Predicted Closing Prices:

May 2023 delivery (CLK23): $76.63

December 2024 delivery (CLZ24): $74.61

December 2028 delivery (CLZ28): $60.17

Method:

I started from a report from the Federal Reserve discussing forecasting the price of oil. In this report, they look at the predictive ability of a number of variables for determining the future price of oil. In addition to the current spot price, some of the variables that are most predictive include the exchange rate with Australian dollars and the commodity research bureau sub-indices for metals and for industrial raw materials. Specifically, they look at the percent change in these variables before the period they are trying to forecast.

I decided to use a neural network to model the future price of oil. As input variables, I used exchange rates with Australian dollars since it had been mentioned in the report, and I added the British Pound, and the Euro because there was sufficient time-series data available for these currencies and because the UK and EU are significant trading partners of the US. The CRB does not calculate the same sub-indices anymore, or if they do, it is not published, so instead as input variables, I used the prices for copper, aluminum, and natural gas, an index for all commodities, and the total monthly durable goods orders. Additionally, I included the consumer price index as an input since inflation has been a significant factor recently. For all of these inputs I included their percent change over the past 1,3,6, and 12 months. Additionally, when modelling the 2028 price, I included the percent change over the past 24 months. Finally, I included the spot price of oil. All of these variables were used to predict what the spot price would be 3, 22, or 70 months after any given day, which corresponds to the time between now and May 2023, December 2024, and December 2028. I realize that the spot price on the date of future delivery is different than the close price of the futures contract, but I figured these should usually be close to each other.

I split the data into training data to tune the model and test data to evaluate the model performance. Since the longer-term models required a longer gap between the input data and the targets, there was less data available to train those models. There were 4481 total (training and test) observations used for the 3-month model, 3828 observations for the 22-month model, and 2789 observations for the 70-month model. The models are trained gradually by repeatedly looking at how the parameters can be changed to most improve the model prediction for a random subset of the training data. I tuned parameters for these models such as the number of layers as number of neurons per layer by eye based on where model performance would plateau and how performance on the test data compared to performance on the training data. More simplistic models were more useful for the longer-term models, likely because there is a weaker relationship between the input variables and the target, and so there is a greater risk of over-fitting. Once I was satisfied with the parameters of the model, I trained each model 12 times (chosen arbitrarily), evaluated them using present conditions to determine a future prediction, and used the mean prediction of those 12 runs as the final estimation for the close price of the futures contracts. The predictions of the 3-month model had a standard deviation of $4.53, the predictions of the 22-month model had a standard deviation of $2.06, and the predictions of the 70-month model had a standard deviation of $8.84. It was surprising that the 3-month model had higher variation than the 22-month model. However, it may be because the model was somewhat more complicated, and so could produce more variability in its predictions.

Federal reserve report: <https://www.federalreserve.gov/pubs/ifdp/2011/1022/ifdp1022.pdf>