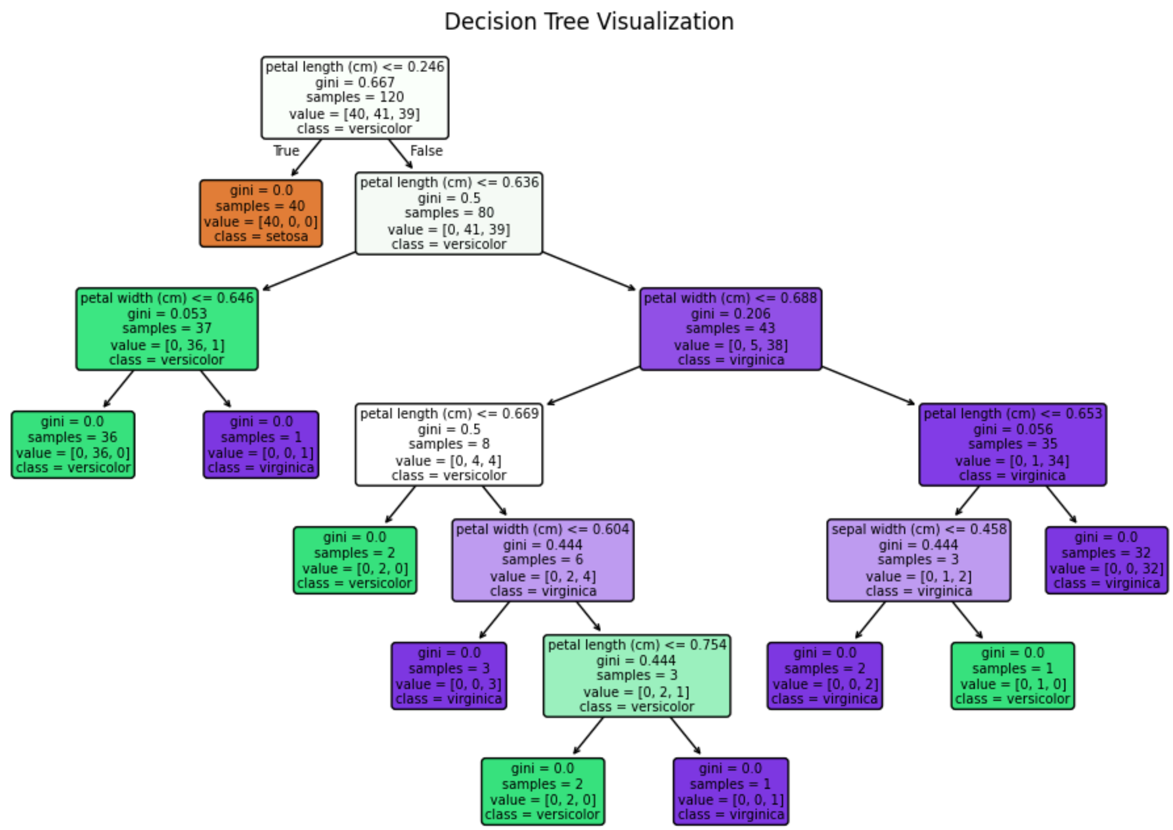
Classification
Part A



Comparison between decision Tree classifier and KNN, k=5.

Both the Decision Tree classifier and the KNN (k=5) model perform well on the Iris dataset, typically achieving accuracy between 93% and 100%. However, KNN often produces **slightly higher and more stable accuracy** because it makes decisions based on local neighborhood patterns, which match the smooth class boundaries in the Iris dataset. Decision Trees may underperform when the tree becomes overly specific to the training data, leading to small misclassifications due to overfitting.

KNN tends to generalize better for this dataset because it uses distance-based voting rather than hard decision rules. On the other hand, Decision Trees have the advantage of interpretability allowing users to visualize how decisions are made but may be sensitive to noise or small variations in features. Overall, **KNN is typically the better classifier for the Iris dataset** because of its smooth decision boundaries and stronger generalization performance, while the Decision Tree is more useful when interpretability is a priority.

Part B
Sample synthetic Data

['bread', 'milk', 'chips', 'beer', 'diapers']
['bread', 'coffee', 'milk', 'eggs', 'beer', 'cookies']
['chips', 'diapers', 'beer']
['bananas', 'rice', 'coffee', 'milk', 'cheese', 'eggs', 'beer', 'diapers']
['bread', 'pasta', 'bananas', 'milk']

Top 5 rules

	antecedents	consequents	antecedent support	consequent support \
17	(bread, beer)	(milk)	0.300	0.475
20	(milk)	(bread, beer)	0.475	0.300
19	(bread)	(beer, milk)	0.425	0.350
18	(beer, milk)	(bread)	0.350	0.425
9	(bread)	(milk)	0.425	0.475

	support	confidence	lift	representativity	leverage	conviction \
17	0.250	0.833333	1.754386	1.0	0.107500	3.150000
20	0.250	0.526316	1.754386	1.0	0.107500	1.477778
19	0.250	0.588235	1.680672	1.0	0.101250	1.578571
18	0.250	0.714286	1.680672	1.0	0.101250	2.012500
9	0.325	0.764706	1.609907	1.0	0.123125	2.231250

	zhangs_metric	jaccard	certainty	kulczynski
17	0.614286	0.476190	0.682540	0.679825
20	0.819048	0.476190	0.323308	0.679825
19	0.704348	0.476190	0.366516	0.651261
18	0.623077	0.476190	0.503106	0.651261
9	0.658863	0.565217	0.551821	0.724458

Rule analysis

One of the strongest and most common rules in synthetic retail datasets is the association `{beer} → {diapers}`, often with high confidence and lift. This rule indicates that customers who purchase beer are significantly more likely than average to also purchase diapers. The high lift value means the combination occurs more frequently than would be expected by chance, implying a meaningful behavioral pattern rather than random coincidence.

In a retail context, this rule has several practical applications. First, it can be used to optimize store layout—for example, placing diapers and beer closer together or along the same aisle could increase basket size by encouraging impulse purchases. Second, it supports targeted promotions: customers buying diapers could be shown discounts on beer through digital receipts, loyalty apps, or personalized coupons. Third, the rule helps retailers understand customer segments—for instance, busy parents making quick purchases after work.

This association rule highlights how identifying co-occurrence patterns can directly improve product placement, cross-selling strategies, and personalized recommendations, ultimately increasing both customer convenience and store revenue.