A Method to Accurately Predict the Waiting Time by the Process in the Case of a One-Stop Service

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Abstract

Clients of a few famous administrations need to stand by inactively for quite a while. These administrations generally have a restricted limit and can serve few clients all at once. It is outside the realm of possibilities for clients to get the help without holding up by any stretch of the imagination; in this manner, it will be worthwhile for clients to know the rough holding up time which they might decide to do different exercises as opposed to remaining in a help line. This article proposes and assesses ways to deal with foresee the holding up time before a client gets the help. Three methodologies of stalling time forecast have been executed and analyzed. These methodologies incorporate Queueing Theory, Average time, and Random Forest. The exploratory outcomes showed that the administered learning calculation, Random Forest, accomplished the most elevated exactness at 85.76% of ear nose and throat center dataset and 81.7% of KhonKaen University mailing station dataset. This article additionally researched highlight significance and observed that the quantity of delaying lines was the most basic element in holding up time forecast.

Keywords:-AI, queueing hypothesis, irregular woods, holding up time forecast

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1. Introduction

Right now, individual's way of life and exercises are generally in a hurry. Hence, their time is most important (Arroyo, 2014; Hensley & Sulek, 2007; Van Riel et al., 2012). In any case, individuals frequently need to go to a few stuffed administrations, like phenomenal wellbeing facilities or mail depots. These administrations as a rule take clients quite a while in holding up prior to getting administration. To make benefits more helpful and ideal, specialist organizations set up a one-stop administration which consolidates the range of administrations to only one spot (Sanit-in & Saikaew, 2019).

These days, a few one-stop administrations, for example, mail centers, banks or eateries have popularity among numerous clients. Ordinarily, clients need to hang tight for quite a while prior to being served. Such a significant delay is probably going to influence clients' fulfillment. Holding up prompts negative connection among clients and the assistance settings, and it influences the initial feeling that the clients have toward the administrations. Obviously the primary relationship impacts the assistance (Arroyo, 2014).

A few ongoing exploration studies have endeavored to handle the issue of administration holding up time. Achmad et al. (Achmad et al., 2021) explored on the most proficient method to diminish holding up time by utilizing Lean Thinking and ECRS strategies (Eliminate, Combine, Rearrange, and Simplify) and the reenactment model at a dental facility. They reasoned that the reproduction model of the dental facility could lessen hanging tight time for the administrations. Safdar et al. (Safdar et al., 2021) planned a calculation for holding up time expectation by utilizing the typical season of short term treatment, the executed electronic and portable application, and the calculation for holding up time forecast. In any case, there was no exploratory outcome announced. Rarh et al. (Rarh et al., 2017) executed the framework to tackle the issue of the holding up season of the eatery table reservation by utilizing time-series expectation. The framework would illuminate holding up chance to clients and assist the supplier with overseeing administrations all the more productively. In any case, there was no holding up time forecast precision detailed. Carvalho et al. (Carvalho & Belo, 2016) fostered a framework for holding up time expectation of a store by utilizing time-series forecast with Linear Regression strategy and the highlights of the store administration. The above talked about related work had ways to deal with take care of the issue by utilizing the reproduction, the computation of the past typical time, or utilizing time-series expectation. This proposed article varies from such related work by utilizing arrangement. We picked order rather than relapse since it would take an unnecessarily huge measure of preparing information to foresee holding up time in a relapse way.

One of the early work that likewise utilized order procedure was the work proposed by Mourão et al.(Mourõo et al., 2017) which proposed the four strategies that included Queueing Theory, Deep Learning, Gradient Boost Machine, and Random Forest for foreseeing the holding up season of a bank, yet the highlights that fabricated the prescient model were well defined for the bank administrations. Albeit a large portion of the investigations (Carvalho & Belo, 2016; Rarh et al., 2017; Safdar et al., 2021) carried out the framework for holding up time expectation, however they didn't concentrate on a few basic highlights influencing holding up time expectation, like the quantity of holding up clients. Then again, the latest work (Mourão et al., 2017) applied a few highlights for the holding up time grouping. In any case, their work could apply to banks in Brazil, rather than some other administrations. Besides, their forecast outcome was regardless of whether the holding up time was over the specific limit. Telling the holding up time reach would be more helpful and ideal.

