EMOTION RECOGNITION IN CHAT CONVERSATIONS

Course: Machine Learning Project

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Roles & Responsibilities

- **Ansh Prem:** Literature Review, Planning
- **Abhay Pratap Singh:** Model Development (DistilBert & BiLSTM)
- **Atul Raj Chaudhary:** Model Development (Roberta)
- **Himanshu Kumar:** Data Analysis (Preprocessing)
- **Sparsh Rastogi:** Stacking and Model Evaluation

INTRODUCTION: PROBLEM & MOTIVATION

Problem Statement:

- To design and implement machine learning models that can classify emotions such as joy,anger,sadness,fear, surprise, and neutral from conversational text.
- **Why is this important? (Motivation):**
- **Human-Computer Interaction:** Building empathetic AI, chatbots, and virtual assistants that understand user sentiment.
- **Mental Health:** Analyzing social media or journal entries to identify potential signs of distress (as a tool for psychological analysis).
- **Customer Insights:** Automatically sorting customer feedback , reviews, and support tickets by emotional tone to prioritize issues.
- **Content Moderation:** Identifying emotionally charged or harmful content online.

LITERATURE REVIEW

- **Traditional Methods:** Early approaches used lexicons (dictionaries of "emotional" words) and classic ML models (e.g., Naive Bayes, SVMs)with TF-IDF features. These struggle with nuance and context.
- **Deep Learning (RNNs/LSTMs):** Models like LSTMs and BiLSTMs became popular for their ability to understand sequential data , capturing some contextual information. This serves as our baseline.
- **Transformers (State-of-the-Art):** Models like BERT, RoBERTa, and DistilBERT (which we use) revolutionized NLP. They use "attention" to weigh the importance of different words in a sentence, leading to a much deeper understanding of context and meaning.
- **Conversational Challenges:** Research (like the provided survey paper)highlights that real-world emotion is even more complex, involving context, sarcasm, and "emotion shift" over a dialogue.

METHODOLOGY: DATASET

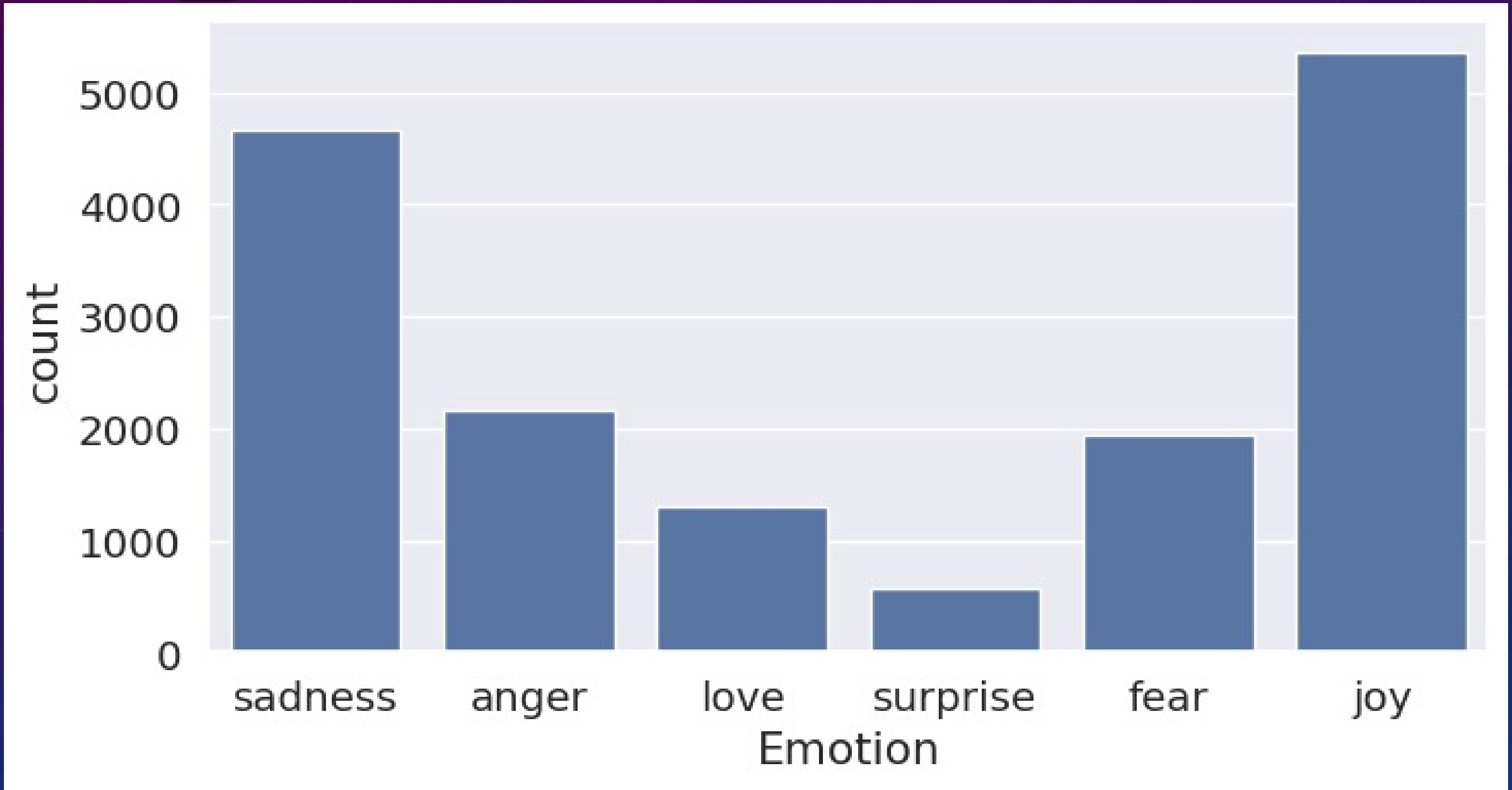
- **Source:** "Emotion Detection from Text" - Kaggle Dataset

