## 4.8 Experiment No. 7

**Aim:** Emotion Detection from Text (NLP + Classification)
Build a model to detect emotions (joy, anger, sadness, etc.) from user-generated text like tweets, comments, or messages.

**Objective:**
To Study:

1. Understand Natural Language Processing (NLP) techniques for text analysis.
2. Preprocess textual data including cleaning, tokenization, and vectorization.
3. Implement a machine learning classification model to detect emotions from text.
4. Evaluate model performance using accuracy, precision, recall, and F1-score.

**Theory:**
Emotion detection is a subfield of NLP that involves identifying the underlying emotional tone in textual data. Text can carry emotions such as joy, anger, sadness, fear, surprise, and disgust.

- NLP techniques allow computers to process and understand human language.
- Text data is unstructured, so preprocessing (cleaning, tokenizing, stemming, or lemmatization) is crucial.
- Feature extraction methods like Bag-of-Words (BoW), TF-IDF, or word embeddings (Word2Vec, GloVe) transform text into numerical vectors suitable for machine learning.
- Classification algorithms (e.g., Logistic Regression, Naive Bayes, Random Forest, or Neural Networks) can then be trained to predict emotion labels.

**Key Components:**

| Component | Description |
|---|---|
| Text Data | User-generated textual content (tweets, comments, messages) |
| Preprocessing | Cleaning, tokenization, stopword removal, stemming/lemmatization |
| Feature Extraction | Transforming text to numerical representations (BoW, TF-IDF, embeddings) |
| Classifier | Machine learning model to predict emotions from features |
| Label/Target | Emotion classes such as joy, sadness, anger, fear, surprise, disgust |
| Evaluation Metrics | Accuracy, Precision, Recall, F1-Score |

**Input:**

1. Text Dataset: Collection of sentences or tweets labeled with emotions.
2. Preprocessing rules: Stopwords, punctuation removal, lowercasing, tokenization.
3. Feature extraction method: BoW, TF-IDF, or embeddings.

**Output:**

1. Predicted Emotion: Emotion label for each input text.
2. Model Performance: Accuracy and other evaluation metrics to measure classification quality.

**Applications:**

1. Social Media Monitoring: Detecting public sentiment or emotional trends.
2. Customer Support: Understanding customer emotions in feedback or chat logs.
3. Mental Health: Monitoring emotional states from messages or online posts.
4. Chatbots: Enhancing responses by recognizing user emotions.

**Conclusion:**
Through this experiment, we successfully implemented an emotion detection system using NLP and classification techniques. The model learned to identify emotions in text, demonstrating the capability of machine learning to extract meaningful insights from unstructured data. This experiment emphasizes the importance of preprocessing, feature extraction, and model evaluation in text-based emotion analysis.