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Predicting Emergency Healthcare Requirements Using Deep Learning

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ABSTRACT

This study proposes an innovative approach to enhance emergency healthcare preparedness using Long Short-Term Memory (LSTM) networks, a sophisticated form of Recurrent Neural Networks (RNNs). The model leverages Deep Learning trends to accurately forecast healthcare requirements during crises, such as pandemics. LSTM's ability to capture long-term dependencies in data enhances predictive accuracy, making it invaluable for proactive healthcare planning. The research explores the efficacy of the LSTM-based predictive model in anticipating emergency healthcare needs, with potential implications for significantly improving response efficiency. By integrating deep learning technology, this approach represents a groundbreaking advancement, ensuring a resilient healthcare system ready to address unforeseen challenges and contribute to the overall well-being of a nation's citizens.

1. INTRODUCTION

Healthcare is the native component for the development of any country worldwide. It is the one aspect that binds the nation together in sake of the serenity of life and without it, people would have to face many challenges for existing. Being the fuel of innovation, healthcare is developing and disseminating advanced and sophisticated, life-improving therapies and at the same moment this system is striving to provide its consumers a diverse range of options.

To build a novel Health care system, delivering comprehensive health care of exceptional quality is more than a financial consideration. Before individuals have access to integrated health care, it needs time and perseverance on the part of a country.

Given the substantial healthcare, the system should make it a point to develop and innovate the models on a care system basis. Health information technology (HIT), in particular, is an important aspect of India's increasing focus on high-quality health care and efficient resource management [1].

However, growing the use of technology in healthcare will have a variety of benefits, the quality benefits will most likely be the most significant. This would, in particular, increase the chance of successful procedures and enable the supply of evidence-based decision assistance to providers, bridging the gap between evidence and practice.

Technology can have great records being clustered with healthcare in developing quality and safe environments while reducing the expenditure as well. Despite having a lot of advantages in associating Technology with healthcare, the system has still not been able to harness the power of technology and bring its assets in use.

With the recent surge in the cases of a pandemic like Covid-19, hospitals and medical institutions need to manage the patient's influx and be decisive for the emergency admissions. It's useful to view prediction estimates, anticipate the class of new customers, have time-based predictions, and discover the variables that explain ED behavior for planning logistical needs. Finding trends in care consumption, which is accessible from the care services, is important for management. There are five components in the machine learning framework in health care is shown in Figure 1.

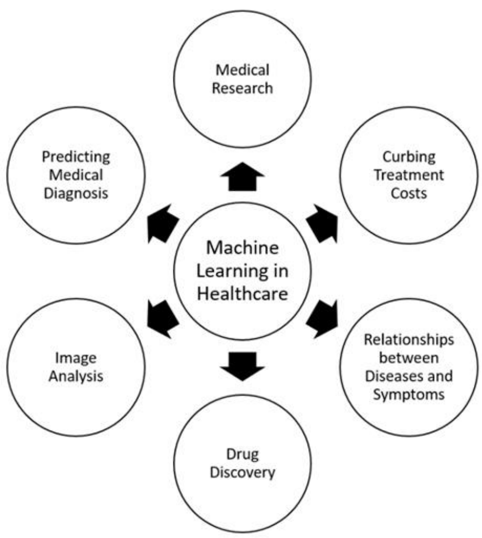

Figure 1. Machine learning in healthcare

The scarcity of emergency healthcare requirements is a serious issue across the country and this situation can worsen the consequences if not carefully mitigated and planned. This certainly happens due to the frequent mismatch between the resources and requirements in healthcare.

Resources controlled inside the ED or resources controlled outside the ED are certain conditions where this resource limitation can affect the actual need in emergencies. The availability of inpatient beds to accept ED patients is perhaps the most critical element affecting ED flow issues.

Artificial intelligence is advancing the world through different administrative operations. Being used for several blooming applications around the globe, its wide range of applications in healthcare marks its potential to explore the healthcare world and make it big.

