

Named Entity Recognition (NER) Using BiLSTM

Objective: Automatically identify and classify named entities within text to enable more precise and meaningful text analysis.

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Project Tools & Libraries

Python

Primary programming language for development

NumPy & Pandas

Data manipulation and preprocessing libraries

Scikit-learn

For preprocessing and model evaluation

TensorFlow & Keras

Deep learning frameworks for model building

Plotly & Matplotlib

Libraries for data visualization and analysis

Livelossplot & TensorBoard

Libraries for tracking model performance

Dataset Overview

Dataset Files

- Train File (train.txt)
- Validation File (val.txt)
- Test File (test.txt)

Dataset Format

Each line in the dataset contains a word along with its associated tag. Sentences are separated by special tokens like . and \$#\$. For example:

```
John B-PER
Doe I-PER
went O
to O
Cairo B-LOC
```

Where:

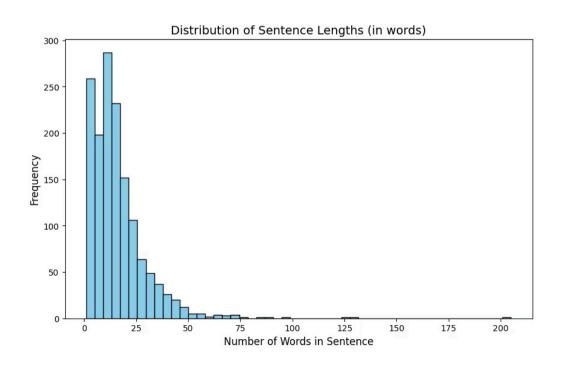
- B-PER stands for Beginning of Person Entity
- I-PER stands for Inside of Person Entity
- O stands for Other (non-entity word)
- **B-LOC** stands for Beginning of Location Entity

Dataset Characteristics

Sentence Length Distribution

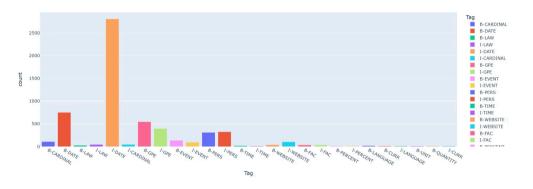
Diverse range of sentence lengths (25-75 words)

Requires specialized preprocessing and modeling to handle variability in input size.



Named Entity Distribution

Broad spectrum of entity types (PERSON, ORGANIZATION, LOCATION, etc.)



Diverse entity distribution provides a robust dataset for training a high-quality NER model.

Preprocessing Steps for NER



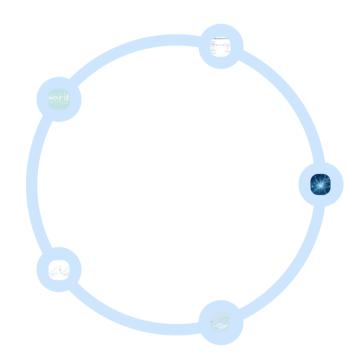
Model Architecture Overview

Embedding Layer

Transforms words into dense vector representations.

Evaluation Metrics

Measured by accuracy and ROC-AUC scores to assess performance.



Bidirectional LSTM Layer

Captures past and future context for better sequence understanding.

Dropout Layers

Spatial and recurrent dropout reduce overfitting with a rate of 0.1.

