Text Emotion Analysis

LNMIIT
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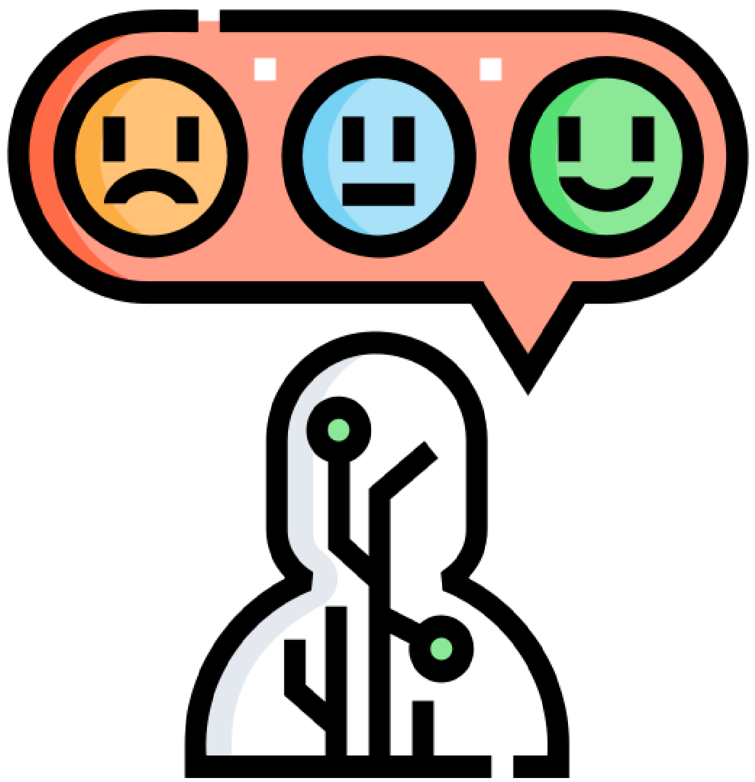

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What is Text Emotion Analysis?

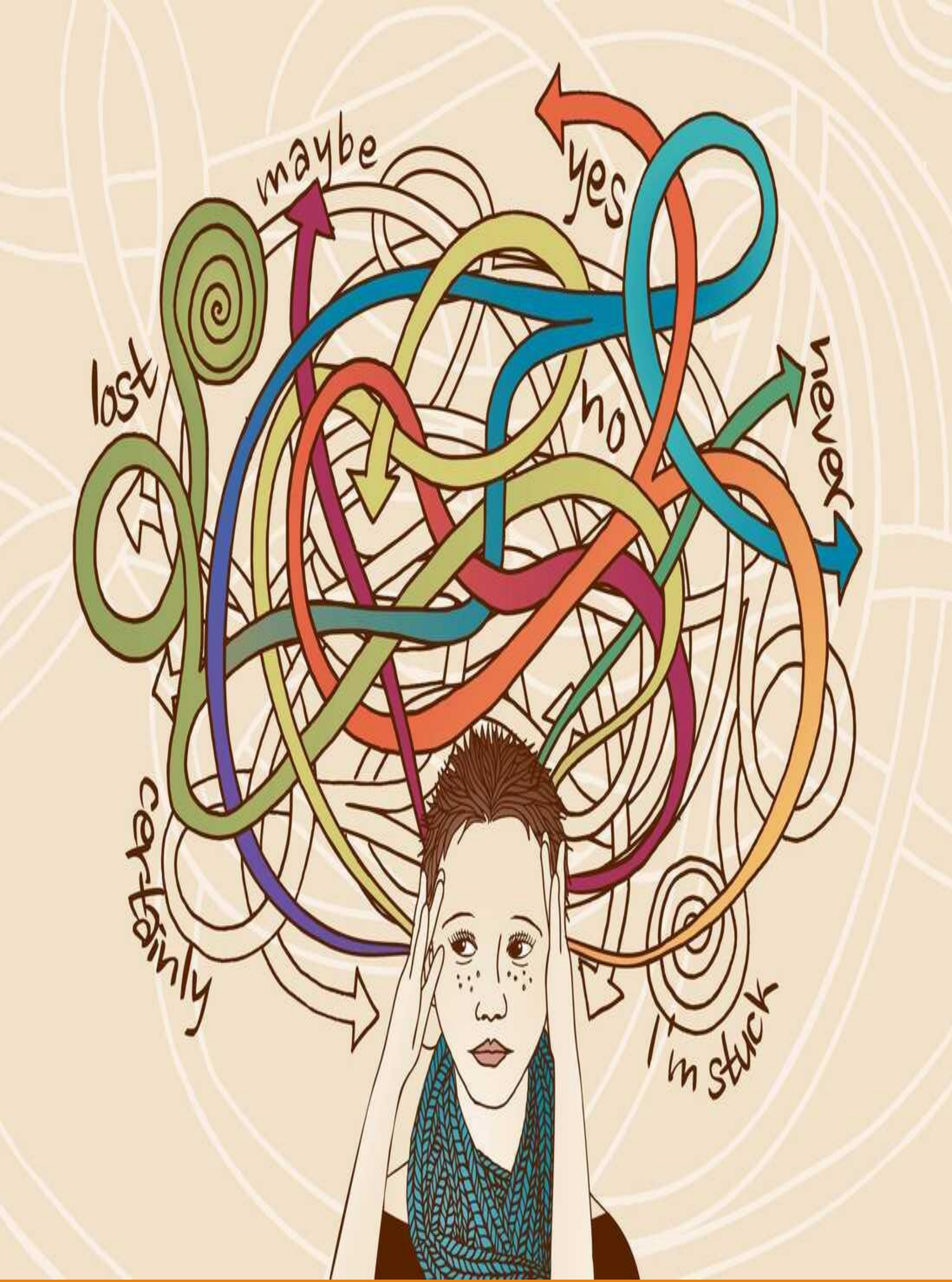
- Text emotion analysis is the process of identifying and understanding the emotional state expressed in written text.

