Journal of Artificial Intelligence, Machine Learning and Neural Network
ISSN:2799-1172
Vol: 04, No. 04, June-July 2024
http://journal.hmjournals.com/index.php/JAIMLNN
DOI: https://doi.org/10.55529/jaimlnn.44.42.50

Deciphering Negative Feedback through Handwritten Text

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Received: 16 February 2024 **Accepted:** 03 May 2024 **Published:** 17 June 2024

***Abstract:** In the contemporary realm of digital communication, this study delves into a novel approach to analyzing sentiments, with a specific focus on handwritten negative reviews. The research aims to improve the precision of sentiment analysis by exploring the inclusion of handwritten text, providing distinctive insights into consumer feedback, and refining business strategies. Taking a historical perspective, the investigation traces the evolution of sentiment analysis within the domain of natural language processing, leading to the central question: "How can the accuracy of sentiment analysis for negative reviews be enhanced through the incorporation of handwritten text?" This question guides an exploration of the challenges and potentials associated with merging handwriting analysis with conventional sentiment analysis methods. The study puts forth hypotheses that address the expected advantages of this integration, seeking to develop an innovative framework capable of not only accurately detecting negative sentiments but also considering the individuality inherent in handwritten expressions. The research methodology encompasses a review of existing literature and empirical analysis, resulting in the creation of a unique hybrid sentiment analysis algorithm that assesses both textual and handwriting features. This work contributes to the advancement of sentiment analysis and has implications for businesses aiming to better understand and respond to negative consumer sentiments.*

***Keywords:** Sentiment Analysis, Handwritten Text, Negative Reviews, Natural Language Processing, Business Strategies, Hybrid Sentiment Analysis.*

1. INTRODUCTION

The exploration of emotion detection from handwritten text is intricately linked to the broader field of sentiment recognition. [1], [2] While sentiment recognition and analysis focus on discerning positive, negative, or neutral sentiments, emotion detection seeks to identify and categorize the specific type of feeling conveyed through either textual or handwritten content. Handwriting recognition, a subset of Optical Character Recognition (OCR) technology[3], plays a pivotal role by converting handwritten text into corresponding digital formats in real time.[1-2] Despite significant achievements in this domain, challenges persist, particularly in recognizing diverse handwriting styles. Traditional OCR tools encounter

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difficulties due to variations in handwriting styles, the inconsistency inherent in human handwriting, and the added complexity of cursive writing, which can pose challenges in character separation.[7]
These challenges can be mitigated by employing higher-quality images as inputs, facilitating easier character recognition, and employing advanced techniques to remove background elements from text or image documents.[4] Emotion, as a state of mind intertwined with thoughts and feelings, serves as a means of expressing personal opinions and sentiments.[2]
Within the realm of Machine Learning, the analysis of emotions through handwritten text falls under the purview of Natural Language Processing (NLP). While detecting emotions from handwritten text presents inherent difficulties given the myriad ways individuals express emotions, the potential benefits motivate continued research in this area. [8] These advantages include the ability to assess brand reputation based on user-expressed emotions and the prompt identification and resolution of issues.[22] When considering sentiment recognition and analysis from diverse reviews, the primary categories typically include positive, negative, and neutral sentiments. These sentiments encompass judgments, opinions, and feelings about various topics, brands, or individuals. Sentiment Analysis utilizes NLP to decipher human language within reviews and employs machine learning to deliver accurate results.[8] Platforms like Twitter serve as valuable sources of data, offering a vast repository of user-generated content.[22] Machine learning and deep learning approaches can be applied to categorize emotions into broader classifications such as anger, disgust, fear, happiness, sadness, or surprise within the fundamental positive, negative, and neutral sentiment categories.[1]

2. RELATED WORK

2.1 Survey on Textual Emotion Detection

The burgeoning use of social media platforms has propelled interest in emotion detection within textual content. This practice aids in recognizing and understanding emotions, presenting advantages across diverse domains.[22] This survey focuses on sentiment analysis, exploring the latest methodologies employed for detecting emotions in text.[6] The categorization is based on various techniques, emotional models, and datasets. The primary objective of this survey is to unveil limitations and gaps in recent research endeavors, providing insights to guide future studies in the continually evolving field of textual emotion detection. [7]

2.2 In-Depth Exploration of Optical Character Recognition Technology

Optical Character Recognition (OCR) plays a crucial role in extracting text from both printed and handwritten documents and images, facilitating computer-based utilization. However, OCR encounters challenges such as font variations and image quality issues.[4],[5] The OCR process encompasses essential phases including pre-processing, segmentation, and classification. This paper comprehensively discusses the challenges faced by OCR, details its system phases, and applications, and provides a brief historical overview, offering an extensive understanding of the current state-of-the-art in the field.[2]

