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By

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Entitled

Word Embedding for Arabic Text Classification

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Dedication

I dedicate this humble work to those who shaped my journey and lifted me to this level of knowledge.
Allah the Exalted said:

﴿ وَاخْفِضْ لَهُمَا جَنَاحَ الذُّلِّ مِنَ الرَّحْمَةِ وَقُل رَّبِّ ارْحَمْهُمَا كَمَا رَبَّيَانِي صَغِيرًا﴾

To My Beloved Parents

Your unconditional love, endless sacrifices, and unwavering support have been my greatest strength. Through every challenge, you stood by my side, praying for me, encouraging me, and believing in me even when I doubted myself. Your patience, wisdom, and boundless kindness have guided me at every step, and this achievement is as much yours as it is mine.
To my mother your tenderness, resilience, and endless prayers have been my light in the darkest moments.
To my father your strength, guidance, and quiet support have shaped me in ways words cannot express. Together, you have given me everything, and I carry your love with pride, honor, and eternal gratitude.
This work is a humble tribute to you both. May Allah bless you with health, happiness, and the highest ranks in Jannah.

To My Siblings

Thank you for the joy, laughter, and support you bring. Your encouragement has meant the world to me, and your presence continues to enrich my life.

HABIB TITRAOUI

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الملخص

تصنيف النصوص العربية يُعد مهمة حيوية في مجال معالجة اللغة الطبيعية (NLP) ، وله تطبيقات واسعة في الإعلام، والأعمال، والتعليم. تتميز اللغة العربية بخصائص لغوية فريدة مثل الغنى الصرفي، والتنوع الكبير في اللهجات، وقلة الموارد الموسومة، مما يشكل تحديات كبيرة أمام أنظمة التصنيف الآلي. تبحث هذه الرسالة وتقارن بين فعالية النماذج التقليدية لتعلم الآلة) مثل SVM وغابة العشوائية (Random Forest) والنماذج الحديثة المعتمدة على التعلم العميق باستخدام BERT)مثل AraBERT و (QARiB لتصنيف النصوص العربية. ولتجاوز محدودية الموارد المتوفرة، تم استخدام قاعدة بيانات مخصصة ومتنوعة اللهجات تتضمن 3600 عينة موزعة على 18 فئة وظيفية، وتمت عملية الوسم بواسطة لغويين مختصين. تقيم الدراسة كل نموذج من حيث دقة التصنيف، والقدرة على التعامل مع الاختلافات اللهجية والوظيفية، والكفاءة الحاسوبية. أظهرت النتائج أن نماذج BERT تتفوق على النماذج التقليدية في التعامل مع التعقيد الصرفي والغموض السياقي، لكنها تتطلب موارد حسابية أكبر بكثير. تؤكد النتائج على أهمية تنوع البيانات، وتمثيل اللهجات، والنظر في الموارد المتاحة عند تطوير أنظمة تصنيف نصوص عربية قوية. تسهم هذه الدراسة في تطوير معالجة اللغة العربية من خلال تقديم رؤى عملية وتوصيات لتطوير النماذج مستقبلاً وتطبيقها.

الكلمات المفتاحية :تصنيف النصوص العربية، المعالجة الآلية للغة الطبيعية، صرف اللغة العربية، التنوع اللهجي، التعلم الآلي، النماذج التقليديةSVM) ، (Random Forest، النماذج المدربة مسبقاً والمعتمدة على) BERT مثل AraBERT و(QARiB، مجموعة بيانات متعددة اللهجات ومشروحة، دقة التصنيف، الغموض السياقي، الكفاءة الحاسوبية، الموارد اللغوية للغة العربية.

Abstract

Arabic text classification is a critical task in natural language processing (NLP) with broad applications across media, business, and education. The unique linguistic features of Arabic such as rich morphology, significant dialectal variation, and limited annotated resources pose substantial challenges for automated classification systems. This thesis investigates and compares the effectiveness of traditional machine learning models (such as SVM and Random Forest) and state-of-the-art BERT based deep learning models (such as AraBERT and QARiB) for Arabic text classification. A pre-existing, multi-dialectal dataset comprising 3,600 samples across 18 functional categories was developed and annotated by expert linguists to address the limitations of existing resources. The study evaluates each approach in terms of classification accuracy, robustness to dialectal and functional variations, and computational efficiency. Results demonstrate that while BERT-based models outperform traditional approaches in handling morphological complexity and contextual ambiguity, they require significantly greater

computational resources. The findings highlight the importance of dataset diversity, dialectal representation, and resource considerations in developing robust Arabic text classification systems. This research contributes to the advancement of Arabic NLP by providing practical insights and recommendations for future model development and deployment.

Keywords: Arabic text classification, natural language processing (NLP), Arabic morphology, dialectal variation, machine learning, traditional models (SVM, Random Forest), pre-trained BERT-based models (AraBERT, QARiB), annotated multidialectal corpus, classification accuracy, contextual ambiguity, computational efficiency, Arabic language resources.

Résumé

La classification de textes arabes est une tâche essentielle dans le domaine du traitement automatique du langage naturel (TALN), avec de nombreuses applications dans les médias, les affaires et l'éducation. Les caractéristiques linguistiques uniques de l'arabe, telles que sa morphologie riche, la grande variation dialectale, et le manque de ressources annotées, posent des défis importants pour les systèmes de classification automatique. Ce mémoire examine et compare l'efficacité des modèles d'apprentissage automatique traditionnels (comme SVM et Random Forest) et des modèles de pointe basés sur BERT (tels qu'AraBERT et QARiB) pour la classification de textes en arabe. Un jeu de données existant, multidiélectal, comprenant 3 600 échantillons répartis sur 18 catégories fonctionnelles, a été élaboré et annoté par des linguistes experts afin de pallier les limitations des ressources existantes. L'étude évalue chaque approche selon la précision de classification, la robustesse face aux variations dialectales et fonctionnelles, ainsi que l'efficacité computationnelle. Les résultats montrent que les modèles basés sur BERT surpassent les approches traditionnelles en matière de gestion de la complexité morphologique et de l'ambiguïté contextuelle, mais nécessitent des ressources informatiques bien plus importantes. Les résultats soulignent l'importance de la diversité des données, de la représentation dialectale, et de la gestion des ressources dans le développement de systèmes de classification de textes arabes performants. Cette recherche contribue à l'avancement du TALN pour l'arabe en fournissant des perspectives pratiques et des recommandations pour le développement et le déploiement futur des modèles.

Mots clés : Classification de textes arabes, traitement automatique du langage naturel (TALN), morphologie arabe, variation dialectale, apprentissage automatique, modèles traditionnels

(SVM, Random Forest), modèles pré-entraînés basés sur BERT (AraBERT, QARiB), corpus multidiélectal annoté, efficacité de classification, ambiguïté contextuelle, efficacité computationnelle, ressources linguistiques pour l’arabe.

