

INTRODUCTION

Since late January 2020, there have been over 17,515,199 cases of SARS-CoV-2 infections in the United Kingdom (UK) (Flynn et al. 2020). The virus causes high fever, coughing, shortness of breath, pneumonia, as well as serious respiratory infections. The periods of high UK hospitalisation numbers were a serious threat to an already overburdened healthcare system. Indeed, the National Health Service (NHS) cannot meet the needs of many patients with urgent medical conditions due to overcrowded hospitals.(Anderson et al. 2021)

It is essential to monitor and forecast new inpatient admissions, during an infectious disease outbreak or pandemic, in order to manage hospital resources efficiently, reduce overcrowding, and improve the quality of care received. To this end, this project focuses on the development of an inpatients' prediction model that may help a hospital's contingency planning during an infectious disease outbreak/pandemic.

The project's aim is the development of a prediction model that forecasts what the expected number of patient admissions will/might be - per day, N days ahead, and per NHS Trust - during an infectious disease pandemic. The aim underlies the research question - how many future admissions should a NHS trust expect during an infectious disease pandemic? The infectious disease in focus is coronavirus 19 disease; and by virtue of the characteristics of SAR-CoV-2 infections & coronavirus 19 disease the project's objectives are to

- Investigate the question, how many days of infection history lead to the most accurate forecasts?
- Forecast the expected daily new admissions for the next 15 days

The next section outlines the project's methods. In relation to model development, we focused on algorithms that use historical data to predict future events.

METHODS

The schematic illustration of *fig. 1* outlines the project's data engineering, modelling, and evaluation steps, which underlie the project's research strategy. This section briefly discusses the research strategy, and the steps.

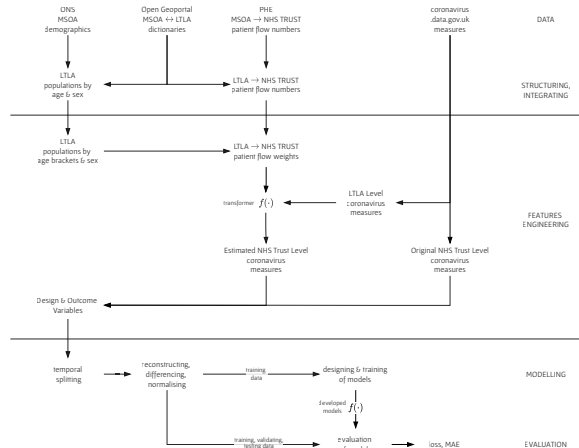


Figure 1: The project's processing, analysis, modelling, and evaluation steps. Please refer to the methodologies section for a brief description of (a) the patient flow weights, and (b) the estimation of NHS trust level measures via flow weights and LTLA level measures. MSA: middle layer super output area, LTLA: lower tier local authority, ONS: office for national statistics, NHS: national health service, PHE: Public Health England.

RESEARCH STRATEGY

In progress ... includes research strategy (Oates 2006)

DATA ENGINEERING

Data Collection.

The data sources are: (a) the coronavirus.data.gov.uk application programming interface (API) for England's SARS-CoV-2 infections measures, (b) the [office for national statistics \(ONS\)](https://ons.gov.uk) for population estimates, (c) [Public Health England \(PHE\)](https://phe.gov.uk) for the annual intake of patients from one or more middle layer super output areas to an NHS Trust, and (d) the [Open Geography Portal \(geoportal\)](https://geoportal.gov.uk) for the middle layer super output area (MSOA) ↔ lower tier local authority (LTLA) geographic codes mappings. The SARS-CoV-2 infections measures of this project span the period 1 March 2020 until 20 January 2022.

Structuring & Integrating.

The structuring and integrating segment of *fig.1* ensures that all the data sets

- have a [structured data file](#) set up, and
- are appropriately mapped

as illustrated.

Features Engineering.

The aim of *fig. 1*'s feature engineering segment is the construction of the design matrix & outcome vector variables. The design matrix variables are the set of predictors, i.e., independent variables. The variables are

- **covidOccupiedBeds**: The no. of beds occupied by coronavirus disease patients.
- **covidOccupiedMV Beds**: The no. of mechanical ventilation beds occupied by coronavirus disease patients.
- **estimatedNewAdmissions**: **The outcome variable.** Estimated by NHS England.
- **EDC0-4, EDC5-9, ..., EDC90+**: The estimated daily cases (EDC) by age group.
- **newDeaths28DaysByDeathDate**: The no. of estimated daily deaths, such that each death occurred *within 28 days of a first positive laboratory-confirmed test*.
- **EDV12-15, EDV16-17, ..., EDV90+**: The estimated no. of daily vaccinations (EDV) by age group; second vaccinations.

