**Question 1: Which class has the least number of samples?**

The class "seborrheic keratosis" has the least number of samples, with a count of 77.

**Question 2: Which classes dominate the data in terms proportionate number of samples?**

The classes that dominate the data in terms of the proportionate number of samples are:

1. "pigmented benign keratosis" with a proportion of 0.206342 (20.63%)
2. "melanoma" with a proportion of 0.195623 (19.56%)
3. "basal cell carcinoma" with a proportion of 0.167932 (16.79%)

These three classes have the highest proportions of samples in the dataset, indicating that they are more represented compared to the other classes.

**Did you get rid of underfitting/overfitting?**

The Third model seems to perform better as the number of epochs increases, indicating that it is learning from the data and improving its predictions over time. However, it's essential to discuss underfitting and overfitting in more detail:

1. Underfitting - This occurs when a model fails to capture the underlying patterns of the data. Indications of underfitting include poor performance on the training data. From the logs, we cam see that our model achieves an accuracy of 0.9505 (or 95.05%) on the training data by the end of the 30th epoch, which indicates that the model is not underfitting, as it performs well on the training data.

2. Overfitting - This happens when the model learns the training data too well, including its noise and outliers, and performs poorly on unseen data. Signs of overfitting include a high accuracy on the training data but a significantly lower accuracy on the validation data. From the logs, we cam see that the final validation accuracy is 0.8382 (or 83.82%), which is somewhat lower than the training accuracy but not significantly so. However, we can

observe that after about the 13th epoch, the validation loss starts increasing while the training loss continues to decrease. This is a sign of overfitting as it shows the model is continuing to adapt itself to the training data (hence the decreasing training loss) but is performing worse on the validation data (hence the increasing validation loss).

**Did class rebalance help?**

The rebalancing of the classes was done correctly, as seen in the even distribution of samples across all classes in the rebalanced dataset. However, the key test of whether this rebalancing helped comes from the performance of the model.

From the results, the model's accuracy is approximately 95% on the training data and 83% on the validation data, indicating good overall performance. This suggests that class rebalancing may have been beneficial.

Yet, to confirm if class rebalancing truly helped, you'd need to compare these results to a model trained on the unbalanced data. If the rebalanced model performs significantly better, particularly for the underrepresented classes, then it's clear that the rebalancing has helped.

In conclusion, with the given model, there are signs that class rebalancing have been beneficial.