This research proposes a calculation for holding up time expectation of any one-stop administration by utilizing general elements that are not well defined for a specific help. Supposedly, our article is the primary that reviews and reports the element significance in the prescient model for holding up season of one-stop administration.

The remainder of the article is coordinated as follows: Section II portrays the foundation of this review, Section III makes sense of the philosophy in getting ready information and the holding up time forecast, and the exploratory outcomes are introduced and broke down in Section IV. At long last, the ends are attracted Section V.

2. Research background

The review examined three methodologies for addressing holding up time in one-stop administration issue. These methodologies included Queueing Theory, Average Time, and Random Forest. We decided to concentrate on these methodologies on the grounds that Queueing Theory is a customary strategy for the expectation of stalling time, Average Time is a fast and simple estimation technique, and Random Forest is a grouping technique that learns information to fabricate the expectation model.

2.1. Queueing Theory

Queueing hypothesis is a numerical investigation of administration frameworks and holding up season of lines in a holding up line. Since the framework has the restricted assets, all clients can't enter the administrations simultaneously. In this manner, the holding up lines are made (Erdelić et al., 2017). In line discipline, the help orders incorporate first started things out served (FCFS), last start things out served (LCFS), irregular choice for administration (RSS), need requesting (PRI), and general discipline (GD) (Mourão et al., 2017).

As per researcher(Erdelić et al., 2017), line model has been made sense of utilizing three variables, in particular, A/S/c where A means the appearance dissemination, S signifies the help dispersion, and c signifies the quantity of administrations.

The contextual analysis in this article, the line discipline is FCFS, also, the line framework is M/M/c. Researcher(Erdelić et al., 2017) portrayed that M/M/c is the multi-server framework where M is a remarkable dissemination of appearance and administration, separately, and c is the quantity of multi-administrations.

For M/M/c line framework, the Utilization Factor (U) is a proportion of appearance, administration rate, and administration point number (2),

$$\rho = \frac{\lambda}{\mu} \qquad (1)$$

$$U = \frac{\rho}{c} = \frac{\lambda}{c\,.\mu} \qquad (2)$$

where the mean appearance rate (λ) is the quantity of clients showing up at the assistance point in one moment, the mean help rate (μ) is the quantity of clients getting the help in one moment, and c is the quantity of administration point at the time (Erdelić et al., 2017).

Researcher (Erdelić et al., 2017)revealed that if $U < 1$, the framework is fixed. The estimation of the viability of the line framework can be registered as follows:

The likelihood of no clients in the framework (P0) can be figured by utilizing Equation (3).

$$P_0 = \left[\frac{c\rho^c}{c!(c-\rho)} + \sum_{n=0}^{c-1}\frac{\rho^n}{n!}\right]^{-1} \qquad (3)$$

The typical number of clients in line for administration (Lq) can be figured by utilizing Equation (4).

$$L_q = \frac{c\rho^{c+1}}{c!(c-\rho)^2}\cdot P_0 + \rho \qquad (4)$$

The typical holding up season of clients in line for administration (Wq) can be registered by taking (Lq) partition by (λ) as show in Equation (5).

$$W_q = \frac{L_q}{\lambda} \qquad (5)$$

2.2. Average Time

The math mean is the amount of all intrigued values separated by the quantity of values (Sun, 2018). On account of time measurements, it is called normal time. For the typical holding up time, Average Time (AT) can be determined by holding up time and the quantity of clients,

$$AT = \frac{1}{n}\sum_{i=1}^{n} w_i = \frac{w_1 + w_2 + \cdots + w_n}{n} \qquad (6)$$

wherewi signifies the holding up season of the ith client, and nis the quantity of clients.

2.3. Random Forest

Directed learning calculations are AI strategies that train information to make the model for expectation as relapse or characterization. In the order, Random Forest is one of the directed learning calculations suggested for building the prescient model due to its elite exhibition and speed (Noyunsan et al., 2018).

