NAWAF ALHARBI MP-2 SOLUTION

1. Classification: Playing Tennis (10 points) Provide necessary steps in the problem solving (e.g. list the steps and intermediate results to calculate entropy, information gain, and GainRatio, prior probabilities). Draw the final decision trees (e.g. use Powerpoint to draw and save as a picture or any other way you prefer)

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

a) Build a decision tree using ID3 algorithm (Information Gain). (3 pts)

b) Build a decision tree using CART algorithm (Gini index). (3 pts)

c) Make predictions of (D15: Rain, Mild, Normal, Strong) using both trees. (2 pts)

d) Use Naïve Bayes classifier to predict the result in (c). (2 pts)

Part A) Build a decision tree using ID3 algorithm (Information Gain).

$$\text{Entropy} = \sum_i - p_i \log_2 p_i$$

$$\Delta = I(before\ splitting) - I(after\ spiltting)$$
$$\Delta = I(parent) - weighted\_average\ (I(children))$$

First we need to calculate the Parent Entropy = $-\frac{9}{14}\log_2\frac{9}{14} - \frac{5}{14}\log_2\frac{5}{14} = 0.9403$

Now we have to calculate the entropy for each class (i.e. Outlook Temperature …etc.) and subtract it from the parent. The one which has gain we choose it as root node.

For outlook we have three subclasses (sunny, overcast and rain) we will calculate the entropy for each subclass and average their entropy.

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes

Entropy (decision | outlook = Sunny) = $-\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5} = 0.9710$

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D3	Overcast	Hot	High	Weak	Yes
D7	Overcast	Cool	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes

Entropy (decision | outlook = Overcast) = 0 (pure set).

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D10	Rain	Mild	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Entropy (decision | outlook = Rain) = $-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5} = 0.9710$

Now we average them as follow:

p(sunny) * Entropy(Sunny) + p(overcast) * Entropy (Overcast) + p(Rain) * Entropy(Rain)

= 5/14 * $0.97 + \frac{4}{14} * 0 + \frac{5}{14} * 0.97 = 0.6936$

Now we calculate the information gain of outlook as follow.

Information Gain (outlook) = 0.9403 **-** 0.6936**= 0.2467**

Now we do the same for temperature

For temperature we have three subclasses (hot, mild and cool) we will calculate the entropy for each subclass and average their entropy.

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D13	Overcast	Hot	Normal	Weak	Yes

Entropy (decision | Temperature = hot) = $-\frac{2}{4}\log_2\frac{2}{4} - \frac{2}{4}\log_2\frac{2}{4} = 1$

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D4	Rain	Mild	High	Weak	Yes
D8	Sunny	Mild	High	Weak	No
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Entropy (decision | Temperature = mild) = $-\frac{4}{6}\log_2\frac{4}{6} - \frac{2}{6}\log_2\frac{2}{6} = 0.9183$

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D9	Sunny	Cool	Normal	Weak	Yes

Entropy (decision | Temperature = cool) = $-\frac{3}{4}\log_2\frac{3}{4} - \frac{1}{4}\log_2\frac{1}{4} = 0.8113$

Now we average them as follow:

p(hot) * Entropy(hot) + p(mild) * Entropy (mild) + p(cool) * Entropy(cool)

= 4/14 * $1 + \frac{6}{14} * 0.9183 + \frac{4}{14} * 0.8113 = 0.9111$

Now we calculate the information gain of outlook as follow: parent entropy- entropy of outlook.

Information Gain (Temperature) = 0.9403 **-** 0.9111**= 0.0292**

Now we do the same for humidity

For humidity we have two subclasses (high and normal) we will calculate the entropy for each subclass and average their entropy.

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D8	Sunny	Mild	High	Weak	No
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Entropy (decision | Humidity= high) = $-\frac{3}{7}\log_2\frac{3}{7} - \frac{4}{7}\log_2\frac{4}{7} = 0.9852$

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes

Entropy (decision | Humidity= high) = $-\frac{6}{7}\log_2\frac{6}{7} - \frac{1}{7}\log_2\frac{1}{7} = 0.5917$

Now we average them as follow:

p(high) * Entropy(high) + p(normal) * Entropy (normal)

= 7/14 * $0.9852 + \frac{7}{14} * 0.5917 = 0.7884$

Information Gain (Humidity) = 0.9403 **-** 0.7884 = **0.1519**

Now we do the same for wind

For humidity we have two subclasses (strong and weak) we will calculate the entropy for each subclass and average their entropy.

