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An Ensemble of Traditional Supervised and Deep Learning Models for Arabic Text-Based Emotion Detection and Analysis

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Abstract:- The dramaticgrowth of usersgenerated contents describing their feelings and emotion aboutproducts, services and events played a special role to bring attention to text based emotion analysis.Emotion analysis from unstructured textual data is an active area of research with numerous practical applications.Text based Emotion detection is one of the challenging tasks in Natural Language Processing. To overcome these challenges, this paper proposesanensemble of feature-based supervised learning and feature-less deep learning models for emotion recognition and analysis in Arabic short text.This paperalso evaluatesthree machine learning algorithms namely Naive-Bayes (NB), K-nearest neighbor (KNN) and meta-ensemble method of NB and KNN for Arabic text-based emotion detection and analysisProposed models are evaluated on theSemEval-2018 and compared with the performances of baseline models. Experimental results clearly show that theenhanced methods outperform other baseline models for Arabic emotion detection and analysis. Results shows that proposed models had a superficial impact on the general quality of Text based Arabic emotion detection and analysis. Results show proposed models outperformed baseline models in terms of weighted-average F-score.

Keywords:- *Emotion analysis, deep learning, machine learning, Arabic language.*

I. INTRODUCTION

With a great amount of online opinion, and reviews generated by social media users about policies, services, and products, understanding extremely important information in social media contents is valuable for many interested groups such as customers, business owners, and stakeholders. People uses social media for several purposes including expressing their viewpointsabout products, politics, which makes different parties such as customers, companies, and governments start to analyze these opinions. In fact, hearing tocustomer's opinions, and reviews play a major role in decision-making processes. In particular, decision makers take into account their peers' past experiences in making decision involves consuming valuable resources, such as time and/or money, people. Identifying and analysingcustomer's opinions in an efficient and right way to understand both their present and potential needs becomes a critical challenge for market-driven product design.People's feelings and thoughts in response to specific contexts are referred to as emotions. Emotion analysis is subfield of sentiment analysis that deals with identifying and analyzing explicit or implicit emotions expressed in user generated text to detect or extract finer-grained emotions such as happy, sad, anger, surprise, frustration, sadness and so on from human languages[1, 2]. Emotion analysis is the combination of emotions (also known as affects) with technology, and it takes its essence from the using emotion analysis to many sectors in order to enable fine-grained decision making. The exponential growth of the Social Web is virally infecting more and more critical business processes such as customer support and satisfaction, brand and reputation management, product design and marketing. In fact, this has pushed text mining and analysis to the forefront of business success. Emotion analysis is essential in the business sector [2, 3]. In order for organizations and individuals to provide better products and servicesto customers, there is a need to detecttheir various emotions that they expressed and then to utilize this information to give recommendations that are suited to the specific need of customers.

Emotion analysis is an important filed of research in the area of Natural Language Processing (NLP). Like any text classification task, several methods and approaches are proposed and adopted foremotion detection andanalysis. Most of these methods and approaches fall into two main methodologies: unsupervised or lexicon based [4-8]and supervised and deep learningmethods[9-16]. In the supervised and deep learning methods, text corpora are used to train models. On the other hand, unsupervised or lexiconapproaches deals with the construction or the use of emotion dictionaries or lexicons such as WordNet-Affect[4, 17] and EmoSenticNet[18]. These emotion lexicons contain emotion search words or keywords such as happy, hate, angry, sad, surprise, and so on.

As Emotion analysis presents new challenges in addition to those faced by sentiment analysis. The first issue is that of emotion representation, where researchers in the field of psychology are still arguing on classifying emotions into a set of distinctive groups and categories. Unlike sentiment analysis where polarity is represented using one scheme (positive, negative and neutral), several schemes for emotion recognition are adopted by research community such as [19] that distinguishes emotions based on six (6) classes, [20] distinguishes 8 basic emotions and [21] distinguishes 22 classes .Arabic is a Semitic language spoken by more than 400 million people. Researchers face various difficulties, including dealing with context,

