Question: 0 1 2

0	34	13	5
1	0	52	0
2	13	0	33

Find Accuracy, Error Precision, Recall, F1, F0.5, F2 score, Support , macro F1 and weighted Average:

For class 0: (Positive Only)

Confusion matrix for class 0:

Actual \ Predicted	Negative(1&2)	Positive(0)
Negative(1&2)	TN = 52+0+33+0 = 85	FP = 0+13 = 13
Positive(0)	TN = 13+5 = 18	TP = 34

1. **Accuracy** = (TP + TN) / (TN + FP + FN + TP)

   = (34 + 85) / (85 + 13 + 18 + 34)

   = 0.7933

So, the accuracy of the model is approximately 0.7933, or 79.33% for class 0. This means that roughly 79.33% of the instances were classified correctly by the model.

2. **Error** = 1 – Accuracy

   = 1 – 0.7933

   = 0.2067

   So, the error of the model is approximately 0.2067 or 20.67% for class 0. This means that around 20.67% of the instances were misclassified by the model.

3. **Precision** = TP / (TP + FP)

   = 34 / (34 + 13)

   = 0.7234

   So, the precision of the model is approximately 0.7234 or 72.34% for class 0. This means that around 72.34% of the instances predicted as positive by the model were actually positive.

4. **Recall** = TP / (TP + FN)

   = 34 / (34 + 18)

   = 0.6538

   So, the recall of the model is approximately 0.6538 or 65.38% for class 0. This means that around 65.38% of the actual positive instances were correctly identified by the model.

5. **F1 Score** = (2 * Precision * Recall) / (Precision + Recall)

   = (2 * 0.7234 * 0.6538) / (0.7234 + 0.6538)

= 0.6868

So, the F1 Score of the model is approximately 0.8889 for class 0. This indicates a harmonic mean of precision and recall, providing a single metric that reflects both aspects of the model's performance.

6. **F0.5 Score** = (1.25* Precision * Recall) / (0.25 * Precision + Recall)

   = (1.25 * 0.7234 * 0.6538) / (0.25 * 0.7234 + 0.6538)

   = 0.7083

   So, the F0.5 Score of the model is approximately 0.7083 for class 0. This indicates a harmonic mean that places more weight on precision, reflecting the importance given to minimizing false positives.

7. **F2 Score** = (5 * Precision * Recall) / (4 * Precision + Recall)

   = (5 * 0.7234 * 0.6538) / (4 * 0.7234 + 0.6538)

   = 0.6666

   So, the F2 Score of the model is approximately 0.6466 for class 0. This indicates a harmonic mean that places more weight on recall, showing the importance given to correctly identifying all actual positive instances, even at the expense of increasing false positives.

8. **Support** = TN + TP

   = 18 + 34

   So, the support of the class 0 is 52. This means that there are a total of 52 instances in the dataset that belong to the class being evaluated.

For class 1: (Positive Only)

Confusion matrix for class 1:

Actual	Negative(0&2)	Positive(1)
Negative(0&2)	TN = 34+5+13+33 = 85	FP = 13+0 = 13
Positive(1)	TN = 0+0 = 0	TP = 52

1. **Accuracy** = (TP + TN) / (TN + FP + FN + TP)

   = (52 + 85) / (85 + 13 + 0 + 52)

   = 0.9133

   So, the accuracy of the model is approximately 0.9133, or 91.33% for class 1. This means that roughly 91.33% of the instances were classified correctly by the model.

2. **Error** = 1 – Accuracy

   = 1 – 0.9133

   = 0.0867

   So, the error of the model is approximately 0.0867 or 8.67% for class 1. This means that around 8.67% of the instances were misclassified by the model.

3. **Precision** = TP / (TP + FP)

   = 52 / (52 + 13)

= 0.8

So, the precision of the model is approximately 0.8 or 80% for class 1. This means that around 80% of the instances predicted as positive by the model were actually positive.

4. **Recall** = TP / (TP + FN)

   = 52 / (52 + 0)

   = 1

   So, the recall of the model is approximately 1 or 100% for class 1. This means that around 100% of the actual positive instances were correctly identified by the model.