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D2	Sunny	Hot	High	Strong	No
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D14	Rain	Mild	High	Strong	No

Entropy (decision | wind = strong) = - $\frac{3}{6}\log_2\frac{3}{6}$ - $\frac{3}{6}\log_2\frac{3}{6} = 1$

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D13	Overcast	Hot	Normal	Weak	Yes

Entropy (decision | wind = weak) = - $\frac{6}{8}\log_2\frac{6}{8}$ - $\frac{2}{8}\log_2\frac{2}{8} = 0.8113$

Now we average them as follow:

p(strong) * Entropy(strong) + p(weak) * Entropy (weak)

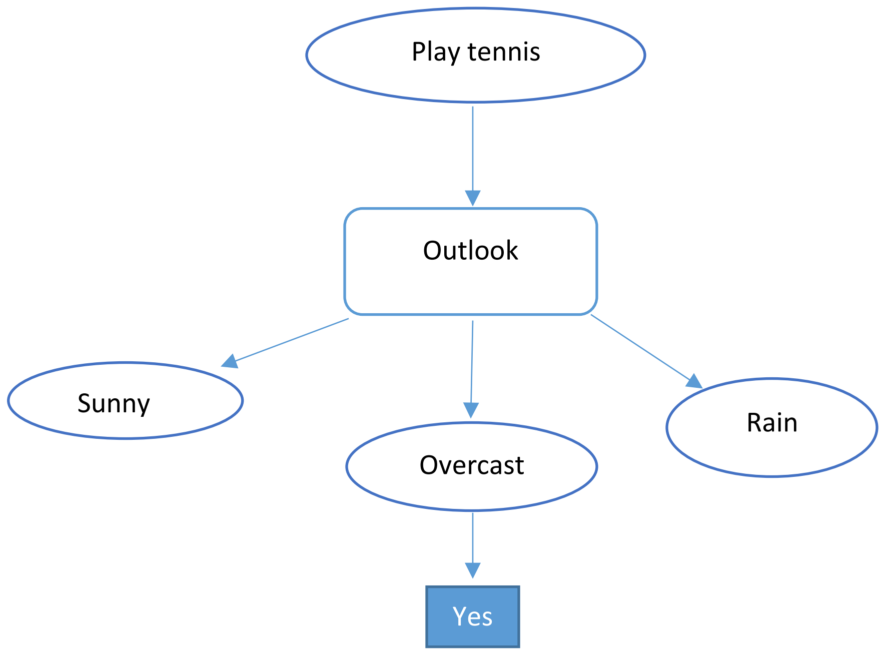
= 6/14 * $1 + \frac{8}{14} * 0.8113 = 0.8922$

Information Gain (wind) = 0.9403 **-** 0.8922 **= 0.0481**

Information Gain (outlook)	**0.2467**
Information Gain (Temperature)	0.0292
Information Gain (Humidity)	0.1519
Information Gain (wind)	0.0481

According to ID3 algorithm we choose the node that has the highest information gain which is outlook.

Now the decision tree look like this



Now our new data is the sunny data. we will calculate parent node for it and calculate information gain for the other classes (temperature , humidity and wind) holding sunny as parent node.

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes

First we need to calculate the **Sunny Parent Entropy** = $-\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}$ = **0.9710**

We calculate entropy for **temperature** (i.e. average entropy for hot, mild, and cold)

E (hot) = $-0-\frac{2}{5}\log_2\frac{2}{5}$ = 0.5288, E (mild) =1, E (cool) = $-\frac{1}{5}\log_2\frac{1}{5} - 0$ = 0.4644

Now we average them as follow

p(hot) * Entropy(hot) + p(mild) * Entropy (mild) + p(cool) * Entropy(cool)

2/5 * 0.5288 + 2/5 * 1 + 1/5 * 0.4644 = 0.7044

Information Gain @ sunny (temperature) = 0.9710 **-** 0.7044 = **0.2666**

We will do the same for humidity and wind

We calculate entropy for **humidity** (i.e. average entropy for high and normal)

