**Literature Review**

Our research focused on articles that used time series models to forecast the spread of covid-19. We found that from the start of the pandemic in March 2020, when the World Health Organization (“WHO”) declared covid-19 a global pandemic, researchers deployed an array of time series models to forecast the spread of the virus in an effort to inform the public about future cases and give support to public health officials when issuing guidance about safety and mitigation measures.

Haytham H. Elmousalami and Aboul Ella Hassanien’s [13] research focused on the Day Level spread of the virus. Their methodology used time series models that take averages of past observations to make predictions of future cases. Moving Average (“MA”), Weighted Moving Average (“WMA”), and Single Exponential Smoothing (“SES”) models were fitted to the data and the results were evaluated using Mean Absolute Deviation (“MAD”), Mean Square Error (“MSE), Root Mean Square Error (“RMSE”), and Mean Absolute Percentage Error (“MAPE”). Their results showed that the SES model had the highest accuracy for confirmed cases, recovered cases, and deaths. Their study showed the exponential growth of the virus without public health mitigation measures such as quarantines and social distancing.

Vasilis Papastefanopoulos, Pantelis Linardatos and Sotiris Kotsiantis [3] used an entirely different modeling approach than Elmousalami and Hassanien. Their models were a combination of linear regression and deep learning neural networks. They applied 6 models across 10 nations, Auto Regressive Integrated Moving Average (ARIMA), Holt-Winters additive model (HWAM), Trigonometric seasonal formulation Box-Cox transformation ARIMA errors and trend component (TBAT), Facebook’s Prophet, Deep AR, a probabilistic forecasting with Auto-Regressive Recurrent Networks, and N-Beats, a neural basis expansion analysis for interpretable time series forecasting.

Unlike Elmousalami and Hassanien, Papastefanopoulos, authors Linardatos and Kotsiantis did not find a “one-size-fits-all” model. Instead, they found that “ARIMA and TBAT demonstrate superior performance in seven out of ten countries, while achieving second best results in another two.” Using RMSE to assess the models, they found “traditional statistical methods such as such ARIMA and TBAT overall prevail over deep learning counterparts such as DeepAR, and N-BEATS—an outcome which, **due to the lack of large amounts of data**.” [3] (emphasis added)

Authors Vinay Kumar, Reddy Chimmula, and Lei Zhang[14] focused solely on using a single deep learning network, Long short term Memory (LSTM), a non-linear approach that uses a Recurrent Neural Network (RNN) to forecast trends. In an RNN, output from the last step is fed as input to the current step. Somewhat similar to the MA, WMA, and SES approach where the weights applied to past observations are manipulated to make forecasts. The difference is that in LSTM networks can retain long term information which is useful if there are lags of unknown duration between important time gaps.

Using data collected in Canada until March 31, 2020, Kumar, Chimmula, and Zhang’s methodology was to use sequential networks to extract the patterns from a time series dataset. The rationale for this approach was that the linear approach often neglects the temporal com- ponents in the data. “They depend upon regression without non- linear functions and failed to capture the dynamics of transmission of infectious diseases like novel corona virus. Statistical models such as Auto Regressive Integrated Moving Average (ARIMA), Moving Average (MA), Auto Regressive (AR) methods overwhelmingly depends on assumptions and such models are difficult for forecasting real-time transmission rates.” In contrast to Papastefanopoulos, Linardatos, and Kotsiantis, they showed that the RMSE of the LSTM had the highest accuracy.

Our review of the literature on covid-19 produced an abundance of articles similar to the ones cited above. Each one used a particular class of model and compared their results. The major differences were the populations that the models applied to and when/how the data was collected. All of the articles provided data supporting health safety measures and warned the public about the spread of the virus. This paper will use a similar approach. It will compare different classes of time series with the added benefits of hindsight and updated/corrected data collection.

**Key Words**

*Pandemic, Covid, Time Series, MAPE, RMSE, ARIMA, Prophet, Cases, Predictions, SARIMA, Forecasting, Comparison, Long short-term Memory (LSTM), Recurrent Neural Network (RNN), Bidirectional LSTM (BiLSTM), Gated Recurrent Units (GRUs), and Variational AutoEncoder (VAE), Support Vector Machines (SVM)*

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