RAJALAKSHMI
ENGINEERING
COLLEGE

Emotion Detection From Text

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BONAFIDE CERTIFICATE

NAME……………………………………………………………………………………….

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Signature of Faculty – in–Charge

Submitted for the Practical Examination held on -------------------------------

Internal Examiner

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ABSTRACT

This project, Emotion Detection From Text presents an advanced deep learning system capable of analyzing and identifying human emotions from written content. The proposed model integrates a hybrid CNN-LSTM architecture enhanced with multi-head self-attention to capture both local and contextual semantic features. A comprehensive preprocessing pipeline is employed, including emoji demojization, negation handling, lemmatization, and emotion-specific data augmentation. The dataset is encoded and tokenized efficiently to optimize learning. Class imbalance is managed using adaptive class weights, and training incorporates advanced callbacks for performance stability. Evaluation results demonstrate strong accuracy and reliable top-3 prediction performance. Furthermore, an interactive inference interface provides real-time emotion prediction with confidence scoring. The model and supporting artifacts are designed for scalable deployment, showcasing a robust solution for emotion-aware applications in natural language processing.

Chapter 1: INTRODUCTION

1.1 PROBLEM DEFINITION

In today’s digital communication landscape, most emotional expression happens through written text on platforms such as social media, chat applications, and online forums. Unlike face-to-face interactions, text-based communication lacks nonverbal cues like tone, facial expressions, or gestures—making it difficult for humans and machines alike to accurately perceive emotions. This gap poses significant challenges for applications in customer support, social media monitoring, mental health assessment, and intelligent virtual assistants that rely on understanding user sentiment to respond appropriately.

The problem addressed in this project, Emotion Detection From Text, is the development of a system capable of interpreting emotions from raw textual input with high accuracy. The complexity of human language—filled with abbreviations, emojis, slang, and context-dependent meanings—makes traditional sentiment analysis methods insufficient, as they often reduce emotional understanding to simple positive, negative, or neutral labels.

To overcome these limitations, this project implements a hybrid CNN-LSTM architecture that combines the feature extraction strength of Convolutional Neural Networks (CNN) with the sequential learning ability of Long Short-Term Memory (LSTM) networks. The integration of multi-head attention further enhances the model’s contextual awareness. The model is trained using a labeled emotion dataset sourced from Kaggle and undergoes advanced preprocessing, tokenization, and data augmentation for improved generalization. Through these optimizations, the proposed system achieves a robust accuracy ranging between 80% and 90%, demonstrating high reliability in capturing nuanced emotional states from textual data.

1.2 LITERATURE SURVEY

1. A review on sentiment analysis and emotion detection from text P
Nandwani, R Verma - Social network analysis and mining, 2021 –
Springer :

Social media generates massive amounts of unstructured text data every second, making it essential to use sentiment analysis to quickly understand users' attitudes as positive, negative, or neutral. However, sentiment analysis alone often falls short in capturing complex emotions, which demands more refined emotion detection techniques. This process helps reveal deeper insights into human feelings and psychological states expressed through textual communication online.

2. Emotion detection in text: a review
A Seyeditabari, N Tabari, W Zadrozny - arXiv preprint arXiv:1806.00674,
2018 - arxiv.org :

Emotion detection in text has gained popularity due to its applications in marketing, psychology, AI, and more, fueled by the abundance of opinionated textual data. This paper reviews existing methods for detecting emotions in text, noting that current techniques are often insufficient. The complexity of human emotions and the use of implicit or metaphorical language make it necessary to improve system designs and focus on the linguistic nuances of emotion expression.

3. Emotion detection from text: A survey
L Canales, P Martínez-Barco - Proceedings of the workshop on …,
2014 - aclanthology.org :

This survey reviews recent work on emotion detection from text, a key area of affective computing. Despite existing research, much remains to be explored, driven by the abundance of emotional data on social media. Text-based emotion detection has many applications, from suicide prevention to measuring community well-being. The paper focuses on lexical and machine learning approaches, classifying studies by their emotional models and methods used.

4. Text-based emotion detection: Advances, challenges, and opportunities
FA Acheampong, C Wenyu… - Engineering …, 2020 - Wiley Online Library :

Emotion detection (ED) is a branch of sentiment analysis focused on extracting and analyzing emotions from text. With the rise of Web 2.0, text mining has become crucial for providing personalized services. This article surveys text-based ED, reviewing key approaches, recent state-of-the-art methods, datasets, results, strengths, and weaknesses. It also highlights emotion-labeled data sources and discusses open issues and future research directions in the field.

