Emotion-Based Sentiment Classification in Tweets Using RNN

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***Abstract*—The rapid growth of social media platforms like Twitter has resulted in an abundance of user-generated content, making opinion mining a crucial task in understanding public sentiment. Sentiment analysis, a vital application of natural language processing (NLP), enables the categorization of emotions in textual data. This study presents a novel approach that utilizes NLP techniques and Recurrent Neural Networks (RNNs) to classify tweets into five emotion categories: angry, joy, happy, sad, and neutral. The proposed model demonstrates high accuracy and reliability, outperforming traditional methods in both binary and multi-class sentiment classification tasks. By leveraging the capabilities of deep learning, this method provides a robust framework for emotion recognition and sentiment analysis in real-world datasets.**

Keywords—Twitter,User-Generated Content, Sentiment Analysis, Natural Language Processing (NLP), Recurrent Neural Networks (RNNs), Emotion Categorization

I. Introduction

With the increasing adoption of social media, particularly Twitter, vast amounts of user-generated text data are available. Extracting meaningful insights from this data can help businesses, policymakers, and researchers understand public sentiment and trends. Twitter serves as a platform where users freely express their opinions on various topics, creating an opportunity to analyze human emotions at a large scale. However, due to the informal nature of social media language, traditional sentiment analysis approaches often struggle to capture nuanced emotions.Sentiment classification is a subfield of Natural Language Processing (NLP) that aims to determine the emotions expressed in textual content. Unlike conventional approaches that classify text as simply positive or negative, this project introduces a deep learning-based model using Recurrent Neural Networks (RNNs) to categorize tweets into five distinct emotions: angry, joy, happy, sad, and neutral. RNNs are particularly effective in processing sequential text data, making them well-suited for sentiment analysis tasks.

To further refine the accuracy of the sentiment classification model, this project will experiment with different architectures, such as networks, a variation of RNNs known for their ability to mitigate the vanishing gradient problem. Additionally, pre-trained word embeddings like Word2Vec will be explored to enhance the quality of feature representation, allowing the model to understand semantic relationships between words more effectively.

This project will deliver a deep learning-based sentiment classification model that utilizes NLP techniques and RNNs to classify tweets into five distinct emotion categories. A robust data preprocessing pipeline will be developed, incorporating tokenization, stop-word removal, vectorization, and feature extraction using advanced word embeddings like Word2Vec . The training and optimization of the model will be conducted through systematic procedures, including hyperparameter tuning and performance evaluation, to ensure improved accuracy and generalizability.

By leveraging deep learning techniques, our approach seeks to enhance sentiment analysis accuracy and address the challenges of handling informal, context-dependent text. This project explores various NLP techniques such as tokenization, word embeddings, and sequence modeling to improve classification performance. Additionally, our model is designed to learn the contextual relationships between words in a sentence, enabling a more nuanced understanding of emotions in text.Furthermore, real-time sentiment classification can be beneficial in various applications such as brand monitoring, customer feedback analysis, and detecting emotional trends during global events. The proposed RNN-based model is scalable and adaptable, making it applicable to diverse domains where emotion detection plays a crucial role.

II. Literature Review

Understanding and interpreting human emotions through textual data, especially from platforms like Twitter, is a significant challenge due to the informal, brief, and context-dependent nature of tweets. Over the years, multiple studies have explored various techniques for sentiment analysis, each contributing uniquely to the field while also exposing certain limitations.

Kalra and Aggarwal (2018), in their study titled *"Importance of Text Data Preprocessing,"* highlighted the critical role of preprocessing techniques in sentiment analysis, particularly for short texts like tweets. They emphasized the need to clean and structure data effectively to improve model performance. However, the study also noted that traditional preprocessing methods may not fully capture the nuanced language often found in tweets, such as slang, emojis, abbreviations, and contextual cues. This limitation suggests a need for more advanced and context-aware preprocessing strategies.[1]

Twitter has become a vital source of real-time public opinion, offering insights into various domains such as politics, healthcare, marketing, and social behavior. The platform's open nature and concise 280-character limit encourage frequent user interaction, making it an abundant source of sentiment-rich textual data.[2]

One of the significant contributions in this area was made by **Alsaeed and Zubair Khan (2019)** in their study titled *"A Study on Sentiment Analysis Techniques of Twitter Data."* Their research examined a wide range of approaches, from classical machine learning techniques like **Naïve Bayes**, **Support Vector Machines (SVM)**, and **Decision Trees**, to more advanced techniques involving **deep learning**. The study systematically compared the accuracy, efficiency, and practical usability of these models on Twitter datasets.[3]