E (high) = $-0-\frac{3}{5}\log_2\frac{3}{5}$ = 0.4422 E (normal) = $-\frac{2}{5}\log_2\frac{2}{5}-0$ = 0.5288

Now we average them as follow

p(high) * Entropy(high) + p(normal) * Entropy (normal)

3/5 * 0.4422 + 2/5 * 0.5288 = 0.4768

Information Gain @ sunny (humidity) = 0.9710 – 0.4768 = **0.4942**

We calculate entropy for **wind (**i.e. average entropy for strong and weak)

E (strong) = 1 E (weak) = $-\frac{1}{3}\log_2\frac{1}{3}-\frac{2}{3}\log_2\frac{2}{3}$ = 0.9183

Now we average them as follow

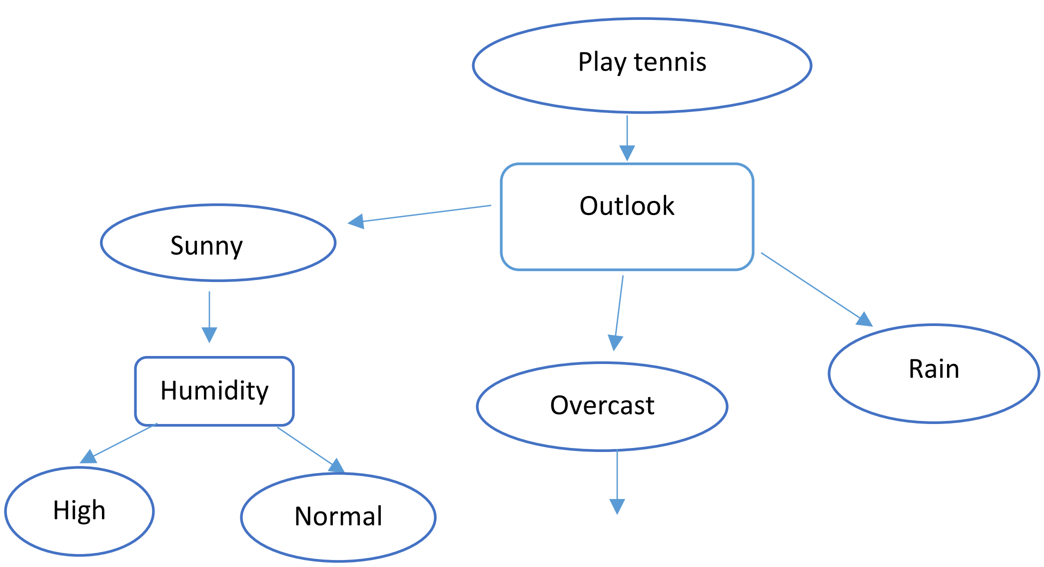
p(strong) * Entropy(strong) + p(weak) * Entropy (weak)

2/5 * 1 + 3/5 * 0.9183 = 0.9510

Information Gain @ sunny (wind) = 0.9710 – 0.9510 = **0.0200**

Information Gain @ sunny (Temperature)	0.2666
Information Gain @ sunny (Humidity)	**0.4942**
Information Gain @ sunny (wind)	0.0200

We will choose the one with high information gain, now our tree looks like this



Yes

Now our new data is the rain data. We will calculate parent node for it and calculate information gain of the other classes (temperature, humidity and wind) holding rain as parent node.

No

Yes

Day	Outlook	Temperature	Humidity	Wind	Play Tennis
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D10	Rain	Mild	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

First we need to calculate the **Rain Parent Entropy** = $-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}$ = **0.8236**

We calculate entropy for **temperature** (i.e. average entropy for hot, mild, and cold)

E (hot) = 0 , E (mild) = $-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}$ = 0.9183 , E (cool) = 1

Now we average them as follow

p(hot) * Entropy(hot) + p(mild) * Entropy (mild) + p(cool) * Entropy(cool)

0 + 3/5* 0.9183 + 2/5 *1 = 0.9510

Information Gain @ Rain (temperature) = 0.9710 **-** 0.9510 = **0.0200**

We calculate entropy for **humidity** (i.e. average entropy for high and normal)

