Main model :
After training using Adaboost and XGBoost, we found that the feature set's variations were not being captured by these models and it was realised that the characteristics of the dataset had to be captured by some other model relevant

to the given data. We used a time series modes, y-direction LSTM, BiLSTM ,ARIMA, SARIMA then since the data variability seemed to be resonant with the time series model attributes. This model could not capture the variation required to get an accurate distribution of procedures. We moved on to capture the data accurately using a feedforward neural network alongside the time series models we were using which were used as priors to the distribution. The posterior was then calculated using the values predicted from the neural network. That distribution seemed to capture the data features reasonably.

Posterior using the predicted values
Output of our neural network was real values and in the train dataset, discrete values were there, so making 1.1 to 1 or 0.9 to 1 would have increased the accuracy and we applied such a round-off technique (taking a range of 0.2) for higher accuracy. We found that this round-off technique helped us achieve higher accuracy on our validation dataset and therefore we used it as a postprocessing technique.

Feature Addition :

- In addition to the given features, we added additional features to our dataset about the weather conditions in Dubai which were scraped from the internet(https://www.timeanddate.com/weather/united-arab-emirates/dubai/historic?month=12&year=2015) and the features - humidity, the wind speed was added to the dataset.
- This allowed us to make the dataset more realistic since these added features might influence the number of procedures required for a speciffic day.

Final score: On the test dataset we obtained an rms score of 1.02 and e^{-rms} to be 0.36.