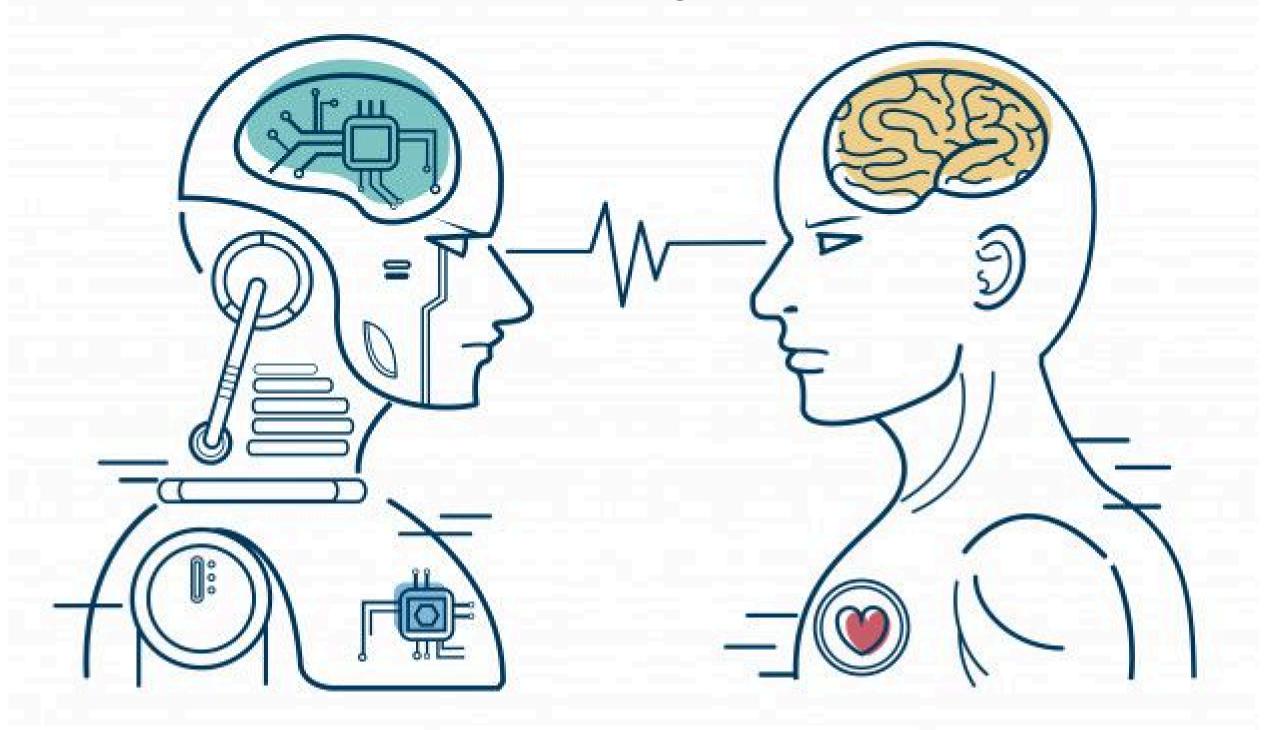
# ARTIFICIAL INTELLIGENCE v/s HUMAN



TEXT CLASSIFIER

#### PROBLEM STATEMENT



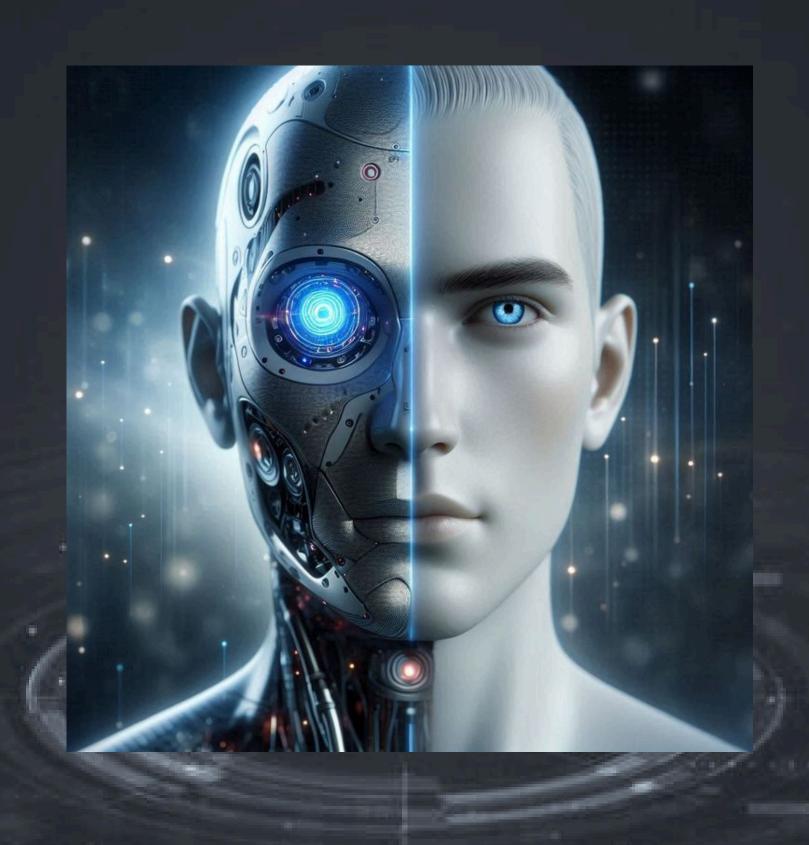
With the rapid advancement of natural language generation models, particularly large language models like GPT, the distinction between human-written and Algenerated text has become increasingly indistinct.