https://www.kaggle.com/datasets/pashupatigupta/emotion-detection-from-text

- **Content:** The data is basically a collection of tweets annotated with the emotions behind them. We have three columns tweet_id, sentiment, and content. In "content" we have the raw tweet. In "sentiment" we have the emotion behind the tweet. Refer to the starter notebook for more insights.
- **Labels (6 Classes):** sadness, joy, love, anger, fear, surprise
- **Data Split:** The dataset is pre-split into three files, which we used directly for training, validation, and testing.
    - train.txt (~16,000 samples)
    - val.txt (~2,000 samples)
    - test.txt (~2,000 samples)

Example:

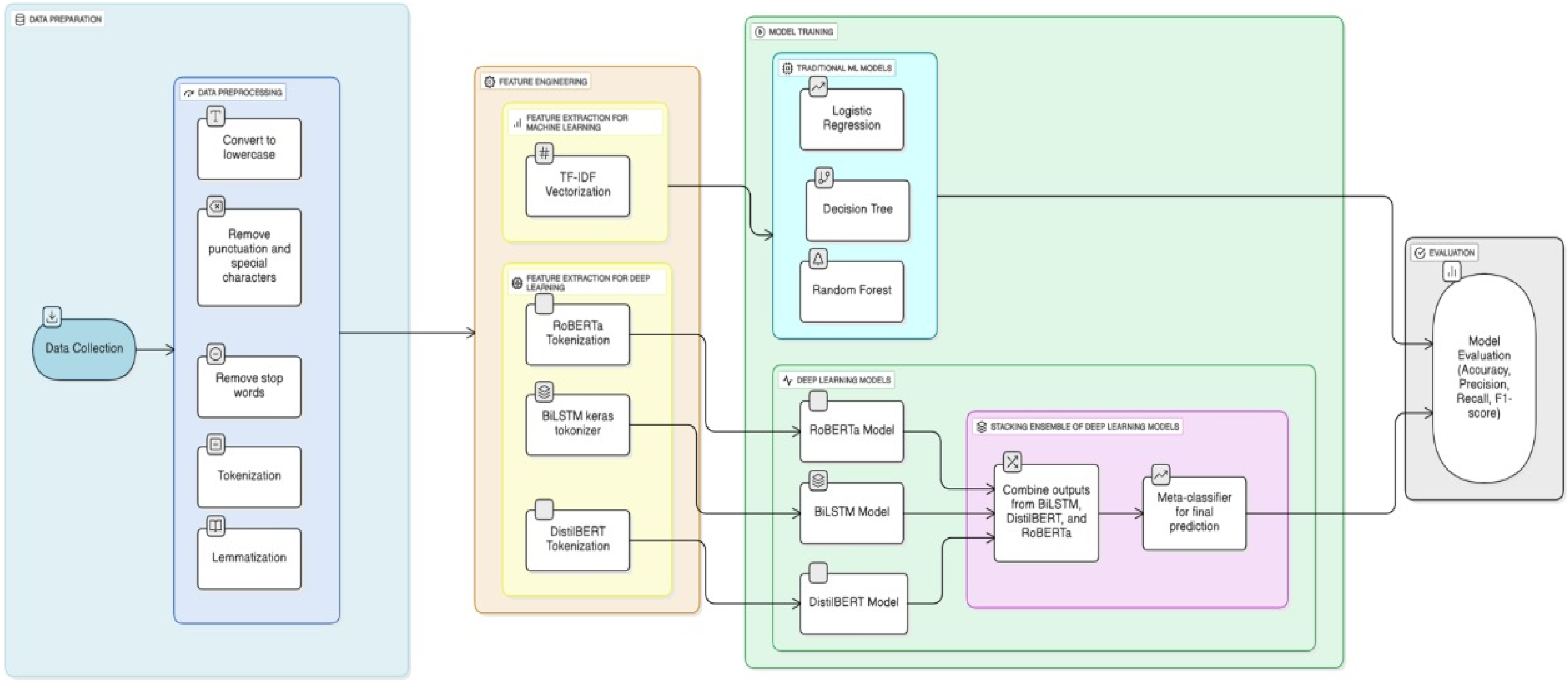
- "i feel so greedy wrong" -> **anger**
- "i feel like i am still hopeful" -> **joy**


