# ML HACKATHON

## Sentiment Analysis with Text and Video Fusion Model

**Team Name:** PESU\_RR\_10\_499\_513\_543\_528

#### **Team Members:**

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## 1. Project Overview

This project focuses on performing sentiment analysis using multimodal data, combining text and video features to classify sentiments. Using early and late fusion techniques, it integrates text-based and video-based models to enhance classification accuracy.

## 2. Data Preprocessing Methods

## **Text Preprocessing:**

- **Stopwords Removal**: A minimal list of stopwords is used to filter out non-informative words.
- **Contraction Expansion**: A predefined dictionary is used to expand common contractions (e.g., "don't" to "do not").
- **Tokenization & Lowercasing**: Text is tokenized, lowercased, and stripped of punctuation.
- **Feature Extraction (TF-IDF)**: The preprocessed text is transformed into a TF-IDF feature matrix with a maximum of 5000 features.

### **Video Preprocessing:**

- Frame Extraction: Frames are extracted from each video using OpenCV.
- Resizing and Grayscaling: Each frame is resized to 48x48 and converted to grayscale.
- **Padding**: For videos with fewer than 30 frames, zero-padding is used to maintain a consistent input shape.

#### 3. Model Architectures

#### Text Model:

• Random Forest Classifier: A random forest with 100 estimators is used to classify sentiments from TF-IDF features. Probabilities from this model serve as input features for the fusion model.

## Video Model (CNN):

- **CNN Layers**: The video model uses a TimeDistributed CNN architecture with layers to extract spatial features from each frame, followed by:
  - Convolution and Pooling Layers: 3x3 Conv2D layers with ReLU activation, followed by MaxPooling layers.
  - Flattening and Pooling: TimeDistributed Flatten and Global Average Pooling layers.
  - o **Dense Layer**: A final dense layer of 128 units with ReLU activation.

## 4. Model Fusion and Training Strategy

#### **Fusion Model:**

- **Early Fusion (Concatenation)**: Video and text features are concatenated after independent processing, with:
  - Dense Layers: Combined dense layers with ReLU activation and dropout for regularization.
  - o **Output Layer**: Softmax output with three units (positive, neutral, negative).

#### Training:

- **Optimizer and Loss Function**: The fusion model is compiled using the Adam optimizer with categorical cross-entropy loss.
- **Training Process**: Both video and text features are trained together with a batch size of 8 over 10 epochs.

#### 5. Output and Results

- **Model Evaluation**: The trained model's performance on the test data was evaluated, providing accuracy and loss metrics.
- Predictions: Predicted sentiments are saved in a CSV file (fusion\_predictions.csv), providing each utterance with its predicted sentiment.

## 6. Code Snippets

#### **Text Preprocessing Example:**

```
def preprocess_text(text):
text = expand_contractions(text)
text = re.sub(r'[^\w\s]', '', text)
text = text.lower().strip()
tokens = text.split()
tokens = [word for word in tokens if word not in stop_words]
return ' '.join(tokens)
```

#### Video Model Creation:

```
def create_video_model(input_shape=(30, 48, 48, 1)):
video_input = Input(shape=input_shape)
x = TimeDistributed(Conv2D(32, (3, 3), activation='relu'))(video_input)
x = TimeDistributed(MaxPooling2D((2, 2)))(x)
x = TimeDistributed(Conv2D(64, (3, 3), activation='relu'))(x)
x = TimeDistributed(MaxPooling2D((2, 2)))(x)
x = TimeDistributed(Flatten())(x)
x = GlobalAveragePooling1D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
return Model(inputs=video_input, outputs=x)
```

## 7. Interfaces and Deliverables

- **Model Outputs**: The final trained fusion model provides sentiment predictions as probabilities, formatted into a CSV output.
- File Naming Convention:
  - Text and Video Data: Consistently organized using Dialogue\_ID and Utterance\_ID (e.g., dia1\_utt1.mp4).
  - Output File: Sentiment predictions stored in submission.csv.