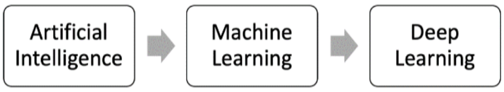

Figure 2. Assets of technology

Artificial Intelligence has played a major role and explored a wide-reaching potential in developing the healthcare system and breaking off the big challenge to adapt to AI in society for social good. The various assets of technology like artificial intelligence, machine learning, and deep learning are shown in Figure 2.

The proper use of machine learning on this data has the potential to revolutionize patient risk assessment across the medical sector, particularly in infectious illnesses. As a result, tailored strategies to limit the spread of healthcare-associated infections might be developed. Healthcare is a subject of large epidemiology, requires careful processing and planning to overcome situations like a Pandemic.

Machine Learning is used to develop features and extract the calibrated parameters with different vectors. Deep Learning is thus another subset that comprehends Machine Learning in a unique form.

These networks are exciting trends in deep learning that can help in forecasting and predicting complex problems with different attributes for short-term and long-term dependencies.

The ability of LSTM to adapt and handle long-term dependencies for any computation proves to be a key factor in developing the healthcare system.

These networks overcome the backpropagation and vanishing gradient problem caused by RNNs by subsidizing cell gates used to transfigure the relevant information to make predictions.

2. LITERATURE REVIEW

The summary of research papers with limitations is added in Table 1.

Table 1. Summary of literature

Reference No.	Motivation and Aim of the Work	Datasets Used	Methods Used in the Work	Limitations
[2]	To forecast the emergency department patients for In-Hospital Mortality with an approach based on Machine learning.	The data was used from ED's for a healthcare system for a period of 12 months.	A machine learning approach, a forest model was used.	The approach was limited to specific elements of the data and leaves out unstructured data attributes.
[3]	To predict the in-patient admissions for an emergency department and execute the results in the hospitals.	The data was collected for the ED Patients from the Boston Healthcare system.	The model used three methods to optimize the research including.	The research included certain data restrictions for the efficiency of the model and lacks generalized demonstration.
[4]	To analyse and depict the usage of current models to predict the hospital bed needs.	According to the research, national data is used for prediction and then cultured into specific regions.	This research utilized a time-series method called as Box-Jenkins approach for predicting the hospital bed occupancy.	This approach concluded its sense with two different data driven methods for forecasting.
[5]	To forecast the requirements for emergency resources during severity and drastic situations using Natural Language Processing.	The dataset was taken by recording the electronic health data for three different Emergency Departments for a specific time period of one year.	The approach used for this research included deploying a LSTM model: a neural network method which was trained and tested extensively on the clinical variables.	The research being retrospective and exclusion of a generalized form of triage instances are some limitations of the given approach.
[6]	To predict and forecast the contagious diseases using an improved deep learning approach.	The dataset is taken from KCDC including four different kinds of data with different atributes for the prediction.	This study used different models for prediction: LSTM model, DNN model and ARIMA model for better efficiency and improved accuracy.	The given research used the data that was specific to using shorter periods of time and particular region specific parts.
[7]	To forecast the influenza prediction using deep learning technology LSTM.	This study gathers details and data influenza ED visits to Taiwan Centres for Disease Control.	This research analyses the historical data and utilizes LSTM model with the help of chronical transitory data.	The study incorporated LSTM instead of RNN for improved efficiency.

3. EXPERIMENT AND METHODS

Machine learning aims to extract more relevant and significant information from massive amounts of data by employing a unique computational approach. The main goal of a machine learning oriented approach is to identify the variables that can contribute to an emergency situation or an infectious outbreak [8].

3.1 Deep learning

Deep learning is a subset of machine learning using the preliminary technique of building neural networks to leap forward with the processing. Artificial neural networks resemble the human brain in its structure with neuron nodes [9, 10].

