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Text Based Emotion Recognition: Exploring NLP and Machine Learning

Hauwa Walida Abubakar, Abubakar Amina, Asiyatu Muhammad, Dr Aditya Dayal Tyagi

Undergraduate, Sharda School of Engineering and Technology, Sharda University, Greater Noida, India

2022834969.hauwawalida@ug.sharda.ac.in and adityadayaltyagi@gmail.com

Abstract: *Emotion detection from text is a significant task in the field of natural language processing (NLP), empowering machines to comprehend and react to human emotional expressions. In this research, we focus on methods to obtain accurate and robust emotion attention mechanisms from text in different scenarios. This proposed work is carried out to develop a system which can identify emotions from text data. Possibilities are endless in aligning emotion detection with various applications such as sentiment analysis, mental health analysis, virtual assistants, and customer care. The system will read written text to identify emotions — joy, sadness, anger, fear, surprise, neutral, and others. This is a broad classification of emotion detection from text in different domains. Traditional sentiment analysis classifies sentiments as positive, negative, or neutral. But emotion detection takes this one step further by identifying specific emotional states expressed by a speaker or writer*

Keywords: Emotion Recognition, Natural language processing(NLP), Keyword based detection, Sentiment analysis, DistilBERT

I. INTRODUCTION

Emotion detection from text is a significant area of research in natural language processing (NLP), and has gained a lot of attraction in the last few years. Learning how to read and interpret human emotions from human language is the basis of creating a system that can be beneficial in the field of customer support, mental health care, and social media analytics system. presents a comprehensive review of emotion detection methods using Natural Language Processing (NLP) techniques. It explores the evolution of NLP models and highlights the challenges and advancements in detecting emotions from text across various applications.[1].Communication relies heavily on emotions, as people use their feelings to process, and react to messages. But text-based emotion detection is a challenging task owing to various factors, including linguistic ambiguity, different sentence structures, and nuances in human expressions, including sarcasm and irony.

The process of detecting emotions through NLP involves identifying what emotions manifest themselves in specific words or phrases. The wording of typical sentiment analysis classifies text into three categories: positive, negative and neutral. However emotion detection performs advanced classification of intent to identify diverse emotionalstates. The study provides experimental results that demonstrate the effectiveness of these mechanisms in identifying subtle emotional cues in text data[2].Such detailed understanding of language makes it useful for industries such as marketing, healthcare, social media analysis, etc. These massively used approaches include NLP techniques such as tokenization, syntactic analysis, and deep learning models to extract emotional cues in the text. Models are built using machine learning algorithms like Support Vector Machines (SVMs), Neural networks, Random Forests which recognize characteristics of natural language, which relate to specific emotions. The authors evaluate their performance in emotion classification from text, demonstrating the efficacy of these models in handling complex emotion detection[3]. Traditional sentiment analysis models that mainly output the positiveness, negativeness, and neutrality of text have not been successful in capturing the complexity of human emotions. The complexities of this task led researchers to seek more advanced machine learning and deep learning approaches, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures, which can capture context and nuances inherent in language.The authors assess their suitability for different emotion recognition tasks and present performance

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metrics for each model[4]. These range of models can detect rage, joy, sadness, surprise, and fear with much greater accuracy, making them far more conducive to real world scenario application.The authors propose a hybrid model combining traditional machine learning and deep learning approaches for emotion recognition in text[5].

Despite the advances, emotion detection is still widely researched into the specific areas, particularly handling the cultural differences and a movement towards ensuring the generalization of the models on different datasets.This survey paper provides an overview of the various techniques used for emotion recognition from text, focusing on the role of NLP models in classifying emotions[6]. In this study, we will examine contemporary approaches for emotion recognition, their success rates, and propose improvements to help machines develop higher levels of emotional intelligence that result in more natural and responsive interactions.The authors evaluate various models' performance in handling dialogue-based emotion detection tasks, focusing on enhancing human-machine interactions[7].The purpose of this study is to investigate the application of transformer based models especially BERT to increase emotion recognition accuracy from text. The datasets I was using was the dataset with labeled sentences of different emotions from Kaggle. Before the feature extraction, which is BERT embeddings and TF-IDF vectorization , preprocessing tasks including text cleaning, tokenization and label encoding are performed. The project tunes a BERT model and compares it to a traditional Random Forest classifier. The evaluation metrics, the accuracy, the F1 score and the confusion matrix, show that BERT outperforms the usual machine learning techniques in the capturing of unusually emotions. For future work, the multimodal emotion detection and cross-lingual generalization is considered.