Irregular Forest is an order that incorporates choice trees and gathering. To consolidate two calculations as displayed in Figure 1, a choice tree is a calculation that partitions the information by crediting and constructing a tree to order the class of a case. A gathering is a characterization that partitions the information for making models and incorporates the result expectation of each model as the class of an occurrence. What's more, Random Forest partitions the information by arbitrarily separating the elements for making the models (Dumka et al., 2020)(Almomani et al., 2021; Mourõo et al., 2017).

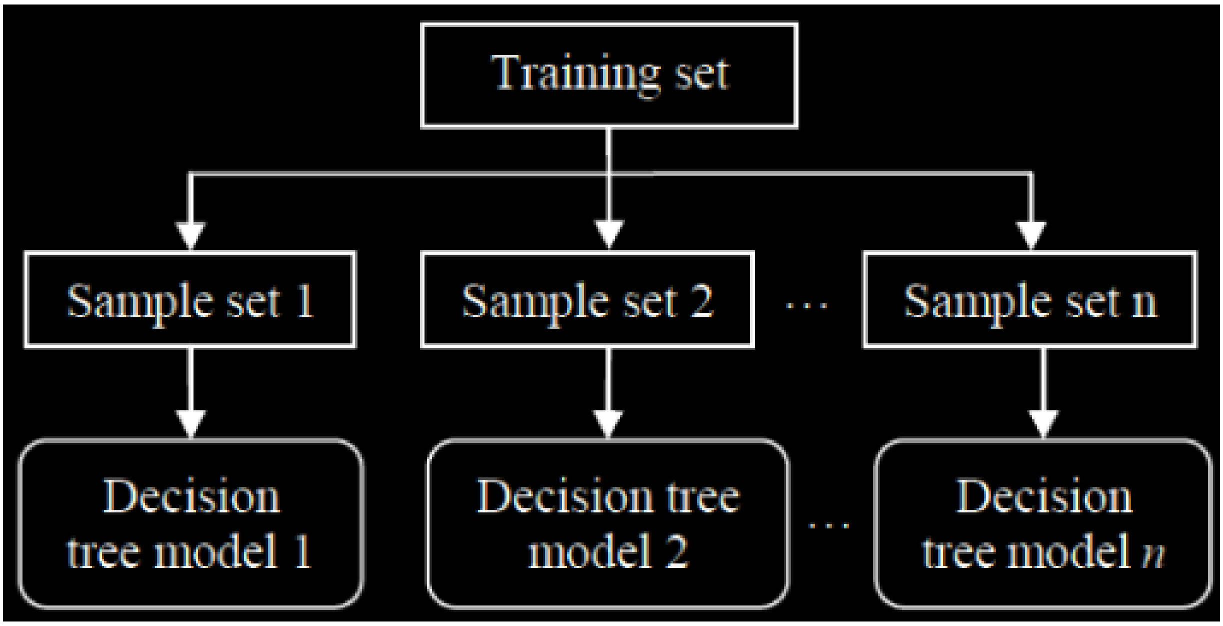

Figure 1: The random forest model

In Random Forest, there is the component significance strategy wherein mean reduction precision is utilized to assess the prescient mistake and element importance (Han et al., 2016; Watcharenwong & Saikaew, 2017).

3. Research methodology

3.1. Framework Overview

The most common way of delaying time expectation incorporates information readiness, constructing a prescient model, and assessment of anticipated result as continues in Figure 2.From Figure 2, the flowchart shows the request for the most common way of stalling time expectation. After datasets were cleaned, the datasets were arbitrarily parted into preparing and testing dataset. Irregular Forest utilized preparing dataset to fabricate a prescient model for grouping the holding up time class. At last, the precision of three calculations: Queueing Theory, Average Time and Random Forest was tried by holding up time expectation of the testing dataset.

