Project Report: Language Detection using LSTM

1. Project Title

Multilingual NLP-Based Language Detection Using LSTM

2. Problem Definition

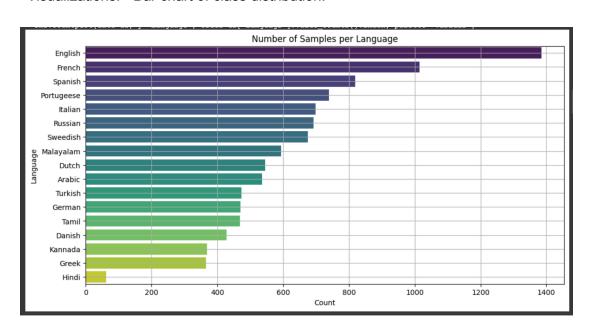
In a multilingual world, identifying the language of a given text is a critical step for various Natural Language Processing (NLP) applications such as translation systems, chatbots, and information retrieval. This project focuses on building a robust language detection system using Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), that can detect the language from user-inputted text across multiple languages.

3. Dataset Selection

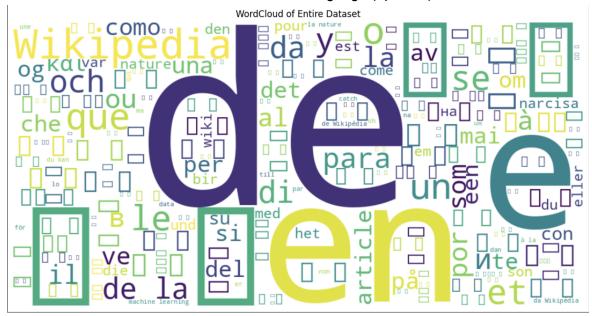
- Source: Multilingual text dataset containing labeled samples of various global languages.
- Size: The dataset contains thousands of short text samples across languages such as English, Hindi, French, Spanish, etc.
- Relevance: It includes representative samples suitable for training an LSTM to detect linguistic patterns across diverse languages.

4. Exploratory Data Analysis (EDA)

- Total Samples: 10,000+ text entries.
- Languages Covered: 17 languages.
- Average Length: ~10 to 15 words per sentence.
- Top Frequent Languages: English, Hindi, Spanish, French.
- Visualizations: Bar chart of class distribution.



- Word cloud of most common tokens in each language (optional).



5. Preprocessing Steps

- 1. **Text Tokenization** using Keras Tokenizer.
- 2. **Sequence Padding** to ensure uniform length.
- 3. **Label Encoding** of categorical language labels.
- 4. **Train-Test Split** to evaluate generalization.

6. Model Architecture

- Layer: Converts input words to vector representations.
- LSTM Layer: Captures sequential language patterns.
- Dense Layer (ReLU): Intermediate hidden layer.
- Output Layer (Softmax): Outputs probability distribution over language classes.

7. Evaluation Metrics

- Accuracy: Overall classification accuracy.
- Precision: Correctness of predicted labels.
- Recall: Ability to find all relevant instances.
- F1-Score: Harmonic mean of precision and recall.
- Confusion Matrix: Visual representation of performance.