This technology encompasses a variety of processing layers that do not require domain knowledge or extensive human engineering, and it comprehends with its own level of computing.

Deep learning may calibrate its internal settings by evaluating the error between the output obtained and the preferred or intended result using an objective function. The observed error can be minimized to some extent by changing these internal settings [11-13].

3.2 Recurrent Neural Networks

This network is based on the idea of storing a layer's output and feeding it back to the input in order to anticipate the layer's output [14].

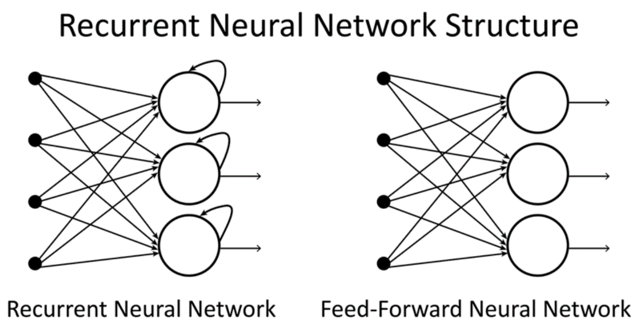

Figure 3. Structure of RNN

However, training an RNN is a rather difficult method due to its vanishing gradient caused by backpropagation dealing as shown in Figure 3. RNNs are not used to deal with long-term dependencies which further causes the method to backlash [15].

4. LONG TERM MEMORY

It has a superior time series prediction effect. For the novel coronavirus, there is an incubation period. LSTM may be used to discover the influencing variables of probable situations when used for time series prediction [16, 17].

4.1 LSTM

When entering LSTM, the user will first travel through a forgetting gate and then via a sigmoid layer, which is also known as the forgetting gate layer.

This problem can be solved with LSTM, which can cope with sequential data while keeping the time series attribute and understanding long-term dependencies. These networks use cell gates to reduce the impact of short-term memory by subsidising the flow of important input [18].

The cell gates are nonlinear summation units that command the activation of a cell and aid in the regulation of data flow. The forget gate can be configured to multiply the cell's prior state. The input gate is in charge of selecting relevant data from the current state [19], while the output gate is in charge of determining the next concealed state. The system model for the structure of LSTM is shown in Figure 4 and Figure 5.

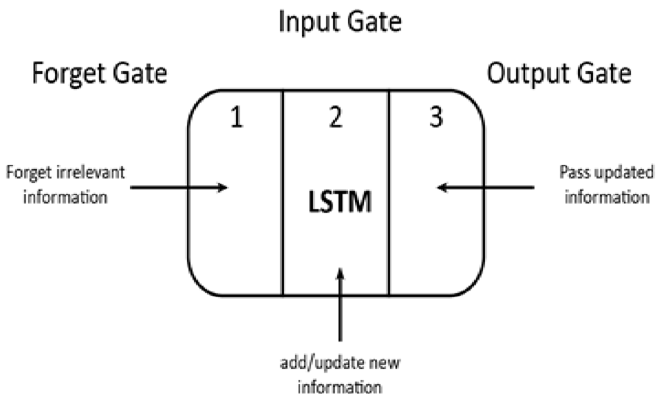

Figure 4. Structure of LSTM

The first component determines whether the preceding timestamp's information should be remembered or is irrelevant and can be ignored.