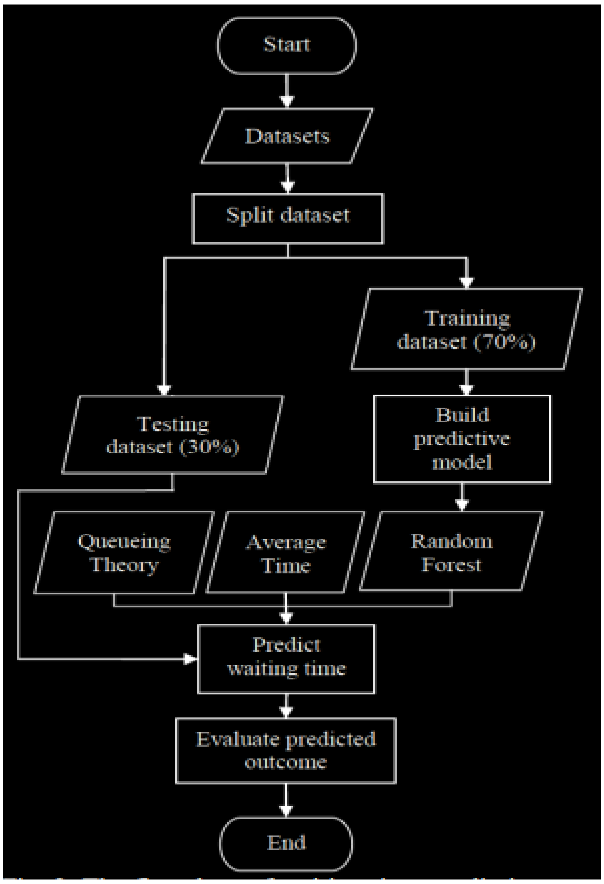

Figure 2: The flowchart of stalling time forecast

3.2. Data Preparation & Analysis

The principal information of this study is the line logs of KhonKaen University mail center from October 16 to November 17, 2017. In view of a versatile application, 3,480 records of information were gathered.

The second information of this study is the line logs of the ear nose and throat facility, Srinagarind Hospital partnered to the Faculty of Medicine of KhonKaen University from June 29 to August 28, 2018. The information were gathered 1,348 records by the line the executives arrangement of the center.

The information purifying interaction incorporated the end of traits that were not used to fabricate prescient models. The holding up time type arrangement from holding up term in help was displayed in Table I and II.

Table I: The Waiting Time Classes OfKhonKaen University Post Office Dataset

Classes	**Duration (Seconds)**
Very short	0 - 60
Short	60 - 120
Medium	120 - 240
Long	240 - 480
Very long	>480

Table I shows the holding up time classes that were arranged from the holding up line length. The holding up time somewhere in the range of 0 and 60 seconds was viewed as exceptionally short, the holding up time somewhere in the range of 60 and 120 seconds thought about short, etc. We separated the holding up time class from the min (2 seconds), max (625 seconds), normal (69 seconds), and standard deviation (96.3 seconds) upsides of the holding up line durationfor the holding up time class of the KhonKaen University mail center dataset.

Table II: The Waiting Time Classes of Ear Nose And Throat Clinic Dataset

Classes	**Duration (Minutes)**
Very short	0 - 20
Short	20 - 40
Medium	40 - 60
Long	60 - 80
Very long	> 80

Table III: The Statistics of Waiting Time Classes of KhonKaen University Post Office Dataset

Classes	Number of Records	Percentage
Very short	2,280	65.52
Short	521	14.97
Medium	468	13.45
Long	174	5
Extremely lengthy	37	1.06

Table IV: The Statistics of Waiting Time Classes of Ear Nose and Throat Clinic Dataset

Classes	Number of Records	Percentage
Exceptionally short	723	53.64
Short	379	28.12
Medium	123	9.12
Long	87	6.45
Extremely lengthy	36	2.67

Table V: The Attributes of Datasets

Features	Description/Type
Number	The line number/Nominal - e.g., 1, 101, or 2001.
Shift	The time of the day/Nominal: {morning, afternoon}
Line Type	The kind of line which clients have been served/Nominal: {mail, bundle, mail and parcel} or {yellow, purple, light green, white, pink, dim green, blue, general, sky blue, old individuals, orange}
Administration Point	The client assistance point/Nominal: {1, 2, 3, 4} or {1, 2}
Made Queue Hours	The hours when the client began pausing/Timestamp: {HH}
Made Queue Day of Week	The day of week when the client entered administration/Nominal: {Monday, Tuesday, Wednesday, Thursday, Friday}
Holding up Duration	The administration holding up time/Numeric (Seconds or Minutes)
Number of Waiting Queue	The number of clients who were sitting tight for administrations/Numeric (Queues)