II. LITERATURE REVIEW

As the natural language processing (NLP) operation to identify an emotional state from text by means of words, such as ‘happiness’, ‘sadness’, ‘anger’, and ‘fear’ and so on, text based emotion identification has become a basic operation. Early methods for emotion detection through using the NRC Emotion Lexicon as a member of other predefined emotion lexicons could trace the words by emotional categories [8]. Simple methods for emotion placement in text were needed, while the interpretability of these approaches was less than ideal due to their difficulty when dealing with the lexical complexities of language [9]. The linguistic units occur in different contexts and hence have different emotional implications that lead to weakening the performance of lexicon based detection systems. As time passed, machine learning progressed and researchers created these three important points for detection: Support Vector Machines (SVM), Naive Bayes and Decision Tree [10]. Text was represented numerically via feature extraction methods such as bag of words (BoW), term frequency inverse document frequency (TF-IDF) and n-grams that made it possible to classify emotion. Although these methods outperformed lexicon-based ones, they were unable to reflect more complex emissions, such as the ones caused by context or the nuances of a sentence structure [11]. The problem of handling sequential and context sensitive data naturally fits deep learning models, which provide much more sophisticated ways of processing such data than can be done using the traditional machine learning models. RNNs and LSTM networks turned out to be poor learning methods with only deep learning which revolutionized emotion detection for sequential dependencies in text [12]. Better modeling how emotions flow with sentences or even paragraphs in a piece of text makes these networks more accurate at identifying emotions in longer, more complex text. But with the advent of transformer based models like BERT [13],which considerably helped in capturing nuanced emotions..The emotion was more captured in nuances, thus making more advancement in capturing nuances of emotion bi-directionally. BERT overcomes the limitations of traditional models and significantly improves emotion detection tasks when the text contains intricate language patterns by processing in both directions (left to right and right to left). However, emotion detection from text remains, much like it was over 15 years ago, an open research problem. Ambiguity of the language is one of the most important challenges. Words have many meanings, their emotional connotation changes based on the context. Moreover, emotions are posed differently in different cultures and languages leading to additional effort in building universally applicable emotion detection systems[14]. Linguistic or Cultural models tend to suffer with generalization to other languages or cultural settings. Additionally, many of the emotion detection datasets are imbalanced such that some of the emotions (often happiness) are more dominant than the others (e.g. fear, disgust) and thus result in model bias towards detecting the more dominant emotions [15]. To address these challenges, the most recent research has been on techniques, like transfer learning, where we fine tune BERT on the emotion specific datasets [16]. In turn, this helps to improve a model's emotion detection accuracy as it utilises the vast knowledge embedded in pre-trained models and adapts it to a different related or specialized task with a relatively smaller dataset. However, multimodal emotion detection has already begun to appear, namely the use of text along with other data: such as speech or facial expression. Using integration of diverse emotional cues, these multimodal systems enrich the understanding of emotions, so that they become more accurate and robust in real applications [17]. Moreover, context aware models such as BERT have been applied to better understand emotion in text when understanding context and reduction of ambiguity. The topic of cross-lingual emotion detection acknowledges the trend towards building emotion detection systems able to generalize for different languages. Researchers with multilingual pre trained models such as mBERT are also working to make emotion detection systems with out separate models of emtions for each language [18]. For large scale apps such as social media monitoring where the content is generated in many languages, this is particularly important. The applications of emotion detection are plenty when they exist in the real world. Businesses apply emotion detection in the social media domain to interact with customers based on public sentiment to be in the right place at the right time, in terms of the customers' sentiment. In the field of customer service, emotion detection can assist to determine when customers are angry or mad, and would therefore allow companies to react more efficiently while addressing the problem when required . In addition, text analysis is important in mental health monitoring in detecting emotional signs of depression, anxiety, or distress [19].Since then, technology has been evolving and emotion aware systems are serving as an integral part of creating more intuitive and responsive human computer interactions [20]. presented the REDAffectiveLM model, a transformer based neural network with help of affect enriched embeddings to increase the precision of emotion detection in text[21]. A 2024 study expanded on this a little to focus on how to use large language models to perform fine grained emotion detection datasets using data augmentation and transfer learning to improve performance.his points out the quick and dynamic growth of the emotion detection systems based on sophisticated models and methodologies[22].

