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Emotion detection using Word2Vec and convolution neural networks

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ABSTRACT

Emotion detection from text plays a very critical role in different domains, including customer service, social media analysis, healthcare, financial services, education, human-to-computer interaction, psychology, and many more. Nowadays, deep learning techniques become popular due to their capabilities to capture inherent complex insights and patterns from raw data. In this paper, we have used the Word2Vec embedding approach that takes care of the semantic and contextual understanding of text making it more realistic while detecting emotions. These embeddings act as input to the convolution neural network (CNN) to capture insights using feature maps. The Word2Vec and CNN models applied to the international survey on emotion antecedents and reactions (ISEAR) dataset outperform the models in the literature in terms of accuracy and F1-score as model evaluation metrics. The proposed approach not only obtains high accuracy in emotion detection tasks but also generates interpretable representations that contribute to the understanding of emotions in textual data. These findings carry significant implications for applications in diverse domains, such as social media analysis, market research, clinical assessment and counseling, and tailored recommendation systems.

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1. INTRODUCTION

Emotion detection has become very important in today's digital era. The ability to automatically identify and express the emotion from a given text has many applications in the fields of customer service, Marketing, healthcare, financial services, psychology, education, and many others. There are various approaches for emotion detection from text such as rule-based, classical learning-based, deep learning-based, and hybrid. The deep learning-based approaches [1] have proved their importance in natural language processing tasks including emotion detection from text. This paper presents an experiment with a combination of Word2Vec embedding and convolution neural network (CNN) model that outperforms the traditional machine learning approach like random forest (RF) and logistic regression (LR) with term frequency-inverse document frequency (TF-IDF) methods [2] and deep learning approaches in the literature. Word2Vec captures the semantic and contextual relationship of a given text which helps in getting a more fine-tuned emotion detection model. The output of Word2Vec embedding goes as input to the CNN model. CNN [3] algorithm is known for its ability to extract the local features and learn nested representations from given input text.

The focus of this research paper is to develop a robust model that can outperform the traditional machine learning model in classifying the emotions in given input text. For the development and evaluation of this model international survey on emotion antecedents and reactions (ISEAR) dataset [4] is used which has seven different emotion categories: anger, disgust, guilt, fear, joy, shame, and sadness. ISEAR dataset was split into the train and validation dataset. The training dataset has 80% of records for training the model and the Validation dataset has 20% records for validating the model.

2. RELATED WORK

This section includes an overview of previous research done in the field of emotion detection using deep learning algorithms including CNNs and Word2Vec embeddings. Ullah *et al.* [5] presents the implementation of different word embedding techniques and applies the CNN to get the best model. It has applied TF-IDF, bag-of-word, and skip-gram word embedding and then used the various deep learning algorithms such as long short-term memory (LSTM), artificial neural network (ANN) and recurrent neural network (RNN) along with CNN. These experiments were performed on Urdu language input data. Riza and Charibaldi [6] introduces a deep learning-based approach to emotion detection. It addresses the challenge of out-of-vocabulary text in emotion classification by employing fastText word embedding techniques combined with an LSTM model. The process begins with the collection of input data from the Twitter platform, which is then subjected to a series of text pre-processing steps. The pre-processed text is transformed into numerical vectors using the fastText word embedding method. Finally, these vectors are fed into the LSTM model, which effectively categorizes the input text into various emotion categories. Sharma *et al.* [7] present a novel approach for short sentence classification in movie reviews, utilizing word embedding and convolutional neural networks. This method demonstrates significant efficacy, particularly for smaller datasets commonly found on social media platforms, and shows superior results compared to other machine learning algorithms. Looking forward, the paper suggests extending this approach to longer sentences or larger datasets, with the potential to achieve even higher accuracy.