- It uses natural language processing and machine learning techniques to detect and classify the emotions conveyed in online reviews, customer feedback, and other textual data.

Problem Statement

- In the era of digital communication accurately deciphering emotions conveyed through text poses a significant challenge.

- This project aims to address this challenge by developing and evaluating advanced deep learning models for text emotion analysis.



Objective

- The primary objective of this project is to explore and evaluate state-of-the-art methods and techniques for text emotion analysis.
- With a focus on achieving accurate and robust emotion detection and classification in diverse textual contexts.

Applications of Text Emotion Analysis

Customer Service

Text emotion analysis helps customer service teams identify and respond to customer sentiment, improving satisfaction and loyalty.

Brand Monitoring

Brands leverage text emotion analysis to track public perception, detect emerging issues, and manage their online reputation.

Healthcare

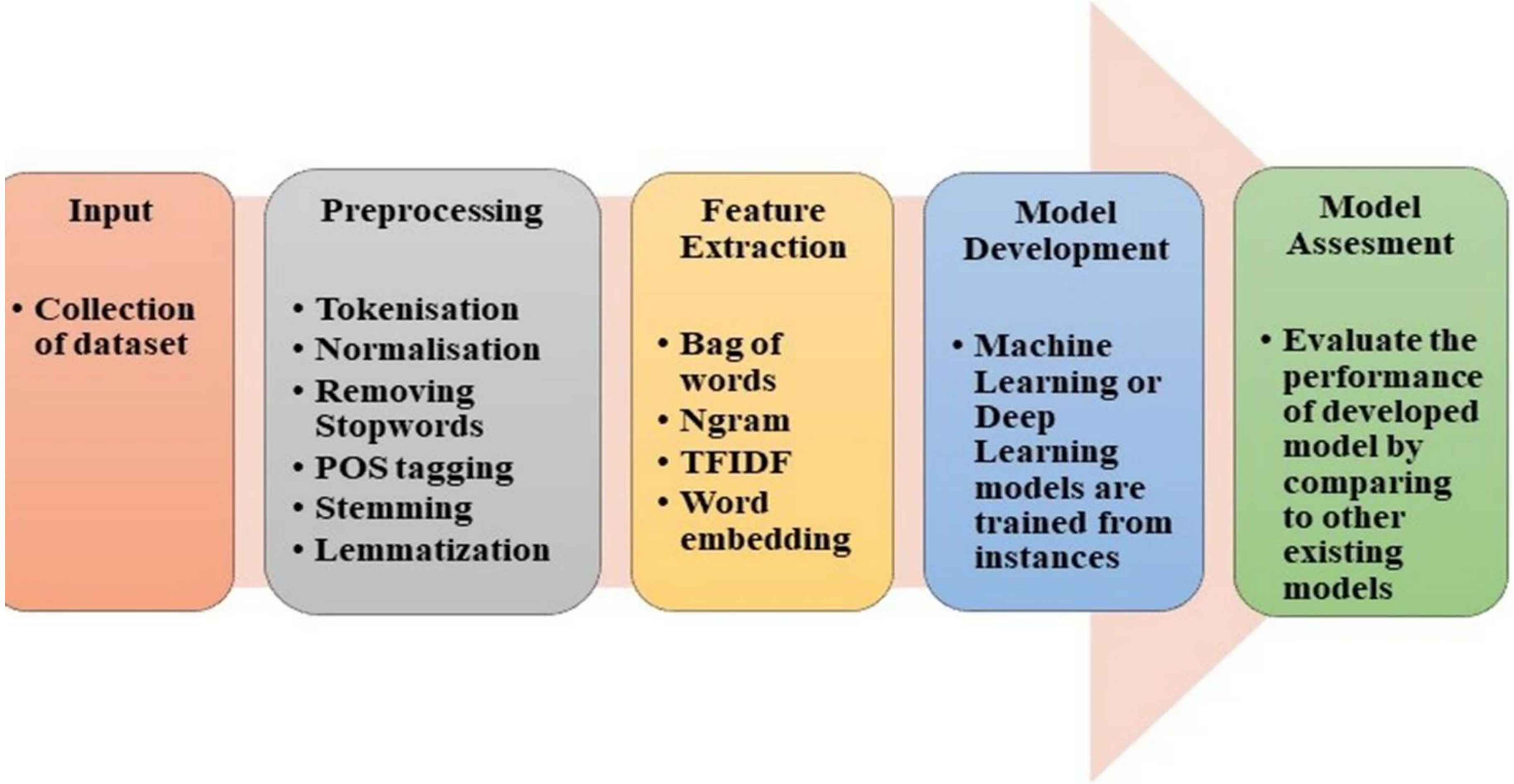
In healthcare, text emotion analysis can help clinicians better understand patient experiences and provide more personalized care.

