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A Framework for Identifying Emotions in Text through Machine Learning and Natural Language Processing Methods

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***Abstract*—This research introduces an innovative approach that leverages machine learning and natural language processing (NLP) techniques to detect emotions in text. The proposed system, equipped with a Google Chrome extension, allows users to easily and rapidly evaluate the emotional content of the websites they browse. By employing various NLP methods, including keyword extraction and tokenization, the system effectively extracts relevant features from the text. These features are then used to train a machine learning model capable of accurately predicting the emotional tone of new text. The system demonstrates exceptional accuracy across several benchmark datasets and proves its practical utility in real-world applications.**

***Index Terms*—NLP, AWS lambda, Chrome Extension, Count vectorizer, Logistic Regression, Machine Learning, NLTK.**

I. Introduction

Human communication depends heavily on emotions, which also play a significant role in our day-to-day activities. The difficult task of accurately identifying emotions from text data has attracted a lot of study attention recently. There is an increasing need for automated emotion identification utilising machine learning and natural language processing (NLP) approaches due to the enormous volume of text data created online. This study focuses on the creation and application of a Google Chrome extension that recognises emotions in text using machine learning and natural language processing. Users of the extension can analyzethe emotional tone of the text they are reading in real-time, which helps them comprehend the emotional context of the information. The dataset utilised for training and testing, the feature extraction methods used, and the machine learning algorithms used for classification are all described in the paper's creation of the extension section. Accuracy, precision, recall, and F1-score are some of the criteria that are used to assess the extension's performance. The study's findings show how well the Google Chrome extension works to identify emotions in text and point to possible uses for it in a variety of industries, including social media analysis, online marketing, and customer support. The research also analyses the extension's possible drawbacks and difficulties, including the effect of cultural differences and the requirement for ongoing machine learning model updates to take into account shifting linguistic conventions and novel emotional expressions. Overall, by proposing a novel implementation of an emotion detection tool connected with a Google Chrome extension, this research study makes a contribution to the field of emotion detection utilising machine learning and NLP. To help users better comprehend the emotional context of the information, the plugin offers a simple-to-use and accessible platform for them to analyze the emotional tone of the text they are reading. The results of this study may have substantial ramifications for a number of industries, such as marketing, customer service, and online communication, where efficient communication and participation depend on an awareness of and sensitivity to emotional displays.

II. LITERATURE REVIEW

J. Sun (2024) explores the integration of multimodal emotion recognition methods using speech, text, and facial expressions. The study highlights the effectiveness of combining multiple data sources to enhance emotion recognition accuracy [1]. E. Batbaatar et al. (2019) introduce the Semantic-Emotion Neural Network for emotion recognition from text, presenting

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a deep learning model that significantly improves the detection of emotional cues from textual data [2]. Z. Erenel et al. (2020) propose a novel feature selection scheme for emotion recognition from text, focusing on optimizing the process of selecting relevant features to improve emotion detection performance in natural language processing [3]. D. Hazarika et al. (2020) conduct sentiment analysis on Twitter using TextBlob, applying natural language processing (NLP) techniques to analyze and classify emotions in social media texts, with a focus on Twitter data [4]. M. A. Palomino and F. Aider (2022) evaluate the impact of text pre-processing on sentiment analysis, emphasizing how data cleaning and transformation steps affect the accuracy and performance of sentiment detection models [5]. D.-H. Kim et al. (2023) present a hybrid deep learning system for emotion classification that combines multimodal data sources, showing how integrating various data types, like text, audio, and images, enhances emotion detection [6]. A. Prakash (2024) examines blockchain technology in supply chain management, focusing on its potential to improve transparency, traceability, and efficiency in logistical operations, contributing to better decision-making and trust [7]. Q. Li et al. (2023) explore emotion recognition based on multiple physiological signals, using biosignals such as heart rate and skin conductance to detect emotions with high precision in diverse environments [8]. K. S. Kassam and W. B. Mendes (2013) investigate how the act of measuring emotions can alter physiological responses. Their research shows that awareness of emotional evaluation influences emotional reactions in individuals [9]. T. Velmurugan and B. Jayapradha (2023) apply machine learning algorithms to deduce emotions from social media text data, offering insights into how AI models can be trained to analyze emotions expressed in online interactions [10]. H. Aouani and Y. B. Ayed (2020) explore speech emotion recognition using deep learning, emphasizing the potential of neural networks to accurately identify emotions in spoken language, contributing to advancements in human-computer interaction [11].