Hasan *et al.* [8] automatic emotion detection from social media posts related to psychological disorders. The authors presented the two-part approach where the first is to develop the emotion classification model using Naïve Bays, support vector machine (SVM), and decision tree algorithms. The second part is to apply that model to social media posts in real-time. Herzig *et al.* [9] presents the various word embedding techniques with a combination of both sparse and dense word vector representation. The author experimented with the one vs all SVM algorithms in five different datasets and found better results compared to other machine learning algorithms. Atmaja and Akagi [10] offers a deep learning strategy for category and dimensional emotion identification from written and spoken formats. Larger datasets enhance accuracy (>60%) and minimize errors (<20%) in both tasks compared to smaller datasets. The amount of emotion categories and dataset size affect accuracy. Spoken texts beat written ones for categorical emotion recognition. However, for dimensional emotion tasks, written texts show better results. Based on various research papers, deep learning algorithms along with word embedding techniques such as Word2Vec prove significant success in capturing the semantic and contextual information in the given text which leads to a better emotion detection model.

3. DATASET AND PREPROCESSING

To train and validate the proposed emotion classification model using Word2Vec-CNN, we utilize the "ISEAR" [11] dataset. This dataset is accepted and used by many researchers to develop the emotion detection model. This dataset was developed through an international survey that gathered the emotions of different participants. During the survey, respondents were assigned specific situations to evoke emotion. Participants were then asked to provide written text descriptions of their emotional state, along with the antecedents (causes or triggers) and reactions associated with those emotions.

3.1. ISEAR dataset description

ISEAR dataset has seven different emotion categories as 'fear', 'guilt', 'anger', 'joy', 'sadness', 'shame' and 'disgust'. It has a total of 7,516 rows and two columns as the "emotion" category and 'text'. These emotional texts in the ISEAR dataset capture the nuances and complexities of human emotions and encourage the model to capture the associations between specific word contexts and emotion categories. Exploratory data analysis was performed by checking the emotion distribution. Each emotion category is almost equally presented in the ISEAR dataset which helps to understand the class imbalance problem in any classification model. Balancing the dataset makes sure that the emotion classification model can learn from a wide range of emotional categories and provide robust and accurate predictions. The distribution of emotion categories in the ISEAR dataset is presented in Figure 1.

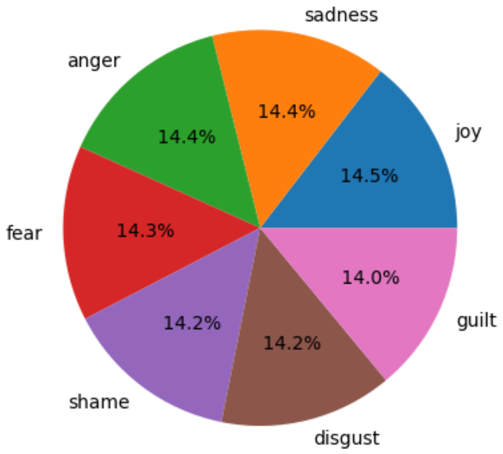

Figure 1. Distribution of different emotions in the ISEAR dataset

3.2. Text pre-processing

The ISEAR dataset needs to be pre-processed to ensure the consistency and quality of the dataset before training the model. These text preprocessing [12] steps are removing noise from the data (such as hashtags, usernames, and punctuation), text normalization (converting text to lowercase), and managing the formatting inconsistencies in the dataset and tokenization of data. Both the train and validation datasets have gone through the text preprocessing steps. After preprocessing the ISEAR dataset, it has 8,993 unique words as individual word tokens. To define the same input size of each record to the model, zero were added and this process is called padding [13]. The maximum word count in any record was defined as the input length of each record. Figure 2, presents the ISEAR training dataset after padding.

```
array([[   0,    0,    0, ...,   18,    5, 1610],
       [   0,    0,    0, ...,  556,   16,   84],
       [   0,    0,    0, ...,    5,   93,   22],
       ...,
       [   0,    0,    0, ...,   19,    2,  650],
       [   0,    0,    0, ...,  351,    9,   77],
       [   0,    0,    0, ...,   54,   69,  679]], dtype=int32)
```

Figure 2. ISEAR training dataset after padding

4. WORD EMBEDDING AND CNN MODEL

4.1. Word2Vec word embedding technique

Word embedding techniques convert the text input into a numerical dense vector. That vector can be used in the classification algorithm further. Word2Vec is one of the widely used word embedding techniques that convert the given text input into a numerical dense vector. This solves the problem of sparse vectors that come in traditional embedding techniques such as count-vectorize, TF-IDF, and co-occurrence metrics. Word2Vec captures the contextual information and semantic relationship in text. It is based on two different deep-learning-based algorithms the continuous bag of words (CBOW) model [14] and the skip-gram model. The job of the CBOW model is to predict the center word with respect to surrounding words. The skip-gram model which is based on the negative sampling method, predicts the surrounding words based on the center word. Word2Vec algorithm offers advantages such as containing semantic relationships, managing out-of-vocabulary words, and present the continuous vector representations that capture contextual information. The Word2Vec architecture is presented in Figure 3.

