Emotion Detection Using Machine Learning on ISEAR Dataset

Abstract

Emotion detection is a crucial task in natural language processing (NLP) and human-computer interaction. This research explores various machine learning and deep learning models to classify emotions using the **ISEAR dataset**. We evaluated traditional classifiers, deep learning models, and hybrid approaches to determine their effectiveness in detecting emotions accurately. Among all models, **LSTM+RoBERTa** achieved the highest accuracy of **88%**, demonstrating the potential of deep learning-based approaches in emotion recognition tasks.

1. Introduction

Emotion recognition is fundamental in areas such as sentiment analysis, affective computing, and psychological analysis. This study aims to classify emotions using machine learning models trained on the **ISEAR dataset**, a widely used dataset for emotion classification. Various models, including traditional classifiers, deep learning architectures, and hybrid models, were tested to achieve optimal performance.

2. Dataset

The **ISEAR (International Survey on Emotion Antecedents and Reactions) dataset** consists of textual data labeled with different emotions. It includes expressions of emotions such as **joy, anger, sadness, fear, disgust, shame, and guilt**. The dataset is preprocessed using standard NLP techniques like tokenization, stopword removal, and lemmatization to improve classification performance.

3. Methodology

3.1 Models Used

- **Traditional Machine Learning Models**:
  - K-Nearest Neighbors (KNN)
  - Decision Tree (DT)
  - Naïve Bayes (NB)
  - Logistic Regression
  - Random Forest (RF)
  - Support Vector Machine (SVM)
- **Deep Learning Models**:
  - Gated Recurrent Units (GRU)
  - Bidirectional GRU (BiGRU)

- Long Short-Term Memory (LSTM)
- Convolutional Neural Network (CNN)
- Transformers (BERT, RoBERTa)

- **Hybrid Models**:
  - GRU + CNN
  - CNN + BiGRU + SVM
  - SVM + RF + XGBoost + CNN
  - LSTM + RoBERTa

3.2 Evaluation Metrics

The models were evaluated based on **Precision, Recall, F1-Score, and Accuracy** to determine their classification performance.

4. Results

The table below summarizes the results of different models on the ISEAR dataset:

Model	Precision	Recall	F1 Score	Accuracy
KNN	33.89	33.72	33.43	34.05
DT	47.24	47.03	46.87	47.23
GRU	51.66	50.9	50.97	50.9
Bi GRU	52.62	51.9	52.12	51.9
LSTM	53.01	53.9	53.22	53.05
Logistic Regrission	52.9	53.04	52.96	53.18
CNN	55.43	55.31	55.22	55.31
RF	55.05	56.05	55.84	56.05
NB	56.03	56.05	55.75	56.05
BERT	57.51	57.39	57.27	57.39
XG BOOST	58.7	58.78	58.88	58.93
SVM	59.44	59.9	60.05	60.17
Stacking Classifier	61.7	61.66	61.72	61.94
RoBERT	73.89	70.21	72.22	73.04

4.1 Hybrid Models Performance

HYBRID MODEL				
Model	**Precision**	**Recall**	**F1 Score**	**Accuracy**
GRU+CNN	30.02	31.44	30.57	31.77
CNN+Bi GRU+SVM	33.55	32.44	32.22	32.44
SVM+ RF+ XGBoost+CNN	55.12	55.08	55.04	55.18
LSTM+ROBERT	86.03	85.21	86.9	88

4.2 Discussion

The **LSTM + RoBERTa hybrid model** outperformed all other models, achieving an **accuracy of 88%**, demonstrating the effectiveness of deep learning and transformer-based architectures in emotion classification. Traditional models such as **SVM and XGBoost** also performed well but lacked the deep contextual understanding that transformer models provide.

5. Conclusion

This study explored various machine learning models for emotion classification on the **ISEAR dataset**. While traditional models provided moderate accuracy, deep learning models, especially **transformers like RoBERTa**, showed superior performance. The best results were achieved using the **LSTM + RoBERTa hybrid model**, which reached **88% accuracy**. Future work may focus on **fine-tuning transformer models, incorporating contextual embeddings, and real-world deployment in applications such as chatbots and sentiment analysis systems**.

6. Future Work

- Exploring larger pre-trained models such as GPT-based architectures
- Expanding dataset diversity for better generalization
- Deploying the model in real-world applications such as mental health monitoring systems