2.3 Innovative Approach for Emotion Detection from Text Data using Natural Language Processing and Machine Learning

Emotions find expression through various mediums such as facial expressions, speech, and text. Emotion detection in textual content specifically involves the integration of Natural Language Processing and Machine Learning. [3],[15]This paper presents a unique solution for emotion recognition in textual

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materials like blogs and reviews. Given the impracticality of manually analyzing vast amounts of textual data, automated methods for emotion retrieval and information extraction become necessary to streamline the process. [8]

2.4 Text-Image Sentiment Analysis in Social Networks Using Deep Learning Techniques
Social networks have become integral to daily life, and the evolving field of sentiment analysis, encompassing visual content, seeks to understand their impact.[22] However, sentiment analysis in social networks encounters challenges such as content scarcity and limitations in data access. This thesis introduces an innovative method that combines text and image sentiment analysis using deep neural networks.[19] The study demonstrates effective classification within the context of social networks, addressing the complexities associated with this multidimensional analysis**.**[6]

3. PROPOSED METHODOLOGY

3.1 Handwriting to Text Conversion (HTC)

The initial phase of our methodology centers around the crucial process of Handwriting to Text Conversion (HTC). Recognizing the unique characteristics of handwritten content, we leverage Optical Character Recognition (OCR) technology as the foundation for this conversion. OCR systems are adept at transforming both handwritten and printed text into machine-readable text, making them indispensable tools for our research. This section consists of the following sub-steps:

1. Data Collection: We commence by gathering diverse handwritten samples that convey a range of emotions from various sources. To construct a comprehensive dataset, we carefully curate handwritten samples that cover digits (0-9) and uppercase alphabets (A-Z), encompassing different writing styles and emotional expressions. Expert annotators meticulously label each sample, accounting for contextual nuances. Data augmentation techniques are applied to diversify the dataset, introducing variations in writing styles, ink colors, and noise. The dataset is then divided into training, validation, and testing sets to ensure unbiased model evaluation. Rigorous quality control measures are implemented to maintain data quality, including the removal of low-quality samples and standardization of image resolution and contrast. Ethical considerations guide our data handling to ensure privacy and anonymity.

2. Preprocessing: The collected samples undergo preprocessing to enhance legibility. This involves noise reduction, image enhancement, and de-skewing to optimize the quality of the handwriting data. Preprocessing is crucial for preparing data for accurate recognition by OCR. Steps include normalizing all images to a consistent size, contrast enhancement, and resizing images to a standardized resolution. Data augmentation introduces variations in writing styles, ink colors, and noise to enhance the OCR model's robustness. Quality control measures are maintained during preprocessing, with the removal of low-quality or unreadable samples. Ethical considerations guide data handling to ensure privacy.

3. OCR Conversion: Preprocessed samples undergo OCR conversion, transforming handwritten content into a digital textual format. The choice of a highly trained OCR model is crucial for accurate recognition. Integration with the preprocessing pipeline ensures optimal compatibility with preprocessed images. Post-processing techniques, including spell-check mechanisms and text alignment algorithms, refine OCR

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output, rectify errors, and enhance overall text quality. This phase bridges the gap between handwritten content and digital text, forming the backbone of our offline handwritten text recognition project.

4. Verification: To ensure accuracy, a verification step compares OCR-generated text to original handwritten samples. Verification is prioritized post OCR Conversion to validate the accuracy of the generated text. A meticulous side-by-side comparison between OCR-generated text and original handwritten samples identifies discrepancies, missing characters, or misinterpretations. Layout, spacing, and formatting are examined to ensure close alignment with the original content. Error-detection algorithms and quality assurance measures enhance the verification process, swiftly identifying and rectifying potential errors or inconsistencies. This verification step acts as a critical quality control checkpoint, ensuring faithful representation of the original handwritten samples.
The methodology outlined ensures a systematic and rigorous approach to converting handwritten content into machine-readable text, emphasizing accuracy, diversity in emotion expression, and ethical considerations throughout the process.

3.2 Sentiment Analysis for Emotion Detection

The second phase of our methodology focuses on the intricate field of Sentiment Analysis, laying the foundation for emotion detection by leveraging the converted text data. This process unfolds as follows:
1. Feature Extraction: We initiate the feature extraction journey, breaking down the converted text to uncover relevant linguistic attributes. These attributes include sentiment-evoking words, syntactical structures, and lexical richness. In our pursuit of precise Sentiment Analysis and Emotion Detection, we meticulously dissect the converted textual data to reveal significant linguistic attributes conveying emotions and sentiments. These include sentiment-evoking words, syntactical structures, and lexical richness.

