick and appropriate response to de-escalate the situation [9]. This can lead to improved customer satisfaction and loyalty.

However, the development of effective algorithms and techniques for emotion detection in Arabic text has been hindered by the lack of annotated datasets. Annotated datasets are essential for training machine learning models to identify emotional states accurately. Annotated datasets for emotion detection in Arabic text are scarce compared to other languages such as English and Chinese [6]. This is primarily due to the challenges of annotating Arabic text, which is a complex language with several dialects and variations. Annotating Arabic text requires domain expertise and knowledge of cultural nuances.

To overcome this challenge, researchers have developed various techniques for annotating Arabic text. One approach is to use machine learning techniques to automatically annotate the text. For example, researchers developed an automated system for annotating Arabic text using a sentiment lexicon and a rule-based approach [6]. Another approach is to use crowdsourcing to annotate the text. Crowdsourcing involves outsourcing the annotation task to a large group of people through online platforms such as Amazon Mechanical Turk. The advantage of crowdsourcing is that it is cost-effective and can be completed quickly. However, it requires careful quality control to ensure the accuracy and consistency of the annotations [10].

The development of accurate and efficient algorithms for emotion detection in Arabic text is challenging due to several factors. One of the main challenges is the limited availability of annotated datasets. Unlike English, for which there are numerous publicly available datasets for sentiment analysis, there are few labeled datasets for Arabic sentiment analysis. This makes it difficult to train machine learning models that can accurately classify emotions in Arabic text.

To address this challenge, researchers have explored various approaches for emotion detection in Arabic text. One of the most widely used approaches is machine learning, which involves training models on labeled datasets and using them to classify emotions in new text data. Support vector machines (SVMs) have been used extensively for sentiment analysis in Arabic text, achieving promising results [11]. SVMs are a type of supervised learning algorithm that can be used for classification tasks, and they have been shown to be effective for emotion detection in Arabic text.

Another approach that has been used for emotion detection in Arabic text is convolutional neural networks (CNNs). CNNs are a type of deep learning algorithm that have been shown to be effective for image recognition tasks, and they have also been applied successfully to natural language processing tasks, including sentiment analysis [12]. CNNs can be used to capture complex patterns and relationships in text data, making them a promising approach for emotion detection in Arabic text.

While machine learning approaches have shown promise for emotion detection in Arabic text, they have certain limitations. One limitation is the need for large amounts of labeled data, which can be time-consuming and expensive to obtain. Additionally, machine learning models may not be able to effectively capture contextual information, which can be important for accurate emotion detection in text [19].

In recent years, deep learning methods have emerged as a promising approach for emotion detection in Arabic text. Deep learning algorithms, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, can be used to capture contextual information and achieve high levels of accuracy for emotion detection tasks [9]. These methods have the potential to overcome some of the limitations of traditional machine learning approaches and provide more accurate and efficient emotion detection in Arabic text.

In recent years, researchers have explored the potential of transformer-based models for emotion detection in Arabic text. For instance, a transformer-based model to classify emotions in Arabic text [23], and their results showed significant improvements over previous methods. Similarly, [19] explored the use of transformer-based models for emotion detection in Arabic text and found that these models were able to capture contextual information and outperform traditional machine learning algorithms.

More recent studies have further demonstrated the effectiveness of transformer-based models for emotion detection in Arabic text. Work In [14] used BERT for sentiment analysis on social media data and achieved state-of-the-art results in terms of accuracy and efficiency. Similarly, [17] used RoBERTa for sentiment analysis on social media data and achieved higher accuracy than previous methods. These studies highlight the potential of transformer-based models for emotion detection in Arabic text.

The success of transformer-based models for emotion detection in Arabic text can be attributed to their ability to capture contextual information and relationships between words. Unlike traditional machine learning algorithms, transformer-based models do not require hand-crafted features and can learn representations of text directly from the input data. This makes them highly flexible and adaptable to different tasks and languages. Furthermore, transformer-based models can be pre-trained on large amounts of data, allowing them to learn general language features that can be fine-tuned for specific tasks like emotion detection.