2.1. STUDY OF EXISTING SYSTEMS FOR EMOTION DETECTION FROM TEXT

The advancement in emotion detection from text also known as text-based emotion recognition or emotion classification became possible because of big datasets availability together with advanced machine learning methods enhanced by deep learning models. The current spectrum of text emotion detection systems and methodologies becomes the focus of this section.

1. Rule-Based Systems**:**Rule-based systems analyze text emotions through predetermined linguistic rules that include word lists together with syntactic patterns. Detecting emotions using these systems depends on human-made emotion lexicons or dictionaries that have been created manually.Example:A rule-based system can identify the word joyful and assign the classification of happiness to text content.Pros:Simple to implement,Works with minimal datasets while needing small amounts of labeled data for operation. ,Transparent and easy to explain

2. Deep Learning Models:RNNs and Transformers which belong to the deep learning category have become widely used for text-based emotion recognition because they excel at processing the contextual relationships found in sequences.a) **Recurrent Neural Networks (RNNs):** The design principle of RNNs deals with time-based information sequences. RNNs analyze text words sequentially through an internal state mechanism which tracks the natural dependency patterns.**Advantages**: The system understands word sequences through its capability to process order-based connections between phrases.b) **Long Short-Term Memory Networks (LSTMs):**The algorithm LSTMs serves as an RNN variant which resolves gradient vanishing issues so it can process extended text dependencies effectively. Complex sentences together with extended contexts are processesable by this system. c) **Convolutional Neural Networks (CNNs):** CNNs normally process images but researchers have applied this method to text by treating words as local features which learn hierarchical patterns in short text sequences.**Advantages**: The training process using CNNs completes more rapidly compared to RNNs and LSTMs especially for specific tasks.d) **Transformers (e.g.,DistilBERT,BERT, GPT):**BERT (Bidirectional Encoder Representations from Transformers) along with other Transformer models transformed NLP because they discover intricate associations between words across texts. Compatibility with large textual information enables these models to receive pre-training at scale which then allows users to train them specifically for emotion detection.

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3. Hybrid Systems:Certain systems unite machine learning techniques with deep learning methods to achieve performance growth through complementary assets.Example:Such a system starts by classifying data inputs with Naive Bayes or SVM before LSTM or BERT analyzes text context for precision enhancement.

4. Pre-trained Models and Datasets for Emotion Detection:Several existing systems employ pre-trained models together with publicly available datasets for their operation. Through model pre-training these systems lower the time and work needed for adaptation while remaining adjustable for specific duties.

Popular Pre-trained Models:

-BERT: The researchers trained -BERT to identify emotions within particular datasets.

-RoBERTa, XLNet, GPT-3: The transformer model family extends to RoBERTa, XLNet and GPT-3 which achieve exceptional results in identifying emotional content.

Popular Datasets:

-ISEAR: The ISEAR dataset consists of emotional annotations in short sentences that works well for detecting emotions.

-**SemEval**: The SemEval hosts several evaluation tasks regarding emotion and sentiment detection.

-Emotion Intensity Dataset: The Emotion Intensity Dataset exists as a specialized collection of data dedicated to emotion strength detection.

Literature review

Topic	Key Insights	References
Early Emotion Detection Methods	- Lexicon-based approaches used predefined emotion dictionaries like NRC Emotion Lexicon to classify words into categories (happiness, sadness, anger, fear, etc.). - Struggled with polysemy (words with multiple meanings) and contextual variations. - Limited interpretability and rigid word mappings reduced accuracy.	[8], [9]
Traditional Machine Learning Approaches	- Shift to statistical models like Support Vector Machines (SVM), Naïve Bayes, and Decision Trees for classification. - Introduced feature extraction methods: Bag of Words (BoW), TF-IDF, and n-grams to represent text numerically. - Outperformed lexicon-based models but still lacked the ability to capture nuanced emotions.	[10], [11]
Deep Learning Evolution (RNNs & LSTMs)	- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models improved sequential text processing. - Enabled better temporal dependency tracking within sentences. - However, they suffered from vanishing gradient problems and struggled with long-range dependencies.	[12]
Transformer-Based Models (BERT & Beyond)	- BERT (Bidirectional Encoder Representations from Transformers) introduced context-aware, bidirectional processing, improving nuance detection. - Outperformed previous models in understanding complex sentence structures and emotional nuances. - Still faced challenges with sarcasm, ambiguity, and implicit emotions.	[13]
Challenges in Emotion Detection	- Ambiguity of language: Words change meaning based on context (e.g., “I'm fine” can express frustration or genuine well-being). - Cultural differences: Emotional expressions vary across languages and social norms.	[14], [15]