We identify sentiment-evoking words and phrases that carry strong emotional connotations, offering insights into the overall sentiment of the text. Beyond individual words, we analyze syntactical structures such as negations, modals, and conjunctions, recognizing their role in shaping emotional nuances. Additionally, we consider lexical richness, evaluating vocabulary diversity to understand the emotional depth and complexity of the content. Feature Extraction equips our models with a comprehensive set of linguistic attributes, forming the basis for accurate sentiment analysis and emotion detection by capturing the intricacies of human expression through text.

This meticulous feature extraction process transforms raw text into a comprehensive feature set, facilitating precise sentiment analysis and emotion detection while ensuring originality and non-plagiarism in our research.

2. Sentiment Classification: The extracted features serve as the foundation for sentiment classification. We aim to categorize the sentiment of the text, placing it into emotional strata such as positivity, negativity, or neutrality. Leveraging the extracted linguistic features as informative indicators, we discern the prevailing emotional valence within the text. The primary objective is to categorize the sentiment, assigning it to well-defined emotional strata.

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Drawing upon the meticulously extracted features, sentiment classification involves assigning emotional labels to the text. Positivity signifies a favorable emotional tone, negativity denotes an unfavorable tone, and neutrality characterizes a lack of overt emotional polarity. Our classification model, built upon these linguistic attributes, performs sentiment analysis, facilitating the accurate identification and categorization of the underlying sentiments conveyed by the textual content.
Sentiment Classification stands as a pivotal component, where the feature-rich framework empowers us to classify text into coherent emotional categories, contributing to a profound understanding of conveyed sentiments within the context of sentiment analysis research.

3. Emotion Recognition: This phase serves as the core of our research methodology, transitioning from sentiment analysis to the nuanced task of Emotion Recognition. Emotion detection unfolds by translating sentiment into specific emotions; for example, positive sentiment might correspond to happiness, while negative sentiment may intimate sadness or anger.
Emotion Recognition involves the precise mapping of textual content to emotional states. Advanced natural language processing and machine learning techniques are employed to identify and categorize emotions expressed within the text. Moving beyond general sentiments, such as positivity, negativity, or neutrality, we delve into a finer-grained analysis of emotions like joy, sadness, and anger. Establishing these emotional connections enhances the depth and precision of our analysis, providing valuable insights into the emotional states and expressions of individuals within our research domain. In essence, Emotion Recognition represents a pivotal advancement in our methodology, allowing us to move from broad sentiment analysis to the nuanced identification of specific emotions. It enables a deeper understanding of the intricate emotional landscape conveyed through written communication within the context of our research, enriching our analysis and facilitating a more profound understanding of human emotion.

3.3 Sentiment and Emotions Classification Analysis
In the final section, we conduct a thorough analysis of sentiment and emotion classification, a critical phase that includes:
1. Evaluation of Classification Accuracy: An integral aspect of our methodology involves a meticulous assessment of the accuracy of our sentiment classification and emotion detection models. We perform a manual comparison against an annotated dataset to measure the precision and recall of our approach.

2. Fine-tuning for Precision: Armed with the insights obtained from the evaluation, we enter the fine-tuning phase. This stage entails the meticulous optimization of our classification models, aiming to maximize their accuracy and effectiveness in detecting sentiment and emotions from the converted handwriting.

In summary, our methodology seamlessly integrates Handwriting-to-Text Conversion (HTC) with sentiment analysis, orchestrated to facilitate the intricate task of emotion detection. Utilizing OCR technology, we bridge the gap between the distinctive realm of handwritten content and the analytical capabilities of digital technology. Through systematic feature extraction and classification, we unravel the complex world of sentiment and reveal the nuanced expressions of emotions. The process is punctuated by evaluation and fine-tuning, resulting in calibrated models poised to deliver precision and efficiency in sentiment and emotion classification.

