REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1S (2024)
http://www.veterinaria.org
Article Received: 07 August 2024
Revised: 28 August 2024
Accepted: 09 September 2024

Deep Learning Techniques For Forecasting Emergency Department Patient Wait Times In Healthcare Queue Systems

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ABSTRACT
A lot of hospitals make use of the duration of patients' stays in queue as a gauge for overcrowding in the emergency room (ER). Many emergency rooms have lengthy wait times, which make it more challenging to provide patients with appropriate care and increases overall expenses. In queuing system applications, Innovative techniques like machine learning and deep learning (DL) have become crucial. In order to forecast Waiting periods for patients in a system, this research will use deep learning techniques for historical queuing variables, either in addition to or instead of queuing theory .SGD, Adam, RMSprop, and AdaGrad were the four optimization algorithms that were applied. To determine which model has the minimum absolute mean error (MAE), there was an algorithmic comparison. To facilitate more comparisons, a traditional mathematical simulation was utilized. The findings demonstrated that the DL model may be used to estimate patients' waiting times utilizing the SGD algorithm, with the lowest MAE of 09.60 minutes (23% reduction of errors) activated. In order to better priorities patients in a queue, this study contributes theoretically to the field of patient waiting time prediction using alternative methodologies by establishing the highest performing model. This study also makes a useful addition by utilizing actual data from emergency rooms. In addition, we suggested models that, compared to a conventional mathematical approach, produced more accurate predictions of patients' waiting times. Our method can be readily applied to the healthcare sector's queue system by utilizing data from electronic health records (EHRs). Since over 40% of people who are admitted to hospitals do so through the emergency rooms (ER), most hospitals suffer from extreme patient overcrowding. Since most ER departments in hospitals have lengthy patient wait times, they are an important component of healthcare facilities.

Keywords: Customer, Queue, EHR, Optimization Algorithm, Phase type Queuing Model

1.Introduction

Queuing is risky in an environment like the healthcare industry since waiting around could be expensive for medical both uncomfortable for patients and workers. Furthermore, it can affect a patient's life or health. One conventional method is queuing theory (QT). Mathematical method that has been applied for many years to the analysis of queuing systems. But because of the drawbacks of the methodology, such as the unfounded presumptions regarding the amount of time needed to complete queuing analysis—the typical Queuing theory approach might not be sufficient for practical uses. As a result, alternative methods are thought to greatly increase ER efficiency, such as deep learning (DL) algorithms. Another type of machine learning technique is deep learning algorithms. Furthermore, new studies demonstrated that the method utilized to estimate ER patient wait times has a limited degree of accuracy. In addition, DL algorithms have even higher accuracy and can minimize human error as compared to conventional methods. The objective of this research was to provide a new and improved model for forecasting wait as well as an essential instrument for responding quickly if long wait times are reported at emergency rooms. Because of a substantial inaccuracy rates in earlier research, this goal was brought on. In contrast to previous studies on this topic, this study's special model minimizes incorrect prediction.

From an applied perspective, DL was applied to create an original technique that uses queuing predictor variables at the emergency room to increase the precision of the waiting time estimate for patients with low acuity. The DL technique was compared to traditional mathematical techniques. The mechanism for monitoring triage at an emergency room in India with 32,815 patients between January and December of 2020 was used to collect realistic data.

According to Abe (2019), there exists a correlation between the duration of waiting times and the degree of discontent among customers. Thus, they are encouraged to consider distributing resources. appropriately in order to reduce line wait times. Enhancing customer service is crucial in the healthcare business to boost overall satisfaction and promote favorable health outcomes. Excessive wait times are a measure of accessibility to medical facilities and have a negative correlation with health outcomes (Liang 2010).