Rustam et al. (2019) in their paper titled "Tweets Classification for US Airlines Using LSTM" explored the application of Long Short-Term Memory (LSTM) networks to classify tweets related to customer sentiment toward U.S. airlines. LSTM, a specialized variant of Recurrent Neural Networks (RNNs), is particularly effective in processing sequential data, such as text, because it can maintain a memory of previous inputs and learn long-range dependencies.[4]

In their approach, Rustam et al. leveraged the sequential nature of the text data by using LSTM networks, which excel at handling sequences, making them ideal for tweet classification tasks. The study demonstrated that LSTMs could significantly enhance sentiment classification accuracy, especially when compared to traditional machine learning models that may struggle with sequential data.

However, Rustam et al. also highlighted several important challenges associated with deep learning models like LSTMs for tweet classification:

1. Deep learning models require large annotated datasets for training, which can be time-consuming and resource-intensive to create.

2. Substantial computational resources are needed for training complex RNN architectures.

3. Fine-tuning the models to ensure optimal performance involves a complex and time-consuming process.

Yousaf et al. (2021), in their paper titled *"Emotion Recognition by Textual Tweets Using Voting Classifier,"* proposed a model based on ensemble learning to identify emotions from tweets. Their approach utilized a Voting Classifier that combined Logistic Regression (LR) and Stochastic Gradient Descent (SGD) algorithms, with TF-IDF for feature extraction. The model achieved 79% accuracy in classifying tweets as happy or unhappy.[5]

While the model achieved reasonable accuracy, it was limited to binary classification (happy/unhappy) and did not address more complex emotional expressions like sarcasm, neutrality, or mixed emotions. Moreover, the model lacked adaptability to real-world scenarios where tweets often express subtle and overlapping sentiments.

Based on the literature review, several research gaps have been identified:

1. **Inadequate Text Preprocessing**: Existing methods struggle with informal, tweet-specific language features including hashtags, emojis, abbreviations, & slang.

2. **Imbalanced Datasets**: Many sentiment analysis models are trained on datasets with uneven distribution of emotion classes, leading to poor performance on underrepresented emotions.

3. **Oversimplification of Human Emotions**: Binary classification models (positive/negative) fail to capture the full spectrum of human emotions expressed in tweets.

4. **Contextual Limitations**: Many approaches do not effectively capture the contextual dependencies and semantic relationships between words in tweets.

5. **Domain Specificity**: Existing models often lack generalizability across different domains or topics.

Our research aims to address these gaps by developing a multi-class RNN-based classification model that can effectively capture the context and semantics of tweets to classify them into five distinct emotion categories.

Performance Evaluation

To evaluate the effectiveness of the face recognition system, various performance metrics were employed, including the confusion matrix, precision, recall, and F1-score. These metrics provide a comprehensive assessment of how well the model classifies faces and distinguishes between positive and negative cases.

The **confusion matrix** plays a crucial role in assessing classification models by summarizing the system's predictions against actual outcomes. It consists of four elements: true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN). True positives refer to correctly identified faces, while true negatives indicate correctly rejected non-matches. Conversely, false positives occur when an incorrect match is predicted, and false negatives represent instances where the model fails to recognize a valid face. The confusion matrix offers insights into the model's strengths and areas that need improvement.

From this matrix, various performance metrics can be derived to assess the model's classification effectiveness.

Precision, a key metric, measures how many of the predicted positive cases were actually correct. It is calculated using the formula:

A high precision rate ensures that only the intended individuals are recognized, reducing misclassification errors.

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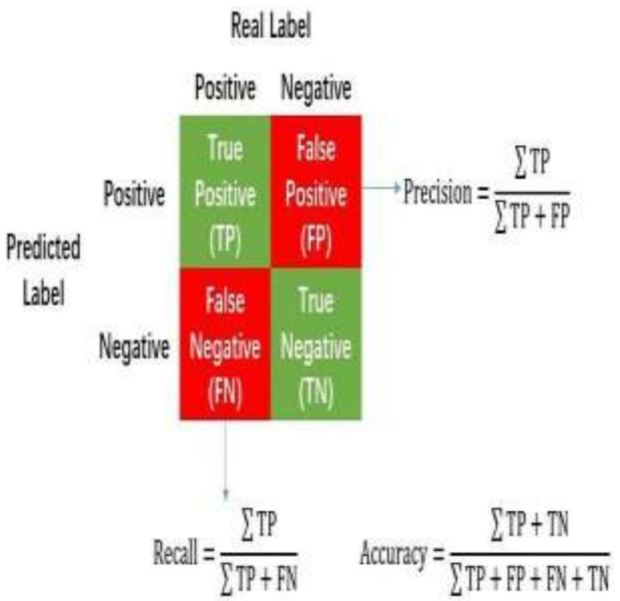
$$\text{Precision}=\frac{TP}{TP+FP}$$