Media and Journalism

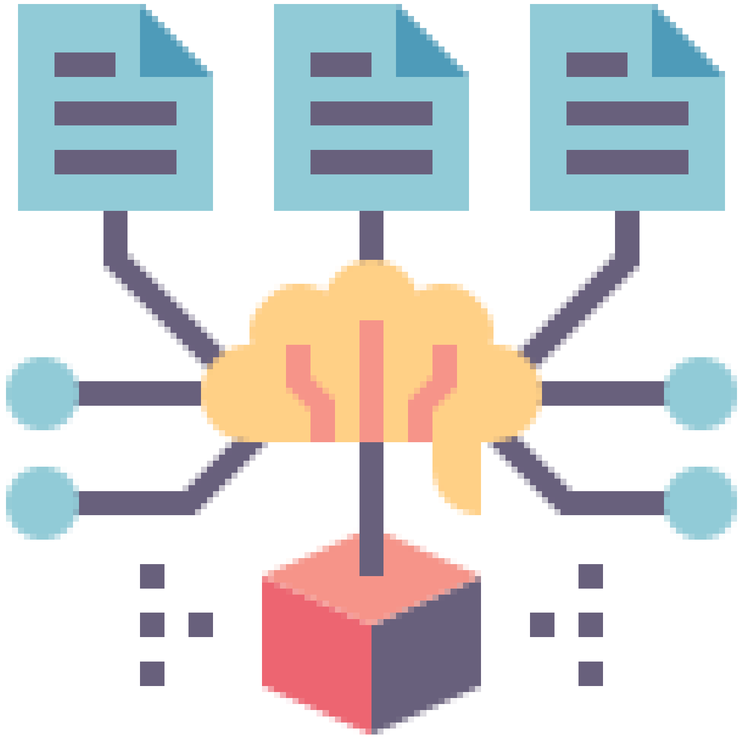
Journalists use text emotion analysis to gauge reader sentiment and optimize content for greater engagement and impact.

Material and Methods

- We selected appropriate data, performed meticulous labeling, developed robust feature vectors, and formulated the hybrid CNN Bi-LSTM approach.