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Various methods, such as mathematical analysis, are generally employed to maximize the efficiency of queuing as well as resource allocation (Bittencourt et al. 2018). Queue models, for instance, are widely used to assess waiting times at hospitals, pharmacies, and more service locations in order to manage high demand. In a similar vein, queuing models are also other service sectors, like airports, that need to have security controls (Abe 2019). Additionally, queue waiting times are thought to be an indicator of how well a traffic control method is working. For example, over 90% of travel time delays and airport traffic congestion are brought on by delays in the queue. (Peterson et al. 1995). Queuing models are also useful in everyday situations when customers have to wait in queue for meals at restaurants or grocery stores. Longer wait times in any system have been linked to increased consumption, based on research (Dong et al. 2019; Ülkü et al. 2020). Lines that proceed slowly, result in longer wait times and greater visibility, It demands the application of more resources.

Observe the following are the ways that this study adds to the body of current literature: First, by utilizing actual data from electronic health records (EHR) on low patient acuity at an emergency room (ER) in India, Models for DL were generated. in addition to or as an alternative to queuing theory for calculating queue waiting times. Secondly, using the MAE metric, DL implementation improved prediction error, resulting in a 24% reduction. Third, according to research experiments conducted; This study offers guidelines for feature extraction and model understandability in examination of waiting times in queues, not only in the field of healthcare but in additional industries as well. We think that researchers as well as practitioners. Working on connected problems in several fields will find value in the findings.

2. Literature Review

Long wait times have been linked to patient discontent, anxiety, rage, and frustration, according to prior studies (Curtis et al. 2018; Sun et al. 2000; Ward et al. 2017). Various approaches have been used in a number of studies to analyze the estimates for ER wait times. For instance, Kuo et al. (2020) predicted ER wait times by combining machine learning and systems thinking. To forecast patient waiting times, Stagge (2020) used a mix of techniques, such as simulation and machine learning; Arha (2017) estimated the waiting period for low patient acuity in the emergency room using a variety of machine learning techniques, including Random Forest and Elastic Net. Lastly, Curtis et al. (2018) Several Neural networks and other machine learning approaches have been created to calculate patient wait times while accounting for a number of variables, such as patient arrival time, total service duration and assessment. Furthermore, research has created prediction models that use techniques like quintile regression to calculate how long low-acuity patients will have to wait for treatment. (Pak, Gannon, and Staib 2020) Our investigation is distinct from earlier studies on this subject. since we increased accuracy by using various DL optimization algorithms. We also considered additional predictors. by obtaining additional information from the patient's arrival time, waiting time in the queue, and departure time (e.g., minute, hour, and day).

Around the world, many hospitals frequently deal with high wait times and overcrowding in their emergency rooms. In the US, the number of visits to emergency rooms rises yearly. (Di et al. 2015). In 2017, The National Institutes of Health (Kaushal et al. 2015; Sasanfar et al. 2020). The medical field is starting to find use for prediction models. An effective technique for addressing seasonal arrival and waiting times is the use of historical information to forecast upcoming client waiting times (Ruben et al. 2010; Cai et al. 2016). Healthcare issues that may have hidden features can be solved and examined using the data stored in electronic health records. Previous research has concentrated on queuing system enhancements in the healthcare industry, primarily on its application in predictive models for behavior analysis. (Eiset et all 2019). Moreover, a study on the projection of queuing behavior has used machine learning. (Srivastava 2016; Stagge 2020). The two projects for research have flawed time series analysis on queue data prediction since they rely on a predictive modeling approach. In the past, waiting periods were examined in the Dong et al. (2019) multi-hospital trial, and the outcomes indicated that patients take the ER waiting time into consideration When choosing where to receive medical services. Statistics show that there are approximately 123.5 million ER visits annually. every year (Kea et al. 2016). ER visits have gone up, yet, wait times have as well. For example, the Health Information Council of Canada noted in 2016 that since 2015, ER Wait times have considerably increased. One practical the best way to address these problems is to evaluate the efficacy of ERs (Rasouli et al. 2019). Making operational choices that cut down on wait times and overcrowding in the emergency department is made easier with the use of the previously provided data (Abir et al. 2019). To predict queuing behaviors in businesses, Stinting and Norrman (2017) compared as a prediction artificial neural networks (ANN) tool with optimization through queuing theory. Positive results from ANN, according to the authors, might be used to forecast the appropriate quality of service each day. In order to optimize the waiting time in the line, a number of prediction strategies have been used in queue analysis (Moreno-Carrillo et al. 2019); But our model with several Optimization techniques are useful for evaluating the ER waiting times for low-acuity patients. Therefore, by