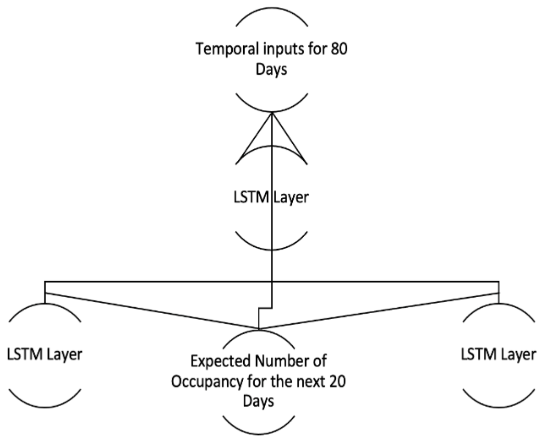

Figure 5. System model for prediction using LSTM

5. DATA SOURCE

The dataset for this prediction model consists of different measures to be predicted the quantity for like number of encounters, hospital beds, medicines and other medical supplies for the given time period. The data is taken for two different countries: Austria and Belgium to predict against the parameter of Daily Hospital Occupancy. The prediction model is trained using the training dataset for the first 80 days and then tested for the training dataset for the next 20 days. The source of this data is the online portal of European Centre for Disease Prevention and Control.

6. DATA MODEL

Once the training phase is over, the framework uses LSTM layers to forecast the cases. The total number of instances on a given day is used as input data [20], and the model is trained for 80 days. After training the framework, the goal of this model is to forecast the number of instances over the following 20 days.

This model forecasted the hospital occupancy for the two countries: Austria and Belgium for a regular daily time interval [21, 22]. Keras is a neural network python library which works well with TensorFlow, making the creation of neural network designs easy and helps in implementing deep learning models.

7. RESULTS

The given table (Table 2) depicts the predicted number of Hospital Occupancy for the Test Data set of 20 days for the country of Austria. The model is trained using the 80 days dataset of hospital occupancy in Austria and then tested against the test dataset [23].

Table 2. Predicted and actual number of hospital occupancy for Austria

Sno.	Date	Expected Occupancy	Actual Occupancy
1	2020-06-20	63	66
2	2020-06-21	65	61
3	2020-06-22	58	59
4	2020-06-23	59	57
5	2020-06-24	53	59
6	2020-06-25	62	60
7	2020-06-26	61	60
8	2020-06-27	55	61
9	2020-06-28	59	62
10	2020-06-29	64	66
11	2020-06-30	62	58
12	2020-07-01	55	65
13	2020-07-02	57	62
14	2020-07-03	63	65
15	2020-07-04	63	60
16	2020-07-05	60	62
17	2020-07-06	63	67
18	2020-07-07	78	81
19	2020-07-08	68	66
20	2020-07-09	61	66

Table 2 shows the prediction accuracy of the model in respect to drawing a comparison between the predicted hospital occupancy and the actual occupancy on a daily basis for Austria.

As seen from Table 2, the model is able to forecast the occupancy on a forefront area in the right direction corresponding to the actual cases.

Table 3 demonstrate the predicted count of hospital occupancy for the test data set of 20 days for the country of Belgium. The model is trained using the 80 days dataset of hospital occupancy in Belgium and then tested against the test dataset.

Table 3 shows the prediction accuracy of the model in respect to drawing a comparison between the predicted hospital occupancy and the actual occupancy on a daily basis for Belgium.

Figure 6 shows the curves for the predicted values of Hospital Occupancy calculated by the model for the training dataset [24, 25]. The blue line is used to analyze the parameter for Belgium and the red line is used to depict the referenced attributes for Austria.

Table 3. Predicted and actual number of hospital occupancy for Belgium

Sno.	Date	Expected Occupancy	Actual Occupancy
1	2020-06-03	720	739
2	2020-06-04	720	702
3	2020-06-05	640	647
4	2020-06-06	577	573
5	2020-06-07	583	576
6	2020-06-08	567	575
7	2020-06-09	534	527
8	2020-06-10	483	484
9	2020-06-11	473	479
10	2020-06-12	431	425
11	2020-06-13	397	395
12	2020-06-14	404	400
13	2020-06-15	399	393
14	2020-06-16	377	371
15	2020-06-17	339	344
16	2020-06-18	325	340
17	2020-06-19	300	308
18	2020-06-20	311	292
19	2020-06-21	283	295
20	2020-06-22	297	293