5000
4000
3000
2000
1000
0
count
sadness
anger
love
surprise
fear
joy
Emotion

METHODOLOGY: PREPROCESSING

- A crucial step to clean the raw text data before feeding it to our models.
- We applied the following steps to all text in the train, validation, and test sets:
- **Lower Casing:** (`"FEELING HAPPY" -> "feeling happy"`)
- **Remove URLs:** (`"check google.com" -> "check"`)
- **Remove Stop words:** (`"i am feeling happy" -> "feeling happy"`)
- **Remove Numbers:** (`"feeling 100% good" -> "feeling % good"`)
- **Remove Punctuation:** (`"feeling % good" -> "feeling good"`)
- **Lemmatization:** (`"feeling" -> "feeling"`, `"running" -> "run"`)
- This standardizes the text and reduces "noise," allowing the models to focus on meaningful words.

Flowchart



DATA PREPARATION
DATA PREPROCESSING
Convert to lowercase
Remove punctuation and special characters
Data Collection
Remove stop words
Tokenization
Lemmatization
FEATURE ENGINEERING
FEATURE EXTRACTION FOR MACHINE LEARNING
TF-IDF Vectorization
FEATURE EXTRACTION FOR DEEP LEARNING
RoBERTa Tokenization
BiLSTM keras tokonizer
DistilBERT Tokenization
MODEL TRAINING
TRADITIONAL ML MODELS
Logistic Regression
Decision Tree
Random Forest
DEEP LEARNING MODELS
RoBERTa Model
BiLSTM Model
DistilBERT Model
STACKING ENSEMBLE OF DEEP LEARNING MODELS
Combine outputs from BiLSTM, DistilBERT, and RoBERTa
Meta-classifier for final prediction
EVALUATION
Model Evaluation (Accuracy, Precision, Recall, F1-score)

METHODOLOGY: SYSTEM ARCHITECTURE

- We implemented and compared four different deep learning approaches:
- **Model 1: BILSTM**
  - A Bidirectional LSTM model trained on the preprocessed text.
- **Model 2: Bagged DistilBERT**
  - Fine-tuned three separate DistilBERT models (a smaller, faster version of BERT)using different random seeds (42, 1, 27).
  - Final prediction is the average probability (soft voting) from all three.
- **Model 3: RoBERTa**
  - Fine-tuned a single, larger RoBERTa model.
- **Model 4: Stacking Ensemble**
  - **Base Learners:** The BiLSTM, DistilBERT, and RoBERTa models from as specific script run.
  - **Meta-Learner:** A Logistic Regression model trained on the *output probabilities* of the base learners.

RESULTS: MODEL 1(DISTILBERT)

- This **model averaged the predictions of three separately trained DistilBERT models.**
- **Test Set Accuracy: 91.30%**
- **Observation: Excellent performance across all major categories surprise (the smallest class) is the most difficult to predict.**

Classification Report (Test Set):

	precision	recall	f1-score	support
anger	0.94	0.93	0.93	275
fear	0.93	0.90	0.91	224
joy	0.94	0.95	0.95	695
love	0.84	0.82	0.83	159
sadness	0.96	0.97	0.97	581
surprise	0.74	0.74	0.74	66
accuracy			0.93	2000
macro avg	0.89	0.89	0.89	2000
weighted avg	0.93	0.93	0.93	2000

RESULTS: MODEL 2 (ROBERTA)

- This is a single, larger, and more computationally expensive transformer model.
- **Test Set Accuracy: 92.65%**
- **Observation:** Better performance, comparable to the DistilBERT. It has a lower recall for `surprise` but higher precision.