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statements contain several emotions, spreading Web slang, and lexical and syntactical ambiguity. Consequently, emotion analysis still an open research problem and researchers face a significant problem in developing a technique that can effectively work across all domains. Previous emotion classification methods usually fail to extract significant features and achieve poor classification performance when applied to processing of short texts or micro-texts. In addition, the cultural of individual significant impact their expressed emotions. However, there are few emotion-labelled resources and few research works in languages other than English.Arabic is a Semitic language spoken by more than 400 million people[22-24]. Arabic are classified into three main types: Classical Arabic (CA), which is used in the Quran, modern standard Arabic (MSA), which is used in formal conversations and writing, and the Arabic dialect (AD), which is used in daily writing and communicationon social media. Despite this, there are few emotion-labeled resources and few research works in Arabic emotion analysis. This paper proposes an enhanced model for Arabic emotion analysis based on meta-ensemble of traditional supervised and deep learning models for Arabic text-based emotion detection and analysis. Besides, this work evaluates three machine learning algorithms Naive-Bayes, K-NN and meta-ensemble methods for Arabic text-based emotion detection and analysis.

The remainder of this paper is organized as follows. Section 2 present the related work while section 3 present theproposed methodology. In Section 4, experiment setup is presented. Section 5 discusses the experimental results. Finally, we conclude our work and discuss future directions of research in Section 6.

II. RELATED WORK

Researchers give increasing attention to the specific problem of emotion recognition, even though there is no agreement over which are the primary emotions of human kinds, the scientific community. Lexicon-based, machine-learning-based, and deep learning-based emotion analysis are the three main techniques[2, 4, 5, 9-11, 13-16, 25, 26]used for Emotion analysis.

Full survey about emotion analysis researchwork,used techniques, available resources are introduced in [1, 2, 25, 26]

The research work for Emotion Analysis in Arabic is not as advanced as is emotion recognition research work for English. The lack of annotated resources in Arabic are the main contributors to this issue.

Mohammad et al. [27] organized the SemEval-2018 Task 1: affect in Tweets, which included five subtasks. The fifth subtask is multi-label emotion recognition in tweets. Datasets are in three languages: Arabic, English, and Spanish.

[28] collected a dataset (IAEDS) for emotion analysis from Facebook posts. They extract n-grams as features and five classifiers are used for testing,ZeroR, J48, NB, multinomial naïve Bayes (MNB) for text, and SVM with SMO. ZeroR and MNB resulted in the worst performances.

[29]designed three deep learning models for Arabic emotion analysis, a deep learning model trained on human-engineered feature (HEF)which include stylistic, lexical, syntactic, and semantic features, a deep learning model trained on deep feature-based (DF), and a deep learning model trained on features from those two models(HEF+DF). The model and are applied. The model was evaluated using the reference dataset of SemEval-2018 Task.F1-score in the experiments was 0.50.

In [30], an Arabic text based emotion analysis is implemented based on a multilayer bidirectional long short term memory (BiLSTM) trained on pre-trained CBOW word embedding model for word representation. The proposed model achieved the best performance results compared with Support Vector Machines (SVM), random forest (RF), and fully connected neural networks.

In [31], Arabic text based emotion analysis is implemented based on Long Short Term Memory (LSTM) neural networks and embedding from Language Models (ELMO). F1-score in the experiments was 0.65.

ELFAIK et al [32], designed a multilabel emotion classification that integrates the transformer-based model for Arabic language understanding AraBERT and an attention-based LSTM-BiLSTM deep model. AraBERT is pre-trained BERT specifically for Arabic language that map each token to the corresponding contextualized embedding, and the attention-based LSTM-BiLSTM determines the label-emotion of input tweets. They combine aBiLSTM layer with the LSTM layer to extract both past and future contexts by means of considering temporal information flow in both directions. Additionally, they used the attentionally weighted representation mechanism to obtain the final sentential representation and capture the most significant part of a target sentence. The model was evaluated using the reference dataset of SemEval-2018 Task 1 (Affect in Tweets) and it achieves significant accuracy (53.82%).

In[33], several approaches for Arabic emotion analysis taskhave been implemented using Deep Learning and ensemble. These approaches are (a) bidirectional Gated Recurrent Unit along with Convolutional neural networks (BiGRU_CNN), (b) conventional neural networks (CNN), and (c) XGBoostregressor (XGB) which is considered as distributed gradient boosting. The ensemble of these three model (BiGRU_CNN, CNN, and XGB) is used to solve Arabic emotionanalysis tasks. The proposed ensemble approach is evaluated using a reference dataset of the SemEval-2018 Task1. Results show that ensemble approach is outperformed baselinemodels with an average Pearson Correlation Coefficient scores of 69.2%.