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utilizing EHR information, the model proposed in this paper can be utilized to give Emergency Room Physicians information regarding how long patients have been waiting in queue,

3. Research Methodology.

This work uses EHR data to forecast Waiting periods for patients in a queue system utilizing deep learning techniques in addition to or instead of queuing theory (QT). The optimal the model with the lowest mean absolute error is then determined through the DL algorithms' comparison. The model is explained, and Figure 1 displays a flowchart of the recommended process. Each step is explained in the subsections

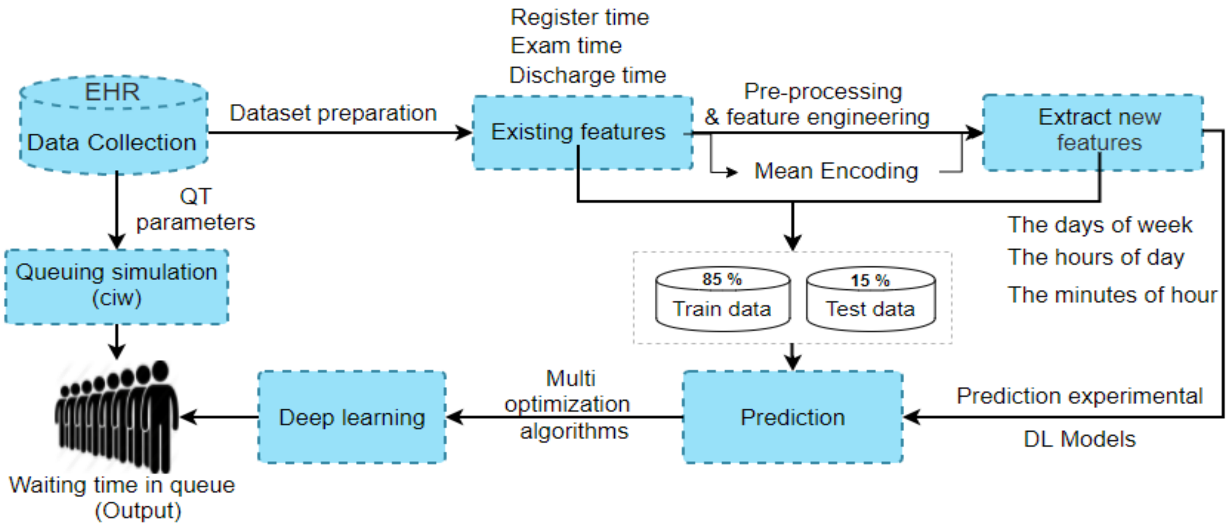

Figure 1

3.1 Description and Preparation of Data

Quality of patient care. The Triage Monitoring system provided the data, which also contains information about hospital ER lineups and their formation over the months of January through December of 2023. From the time a patient enrolled until they As it left the hospital, it monitored and documented their flow through the facility. These are the primary sources. for using machine learning, particularly when estimating how long a new patient will have to wait in queue. These comprised the time it took to check into the queue (arrival/registration time), wait in queue (waiting time), visit the server (service time/doctor exam time) and total amount of time spent using the system processes. The main data that were taken out of the EHR were placed at random. The information was cleansed, examined, and finished in several steps:1 Initially, we used the arrival/register time to transform our data into weeks. Step 2 created daily data using the data from Step 1. Step 3: To create entries in the order of arrival, the data were sorted according to arrival time. Step 4: We eliminated the data from our analysis if it contained high or missing values (manually inserted errors). Only individuals with acuities ranging from level 3 to level 5 were included in Step 5, as these patients accounted for over 60% of the information we gathered. Following data cleansing, these patients included over 20,808 patients that were employed in the training model. Additionally, names and patient IDs that were deemed unnecessary were eliminated from the dataset.