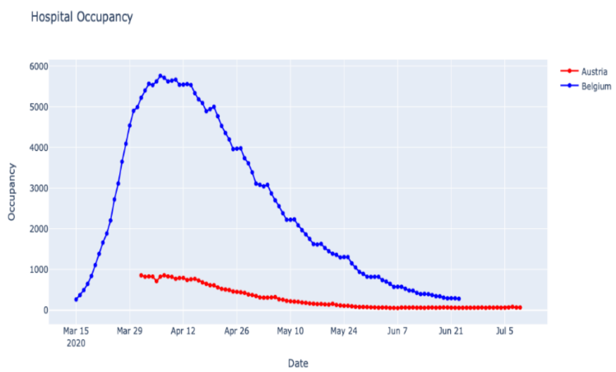

Figure 6. Hospital occupancy predicted for the training set for Austria and Belgium

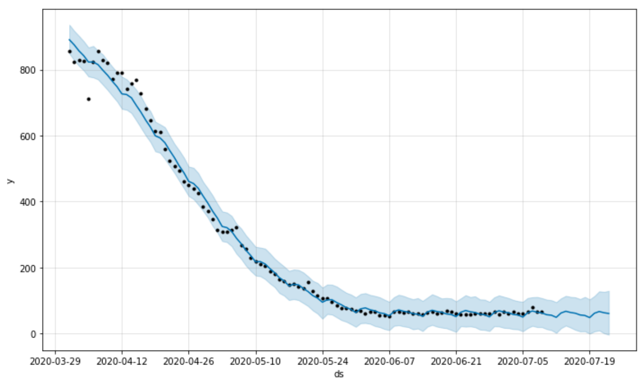

Figure 7. Hospital occupancy predicted for Austria

Figure 7 is used here to show and analyze the predicted results for Austria for a total span of 100 days including the 80 days of the training set and 20 days of test dataset.

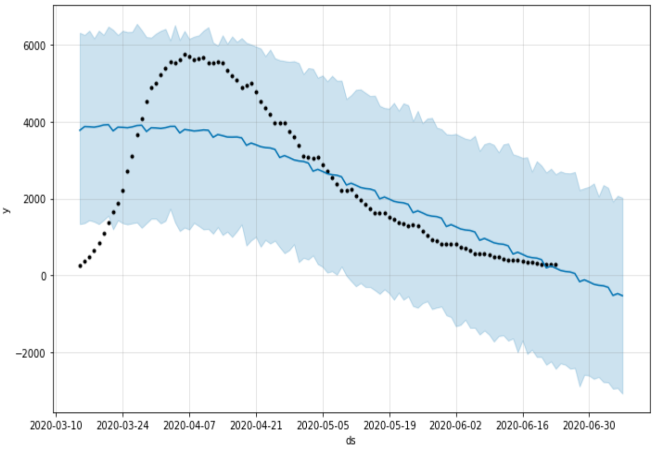

Figure 8. Hospital occupancy predicted for Belgium

Figure 8 is used to analyze the predicted results for the total span of 100 days for Belgium including the training set and the test dataset.

8. CONCLUSIONS

The aim of this research is to forecast and predict the Emergency Healthcare Requirements to address the problem of emergency admissions using an improved approach of LSTM, deploying a neural network model in Deep Learning. Time series prediction can be defined well with the problem statement for the prediction of the number of emergency healthcare resources, and the LSTM model has a favorable influence.

Proposed technique is a handy way of dealing with prediction case scenario for short term dependencies, a neural network model that can act as a feedforward network and solve the issue of prediction. But due to the short term dependencies, this research has been aimed to develop a robust and flexible model using the technology of LSTM.

The network solved the problem of dealing with the long time series data using their specially calibrated cell gates which helped in subsidizing the relevant information and leaving out the rest. This technique helped the model become efficient and effective as well.

This research solved its purpose of building a flexible model to predict emergency healthcare requirements using deep learning optimizing LSTM. In the future, the model is aimed to improve its prediction accuracy reaching out to a larger set of variables and a probable dataset based on real-time data.

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