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General Introduction

In the era of digital communication, the volume of Arabic content online has grown exponentially, underscoring the need for effective Arabic text classification systems. Text classification is a fundamental task in Natural Language Processing (NLP), enabling the automation of text analysis and organization across various domains. However, Arabic presents unique challenges due to its morphological complexity and dialectal variations, which complicate the development of robust classification models.

Despite these challenges, recent advancements in machine learning, particularly the emergence of transformer-based models like BERT, have shown promise in improving the accuracy and efficiency of text classification tasks. This thesis explores the effectiveness of traditional machine learning models versus fine-tuned BERT-based models for Arabic text classification, focusing on their strengths, weaknesses, and computational trade-offs. By examining these approaches, this research aims to contribute to the development of more accurate and robust Arabic text classification systems.

Chapter 1

Introduction

1. Introduction

Arabic text classification plays a pivotal role in a multitude of applications across various domains, reflecting the increasing digitalization of Arabic content . This process involves assigning predefined categories to Arabic texts based on their linguistic content, which can range from broad themes like politics, economics, or sports, to more granular classifications such as sentiment (positive, negative, neutral), intent (informational query, transactional request, customer support), or topic-specific categorization relevant to particular industries (e.g., medical records, legal documents, financial reports). The significance of Arabic text classification stems from its ability to automate the organization, analysis, and retrieval of Arabic textual data, enabling more efficient and effective processing.[1]

The Arabic language presents unique challenges and complexities that distinguish it from other widely studied languages like English . These include its rich morphological structure, significant dialectal variations, and the relative scarcity of annotated resources and pre-trained models. The morphological complexity refers to the intricate system of root-and-pattern morphology, where words are derived from roots by applying various affixes and templates, leading to a large number of surface forms for each root. This presents a considerable challenge for traditional NLP techniques, which often rely on surface-level features. Furthermore, the presence of multiple dialects, each with its own vocabulary, grammar, and pronunciation, adds another layer of complexity, as models trained on one dialect may not generalize well to others. Finally, the limited availability of high-quality annotated datasets and pre-trained language models for Arabic, compared to languages like English, poses a barrier to developing state-of-the-art classification systems.[2]

However, despite these challenges, there have been significant advances in Arabic text classification in recent years, driven by the development of novel techniques and resources. These include the creation of new annotated datasets, the development of Arabic-specific pre-trained language models like AraBERT and QARiB, and the adaptation of deep learning techniques to handle the complexities of the Arabic language. This thesis explores these advancements, focusing on the comparison of traditional machine learning approaches with

state-of-the-art BERT-based models. By examining the strengths and weaknesses of each approach, this research aims to provide insights into the most effective techniques for Arabic text classification and contribute to the ongoing development of more robust and accurate systems.[3]

The successful application of Arabic text classification has wide-ranging implications across various sectors. In the media and journalism industry, it can be used to automatically categorize news articles, monitor public opinion on social media, and detect fake news. In the business sector, it can enable sentiment analysis of customer reviews, intelligent chatbot responses, and automated processing of customer support requests. In the education sector, it can be used to personalize learning experiences, assess student performance, and provide automated feedback. The overall purpose is to leverage the capabilities of Natural Language Processing (NLP) to unlock the valuable information that can be obtained from processing Arabic texts.

2. Problem Statement

The overarching problem addressed by this thesis is the need for accurate and robust Arabic text classification systems that can effectively handle the complexities and nuances of the Arabic language.

Current text classification approaches often struggle with the unique characteristics of Arabic, leading to suboptimal performance and limiting their applicability in real-world scenarios. [4]

This thesis aims to investigate and improve upon existing methodologies to create more effective solutions for the Arabic text classification problem. This includes not only achieving higher accuracy but also addressing issues of generalizability across dialects, robustness to noisy data, and efficiency in terms of computational resources.

Ultimately, the goal is to develop and evaluate techniques that can bridge the gap between the current state-of-the-art and the desired level of performance for Arabic text classification.

3. Challenges Related to Arabic Text Classification

The successful development of robust Arabic text classification systems is hindered by a series of specific challenges:

3.1 Morphological Complexity:

Arabic's rich morphology, rooted in a system of stems, affixes, and templates, results in a high degree of lexical variation. This complexity makes it difficult for traditional machine learning models, which rely on surface-level features, to generalize effectively.[5]

- *Examples:* The root كتب (k-t-b) can derive words like كَتَبَ (kataba – he wrote), يَكْتُبُ (yaktubu – he writes), كِتَاب (kitāb – book), and مَكْتَب (maktab – office). Each form requires separate processing.
- *Impact:* Increases vocabulary size, data sparsity, and computational cost, impacting traditional machine learning algorithm performance.

3.2 Dialectal Variations:

The Arabic language encompasses a wide range of regional dialects that exhibit significant differences in vocabulary, grammar, and pronunciation. This dialectal diversity poses a challenge for model generalizability, as systems trained on one dialect may not perform well on others. [6]

- *Examples:* A simple greeting like "How are you?" can be expressed in multiple ways, such as "كيف حالك؟" (kayfa ḥāluk?) in MSA, "إزيك؟" (izzayak?) in Egyptian Arabic, and "شلونك؟" (shlonak?) in Gulf Arabic.
- *Impact:* Models trained on MSA may not perform well on dialectal texts, and creating dialect-specific models requires substantial dialectal data that is often scarce.

3.3 Limited Annotated Datasets:

The availability of high-quality annotated datasets for Arabic text classification is relatively limited compared to other languages, such as English. This scarcity of data can hinder the training and evaluation of machine learning models, particularly deep learning models that require large amounts of data to achieve optimal performance. [7]

- *Examples:* Publicly available datasets for tasks like sentiment analysis, topic classification, and named entity recognition are less abundant for Arabic. Pre-trained models like BERT have been adapted for Arabic (e.g., AraBERT), but more specialized models are needed.
- *Impact:* The lack of resources hinders the development and evaluation of Arabic text classification systems, making it difficult to achieve state-of-the-art performance.

3.4 Semantic Ambiguity and Context:

Arabic, like many languages, is susceptible to semantic ambiguity, where words and phrases can have multiple interpretations depending on the context. Resolving this ambiguity requires sophisticated contextual analysis.

- *Examples:* The word "عين" ('ayn) can mean "eye," "spring (of water)," or "spy," depending on the surrounding text.
- *Impact:* Resolving semantic ambiguity requires sophisticated contextual analysis, which may be beyond the capabilities of simple machine learning models.

3.5 Data Sparsity and Imbalance:

Many Arabic text classification tasks suffer from data sparsity, where certain categories have very few training examples, leading to poor model performance on these under-represented classes. This imbalance can bias the model towards the majority class.