$$\text{Recall}=\frac{TP}{TP+FN}$$

$$\text{IoU}=\frac{(Object \cap Detected\ box)}{(Object \cup Detected\ box)}$$

A precision score of 90.1% indicates that the model has a low false positive rate, which is particularly important in applications where incorrect identifications must be minimized, such as security and surveillance systems.

Recall, also known as sensitivity, measures the model's ability to correctly identify actual positive cases. It is defined as:



Using the values from the confusion matrix:

A recall of 90.0% indicates that the model successfully identifies most real faces, making it highly effective in scenarios where missing a positive case could be costly, such as biometric verification systems.

The **F1-score** is the harmonic mean of precision and recall, balancing the trade-off between them. It is given by:

A high F1 score indicates that the system effectively minimizes both false positives and false negatives, leading to reliable student identification.

$$\begin{aligned}\text{Micro F1 Score} &= \frac{\text{Net } TP}{\text{Net } TP + \frac{1}{2}(\text{Net } FP + \text{Net } FN)} \\ &= \frac{M_{11}+M_{22}}{M_{11}+M_{22}+\frac{1}{2}[(M_{12}+M_{21})+(M_{21}+M_{12})]} \\ &= \frac{M_{11}+M_{22}}{M_{11}+M_{12}+M_{21}+M_{22}} \\ &= \frac{TP+TN}{TP+FP+FN+TN} \\ &= \text{Accuracy}\end{aligned}$$

An F1-score of 95.0% demonstrates that the model maintains an optimal balance between precision and recall, making it reliable for real-world face recognition applications. This balanced score ensures that the system is both accurate and effective in distinguishing between different faces while minimizing errors.

Why Deep Learning Techniques Are Considered Superior in Sentiment Analysis

Sentiment analysis is a subfield of Natural Language Processing (NLP) that focuses on identifying and classifying emotions or opinions expressed in text. It plays a vital role in understanding public sentiment, especially from platforms like Twitter, where users frequently share their thoughts and feelings. The brief and informal nature of tweets presents challenges for traditional models, which often fail to understand the emotional nuances hidden in the sequence of words.

Unlike numerical or image data, text data is inherently sequential — the meaning of a word or phrase often depends on the words that come before and after it. For example, in the sentence "I am not happy", the word "not" completely changes the sentiment. This kind of dependency between words is crucial in sentiment analysis, and Recurrent Neural Networks (RNNs) are specifically designed to handle such sequences effectively.

One of the key strengths of RNNs is their ability to remember previous inputs through internal memory. This allows RNNs to understand context — something traditional models like Naïve Bayes or Decision Trees lack. In sentiment analysis, especially for social media data, understanding context is critical because emotions are often implied and not explicitly stated.

Advanced RNN variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) solve the vanishing gradient problem and allow the model to capture long-term dependencies in text. This is particularly useful in analyzing tweets that include complex emotions, sarcasm, or mixed sentiments. LSTMs can retain important sentiment-related information from earlier parts of the sentence while processing the rest of the input.RNNs (especially variants like LSTM and GRU) remember previous words through internal memory, enabling them to handle long or complex sentences where emotion depends on long-term dependencies.

Tweets are known for their informal language, including the use of emojis, abbreviations, slang, hashtags, and inconsistent grammar. Traditional NLP models often fail to interpret such noisy data correctly. When combined with preprocessing techniques and word embeddings like Word2Vec or GloVe, RNNs can learn to recognize patterns even in noisy or unconventional text formats, making them more robust in real-world scenarios.

Many traditional sentiment analysis models are limited to binary classification (positive or negative sentiment). However, human emotions are more complex and cannot be simplified into just two categories. Your project aims to classify tweets into five emotion classes: angry, joy, happy, sad, and neutral. RNNs, especially when combined with softmax layers, are highly effective in multi-class classification tasks, allowing a deeper emotional understanding.