The first three are original NHS Trust level measures available via the coronavirus.data.gov.uk API, whereas the remaining variables are project estimated NHS Trust level measures. An estimated NHS Trust value is

$$e_t = \sum_l \lambda_{l,t} m_l$$

whereby

$$\lambda_{l,t} = \frac{\beta_{l,t}}{\rho_l}$$

and

variable	description
l	A LTLA
t	A NHS Trust
m_l	A LTLA measure from coronavirus.data.gov.uk, e.g., the no. of daily cases.
e_t	An estimate NHS Trust level measure w.r.t. LTLA regions from whence it has received patients.
$\lambda_{l,t}$	The flow weight from a LTLA to a NHS Trust.
ρ_l	The patient population of a LTLA.
$\beta_{l,t}$	The number of LTLA patients \rightarrow NHS Trust w.r.t. a specified year

MODELLING

The Algorithms

The SARS-CoV-2 infections measures have both spatial and temporal features, i.e., the spatially spread set of NHS Trusts, and the infection dynamics, respectively. A number of algorithms have been developed for spatio-temporal prediction problems. The project focuses on **(a)** Long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997), **(b)** Gated Recurrent Unit (GRU) (Cho et al. 2014), and **(c)** [Temporal] Convolutional Neural Networks (CNN) (Bai, Kolter, and Koltun 2018), because they were developed for

- Spatio-temporal problems.
- Learning from the past.

Forecasting & History

The outlined algorithms forecast 15 days into the future w.r.t. “varying days of history” (*fig. 2*).

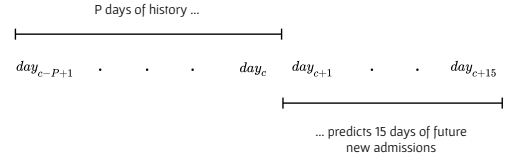


Figure 2: Prediction windows logic

Pre-modelling Procedures

The pre-modelling procedures are

- Temporal Splitting
- Differencing
- Reconstruction
- Normalisation

A temporal splitting step splits a data set into training, validation, and testing data sets along the time dimension. A training, validation, and testing data set, per NHS Trust, is created. In relation to this project, after differencing each variable point is

$$x_{t+1} - x_t$$

Reconstruction refers to the merging of the data splits per trust into 3 data sets; a training, validation, and testing data set. Merging is not by concatenation, it's a positional merge that is appropriate for developing an overarching model instead of a model per entity. For

example, instead of a model for each of the 140 NHS Trusts, a single overarching model.

Finally, the normalisation step ensures a standard scale across all variables.

EVALUATION

The results section summarises the modelling results. Model evaluation is via the error measures

$$\text{loss} = \frac{1}{N} \sum_{n=1}^N (y_t(n) - y_p(n))^2$$

$$\text{MAE} = \frac{1}{N} \sum_{n=1}^N |y_t(n) - y_p(n)|$$

wherein

variable	description
y_t	a true outcome value
y_p	a predicted outcome value
loss	the mean squared error
MAE	the mean absolute error
N	the length of the outcome vector

RESULTS

MODEL EVALUATION

Let the *history window* be the number of past days of data used for predictions.

The graphs of *fig. ...* summarise the validation & testing phase MAE. Per algorithm type, and regardless of the history window, the testing phase MAE values are higher than the validation phase values. The LSTM error values are consistently low. Whereas, the CNN error values are rather haphazard, especially the testing phase values. The pattern of the CNN errors might be due to the overfitting, or perhaps a different CNN architecture might be appropriate. The lowest LSTM MAE value is due to a 39-day history window.

The pattern of the loss & MAE values are quite similar (Cf. *fig. & fig.*). Once again, the LSTM error values are consistently low (*fig. ...*). The CNN testing phase errors

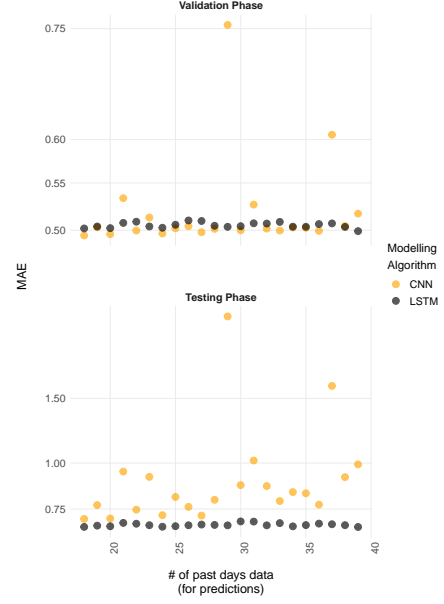


Figure 3: The mean absolute errors of the validation and testing phase.