There a few exist emotions labeled datasets for Arabic. The availability of rich resources in Arabic language and its dialects such as can greatly change the narrative and encourage research in emotion analysis in Arabic languages.

III. METHODOLOGY

In this work, a unified methodology that includes all the phases required in emotion detection and analysis.The proposed methodology consists of several phases ranging frompre-processing, data representation, feature selection, and emotion analysis as shown in Figure 1. The main aim of this paperis to design an ensemble of traditional supervised machine learning and feature-less deep learning models for Arabic text-based emotion detection and analysis.

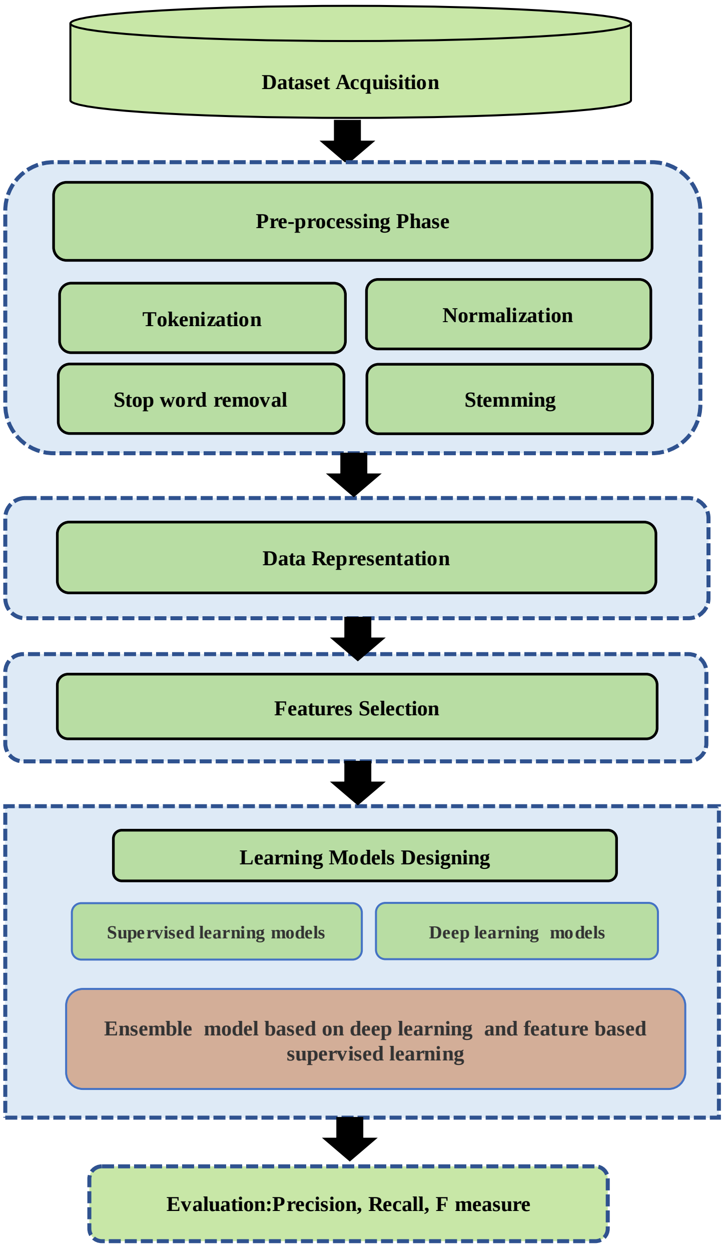

Fig. 1: The Framework of the Arabic Emotion Analysis

A. Pre-Procssing:

Like any user generated content, reviews/data collected from social media platforms/sites are highly unstructured, making emotion analysis difficult. These data often contain spelling errors, short form of words, redundant characters, spelling errors, special characters, symbols and Html codes. Therefore, pre-processing of data is important before processing it in any following step. The pre-processing stage also can be regarded as dimensionality reduction step as it helps to reduces the dimensionality by normalizing different form of words and deleting noisy stop words such as prepositions, conjunctions, and articles that does not affect the polarity and frequently appears in reviews and opinions texts. In the pre-processing phase, several natural language processingstepsare conducted. The pre-processing in this work includes 1) okenization; 2) normalization; and 3) stop word removal. In normalization, noise such as non-Arabic words or characters are removed and normalization also converts different forms of Arabicwords intoa consistent form. been removed from the text. In tokenization, reviews are converted to bag of words representation depend on punctuation marks and white spaces in delimiting word boundaries (or main tokens). Reviewscontain many stop words such as pronouns, prepositions, and conjunctions. In stop word removal, these words are removed from training and testing data.The reason of removing such words is they are frequently appearing in texts from all classes and do not aid in classesdiscrimination.