The duration of the triage service was combined with the waiting time (for the duration from arrival to the initial doctor's appointment) due to the fact that the dataset alone included one server (the examination by the physician). These patients are thought to be as non- haste or less haste. These patients are typically seen on a first-come, first-served basis and not necessary emergency attention. Consequently, the duration that the algorithms for machine learning must wait try the output variable in this model is to anticipate. In the dataset, the average the waiting period was 43.65 minutes, with a 28.0-minute median and a 21.34-minute standard deviation. To offer some initial perspectives regarding our model data, many input factors were examined, such as waiting time, service time, and the number of persons waiting compared to the days of the week. The period of time from the beginning of the patient's medical care to the conclusion of that care is known as the service time in our data. Here, for example, the collection (new features gathered) is employed to compute the number of patients in the queue along with the quantity of sufferers for each new patient. In order to get the total quantity of patients in the queue, we added up the arrival and waiting times for each patient who left the queue before calculating the quantity of individuals who were still waiting. each time a new patient entered. Preparing data and choosing features are widely used methods related to machine learning.

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3.2 Pre-processing and Engineering of Features

A crucial component of the structure of the machine learning model that impacts the performance of the model is feature selection, or the selection of predictors (Chandrashekar and Sahin 2014). In this study, key characteristics were taken from the patient entering the queue, including the hour, day, and minute. The patient's departure time and queue waiting time were also taken. The three primary characteristics are as follows:
1) The day fell between Monday (0) and Sunday (6).
2) The time in hours, ranging from 0 to 23.
3) Minutes, commencing at 0 minutes and extending until the 59th minute.
The data was encoded using mean target encoding. Categorical features, and the dataset's preexisting features were mined for new features. We implemented the extraction of features technique, as described by Kyritsis and Michel (2019), and it was used in the bank. Our data was encoded with the additional features using the mean target encoding, which provides greater cardinality features for regression problems and is a quick method for encoding the majority of categorical variables. (Pargent et al. 2019).

3.3 Experimental Prediction

This study employed Python 3.7.3 and Tensor Flow 2.0.0.-beta1 for its explore with machine learning. Furthermore, a variety of libraries among them Matplotlib, Date Time, and Pandas, were utilized to prepare and pre-process the data. Consequently, we divided our dataset into two factions—the test set, which consisted of 14%, and the training set, which consisted of 84%—in order to verify and assess the sensitivity of the model's performance. Throughout the training procedure, the test set remained secret. Additionally, by confirming our model, because test harnesses demonstrate how sensitive a method is to applied data or new data that can be added into the model, they are used to provide a fair evaluation measure how well the model performs when generating predictions using fresh data. For this model, several optimization strategies were tried until the best with the lowest MAE was found. One statistic used to assess the accuracy of the machine learning model's performance is MAE It provides a sense of the error's size. By deducting the predicted value from the actual value, as indicated by the Equation, it computes all recorded means for the absolute errors.

$$MAE = \frac{\sum_{i=1}^{n} abs(yi-\lambda(Xi)}{n} \tag{1}$$

Equations (2) to (12) below are quoted and summarized from Ruder (2016). Regarding the network weights' iterative update based on our data training, we utilized various optimizer algorithms, such as SGD, Adam, Adagrad, and RMSprop. The optimization process known as stochastic gradient descent (SGD) keeps a constant learning rate (referred to as alpha) throughout training for all weight changes. Each parameter, or network weight, has a learning rate. that is tracked and individually adjusted as the learning process progresses. SGD, in contrast, updates a parameter for every training example. x^i and label y^i

$$\theta=\theta-\eta\cdot\nabla_{\theta}J(\theta;x^i;y^i) \qquad [\ \theta=\theta-\eta\cdot\nabla\theta J(\theta)\ ]\text{using} \quad (2)$$