Dataset & Labeling

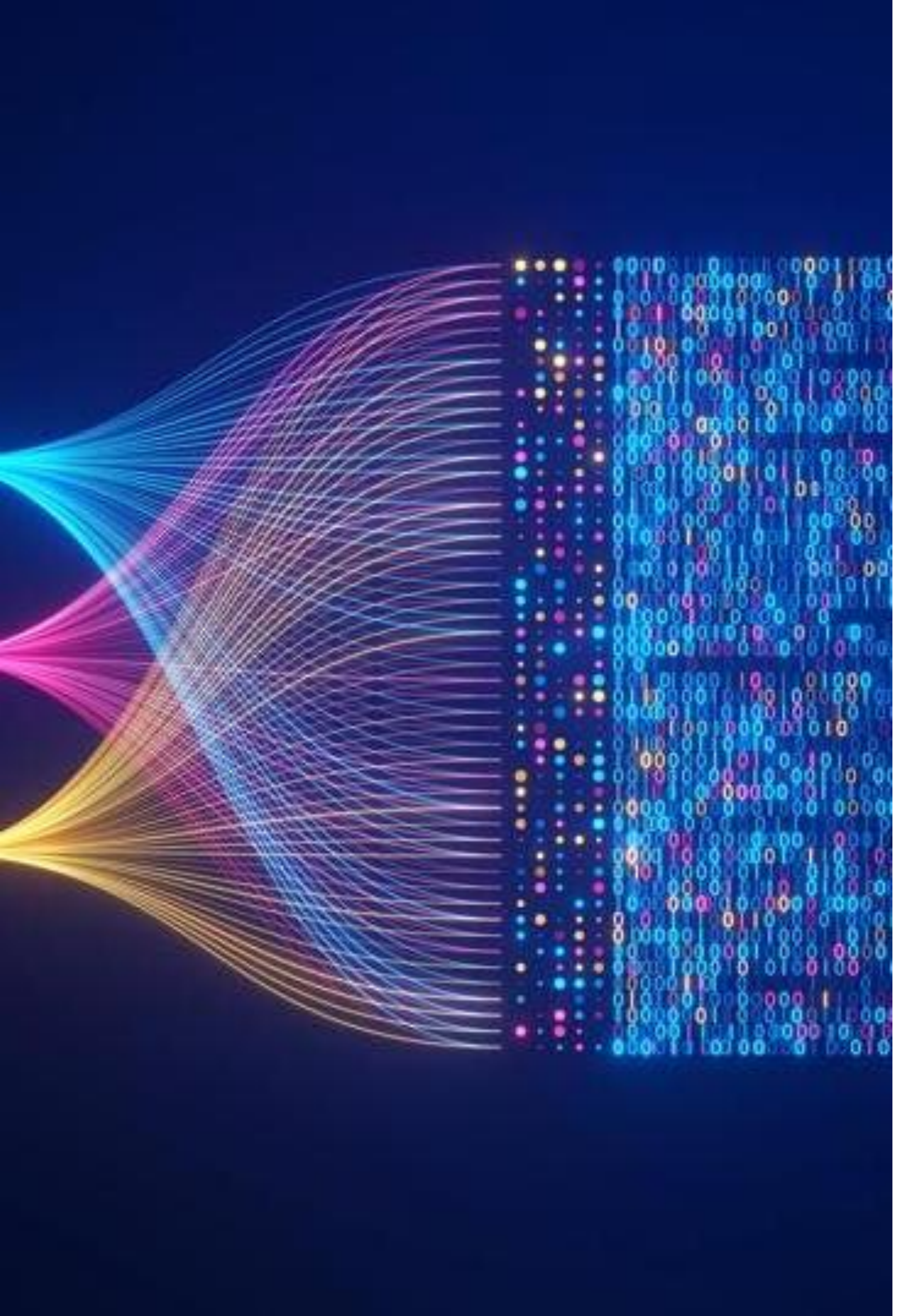


- Datasets are structured collections of data in spreadsheets, databases, or text files, containing diverse information for analysis and processing.
- Emotion labels ('joy', 'fear', 'anger', 'sadness', 'neutral') mapped to unique integer values via predefined encoding, facilitating machine learning.

Preprocessing & Feature Extraction

- Text preprocessing is a vital component of text classification, encompassing a range of techniques to prepare and transform text data for analysis.

- Feature extraction transforms raw data (text, images, signals) into suitable formats for deep learning algorithms, converting text into numerical features.



Model Selection

Machine Learning Models:

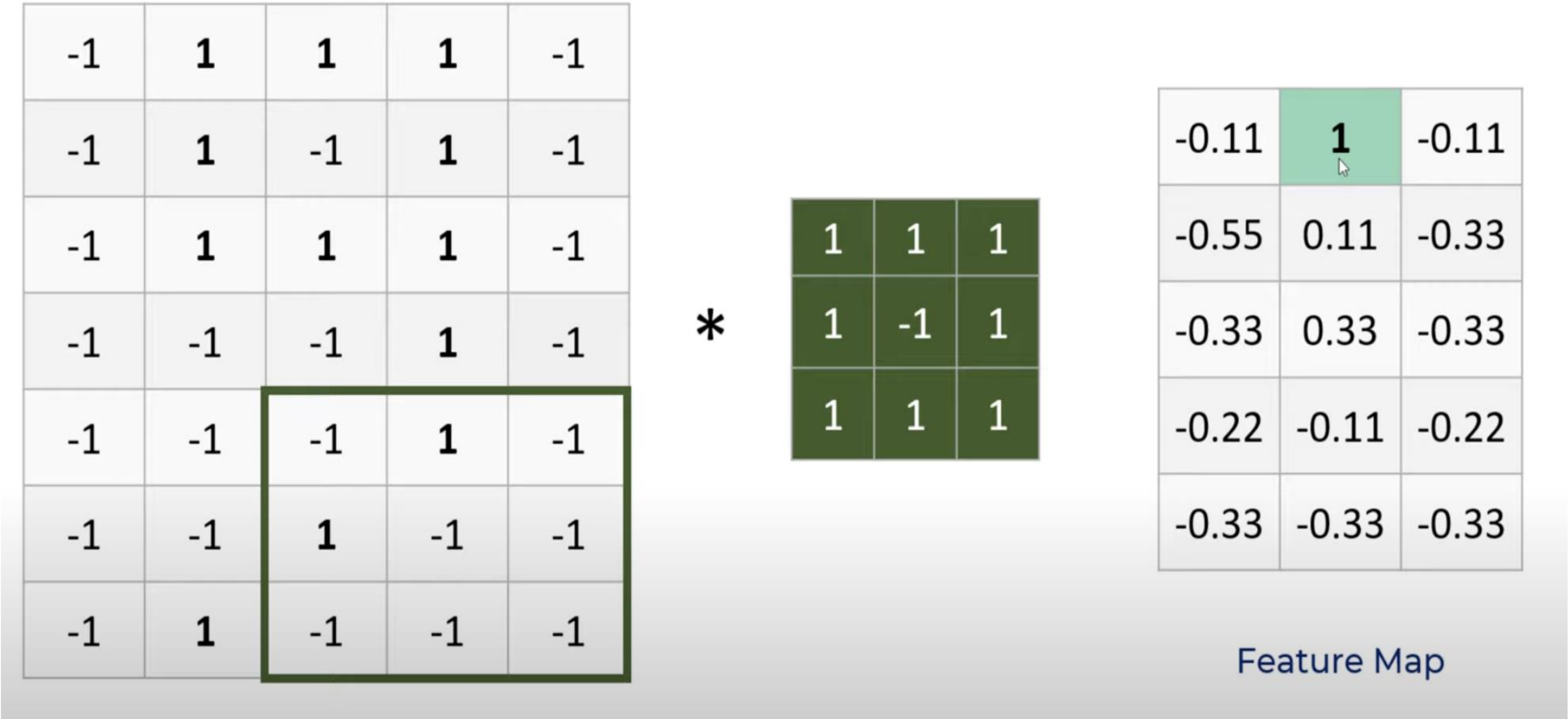
- Support Vector Machines (SVM)