This convergence poses significant challenges across various domains where the authenticity of authorship is critical.

There is a growing and urgent need for automated systems capable of accurately distinguishing between text authored by humans and that generated by artificial intelligence.

Such a system is essential for maintaining academic integrity, ensuring transparency in journalism, verifying originality in creative writing, and upholding trust in usergenerated content on digital platforms.

#### MOTIVATION



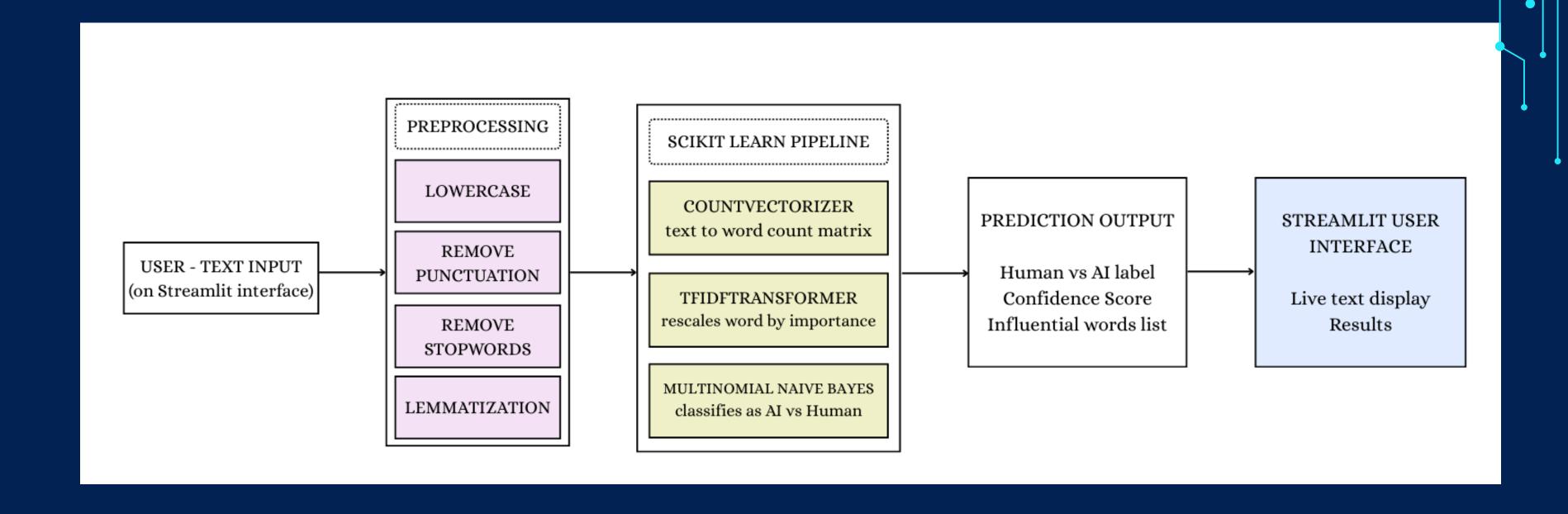
1. Ensuring Academic Integrity and Authorship

As Al-generated content becomes increasingly sophisticated, there is a pressing need to safeguard academic environments from unethical practices such as automated essay writing or plagiarism via generative models.

