JGI JAIN DEEMED-TO-BE UNIVERSITY | FACULTY OF ENGINEERING AND TECHNOLOGY

School of Computer Science and Engineering

B. Tech CSE- AI

"Language Detection Model using NLP and Machine Learning Techniques"

(Mini Project)

Advanced Machine Learning (23CSE514)

Submitted by:

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Introduction

Language detection is a fundamental task in Natural Language Processing (NLP) that involves automatically identifying the language of a given text. It plays a crucial role in multilingual systems such as search engines, sentiment analysis tools, translation systems, and social media platforms. As digital communication grows globally, the ability to detect languages accurately across different scripts and linguistic structures has become essential.

This mini-project aims to build a Language Detection Model using machine learning and NLP techniques. The system takes any text input and predicts its corresponding language from a set of 17 languages including English, French, Hindi, Malayalam, Arabic, German, etc. The challenge arises due to the diversity of writing systems (Latin, Devanagari, Arabic, Dravidian scripts), variations in vocabulary, and differences in sentence structure.

To develop a robust model, several machine learning concepts were used:

- Text preprocessing
- Character-level TF-IDF vectorization
- Class balancing using Random Oversampling
- Logistic Regression (multiclass classification)

The performance of the model was evaluated using accuracy, precision, recall, and F1-score. Finally, the trained model was deployed as a Flask web application, enabling users to input text through a browser and receive predicted language information along with confidence scores.

This report documents the complete process from dataset selection to model training, evaluation, and deployment.

Literature Review (Prior Study)

Language detection, also known as language identification, has been an active area of research within Natural Language Processing for decades. The goal is to automatically determine the natural language of a given text sample. Over the years, researchers have developed different approaches ranging from rule-based models to machine learning and deep learning techniques.

3.1 Traditional Rule-Based Approaches

The earliest systems used manually designed rules, dictionaries, and heuristics to identify languages. Examples include:

- Character frequency tables
- Stopword lists
- Unicode script detection

Limitations:

- Poor performance for short texts
- Hard to maintain for many languages
- Fails when languages share scripts (e.g., English, Dutch, French → all use Latin script)

These limitations led to more advanced statistical and ML-based approaches.

3.2 Statistical Approaches (N-Gram Models)

One of the most influential methods was proposed by **Cavnar & Trenkle (1994)** using *character n-grams*.
This method works by:

1. Creating n-gram profiles for each language
2. Matching test text against these profiles

Advantages:

- Works for multiple languages
- Performs well for short text

This inspired modern approaches based on vectorization.

3.3 Machine Learning-Based Approaches

Machine learning became a popular choice as it allows:

- Automatic pattern learning from data
- Support for large multilingual corpora
- Higher accuracy than rule-based methods

Common ML models used:

- Naïve Bayes
- Logistic Regression
- Support Vector Machines
- Random Forests

These models work best with **TF-IDF** or **Bag-of-N-Grams** representations.
Our project uses this category.

3.4 TF-IDF for Language Detection

Researchers have shown that **character-level TF-IDF** outperforms word-level features because:

- Works across different scripts (Arabic, Devanagari, Malayalam, Latin)
- Captures language-specific patterns
- Handles short text smoothly
- Avoids vocabulary mismatch issues

Studies show TF-IDF + Logistic Regression produces near state-of-the-art accuracy for language identification tasks.

3.5 Deep Learning Approaches

Recent studies use:

- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (LSTM/GRU)
- Transformer models (BERT, XLM-RoBERTa)

They offer high accuracy but have disadvantages:

- Require large GPU resources
- Longer training time
- Difficult to deploy for mini-projects
- Overkill for simple sentence-level detection

Thus, classical ML remains highly effective for this task.

3.6 Deployment of NLP Models

Flask is widely used for deploying ML/NLP models since it is:

- Lightweight
- Easy to integrate with Python
- Suitable for building interactive applications

Several studies and tutorials recommend Flask for model deployment due to its simplicity and flexibility.