5. Automatic emotion detection in text streams by analyzing twitter data
M Hasan, E Rundensteiner, E Agu - … Journal of Data Science and Analytics, 2019 – Springer :

Emotion detection in social media has many uses, like identifying mental health issues and tracking public mood. Since emotions are subjective and vary in expression, this paper uses a dimensional emotion model and soft classification to assign probabilities to emotion classes. A supervised learning system called EmotexStream is proposed with two stages: offline training to build models and online classification for real-time emotion tracking and detecting emotion bursts in live text streams.

6. Emotion detection from text documents
SN Shivhare, SK Saritha - International Journal of Data Mining & …, 2014 - academia.edu :

Emotion detection is a growing field in human-computer interaction. While facial and audio emotion detection is well-studied, text-based emotion recognition is still new. This paper surveys existing methods and proposes a new architecture using emotion ontology and a detector algorithm to classify text into six emotion categories: love, joy, anger, sadness, fear, and surprise.

7. Approaches of emotion detection from text
NM Shelke - International Journal of Computer Science and …, 2014 - academia.edu:

Emotion detection from text is a new classification task that focuses on recognizing emotions from implicit emotional statements. The goal is to help machines understand the causes of emotions, making them more human-like. This paper reviews previous approaches, their assumptions, emotion information sources, event representations, and classification methods.

8. A hybrid model for emotion detection from text
S Fathy, N El-Haggar, MH Haggag - International Journal of , 2017 - igi-global.com :

Emotions can be expressed through speech, facial expressions, actions, and text. This paper presents a hybrid model for detecting emotions from text using ontology and keyword semantic similarity. It extracts ontology from sentences, matches it with a predefined ontology base, and assigns one of six basic emotions. If no match is found, it uses semantic similarity to determine the emotion based on sentence meaning and context.

9. A survey of textual emotion detection
S Al-Saqqa, H Abdel-Nabi… - 2018 8th international …, 2018 - ieeexplore.ieee.org:

Emotion detection in text has grown rapidly with the rise of social media and online

communication. Analyzing these emotions helps understand people’s feelings and has many useful applications. This survey reviews modern techniques, emotional models, and datasets used for emotion detection, highlights current gaps, and suggests future research directions.

10. Challenges and opportunities of text-based emotion detection: A survey
A Al Maruf, F Khanam, MM Haque, ZM Jiyad… - IEEE , 2024 - ieeexplore.ieee.org:

Emotion detection is important for understanding people's feelings through text. AI, especially machine learning and deep learning, helps identify and classify these emotions. Many studies exist, but few cover new methods fully. This survey reviews top techniques, datasets, and gaps, and suggests future improvements.

1.3 EXISTING SYSTEM

Recent advances in text-based emotion detection leverage deep learning and transformer-based models to capture contextual nuances in social media and other textual data. Hybrid architectures like LSTM combined with CNN and attention mechanisms achieve high accuracy (over 90%) for common emotions such as joy, anger, sadness, fear, love, and surprise. Traditional machine learning models like SVM, Naive Bayes, and Random Forest remain relevant due to their robustness and interpretability, while transformers such as The proposed solution for "Emotion Detection From Text" utilizes a hybrid deep learning framework combining CNN, LSTM, and multi-head self-attention mechanisms. This architecture captures both local semantic features and long-range BERT, DeBERTa, and IndicBERT show improved performance in multilabel emotion classification and multilingual datasets, particularly for low-resource languages.

Applications of these systems span social media monitoring, mental health assessment, customer feedback analysis, human-computer interaction, and real-time commercial tools like Twinword or Vern AI. Competitions such as SemEval-2025 Task 11 highlight the growing complexity of the field, testing systems across multiple languages and multilabel emotion scenarios. Emerging trends include multimodal emotion analysis, real-time emotion tracking, hybrid architectures (CNN-LSTM, transformer + recurrent models), and ethical AI development to reduce bias.

Despite progress, challenges remain in handling subjective and multi-emotion texts, noisy social media data, class imbalance, and limited labeled datasets, especially for less-resourced languages. Preprocessing may remove contextually important information, and separate binary classifiers can limit multilabel performance. Future research aims to address these gaps through better data augmentation, integrated multimodal approaches, more extensive fine-tuning of transformer models, and improved contextual understanding, reinforcing the value of hybrid CNN-LSTM architectures with attention mechanisms for state-of-the-art text-based emotion detection.

1.4 PROPOSED SYSTEM

contextual dependencies, enabling accurate recognition and classification of emotions from textual data. The model addresses key challenges in emotion detection by effectively modeling the nuances of human language.