E (high) = 1 , E (normal) = $-\frac{2}{3}\log_2\frac{2}{3} - \frac{1}{3}\log_2\frac{1}{3}$ = 0.9183

Now we average them as follow: p(high) * Entropy(high) + p(normal) * Entropy (normal)

2/5 * 1 + 3/5 * 0.9183 = 0.9510

Information Gain @ Rain (humidity) = 0.9710 – 0.9510 = $\mathbf{0.0200}$

We calculate entropy for **wind (**i.e. average entropy for strong and weak)

E (strong) = $-0 - \frac{2}{5}\log_2\frac{2}{5}$ = 0.5288 E (weak) = $-\frac{3}{5}\log_2\frac{3}{5} - 0$ = 0.4422

Now we average them as follow: p(strong) * Entropy(strong) + p(weak) * Entropy (weak)

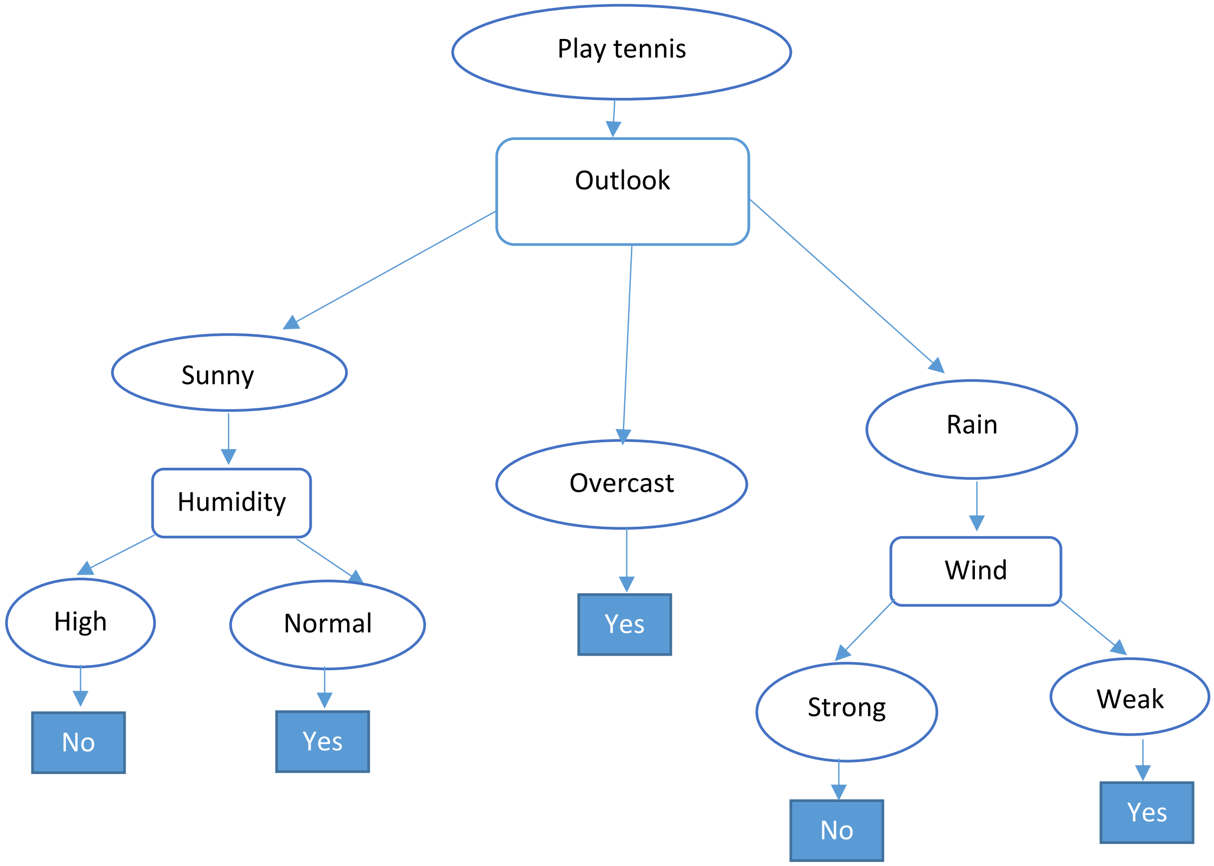
2/5 * 0.5288 + 3/5 * 0.4422 = 0.4768

Information Gain @ sunny (wind) = 0.9710 – 0.9510 **= 0.4942**

Information Gain @ sunny (Temperature)	0.0200
Information Gain @ sunny (Humidity)	0.0200
Information Gain @ sunny (wind)	**0.4942**

We will choose the one with high information gain, now our tree looks like this

Now our final decision tree is as follow



Part b) Build a decision tree using CART algorithm (Gini index).