Deep Learning Models:

- Long Short-Term Memory (LSTM) networks
- CNN-BiLSTM models
- Transformer-based models (e.g., BERT, GPT)

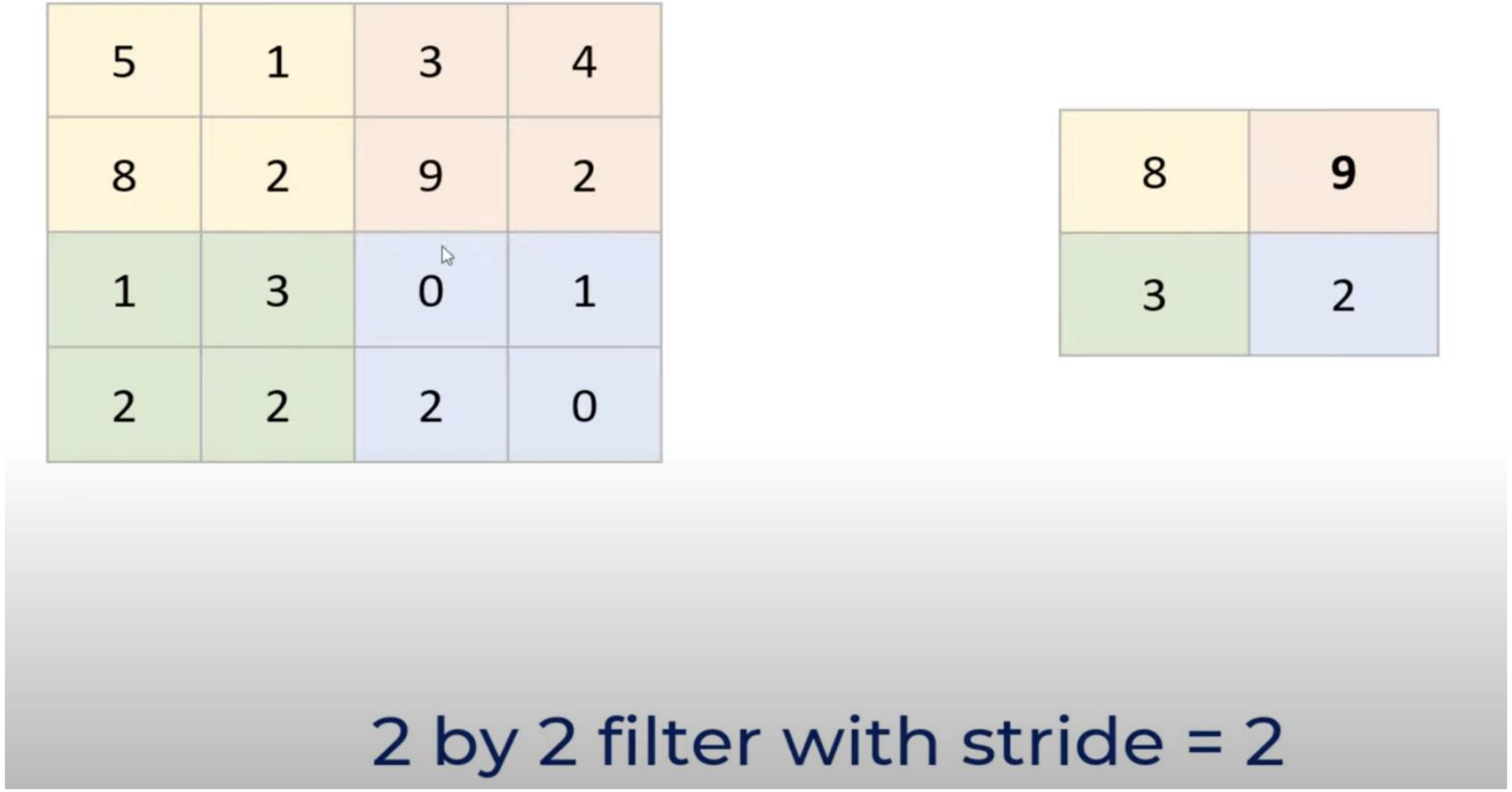
Convolutional Neural Networks (CNNs)

- Best for feature extraction.
- Features can be phrases like "not good" or "very happy", word-embedding etc.