B. Feature SelectionPhase

Curseofhigh dimensionality is major problem in text mining where the size of generated features is rather huge. One of the most important steps in emotion analysis is feature selection or dimensionality reduction in which only discriminating features is selected. After preprocessing and data representation steps, large percentages of features arenot discriminative. Given hugesize of features obtained, only tiny fractions of these features carry valuable information towards emotion analysis. As a consequence, asuitable featureselection method that reduces sizeof features is needed.Feature selection can be defined as is the process of selecting the smallest subset of features so the dimensionality is optimally reduced while the analysis performance does not significantly decrease.This work uses total sumensemble feature selection method thatcombines three filter-based methods (information gain, odd ratio and chi-squared).

a) Total Sum Ensemble Feature Selection:
In this step, the outputs of the three filter based feature selection methods (the here ranked lists of the top n features of the best are combined by using a total sum, which represents the total score $\boldsymbol{F_T(t)}$:

$$\boldsymbol{F_T(t)} = \sum_{i=1}^{T} \boldsymbol{fs_i(c,w)} \qquad (1)$$

where every $\boldsymbol{fs_i}$is one of the threefeature selection methods that returns the calculated scorewith respect to word total sum and a class c.The main aim of this step is to combine the three ranked lists of features produced by three feature selection methods into one list. The ensemble combines the strength of its individuals (three base filter based feature selection methods).

b) Information Gain:

The information gain (IG) methodis employed in the ranking of the most relevant features. It is used to measure the impurity of attributes and to find the best split of attributes in decision trees. The information gain ratio formula is shown as below. The value obtained in the calculation of IG for each attribute is useful in determining the correct classification of any class.

$$\begin{aligned} \mathrm{IG}(w) &= -\sum_{i=1}^{|c|} p(c_i)\log p(c_i) \\ &+ p(w)\sum_{i=1}^{|c|} p(c_i|w)\log p(c_i|w) \\ &+ p(\overline{w})\sum_{i=1}^{|c|} p(c_i|\overline{w})\log p(c_i|\overline{w}) \end{aligned} \quad (2)$$

w =the feature w
c_i =classc_i

Where $\mathrm{p}(\mathrm{c_i})$denotes the probability that class$\mathrm{c_i}$occurs; $\mathrm{p}(\mathrm{w})$ denotes the probability that wordw occurs, and $\mathrm{p}(\overline{\mathrm{w}})$ denotes the probability that word w does not occur.

c) Chi-Squared Statistic (χ^2):

χ^2 is one commonly used feature selection. Chi-square estimates whether the class label is independent of a feature. Chi-square score with class$c$ and feature/word w is defined as:

$$\chi^2(c,w) = \frac{N \times (AD\text{-}BC)}{(A+C)(B+C)(A+B)(C+D)} \quad (3)$$

where $\boldsymbol{A}$is the number of times that w and c co-occur,$\boldsymbol{B}$ is the number of times that $w$occurs without c,$\boldsymbol{C}$ is the number of times that c occurs without w, $\boldsymbol{D}$ is the number of times that neither c nor w occurs, and $\boldsymbol{N}$ is the total number of reviews.

d) Odd Ratio :

Odd Ratio reflects the odds of the word occurring in the positive class normalized by that of the negative class. The odds ratio for a feature f is calculated using the following equation:

$$\text{Odd Ratio (f)} = \frac{\mathrm{A} * \mathrm{D}}{\mathrm{C} * \mathrm{B}} \quad (4)$$

C. Emotion Analysis/Classification Phase :

This section describes the proposed supervised and deep ensemble learning models. Second, it describes base supervised machine learning and deep learning classifiers. The main idea of the proposed an ensemble learning models is to combine a set of diverse base-classifiers includes feature based supervised learning models and deep learning models for Arabic text-based emotion analysis. The ensemble combines set of learning models (NB, KNN andBI-LTSMdeep learning) using a meta-classifier, as shown in figure 2.