Classification Report (Test Set):

	precision	recall	f1-score	support
anger	0.95	0.91	0.93	275
fear	0.87	0.92	0.89	224
joy	0.93	0.97	0.95	695
love	0.88	0.79	0.83	159
sadness	0.96	0.98	0.97	581
surprise	0.84	0.56	0.67	66
accuracy			0.93	2000
macro avg	0.91	0.85	0.87	2000
weighted avg	0.93	0.93	0.93	2000

RESULTS: MODELS 3 & 4 (BILSTM & STACKING)

The Stacking Ensemble used a Logistic Regression meta-learner, trained on the outputs of the base models (BiLSTM, DistilBERT, RoBERTa).

- **BILSTM Accuracy:** ~91.30%
  - The BiLSTM model performed good, but we found out that pre-modeled were performing slightly better.
- **Stacking Ensemble Accuracy:** 93.40%
  - This complex ensemble performed *worse* than the standalone DistilBERT (91.30%) and RoBERTa (92.65%).

DISCUSSION: KEY OBSERVATIONS

- **Transformers are State-of-the-Art:** The pre-trained transformer models (DistilBERT, RoBERTa) outperformed the BiLSTM model. This confirms that pre-trained knowledge is critical for this task.

- **Bagging > Single Model (Slightly):**
  Applying the bagging ensemble technique led to consistent performance improvements for both transformer models.
  The DistilBERT model improved from **91.30% → 92.95%**, while **RoBERTa** improved from **92.65% → 93.00%**.
  This suggests that aggregating predictions from multiple fine-tuned versions of the same model can effectively **stabilize predictions**, **reduce overfitting**, and provide a small but meaningful boost in overall accuracy.

- The **Stacking Ensemble** achieved the **highest overall accuracy (93.40%)**, outperforming all individual models and bagging variants.
  This demonstrates that **combining diverse mcodels** (DistilBERT, RoBERTa, BiLSTM) through a meta-learner can effectively leverage their complementary strengths and reduce prediction variance.

CONCLUSION: TAKEAWAYS

•Overall, the results confirm that **ensemble learning techniques** such as **bagging and stacking** provide measurable benefits for transformer-based mood classification.
While **individual models** like **RoBERTa (92.65%)** and **DistilBERT (91.30%)** already perform strongly, applying **bagging** improved their accuracies to **93.00%** and **92.95%**, respectively — showing that ensemble averaging effectively enhances model stability and reduces variance.
Moreover, the **stacking ensemble** further combined the strengths of multiple models to achieve the **highest accuracy of 93.40%**, demonstrating that diverse model collaboration yields the most robust and generalizable performance.

•**Ensembling pre-trained transformer models** not only boosts predictive accuracy but also improves reliability, making it a practical and powerful approach for mood and sentiment analysis in conversational text.

LIMITATIONS

- **No "Real" Context:** This dataset classifies isolated sentences. In the real world, emotion depends on conversational history (e.g., "Yeah" can be happy or sad). Our models would fail at this.

- **Imbalanced Data:** The `surprise` class had very few samples (66 in the test set), making it difficult for the models to learn and resulting in the lowest F1-score.

- **Simple Emotions:** The 6 categories are broad. The models cannot detect more nuanced states like "frustration" (a mix of anger and sadness) or detect sarcasm (where the literal words are a lie).

- **Domain and User Dependency:** Chat data varies across platforms, cultures, and languages. Example: “Lit” or “fire” may express excitement among young users but be misunderstood by models trained on formal text. Models often don’t generalize well to new domains or slang-heavy data.

REFERENCES

- **Dataset:** Gupta, P. (2018). *Emotion Detection from Text*. Kaggle. https://www.kaggle.com/datasets/pashupatigupta/emotion-detection-from-text
- **Survey Paper:** Poria, S., Majumder, N., Mihalcea, R., & Hovy, E. (2019). Emotion Recognition in Conversation: Research Challenges, Datasets, and Recent Advances. *IEEE Access*.
- **New Paper:** Al-Hashedi, K. A., Al-Dubai, A. A., & Ghallab, F. A. (2025). Emotion detection from text using a new deep learning model with attention mechanism. *Scientific Reports*, *15*(1), 15501.
- **DistilBERT:** Sanh, V., et al. (2019). *DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter*.
- **RoBERTa:** Liu, Y., et al. (2019). *RoBERTa: A Robustly Optimized BERT Pretraining Approach*.
- **BiLSTM:** Hochreiter, S., & Schmidhuber, J. (1997). *Long short-term memory*.