AUTOMATED RECIPE CREATION USING RECURRENT NEURAL NETWORKS

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Approach

- Gathered an extensive database of actual recipe texts and preprocessed the information by eliminating special characters and changing it to lowercase.
- In order to prepare input-target sequences for next-character prediction, each distinct character was mapped to a numeric index.
- Recurrent Neural Network (RNN) model with Dense, LSTM, and Embedding layers was constructed and trained to reduce loss and increase accuracy
- Using a seed input, the trained model predicts one character at a time to create new recipe instructions.

01 **Dataset Collection**

02 **Text Cleaning and Preprocessing**

03 **Character Mapping and Sequence Preparation**

04 **RNN Model Building**

05 **Model Training**

05 **Evaluate Model**

06 **Recipe Generation from seed text**

Character-Based Deep Learning for Recipe Text Generation Using LSTM Networks

In today's hectic world, meal planning and recipe writing can be difficult, particularly when adjusting to new resource, cultural, and culinary contexts.

This research investigates the automatic generation of realistic recipe instructions, character by character, using deep learning, more especially Recurrent Neural Networks (RNNs).

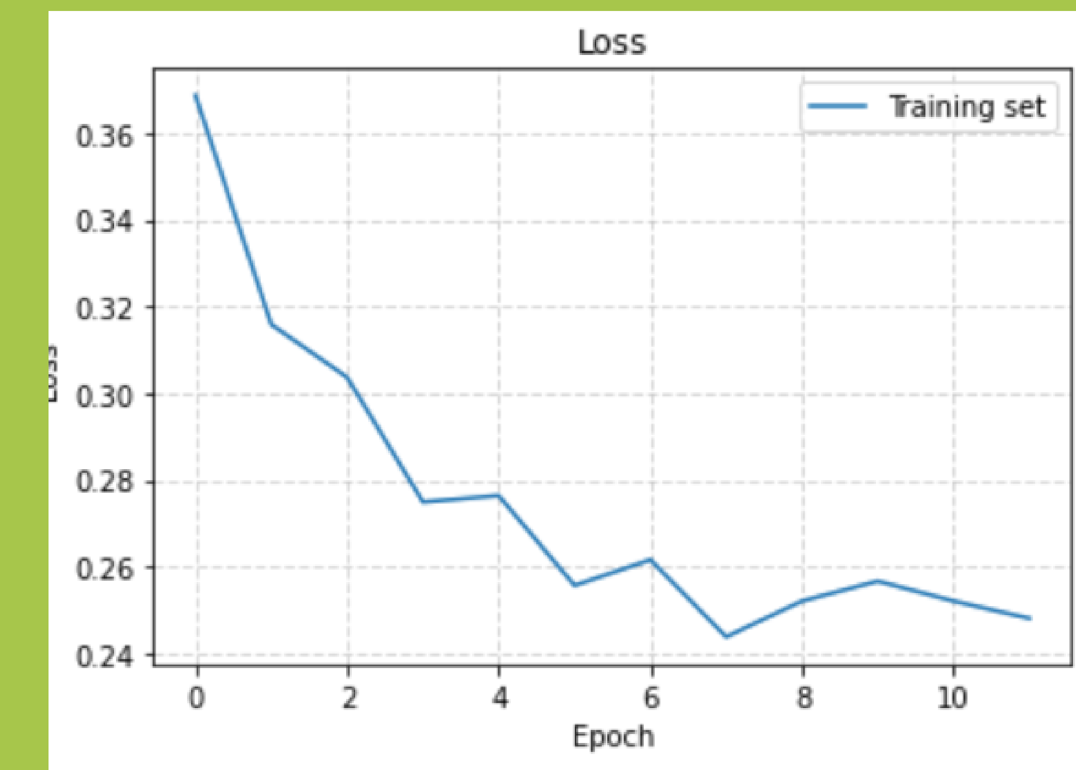
Our model learns the natural order, structure, and style of cooking instructions through extensive training on genuine recipes, allowing for the dynamic generation of new, cohesive recipes.

Model Structure and Components

- Sequential RNN architecture for character-level prediction.
- Embedding Layer: Converts character indices into dense feature vectors.
- LSTM Layer: Captures sequence patterns and dependencies.
- Dense Layer: Predicts the next character from learned features.
- Loss Function: Sparse Categorical Crossentropy.
- Optimizer: Adam

```
Model: "sequential_13"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_13 (Embedding)     (64, None, 256)           45056
_________________________________________________________________
lstm_9 (LSTM)                (64, None, 1024)          5246976
_________________________________________________________________
dense_8 (Dense)              (64, None, 176)           180400
=================================================================
Total params: 5,472,432
Trainable params: 5,472,432
Non-trainable params: 0
```

Training Results



- Final Accuracy: 65.7%
- Final Loss: 1.28
- Initial Accuracy: ~55%
- Initial Loss: ~2.0

The model demonstrated strong convergence.

Loss decreased consistently across epochs.

Accuracy steadily improved as the model learned the structure of recipe text.

Early stopping was applied to prevent overfitting.

Future Work

- Upgrade to word-level models for better grammatical quality.
- Expand training datasets to cover broader cuisine types.
- Explore Transformer architectures (e.g., GPT models) for superior results.
- Implement ingredient-specific or diet-specific recipe generation controls.