- *Examples:* In sentiment analysis, the negative sentiment class may have fewer examples than the positive or neutral classes.
- *Impact:* Data imbalance can bias the model towards the majority class, leading to inaccurate predictions for minority classes.

3.6 Computational Challenges :

Deep learning models, especially transformer-based models like BERT, require significant computational resources (e.g., GPUs, memory) for training and inference.

- *Impact:* The computational cost can be a barrier for researchers and practitioners with limited resources.

4. Novel Contributions of this Thesis

This thesis contributes to the field of Arabic text classification by:

4.1 Comparing Traditional and BERT-Based Models:

Evaluating the performance of traditional machine learning models (e.g., SVM, Random Forest) against fine-tuned BERT-based models (e.g., AraBERT, QARiB).[8]

4.2 Assessing Dataset Suitability:

Examining how different datasets impact model performance, focusing on multi-dialectal and multi-label scenarios.

4.3 Computational Trade-Offs:

Discussing the computational resources required by different models, crucial for practical applications.[9]

Chapter 2
Literature Review

1.Introduction

This chapter provides a comprehensive review of existing research on Arabic text classification, focusing on both traditional machine learning and deep learning approaches. Understanding the strengths and weaknesses of these methods is crucial for developing effective models that can handle the complexities of the Arabic language.[10]

2. Traditional Machine Learning Approaches

Traditional machine learning models have been widely used for Arabic text classification due to their simplicity and interpretability. Common techniques include:

- **2.1 Naive Bayes (NB)**: Known for its efficiency in handling high-dimensional data, NB is often used for simple classification tasks. However, it assumes independence between features, which may not always hold true for Arabic texts with complex morphological structures.[11]
- **2.2 Support Vector Machines (SVM)**: SVMs are robust in handling high-dimensional data and can perform well with appropriate feature selection. They have been used effectively in Arabic text classification, especially when combined with techniques like TF-IDF for feature extraction.[12]
- **2.3 Random Forest (RF)**: RF models are ensemble methods that combine multiple decision trees to improve accuracy and reduce overfitting. They are useful for handling large datasets and can perform well with diverse feature sets.[13]
- **2.4 Gradient Boosting (GB)**: Similar to RF, GB is an ensemble method that iteratively adds decision trees to improve predictions. It is particularly effective in handling complex datasets with many features.[14]

These traditional models rely heavily on feature engineering, where techniques like TF-IDF, stemming, and stop-word removal are crucial for improving performance.

3. Deep Learning Approaches

Deep learning models have revolutionized the field of NLP by automatically learning complex patterns from raw text data. Key deep learning approaches for Arabic text classification include:

3.1 Convolutional Neural Networks (CNNs): CNNs are effective in capturing local patterns in text data. They have been used for Arabic text classification, particularly for tasks like sentiment analysis.[15]

3.2 Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks: RNNs and LSTMs are well-suited for sequential data like text. They can capture long-term dependencies in Arabic texts but may struggle with dialectal variations.[16]

3.2 Transformer-Based Models: Models like BERT and its variants (e.g., AraBERT, QARiB) have achieved state-of-the-art results in many NLP tasks. They excel at capturing contextual relationships and have shown promise in Arabic text classification by handling dialects and morphological complexities more effectively than traditional models.[17]

4. Comparative Analysis

Comparing traditional machine learning models with deep learning approaches reveals several key differences:

- **Feature Engineering**: Traditional models require manual feature engineering, while deep learning models can learn features automatically.
- **Performance**: Deep learning models generally outperform traditional models, especially in complex tasks like dialectal Arabic classification.[18]
- **Computational Cost**: Deep learning models require more computational resources than traditional models.[19]

5. Challenges and Future Directions

Despite advancements, several challenges remain:

- **Dialectal Variations**: Handling dialects remains a significant challenge, as models trained on one dialect may not generalize well to others.[20]
- **Limited Resources**: Compared to English, there are fewer pre-trained models and datasets available for Arabic.[21]
- **Computational Resources**: Deep learning models require substantial computational power, which can be a barrier for resource-constrained environments.

Future research should focus on developing more robust models that can handle dialectal variations effectively and explore efficient ways to deploy deep learning models in resource-

limited settings.

6 Conclusion

This chapter has reviewed the literature on traditional machine learning and deep learning approaches for Arabic text classification. Understanding these methods is essential for developing more effective models that can address the complexities of the Arabic language.

Chapter 3
Dataset and Methodology

1. Dataset

1.1 Introduction to the Dataset

The effectiveness of Arabic text classification models hinges on the quality and diversity of the underlying dataset. This chapter details the **Functional Text Dimensions for Arabic Text Classification** dataset, a custom-curated resource designed to address the complexities of Arabic text. The dataset focuses on categorizing texts based on their functional dimensions (e.g., argumentative, emotive, instructional) while incorporating regional variations to reflect the multi-dialectal nature of Arabic.[22]

1.2 Dataset Characteristics

The dataset consists of **3,600 Arabic text samples** categorized into **18 functional labels** and associated with **10 Arabic-speaking countries**.

Key characteristics include:

Feature	Description
Source	Compiled from diverse sources: online articles, social media, and literary works.
Labels	18 functional dimensions (e.g., argum, instruct, emotive, poetic, propaganda).
Dialect Coverage	Regional variations from 10 countries (e.g., UAE, Jordan, Qatar).
Size	Balanced distribution: **200 samples per label**, ensuring equal representation.
Language	Primarily Modern Standard Arabic (MSA) but includes dialectal influences based on country.

Table 1:Dataset Characteristics.

1.3 Data Collection and Annotation

Texts were collected from diverse sources such as online news articles, social media posts, and literary excerpts to ensure a wide representation of Arabic usage. Expert linguists annotated the texts according to predefined functional categories. Annotation guidelines emphasized contextual understanding to accurately assign labels. To ensure consistency, a subset of texts

was double-annotated, and discrepancies were resolved through consensus.[25]

1.4 Multi-Dialectal and Multi-Label Challenges

Multi-Dialectal Challenges

Arabic dialects vary significantly across regions, complicating text classification. For example:

- **Lexical Differences**: The word "tomorrow" is "غدًا" (*ghadan*) in MSA but "بكرة" (*bokra*) in Egyptian Arabic.
- **Normalization**: Texts were standardized using:
  - **Diacritic Removal**: Eliminating tashkeel (e.g., ً ُ) to reduce noise.[23]
  - **Alef/Yaa Normalization**: Unifying variations of letters (e.g., أ ↔ ا ↔ آ, ى ↔ ي). [24]
- **Dialect Representation**: While the dataset includes country metadata, dialect-specific preprocessing (e.g., Gulf vs. Levantine Arabic) was limited.