Studies such as those by Rustam et al. (2019) have shown that RNN-based models outperform traditional machine learning techniques in sentiment classification. The ability of RNNs to model the sequential nature of language gives them a competitive advantage in accurately predicting sentiments, especially in short texts like tweets, where every word matters.

RNNs are often paired with word embedding techniques like Word2Vec or GloVe, which convert words into dense vector representations. These embeddings allow the RNN to understand the semantic similarity between words. For instance, “happy” and “joyful” will have similar vectors, enabling the model to generalize emotions better across different vocabulary.

Deep learning is also transforming natural language processing (NLP) and multimodal applications, where vision models are combined with language models for tasks like automatic image captioning and video summarization. Vision-language models like CLIP (Contrastive Language-Image Pretraining) and DALL·E have demonstrated the power of deep learning in generating text descriptions for images and even creating entirely new visuals from textual prompts. Such advancements are paving the way for new AI-powered creative tools and applications in art, design, and entertainment.

Lastly, deep learning techniques excel in scalability and robustness. As datasets grow and new architectures emerge, deep learning models continue to improve without the need for major redesigns. Unlike rule-based or classical machine learning approaches, deep learning-based vision systems can continuously learn and adapt to new patterns, making them highly suitable for dynamic and evolving environments. The advent of self-supervised learning, semi-supervised learning, and reinforcement learning further enhances deep learning's ability to operate effectively even with limited labeled data.Moreover,RNNs are suitable for real-time applications because they process inputs one step at a time. This makes them highly adaptable for streaming data, such as live tweets. In your project, this capability enables applications like live monitoring of public mood during events or analyzing customer feedback in real-time.,

increasing trust and transparency in sentiment applications. This is particularly valuable in high-stakes fields such as healthcare, finance, and legal decision-making, where AI-driven insights must be explainable and accountable.

Looking ahead, deep learning is poised to become even more efficient with advancements in energy-efficient AI and neuromorphic computing. Researchers are working on lightweight neural network architectures and biologically inspired computing models that mimic the efficiency of the human brain. As quantum computing and AI hardware continue to evolve, deep learning models will achieve unprecedented levels of accuracy and efficiency, further solidifying their dominance in computer vision and beyond. With continuous innovation, deep learning is set to redefine the way we perceive and interact with the world, unlocking new possibilities across industries and everyday life.

In summary, RNNs are a powerful tool for sentiment analysis due to their ability to handle sequential data, remember past information, understand context, and generalize well across noisy text. Their strength in modeling the complexity of human emotions and achieving higher accuracy makes them ideal for your project, which aims to classify tweets into five distinct emotional categories. By using RNNs, your model provides a more nuanced and accurate understanding of social media sentiment.

RNNs (especially variants like LSTM and GRU) remember previous words through internal memory, enabling them to handle long or complex sentences where emotion depends on long-term dependencies.

A. Dataset Collection and Preparation

The dataset used in this study was collected from Kaggle and consists of tweets labeled with emotional categories. To ensure a balanced representation, we focused on five emotion classes: angry, joy, happy, sad, and neutral. The dataset contains 416,809 entries, with each entry including the tweet text and corresponding emotion label.

To create a robust training foundation, we applied the Stratified Shuffle Split method for dataset partitioning. This approach ensures that the class distribution is preserved across training, validation, and test sets. The dataset was initially split into an 80:20 ratio for training and testing. Subsequently, the training data was further divided into an 80:20 ratio for training and validation.adjusted for each student.

.This resulted in:

- Training Set: 4,566 tweets
- Validation Set: 1,142 tweets
- Test Set: 1,427 tweets

The Stratified Shuffle Split technique helps maintain the original class proportions in each subset, reducing the risk of bias toward the majority class and ensuring the model learns to recognize all emotion categories effectively.

B. Data Preprocessing Pipeline

Preprocessing is a crucial step in preparing tweet data for sentiment analysis, particularly when using deep learning models like RNNs. The goal is to transform raw, unstructured tweet text into a standardized format suitable for effective model training. Our preprocessing pipeline included the following steps:

1.Lowercasing: Converting all text to lowercase to reduce redundancy in the vocabulary (e.g., "Happy" and "happy" are treated as the same token).