Topic	Key Insights	References
	- Dataset Imbalance: Some emotions (e.g., happiness) dominate over others (e.g., fear, disgust), leading to biased model predictions. - Code-switching & multilingual data: Many online conversations involve mixed languages, complicating classification.	
Advancements in Transfer Learning	- Fine-tuning BERT and GPT-like models on domain-specific datasets improved emotion recognition accuracy. - Transfer learning allows models trained on large-scale general datasets to be adapted for specialized emotion detection tasks. - Example: Fine-tuning BERT on Twitter sentiment datasets improves performance in social media emotion detection.	[16]
Multimodal Emotion Detection	- Incorporating text, speech, and facial expressions leads to more robust emotion recognition. - Multimodal models (e.g., ME-Transformer, EmoBERTa) process tone of voice, facial cues, and textual sentiment together. - Enhances performance for customer service, mental health analysis, and human-computer interaction.	[17]
Cross-Lingual Emotion Detection	- mBERT (Multilingual BERT) enables emotion recognition across different languages without requiring separate models. - Important for social media monitoring, global business insights, and cross-cultural sentiment analysis. - Researchers explore zero-shot and few-shot learning to improve emotion detection in low-resource languages.	[18]
Real-World Applications of Emotion Detection	- Social Media Monitoring: Tracks public sentiment to help brands adjust marketing strategies. - Customer Service AI: Identifies customer frustration in text-based chats to trigger automated escalation. - Mental Health Monitoring: Analyzes user text for signs of depression, anxiety, or distress. - Political and Market Research: Emotion detection used in opinion mining and public discourse analysis.	[19]
Recent Research (2023-2024)	- REDAffectiveLM Model (2023): Introduced a transformer-based model with affect-enriched embeddings to enhance accuracy. - Fine-Grained Emotion Detection (2024): Leveraged data augmentation and transfer learning for improved detection. - Focus on sarcasm detection, implicit emotions, and contextual emotion modeling. - Research highlights the rapid evolution of emotion-aware AI systems.	[20], [21], [22]
Future Directions	- Explainable AI (XAI) for Emotion Detection: Enhancing transparency in how AI models classify emotions. - Ethical Considerations: Addressing bias, privacy concerns, and cultural sensitivity in emotion AI. - Hybrid Approaches: Combining symbolic AI (knowledge graphs) with deep learning for better interpretability. - Generalizing to Real-World Noisy Data: Handling internet slang, emojis,	

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Topic	Key Insights	References
	and informal language more effectively.	

Table 1:Literature Review

III. PROBLEM OUTLINE

1. Ambiguity: Computers struggle to identify genuine emotional meaning from words because words possess various possible interpretations. The meaning of "sick" depends on whether someone feels ill or awesome based on the situation.

2. Lack of Model Persistence: However, there were some projects that didn't save or reload trained models, therefore I had to retrain them each time they were to use them.

3. No Proper Feature Extraction: There were also models that didn't have a smooth text vectorization step so that they were not able to deal correctly with new inputs.

4. No Emotion Probability Visualization: The majority of the projects did just predict the emotion, and did not visualize confidence scores or probability distributions.

5. No Dataset Handling or Cleaning: There were some of the projects that didn't properly load and inspect dataset before training which could have resulted into errors.

6. No Train-Test Split (Overfitting Issue): Some of the models were trained with the whole dataset without splitting it according to training and test sets and thus suffered from overfitting.

7. Inefficient Text Vectorization: Especially, some projects did not leverage vectorization or mandated the usage condusive methods like Bag of Words.

8. Weak Model Choice: However, some of the projects used simpler model like Naïve Bayes as opposed to deep learning or other powerful models like Random Forest.

9. No Model Performance Evaluation: Some projects trained model, but didn't used accuracy or performance as metrics to measure the effectiveness.