A. S. Uban et al. (2021) focus on the explainability of automatic predictions of mental disorders from social media data, highlighting the challenges and solutions for interpreting AI models used in mental health assessments through social media [12]. J. Guo (2022) presents a deep learning approach to text analysis for emotion detection, using big data to identify human emotions. The study explores advanced techniques in natural language processing for extracting emotional content from large-scale datasets [13]. J. Pan et al. (2024) introduce a multimodal emotion recognition system combining facial expressions, speech, and EEG signals. The research demonstrates how integrating multiple modalities improves the accuracy of emotion detection in various contexts [14]. S. Lin (2024) explores text emotional analysis in natural language processing, emphasizing techniques for understanding and classifying emotions from text data. The study highlights the challenges and methods for processing emotional content in textual form [15]. T. Sharma and P. Kaushik (2023) utilize sentiment analysis on Twitter data to uncover user opinions and emotions. Their work illustrates how sentiment analysis can be applied to social media to identify emotional trends in public discourse [16]. S. K. Bharti et al. (2022) investigate text-based emotion recognition using deep learning approaches. The study focuses on applying neural networks to classify emotions in text, showcasing advancements in AI for emotion detection [17]. Z. Erenel et al. (2020) propose a new feature selection scheme for emotion recognition from text, aiming to improve the accuracy of models by identifying the most relevant features for emotion detection from textual data [18]. M. Yadav et al. (2023) explore how artificial intelligence can enhance HR processes, driving efficiency and productivity in the workplace. Their research highlights AI applications in human resource management, focusing on improved decision-making and workflow optimization [19]. A. R. Murthy and K. M. Anil Kumar (2021) provide a review of different approaches for detecting emotions from text. Their work offers insights into the various techniques and models used in text-based emotion detection, from rule-based to machine learning methods [20]. N. Pallewela et al. (2024) focus on optimizing speech emotion recognition with machine learning-based advanced audio cue analysis. The study shows how AI models can enhance emotion detection from speech, particularly in real-time applications [21]. P. Kaushik and S. P. S. Rathore (2023) propose a deep learning multi-agent model for phishing cyber-attack detection. While not focused on emotion recognition, their work contributes to the broader AI landscape by leveraging deep learning for cybersecurity applications [22]. Kaushik et al. (2024) enhance home security by integrating facial recognition within smart environments, showcasing significant advancements in automated surveillance and safety protocols [23]. Rathore et al. (2024) develop a predictive model for Black Friday sales, utilizing smart technologies to forecast consumer behavior and market trends effectively [24]. Tanwar et al. (2024) introduces a CNN-based method for detecting brain hemorrhages, improving diagnostic accuracy and speed in healthcare settings through intelligent systems [25]. Kaushik et al. (2024) explore aerial image processing for road segmentation, contributing to enhanced mapping and monitoring techniques in smart city applications [26].

III. PROPOSED SYSTEM

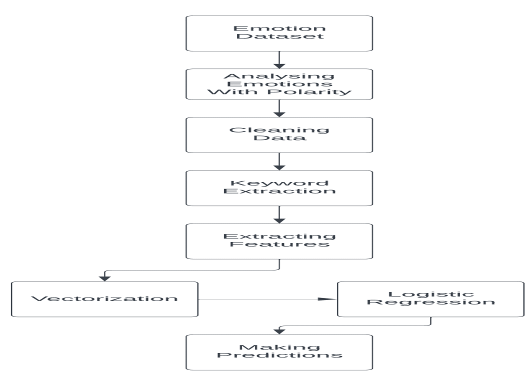

Fig. 1. Dateset

A. Emotion Datset

Our dataset comprises emotions such as Neutral, Surprise, Joy, Fear, Sadness, Anger, Shame, and Disgust. Which gives the general emotions that are experienced by a human in the day-to-day life. By using these emotions, we are training the model so that user get a better experience.