Appearance Rate	The client appearance rate at that point/Numeric (client each moment)
Administration Rate	The client care rate at that point/Numeric (client each moment)
Holding up Time Class	The target credits are grouped from holding up time span/Nominal: {very short, short, medium, long, very long}

Table II shows the grouping of stalling time classes from the holding up line term. The holding up time somewhere in the range of 0 and 20 minutes was viewed as extremely short, the holding up time somewhere in the range of 20 and 40 minutes thought about short, etc.

The holding up time classes were isolated from the min (2 minutes), max (113 minutes), normal (25 minutes), and standard deviation (20 minutes) upsides of the holding up term of the ear nose and throat facility dataset.

The information examination in this segment was viewed as a measurements of line design as displayed in Table III and IV.

The measurements of delaying time classes are displayed in Table III. For KhonKaen University mailing station dataset, the holding up time classes were arranged from the holding up length of the 3,480 records. The rates of records in the five holding up time classes are as per the following: exceptionally short 65.52%, short 14.97%, medium 13.45%, long 5%, and extremely lengthy 1.06%.

Table IV shows the measurements of delaying time classes the holding up length of the ear nose and throat facility dataset was ordered to holding up time classes. The rates of records in the five holding up time classes are as per the following: exceptionally short 53.64%, short 28.12%, medium 9.12%, long 6.45%, and extremely lengthy 2.67%.

The models were worked from the highlights as displayed in Table V. Just Average Time utilized the holding up time include (Waiting Duration) for seeing as the math normal.

3.3. Holding up Time Prediction

The datasets of this review were haphazardly parted into two datasets: preparing (70%) and testing (30%) dataset. The KhonKaen University mail center dataset has preparing dataset: 2,436 records and testing dataset: 1,044 records. The ear nose and throat center dataset has preparing dataset: 943 records and testing dataset: 405 records.