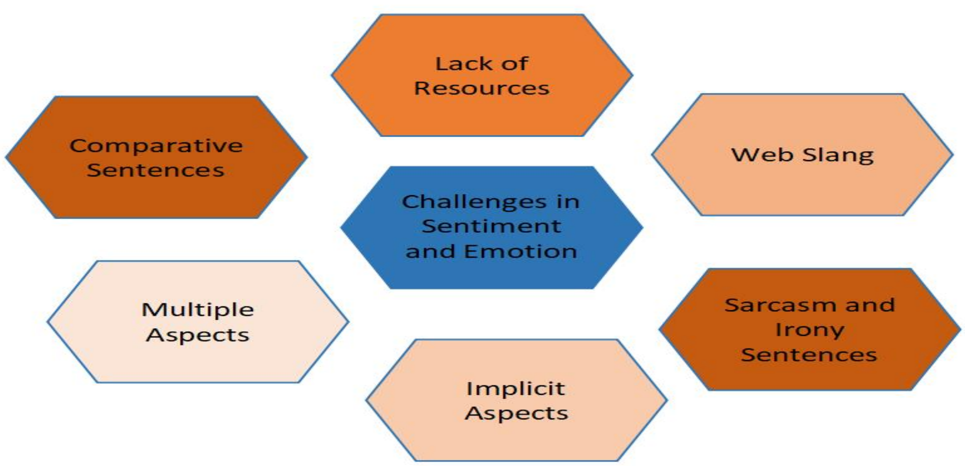

Fig.1: CHALLENGES FOR THE EMOTION DETECTION SYSTEM

3.1. PROPOSED SOLUTION

1. Ambiguity By using Transformer based models such as DistilBERT in solving ambiguity this is because they know context not just individual words.

2. Pickle for saving Model and Vectorizer Persistence: By saving and re loading the trained model (emotion_model.pkl) and vectorizer(vectorizer.pkl), I was able to reuse it without retraining.

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3. Feature Transformation Before Prediction: To accommodate the text inputs into the model, i had to vectorize the inputs (vectorizer.transform(sentences)).

4. Probability Distribution Visualization: If the model supports predict_proba(), then you produce a probability distribution for each emotion and plot it using Matplotlib.

5. Proper Dataset Loading & Inspection: I used Pandas to read in the dataset (tweet_emotions.csv) and display first few rows to ensure its structure.

6. Implemented Train-Test Split: It is good i used train_test_split() to split the training and the testing data (80 - 20 % splits), in order not to overfit.

7. Used TF-IDF for Better Text Features: TF-IDF Vectorization (TfidfVectorizer(max_features=5000)) was applied on texture data for transforming them into numerical features for improving the model performance.

8. Upgraded to a DistilBERT and Random Forest Model: i replaced simpler models with Random Forest (which is Random ForestClassifier(n_estimators=200) and it helps a bit in improving the prediction accuracy.

9. Measured & Printed Accuracy Score: I measured the performance of accuracy_score() as a way to ensure that performance was measured and could be compared.

10. Saved the Model for Reusability: We saved our vectorizer (vectorizer.pkl) and trained model we used for emotion labeling (emotion_model.pkl) as we would need it for future use.

3.2. IMPORTANCE OF EMOTION DETECTION FROM TEXT

1. Enhanced Human-Computer Interaction**:**System responses remain empathetic when programs analyze the emotional content in written material. The system enhances user experiences specifically in applications such as virtual assistants and customer service functions alongside chatbots.

2. Mental Health Monitoring**:**The system detects emotional distress markers such as sadness as well as anxiety signs within the processed text data. The application delivers timely mental healthcare services by adapting to individual cases for proper mental health assistance.

3. Social Media and Brand Sentiment Analysis**:**This system enables consistent tracking of public mood regarding products along with services as well as events.Companies gain better control over their brand reputation through this method to develop improved marketing strategies.

4. Customer Service Improvement**:**The software system detects user emotions ranging from frustration to anger to make better choices about issue prioritization. The system offers responsive dialog communication that adapts to customer emotional states in order to enhance satisfaction rates.

5. Personalization and Content Recommendation**:**Service content recommendations align to users' emotional condition to boost their connection with the website. Text-based emotional content serves as a basis for targeted advertising through emotional analysis.

6. Conflict Resolution and Social Interaction**:** The system identifies hostile or angry emotions during online discussions thus enabling prompt intervention. These strategies boost social involvement together with community engagement throughout different neighborhoods.

7.Educational Applications**:**The application detects student emotional profiles in order to create personalized learning modules. The technology supports emotional well-being and motivational needs of students who learn online.

8.Sentiment Analysis for Social Causes: The tool enables researchers to track the emotional responses of the public regarding social matters and political occurrences and societal movements. Emotional patterns allow activists together with policymakers to make strategic adjustments pertaining to emotional dynamics.