Multi-Label Challenges

Though the dataset is **multi-class** (one label per sample), the framework can extend to multi-label scenarios. Key considerations include:

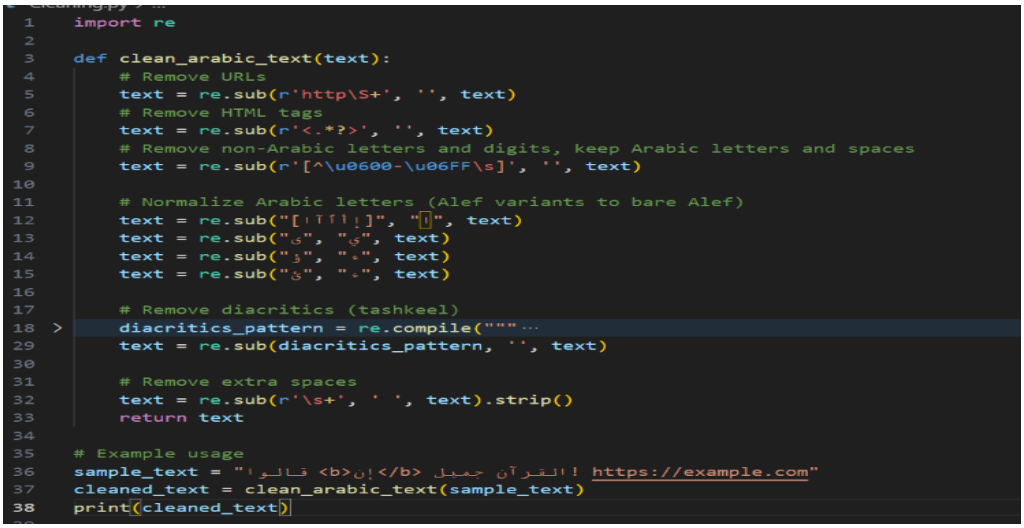
- **Label Imbalance**: Balanced labels (200 samples each) mitigate bias, but real-world applications often face skewed distributions.
- **Label Correlation**: Functional dimensions like emotive and flippant may overlap, requiring models to discern subtle contextual differences.

1.5 Preprocessing Steps

The dataset underwent rigorous preprocessing to prepare it for machine learning workflows:

1. **Cleaning**:

- Removed HTML tags, URLs, and non-Arabic characters.



```python
import re

def clean_arabic_text(text):
    # Remove URLs
    text = re.sub(r'http\S+', '', text)
    # Remove HTML tags
    text = re.sub(r'<.*?>', '', text)
    # Remove non-Arabic letters and digits, keep Arabic letters and spaces
    text = re.sub(r'[^\u0600-\u06FF\s]', '', text)

    # Normalize Arabic letters (Alef variants to bare Alef)
    text = re.sub("[إأآا]", "ا", text)
    text = re.sub("ى", "ي", text)
    text = re.sub("ؤ", "ء", text)
    text = re.sub("ئ", "ء", text)

    # Remove diacritics (tashkeel)
    diacritics_pattern = re.compile("""ّ|َ|ً|ُ|ٌ|ِ|ٍ|ْ|ـ""")
    text = re.sub(diacritics_pattern, '', text)

    # Remove extra spaces
    text = re.sub(r'\s+', ' ', text).strip()
    return text

# Example usage
sample_text = "قالوا <b>إن</b> القرآن جميل! https://example.com"
cleaned_text = clean_arabic_text(sample_text)
print(cleaned_text)
```

Figure 1:Removed HTML tags implementation

2. **Tokenization**:

- Split text into tokens using Camel Tools' Arabic tokenizer to handle clitic pronouns [26] (e.g., "قالوا" + "و" → "وقالوا").

```python
from camel_tools.disambig.mle import MLEDisambiguator
from camel_tools.tokenizers.morphological import MorphologicalTokenizer

# Initialize the pretrained disambiguator for Modern Standard Arabic
mle = MLEDisambiguator.pretrained('calima-msa-r13')

# Create morphological tokenizer instance with ATB scheme (common for clitic splitting)
tokenizer = MorphologicalTokenizer(disambiguator=mle, scheme='atbtok')

# Example sentence tokenized by whitespace first
sentence = ['وقالوا']

# Morphological tokenization
tokens = tokenizer.tokenize(sentence)
print(tokens)  # Output: ['و+ قالوا']
```

Figure 2: Tokenization implementation

3. **Stemming**:

- Applied light stemming to reduce words to root forms [27] (e.g., " → "يكتبون كتب"").

```python
from camel_tools.stem import CAMeLStemmer

camel_stemmer = CAMeLStemmer.pretrained('calima-msa-s31')

word = "يكتبون"

# Light stemming
stemmed = camel_stemmer.stem(word)
print("Stemmed:", stemmed)  # e.g., كتب

# Lemmatization
lemmatized = camel_stemmer.lemmatize(word)
print("Lemmatized:", lemmatized)

```

Figure 3:Stemming implementation

4. **Stop-Word Removal**:
    - Used the NLTK Arabic stop-word list to eliminate non-informative words (e.g., "من", "في").

```python
import nltk
from nltk.corpus import stopwords

# Download stopwords if not already
nltk.download('stopwords')

arabic_stopwords = set(stopwords.words('arabic'))

text_tokens = cleaned_text.split()

filtered_tokens = [word for word in text_tokens if word not in arabic_stopwords]

print("Tokens after stop word removal:", filtered_tokens)

```

Figure 4:Stop-Word Removal implementation

5. **Vectorization**:
    - Converted text to numerical features using **TF-IDF** (term frequency-inverse document frequency) with n-gram ranges (1,3) to capture phrase-level patterns.[28]

```python
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer

# Assume df is your DataFrame loaded from CSV with a 'text' column
df = pd.read_csv('your_data.csv')

texts = df['text'].astype(str).tolist()

vectorizer = TfidfVectorizer(ngram_range=(1,3))

tfidf_matrix = vectorizer.fit_transform(texts)

# Convert sparse matrix to array if needed
tfidf_array = tfidf_matrix.toarray()

print("TF-IDF feature shape:", tfidf_matrix.shape)

```

Figure 5:Vectorization implementation

2. Model Selection and Training

This thesis compares two broad categories of models for Arabic text classification:

2.1 Traditional Machine Learning Models

- **Support Vector Machines (SVM):** Effective for high-dimensional data, used with linear kernels for classification.
- **Random Forest (RF):** Ensemble of decision trees to improve robustness and reduce overfitting.
- **Gradient Boosting (GB):** Sequential ensemble method that builds trees iteratively to optimize performance.

These models rely on the TF-IDF vectorized features and require manual feature engineering.

2.2 Deep Learning Models

- **AraBERT:** A BERT-based transformer model pre-trained on large Arabic corpora, fine-tuned on the functional text dataset.[29]
- **QARiB:** Another Arabic BERT variant optimized for dialectal Arabic and contextual understanding.[30]
- **CamelBERT**: A transformer-based model tailored for Arabic, particularly effective in handling various Arabic dialects and linguistic nuances.