After preprocessing the ISEAR dataset, Word2Vec converted the text data into an embedding matrix. Each word of the corpus was mapped to the pre-trained Word2Vec vector and formed the embedding word matrix that is used by classification algorithms as input to develop the model. For the ISEAR dataset, the number of dimensions for word embedding is 300.

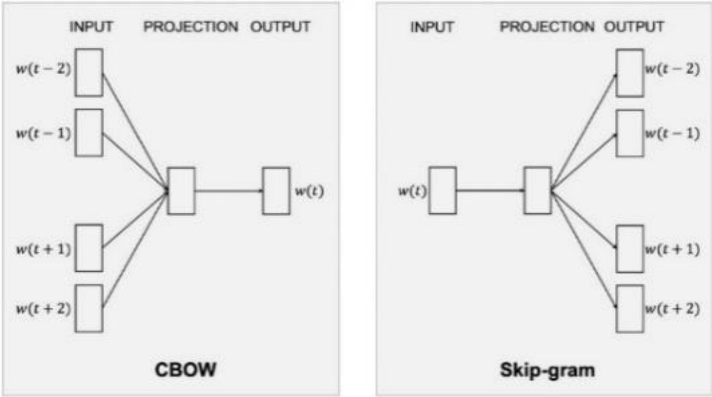

Figure 3. CBOW and skip-gram architecture [15]

4.2. CNNs model

CNNs have demonstrated outstanding performance in the text classification tasks. They can capture the local features by applying the convolution operation and understand the hierarchical representations of input data. The CNN architecture [16] includes the convolution layer, pooling layer, fully connected layer, and Output layer. Figure 4, presents the CNN architecture. Overall, Figure 5, presents the proposed approach for the emotion classification model.

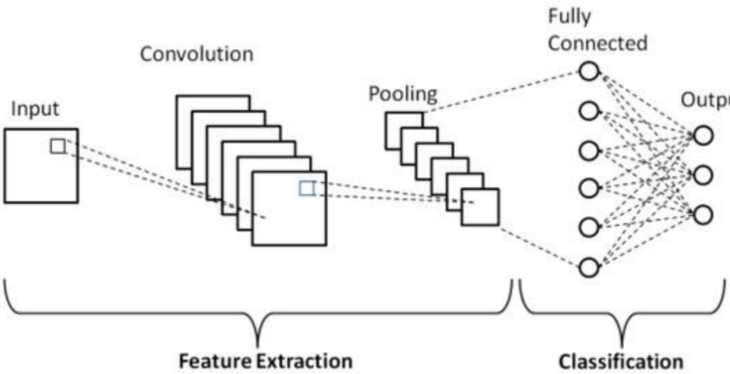

Figure 4. CNN architecture [17]

Figure 5. Proposed model architecture

5. EXPERIMENTAL SETUP, RESULTS, AND INSIGHTS

For Word2Vec, we utilized the pre-trained Word2Vec embeddings generated from a large corpus of unlabelled text data. These word embeddings capture the semantic and contextual information necessary for understanding emotional expressions. The CNN model architecture was implemented in Google Collab using TensorFlow and Keras. We configured the CNN model with a convolutional 1D layer, having 256 filters, and kernel size 3. The internal layer uses the ReLU activation function and SoftMax activation function in the output layer. We applied the categorical_crossentropy as a loss function and used the Adam optimizer. Figure 6, presents the CNN model architecture that was implemented while developing the proposed model.

```
Model: "sequential_17"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_17 (Embedding)    (None, 179, 300)          2698200

 conv1d_17 (Conv1D)          (None, 177, 128)          115328

 global_max_pooling1d_17 (Gl  (None, 128)              0
 obalMaxPooling1D)

 flatten_17 (Flatten)        (None, 128)               0

 dense_27 (Dense)            (None, 7)                 903

=================================================================
Total params: 2,814,431
Trainable params: 116,231
Non-trainable params: 2,698,200
_________________________________________________________________
```