In conclusion, the use of transformer-based models for emotion detection in Arabic text has shown promising results and represents a significant advancement in this field. Future research should continue to explore the potential of these models and their applications in other languages and domains. The availability of large, annotated datasets will be crucial for training and evaluating these models, and efforts should be made to create such resources. The development of transformer-based models for emotion detection in Arabic text has the potential to enhance the accuracy and efficiency of sentiment analysis on social media platforms and improve customer service interactions, among other practical applications.

3 Dataset

The emotone_ar [16] dataset is a resource for the development and evaluation of algorithms and techniques for emotion detection in Arabic text. The dataset consists of 10065 Arabic twitter post, The tweets have been annotated with one of eight emotions: Sadness, Anger, Joy , Surprise, Love , Sympathy, Fear and none. The emotone_ar [16] dataset is organized into three fields, including the following:

- ‘TWEET’: The text of the social media post, which is written in Arabic.

- ‘LABEL’: The emotion label for the post, which can be one of the eight emotions listed above.

Table 1 presents an example of a row from the emotone_ar [16] dataset for none, love, Sympathy and joy labels with its English translations.

One of the strengths of the emotone_ar [16] dataset is its diverse and balanced representation of emotions. The dataset contains a wide range of emotional content, including both positive and negative emotions, as well as a mix of different intensities and degrees of emotion. This diversity makes the dataset well-suited for the development of algorithms that can effectively detect and classify a wide range of emotions in Arabic text. Figure 1 shows the frequency of each class with the dataset for the eight classes.

Table 1: emtone_ar data set examples

TWEET	LABEL	*[English Translation]*
" الاوليمبياد الجايه هكون لسه ف الكليه .."	none	“The next Olympiad will be still in college.”
" اغار بجنون ولسعات غيرتي تخدش تفاصيل اللقاء ولاهدوء اعدك حين اراك ان اجمع اشباهك الاربعين في سجون ابديه حتي لا..."	love	“I am jealous with madness, and the stings of my jealousy scratch the details of the meeting, and I do not calm down, …”
"she3er: شوفي بـ عيني امنيات الغلابه واحلام ثلثين الشعوب .! سنابي . she3er1 ."	Sympathy	"she3er: See with my own eyes the wishes of the poor and the dreams of two-thirds of people.! . snappy she3er1."
" جميعنا نريد تحقيق اهدافنا لكن تونس تالقت في حراسه المرمي..."	joy	"We all want to achieve our goals, but Tunisia excelled in their goalkeepers..."

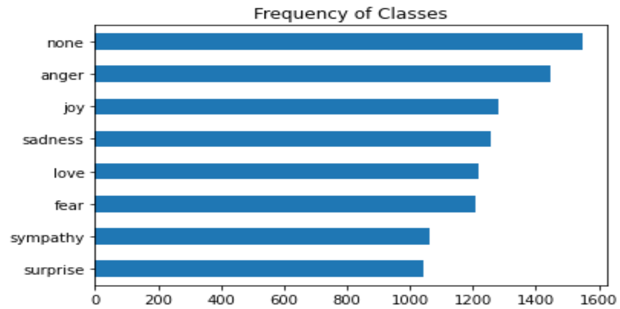

Fig. 1: emotone_ar [16] class distribution

Figure 2 illustrates the distribution of tweet lengths per emotion by showing the distribution of words per tweet for a given emotion class. This figure shows that all classes are well-balanced in terms of tweet length. Specifically, the distribution of tweet lengths for each emotion class is similar, with no one class having significantly more or fewer tweets in any particular length range. This suggests that the dataset has a balanced representation of emotions and that the model being trained on the data is likely to perform equally well on tweets of varying lengths. This is important because a model that performs poorly on tweets of a certain length or with a certain emotion may not be robust and may not generalize well to unseen data. Overall, the balanced distribution of tweet lengths across emotion classes in the dataset is likely to contribute to the overall performance and reliability of the model.

