**Hybrid BERT vs Hybrid BERT with Hypertuning**

**Common Foundation:**

Both reports describe a **hybrid machine learning model** that combines:

* **BERT** for contextual embedding of product descriptions.
* **LightGBM** for structured classification to predict the **week (1–8) when a product will be on discount**.
* Input features such as product descriptions, historical sale data, and price information.
* A synthetic dataset of approximately **24,575 samples** across 8 weeks.

**Key Differences:**

|  |  |  |
| --- | --- | --- |
| **Category** | **Hybrid BERT** | **Hybrid BERT with Hypertuning** |
| **Feature Engineering** | Minimal detail; limited to raw features like product description, last sale week, price changes | Extensive feature engineering: days since last sale, price diff, average cycle, is discounted |
| **Hyperparameter Tuning** | Not explicitly used; LightGBM uses default or lightly tuned parameters | **Yes — Optuna used** to optimize parameters like learning\_rate, num\_leaves, max\_depth, min\_data\_in\_leaf |
| **Best Parameters** | Not reported | Best trial (Trial 14): learning\_rate=0.147, num\_leaves=134, max\_depth=6, min\_data\_in\_leaf=47 |
| **Model Accuracy** | **0.698 (69.8%)** | **0.8908 (89.1%)** — Significant improvement post tuning and feature engineering |
| **Macro F1 Score** | **0.670** | **0.7797** |
| **Weighted F1 Score** | **0.701** | **0.8903** |
| **RMSE / MAE** | **RMSE: 1.11 weeks**, **MAE: 0.52 weeks** | **RMSE: 0.5259 weeks**, **MAE: 0.1538 weeks** — Indicating better proximity to actual values |
| **Classification Report** | Summarized with macro and weighted averages | **Detailed per-class metrics** for Weeks 1 to 8, showing performance class-wise |
| **Confusion Matrix** | Basic diagonal dominance and adjacent week misclassifications | Specific callouts: high accuracy for Weeks 4–8, Week 1 misclassified due to class imbalance |
| **Visual Analysis** | Mentioned, but not supported with detailed figures or insights | **Bar chart analysis** of precision, recall, F1 per class + prediction error distribution included |
| **Challenges & Fixes** | Only recommendations | **Detailed list of encountered issues** and how each was resolved (e.g., BERT integration, LightGBM warnings) |
| **Recommendations for Future Work** | High-level: handle imbalance, try alternate models | Detailed: SMOTE, RetailBERT, class weights, real-time API, time-based CV splits, probability thresholds |
| **Conclusion** | Describes the hybrid model’s strengths and general effectiveness in forecasting | **Emphasizes the enhanced accuracy, error reduction**, and readiness for real-time deployment |

**Summary:**

|  |  |  |
| --- | --- | --- |
| **Aspect** | **Hybrid BERT** | **Hybrid BERT with Hypertuning** |
| Completeness | Moderate | High |
| Performance | Acceptable | Excellent |
| Technical Depth | Moderate | Advanced |
| Use of Tuning & FE | No | Yes |
| Evaluation | General | Granular + Visual |

**Recommendation:**

**Hybrid BERT with Hypertuning** is a **significantly improved** version of the initial model, achieving:

* Better model accuracy and generalization.
* Reduced error rates (RMSE & MAE).
* Clear class-wise performance visibility.
* Robust pipeline ready for deployment or further research.