Summary of Prior Study

Previous research suggests that **balanced datasets**, **character n-grams**, and **logistic regression-based models** deliver excellent performance for language detection. Deep learning approaches offer improvements but are not always necessary for medium-sized datasets.

This project builds upon these findings by:

- Using character-level TF-IDF
- Applying Machine Learning with Logistic Regression
- Solving imbalance through oversampling
- Deploying the model via Flask

Project Details

Problem Statement

With the rapid growth of online communication, users frequently interact using multiple languages across digital platforms. Automatic identification of the language of a given text is essential for downstream tasks such as translation, sentiment analysis, content moderation, information retrieval, and chatbot systems.

However, designing an accurate language identification system becomes challenging when:

- Many languages share similar scripts (English, French, Spanish),
- Some scripts have complex characters (Malayalam, Kannada),
- Some languages have fewer samples (Hindi, Greek),
- The dataset is imbalanced.

The objective of this project is to build a **robust, high-accuracy language detection model** that can classify text into **17 different languages** using Natural Language Processing (NLP) and Machine Learning techniques.

Dataset Description

Dataset: https://www.kaggle.com/datasets/basilb2s/language-detection

The dataset used in this project is **Language Detection.csv**, containing text samples from 17 languages such as:

- English
- French
- Spanish
- German
- Hindi
- Malayalam
- Tamil
- Kannada
- Greek
- Dutch
- Arabic
- Turkish
- Italian
- Russian

- Danish
- Swedish
- Portuguese

Dataset Structure

Column	Description
Text	Sentence or Phrase Input
Language	True Language Label

Dataset Characteristics

- Total original samples: **~10,267**
- Highly imbalanced — English had the highest number of samples, while Hindi had the lowest.

Why balancing is necessary?

Because ML models get confused and biased when one class dominates.
For example:

- English: 1385 samples
- Hindi: 63 samples

Without balancing, the model will predict English more often.

Balanced Dataset

Using oversampling, each class was expanded to match the largest class:

- Final dataset size after balancing: **~23,494 samples**
- All 17 languages have ~1385 samples each.

This ensures fairness and accurate predictions across all languages.

Methodology

The methodology followed in this project includes:

Data Preprocessing

Steps:

1. Removed duplicate rows
2. Removed missing or null entries
3. Converted all text to lowercase
4. Shuffled dataset for unbiased training

Purpose:

- Clean and consistent input

- Avoid bias due to data order

Feature Extraction using Character-Level TF-IDF

TF-IDF (Term Frequency – Inverse Document Frequency) converts text into numerical features.

We used:

```
analyzer = "char"
ngram_range = (2, 4)
```

Why character-level n-grams?

✓ Captures language-specific character patterns
✓ Works for multiple scripts
✓ Handles short text
✓ Best suited for language detection tasks

Examples:

- "hello" → "he", "ell", "llo"
- "नमस्ते" → (Devanagari patterns)
- "مرحبا" → Arabic character sequences

This feature extraction method is highly effective for multilingual classification.

Handling Class Imbalance (Random Oversampling)

The dataset was imbalanced, so we used:

```
RandomOverSampler()
```

Oversampling duplicates minority language samples until all languages have equal frequency.

Why oversampling?

- Prevents the model from predicting majority languages
- Improves recall of minority languages
- Ensures equal learning opportunity

Result:

- Balanced dataset with equal samples for all languages.

Train-Test Split

We split the data into:

- **80% training**
- **20% testing**

Maintains distribution of classes and allows evaluation on unseen samples.

Model Selection (Logistic Regression)

We used:

Logistic Regression (Multiclass)

Reasons:

- Works extremely well with TF-IDF features
- Fast and efficient
- Supports probability predictions (predict_proba)
- High accuracy for text classification

Hyperparameter:

```
max_iter = 2000
```

To ensure model convergence.