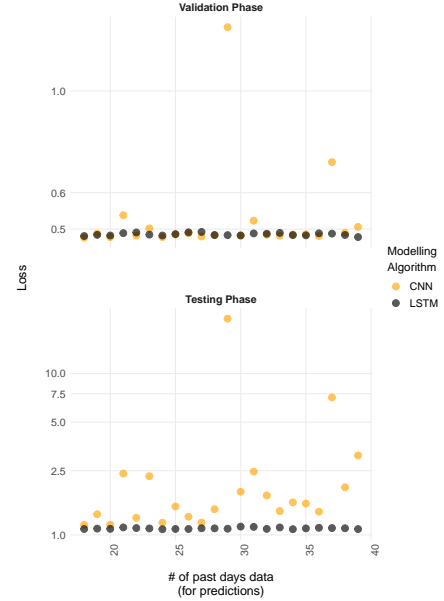


Figure 4: Loss w.r.t. the ...

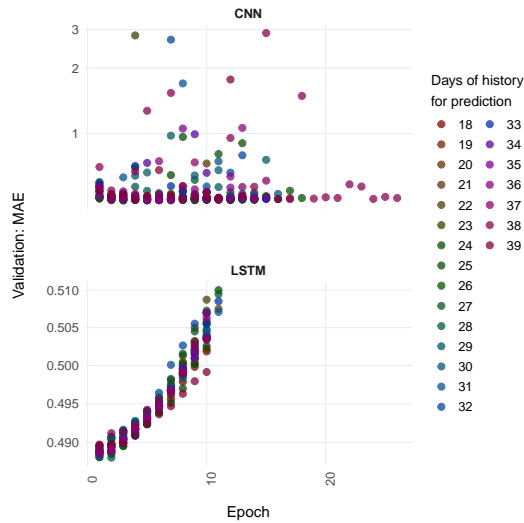


Figure 5: Pending

are quite haphazard, but its validation phase errors are almost consistent.

The validation loss MAE for the LSTM and CNN were compared against the epoch with number of days as the third variable (Figure 4). In the CNN, though the loss were spread out, low loss value was in consensus when the 39 past days data was used as the input. In the LSTM, loss was not as spread out as the loss in the CNN. The loss was higher when the smaller number of the days was used as the input compared to the loss where more than 35 days were used as the input.

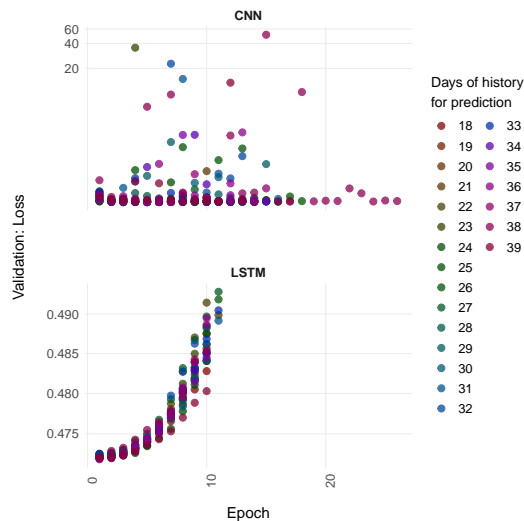


Figure 6: The loss errors

The validation loss MSE for the LSTM and CNN were

compared against the epoch with number of days as the third variable (Figure 5). The pattern was the same as the MAE, low loss values was noted in when a greater number of days were used as the input in CNN and LSTM. The loss of the LSTM seemed to lower than the loss noted in the MAE.

More number of days were given as the input the less loss in noted in both the LSTM and CNN. The LSTM showed a pattern in the loss distribution in the testing phase, where as the CNN loss were more spread out. There was a stark difference in the loss between the CNN in the validation phase and the testing phase.

Altogether, it seems

- it is possible to predict future patient admissions
- the estimated NHS Trust level values might be robust ... should be tested
- What implications would your analysis' results have? How do your findings relate to the original question?

BIASES & VALIDITY

- Were there potential biases in your work?
- Validity (remember to discuss what would have been done differently to address identified limitations)

CONCLUSIONS

In general, it is nigh impossible to state whether one algorithm is better than the other. Why? Numerous architectures can be designed per algorithm type. An option might be ...

Options that would have improved the model include ... boosting

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