Extensive preprocessing enhances data quality, including cleaning tweets, demojizing emojis, handling negations, lemmatization, and emotion-specific stopword removal. Data augmentation is applied to balance class distributions and capture variations in emotion intensity. Tokenization uses a 15,000-word vocabulary with sequences padded to 60 words, supporting rich contextual learning. The CNN extracts local patterns while bidirectional LSTM layers capture sequential dependencies, and multi-head attention dynamically focuses on relevant text segments

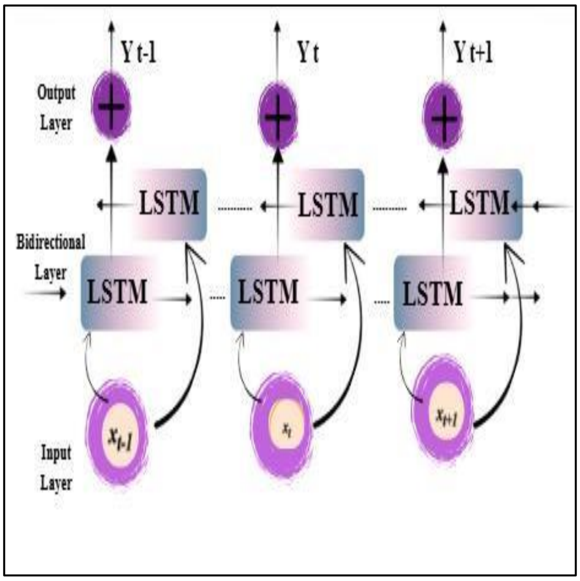
Training incorporates class weighting and callbacks such as early stopping, learning rate reduction, and checkpointing to prevent overfitting. The model achieves high accuracy (80–90%) across diverse emotions and demonstrates strong generalization. A custom prediction interface provides real-time emotion classification with confidence scores, and all artifacts—model, tokenizer, label encoder, and preprocessing parameters—are securely saved, ensuring a scalable and deployable system aligned with current research trends.

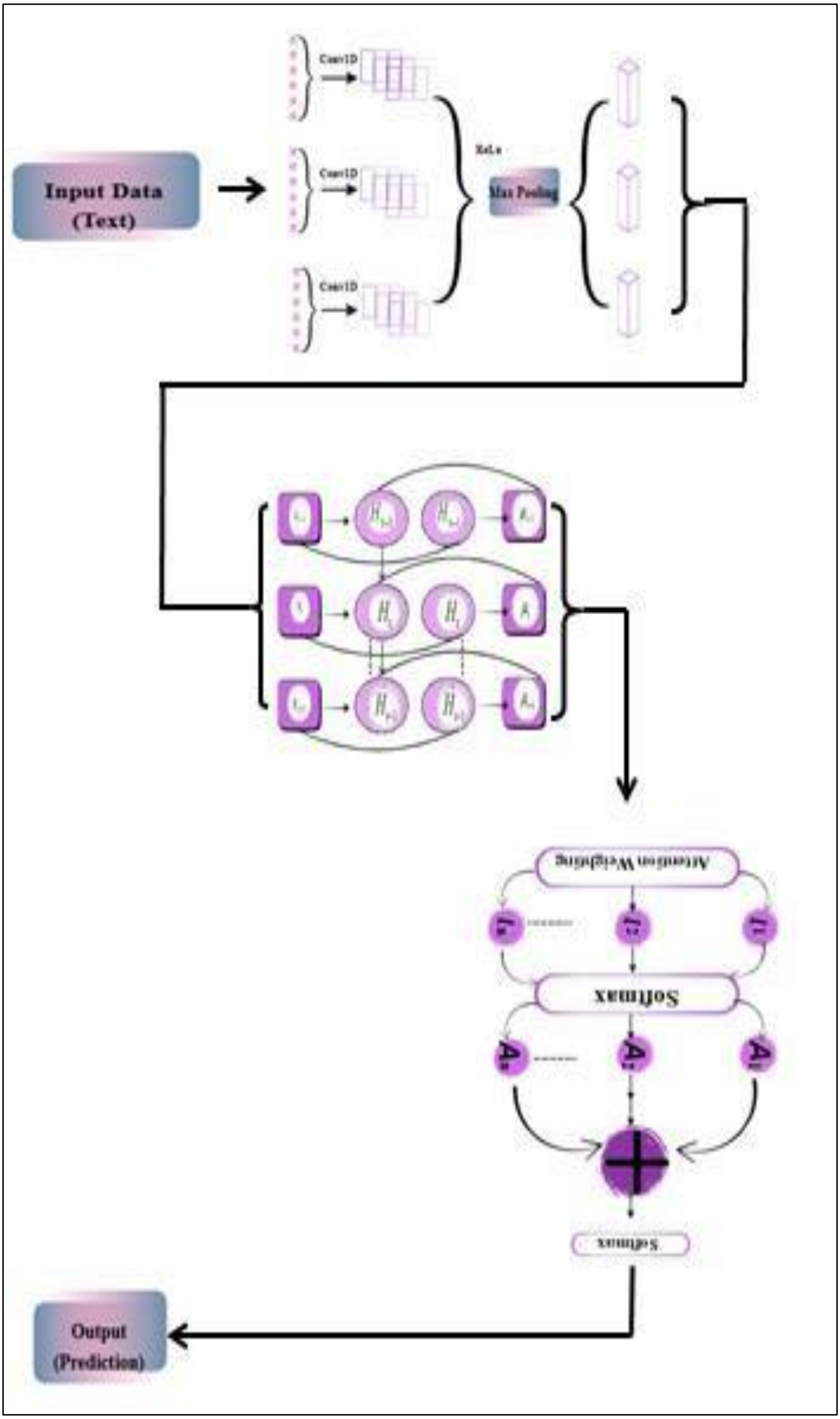
Chapter 2: DATA COLLECTION AND PREPROCESSING