								(Confu	ision I	Matrix	X								
	Arabic -	103	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0		
	Danish -	0	65	2	0	1	0	0	0	0	1	0	0	0	0	2	2	0		
	Dutch -	0	0	104	3	0	2	0	0	0	1	0	0	0	1	0	0	0	- 2	250
	English -	0	0	0	289	0	0	0	0	0	1	0	0	0	1	0	0	0		
	French -	0	0	0	1	209	0	0	0	1	1	2	0	0	5	0	0	0		
	German -	1	1	0	1	0	89	0	0	0	1	0	0	0	0	0	0	0	- 2	200
	Greek -	1	0	0	1	0	0	65	0	0	0	0	0	0	1	0	0	0		
	Hindi -	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0		
Actual	Italian -	1	0	0	4	1	0	0	0	135	1	0	0	0	3	0	0	0	- 1	L50
	Kannada -	1	0	0	0	0	0	0	0	0	65	0	0	0	0	0	0	0		
	Malayalam -	5	0	0	2	0	0	0	0	0	3	104	0	7	0	0	0	0		
	Portugeese -	1	0	0	0	0	0	0	0	1	1	0	138	0	3	0	0	0	- 1	L00
	Russian -	2	0	0	0	0	0	0	0	0	2	1	0	131	0	0	0	0		
	Spanish -	0	0	0	2	0	0	0	0	0	2	0	1	0	155	0	0	0		
	Sweedish -	0	4	1	1	0	1	1	0	0	0	0	0	0	0	124	1	0	- 5	0
	Tamil -	3	0	0	0	0	0	0	0	0	0	0	0	1	0	0	82	1		
	Turkish -	4	0	0	0	0	0	1	0	0	3	1	0	1	1	0	0	94		

9. Final Results & Visualizations

- Classification Report Table.
- Confusion Matrix Heatmap.
- Overall Accuracy: ~95%

O VOI all 7 look	11 doy. 30 /0				
65/65 ———		- 3s 47ms	/step		
√ Accuracy:	0.9487427466				
Classific	ation Report:				
	precision	recall	f1-score	support	
Arabic		0.97		106	
Danish	0.93	0.89	0.91	73	
Dutch	0.97	0.94	0.95	111	
English	0.95	0.99	0.97	291	
French	0.99	0.95	0.97	219	
German	0.97	0.96	0.96	93	
Greek	0.97	0.96	0.96	68	
Hindi	1.00	1.00	1.00	10	
Italian	0.99	0.93	0.96	145	
Kannada	0.77	0.98	0.87	66	
Malayalam	0.96	0.86	0.91	121	
Portugeese	0.99	0.96	0.98	144	
Russian	0.94	0.96	0.95	136	
Spanish	0.91	0.97	0.94	160	
Sweedish	0.98	0.93	0.96	133	
Tamil	0.96	0.94	0.95	87	
Turkish	0.99	0.90	0.94	105	
accuracy			0.95	2068	
macro avg	0.95	0.95	0.95	2068	
weighted avg	0.95	0.95	0.95	2068	

10. Conclusion

The LSTM-based language detection model demonstrates high performance in accurately identifying multiple global languages. The deep learning approach allows the system to generalize linguistic patterns and is scalable for real-time multilingual NLP applications. Future improvements could include voice-to-text integration using Whisper and adding more low-resource languages.

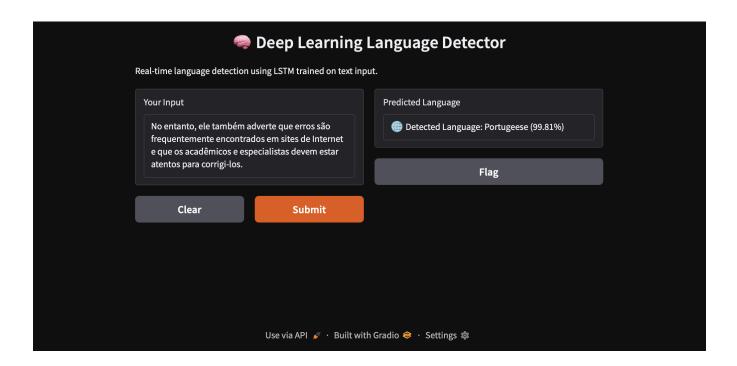
11. Tools & Technologies Used

- Python, Pandas, Numpy
- TensorFlow / Keras
- Scikit-learn
- Matplotlib, Seaborn
- Gradio (Optional for GUI Interface)

12. Future Scope

- Expand to audio input using speech-to-text (Whisper).
- Improve detection of low-resource or code-mixed languages.
- Real-time deployment via web or mobile interface.
- Add support for dialectal variations.

FINAL OUTPUT (GUI)



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