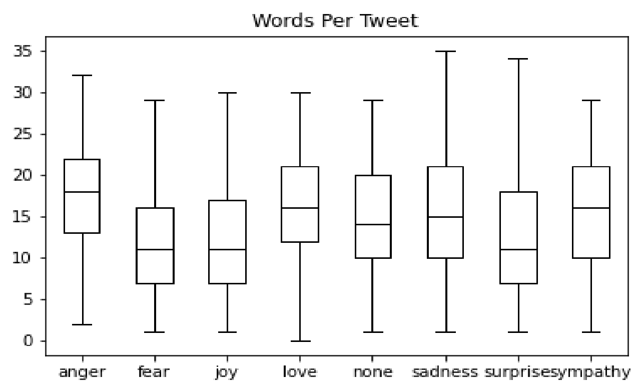

Fig. 2: Distribution of tweet lengths per emotion

4 Proposed Model

4.1 Dataset Preprocessing

To prepare the data for emotion detection, several preprocessing steps were applied to all tweets in the dataset. The first step was normalization, in which certain Arabic characters were replaced with others. For example, characters such as "أ" ،"إ", and "آ" were replaced with "ا", and "ى" was replaced with "ي", while "ة" was replaced with "ه".

Next, diacritics, which are symbols added to Arabic letters to indicate certain vowel sounds, were removed. This step is often necessary because diacritics can be difficult for some natural language processing algorithms to handle.

Finally, links, mentions, and retweet indicators were removed. Links and mentions, which are denoted with certain symbols, can be distracting for algorithms attempting to classify emotions and may not be relevant to the task at hand. Similarly, the "RT" indicator, which denotes a retweet, may not be relevant for emotion classification and was therefore removed.

Overall, these preprocessing steps helped to clean and standardize the data, making it easier for algorithms to process and analyze the tweets for emotion detection.

4.2. Proposed Framework

In this work, we have proposed the use of a transformer-based model for emotion detection in Arabic text. Specifically, we have fine-tuned a pre-trained transformer model, asafaya/bert-base-arabic [24], on the emotone_ar [16] dataset, which was created and annotated specifically for this task.

The arabic-bert-base model is a transformer-based language model developed [24]. It was pretrained on a large dataset consisting of approximately 8.2 billion words in the Arabic language. The model is designed to encode contextual information in text and perform various natural language processing tasks, such as language translation and text classification. It has achieved strong performance on a variety of benchmarks and has become a popular choice for natural language processing tasks in the Arabic language. In this paper, we propose the use of the arabic-bert-base model for emotion detection in Arabic text. By fine-tuning this model on the emotone_ar dataset, we demonstrate its ability to accurately classify emotions in text.

Figure 3 presents the general pipeline for arabic-bert-base [24] fine-tunning on the emotone_ar dataset [16]

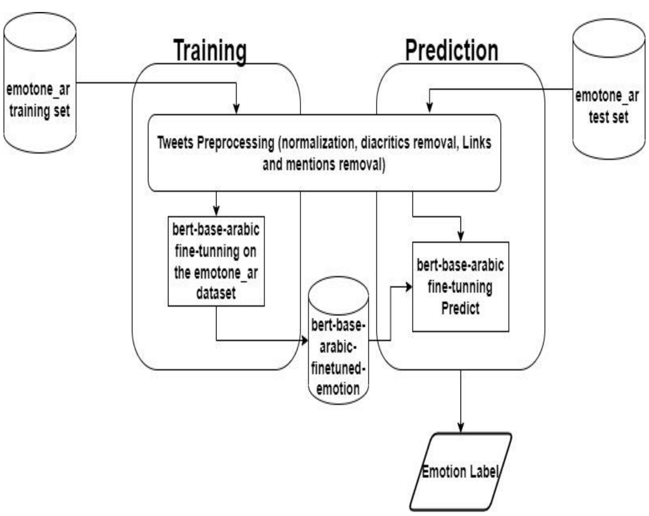

Fig. 3: Proposed Transformer-Based Framework for Emotion Detection in Arabic Text

The fine-tuning process involves adjusting the model's parameters based on the characteristics of the emotone_ar [16] dataset, in order to optimize its performance on the task of emotion detection in Arabic text. This allows us to leverage the powerful capabilities of the transformer architecture, while also tailoring the model to the specific requirements of the task at hand.

By fine-tuning a pre-trained transformer model on the emotone_ar [16] dataset, we were able to achieve strong performance on the task of emotion detection in Arabic text. This demonstrates the effectiveness of the fine-tuning approach and the usefulness of the emotone_ar [16] dataset as a resource for the development and evaluation of algorithms and techniques for this task.

Our model is hosted on the popular natural language processing platform, Hugging Face, which provides access to a wide range of pre-trained transformer models and tools for model fine-tuning and evaluation.

