Identifying Key Entities in Recipe Data

1. Objective

This project focuses on building a system that can recognize important components in cooking recipes using a Named Entity Recognition (NER) approach. Specifically, it identifies entities such as:

- Ingredients
- Quantities
- Measurement units

By extracting these elements from unstructured text, recipes can be converted into a structured format. This structured data can then support use cases like nutritional tracking, automated grocery lists, and interactive cooking apps.

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2. Methodology

Data Preparation

- The recipe text comes pre-tagged using the IOB format, which marks each word as the beginning (B), inside (I), or outside (O) of an entity.
- This format is commonly used for labeling sequences in NER tasks.

Feature Engineering

Each token (word) is enriched with several features to improve prediction, including:

- The lowercase version of the word
- Part-of-speech (POS) information
- Prefixes and suffixes (e.g., first/last few characters)
- Whether it's a digit or capitalized
- Word position and other contextual cues

Model Development

- The model is built using the sklearn-crfsuite implementation of Conditional Random Fields (CRF), which is well-suited for identifying patterns in sequential data.
- It was evaluated based on standard classification metrics: precision, recall, and F1-score.

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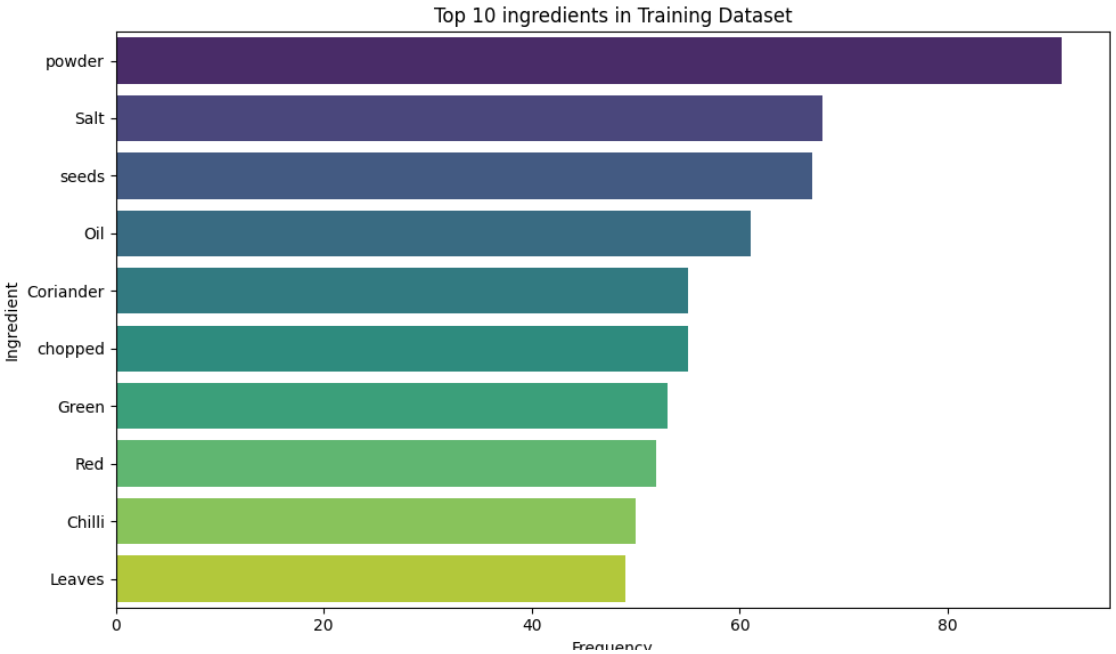
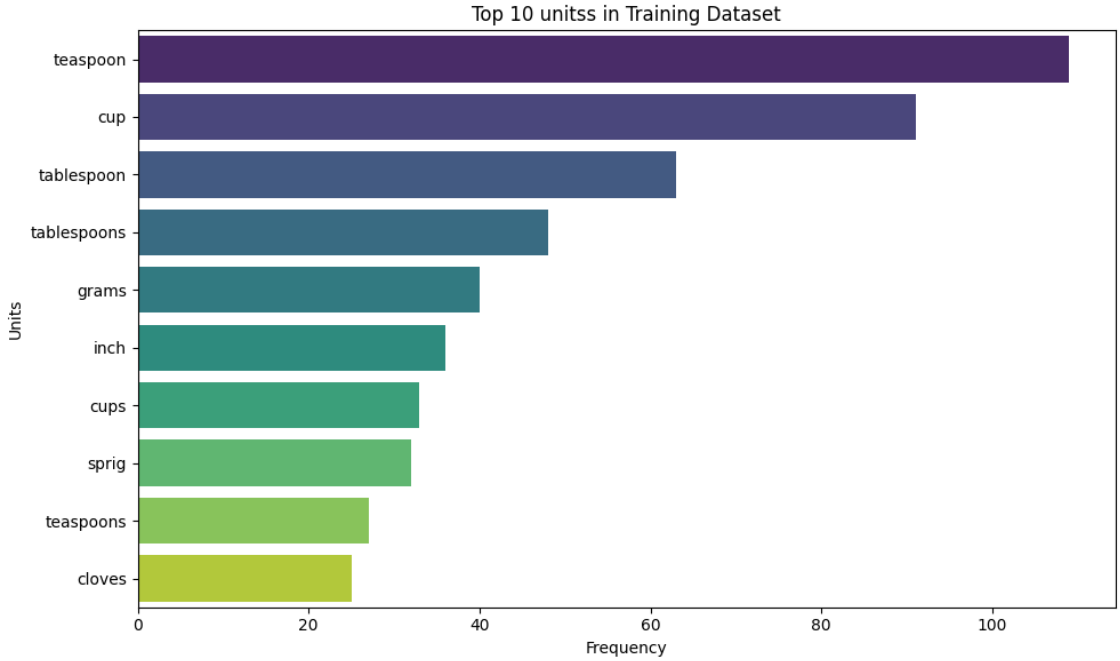
3. Visualizations and Insights

Entity Frequency

Visual analysis showed that common ingredients like **powder**, **salt**, and **seeds** were among the most frequently mentioned. Similarly, **teaspoon**, **cup**, and **tablespoon** were the top units identified in the dataset.





- Ingredients are the most frequently tagged entity.
- Units and quantities follow consistent patterns, making them easier to recognize.

Model Performance

Entity	Precision	Recall	F1-score	Support
Ingredient	0.99	0.99	0.99	1611
Quantity	0.99	0.97	0.98	294
Unit	0.96	0.95	0.95	244
Overall Accuracy			**0.98**	2149

Insights:

- Ingredient detection is highly accurate, thanks to effective feature design.
- Quantities and units have slightly lower recall, possibly due to irregular expressions like "a pinch" or "half".
- The model is well-balanced, with macro and weighted F1-scores around 0.97–0.98.

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4. Assumptions Made

- The dataset is accurately annotated using the IOB format.
- Each sentence or recipe line is treated independently.
- The model does not rely on pretrained embeddings or language models.
- All features are manually engineered.

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5. Conclusion

The CRF-based NER model achieves strong performance with 98% overall accuracy in identifying entities in recipe data. Its success demonstrates the effectiveness of traditional feature-based models in structured text domains where patterns are predictable and consistent.