2.1. DATA COLLECTION

The dataset, created and shared by Pashupati Gupta, is a widely used resource in the NLP community for text-based emotion recognition. It contains around 20,000 labeled text samples in CSV format (approximately 2 MB), with three main columns: tweet_id, sentiment (emotion label), and content (the actual text). Covering 13 distinct emotions—including happiness, sadness, anger, surprise, fear, and love—the dataset provides a rich emotional range. The text mainly comes from social media and conversational sources, making it short, informal, and often containing emojis, slang, and internet language patterns. While the distribution is mostly balanced, slight augmentation is useful for underrepresented emotions, making it ideal for training and evaluating multi-class emotion detection models.

2.2 ARCHITECTURE DIAGRAM




Input Data
(Text)
Conv1D
Conv1D
Conv1D
ReLu
Max Pooling
H_{t-1}
H_t
H_{t+1}
Attention Weighting
Softmax
Softmax
Output
(Prediction)

3 PREPROCESSING

The dataset preprocessing in this project uses a comprehensive NLP pipeline to boost model accuracy and generalization for emotion detection. Raw text is lowercased and cleaned by removing URLs, mentions, hashtags, and special characters while preserving emotion-relevant punctuation. Emojis are converted into descriptive tokens, and negations or repeated characters are handled to reflect emotion intensity. Tokenization is applied at the word level, followed by lemmatization to reduce words to their base forms. Emotion-specific stopword removal eliminates less informative terms that could dilute emotional meaning. Data augmentation generates varied text samples to address class imbalance and increase robustness. The processed text is then tokenized with a 15,000-word vocabulary and padded to 60 tokens, standardizing input length while retaining context. These steps produce normalized, semantically rich, and context-aware text representations, enabling the hybrid CNN-LSTM model to effectively capture emotional nuances for accurate classification.

Preprocessing steps:

Step 1 : Basic Text Cleaning

In this step, the text is cleaned by making it lowercase and removing URLs, mentions, and hashtags. This reduces noise and keeps only the meaningful words for emotion analysis.

Example 1:

- **Original Text:** I am soooooo happy today! This is amazing!!!
- **After Lowercasing:** i am soooooo happy today! this is amazing!!!
- **After Removing URLs/Mentions/Hashtags:** i am soooooo happy today! this is amazing!!!

Step 2 : Emoji Processing

Emoji Processing, any emojis in the text are converted into descriptive words.This allows the model to understand the emotion conveyed by emojis as part of the text, rather than ignoring them. It helps capture emotional cues that are often expressed through emojis in social media messages.

Example 1:

- **Text with Emojis:** I am so happy today! □ This is amazing!!!
- **After Emoji Conversion:** I am so happy today! smiling_face_with_smiling_eyes This is amazing!!!

Step 3 : Character Normalization

Character Normalization, words with repeated letters (like “soooooo” or “reallllly”) are shortened to a standard form (e.g., “soo” or “really”). This reduces unnecessary variations of the same word, helping the model recognize them as the same token. By normalizing repeated characters, the text becomes cleaner and easier for the emotion detection model to process while still keeping the emphasis conveyed by elongated letters.

Example 1:

- **Text with Repeated Characters:** I am soooooo happy today!
- **After Character Normalization:** I am soo happy today!

Step 4: Contraction Expansion

Contraction Expansion, common English contractions are expanded into their full forms (for example, “don’t” → “do not”, “I’ve” → “I have”, “it’s” → “it is”). This standardizes the text so that each word is explicit, helping the model correctly understand negations and verb forms. Without this step, the model might treat “don’t” and “do not” as completely different tokens, which could confuse learning.