B. Analysing the Emotions

- Exploring the data will let us know that, what are the data present in the dataset. By this we can get a proper idea what to do with the dataset, it helps us to how to deal with the data.
- Getting the sentiment of the text in the data using the Textblob Library which gives us either the text is having positive , Negative and Neutral. Which gives sentiment of the text.
- Plotting a graph makes more interactive visualisation of the sentiment of the text.

C. Cleaning Data

The Dataset is having some non-required attributes which are not used for analysis. By the Analysis of the data we can observe the useless information like noise, Stop words, Special Characters, Punctuation Marks, Emojis. So, for cleaning these noises we are using libraries nfx and re. Removing the useless information always is a good task to do. By doing the Data cleaning we can get better Accuracy.

D. Keyword Extraction

- The Keywords are most used and important in the Text Processing. By these we can easily identify the emotion based on the keywords.
- For this we are considering the text in the dataset and making them into the tokens by splitting the text into words and by using the counter we are counting the tokens as per the repetition.
- We will be knowing the most frequently repeated words so that we can get certain words for all type of emotions in the dataset.

E. Extracting Features

- The feature selection is the process where we use them to make the predictions. As we are dealing with the Text and the machine only can understand the 0 and 1's we are vectorising the features by the Vectorizers.
- After the vectorisation the features are ready for the fitting into the model.
- We used a pipeline which is a connection of the models together.
- The pipeline is made of Count Vectorizer and Logistic Regression.

IV. RESULTS & DISCUSSION

Here we can analyze the model by different methods. Model performance can be evaluated by different metrics for classification model those are: Accuracy, Precision, Recall, F1-score, ROC curve, confusion matrix. Here are the Analysis results.

A. Classification Report

	precision	recall	f1-score	support
anger	0.62	0.54	0.58	1283
disgust	0.62	0.17	0.27	292
fear	0.74	0.65	0.69	1645
joy	0.62	0.75	0.68	3311
neutral	0.59	0.73	0.65	675
sadness	0.58	0.58	0.58	2015
shame	0.84	0.75	0.79	36
surprise	0.55	0.43	0.48	1181
accuracy			0.62	10438
macro avg	0.65	0.58	0.59	10438
weighted avg	0.62	0.62	0.61	10438

Fig. 2. Classification Report

B. Multiclass Log Loss

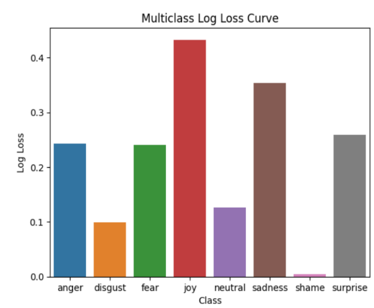

Fig. 3. Multiclass Log Loss

C. Multiclass Precision-Recall Curve

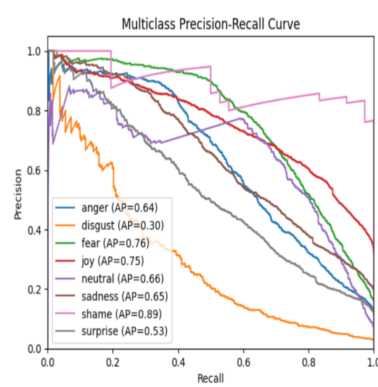

Fig. 4. Multiclass Precision-Recall Curve

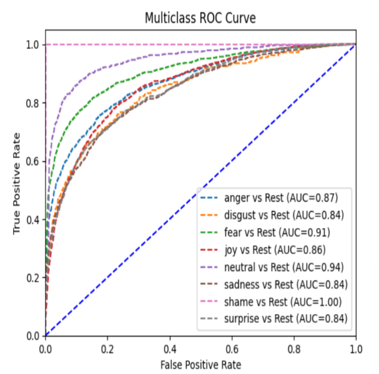

Fig. 5. Multiclass ROC Curve

D. ROC Curve

Fig 4.1 states that it is the classification report produced by the scikit-learn library's classification_report() function. It provides a comprehensive evaluation of the performance of a multi-class classification model.