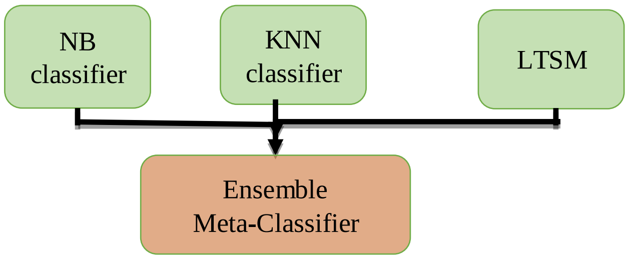

Fig. 2: The general architecture of the proposed ensemble

The output for all base classifiers is considered as a new feature for meta-learning. The classification model used for this purpose is naïve BayesThis model combines the output of the three classifiers.

a) Naive Bayes (NB) Classifier :

The Naive Bayes (NB) algorithm is a widely used algorithm for emotion detection and analysis. Given a feature vector table, the algorithm computes the posterior probability that the document belongs to different classes and assigns it to the class with the highest posterior probability. The major advantage of NB emotion detection and analysis algorithms is that they are easy to implement, often they have superior performance.

b) K-Nearest Neighbour(K- NN):

The K-nearest neighbor (KNN) is a typical example-based classifier. Given a test document d, the system finds the K-nearest neighbors among training documents. The similarity score of each nearest neighbor's document to the test document is used as the weight of the classes in the neighbor's document. The weighted sum in KNN categorization can be written as in Equation 3.10:

$$\mathrm{score}(d,t_i) = \sum_{d_j = KNN(d)} sim(d,d_j)\,\delta(d_j,c_i) \quad (5)$$

Where KNN *(d)* indicates the set of K-nearest neighbours of document d. If d_jBelongs toc_i, $\delta(d_j,c_i)$ equals 1, or other-wise 0. For test document$d$, it should belong to the class that has the highest resulting weighted sum.

c) BI-LSTM: bidirectional Long short term memory

Bi-LSTM is to overcome the gradient vanishingproblem of RNN. BiLSTM combinesbidirectional recurrent neural network (BiRNN) models andLSTM units is used to capture the context information. Bi-LSTM are inspired by BiRNN that use two hidden layers to parse sequence inputs in both forward and backward paths. Bi-LSTMs combine two hidden layers into one output layer.

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IV. EXPERIMENTAL SETTING

Several experiments are conducted to evaluate baseline and enhanced models for Text based Arabic emotion detection and analysis models. several experiments are conducted to measure the performance of baseline supervised models along with four statistical -based feature selection methods.

This research made several experiments to evaluate proposedensemble of supervised learning and deep learning models. All experiments are conducted using SemEval-2018 dataset.

SemEval-2018:The dataset is collected from twitter and labeled using eleven 11 eleven emotions: anger, anticipation, disgust, fear, happiness, love, optimism, pessimism, sadness, surprise, and trust. The dataset is divided into training, development, and testing datasets. Table 1 gives description of SemEval-2018 dataset.

Emotion	Training	Development	Testing
Anger	899	215	609
Anticipation	206	57	158
Disgust	433	106	316
fear	391	94	295
Happiness	605	179	393
Love	562	175	367
Optimism	561	169	344
pessimism	499	125	377
sadness	842	217	579
Supervise	47	13	38
Trust	120	36	77

Table 1: Description Of Semeval-2018 Dataset.

The standard classification measurement precision, recall, and F-measure are used to assess the proposed model. Precision(*Pi*), Recall (*Ri*) andF-measure (*Fi*) aredefined mathematicallyas presented.

$$P_i = \frac{TP_i}{TP_i + FP_i} \qquad (6)$$

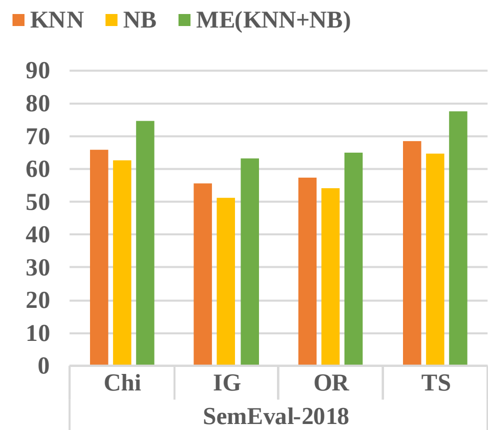
$$R_i = \frac{TP_i}{TP_i + FN_i} \qquad (7)$$

$$F_i = \frac{2(P_i * R_i)}{P_i + R_i} \qquad (8)$$

Finally, all the experiments are performed on both corpora which are divided into 90% for training the proposed model, while 10% used for testing.