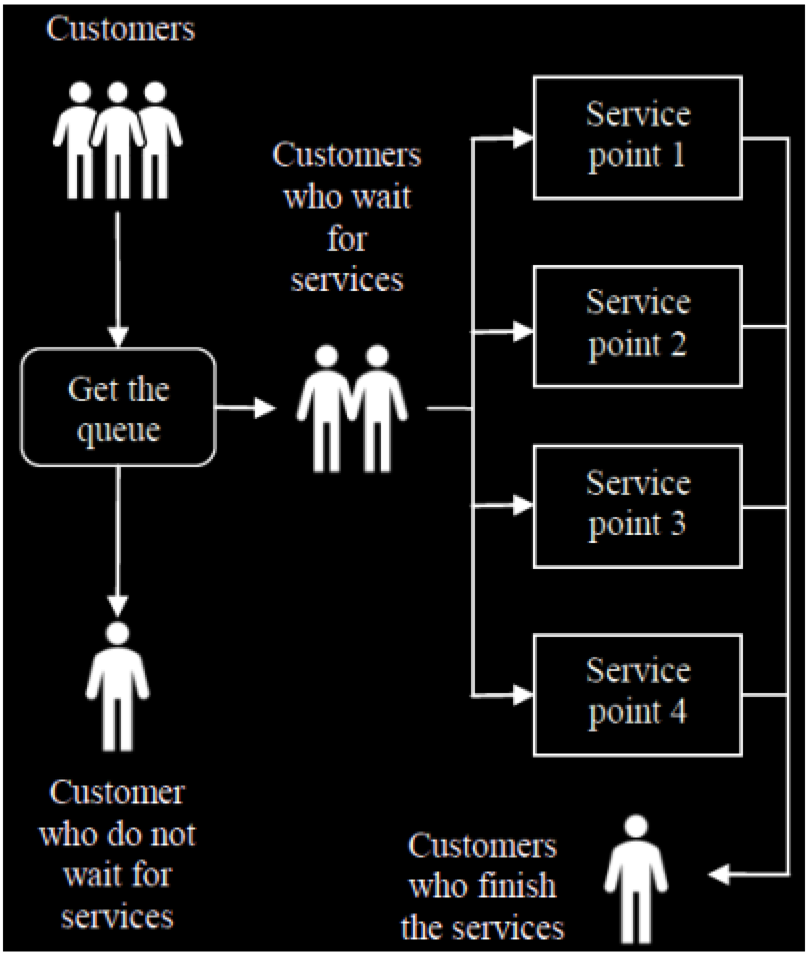

Figure 3: The line framework chart of KhonKaen University mail center

For the holding up time expectation of Queueing Theory, the dataset is a M/M/c queueing framework where c is the quantity of administration focuses that can be run simultaneously. The queueing arrangement of KhonKaen University mail center is displayed in Figure 3. We considered factors following the condition (1)- (4) for anticipating the holding up line time. The holding up times were anticipated by Equation (5) involving the appearance rate and the normal of clients in the line from (4).

The queueing arrangement of ear nose and throat facility dataset is a M/M/c queueing framework where c is two assistance focuses following Figure 4. We considered factors following the condition (1)- (5) for anticipating the holding up line time.

One more technique for anticipating the holding up time is the computation of the typical holding up opportunity in every day and hours. For the dataset of the review, the holding up time expectation followed the Equation (6), with the information separated into every day and time span to track down the normal of the holding up time.

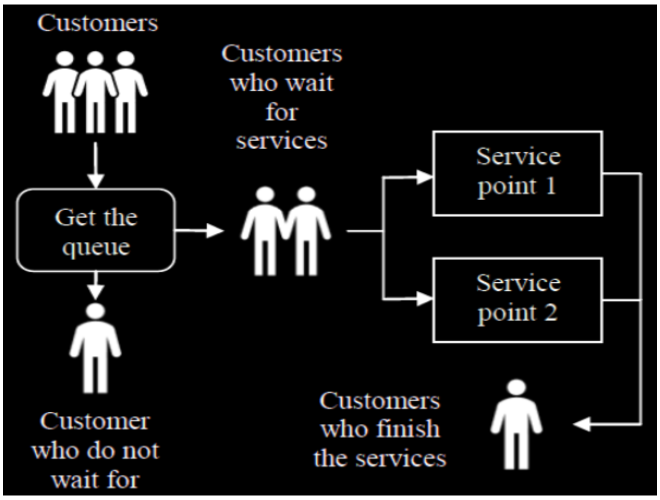

Figure 4: The line framework chart of ear nose and throat facility

The grouping of Random Forest utilized R language to construct a prescient model. The holding up length was prohibited from the preparation dataset for making a model in light of Random Forest on the grounds that the characterization involved the holding up time as the objective trait. The holding up time term was just utilized for working out the normal holding up time.

To find the best Random Forest model with a dataset, we tested calculation in the preparation model by designing the quantity of trees from 100 to 500, by 50 to figure out the most ideal number of trees. The upsides of other boundary settings were default values in the library gave in R language.

4. Experimental results and discussion

The trial results incorporate the exactness of three strategies and component significance of qualities influencing the holding up time expectation.

4.1. Accuracy

Table VII: The Accuracy of KhonKaen University Post Office Dataset

Methods	**Accuracy (%)**
Queueing Theory	65.23
Normal Time	64.94
Irregular Forest	81.7

For the exactness assessment of Queueing Theory and Average Time, the precision is figured in light of the anticipated time and the holding up time class as in Table I and II.

Then again, Random Forest exactness is accounted for in light of the result from a capability in the randomForest library in R language. The exactness of three techniques are displayed in Table VII and VIII.

Table VII shows the precisions of the three techniques from the KhonKaen University mail center dataset. Normal Time has minimal exactness at 64.94%, Queueing Theory has the better exactness at 65.23%, and Random Forest is the best model with an accuracy of 81.70%, and the quantity of trees is 450 trees.