Adam stands for adaptive moment estimation, which combines momentum and RMSprop stands for Root Mean Square Propagation. Additionally, it can be applied in place of the conventional stochastic gradient descent process to iteratively update network weights using training data (Kingma et al. 2014). When keeping an average that decays exponentially of the prior squared gradient vt, Adam can also be utilized similarly to Adadelta and RMSprop (Ruder 2016). Additionally, it maintains an exponentially decreasing mean of historical gradients mt, such as momentum:

$$m_t=\beta_1\ m_{t-1}+(1-\beta_1)g_t \tag{3}$$

$$v_t=\beta_2\, v_{t-1}+(1-\beta_2)\ g^2_t \tag{4}$$

The name of the technique comes from the fact that: mt represents first moment (the mean) estimates and v_t represents the second moment (the uncaught variance) of the gradients, respectively, Since the writers of Adam noted that m_t and v_t are biased towards zero, particularly in the early with low decay rates and at intervals of time. (e.g., β_1, and β_2 are near to one), m_t and v_t are initialized as vectors of zero. By computing the first- and second-moment corrected bias estimations, m_t and v_t β_2 compensate for these biases:

$$m'_t=\frac{m_t}{1-\beta_1^t} \tag{5}$$

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$$v'_t = \frac{v_t}{1-\beta_2^t} \qquad (6)$$

The Adam update rule is then produced by using these as demonstrated in RMSprop to update the parameters:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t + \epsilon}}\ m_t \qquad (7)$$

RMSprop keeps track of per-parameter learning rates that are adjusted according to the weight gradient's average recent magnitudes, which includes changes in weight's rate of change. Although Geoff Hinton suggested RMSprop, an unreleased adaptive learning rate approach, it is a very effective method (McMahan and Streeter 2014). Adadelta's initial update vector, an expansion of the AaGrad optimization technique, is actually the same as RMSprop

$$E[g^2\ ]_t\ =\ 0.9E[g^2]_{t-1} + 0.1\ g_t^2 \qquad (8)$$

$$\theta_{t+1} = \theta_t\ \ - \frac{\eta . g_t}{\sqrt{E[g^2] + \epsilon}} \qquad (9)$$

Where: $[g^2]_t$ is the squared gradients' declining average over the previous. For issues AdaGrad, or adaptive gradient, sustains a per-parameter learning rate that enhances efficiency. when dealing with sparse gradients, such as those seen in issues with natural language and computer vision. (Brownlee 2020). Different learning rates are used by AdaGrad for each time step t for every parameter θ_i. Initially, AdaGrad updates its per-parameter, which is subsequently vector zed for conciseness; $g_{t,i}$ is defined as the gradient of the objective function with respect to the parameter θ_i at time step t:

$$g_{t,i} = \nabla_{\theta_t} J(\theta_{t,i}) \qquad (10)$$

Then, at the updates for every parameter at each time step t θ(t) using stochastic gradient descent become

$$\theta_{t+1,i} = \theta_{t,i} - \eta . \theta g_{t,i} \qquad (11)$$

Based on the previously calculated gradients for θ_i, AdaGrad adjusts the overall learning rate (η) for each parameter at time step t i in its update rule.

$$\theta_{t+1,i}\ = \theta_{t,i}\ - \frac{\eta}{\sqrt{G_{t,ii+\epsilon}}}\ \ .g_{t,i} \qquad (12)$$

Where: A diagonal matrix, $G_t \in \mathbb{R},^{dXd}$ has diagonal elements i, i, which represent the total squares of the gradients up to the time step with respect to $\theta\ \ .t\ ^{11}$ Additionally, the smoothing term Δ (often on the order of $1e{-}8$) prevents division by zero. Next, hidden layers employed the Rectified Linear Unit (ReLU).. A linear function is the ReLU activation function. that, in the event that the input is positive (x), will output the value directly; if not, it will output zero. (In other words, it will return zero if it receives any negative output (Hara et al. 2015). It is employed in this model because, in comparison to other optimization functions (such as the Sigmoid Function), it produces superior results and is more comfortable to train. ReLU is expressed as Equation (13):

$$f(x) = \max(0, x) \qquad (13)$$

4. Results

Our goal in this study was to use queuing theory in conjunction with a DL technique. DL is among Artificial neural network-based machine learning techniques

The libraries created by DL, including Keras, are what give it its power because they make it simple and quick to build vast networks. Furthermore, utilizing the Ciw library, a simulation A queuing system model was developed so that it could be compared to the DL model. According to Palmer et al. (2019), A discrete event simulation (DES) library called Ciw is used for queuing networks that is supported by Python.