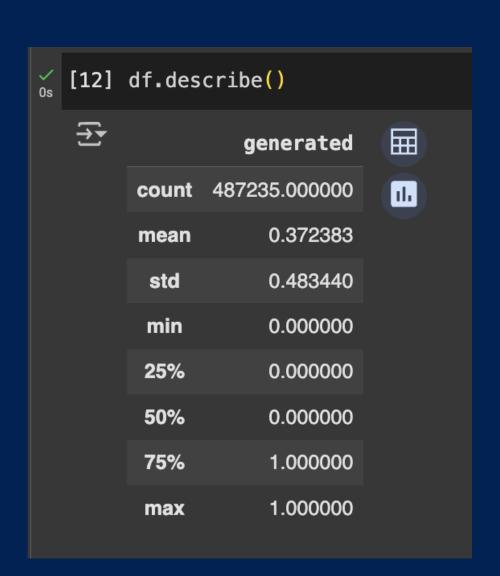
- 2. Enhancing Trust in Content Authenticity
  Distinguishing between human and Al-generated text supports media outlets, publishers, and digital platforms in combating misinformation, maintaining credibility, and ensuring transparency in authorship.
- 3. Advancing Linguistic Understanding of Human vs Al Text

Exploring the subtle differences in language usage between Al and human authors contributes to the broader field of computational linguistics.

## ARCHITECTURE DIAGRAM



### IMPLEMENTATION DETAILS



#### Stop Words Removal

```
[] import nltk
    from nltk.corpus import stopwords

# Download 'punkt' and 'stopwords' resources if not already downloaded
    nltk.download('punkt')
    nltk.download('stopwords')
    nltk.download('punkt_tab') # Download the missing punkt_tab data package

def remove_stopwords(text):
    stop_words = set(stopwords.words('english'))
    words = nltk.word_tokenize(text) # This now uses the downloaded punkt resource
    filtered_words = [word for word in words if word.lower() not in stop_words]
    filtered_words = '.join(filtered_words)
    return filtered_words

df['text']=df['text'].apply(remove_stopwords)
```

→ Total Texts: 487235

Human Written Texts: 305797 AI Generated Texts: 181438

#### IMPLEMENTATION DETAILS

```
pipeline.fit(X_train, y_train)

Pipeline

CountVectorizer

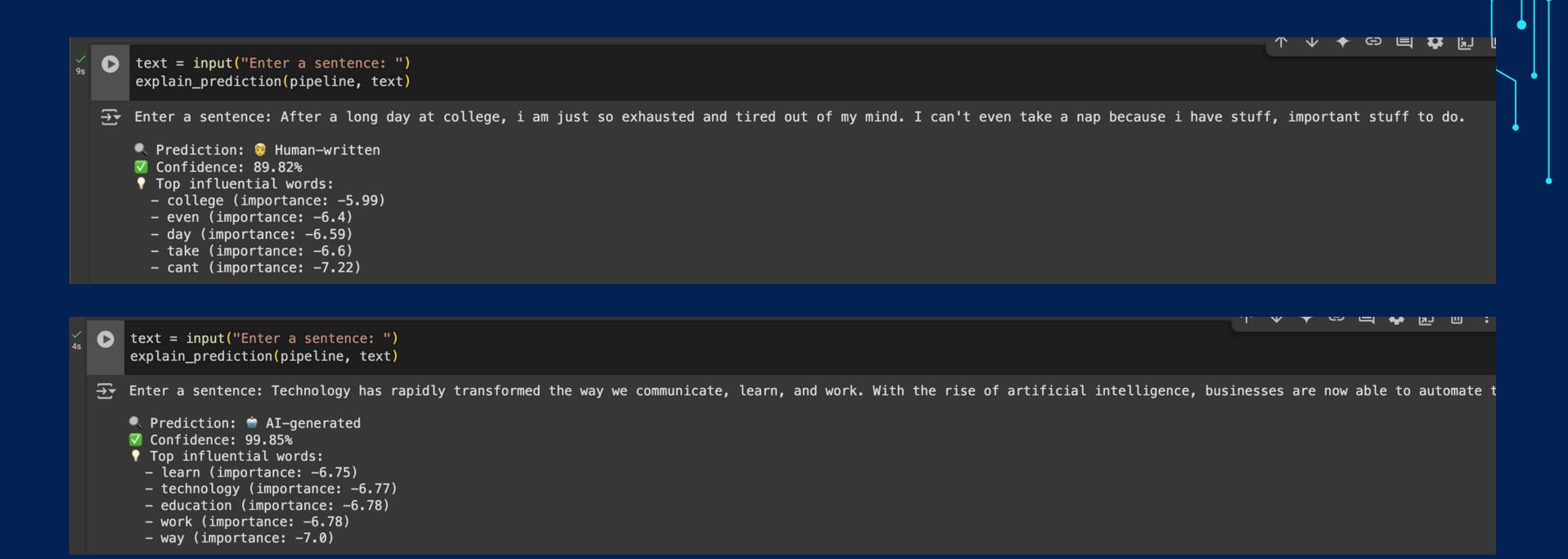
TfidfTransformer

MultinomialNB

MultinomialNB
```

```
[34] import joblib
     import re
    import nltk
    from nltk.corpus import stopwords
    from nltk.stem import WordNetLemmatizer
    # Download required NLTK data
    nltk.download('stopwords')
    nltk.download('wordnet')
    # Load the trained classifier
    pipeline = joblib.load('text_classifier_pipeline.pkl')
    # Preprocessing function
    def preprocess(text):
        text = text.lower()
        text = re.sub(r'[^\w\s]', '', text)
        stop words = set(stopwords.words('english'))
        lemmatizer = WordNetLemmatizer()
        words = text.split()
        words = [lemmatizer.lemmatize(w) for w in words if w not in stop_words]
        return " ".join(words)
    # === Interactive Input ===
    user_input = input(" Enter the text to classify:\n")
    preprocessed = preprocess(user_input)
    prediction = pipeline.predict([preprocessed])[0]
    # Output result
    if prediction == 0:
        print("\n for This text is classified as: Human-written")
    else:
        print("\n@ This text is classified as: AI-generated")
```

