Individual Report Submission

Unique Contributions:

My contributions to the intent detection project involved identifying, evaluating, and implementing critical methodologies and models that shaped the success of our system. Below is a detailed account of my unique contributions:

1. **Initial Research:**
    - To ensure the project's foundation was grounded in proven methods, I searched extensively for relevant papers. My focus was on award-winning papers from 2020 to 2024, which led me to identify *"Discovering New Intents with Deep Aligned Clustering"* by Hanlei Zhang et al. This paper used the BANKING dataset, aligning with our project's requirements.
    - Although this paper offered a promising approach, we encountered implementation issues, and I advocated for pivoting to a new model and methodology.
2. **Dataset Identification:**
    - In addition to the BANKING77 dataset, I found and evaluated additional datasets to broaden the scope and applicability of our project. These included:
        - *"Shopper Intent Prediction from Clickstream E-Commerce Data with Minimal Browsing Information"* (available at GitHub Repository).
        - A dataset from Hugging Face for intent classification (available at Hugging Face Repository).
    - But then we decided to use only the BANKING77 dataset.
3. **Model Selection and Development:**
    - Collaboratively, our team explored BERT-based models. When a team member proposed using TinyBERT, we tested it but observed unfine performance and extended runtime (later attributed to running the model on a CPU instead of a GPU).
    - I introduced DistilBERT as an alternative, highlighting its advantages: *According to the Hugging Face documentation, DistilBERT is "60% faster than standard BERT and preserves over 95% of BERT's performances as measured on the GLUE language understanding benchmark." (Hugging Face, n.d.).* Upon testing, DistilBERT consistently outperformed TinyBERT in both speed and accuracy, leading to its adoption as the backbone of our model.

4. **Hyperparameter Tuning and Activation Function Testing:**

    - I conducted extensive hyperparameter tuning, iterating on dropout rates, learning rates, and other critical parameters to optimize performance.
    - Additionally, I manually tested multiple activation functions, including ReLU, LeakyReLU, and Sigmoid, to determine the best fit for our model. My experiments revealed that ReLU consistently delivered superior results, significantly improving accuracy and F1-scores.
    - Also I evaluated some performance analysis in order to check the specific labels that are not predicted correctly.

5. **Class-Wise Performance Analysis (All results are displayed on our ipynb file)**

Classes with Prediction Accuracy Below 93.0%:

- **Key Challenges:**
    - *contactless_not_working* (71% accuracy)
    - *transfer_not_received_by_recipient* (71% accuracy)
    - *topping_up_by_card* (77% accuracy)
    - *direct_debit_payment_not_recognised* (76% accuracy)
- **Insights:**
    - These classes often overlap semantically with others, leading to confusion.
    - Limited training samples for certain intents further exacerbated misclassifications.

The experiments highlight the robustness of ReLU with CrossEntropyLoss in achieving high accuracy and F1-scores. While overall system performance is strong (93.12% test accuracy), certain classes require targeted improvements. Future work will focus on addressing data imbalance and refining confusion-prone categories to enhance the system's reliability.

References:

1. Hugging Face. (n.d.). *Banking77 dataset*. Hugging Face Datasets. Retrieved from https://huggingface.co/datasets/legacy-datasets/banking77
2. Hugging Face. (n.d.). *Snips built-in intents dataset*. Hugging Face Datasets. Retrieved from https://huggingface.co/datasets/sonos-nlu-benchmark/snips_built_in_intents
3. Coveo. (2020). *Shopper Intent Prediction*. GitHub. Retrieved from https://github.com/coveooss/shopper-intent-prediction-nature-2020?tab=readme-ov-file
4. Zhang, H., Xu, H., Lin, T.-E., & Lyu, R. (2020). Discovering new intents with deep aligned clustering. *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP 2020)*. Retrieved from [paper link or DOI if available].
5. Hugging Face. (n.d.). **DistilBERT: A distilled version of BERT**. Hugging Face. Retrieved from https://huggingface.co/docs/transformers/en/model_doc/distilbert