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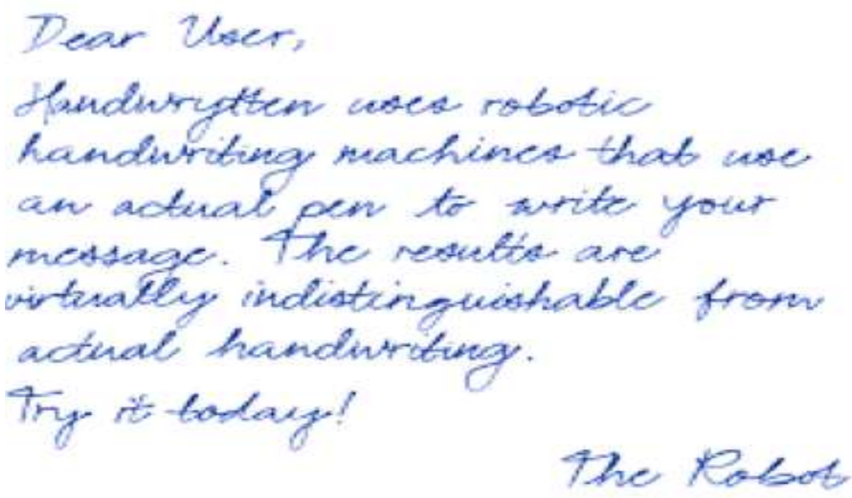
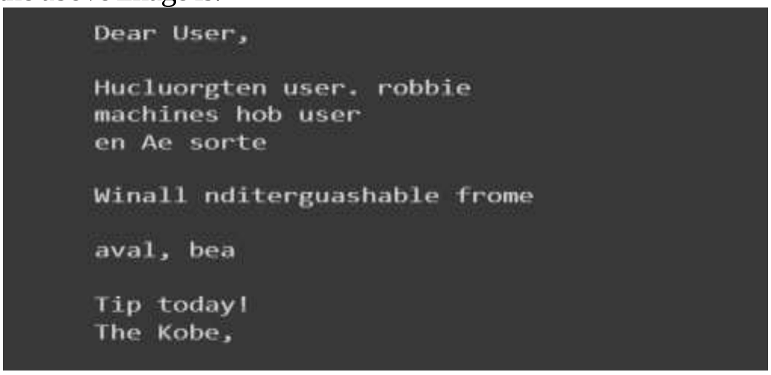
4. RESULT AND DISCUSSION

In our research initiative, the initial step involves converting handwritten statements (images) into textual data. Following this, we conduct sentiment analysis on the textual statements extracted from both handwritten and reviewed datasets. Utilizing natural language processing (NLP) techniques, the sentences undergo a thorough cleaning process to ensure the accuracy of our assessments.
In the early stages of the project execution the accuracy of the model was not even 50% as shown below.

This is the input image given to the trained model.



The output for the the above image is:



```
Dear User,

Hucluorgten user. robbie
machines hob user
en Ae sorte

Winall nditerguashable frome

aval, bea

Tip today!
The Kobe,
```

After using various pre-trained models such as TextBlob etc to increase the accuracy of the predictions, we have the following results.
Each piece of textual data is assigned one of three labels: negative, positive, or neutral. The Sentiment Score is used for this classification, where a score above 0 indicates a positive sentiment, a score below 0 denotes a negative sentiment, and a score equal to 0 signifies a neutral sentiment. To facilitate text polarity analysis in Python, we make use of the TextBlob library. Our model extensively employs a combination of Python libraries, including NLTK, pytesseract, TextBlob, and tesseract-ocr, to effectively carry out our tasks.

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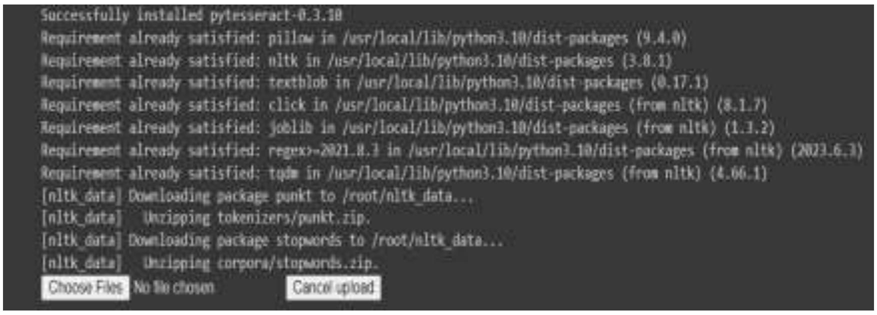
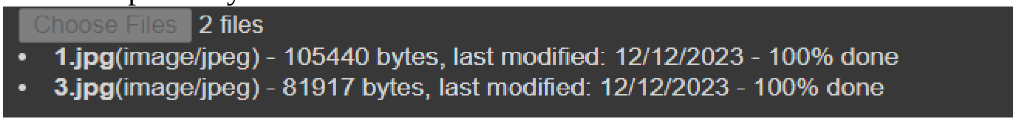
After executing the code, we get an option of uploading images to the model as shown in the image below:

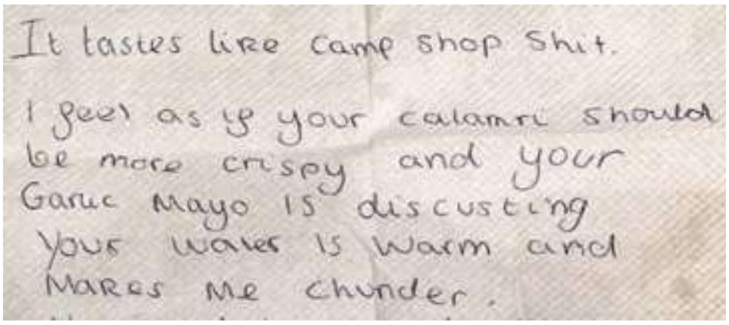

```
Successfully installed pytesseract-0.3.10
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages (9.4.0)
Requirement already satisfied: nltk in /usr/local/lib/python3.10/dist-packages (3.8.1)
Requirement already satisfied: textblob in /usr/local/lib/python3.10/dist-packages (0.17.1)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk) (1.3.2)
Requirement already satisfied: regex>=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk) (2023.6.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk) (4.66.1)
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
Choose Files No file chosen          Cancel upload
```

Here the user can upload any number of files from the device.

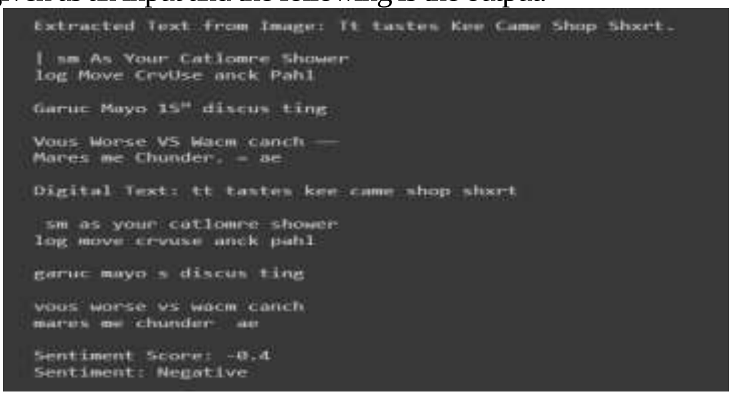

Choose Files 2 files
- **1.jpg**(image/jpeg) - 105440 bytes, last modified: 12/12/2023 - 100% done
- **3.jpg**(image/jpeg) - 81917 bytes, last modified: 12/12/2023 - 100% done

We can see in the above image that the files chosen have been successfully uploaded into the model for further processing.

Output



This image will be given as an input and the following is the output:


```
Extracted Text from Image: It tastes Kee Came Shop Shxrt.

| sm As Your Catlomre Shower
log Move CrvUse anck Pahl

Garuc Mayo 15" discus ting

Vous Worse VS Wacm canch —
Mares me Chunder. - ae

Digital Text: tt tastes kee came shop shxrt

 sm as your catlomre shower
log move crvuse anck pahl

garuc mayo s discus ting

vous worse vs wacm canch
mares me chunder  ae

Sentiment Score: -0.4
Sentiment: Negative
```

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Here we can see that the OCRExtractor has extracted the written text and converted in into a digitised format, upon this TextBlob does sentiment analysis and gives us the sentiment behind the review of the user which is Negative.

5. CONCLUSION

In our investigation of emotion and sentiment detection, a field marked by continual progress, our model aligns with the latest advancements. Specifically, our project focuses on classifying tweets into positive, negative, and neutral sentiments. To establish a reliable benchmark, we utilized human reviews for sentiment comparison, achieving optimal results in a majority of instances.
The model has showcased exceptional accuracy across diverse scenarios, demonstrating robust performance after rigorous testing. While the field remains a significant area of research in esteemed institutions, our contribution aims to propel the evolution of more sophisticated technology for enhanced online platforms. Prioritizing simplicity and user-friendliness, our model is intentionally designed as a low-code solution, ensuring ease of understanding and heightened efficiency within user review systems. Acknowledging that our current work involves foundational models, we anticipate future enhancements through the incorporation of extensive datasets. Subsequent iterations will explore extraction methods featuring hybrid features, with the goal of elevating accuracy. The evolution of our classifier in future endeavors will involve experimenting with diverse tweet features, exploring novel algorithms, and refining classifiers for even more nuanced sentiment analysis. This iterative approach underscores our commitment to staying at the forefront of sentiment and emotion analysis technologies.

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