If a data set D contains examples from n classes, gini index, gini(D) is defined as

$$gini(D) = 1 - \sum_{j=1}^{n} p_j^2$$

If a data set D is split on A into two subsets D1 and D2, the gini index gini(D) is defined as

$$gini_A(D) = \frac{|D_1|}{|D|} gini(D_1) + \frac{|D_2|}{|D|} gini(D_2)$$

§ Reduction in Impurity:

$$\Delta gini(A) = gini(D) - gini_A(D)$$

First we compute gini index for dataset as follow:

$1 - \left(\frac{9}{14}\right)^2 - \left(\frac{5}{14}\right)^2$ = 0.4592

Now we will calculate gini index for each class attributes as follow

First outlook:

Gini (PlayTennis| Outlook =Sunny) = $1 - \left(\frac{2}{5}\right)^2 - \left(\frac{3}{5}\right)^2$ = 0.4800

Gini (PlayTennis| Outlook =Overcast) = $1 - \left(\frac{4}{4}\right)^2 - 0^2 = 0$

Gini (PlayTennis| Outlook =Rain) = $1 - \left(\frac{3}{5}\right)^2 - \left(\frac{2}{5}\right)^2$ = 0.4800

Therefore, the Gini index after the outlook test is applied is

Gini (outlook) = 5/14 * 0.4800 + 4/14 * 0 + 5/14 * 0.4800 = 0.3429

Delta gini(outlook)= gini(play_tennis)- gini (outlook) = 0.4592-0.3429= **0.1163**

Now we do the same for temperature

Gini (PlayTennis| Temperature =Hot) = $1 - \left(\frac{2}{4}\right)^2 - \left(\frac{2}{4}\right)^2$ = 0.5000

Gini (PlayTennis| Temperature =Mild) = $1 - \left(\frac{4}{6}\right)^2 - \left(\frac{2}{4}\right)^2$ = 0.3056

Gini (PlayTennis| Temperature =Cool) = $1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2$ = 0.3750

Therefore, the Gini index after the Temperature test is applied is

4/14 * 0.5000+ 6/14 * 0.3056 + 4/14 * 0.3750 = 0.3810

Delta gini(temperature)= gini(play_tennis)- gini (temperature) = 0.4592-0.3810= **0.0782**

Now we do the same for humidity

Gini (PlayTennis|Humidity=High) = $1 - \left(\frac{3}{7}\right)^2 - \left(\frac{4}{7}\right)^2$ = 0.4898

Gini (PlayTennis|Humidity=Normal) = $1 - \left(\frac{6}{7}\right)^2 - \left(\frac{1}{7}\right)^2$ = 0.2449

Therefore, the Gini index after the humidity test is applied is

7/14 *0.4898 + 7/14 * 0.2449 = 0.3674

Delta gini(Humidity)= gini(play_tennis)- gini (humidity) = 0.4592-0.3674= **0.0918**

Now we do the same for wind

Gini (PlayTennis|Wind=strong) = $1 - \left(\frac{3}{6}\right)^2 - \left(\frac{3}{6}\right)^2$ = 0.5000

Gini (PlayTennis|Wind=weak) = $1 - \left(\frac{6}{8}\right)^2 - \left(\frac{2}{8}\right)^2$ = 0.3750