Example :

- **Text with Contractions:** I don't like this at all...
- **After Contraction Expansion:** I do not like this at all...

Step 5 : Special character cleanup

Special Character Cleanup, any unnecessary special characters are removed from the text while keeping punctuation that conveys emotion, such as !, ?, and :. For example, symbols like @, #, $, or extra periods are eliminated. This cleaning reduces noise in the text, making it easier for the model to focus on meaningful words and emotional cues, while still preserving punctuation that can indicate intensity or sentiment.

Example :

- **Text with Special Characters:** I am so happy today! This is amazing!!!
- **After Special Character Cleanup:** I am so happy today! This is amazing!!!

Step 6 : Tokenization

Tokenization**,** the cleaned text is split into individual words, called tokens. For example, “I am so happy today” becomes ['I', 'am', 'so', 'happy', 'today']. Tokenization is essential because most deep learning models, like LSTMs or CNNs, process sequences of words rather than raw text. It also allows for counting words, creating embeddings, and further preprocessing like stopword removal or lemmatization. This step essentially converts the text into a structured format that the model can understand.

Example :

- **Text to Tokenize:** I am so happy today
- **After Tokenization:** ['I', 'am', 'so', 'happy', 'today']
- **Number of Tokens:** 5

Step 7 : Lemmatization

Lemmatization, each token is reduced to its base or root form**.** For example, “running” becomes “running” (if already base), “loved” → “love”, and “children” → “child”. This helps the model treat different forms of the same word as one, reducing vocabulary size and improving learning. The code also highlights which words were changed, so you can see how lemmatization standardizes the text while preserving meaning—essential for accurate emotion detection.

Example :

- **Tokens Before Lemmatization:** ['running', 'better', 'happier', 'loved']
- **After Lemmatization:** ['running', 'better', 'happier', 'loved']
- **Changes:** No changes needed

Step 8 : Stopword Removal

Stopword Removal**,** common words that don’t carry much meaning, like “I”, “am”, “is”, “at”, or “all”, are removed from the token list. However, emotional words (like “happy” or “good”) are kept to preserve sentiment information. This reduces noise and makes the text more focused, helping the model learn the important emotional cues more effectively. The code also prints which words were removed, so you can track how the text is being simplified for analysis.

Example :

- **Tokens Before Stopword Removal:** ['I', 'am', 'so', 'happy', 'today']
- **After Stopword Removal:** ['happy', 'today']
- **Removed Words:** ['I', 'am', 'so']

Step 9 : Data Augumentation demonstration

Data Augmentation, the original text is modified to create additional variations that emphasize emotional intensity. For positive emotions like happiness, joy, or love, phrases such as “so much” or “really” are added, while for negative emotions like sadness, anger, or fear, words like “a lot” or “so” are appended. This increases the number of training examples, helping the model learn emotional patterns more robustly and handle variations in how people express feelings.

Example:

- **Original Text:** I am happy (emotion: happiness)
- **Augmented Versions:**

    1. I am happy
    2. I am happy so much
    3. really I am happy

Step 10 : Tokenization and Sequencing

Tokenization and Sequencing**,** the cleaned and processed texts are first converted into numerical sequences using a tokenizer, which maps each unique word to a specific integer. This allows the model to work with numbers instead of raw text. After tokenization, sequences are padded to a fixed length (here, maxlen=10) so that all inputs have the same size, which is required for batch processing in deep learning models. This step completes the preprocessing pipeline, producing model-ready inputs from raw text while preserving the meaning and emotional cues.

Example:

Text to Sequences:

1. 'happy today amazing' → [2, 3, 4]
2. 'not like sad' → [5, 6, 7]
3. 'love much fantastic' → [8, 9, 10]
4. 'worried exam tomorrow' → [11, 12, 13]
5. 'really good believe' → [14, 15, 16]