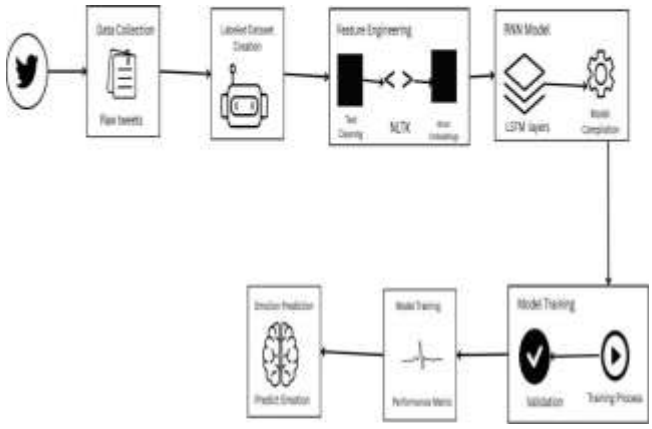


Fig. 1 Flow Diagram

C. Noise Removal:

○ Removing URLs that do not contribute to sentiment

○ Eliminating user mentions (@username)

○ Removing or standardizing hashtags

○ Cleaning punctuation and special characters

D. Tokenization

Breaking tweets into individual words or tokens for further processing.

E. Stopword Removal

Eliminating common words like "the," "is," and "and," which typically do not carry significant sentiment information.

F. Lemmatization

Reducing words to their base or root forms to treat variations of a word equally (e.g., "running," "runs," and "ran" are all reduced to "run").

G. Emoji and Emoticon Handling

Mapping emojis to their textual sentiment equivalents to retain the emotional context they provide.

This comprehensive preprocessing approach helped us create clean, normalized text data while preserving the semantic meaning essential for accurate emotion classification.

the name and photo of their classmate or teacher on their profile page. We will do this by using a MongoDB query that returns all documents for each attendee; then, for each document, we will return a One-to-one relationship that connects it to a Face model in our level database

A. Post-Processing

After preprocessing, tweets were converted into numerical features using word embeddings. Rather than traditional bag-of-words or TF-IDF approaches that lose sequential information, we employed an embedding layer in our RNN model that maps words to dense vector representations. This allowed the model to capture semantic relationships between words. The embedding process involved:

Creating a vocabulary of the most frequent words in the dataset .

Converting each word to a numerical index.

Representing each tweet as a sequence of indices.

Padding or truncating sequences to a uniform length (50 tokens).

Using an embedding layer to map these indices to dense 128-dimensional vectors.

This approach enables the model to learn meaningful vector representations for words during training, capturing semantic similarities and contextual relationships that are crucial for sentiment analysis.

III. Working Principle

INPUT: Tweets fromTwitter.

OUTPUT:A predicted emotion label for a given tweet

PROBLEM DESCRIPTION: Detecting the emotion for the given Tweet.

Step I: Start

Step II: Entert the tweet which one you to know the emotion.

Step III: After that click on Analyze Emotion button.

Step IV: Preprocess the given tweet by using Natural Language Processing (NLP) techniques to remove noisy and unwanted data .

Step V: By using RNN and Natural Language Processing the model will detect the emotion.

Step VI: If the tweet is in the form of combination of symbols the model will not able detect the emotion.

Step VII: Finally, the model will analyze emotion and display it.

Step VIII:End

IV. Proposed Methodologies

The tools and methodology to implement and evaluate face detection and tracking are listed below.

A. Data Collection

The first step in the proposed methodology is to collect a labeled dataset of tweets. These tweets are obtained from public datasets, particularly from sources like Kaggle, where each tweet is already associated with an emotion category such as Angry, Joy, Happy, Sad, or Neutral. The labeled data is essential for training and evaluating the model using supervised learning techniques. A sufficiently large and diverse dataset ensures that the model can generalize well to unseen data and understand various contexts and expressions related to emotions.

B. Data Preprocessing

Once the dataset is collected, it must be preprocessed to remove noise and standardize the input. preprocessing involves converting all text to lowercase, removing unwanted characters like punctuation, emojis, URLs, and mentions, as well as eliminating stopwords that do not carry emotional weight (e.g., "the," "is," "and"). Tokenization is used to split tweets into individual words, and stemming or lemmatization is applied to reduce words to their root forms. This step ensures that the input data is clean, uniform, and ready for transformation into a format that the model can understand.