Therefore, the Gini index after the Wind test is applied is

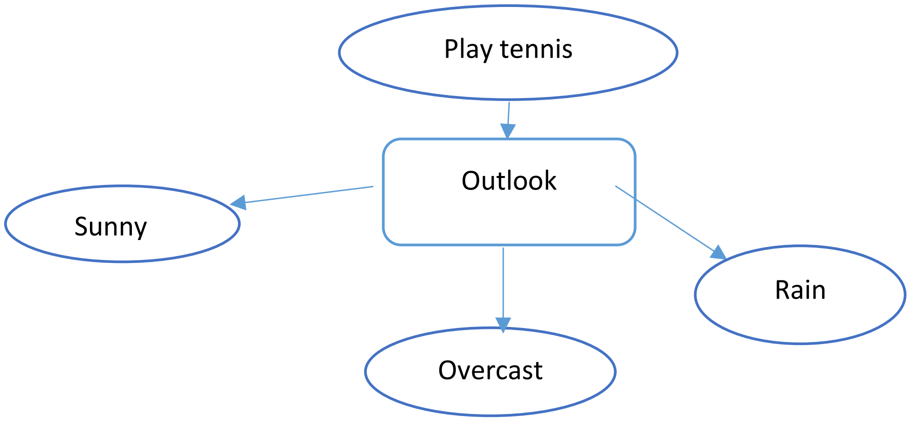
6/14 *0.5 + 8/14 * 0.3750= 0.4286

Delta gini(wind)= gini(play_tennis)- gini (wind) = 0.4592-0.4286= **0.0306**

Delta gini(outlook)=	**0.1163**
Delta gini(temperature)=	0.0782
Delta gini(Humidity)=	0.0918
Delta gini(wind)=	0.0306

We will choose the largest delta gini index which is outlook as node.

So our decision tree will be like this



Now we will calculate the gini index for sunny as follow

$1 - \left(\frac{2}{5}\right)^2 - \left(\frac{3}{5}\right)^2$ = 0.4800

Now we do the same for temperature

Gini (sunny| Temperature =Hot) = $1 - 0^2 - \left(\frac{2}{2}\right)^2$ = 0

Gini (sunny| Temperature =Mild) = $1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2$= 0.5000

Gini (sunny| Temperature =Cool) = $1 - \left(\frac{1}{1}\right)^2 - 0^2$= 0

Therefore, the Gini index after the Temperature test is applied is

2/5* 0+ 2/5 * 0.5000+ 1/5 * 0 = 0.2000

Delta gini(temperature @sunny)= gini(sunny)- gini (temperature) = 0.4800 - 0.2000= **0.2800**

Now we do the same for humidity

Gini (sunny| Humidity=High) = $1 - 0^2 - \left(\frac{3}{3}\right)^2$ = 0

Gini (sunny| Humidity =Normal) = $1 - \left(\frac{2}{2}\right)^2 - 0^2$= 0

Therefore, the Gini index after the Humidity test is applied is

3/5* 0+ 2/5 * 0 = 0

Delta gini(humidity @sunny)= gini(sunny)- gini (humidity) = 0.4800 - 0= **0.4800**

Now we do the same for wind

Gini (sunny| Wind=strong) = $1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2$ = 0.5000

Gini (sunny| Wind=weak) = $1 - \left(\frac{1}{3}\right)^2 - \left(\frac{2}{3}\right)^2$ = 0.4444

Therefore, the Gini index after the Wind test is applied is

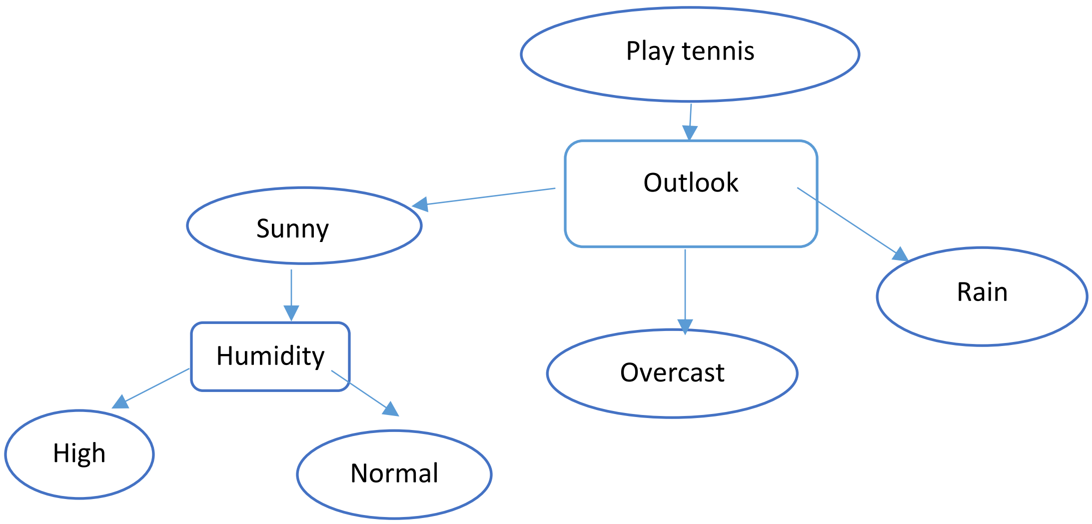
2/5 *0.5000 + 3/5 * 0.4444= 0.