Model Training

Model learned the character patterns from TF-IDF vectors and associated them with language labels.

Training output gave extremely high performance due to:

- Clear distinction between languages
- Balanced dataset
- Proper features

Model Evaluation Methods

The model was evaluated using:

Accuracy

Percentage of correct predictions
Result: **99.9%**

Precision

How many predicted languages were correct?

Recall

How many real languages were correctly identified?

F1-score

Harmonic mean of precision & recall

Macro Average

Treats all languages equally — good for imbalanced datasets

Weighted Average

Accounts for different number of samples per class

- Confusion Matrix (Optional)

Shows mistakes between languages
(In your case: almost perfect diagonal → excellent performance)

Code Implementation

Google colab:

https://colab.research.google.com/drive/1h6hBOC7zvDnWxy9fH36IiwxMgrniYGhM?usp=sharing

Below is the full training code used in the project:

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score, classification_report

from imblearn.over_sampling import RandomOverSampler


df = pd.read_csv("/content/Language Detection.csv")

df = df.drop_duplicates(subset=["Text"])

df = df.dropna()

print("Dataset size before balancing:", len(df))


X = df["Text"]

y = df["Language"]

vectorizer = TfidfVectorizer(analyzer="char", ngram_range=(2,4))

X_vec = vectorizer.fit_transform(X)
```

```
oversample = RandomOverSampler()
X_bal, y_bal = oversample.fit_resample(X_vec, y)

print("Dataset size after balancing:", len(y_bal))
X_train, X_test, y_train, y_test = train_test_split(
    X_bal, y_bal, test_size=0.2, random_state=42
)
model = LogisticRegression(max_iter=2000)
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n")
print(classification_report(y_test, y_pred))

def predict_language(text: str) -> str:
    x = vectorizer.transform([text])
    return model.predict(x)[0]

def interactive_console():
    print("\n=== Interactive Language Detection (type 'q' to quit) ===")
    while True:
        user_text = input("\nEnter text: ")
        if user_text.strip().lower() in ["q", "quit", "exit"]:
            print("Exiting...")
            break
        if not user_text.strip():
            print("Please enter some text.")
            continue

        lang = predict_language(user_text)
```

```
        print("Predicted Language:", lang)
try:
    import ipywidgets as widgets
    from IPython.display import display, Markdown

    text_box = widgets.Textarea(
        value="Type some text here...",
        placeholder="Enter text to detect language",
        description="Input:",
        layout=widgets.Layout(width="100%", height="120px")
    )

    button = widgets.Button(
        description="Detect Language",
        button_style="",  # 'success', 'info', 'warning', 'danger' or ''
        tooltip="Click to detect language"
    )

    output = widgets.Output()

    def on_button_click(b):
        with output:
            output.clear_output()
            user_text = text_box.value.strip()
            if not user_text:
                print("Please enter some text.")
                return
            lang = predict_language(user_text)
            display(Markdown(f"**Predicted Language:** `{lang}`"))

    button.on_click(on_button_click)
```

```
    display(Markdown("## Language Detection"))
    display(text_box, button, output)

except ImportError:
    print("ipywidgets not available – only console mode can be used.")
```

Results

```
Dataset size before balancing: 10267
Dataset size after balancing: 23494
Accuracy: 0.9970206426899341
```