Figure 6. Proposed CNN model architecture

The proposed approach achieved the state-of-the-art results with comparison of other machine learning algorithms. We also experimented with other machine learning algorithms such as RF [18], Naïve Bayes [19], LR [20], and SVM [21] along with TF-IDF [22] word embedding technique. We found that our proposed approach is performing well in all seven different categories. We considered the F1-score, accuracy, precision, and recall as model validation matrices [23]. Figure 7, present the various validation matrices on ISEAR validation dataset.

```
              precision    recall  f1-score   support

       anger       0.59      0.56      0.58       227
     disgust       0.64      0.62      0.63       204
        fear       0.73      0.72      0.72       200
       guilt       0.61      0.53      0.57       209
         joy       0.75      0.85      0.80       233
     sadness       0.55      0.71      0.62       205
       shame       0.63      0.50      0.56       226

    accuracy                           0.64      1504
   macro avg       0.64      0.64      0.64      1504
weighted avg       0.64      0.64      0.64      1504
```

Figure 7. Evaluation matrix on validation dataset

Confusion metrics on the validation dataset is presented in Figure 8. That shows how each category behaves in model prediction. The proposed approach classifies joy, fear, and sadness with good accuracy. That is visible in confusion metrics.

The receiver operating characteristic area under the curve (ROC AUC) statistic assessed the model's emotion category classification. Based on threshold settings, this measure gives a complete picture of the model's classification performance. Anger scored 0.87, disgust 0.91, fear 0.93, guilt 0.86, pleasure 0.97, sorrow 0.90, and humiliation 0.88. These ratings demonstrate the model's versatility, with joy being the most discriminative. Across multiple emotional categories, the model had an exceptional average ROC AUC score of 0.90, demonstrating its remarkable generalizability. Figure 9, presents the ROC curve.

Table 1, presents the F1-score for all emotional categories across all experiments that are carried out in this research. The TF-IDF and Naïve Bayes combination yielded an F1-score of 0.56, with 'Joy' scoring the best at 0.67. With RF, the score dropped to 0.54. LR and TF-IDF scored 0.58, with 'Joy' scoring 0.70. TF-IDF with SVM maintained a 0.56 score. Word2Vec and CNN surpassed the others with an F1-score of 0.64 and 'Joy' at 0.80. Our proposed approach of Word2Vec and CNN performed better than other approaches.

Table 2 shows a full review of how different research studies' methods compare in terms of their accuracy, recall, and F1-score measures. Balahur *et al.* [24] reported values of 0.38 for both precision and F1-score and 0.39 for recall. On the other hand, Razek and Frasson [25] obtained a precision of 0.23, a recall of 0.45, and an F1-score of 0.27. Atmaja and Akagi [10] demonstrated relatively balanced metrics with precision, recall, and F1-score all measuring around 0.54 to 0.56. The investigation conducted by Marco showed that the utilization of embeddings resulted in improved measures. The GoogleEmb methodology yielded results ranging from roughly 0.62 to 0.63, while the GloVeEmb approach consistently reported a value of 0.62 across all three measures. The FastTextEmb method exhibited values that fluctuated between 0.63 and 0.64. Our proposed approach Word2Vec combined with a CNN model attained metrics of 0.64 across all three categories.

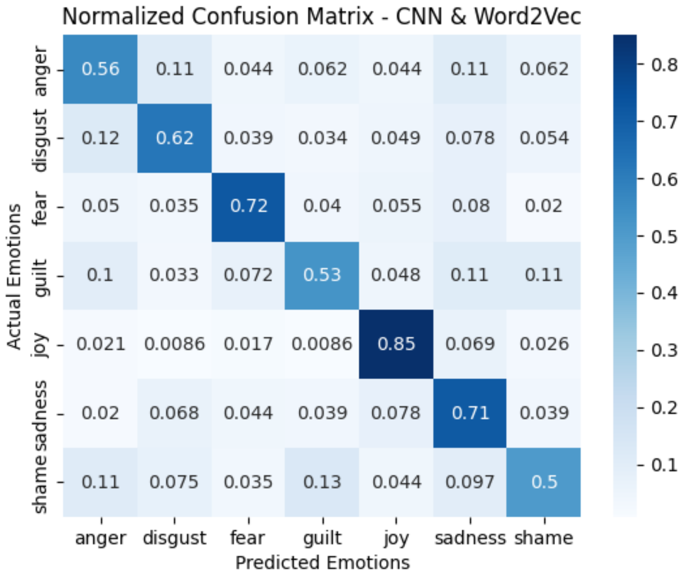

Figure 8. Confusion matrix on validation dataset (self)