#### IMPLEMENTATION DETAILS



### RESULTS

[41] from sklearn.metrics import classification\_report print(classification\_report(y\_test,y\_pred)) **₹** precision recall f1-score support 0.0 0.94 0.99 0.96 91597 1.0 0.98 0.89 0.94 54574 0.95 146171 accuracy 0.96 0.94 0.95 146171 macro avg weighted avg 0.95 146171 0.96 0.95

#### STREAMLIT APP

# ## Human vs Al Text Classifier with Confidence & Explanation

Enter your text below:

After a long day at college, i am just so exhausted and tired out of my mind. I can't even take a nap because i have stuff, important stuff to do.

- Classify
- This text is classified as Human-written
- Confidence: 89.82%

#### Top Influential Words:

- college (importance: -5.99)
- even (importance: -6.4)
- day (importance: -6.59)
- take (importance: -6.6)
- cant (importance: -7.22)

# Human vs Al Text Classifier with Confidence & Explanation

Enter your text below:

Technology has rapidly transformed the way we communicate, learn, and work. With the rise of artificial intelligence, businesses are now able to automate tasks, analyze vast datasets, and deliver personalized experiences to customers. Al tools are revolutionizing industries such as healthcare, finance, and education by improving efficiency and accuracy.

- Classify
- make This text is classified as AI-generated
- Confidence: 99.85%

#### Top Influential Words:

- learn (importance: -6.75)
- technology (importance: -6.77)
- education (importance: -6.78)
- work (importance: -6.78)
- way (importance: -7.0)

### SCOPE AND LIMITATIONS

- 1. Focus on Short to Medium-Length English Texts
  The current system is optimized for analyzing short to moderately long passages written in English, such as essays, paragraphs, and opinion-based writing. It may not be well-suited for analyzing highly technical documents, multi-language content, or full-length books/articles without further customization or preprocessing adjustments.
- 2. Utilization of Classical Machine Learning Techniques
  This project leverages classical machine learning models—
  specifically a Multinomial Naive Bayes classifier—within a Scikitlearn pipeline these models are lightweight, interpretable, and
  effective for text classification tasks but may not capture deeper
  contextual semantics.
- 3. Reduced Performance on Heavily Paraphrased or Noisy Inputs The classifier's accuracy may decline when presented with content that is deliberately paraphrased, syntactically unconventional, or embedded with excessive noise



#### FUTURE WORK

- 1. Integration of Transformer-Based Language Models
  To enhance contextual understanding and improve classification accuracy, future iterations of the system can incorporate state-of-the-art transformer-based models such as BERT, RoBERTa, or DistilBERT.
- 2. Support for Batch Classification via File Uploads
  To accommodate large-scale use cases, the system could be extended to accept bulk inputs through .txt, .csv, or .json file uploads.
- 3. Automated Generation of PDF Reports

For documentation and audit purposes, the system could include functionality to generate detailed PDF reports for each classification result. These reports would summarize the input, predicted label, confidence score, and influential words, providing a standardized format for record-keeping, review, or academic assessment.