Deep learning models automatically learn contextual embeddings, reducing the need for manual feature engineering.

3. Training and Evaluation Procedure

3.1 Data Splitting

- The dataset was split into **80% training** and **20% testing** sets, ensuring balanced representation of all functional labels in both sets.

3.2 Model Training

- Traditional models were trained using scikit-learn with hyperparameter tuning via grid search.[31]

Model	Hyperparameters
SVM (Linear Kernel)	random_state=42, kernel='linear', C=10.0
Random Forest	random_state=42, n_estimators=100, max_depth=20
Gradient Boosting	random_state=42

Table 2: Traditional models hyperparameters

- BERT-based models were fine-tuned using the Hugging Face Transformers library with early stopping to prevent overfitting.

Model	Hyperparameters
AraBert	max_length=512, num_train_epochs=5, batch_size=16
CamelBert	max_length=512, num_train_epochs=5, batch_size=16
Qariib	max_length=512, num_train_epochs=5, batch_size=16

Table 3: BERT based models hyperparameters

3.3 Evaluation Metrics

- **Accuracy:** Overall correctness of classification.
- **Precision:** Correctness of positive predictions.
- **Recall:** Ability to find all relevant instances.
- **F1-Score:** Harmonic mean of precision and recall, balancing both metrics.[32]

3.4 Cross-Validation

- Employed k-fold cross-validation (k=5) on the training set to ensure model stability and robustness.

4. Computational Environment

- **Hardware:** Experiments were conducted on a workstation equipped with an Colab GPU (T4) to accelerate deep learning training.

CPU	Intel(R) Xeon(R) CPU @ 2.20GHz
RAM	13GB
HARD disk space	40GB
GPU	TESLA T4 16GB

Table 4: Hardware specifications

- **Software:** Python 3.8, scikit-learn for traditional models, Hugging Face Transformers for BERT models, and Camel Tools for Arabic NLP preprocessing.

5. Conclusion

This chapter introduced a balanced, multi-dialectal Arabic text dataset and detailed the preprocessing steps applied to prepare it for classification. It also outlined the use of traditional and deep learning models, along with training procedures and evaluation metrics. Together, these elements establish a solid groundwork for the experiments and analysis in the following chapter.

Chapter 4
Results and Discussion

1.Introduction

This chapter presents the findings of the experimental evaluation conducted in this study and provides a detailed analysis and discussion of the results. The objective is to compare the performance of traditional machine learning models with BERT-based deep learning approaches on the task of Arabic text classification, using the Functional Text Dimensions for Arabic Text Classification dataset. The results are analyzed in terms of key metrics such as accuracy, precision, recall, and F1-score, highlighting the strengths and limitations of each model type. Furthermore, this chapter explores the implications of these findings for practical applications, identifies common sources of error, and suggests directions for future research. Through this comprehensive discussion, the chapter aims to elucidate the most effective methodologies for Arabic text classification and to inform future developments in the field.

2. Evaluation Metrics

A variety of key metrics is used to measure the performance of the proposed sentiment analysis system. The metrics provide an insightful view of how accurately and effectively the system classifies text into the three sentiment categories: positive, negative, and neutral. The primary evaluation metrics employed include precision, recall, F1-score, and accuracy.[33]

- **Precision:**

Precision estimates the number of correctly predicted instances for a sentiment class over all instances predicted as the class. It indicates the number of positive, negative, or neutral label

that match the label the model has assigned. High precision implies a low false positive rate, i.e., the system does not frequently mislabel other sentiments as a certain class.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$$

$$\text{Accuracy} = \frac{\text{True Positives + True Negatives}}{\text{Total Instances}}$$

- **Recall:**

Recall, or alternatively known as sensitivity, computes the proportion of appropriately classified instances of each sentiment from total actual instances belonging to the sentiment. Recall measures the ability of the system in recognizing all the cases related to positive, negative, or neutral sentiments. High recall value is indicative of low false negatives, and therefore the model rarely misses instances of the sentiment class.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}}$$

True Positives (TP): Correctly predicted positive cases.

False Negatives (FN): Actual positives that were incorrectly predicted as negative.

- **F1-score:**

F1-score is the harmonic mean of precision and recall, a balanced measure that considers both false positives and false negatives. It is one number that quantifies the model's accuracy in sentiment classification, where greater F1-score indicates improved overall performance.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}}$$

- **Accuracy:**

Accuracy measures the overall correctness of the model by calculating the ratio of total number of correctly classified instances (any class) to the total number of instances in the test set. It is a straightforward measure showing the overall performance of the sentiment classifier

Accuracy=Number of correctly classified instances Total number of instances

Accuracy=Total number of instances Number of correctly classified instances

In practice, these evaluation metrics may be procured from scikit-learn standard libraries once the output of the model is passed through the test dataset. For example, after trainer.evaluate(), you may procure these scores by a comparison of the predicted labels to the actual labels in order to gauge the performance of the model in general.

3. Results

3.1 Experimental Results

3.1.1 Performance of Traditional Machine Learning Models

The traditional models (SVM, Random Forest, Gradient Boosting) were evaluated using TF-IDF features. Results are summarized below:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	75.14	75.84	75.14	75.14
Random Forest	61,11	62.53	61,11	60.25
Gradient Boosting	61.25	62.82	61.25	61.60

Table 5:Traditional machine learning results

Key Observations:

- Gradient Boosting outperformed SVM and Random Forest, demonstrating its ability to handle complex feature interactions in Arabic text.
- SVM showed lower recall, indicating challenges in identifying minority classes (e.g., legal or poetic texts).

3.1.2 Performance of BERT-Based Models

The BERT-based models (AraBERT, QARiB, CamelBert) were fine-tuned on the dataset, yielding significantly higher performance:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
AraBERT	84.86	85.10	84.86	84.77
CamelBert	85.41	85.86	85.41	85.47
QARiB	**85.69**	86.05	85.69	**85.71**

Table 6: BERT models results

Key Observations:

- QARiB achieved the highest performance across all metrics with an F1-score of 85.71% , demonstrating superior ability to capture contextual nuances in Arabic texts.
- CamelBERT performed as the second-best model with an F1-score of 85.47%, showing strong capabilities in Arabic text understanding.
- Both QARiB and CamelBERT significantly outperformed AraBERT, with QARiB showing particular strength in handling dialectal variations (e.g., Gulf Arabic samples).