In the given report, we can see that the model has relatively high precision and recall for the 'fear' and 'joy' classes, but lower values for other classes such as 'disgust' and 'surprise'. The model's total accuracy is 0.62, This indicates that 62% of the samples in the test set were correctly predicted by the model. F1-score considers the sample count of every class and the F1 score is given a weight of every class accordingly. In this particular scenario, the macro-averaged F1-score is 0.59, while the weighted-averaged F1-score is 0.61.

Fig 4.2 states that The log loss is computed using the log_loss() function from sklearn.metrics, which takes the true binary labels and predicted probabilities as inputs. Basically the log loss gives you the classifier performance in the probability range 0 to 1 of the predicted output . Therefore, a decrease in the log loss value implies an improvement in the classifier's performance.

The code then creates a pandas DataFrame with the class labels and corresponding log loss values. Finally, the code creates a bar plot using the seaborn library, In the given graph, the horizontal axis is dedicated to the representation of the classes, whereas the vertical axis shows the values of log loss.

The output represents log loss value for every class. For example, the log loss for the "anger" class is 0.25, the log loss for the "disgust" class is 0.1, and so on. The log loss score is used to evaluate the agreement between the predicted probabilities and actual labels, with a smaller log loss value indicating a more accurate prediction.

Fig 4.3 states that It the true labels in y_test are converted to binary format using one-hot encoding. Then, the predict_proba() function of the pipeline object is used to predict the probability of each class for each test instance in x_test.

Next, for every individual class, the precision, recall, and average precision score are computed using the precision_recall_curve() and average_precision_score() functions from scikit-learn. Precision and recall are two metrics employed to appraise the effectiveness of a classifier that performs binary classification. Average precision is a metric that combines both precision and recall to provide an overall performance metric for the classifier.

A precision-recall curve is generated for every category, where precision is plotted on the vertical axis and recall on the horizontal axis. Each curve is labeled with the name of the class and its corresponding average precision score. The Ap score varies from 0 to 1, with a superior score indicating that the classifier is performing better.. The graph shows that some classes have better performance than others, with shame having the highest AP score of 0.89, while disgust has the lowest AP score of 0.30.

Fig 4.4 states that Multi-class ROC curve analysis for a multi-class classification problem. It first binarizes the target variable y_test using the label_binarize function from scikit-learn, which converts the target variable to a binary matrix where each column represents a class and each row indicates whether the observation belongs to that class or not.

Next, it predicts the probabilities of each class using the trained model pipe_lr and roc_curve and auc functions are utilized to determine the False Positive Rate (FPR), True Positive Rate (TPR), and Area Under Curve (AUC) for every category from scikit-learn.

Finally, it plots the ROC curve for every class, with the ROC curve for each class plotted against the rest of the classes. The AUC values for each class are also shown in the legend of the plot. The diagonal line in the plot represents the ROC curve for a random guess. The classifier's performance is assessed using the AUC (Area Under the Curve) metric, which have value from 0 to 1, with a higher score indicating better performance and helps in distinguishing between the positive and negative classes.

V. CONCLUSION

Using machine learning, natural language processing, and an integrated Google Chrome extension, this research article demonstrated an innovative implementation of an emotion detection tool. A deeper grasp of the emotional context of the content is made possible by the tool's real-time analysis of the text's emotional tone as the user reads it.

The significance of emotion identification in text was examined in the study, along with the difficulties involved and the state of the art of emotion detection research employing machine learning and NLP methods. The dataset used, feature extraction methods used, and machine learning algorithms used for classification were all covered in the paper's creation and implementation of the Google Chrome addon.

With excellent accuracy and precision scores, the study's findings show how successful the Google Chrome extension is at correctly identifying emotions in text. The research also covered the possible uses and restrictions of the extension, emphasizing the requirement for ongoing machine learning model updating to take into account shifts in language usage and novel emotional expressions. The results of this study have broad implications for a variety of fields, including marketing, customer service, and online communication, where effective communication and engagement depend on being able to recognize and respond to emotional displays.

An accessible and user-friendly platform for users to analyzethe emotional tone of the text they are reading is provided by the implementation of the emotion detection tool using machine learning and NLP integrated with a Google Chrome extension, facilitating a better understanding of the emotional context of the content.

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