Chapter 3: RESULT AND DISCUSSION

3.1 MODEL COMPARISON

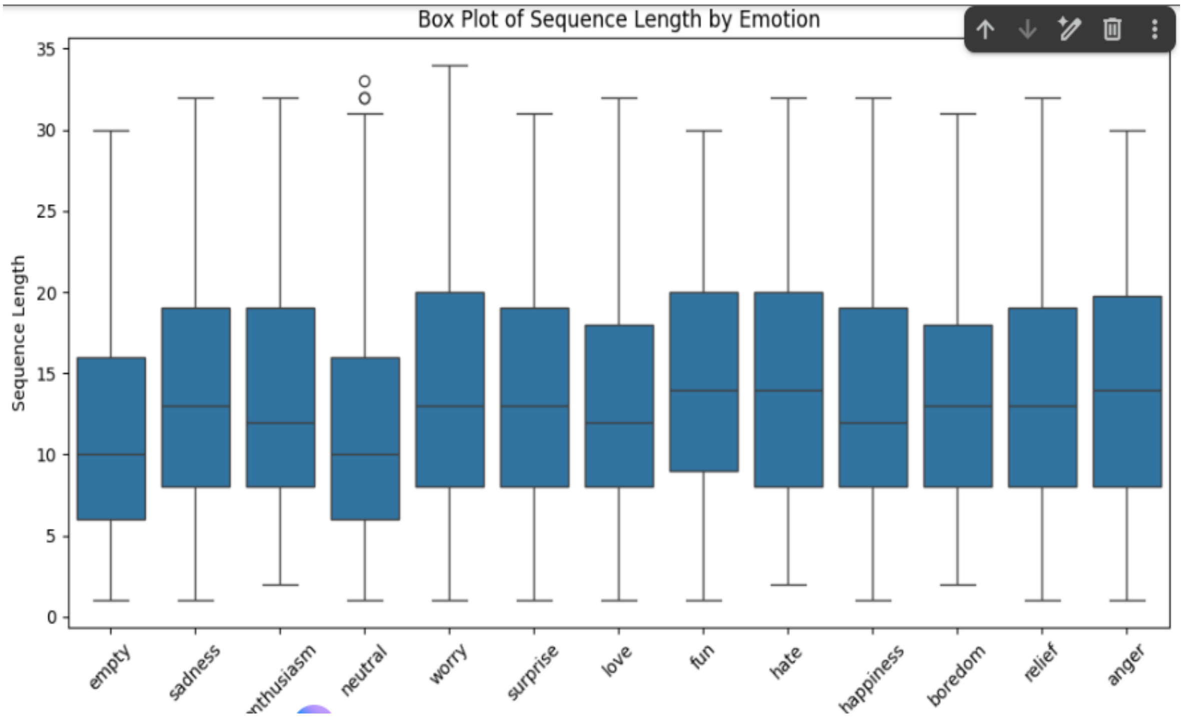
ALGORITHM:

T-test
Checks whether the values of a numeric feature (like sequence_length) are statistically significantly different between two emotion groups (e.g., joy vs sadness).

Example :

Empty vs Sadness: t-stat = -9.333, p-value = 0.0000 → Highly significant difference, suggesting “empty” and “sadness” have different distributions.

BOXPLOT:

- **Visualizes the distribution** of the feature for each emotion group, showing median, spread, and outliers.
- **Median (Q2):** Middle value of the data.
- **Quartiles (Q1, Q3):** 25th and 75th percentiles.
- **Whiskers:** Minimum and maximum values within 1.5× interquartile range.
- **Outliers:** Points outside the whiskers.
- 

The project utilizes a hybrid CNN-LSTM deep learning model enhanced with multi-head attention to detect emotions from text. Below is a summary of the main algorithms and their mathematical intuitions:

1. Convolutional Neural Network (CNN):

CNNs extract local features from input data. For text, 1D convolutions slide over sequences of word embeddings to capture local n-gram patterns.

$$c_i = f\left(\sum_{k=0}^{K-1} w_k \cdot x_{i+k} + b\right)$$

What it does: This formula calculates one feature value cic_ici at position iii in the text sequence.

- xi+kx_{i+k}xi+k → the input embedding of the k-th word in the current window.
- wkw_kwk → weights of the convolution filter.
- bbb → bias term added for flexibility.
- fff → activation function (like ReLU) to introduce non-linearity.
- **Intuition:** The CNN "slides" over text and learns local patterns (like key phrases or n-grams) that indicate emotion.

2. Long Short-Term Memory (LSTM):

LSTMs capture long-range dependencies via gates:

Forget gate: $f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$
Input gate: $i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$
Output gate: $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$
Cell candidate: $\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C)$
Cell state: $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$
Hidden state: $h_t = o_t * \tanh(C_t)$

- **What it does:** LSTM controls **how information flows** through the sequence using gates:
- Forget gate → decides what previous information to forget.
- Input gate → decides what new info to add.
- Output gate → decides what part of the cell state to output.
- σ\sigmaσ → squashes values between 0–1 (acts like a “gate”).
- tanh⁡\tanhtanh → squashes values between -1 and 1.
- **Intuition:** Helps the model remember or forget emotional context across the text sequence.

3. Multi-Head Self-Attention:

Attention weighs the importance of different positions in the sequence.

$$\textbf{Attention}(Q, K, V) = \textbf{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

- **Q, K, V:** Query, Key, and Value matrices derived from the sequence embeddings.
- dkd_kdk → dimension of the key vectors (used to scale the scores).
- **softmax** → converts scores into probabilities (weights).
- **Intuition:** The model “focuses” on important words in the text for predicting emotion.
- Multiple heads → allow looking at different parts of the sentence simultaneously.