Table VIII: The Accuracy of Ear Nose and Throat Clinic Dataset

Techniques	Accuracy (%)
Queueing Theory	-
Normal Time	68.89
Irregular Forest	85.76

The precisions of the three techniques are displayed in Table VIII. Queueing Theory was not applied to holding up time forecast of ear nose and throat facility dataset, Average Time has minimal exactness at 68.89%, and Random Forest is the best model with an accuracy of 85.76%, and the quantity of trees is 250 trees.

As to exactness while utilizing Queueing Theory, we counseled factors following the condition (1)-(5) for the holding up line time expectation. The Utilization Factor (U) was found more than 1 from the pace of appearance rate (λ), administration rate (μ), and c. In view of the outcomes, the holding up time will watch out for vastness and the queueing framework isn't fixed. Queueing Theory can't be applied to the ear nose and throat facility dataset in light of the fact that the queueing framework and line need are mind boggling and the help design is sporadic. From Table VII and VIII, Random Forest model accomplishes the most noteworthy exactness since Random Forest is a regulated gaining calculation that varies from Queueing Theory and Average Time which depend on numerical equations.

4.2.Include Importance

In Random Forest model, highlight significance is explored to figure out the elements that influence the result expectation the most.

The fundamental elements that were utilized for expectation of stalling time in one-stop administration are outlined through the mean reduction precision chart. The mean abatement precision diagram shows the worth of the elements that are presumably the essential driver of exactness in expectation.

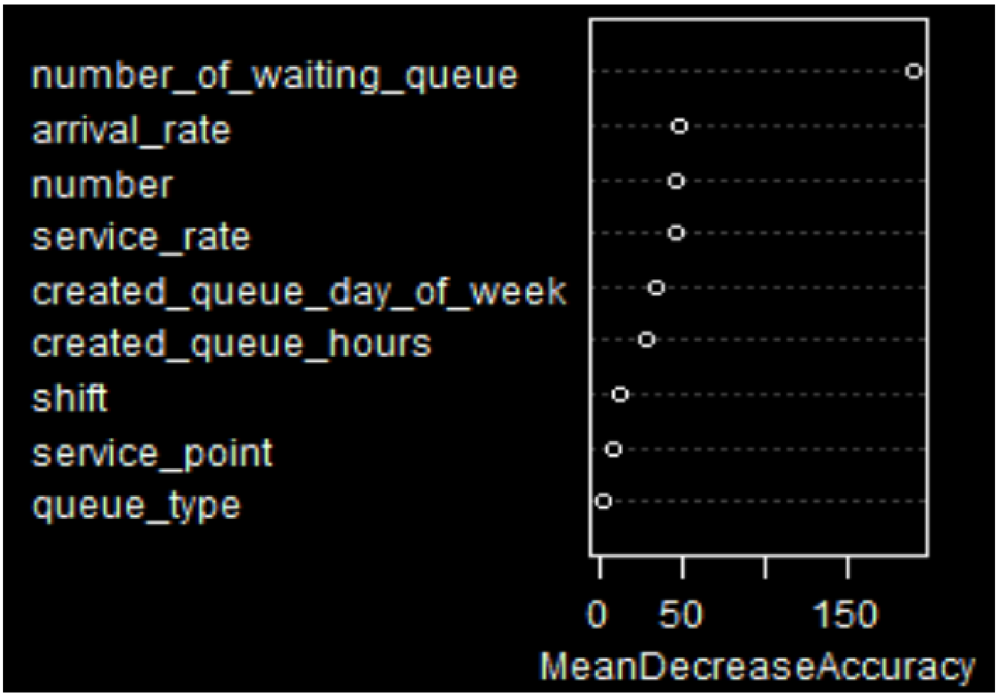

Figure 5: The mean abatement precision of KhonKaen University mail center dataset

From Figure 5, for KhonKaen University mail center dataset, the quantity of delaying lines is the best component in the order of the holding up time. The following fundamental elements are the appearance rate, the line number of delaying time every day, the help rate, the made line of the week, and the made line in hours, separately. Then again, the shift time of the day is less pertinent to the line framework. The most un-huge elements are the help point and line type.