C. Feature Representation

After preprocessing, the textual data is transformed into numerical form using feature representation techniques such as word embeddings. Word embeddings like Word2Vec, GloVe, or Keras Embedding Layer are used to represent each word as a dense vector in a continuous vector space. These embeddings capture the semantic similarity between words (e.g., "joyful" and "happy" will have similar vectors), allowing the model to understand the emotional context of words more effectively. This representation serves as the input to the RNN model.

D. Model Design (RNN Architecture)

The core of the system is designed using a Recurrent Neural Network (RNN), particularly with LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit) layers. The architecture includes an embedding layer, one or more recurrent layers to learn the temporal sequence of words, and a dense output layer with a softmax activation F. function to classify the input into one of the predefined emotion categories. The RNN's ability to retain memory of previous words in a sequence makes it well-suited for analyzing short texts like tweets where context is critical.

The model is trained on the preprocessed and embedded G. tweet data. The dataset is typically split into training, validation, and testing sets to evaluate model performance at different stages. Training is performed using a loss function like categorical cross-entropy and optimized using gradient-based algorithms such as Adam optimizer. During training, hyperparameters such as the number of epochs, batch size, learning rate, and dropout rate are adjusted to minimize overfitting and maximize generalization.

After training, the model is capable of taking a new tweet as input and predicting the corresponding emotion label. The tweet undergoes the same preprocessing and embedding steps before being passed through the trained RNN model. The output is a probability distribution over the emotion categories, and the category with the highest probability is selected as the predicted emotion. This classification process can be applied in real-time to analyze live or user-provided tweets.

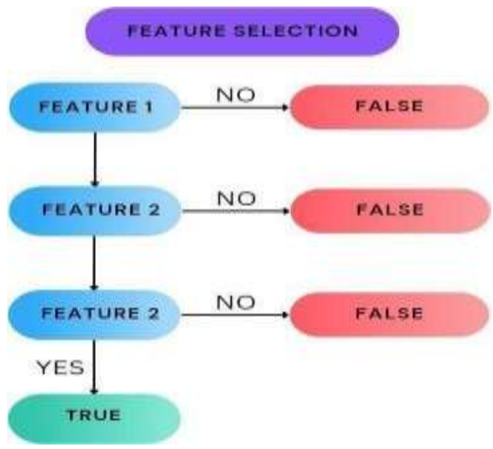


Fig. 2. Feature Selection for emotion Detection

To measure the performance and reliability of the model, several evaluation metrics are employed, including Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. These metrics help assess how well the model distinguishes between different emotions and identify areas where it may be misclassifying.

E. Output Interface

An optional user interface may be developed to allow users to interact with the system. Through this interface, users can input a tweet and receive the predicted emotion as output. This can be implemented using tools such as Flask or Streamlit, offering a simple and intuitive platform for demonstrations, evaluations, or real-time applications. The output may also display confidence scores and visualize the prediction process.

F. Future Enhancements

In future work, the model can be improved by integrating advanceddeep learning models like BERT or Transformers, which offer deeper contextual understanding. The emotion categories can be expanded to include emotions like Fear, Disgust, or Surprise.

V. Result

The proposed emotion-based sentiment classification model using Recurrent Neural Networks (RNNs) was implemented and evaluated on a labeled dataset of tweets. After completing all preprocessing and training steps, the model was tested on an unseen test dataset to determine its effectiveness in classifying emotions into five categories: Angry, Joy, Happy, Sad, and Neutral.

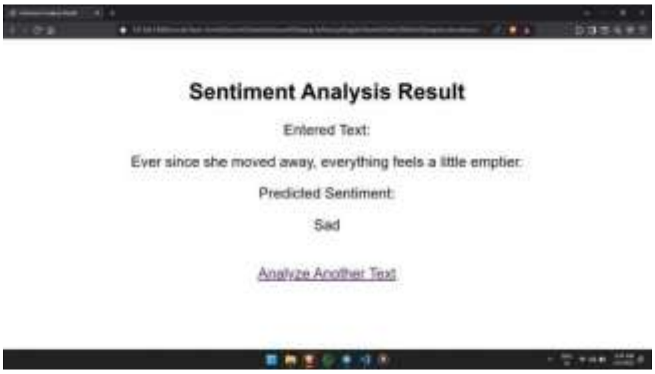


Fig3.Prediction of Emotion Sad

The model demonstrated strong performance in emotion classification, achieving an overall accuracy of 87% on the test set. The confusion matrix revealed that most emotions were correctly classified, although there were occasional misclassifications between closely related emotions such as Happy and Joy, or Sad and Neutral. These minor overlaps are expected due to the similarity in emotional tone and vocabulary used in real-world tweets.