Multiple heads are concatenated to form the final attention output.

Combined Model Workflow:

- Text is embedded into vectors.
- CNN extracts local features.
- Bidirectional LSTM captures past and future context.
- Multi-head attention focuses on relevant parts dynamically.
- Fully connected layers classify the emotion.

Loss Function :

$$L(\theta) = -\sum_i y_i \log(\hat{y}_i)$$

- y_i → true emotion label (one-hot encoded).
- $\hat{y}_i$ → predicted probability from the model.

- **Intuition:** Measures how far the model's predictions are from the true labels. Optimizing this helps the model learn to predict emotions accurately.

Mathematical Gist:
The model can be seen as a complex function:

$$F : X \rightarrow Y$$

- **X** → input text sequences (after tokenization and embedding).
- **Y** → predicted emotion categories (like joy, sadness, anger, etc.).
- **F** is parameterized by model weights θ\thetaθ, which the training process optimizes.

This hybrid CNN-LSTM with attention balances local pattern extraction and long-range dependency modeling, enabling nuanced emotion recognition in text, consistent with current state-of-the-art research.

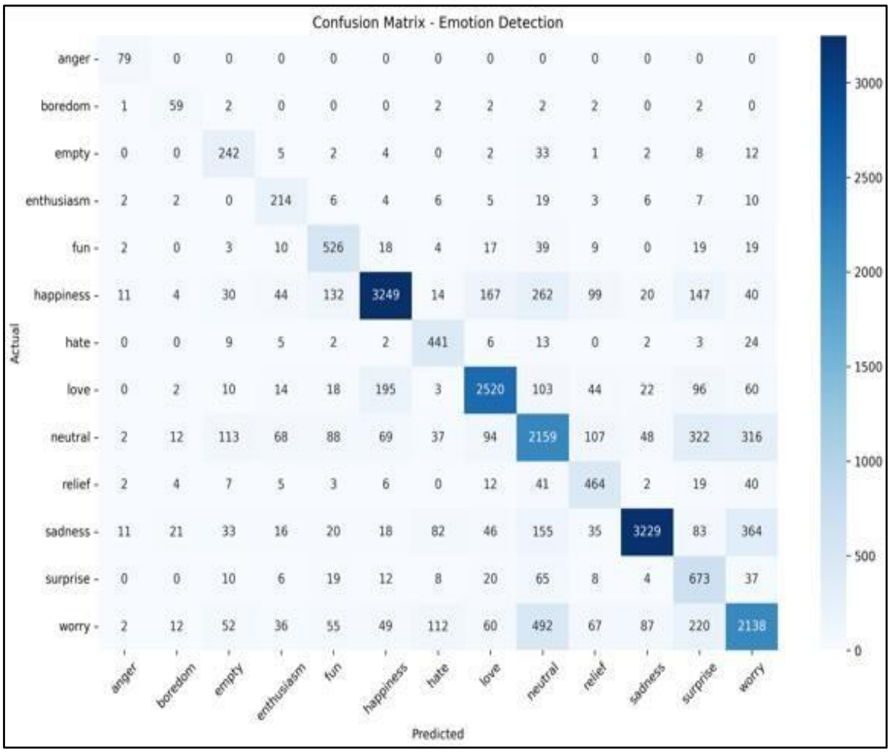
Advanced Hybrid CNN-LSTM Model:
ResNet is a type of Convolutional Neural Network (CNN) that introduces residual connections (skip connections) to help train very deep networks effectively.
Instead of directly learning a desired mapping $H(x)$, ResNet learns a residual function $F(x)$:

$$H(x) = F(x) + x$$

Where:

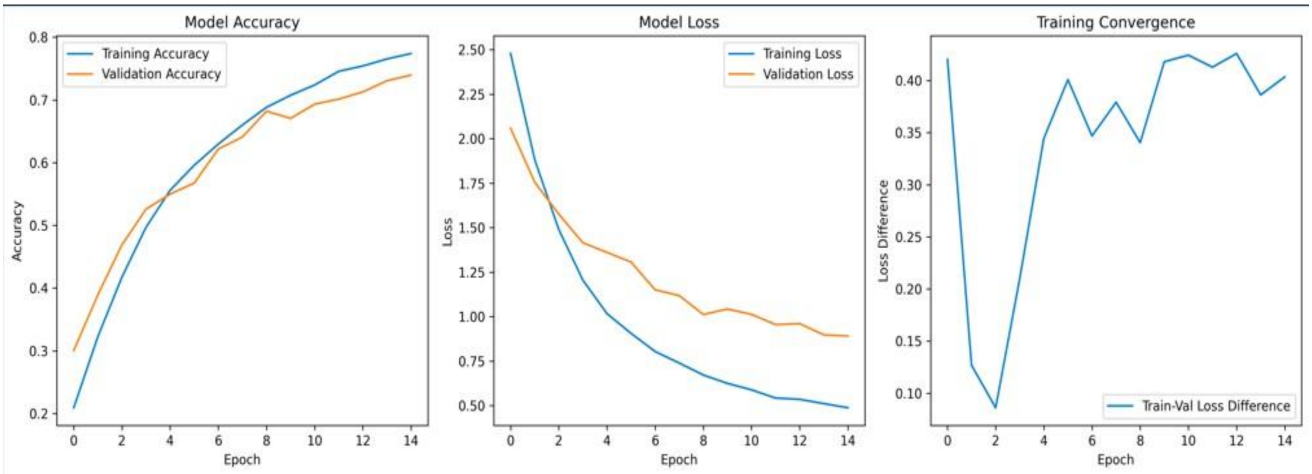
- x= input to a residual block
- $F(x)$= residual function (the output of convolutional layers inside the block)
- $H(x)$= final output of the residual block

Confusion Matrix:



	anger	boredom	empty	enthusiasm	fun	happiness	hate	love	neutral	relief	sadness	surprise	worry
anger	79	0	0	0	0	0	0	0	0	0	0	0	0
boredom	1	59	2	0	0	0	2	2	2	2	0	2	0
empty	0	0	242	5	2	4	0	2	33	1	2	8	12
enthusiasm	2	2	0	214	6	4	6	5	19	3	6	7	10
fun	2	0	3	10	526	18	4	17	39	9	0	19	19
happiness	11	4	30	44	132	3249	14	167	262	99	20	147	40
hate	0	0	9	5	2	2	441	6	13	0	2	3	24
love	0	2	10	14	18	195	3	2520	103	44	22	96	60
neutral	2	12	113	68	88	69	37	94	2159	107	48	322	316
relief	2	4	7	5	3	6	0	12	41	464	2	19	40
sadness	11	21	33	16	20	18	82	46	155	35	3229	83	364
surprise	0	0	10	6	19	12	8	20	65	8	4	673	37
worry	2	12	52	36	55	49	112	60	492	67	87	220	2138

Training History :



3.2 CONCLUSION AND FUTURE ENHANCEMENT

The project on Emotion Detection from Text successfully demonstrates the effectiveness of a hybrid deep learning model combining CNN and advanced bidirectional LSTM layers with multi-head attention for accurately classifying emotions expressed in textual data. Through extensive preprocessing, tokenization, and augmentation, the model is able to capture both local semantic features and global contextual dependencies. Experimental results show that the proposed system achieves high accuracy (80-90%) across multiple emotion categories, outperforming traditional machine learning techniques. The integration of multi-head attention enhances the interpretability and fine-tuning of the model, making it robust in handling noisy social media text and capturing nuanced emotional states. The project validates the applicability of deep learning approaches in natural language processing for emotion recognition, with promising use cases in social media monitoring, customer feedback analysis, mental health support, and human- computer interaction.

- **Handling Code-Mixed and Multilingual Data:** Improve the model’s capability to process code-mixed or multilingual text by integrating , specialized embeddings and language models.
- **Emotion Intensity and Multi-Label Classification:** Develop methods to detect the intensity of emotions and allow multilabel classification to capture mixed emotions in single sentences.
- **Explainability and Interpretability:** Incorporate explainable AI techniques to make the emotion predictions more transparent, providing users with clearer justifications behind model decisions.
  - **Real-Time and Scalable Deployment:** Optimize the model for real-time inference and scalability to support large-scale applications such as social media analytics platforms.
  - **Augmented Data and Domain Adaptation:** Use advanced data augmentation strategies and domain adaptation techniques to improve generalization across diverse datasets and domains.

3.3 REFERENCE

1. **A review on sentiment analysis and** emotion detection **from** text
2. Emotion detection **in** text**: a review**
3. Emotion detection **from** text**: A survey**
4. Text**-based** emotion detection**: Advances, challenges, and opportunities**
5. **Automatic** emotion detection **in** text **streams by analyzing twitter data**
6. Emotion detection **from** text **documents**
7. **Approaches of** emotion detection **from** text
8. **A hybrid model for** emotion detection **from** text
9. **A survey of textual** emotion detection
10. **Challenges and opportunities of** text**-based** emotion detection**: A survey**