4.1 DL Models

To apply DL mode, the Python Keras library was utilized. There are four input visible layers, one hidden layer with 25 neurons and another with 18 neurons. and one output for the output layer were employed in the training process. Following

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150 model training epochs. Figure 2 compares the real waiting period for the finest performing optimization techniques (SGD) with the model-predicted average waiting time. The orange colour indicates the anticipated waiting time, and the blue colour indicates he real (genuine) duration of waiting. It indicates that the estimated waiting time and the actual waiting time are most similar. The concept of wonderful or bad model score only becomes sense considered in relation to the other model's skill score.

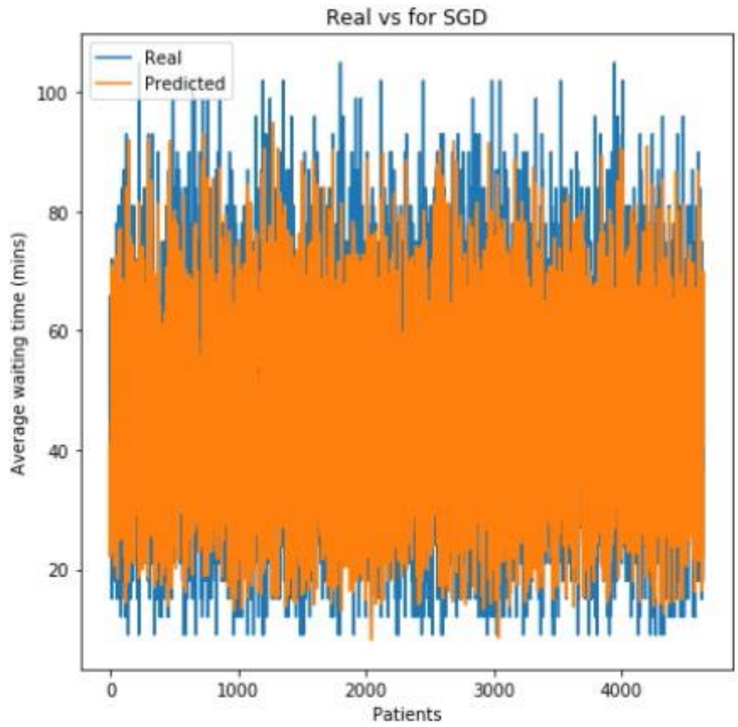

Figure 2

The same set of data is used to compare and train several optimization methods.
Table 1 lists the four optimization techniques used in our experiment from high to low MAE. At 10.80 minutes, the stochastic gradient descent (SGD) approach possessed the lowest MAE, followed by the RMSprop algorithm and the Adam and AdaGrad optimization technique, which took about 12 minutes. Following a thorough adjustment of all associated hyper parameters included in the model, [25-18-1] architecture values were determined to be appropriate in relation to the neural network in this model.

Table 1 DL model synopsis (MAE findings)

Methods of Optimization	Architecture of Networks	Mean Absolute Error
Aa gradient	[25-18-1]	11.68minutes
Adaptive Moment estimation	[25-18-1]	10.27 minutes
Root mean square propagation	[25-18-1]	10.23 minutes
Stochastic gradient descent	[25-18-1]	09.70 minutes

As seen in Figure 3, the model's performance for each optimization on training and validation datasets strategies is comparable when plotted against loss. If these parallel plots begin to routinely diverge, the two dataset's losses might use this as a cue to cut instruction in a previous era. Furthermore, it displays the similar proficiency of the various optimization techniques on the train and validation datasets. Changing the weights and learning rate of our DL model,