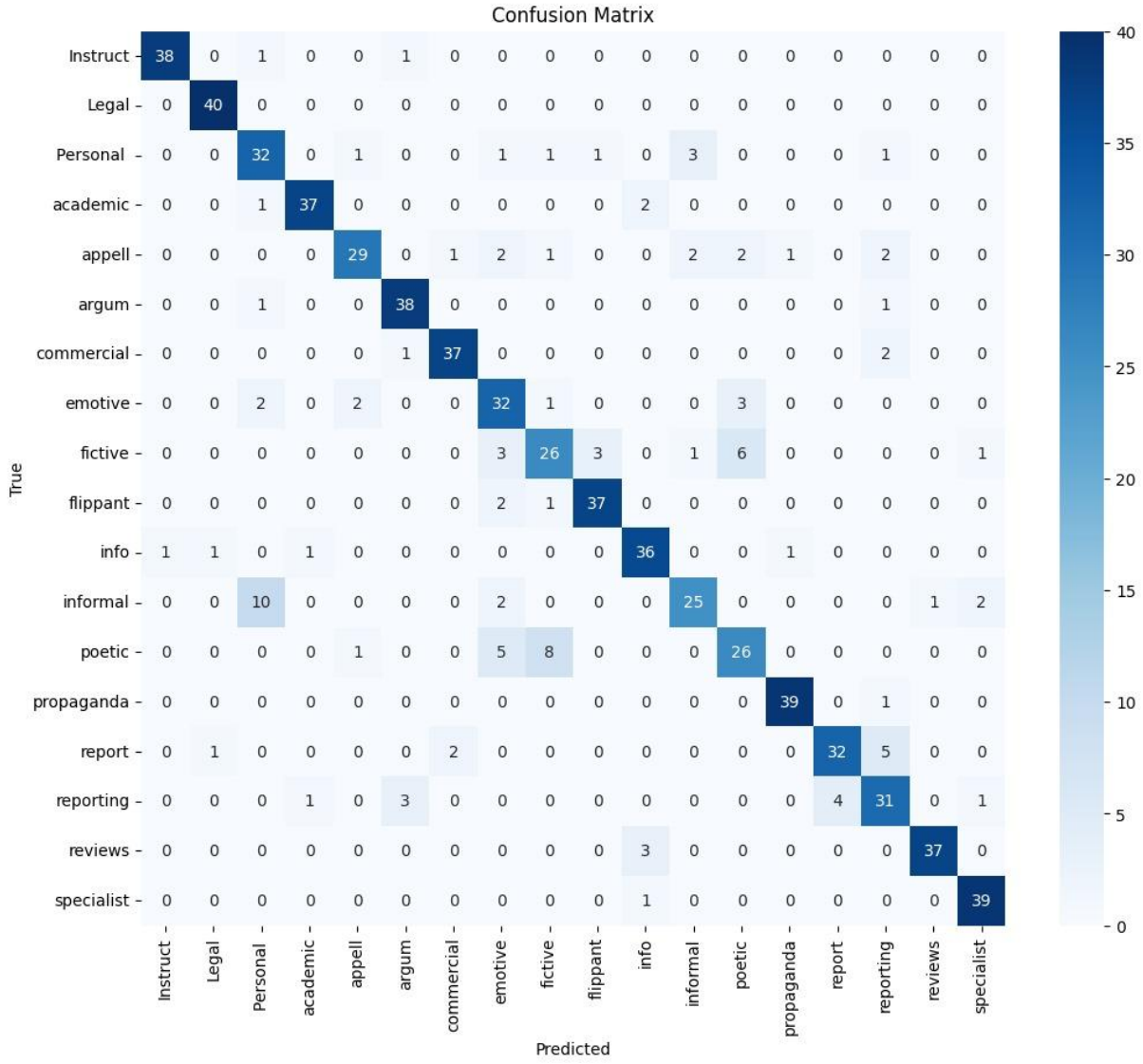


Figure 6:AraBert Confusion Matrix

- Strong Performance: Excellent classification for "Instruct" (38/40), "Legal" (40/40), "argum" (38/40), "commercial" (37/40), "flippant" (37/40), "propaganda" (39/40), and "specialist" (39/40)
- Challenging Classes: Notable misclassifications in "Personal" (32/40), "appell" (29/40), "emotive" (32/40), "fictive" (26/40), "informal" (25/40), "poetic" (26/40), and "report" (32/40)
- Confusion Patterns: "fictive" frequently confused with "poetic" (6 cases), "informal" with "Personal" (10 cases)