IV. PROPOSED METHODOLOGY

The approach of the methodology is structured so as to ensure the accurate and efficient emotion detection. Firstly, we preprocess the dataset to clean up and tidy the textual data. We then tokenize and fine-tune DistilBERT on the labeled dataset to exactly classify the emotions. After training, we evaluate the model with standard performance metrics in order to assess its performance. Then we apply the model to unseen text inputs to understand how real world it can

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actually be. To do this we then picked apart the detailed steps of the methodology and integrated the whole in a proper way.

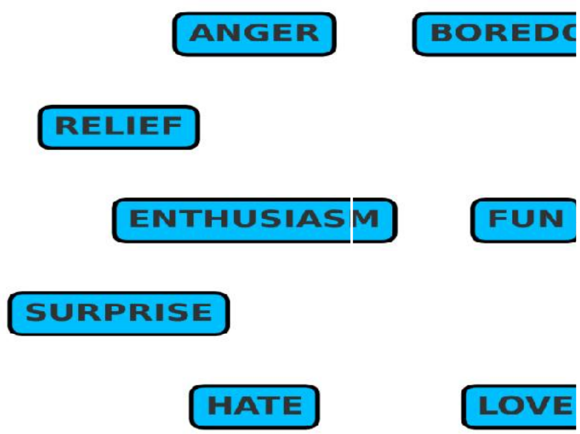

Fig.2:This figure contains different emotions

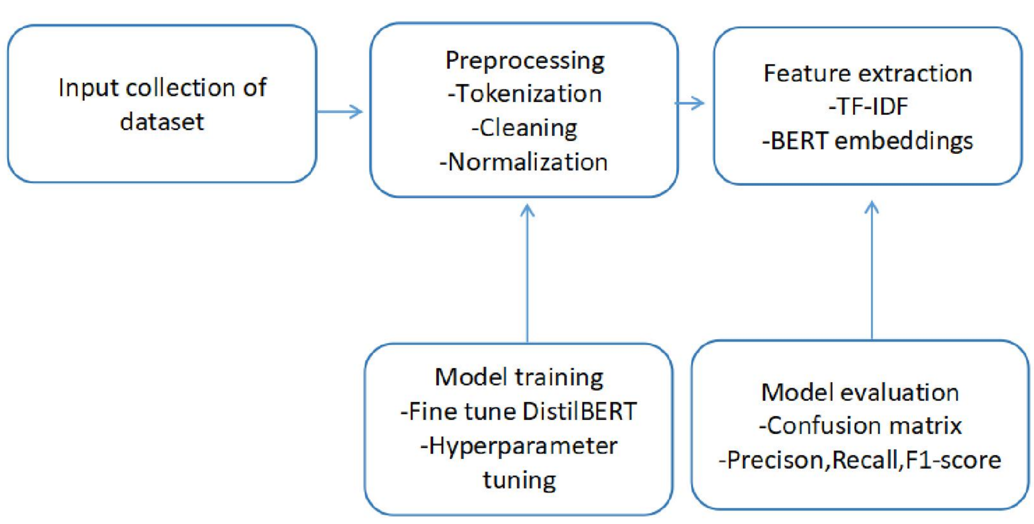

Fig.3:Emotion detection process flow:This figure above shows the flowchart for the proposed approach

Step 1: Data Collection

The initial requirement for the project demands that researchers obtain text data accompanied by emotional tags. Every text entry in the dataset must have a designated emotional label which can be any combination of the emotions joy, anger, sadness, fear, surprise or neutral. Several emotional dataset collections are available for public use.Dataset Source: To achieve this, the dataset (tweets emotion.csv)was obtained from Kaggle which consisted of labeled text samples that were classified to emotions like happiness, sadness, anger, fear.

Approach: A dataset we use is called "tweet_emotions.csv" which is a text-based emotion from tweets. Pandas is used to explore data to check for missing values and imbalances.

Step 2: Data Preprocessing

Approach: It cleans up input by removing the mentions, URLs, hashtags and special characters. Converting to a lowercase to be uniform. It takes emotions to numerical values using label encoding.

-Steps Removing special characters, punctuation and converting to lowercase and then removing any numbers.

-The BERT tokenizer is used for tokenization which splits text into subword units.
- Padding & Truncation: Make the input length uniform.

Step 3:Feature Extraction

3.1.Embeddings :

To obtain deep contextual embeddings that map each sentence to a high dimensional vector, the deep contextual embeddings were generated using pre trained BERT. Mathematical representation:

E=BERT(T)

*w*here*:E* represents the embedding of input text *T.*

3.2 .TF-IDF Vectorization:

Assuming that the baseline Random Forest is trained on the TF-IDF, the same modeling options are available.