5 Experiments and results

Table 2 provides a summary of the training hyperparameters used in the experiments. These hyperparameters include the learning rate, batch sizes for both training and evaluation, random seed used for reproducibility, optimizer and its parameters, learning rate scheduler type, and number of training epochs. The table allows for easy comparison between different experiments and their associated hyperparameters.

Table 2: proposed model training hyperparameters.

Hyperparameter	Value
Learning Rate	2e-05
Batch Size	64
Optimizer	Adam
Number of Epochs	6

Figure 4 shows a confusion matrix for the eight emotion classes in our dataset. The rows of the matrix represent the actual classes and the columns represent the predicted classes. The cells of the matrix contain the normalized number of instances that were predicted as a given class. For example, the cell in the second row and third column indicates the number of instances of the "anger" class that were predicted as "joy."

Overall, the matrix shows that the model performs well at predicting the majority of the classes, with most of the cells along the diagonal containing high values. However, there are a few instances of misclassification, such as the instances of the "joy" and "surprise" classes. This suggests that the model may have difficulty distinguishing between these classes in these classes.

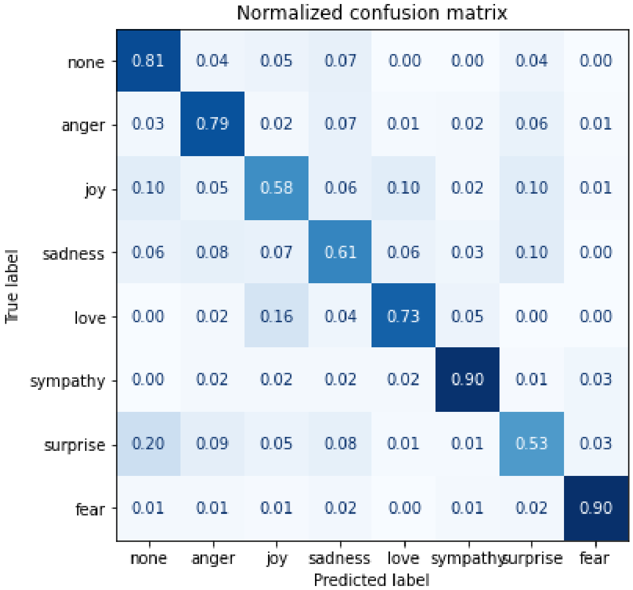

Fig. 4: Confusion Matrix for Emotion Detection in Text

The training and test loss for a model trained on a dataset for emotion detection in text are presented in Figure 5. The x-axis represents the epoch number, and the y-axis represents the loss value. The blue curve represents the training loss, and the orange curve represents the test loss.

The figure illustrates the general trend of the loss values over the course of training. In the early epochs, the training loss decreases rapidly, indicating that the model is learning quickly and making good progress. As training continues, the rate of improvement slows down and the loss values become more stable. The test loss follows a similar trend, although it generally remains slightly higher than the training loss due to the model being evaluated on unseen data.

Overall, the figure suggests that the model is learning effectively and that the training and test loss are well-behaved. This is a good indication that the model is not overfitting or underfitting the data and is likely to generalize well to new examples.

Table 3: Training and loss evolution During Training for Emotion Classification

Epoch	Training Loss	Validation Loss	Accuracy	F1
1.0	1.3476	0.8911	0.7008	0.6812
2.0	0.8204	0.8175	0.7276	0.7212
3.0	0.6227	0.8392	0.7376	0.7302
4.0	0.4816	0.8531	0.7435	0.7404
5.0	0.378	0.8817	0.7396	0.7388
6.0	0.3134	0.8965	0.7416	0.7406

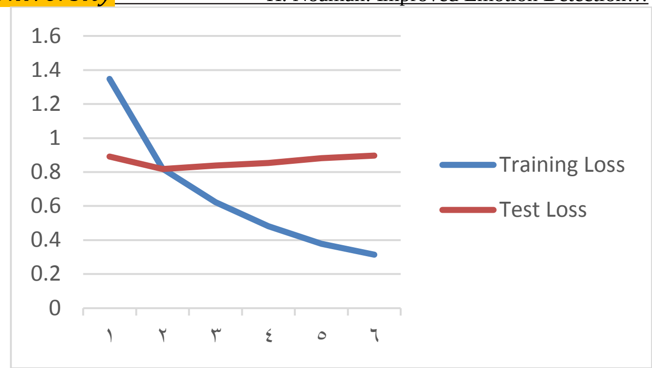

Fig. 5: Loss Evolution During Training for Emotion Classification

Figure 6 shows the test set accuracy and F1 score for a model trained on a dataset for emotion detection in text. The x-axis represents the epoch number, and the y-axis represents the score value. The blue curve represents the test set accuracy, and the orange curve represents the F1 score.