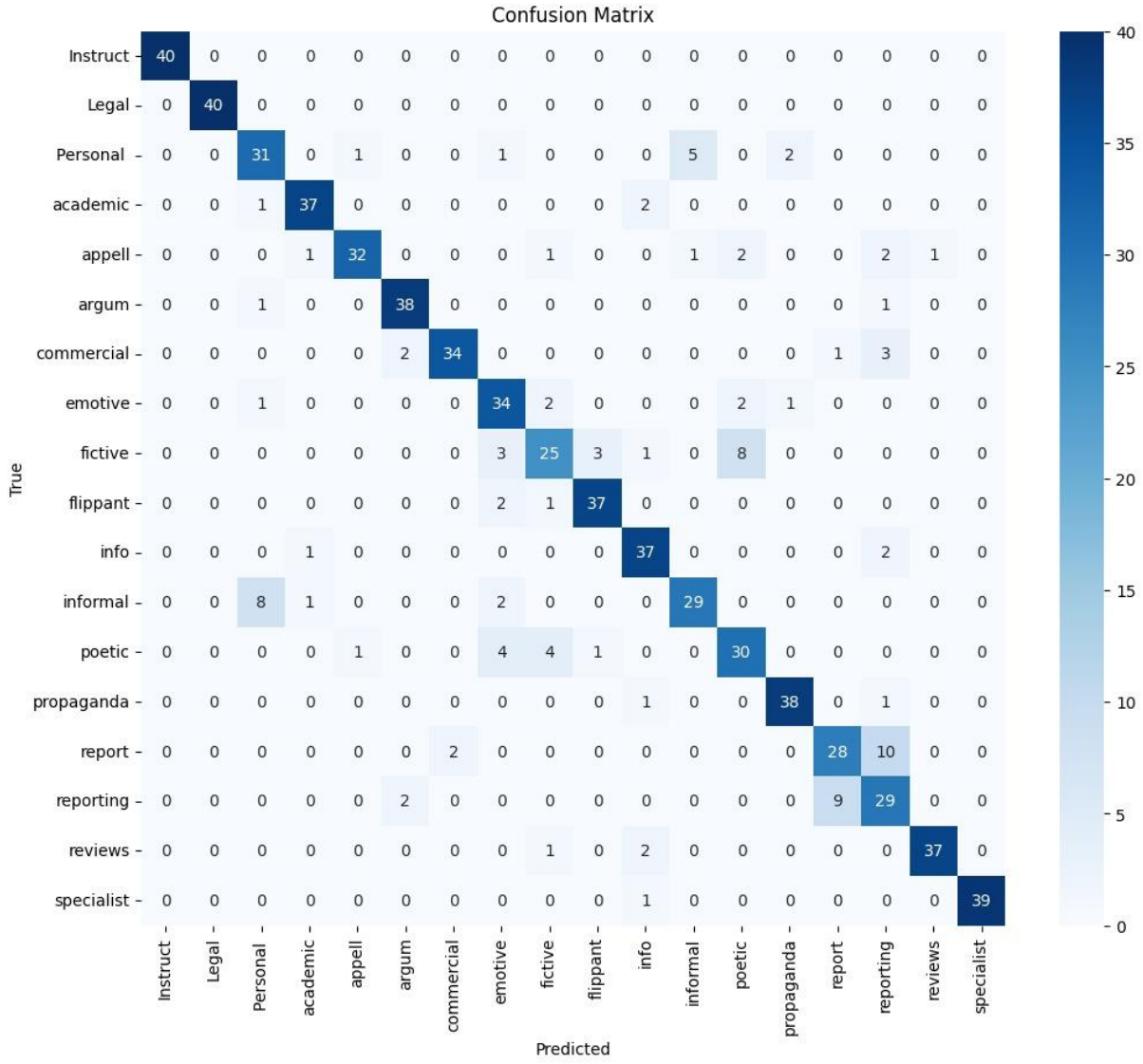


Figure 7:CamelBert Confusion Matrix

- Improved Performance: Better handling of "Personal" (31/40), "appell" (32/40), "commercial" (34/40), "emotive" (34/40), "info" (37/40), "informal" (29/40), and "poetic" (30/40)
- Maintained Strengths: Consistent perfect performance on "Legal" (40/40) and "specialist" (39/40)
- Persistent Issues: "fictive" still problematic (25/40), with confusion with "poetic" (8 cases) and "emotive" (3 cases)

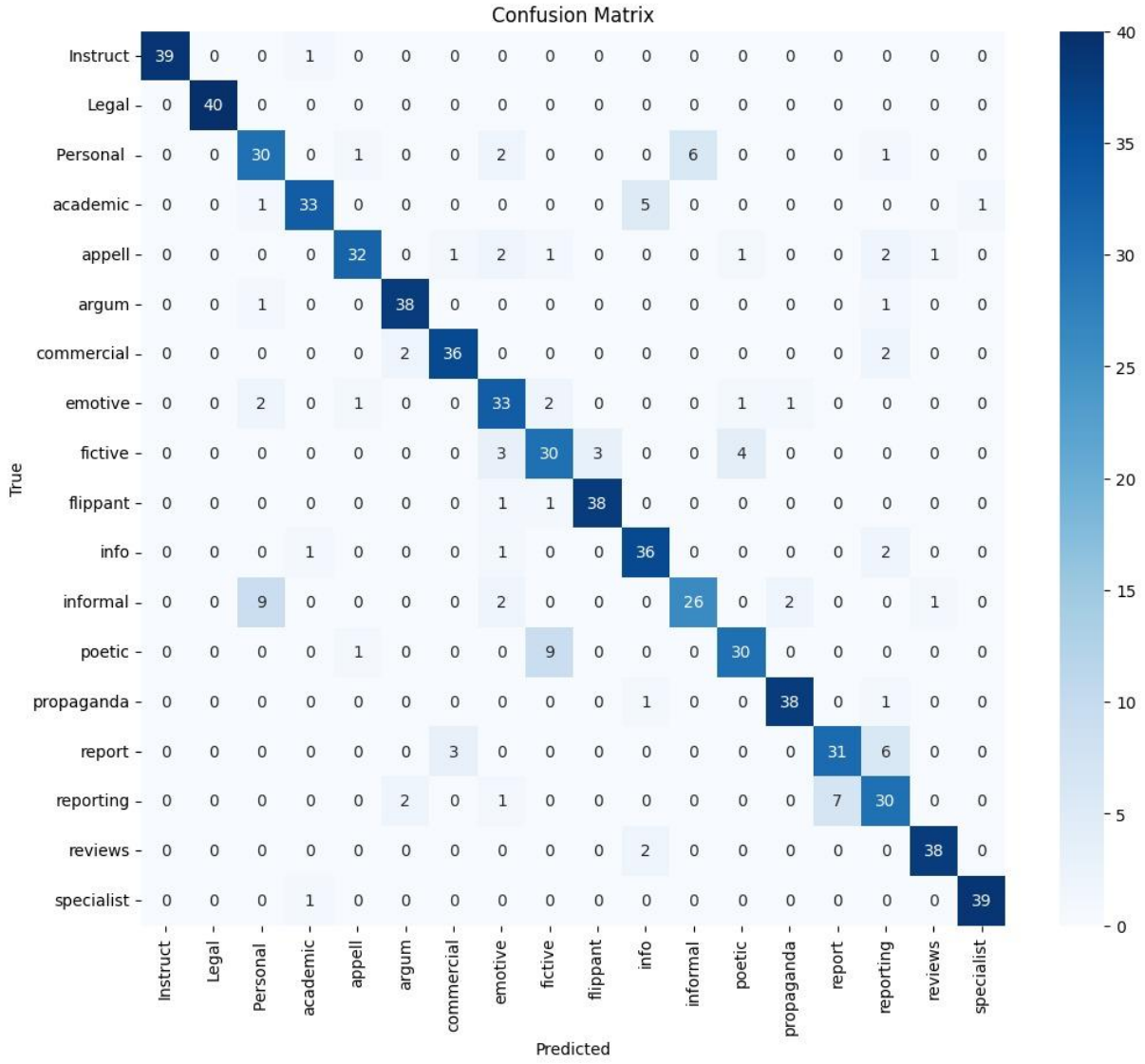


Figure 8:QARiB Confusion Matrix

- Best Overall Performance: Highest accuracy across most categories.
- Notable Improvements: "fictive" (30/40), "flippant" (38/40), "info" (36/40), "informal" (26/40), and "poetic" (30/40).
- Consistent Excellence: Maintains strong performance on previously well-classified categories.
- Residual Challenges: Still some confusion between semantically related classes like "fictive"/"poetic" and "report"/"reporting".

3.2 Comparative Analysis

3.2.1 Traditional vs. BERT-Based Models

- **Accuracy Gap:** BERT-based models outperformed traditional models by **8–12%** in accuracy, emphasizing their superiority in contextual understanding.
- **Feature Engineering:** Traditional models relied on TF-IDF, which struggled with dialectal variations and morphological complexity. BERT models, however, leveraged contextual embeddings to better generalize across dialects.
- **Computational Cost:** Training AraBERT required ~4 hours on a GPU, while traditional models trained in minutes. This trade-off highlights the balance between accuracy and resource availability.