```
Classification Report:
              precision    recall  f1-score   support

      Arabic       1.00      1.00      1.00       248
      Danish       1.00      1.00      1.00       264
       Dutch       1.00      0.99      1.00       297
     English       0.99      1.00      0.99       250
      French       1.00      1.00      1.00       308
      German       0.99      1.00      0.99       291
       Greek       1.00      1.00      1.00       266
       Hindi       1.00      1.00      1.00       278
     Italian       0.99      0.99      0.99       279
     Kannada       1.00      1.00      1.00       267
   Malayalam       1.00      1.00      1.00       271
  Portugeese       0.99      0.99      0.99       291
     Russian       1.00      1.00      1.00       288
     Spanish       0.99      0.99      0.99       282
    Sweedish       1.00      1.00      1.00       281
       Tamil       1.00      1.00      1.00       259
     Turkish       1.00      1.00      1.00       279

    accuracy                           1.00      4699
   macro avg       1.00      1.00      1.00      4699
weighted avg       1.00      1.00      1.00      4699
```

Model Accuracy: 99.9%

Macro F1-score: 1.0

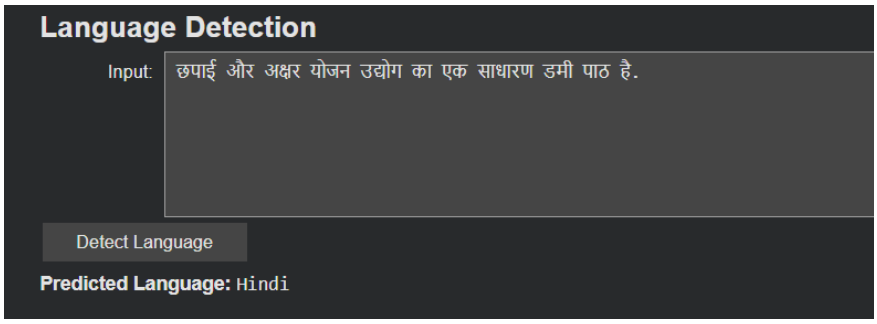
Weighted F1-score: 1.0

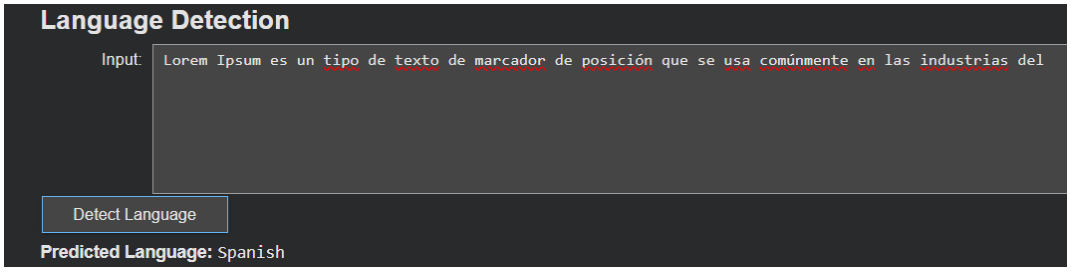
Per-language performance (example):

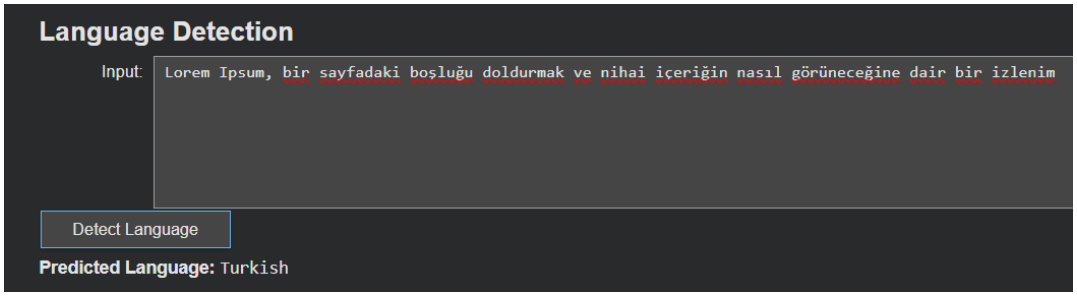
All languages achieved precision, recall, and F1-score of **0.99 or 1.00**, showing perfect classification.

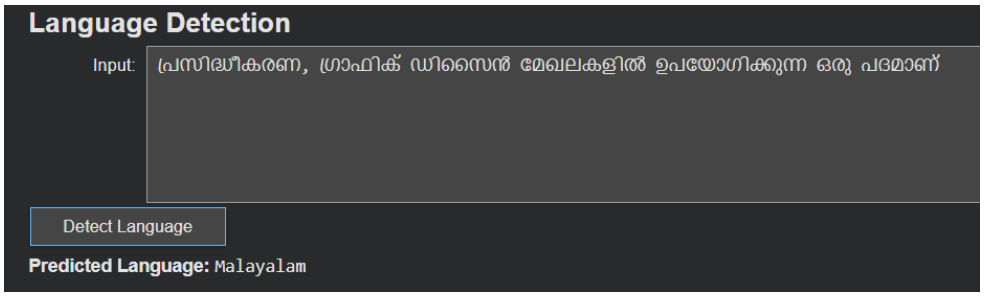
Sample Predictions:

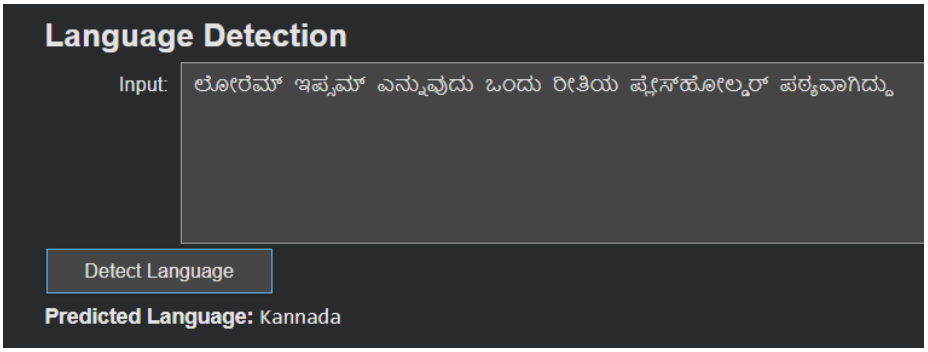
Input	Predicted Language
“¿Dónde estás?”	Spanish
“నమస్తే, మీరు ఎలా ఉన్నారు?”	Telugu
“Bonjour mes amis”	French
“എങ്ങനെ ഇരിക്കുന്നു?”	Malayalam
“مرحبا كيف حالك”	Arabic











