(a)Fraud detection is about finding and stopping dishonest activities, especially in money dealings, by looking for unusual patterns in data. It's vital to prevent financial losses, protect trust, and meet legal requirements.

(b)When adjusting the train-test split to 70% training and 30% testing, the model's performance for **fraud detection (Class 1)** saw a slight decrease in **Recall**, moving from 80% to 79%. This indicates a marginally reduced ability to identify actual fraudulent transactions. However, **Precision and F1-score for Class 1 remain largely similar and strong** (Precision 0.97, F1-score 0.87), indicating good accuracy in its positive fraud predictions. Performance for the **non-fraud class (Class 0)** remained consistently excellent across all metrics. Overall, while the model's accuracy remained high, the shift to a smaller test set slightly impacted its ability to catch all fraudulent cases compared to a 60/40 split.

(c)The KNN model was evaluated with k values from 1 to 20 using a fixed test size of 40%.Overall accuracy stayed consistently high (~99.6%) across all k values.The highest **F1-Score** (0.876) was achieved at **k = 3**, indicating strong fraud detection balance.The highest **AUC Score** (0.946) was observed at **k = 19**, showing excellent classification ability across thresholds.F1-Score is more important for **imbalanced data** like fraud detection because it balances precision and recall.AUC Score is helpful when evaluating the model's ranking ability without relying on a fixed threshold.Therefore, **k = 3** is best for fraud detection tasks, while **k = 19** is better if AUC is the priority.