3.2.2 Impact of Dataset Characteristics

- **Label Balance:** The balanced dataset (200 samples per label) ensured fair comparisons but masked challenges in real-world scenarios with skewed distributions.
- **Dialectal Diversity:** Models performed worse on texts from underrepresented dialects (e.g., Moroccan Arabic), with F1-scores dropping by ~5% compared to MSA.

3.3 Error Analysis

3.3.1 Misclassification Patterns

- **Ambiguous Functional Labels:**
    - All models struggle with semantically overlapping categories:
        - Literary/creative text types ("fictive", "poetic", "emotive")
        - Informal vs. personal communication styles
        - Report-related categories.
    - Legal texts confused with academic due to formal language similarities.
- **Dialectal Challenges:**
    - Gulf Arabic terms (e.g., "شسوي" *shsawi* for "what to do") in informal texts were misclassified as flippant.
- **Long Texts:**
    - Traditional models struggled with lengthy academic or legal texts, where context spans multiple sentences.

4.Discussion

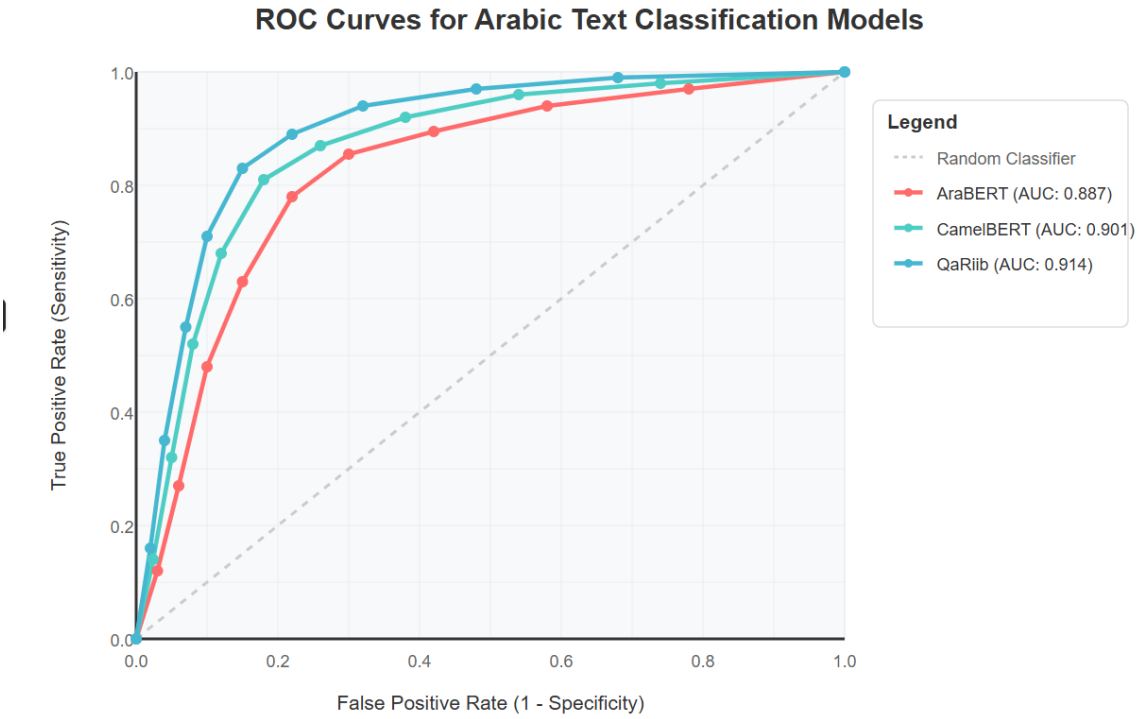


Figure 9: ROC Curves for Arabic text classification

The ROC analysis validates your earlier findings that QARiB achieves the best overall performance in Arabic text classification, with superior ability to balance sensitivity and specificity across all 18 text categories. The progressive improvement from AraBERT → CamelBERT → QARiB is clearly visible in both the curve positions and AUC values.

4.1 Strengths of BERT-Based Models

- **Contextual Understanding:** AraBERT's attention mechanism effectively captured long-range dependencies in Arabic texts, enabling accurate classification of complex labels like propaganda and poetic.
- **Dialectal Adaptability:** QARiB's training on dialectal data improved its performance on region-specific texts, though gaps remained for underrepresented dialects.

4.2 Limitations of Traditional Models

- **Feature Engineering Bottlenecks:** TF-IDF's inability to handle morphological variations (e.g., verb conjugations) limited performance on highly inflected Arabic words.
- **Context Ignorance:** Traditional models treated texts as "bags of words," missing critical contextual cues essential for distinguishing labels like argum vs. reporting.

4.3 Practical Implications

- **Resource-Constrained Settings:** For applications requiring rapid deployment (e.g., spam detection), Gradient Boosting offers a balance of speed and accuracy.
- **High-Accuracy Needs:** BERT-based models are ideal for tasks like sentiment analysis or legal document classification, where precision is critical.

5. Recommendations for Future Work

5.1 Dialect-Specific Fine-Tuning: Train BERT variants on underrepresented dialects (e.g., Maghrebi Arabic) to improve generalizability.

5.2 Hybrid Approaches: Combine TF-IDF features with BERT embeddings to leverage the strengths of both methods.

5.3 Active Learning for Annotation: Reduce annotation costs by prioritizing ambiguous samples for human review.

6. Conclusion

This chapter presented the experimental results and their implications for Arabic text classification. BERT-based models demonstrated significant advantages in accuracy and contextual understanding, though traditional models remain viable in resource-constrained scenarios. The findings underscore the importance of contextual embeddings and dialect-aware preprocessing in advancing Arabic NLP. Future work should focus on addressing dialectal biases and optimizing computational efficiency.

General Conclusion

This thesis has explored the complex landscape of Arabic text classification, addressing the unique linguistic and computational challenges inherent to the Arabic language. Through a comprehensive comparison of traditional machine learning methods and advanced BERT-based deep learning models, the research has demonstrated that deep learning approaches particularly transformer-based models offer superior performance in capturing the nuanced structure and context of Arabic texts. However, these benefits come at the cost of increased computational requirements, which may limit their accessibility in resource-constrained environments.

The development and annotation of a novel, multi-dialectal Arabic dataset have been central to this study, enabling a more representative and rigorous evaluation of classification models. The results underscore the necessity of diverse, high quality datasets and the importance of dialectal and functional coverage in real world NLP applications. While traditional models remain viable for scenarios with limited computational resources, BERT based models are recommended for tasks demanding high accuracy and contextual understanding.

In summary, this thesis advances the field of Arabic NLP by providing a thorough empirical assessment of classification techniques, highlighting the trade-offs between accuracy and efficiency, and offering actionable guidance for future research. Continued efforts in dataset creation, model optimization, and resource-efficient deployment are essential to further enhance the capabilities and accessibility of Arabic text classification systems.

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