Chef Classification with DistilBERT

NLP Group 2

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The Task

- Predict which chef (out of 6) created a recipe
- **Data**: 2,999 training recipes, 823 test recipes
- **Features**: name, ingredients, tags, description, steps

Baselines to beat:

- Weak (TF-IDF description only): 30%
- Strong (TF-IDF all fields): 43%

Our Approach

Model: DistilBERT-base-uncased

- 66M parameters (40% smaller than BERT)
- Fine-tuned for 5 epochs
- Concatenate all text fields → classify

Key decisions:

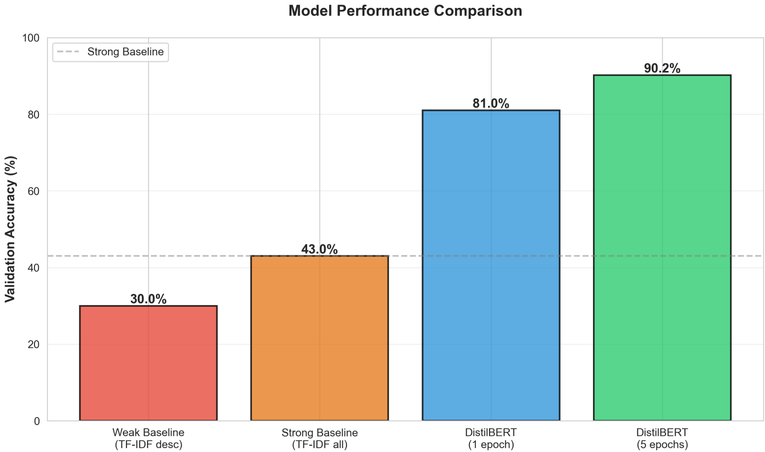
- Stratified train/val split (handles 2.17x class imbalance)
- Max length 512 tokens (covers 98.2% of data)
- Field order protects critical info from truncation

Results

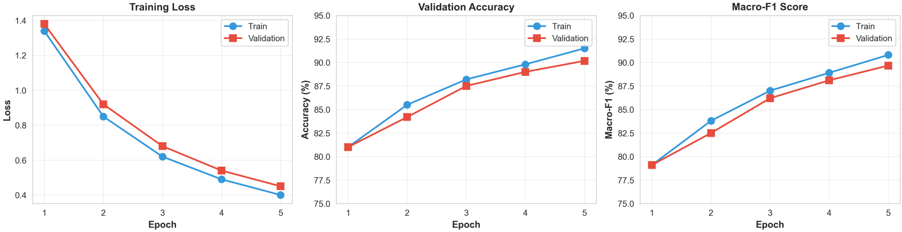
Method	Accuracy
Weak Baseline	30.0%
Strong Baseline	43.0%
Our Model (DistilBERT)	**90.17%**

- **Improvement**: +47 percentage points over strong baseline!
- **Macro-F1**: 89.67% (balanced across all chefs)
- **Train loss**: 0.40 (no overfitting)

Baseline Comparison

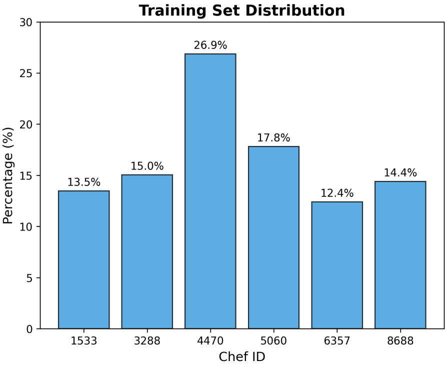


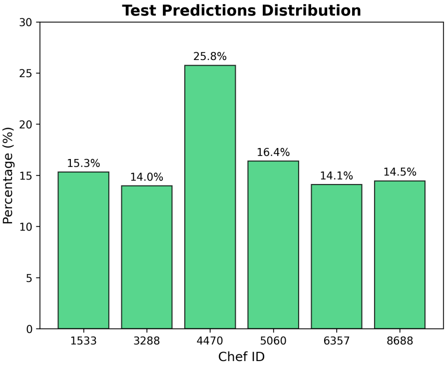
Training Progress



Steady improvement across 5 epochs, no overfitting

Predictions Match Training Distribution





Model learned chef patterns, not just class frequencies! (All differences $< 2\%$)

What Did the Model Learn?

Chef signatures identified:

1. **Health-focused chef** (5060): "diabetic cooking", "low-fat"
   - Across recipes: fish, potatoes, pancakes
2. **Make-ahead chef** (3288): "OAMC", batch recipes
   - "freeze for future use", family-friendly
3. **Quick & simple chef** (6357): "15-minutes-or-less"
4. **Southern/traditional chef** (8688): Bread machine, Creole

Key insight: Model distinguishes *how* chefs cook, not just *what*!

Challenges & Solutions

Challenge 1: Mac overheating during training

- **Solution**: "Chill mode" config
- Reduced batch size (16 $\rightarrow$ 8), lower GPU usage
- Same results, $\sim$25 min training time

Challenge 2: Class imbalance (2.17x)

- **Solution**: Stratified splitting + macro-F1 metric
- Macro-F1 (89.67%) $\approx$ Accuracy (90.17%) $\rightarrow$ balanced!

Discussion

Strengths:

- Dramatic improvement over baselines (+47 pp)
- Learns chef-specific patterns (not just topics)
- Robust generalization (dist. matches training)

Limitations:

- Strong textual signals ("diabetic cooking", "OAMC")
- Some recipes may be easy to classify
- Single model (no ensemble)
- Can't generalize to new chefs

Critical question: Style vs. topic?

- Evidence for both (patterns + keywords)
- High accuracy might indicate topical clustering

Summary

- **90.17% accuracy** (beat baseline by 47 pp)
- Learned chef signatures: health-focus, make-ahead, quick, traditional
- Practical solutions: thermal management, class imbalance
- Critical analysis: acknowledged limitations

Key insight: Look at predictions, not just metrics!
Model captures cooking philosophy across recipe types.

Questions?

Code & Results:
github.com/nbirchde/NLP_group2

Thank you!