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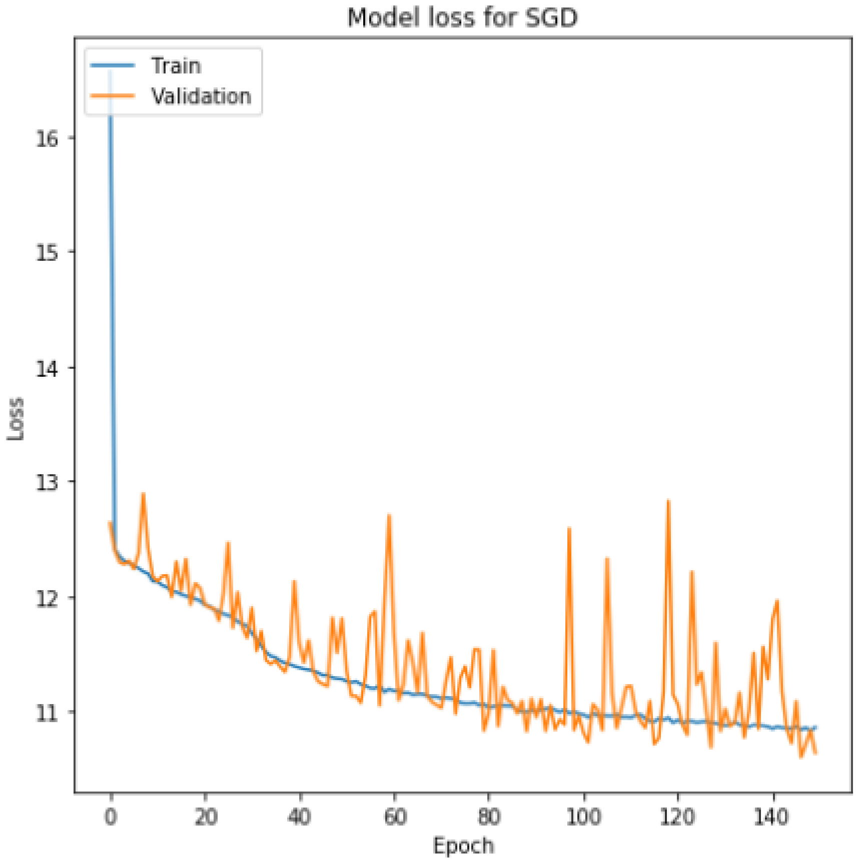

Figure 3

4.2 QT Models

The study's model was simulated using the traditional queue theory method. The same information utilized in the DL model were used to calculate the rates of arrival (λ) and service (μ). As indicated in (Appendix A Table 1), data was used for a single day, and it is considered that the service time probability distribution follows A distribution that is exponential. The quantity of patients who arrive in a particular amount of time is calculated using the Poisson distribution. The queuing model of the M/M/1 system was utilized to replicate the examination and depict the ER system since patients with level 3 through 5 acuities were used in this study. Initially, the model runs for 1,440 minutes, or a full day. The model requires 90-time units for both warm-up and cool-down phases and it runs for ten simulations in a to ensure sure the simulation truly replicates reality. Since different seeds were used each time, the outcomes of each trial varied. The average result was then applied to the trial findings (56.13, 68.06, 42.26, 61.12, 63.52, 63.12, 70.64, 78.55, 63.52, 58.30 in minutes) in order to obtain a more confident response. Thus, the model ran for one day plus 200 minutes (1,530 minutes) for each experiment. The model used for simulation yielded a imply waiting period of 58.30 minutes for patients, and a service time of 52.30 minutes. When QT is used to compare the dataset's results to the DL models, the average wait period is roughly 43.65 minutes, which is in line with what the DL models predicted.

5. Discussion

Waiting time prediction faces problems from stochastic and urgent procedures in the emergency room. For instance, the ER treats patients with high acuity effectively in an emergency setting, but it is usually less effective when treating patients with non-urgent conditions. Consequently, there is a rise in ER occupancy. Individuals needing extremely urgent care avoid waiting times while non-urgent individuals wait in the ER, which could lengthen wait times for non-urgent patients. Additionally, related to attention needs at the patient level (e.g., level 3 to level 5), those with non-emergency instances may differ according to each instance. Nonetheless, it has been demonstrated that high acuity patients' service delays and overall ER waiting times are significantly impacted by low acuity care (Arha 2017). This study's goal was to produce a more precise estimate of the waiting time model and to provide a essential instrument or responding quickly if long wait times are reported at emergency rooms. For example, this model is compared to other models of a similar nature in order to estimate ER waiting times. Models with an accuracy of mean-square error ranging from 0.14 to 0.21 were created by Kuo et al. in 2020. The number of patients in a line (for arrival to the patient's location, triage, consultation, and departure)