Optimization & Loss

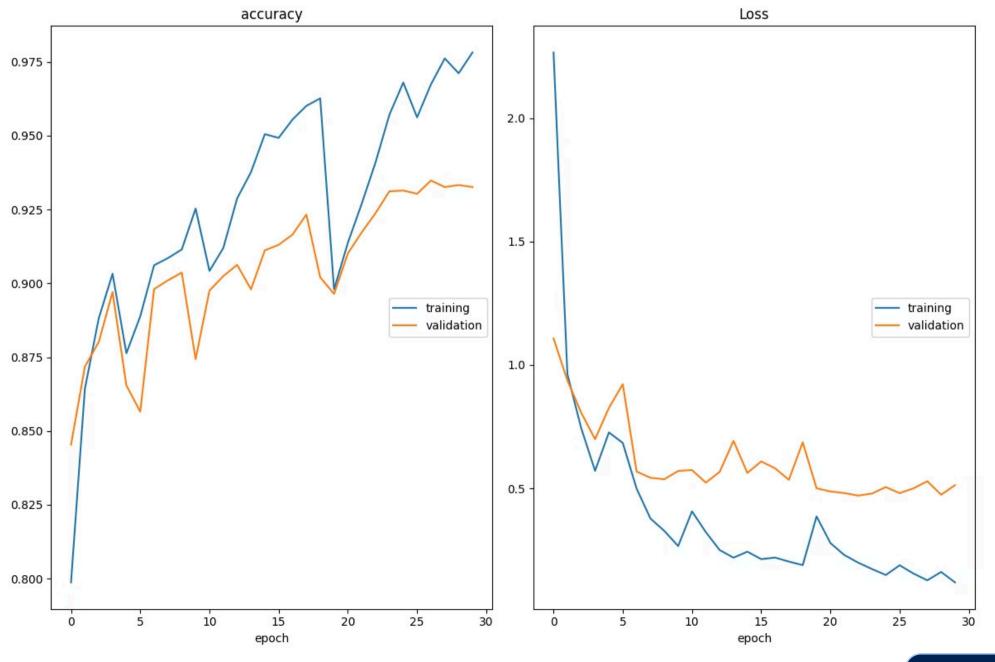
Uses Adam optimizer and sparse categorical crossentropy loss.

Training Configuration

- **Epochs:** 30 cycles for model convergence
- Batch Size: 32 samples per gradient update
- Validation Split: 20% of data reserved for validation
- EarlyStopping: Patience set to 7 to prevent overfitting
- ModelCheckpoint: Automatically saves the best performing model
- Callbacks: Includes LiveLossPlot and TensorBoard for monitoring progress

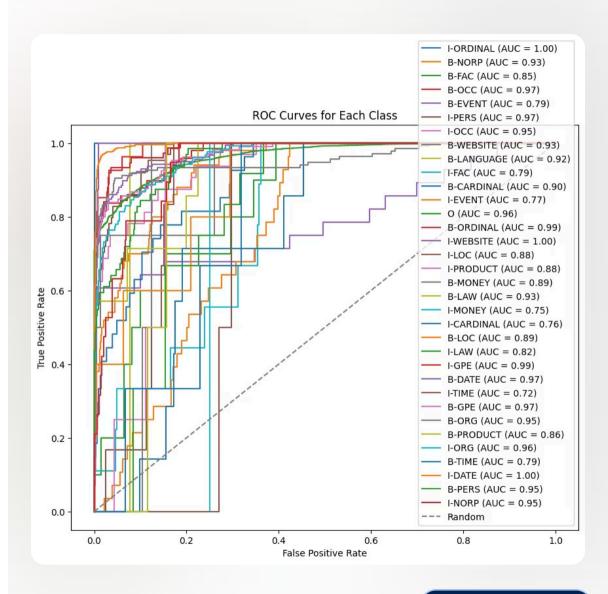
Training Performance Metrics

	Training	Test Accuracy
Accuracy	97.5%	93%
Loss	0.18	0.48 (overfitting after epoch 20)
Optimizer	Adam optimizer	
Loss Function	Sparse categorical crossentropy	
Batch Size	32	
EarlyStopping	Patience set to 3 epochs to prevent overfitting	



ROC-AUC Curve Performance

 The ROC-AUC scores provide insights into the model's performance across different classes, allowing for better understanding of its predictive capabilities.



Limitations of the BiLSTM Model



Data Imbalance: Bias towards frequent entities like Person



Model Complexity:
Struggles with long
dependencies and
overfitting



Arabic Language:
Morphological and
syntactic challenges



Entity Boundaries:
Hard to detect
boundaries in long or
nested entities



Next Steps & Improvements

Enhance Model

Explore advanced architectures and hyperparameter tuning

Expand Dataset

Include more entity types and larger annotated data

Deploy & Monitor

Integrate model into applications and track real-world performance