Delta gini(wind @sunny)= gini(sunny)- gini (wind) = 0.4800 - 0.4666= **0.0134**

Delta gini(temperature @sunny)=	0.2800
Delta gini(Humidity @sunny)=	**0.4800**
Delta gini(wind @sunny)=	0.0134

We will choose the largest delta gini index which is humidity as node

So our decision tree will be like this



No Yes

we will calculate the gini index for rain as follow

$1 - \left(\frac{3}{5}\right)^2 - \left(\frac{2}{5}\right)^2$ = 0.4800

Now we do the same for temperature

Gini (rain| Temperature =Hot) = 0

Gini (rain| Temperature =Mild) = $1 - \left(\frac{2}{3}\right)^2 - \left(\frac{1}{3}\right)^2$ = 0.4444

Gini (rain| Temperature =Cool) = $1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2$ = 0.5000

Therefore, the Gini index after the Temperature test is applied is

0+ 3/5 * 0.4444 + 2/5 * 0.5000= 0.4666

Delta gini(temperature @rain)= gini(rain)- gini (temperature) = 0.4800 - 0.4666= **0.0134**

Now we do the same for humidity

Gini (rain| Humidity=High) = $1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2$ = 0.5000

Gini (rain| Humidity =Normal) = $1 - \left(\frac{2}{3}\right)^2 - \left(\frac{1}{3}\right)^2$ = 0.4444

Therefore, the Gini index after the Humidity test is applied is

2/5* 0.5000+ 3/5 * 0.4444 = 0.4666

Delta gini(humidity @rain)= gini(rain)- gini (humidity) = 0.4800 – 0.4666= **0.0134**