V. RESULTS AND DISCUSSION

First, several experiments are carried out to evaluates three baseline text based Arabic emotion analysis models (K-nearest neighbourclassifier (KNN), Naive Bayes (NB) and meta- ensemble method of NB and KNN) along with fourfeature selection methods namely odd ratio(OR), information gain (IG) and chi-square(CHI) and Total Sum Ensemble (TS). Figure 3, the performance (F-measure) the best results obtained by baseline text based Arabic emotionanalysis models withfour feature selection methods where all experiments are conducted using SemEval-2018 dataset. The general aim here is to studyhow traditional machine learning performs with emotion detection and analysisand how feature selection methods affect theirmodels. It can be noted that results obtained with Naive Bayes (NB) method is lower than obtained with and K-nearest neighbour classifier (KNN) methods with all feature selection methods.Results also show that total sum Ensemble feature selection method results outperforms all other three individual filter-based feature selection methods with three baseline models (K-nearest neighbourclassifier (KNN), Naive Bayes (NB) and meta- ensemble method of NB and KNN).It can be observed that the enhanced meta-ensemble model outperforms other baseline classifiers with all feature selection methods. The meta-classifier combines the strength of its individuals (base-classifiers). It expected when several individual classifiers agree on classifying most of the cases and only disagree with small cases (when one of them becomes wrong), then combining these classifiers always achieves higher results. Besides, combining the decision of several single classifiers which achieve a high result, better than individual classifier (base-classifier).



	Chi	IG	OR	TS
KNN	65.87	55.51	57.29	68.49
NB	62.7	51.23	54.14	64.64
ME(KNN+NB)	74.73	63.2	64.9	77.74

Fig. 3: Performance (F-measure) the best results obtained by baseline text based Arabic emotion analysis models withodd ratio(OR), information gain (IG) and chi-square(CHI) and Total Sum Ensemble (TS)

Second, several experiments are conducted toevaluate theproposed meta-classifier ensemble learning model which combines a set supervised learning and deep learning models for Arabic text-based emotion analysis. This meta-classifier ensemble learning combines NB, KNNand Bi-Directional LTSM.Table 2 show the results of the proposed ensemble method with the four feature selection methods namely odd ratio, information gain and chi-square and Total Sum Ensemble. As observed, experiments show that proposed meta-classifier ensemble learning model significantly outperforms all other models on SemEval-2018.

Table 2 Performance of enhanced model deep and traditional Meta Classifier (DTMC) with oddratio, information gain and chi-square and Total Sum Ensemble.

	SemEval-2018
DTMC+CHI	81.15
DTMC+IG	69.21
DTMC+OR	70.07
DTMC+TS	84.6

The results obtained show that the results of allclassification models are significantly improved with Total sum ensemble feature selection method. It can also be observed that the enhanced deep and traditional meta-classification ensemble model with the outperforms all baselineclassification models. These findings reveal that the proposed deep and traditional meta-classification ensemble model is the most suitable technique for Text based Arabic emotion detection and analysis.

VI. CONCLUSION

This paper empirically evaluates three baseline machine learning methods namely K-nearest neighbourclassifier (KNN), Naive Bayes (NB) and meta-ensemble of KNN and NB with fourfeature selection methods namely odd ratio(OR), information gain (IG) and chi-square(CHI) and Total Sum Ensemble (TS)for Arabic emotion task. In addition, this paper introducesText based Arabic emotion detection and analysis enhanced meta-classifier ensemble learning model which combinestwo traditional learning (KNN and NB) and one deep learning model(Bi-Directional LTSM) for Arabic text-based emotion analysis. Experimental results demonstrate these findings reveal that the proposed deep and traditional meta-classification ensemble model is the most suitable technique for Arabic text-based emotion analysis.Future work should build ensemble methods that combine advanced deep learning models such as attention-based bidirectional CNN-RNN deep model.

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