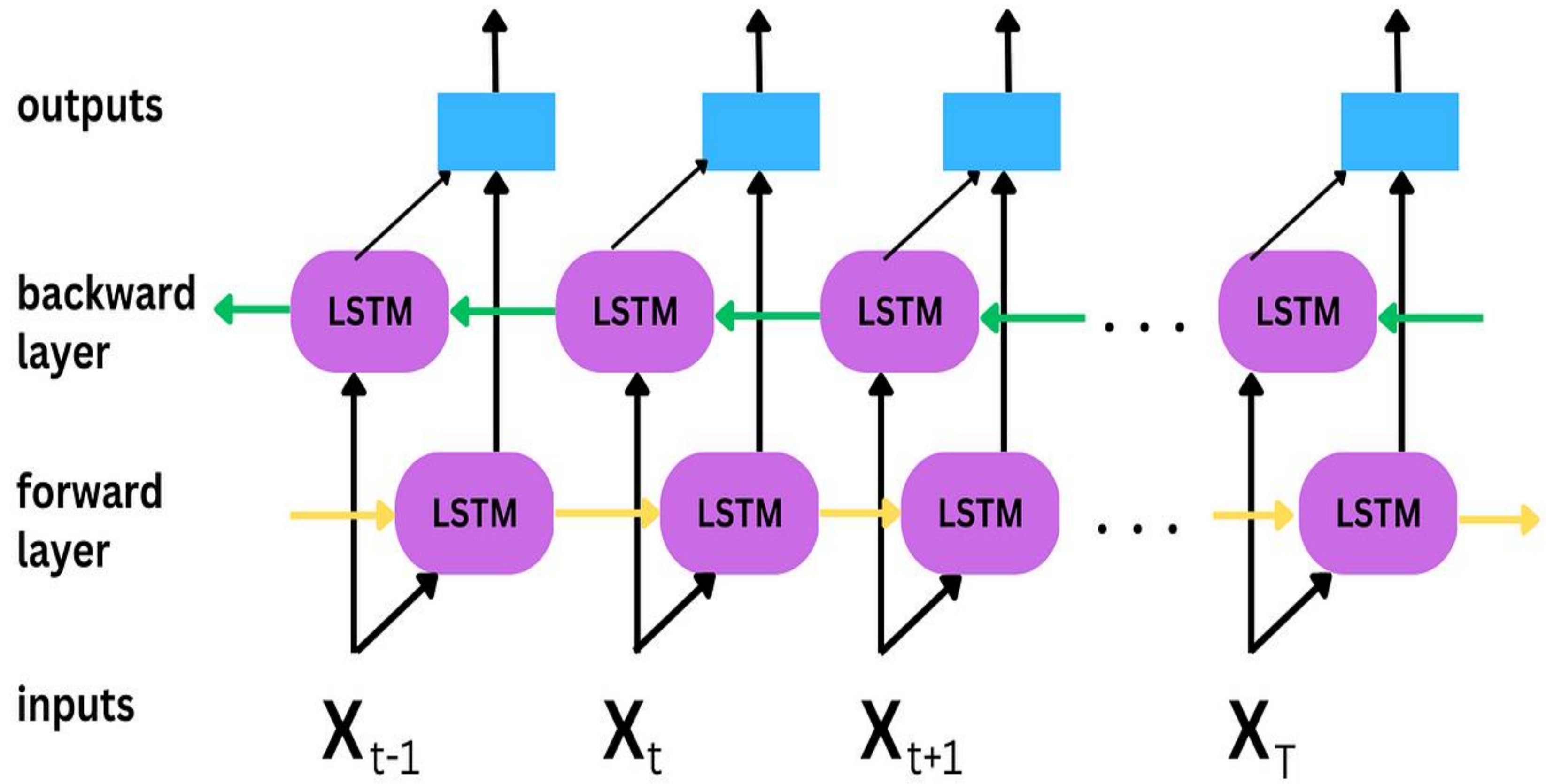
Pooling layer

- Pooling layer helps reduce the size of data.
- Reduces over-fitting as there are less parameters.
- Model is more tolerant towards variations.



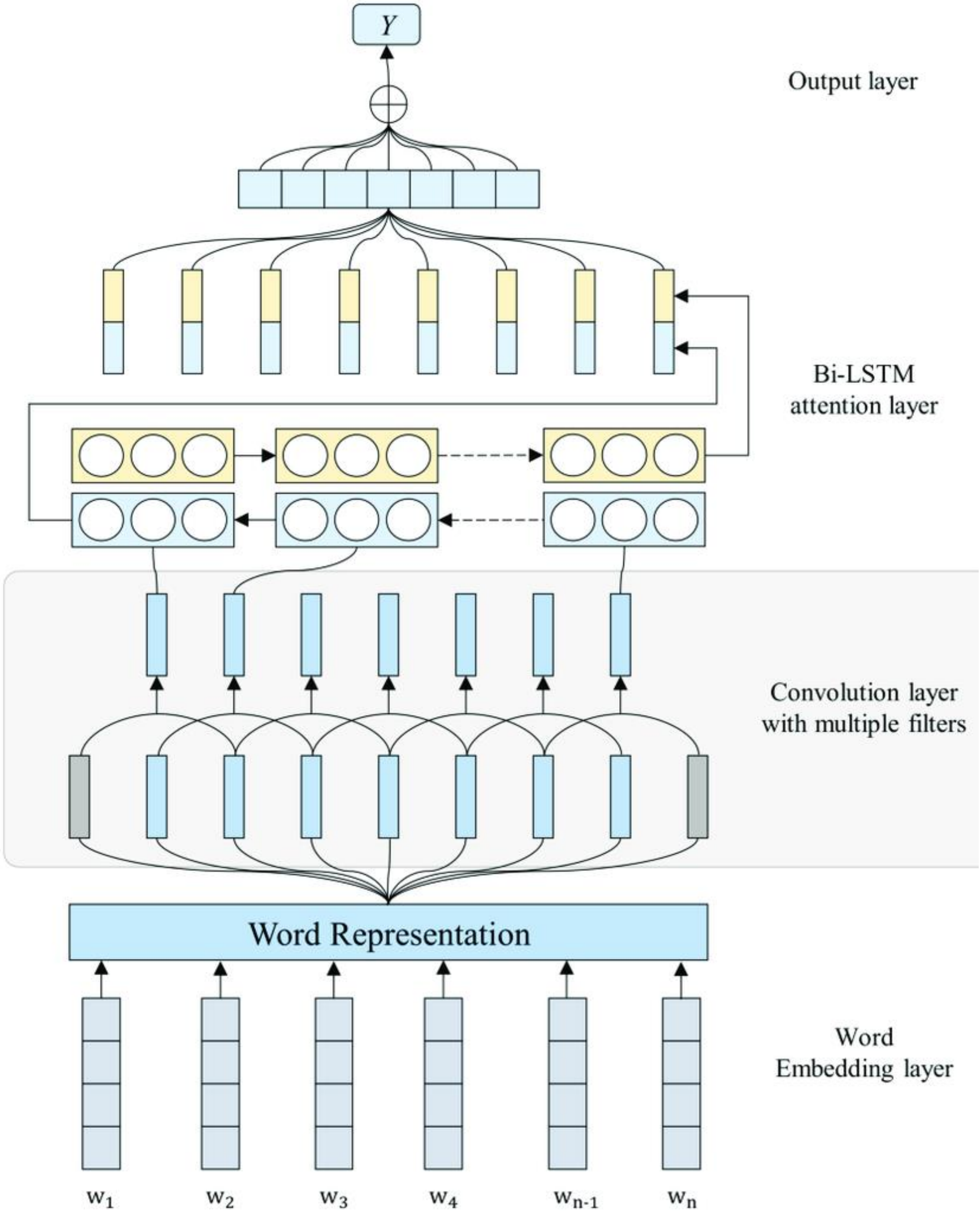
Why Bi-LSTM?