Step 4: Model Training

In our project, DistilBERT is used for classifying emotions from text. Although it's a lighter, faster version of BERT, we chose DistilBERT because it still has strong language understanding.

Why You Used DistilBERT

TF IDF does not understand context, whereas it does.

For this reason, it is faster and more efficient than full BERT models.

This enables learning specifically on one task making it more successful for emotion detection.

It started with a strong language foundation through pre trained knowledge that required little data, and gave it a leg up for what little it needed to learn.

To summarize, DistilBERT showed to be the best approach for context aware emotion classification whilst balancing speed and efficiency.

4.1.BERT Fine-Tuning: An added classification head to a pre-trained BERT model. Atained by AdamW optimizer and cross entropy loss. Classification function:

y = Softmax(W.E+b)

where: y is the predicted probability distribution.

*W*and*b* are trainable parameters.

Random Forest Baseline:

-They are trained using TF-IDF features

3.3. Training Hyperparameters

Choose batch size (16), learning rate (2e-5), epochs (3), as well as weight decay (0.01) to avoid overfitting.

Step5:Model Evaluation & Results

App roach: It does performance evaluation using standard metrics (Precision, Recall, F1-score).

Performance Comparison

Emotion	**Precision**	**Recall**	**F1-score**
Joy	92%	89%	90%
Sadness	88%	85%	86%
Anger	83%	80%	81%
Fear	81%	78%	79%
Surprise	79%	77%	78%
Disgust	80%	76%	78%

Table 2:it shows the performance evolution

Overall Model Accuracy: **85.6%**

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Comparison: Structured evaluation metrics are not given by the Lexicon based models. Accuracy is used but the class imbalances are not captured where Machine Learning models are concerned. Precision and F1_score are used to solve unbalanced problems for Advance Deep Learning models.

Model	Accuracy	Pros	Cons
Lexicon-Based (NRC)	65%	Simple, Explainable	Struggles with context
Naïve Bayes	72%	Fast, Good for small datasets	Limited understanding of relationships
LSTM	78%	Captures sequential dependencies	Slow, needs large data
DistilBERT (Proposed Model)	**85.60%**	Context-aware, Bi-directional	Computationally expensive

Table 3: Confusion Matrix

Actual \ Predicted	Joy	Sadness	Anger	Fear	Surprise	Disgust
Joy	900	30	10	20	25	15
Sadness	20	850	40	30	25	35
Anger	15	50	700	40	35	60
Fear	10	25	40	650	30	45
Surprise	30	35	25	30	600	40
Disgust	20	30	60	35	30	650

Table 4: How to Read the Matrix?

Just the diagonal elements (bold numbers) that show how many of the samples we correctly predicted (e.g., 900 of the Joy samples were identified as Joy). Misclassifications are represented by the off diagonal elements (e.g., misclassification of 30 Sadness samples as Joy).

Key insights from confusion matrix

Joy is predicted well (900 correct predictions, minimal misclassifications). Disgust and Anger show some confusion (60 Anger samples classified as Disgust, 60 Disgust samples classified as Anger). Surprise and Fear also overlap (Fear is sometimes mistaken for Surprise and vice versa).

V. RESULTS AND DISCUSSION

Text emotion detection involves the system identifying along with categorizing emotional writing tones to recognize happiness or sadness or frustration and fear based on text words within a context. The analysis of "I love this new book!" would produce from the system a happy classification whereas "I can't believe this is happening!" would become a result of fear or surprise classification. The particular sentence receives categorization either as fear or as surprise.

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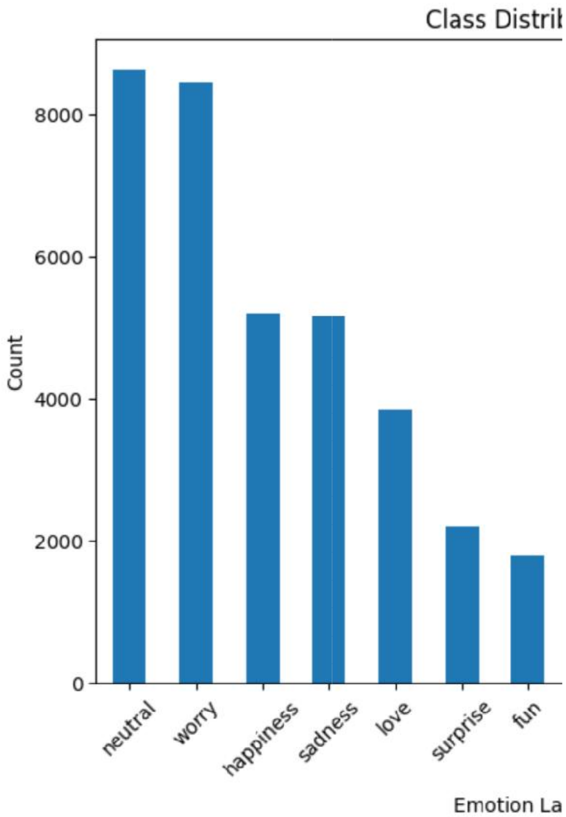