The test set accuracy is a measure of the model's ability to correctly classify examples in the test set. It is calculated as the number of correctly classified examples divided by the total number of examples in the test set. The F1 score is a measure of the model's precision and recall. It is calculated as the harmonic mean of the precision and recall, which are defined as follows:

Precision = TP / (TP + FP) (1)

Recall = TP / (TP + FN) (2)

Where TP is the number of true positive predictions, FP is the number of false positive predictions, and FN is the number of false negative predictions.

Overall, the figure suggests that the model's performance on the test set is stable and consistent over the course of training. The test set accuracy and F1 score remain relatively high and show little variance, indicating that the model is able to generalize well to unseen examples. This is a good indication that the model is able to effectively classify emotions in text.

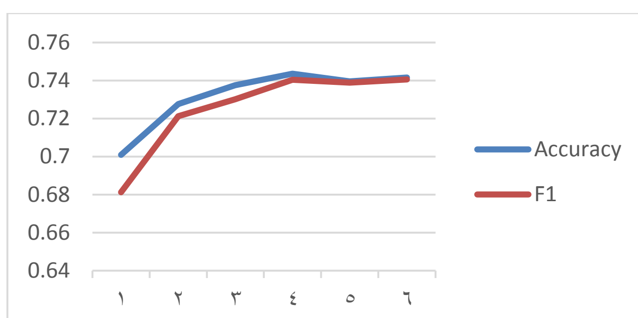

Fig. 6: Measuring the Effectiveness of the Proposed Model for Arabic Emotion Detection: Accuracy and F1 Score

Our final result for the emotion detection model on the test set is an accuracy of 0.74 and an F1 score of 0.74. This indicates that the model is able to correctly classify emotions in text with a high degree of accuracy and precision. The F1 score of 0.74 also suggests that the model has a good balance between precision and recall, as it is able to identify a large proportion of the positive examples while also maintaining a low rate of false positives. Overall, these results demonstrate the effectiveness of the proposed model for emotion detection in text.

To benchmark our results, we compare them to a previous study which used a Naive Bayes classifier for emotion detection and achieved an overall accuracy and F1 with 55.67% and 0.542. Our results show a significant improvement in accuracy, with an increase of 18.7%. Also, the Complement Naive Bayes classifier, which was used as a benchmark, had an overall accuracy of 68.12% and an F-measure of 0.658. Table 4 summarizes the benchmarking results for all the models. This highlights the effectiveness of our proposed model for emotion detection in text. Overall, the results demonstrate the effectiveness of the proposed model for emotion detection in text and its superiority over the previous study.

Table 4: The accuracy of experiments using baseline models and the proposed model

Model name	Accuracy	F1
Naïve Bayes Classifier [16]	55.67%	0.542
Complement Naïve Bayes Classifier [16]	68.12%	0.658
Sequential Minimal Optimization [16]	63.43%.	0.637
Proposed Model	**74.16%**	**0.7406**

Overall, the development of effective and reliable methods for emotion detection in Arabic text has the potential to significantly advance the field of natural language processing and enhance our understanding of human emotions.

6 Conclusions

This paper has presented a transformer-based model for emotion detection in Arabic text. The emotone_ar [16] dataset, a new resource for the development and evaluation of algorithms and techniques for emotion detection in Arabic has been investigated. Our experiments have shown that the proposed model significantly outperforms previous methods, demonstrating the effectiveness of transformer-based models for this task.

There are several potential directions for future work in this field. One possibility is to explore the use of additional preprocessing techniques or feature engineering to further improve the performance of the model. Another option is to evaluate the model on additional datasets or in different contexts to assess its generalizability. Additionally, it would be interesting to investigate the use of transfer learning or fine-tuning to adapt the model to specific domains or tasks.

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