- Traditional neural networks don't have persistence.
- Unfortunately, as that gap grows, RNNs become unable to learn to connect the information.
- Bi-LSTMs are explicitly designed to avoid the long-term dependency problem.



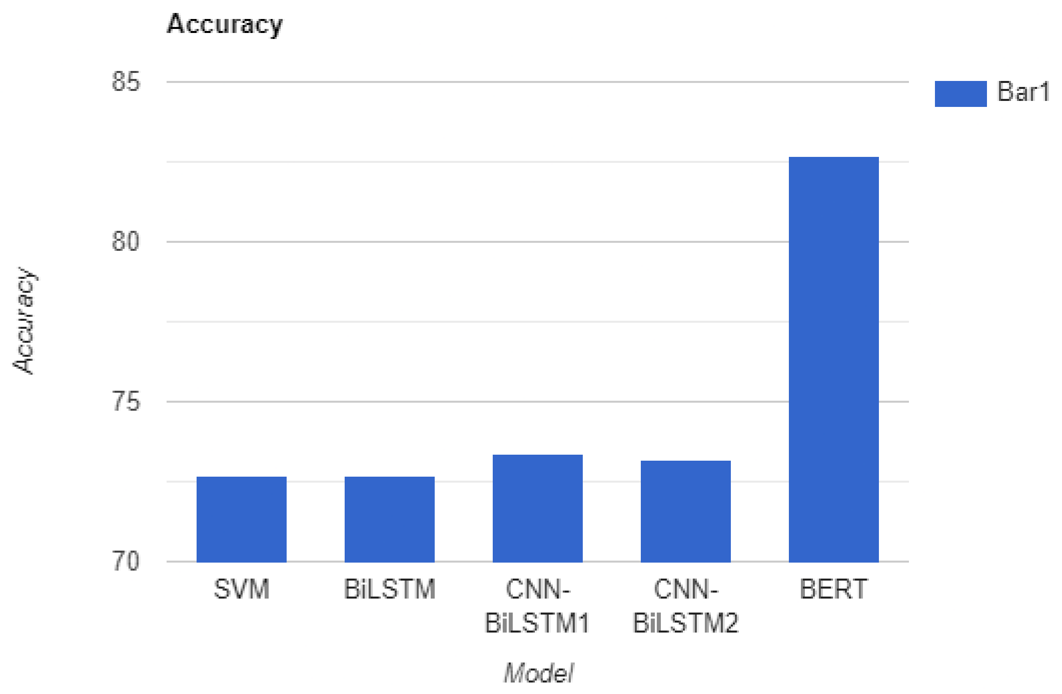
Hybrid model (CNN+Bi-LSTM)

- The hybrid model combines the strengths of Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) for text emotion analysis.
- The CNN captures local features and patterns, while the Bi-LSTM models long-range dependencies in the text.