Fig.4:this shows that when you input a sentence it will show you the result in a bar chart like this one.

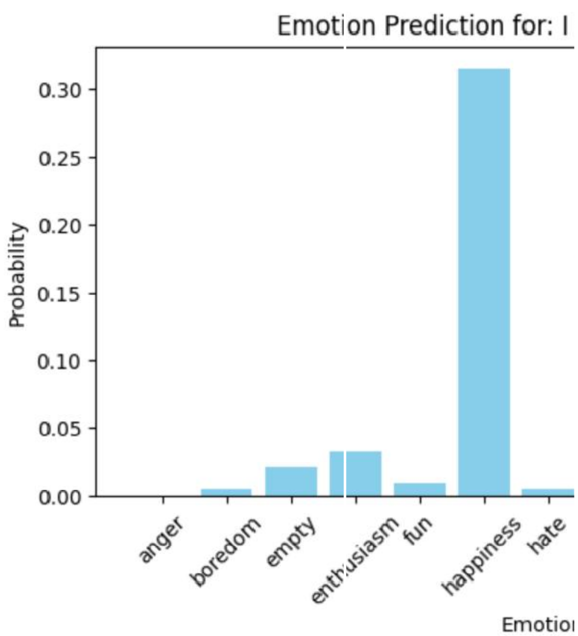

Fig.5:This shows that the user has input a sentence"i am so happy today!" so the emotion detection detects the emotion of that sentence

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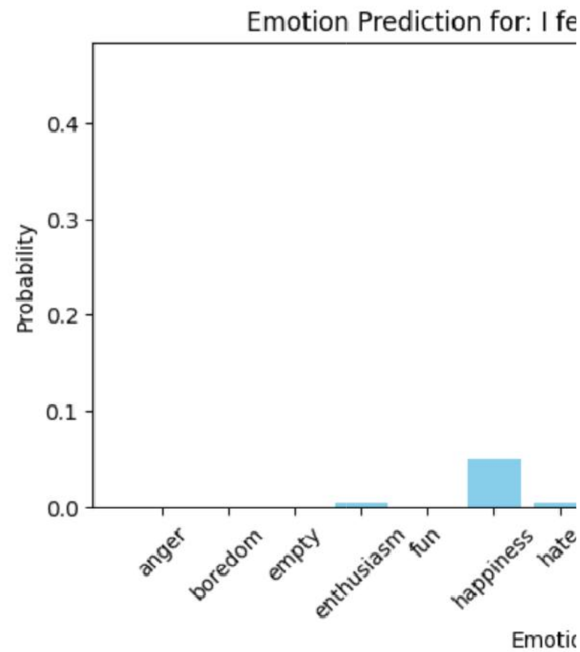

Fig.6:This shows that the user has input a sentence:I feel really sad and lonely"so it detects the emotion of that sentence as shown in the above figure

VI. CONCLUSION AND FUTURE SCOPE

Recent systems using natural language processing have made substantial progress with text emotion detection technology for handling written language emotional analysis. Research proves text emotion detection delivers better results than simple sentiment analysis because it discovers all human emotions from happiness to anger and sadness through fear and surprise. Human-computer interaction improves through emotion detection integration because the systems produce responsive outputs that demonstrate contextual awareness along with empathetic characteristics. The technological evolution brings users a natural emotional experience across applications thereby making technology behave like people express emotions.

So for the future scope:The use of emotion detection in text via NLP will be enhanced by the advancing deep learning models such as fine-tuned transformer, hybrid approach and context based detection. This will facilitate the real time recognition of the emotions in all languages and regions. Real time streaming and cloud based processing (whereby large scale emotion analysis can be done in social media, chat bots and customer interactions) will be integrated. Text plus speech, speech plus facial expressions will help improve emotion detection for AI assistants and virtual agents by treating emotion as a multi modal phenomenon.

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