Now we do the same for wind

Gini (sunny| Wind=strong) = $1 - 0^2 - \left(\frac{2}{2}\right)^2$ = 0

Gini (sunny| Wind=weak) = $1 - \left(\frac{3}{3}\right)^2 - 0^2$ = 0

Therefore, the Gini index after the Wind test is applied is

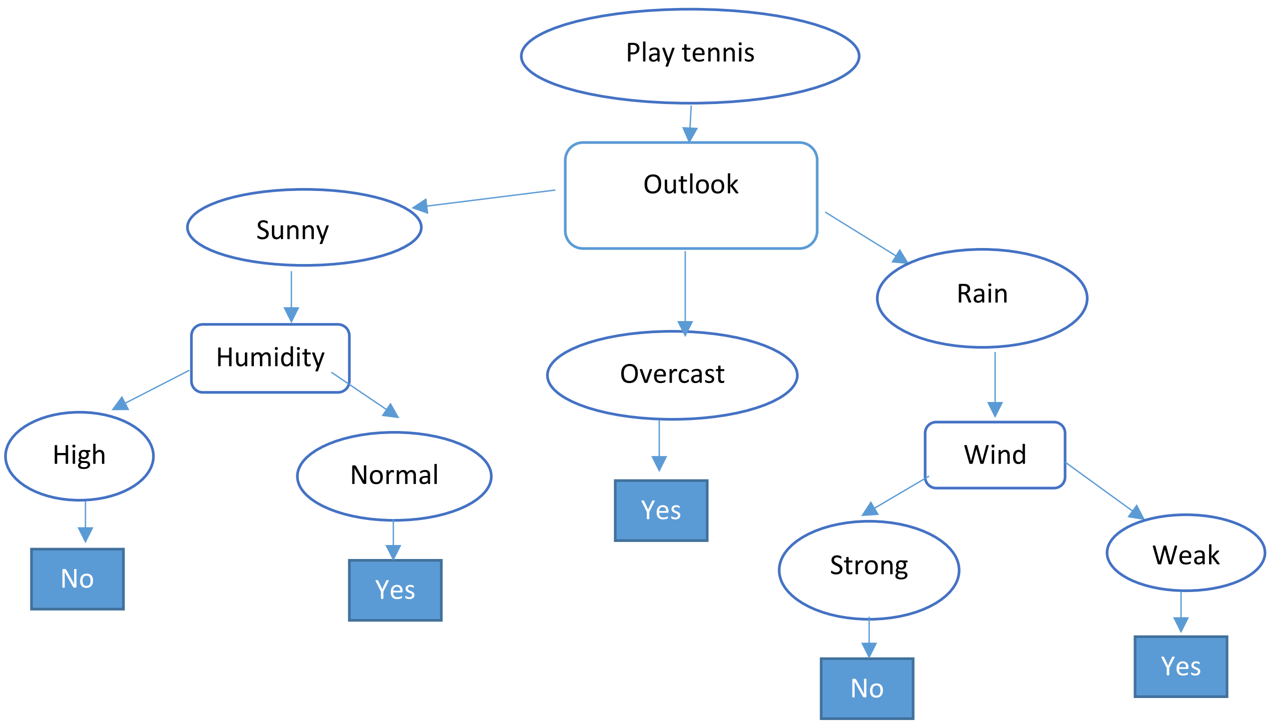
2/5 *0 + 3/5 * 0= 0

Delta gini(wind @rain)= gini(rain)- gini (wind) = 0.4800 - 0= **0.4800**

Delta gini(temperature @rain)=	0.0134
Delta gini(Humidity @rain)=	0.0134
Delta gini(wind @rain)=	**0.4800**

We will choose the largest delta gini index which is wind as node

So our final decision tree will be like this



Part c) Make predictions of (D15: Rain, Mild, Normal, Strong) using both trees. (2 pts)

Based on both trees the player will not play on D15.

Part d) Use Naïve Bayes classifier to predict the result in (c). (2 pts)

- Bayes theorem: $$P(C \mid A) = \frac{P(A \mid C)P(C)}{P(A)}$$

$$\overset{\text{posterior}}{P(C \mid \mathbf{x})} = \frac{\overset{\text{prior}}{P(C)}\,\overset{\text{likelihood}}{p(\mathbf{x} \mid C)}}{\underset{\text{evidence}}{p(\mathbf{x})}}$$

Class: C1:play_tennis = yes , C2: play_tennis = no

Features:X = (outlook= sunny, overcast and rain, Temperature = hot, mild and cool, Humidity= high and normal, Wind= strong and weak)

Now we calculate probabilities

P(Ci): P(play_tennis = yes) = 9/14 = 0.6428 and P(play_tennis = no) = 5/14= 0.3571

Compute P(X|Ci) for each calss

D15: Rain, Mild, Normal, Strong

P(Outlook= rain| play_tennis = yes) = 3/5 = 0.6

P(Outlook= rain| play_tennis = no) = 2/5 = 0.4

P(Temperature = mild| play_tennis = yes) = 4/6 = 0.67

P(Temperature =mild | play_tennis = no) = 2/6 = 0.33

P(Humidity= normal| play_tennis = yes) = 6/7 = 0.85

P(Humidity= normal| play_tennis = no) = 1/7= 0.14

P(Wind= strong | play_tennis = yes) = 3/6 = 0.5

P(Wind= strong | play_tennis = no) = 3/6= 0.5

P(X|Ci) : P(X| play_tennis = yes) = 0.6*0.67*0.85*0.5 = 0.1709

P(X| play_tennis = no) = 0.4*0.33*0.14*0.5 = 0.0092

P(X|Ci)*P(Ci) : P(X| play_tennis = yes)* P(play_tennis = yes) = 0.1709*0.6428 = 0.1099

P(X| play_tennis = no) * P(play_tennis = no) = 0.0092*0.3571 = 0.0033

Using naïve bayes the player will play tennis on D15.