5. **F1 Score** = (2 * Precision * Recall) / (Precision + Recall)

   = (2 * 0.8 * 1) / (0.8 + 1)

   = 0.8889

   So, the F1 Score of the model is approximately 0.8889 for class 1. This indicates a balanced performance between precision and recall, with higher scores indicating better performance.

6. **F0.5 Score** = (1.25* Precision * Recall) / (0.25 * Precision + Recall)

   = (1.25 * 0.8 * 1) / (0.25 * 0.8 + 1)

   = 0.8333

   So, the F0.5 Score of the model is approximately 0.8333 for class 1. This indicates a performance weighted more towards precision, reflecting the importance given to minimizing false positives.

7. **F2 Score** = (5 * Precision * Recall) / (4 * Precision + Recall)

   = (5 * 0.8 * 1) / (4 * 0.8 + 1)

   = 0.9524

   So, the F2 Score of the model is approximately 0.9524 for class 1. This indicates a performance weighted more towards recall, showing the importance given to correctly identifying all actual positive instances, even at the expense of increasing false positives.

8. **Support** = FN + TP

   = 0 + 52

   So, the support of the model is 52 for class 1. This means that there are a total of 52 instances in the dataset that belong to the class being evaluated.

For class 2: (Positive Only)

Confusion matrix for class 2:

Actual	Negative(0&1)	Positive(2)
Negative(0&1)	TN = 34+13+52+0 = 99	FP = 5+0 = 5
Positive(2)	TN = 13+0 = 13	TP = 33

1. **Accuracy** = (TP + TN) / (TN + FP + FN + TP)

   = (33 + 99) / (99 + 5 + 13 + 33)

   = 0.88

   So, the accuracy of the model is approximately 0.88, or 80%. This means that roughly 80% of the instances were classified correctly by the model.

2. **Error** = 1 – Accuracy

   = 1 – 0.88

   = 0.12

   So, the error of the model is approximately 0.12 or 12%. This means that around 12% of the instances were misclassified by the model.

3. **Precision** = TP / (TP + FP)

   = 33 / (33 + 5)

   = 0.8684

So, the precision of the model is approximately 0.8684 or 86.84%. This means that around 86.84% of the instances predicted as positive by the model were actually positive.

4. **Recall** = TP / (TP + FN)

   = 33 / (33 + 13)

   = 0.7173

   So, the recall of the model is approximately 0.7173 or 71.73%. This means that around 71.73% of the actual positive instances were correctly identified by the model.

5. **F1 Score** = (2 * Precision * Recall) / (Precision + Recall)

   = (2 * 0.8684* 0.7173) / (0.8684+ 0.7173)

   = 0.7857

   So, the F1 Score of the model is approximately 0.7857 for class 2. This indicates a balanced performance between precision and recall, with higher scores indicating better performance.

6. **F0.5 Score** = (1.25* Precision * Recall) / (0.25 * Precision + Recall)

   = (1.25 *0.8684* 0.7173) / (0.25 * 0.8684+ 0.7173)

   = 0.8333

   So, the F0.5 Score of the model is approximately 0.8333 for class 2. This indicates a performance weighted more towards precision, reflecting the importance given to minimizing false positives.

7. **F2 Score** = (5 * Precision * Recall) / (4 * Precision + Recall)

= (5 *0.8684* 0.7173) / (4 *0.8684+ 0.7173)

= 0.74316

So, the F2 Score of the model is approximately 0.74316 for class 2. This indicates a performance weighted more towards recall, showing the importance given to correctly identifying all actual positive instances, even at the expense of increasing false positives.

8. **Support** = FN + TP

   = 13+ 33

   = 46

   So, the support of the model is 46 for class 2. This means that there are a total of 46 instances in the dataset that belong to the class being evaluated.

Macro F1 = (1/N) * sum(F1_scores)

= (0.6868 + 0.8889 + 0.7857) / 3

= 0.7871

So, the macro F1 score of the model is approximately 0.7871. This provides an overall evaluation of the model's performance across all classes, giving equal weight to each class.

Weight Average = sum(Ni * F1i) / Ni

= (52 * 0.6868 + 52 * 0.8889 + 46 * 0.7857) / (52 + 52 + 46)

= 0.78719

So, the weighted average F1 score of the model is approximately 0.7871. This provides an overall evaluation of the model's performance across all classes, taking into account both the F1 score and the distribution of instances among classes.