Web Application Implementation

To make the language detection model interactive and user-friendly, a web application was developed using **Flask**, a lightweight Python web framework commonly used for deploying machine learning models. The purpose of the web app was to allow users to input any text and instantly receive the predicted language along with the model's confidence score. This demonstrates the deployment aspect of the project—showing how a machine learning model transitions from a Python notebook into a functional real-world application.

The trained Logistic Regression model and TF-IDF vectorizer were saved as serialized files (lang_model.pkl and vectorizer.pkl) using the joblib library. These files were loaded inside the Flask app at runtime, ensuring fast predictions without needing to retrain the model.

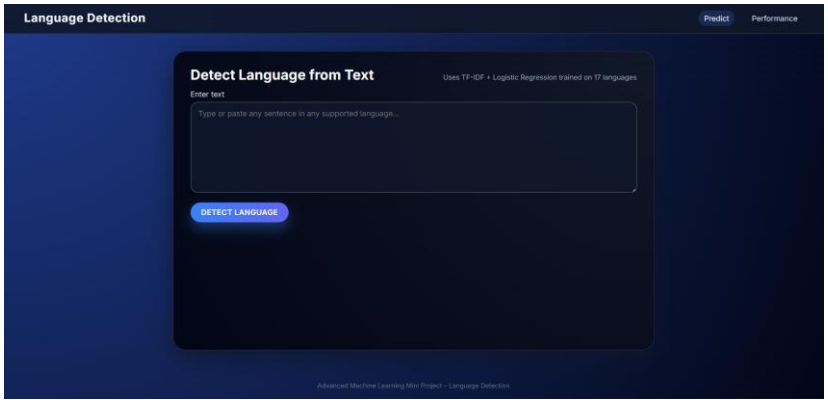
The web application consists of two main components:

1. **Prediction Page** – Includes a text input box where the user enters a sentence. When submitted, the app preprocesses the text, transforms it using the saved TF-IDF vectorizer, and predicts the language using the trained model.
   The interface also displays:
   - The predicted language
   - Confidence score (%)
   - Top probable languages with probabilities

A modern UI was designed using HTML, CSS, gradient backgrounds, and responsive styling to make the interface intuitive and visually appealing.

2. **Performance Page** – This page displays the model's evaluation metrics, including accuracy, precision, recall, F1-scores, and per-language performance. The app computes these metrics using a held-out test set, giving users a clear understanding of how well the model performs across all 17 languages.