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and the patient's arrival time and triage categories, and the number of physicians (after the patient's arrival, within three hours) were among the significant variables included in the model. A local triage system (Hong Kong) is implemented, which places limitations on the suggested model by Kuo et al. Furthermore, Arha (2017) used a basic regression model to estimate how long patients stay in would have to wait in an emergency room in Tennessee for a regional triage system. Similar predictor variables, such as day of the week, time of day, and month of the year, were employed by Arha, and the predicted accuracy was measured by the mean square error (Arha 2017). Clinical data must be gathered in order to compute this model variable and contrast it with the model that is recommended. Additionally, Pak et al. (2020) created a A waiting time prediction model with a 25% mean squared prediction error overall accuracy for patients with low acuity who are placed in the waiting room Comparing the suggested models with SGD and RMSprop algorithms to the model improvement in Pak et al. (2020), the prediction errors were decreased by 24%. The data availability is one of the study's weaknesses; not all ER data, such as the patient's type of injury, the time it takes to analyze an X-ray, and the duration of a laboratory test, was included. The dataset's contents were extracted. In addition, data hunger is another name for DL; in this instance, data was gathered for a single year. The results indicate that the lowest MAE was attained at 10.80 minutes; however, if more data is collected, this could drop. 28,808 patients (acuities level 3 through 5) were included in the experiment for training after missing data and other levels (level 1 to 2) were eliminated. When compared to a predicted average waiting time, a significant improvement in waiting time prediction using existing data was demonstrated. Furthermore, the model may be easily integrated with related information within an electronic health record. The second drawback is the possibility of regional variations in the patient levels (designated as levels 1 through 5) in the local triage system. For instance, in this data, levels 1 and 2 were classified as high critical and levels 3 to 5 as low urgent; however, this may differ in alternative ER triage methods across the world. The third drawback is that the study was only conducted in one area, which may have an influence on the model's accuracy and necessitate additional Endeavour to verify the model utilizing information from additional ERs in various places as well as using various populations.

6. Conclusion

This study presents a new model utilizing DL techniques and ER data was developed to increase the precision of low acuity patient waiting time prediction. The study predicted Waiting periods for patients in a queue system using historical queuing characteristics in addition to or instead of using conventional methods (queuing theory). Because of the restrictions on the old methods— like the unreasonable presumptions about the dispersion of time needed to do accurate queuing analysis—they might not be adequate in real-world applications. Additionally, in comparison to conventional techniques, DL algorithms can attain higher accuracy and minimize human error. Thus, to greatly increase ER efficiency, It is necessary to use other techniques like DL algorithms. A unique waiting time prediction model was developed for this reason, and it serves as a essential instrument for responding quickly in the event that emergency rooms report lengthy wait times. Adam, AdaGrad, RMSprop, and SGD are the four optimization algorithms that were evaluated in order to determine which one had the best accuracy when taking MAE metrics into account. Additionally, algorithms were contrasted with conventional mathematical techniques, and Indian monitoring system for triage data was used. The outcomes demonstrated that the DL model performed better than the traditional method regarding the accuracy of the predictions. Furthermore, n contrast to previous studies on this topic, the special model employed in this investigation provided a 24% error reduction. In order to better priorities patients waiting in queue, the theoretical contribution of this study is the use of various approaches to predict waiting periods for patients. Through the creation of the best-performing model. This study also makes a useful addition by utilizing actual data from emergency rooms. Additionally, methods that anticipate there have been given patient wait times that are more accurate than traditional mathematical models.
Additional details from EHRs could be incorporated into the model, such as other queuing predictor parameters, in future and expanded study. Furthermore, it is possible to incorporate various datasets from various hospitals and places. It was possible to anticipate the service duration for identically matched patients of acuity. This model might also be used with various machine learning algorithms, for instance, linear and nonlinear regression. The concept could be applied to address connected problems across multiple industries or domains, say, a customer lines and services. Future work could involve deploying the model as a web application so that patients can sign up ahead of time to use EHR data.

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Revised: 28 August 2024
Accepted: 09 September 2024

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