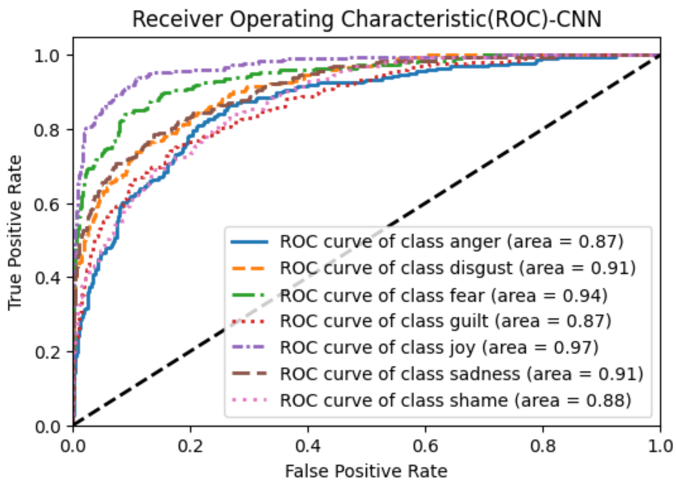

Figure 9. Confusion matrix on validation dataset

Table 1. F1-score comparison of various approaches

Approach	Joy	Sadness	Anger	Fear	Shame	Disgust	Guilt	Overall
TF-IDF + Naïve Bayes	.67	.62	.49	.62	.47	.57	.46	.56
TF-IDF + RF	.63	.59	.43	.61	.47	.55	.47	.54
TF-IDF + LR	.70	.64	.50	.68	.49	.58	.49	.58
TF-IDF + SVM	.71	.61	.46	.68	.47	.55	.47	.56
Word2Vec + CNN	.80	.62	.58	.72	.56	.63	.57	.64

Table 2. Comparison of previous research approaches

Approach	Precision	Recall	F1-score
Balahur *et al.* [24]	.38	.39	.39
Razek and Frasson [25]	.23	.45	.27
Atmaja and Akagi [10]	.56	.54	.54
Nazarenko *et al.* [26]	-	.54	.57
Polignano *et al.* [27]- SVM	.57	.57	.56
Polignano *et al.* [27]- Naïve Bayes	.37	.42	.37
Polignano *et al.* [27]- Random Forest	.49	.49	.49
Polignano *et al.* [27]- GoogleEmb	.62	.63	.62
Polignano *et al.* [27]- GloVeEmb	.62	.62	.62
Polignano *et al.* [27]- FastTextEmb	.64	.63	.64
Word2Vec + CNN	.64	.64	.64

6. CONCLUSIONS

In this research paper, we presented the Word2Vec-CNN model, a combination of Word2Vec embeddings and CNN for detecting emotion. This research aimed to develop a robust and interpretable classification model for emotion detection in textual data. Through our experiments on the ISEAR dataset, we found the effectiveness of the Word2Vec-CNN model in classifying emotions expressed in the input text. The proposed model achieved competitive performance in terms of F1-score, recall, precision, and accuracy, proving its capability to capture hidden emotions and associations between word contexts and emotions. The combination of Word2Vec word embeddings allowed the model to capture semantic relationships and contextual information, enhancing its understanding of the nuanced emotional content in text. The model extracted local features and learned hierarchical representations, enabling a robust emotion classification technique. The proposed approach has significant implications for various domains, including social media analysis, customer emotions analysis, and human-computer interaction. There is still room to enhance the accuracy of the model by exploring other transfer-learning-based word embedding algorithms. Hence, future research will focus on enhancements to the model architecture, transfer-learning-based word embeddings, and explore multi-modal approaches for emotion understanding.

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