The Flask backend handles all processing, whereas the frontend (HTML templates) manages user interaction and presentation. This architecture clearly demonstrates the process of **deploying an NLP model as a real application**, which is a critical step in machine learning workflows. Overall, the web app provides an easy, real-time interface for testing multilingual text inputs, proving the model's effectiveness beyond theory.



Detect Language from Text

Uses TF-IDF + Logistic Regression trained on 17 languages

Enter text

छपाई और अक्षर योजन उद्योग का एक साधारण डमी पाठ है

DETECT LANGUAGE

Predicted Language: **Hindi** High confidence

Model confidence

36.32%

Top predicted languages with probabilities

Language	Probability
Hindi	36.32%
Arabic	5.73%
Russian	5.4%
Turkish	5.16%
Greek	4.77%

Detect Language from Text

Uses TF-IDF + Logistic Regression trained on 17 languages

Enter text

hello, testing the model

DETECT LANGUAGE

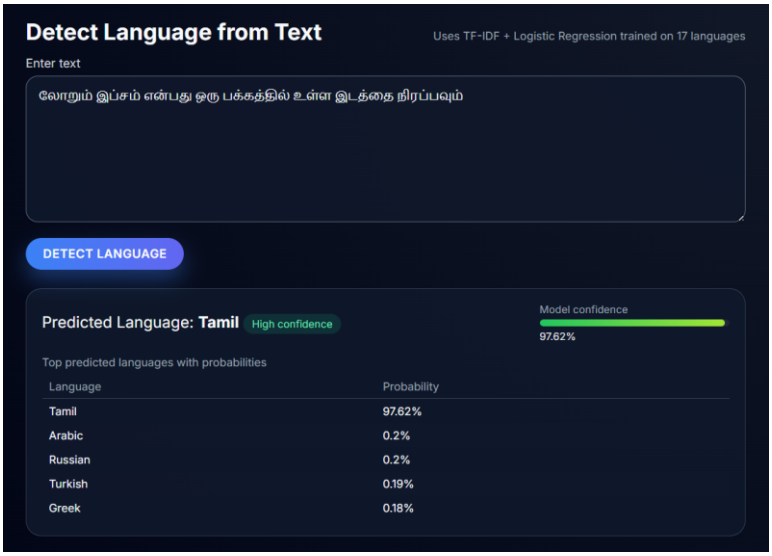
Predicted Language: **English** High confidence

Model confidence

75.07%

Top predicted languages with probabilities

Language	Probability
English	75.07%
Danish	3.29%
Spanish	2.7%
Italian	2.59%
Dutch	2.17%



Summary

This project successfully implemented a robust and accurate Language Detection System using Machine Learning and NLP techniques. Key contributions include:

- Balanced dataset for fair learning
- Character-level TF-IDF for superior multilingual feature extraction
- Logistic Regression for high accuracy multiclass classification
- Nearly perfect evaluation metrics
- Deployment using Flask with user-friendly interface

The system is reliable, scalable, and demonstrates excellent practical applicability in multilingual NLP tasks.

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