

இப்படத்தில் வரும் சம்பவங்கள் யாவும் கற்பனையே.. நேத்தின் அளவிற்கு கொடூரமாவை அல்ல..

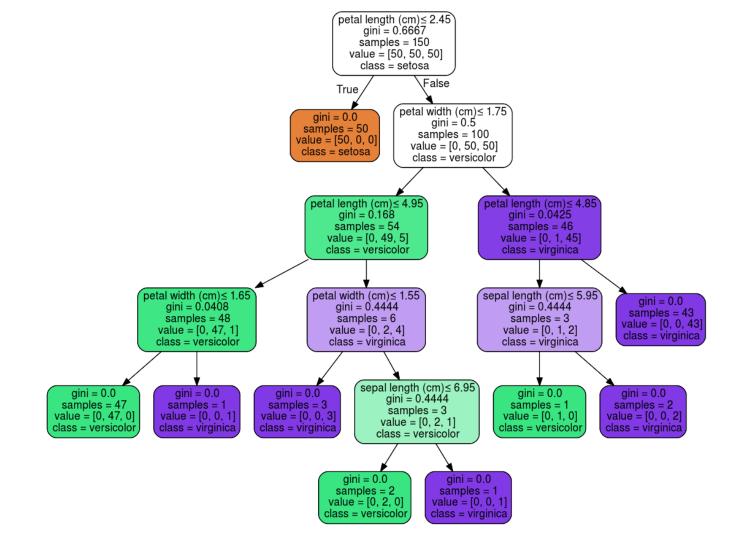
இதுவரை – ID3 vs C4.5 vs CART



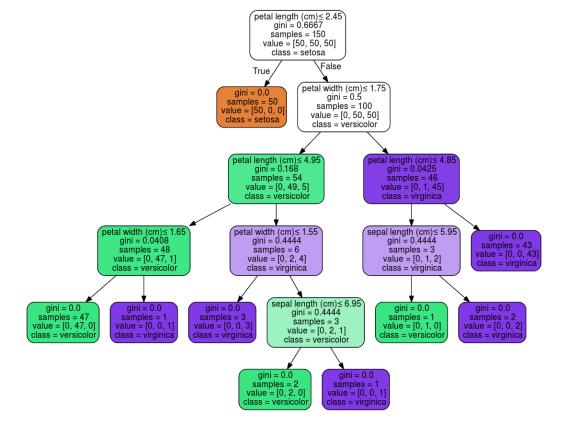
Decision Trees Comparison

Features	ID3	C4.5	CART
Type of data	Categorical	Continuous and	continuous and
P1. D-		Categorical	nominal
.,/0	25		attributes data
Speed	Low	Faster than ID3	Average
Boosting	Not supported	Not supported	Supported
Pruning	No \	Pre-pruning	Post pruning
Missing Values	Can't deal with	Can't deal with	Can deal with
Formula	Use information	Use split info	Use Gini
	entropy and	and gain ratio	diversity index
	information Gain		

• Simple to understand, interpret, visualize.



• Decision trees implicitly perform variable screening or feature selection.





• Can handle both numerical and categorical data. Can also handle multi-output problems.



• Decision trees require relatively *little effort from users for data preparation*.



 People tend to believe Decision Trees because we can give justification on why model choose to give an output



• Decision-tree learners can create over-complex trees that do not generalize the data well. This is called overfitting.



 Decision trees can be unstable because small variations in the data might result in a completely different tree being generated. This is called variance, which needs to be lowered by methods like bagging and boosting.



 Greedy algorithms cannot guarantee to return the globally optimal decision tree. This can be mitigated by training multiple trees, where the features and samples are randomly sampled with replacement.



• Decision tree learners create *biased trees if some classes dominate*. It is therefore recommended to balance the data set prior to fitting with the decision tree.



Decision Tree Applications

- Business Management
- Customer Relationship Management
- Fraudulent Statement Detection
- Energy Consumption
- Fault Diagnosis
- Healthcare Management