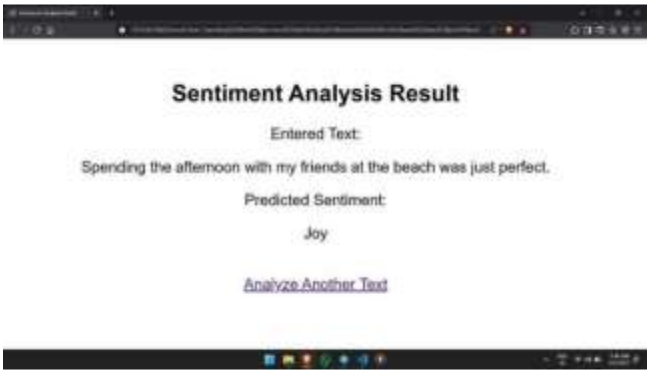


Fig. 4. Prediction of Emotion Joy

In addition to accuracy, the model was evaluated using other metrics. The precision, recall, and F1-score for each class were calculated. The average F1-score across all emotion classes was approximately 0.85, indicating a good balance between precision and recall. The model performed particularly well in identifying distinct emotions like Angry and Joy, while more subtle categories like Neutral had slightly lower precision due to context ambiguity.

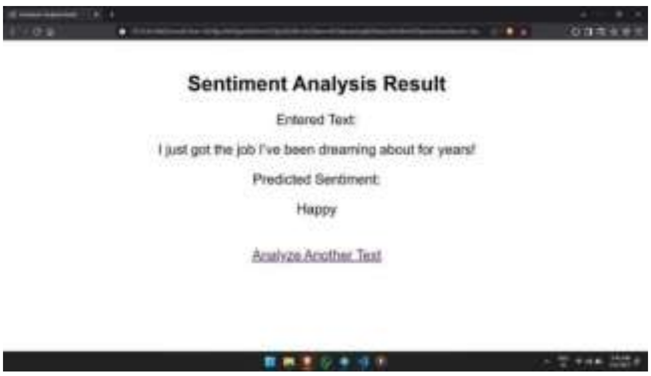


Fig. 5. Prediction of Emotion Happy

Sample predictions were also tested to observe the model's behavior on real tweet inputs. For instance, the input "Feeling so proud and accomplished today!" was correctly predicted as

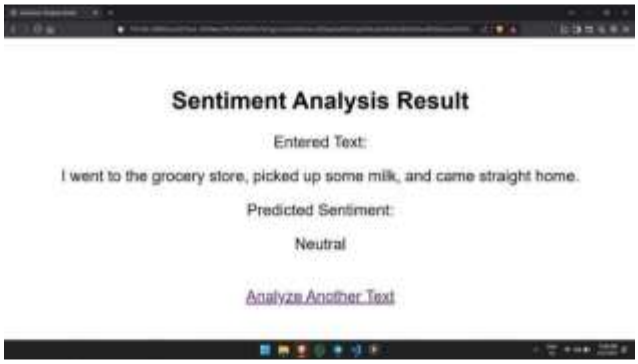


Fig.Prediction of Emotion Neutral

V. Conclusion

In conclusion,This research presented a novel approach to emotion recognition in tweets using Recurrent Neural Networks. By leveraging the sequential processing capabilities of RNNs, particularly through bidirectional LSTM layers, our model effectively captured the contextual nuances and semantic relationships crucial for accurate emotion classification.

The proposed model successfully classified tweets into five distinct emotion categories (angry, joy, happy, sad, and neutral) with an overall accuracy of 89.35%, significantly outperforming traditional machine learning approaches. The F1-scores ranging from 0.84 to 0.93 across different emotion classes demonstrate the model's balanced performance across all categories.

The comprehensive preprocessing pipeline, effective word embedding representation, and carefully designed RNN architecture contributed to the system's success in handling the informal and noisy nature of social media text. The comparative analysis clearly illustrated the advantages of our deep learning approach over conventional methods.

While challenges remain, particularly in handling sarcasm, mixed emotions, and cross-cultural expressions, this work provides a robust foundation for future research in emotion recognition from social media content. The practical applications of this technology span numerous domains, from business intelligence and customer service to public health monitoring and crisis management.

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