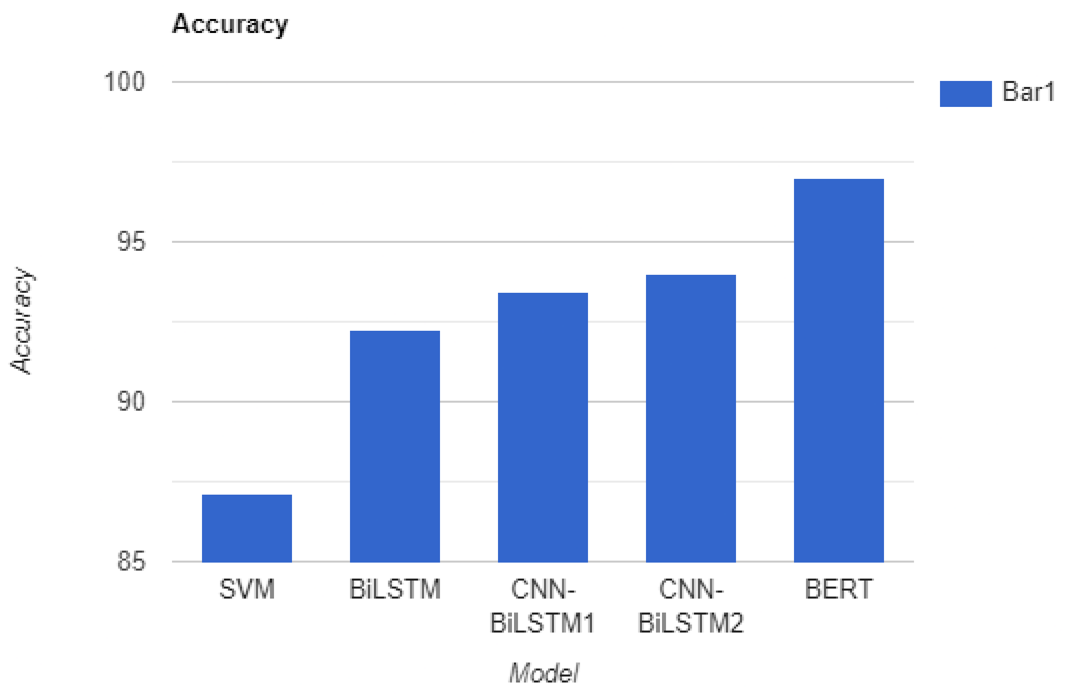


Observation

Dataset-1



Dataset-2



F1 Score, Precision & Recall

Emotion	Precision	Recall	F1-score
Anger	0.94	0.95	0.94
Fear	0.94	0.86	0.90
Joy	1.00	0.91	0.95
Love	0.77	1.00	0.87
Sadness	0.98	0.97	0.97
Surprise	0.75	0.99	0.85

Testing

Message: ['I saw a tiger entering my house while i was alone']

Probabilities for each emotion in given message:

sadness: 33.21581482887268
joy: 1.5119134448468685
love: 0.06470673251897097
anger: 8.698828518390656
fear: 56.042128801345825
surprise: 0.4666124004870653

predicted: fear

Future Work

Multimodal Fusion

Integrating text with other modalities, such as audio, video, and facial expressions, to provide a more comprehensive understanding of emotional states.

Advanced Model Architectures

Exploring the use of transformer-based models, attention mechanisms, and other deep learning techniques to further improve emotion analysis performance.

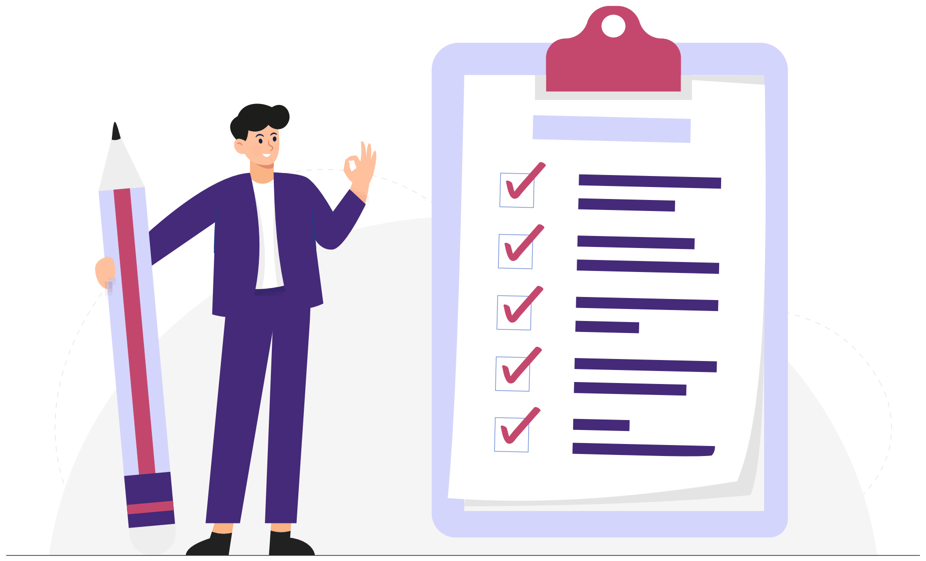
Cross-Lingual Emotion Analysis

Developing models that can effectively analyze emotional content across different languages and cultural contexts.

Diverse Dataset Curation

Collecting and annotating larger, more diverse datasets to capture the richness and complexity of human emotional expression.

Conclusion



- The CNN-BiLSTM hybrid model effectively captured emotional cues from text.
- Dataset variation affects model effectiveness, stressing the importance of dataset selection.
- Using Word2Vec and Glove embeddings improved model performance by capturing word relationships and context.
- Future research should explore advanced architectures, alternative embeddings, and address challenges like domain adaptation for better real-world applications.

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Thank you.