From Figure 6, for ear nose and throat center dataset, the best component in the holding up time arrangement is the quantity of stalling lines. The following huge highlights arethe administration rate, the appearance rate, the made line of the week, the made line in hours, the line number of stalling time every day, and line type, separately. Then again, the help point is less pertinent to the line framework. The most un-huge component is the shift time of the day.

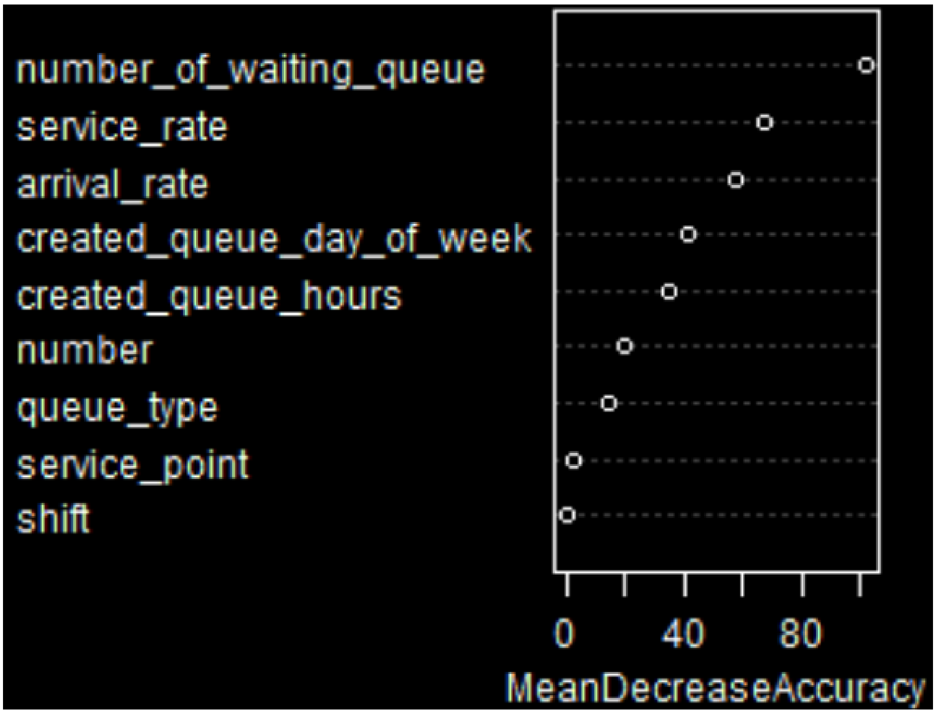

Figure 6: The mean abatement precision of ear nose and throat facility dataset

From the component significant of both datasets, the quantity of delaying lines is the main element of order and building the prescient model on the grounds that the quantity of stalling lines is the element that demonstrates the amount of the assistance at that point. The highlights that show the distinction of the assistance design, queueing framework, and line need between the KhonKaen University mail center and the ear nose and throat facility are the following significance elements of each dataset. The appearance rate and line number of the KhonKaen University mail center dataset demonstrate the help has the fixable example. The assistance and appearance pace of the ear nose and throat facility dataset show that the holding up season of the queueing framework relies upon the help pace of specialist organizations and the assistance design isn't fixable.

5. Conclusion

The article proposes and assesses the model for the holding up time expectation in one-stop administrations. Three methodologies have been executed and looked at including Queueing Theory utilizing M/M/c example, Average Time forecast, and Random Forest calculation. In light of the trial results, the technique that accomplishes the most elevated precision is Random Forest calculation: ear nose and throat center dataset which brings about the exactness of 85.76% and KhonKaen University mailing station dataset which brings about the precision of 81.70%. The main element of both datasets is the quantity of stalling lines.Later on, the specialists are intrigued to utilize other datasets of one-stop administration and concentrate new elements, for example, the climate that might influence holding up time expectation.

References:

[1] Achmad, A. R., Hapsari, I., & Prayogo, D. N. (2021). *Layout Design of Distributor Warehouse PT. X in Sidoarjo*.

[2] Almomani, O., Almaiah, M. A., Alsaaidah, A., Smadi, S., Mohammad, A. H., & Althunibat, A. (2021). Machine learning classifiers for network intrusion detection system: comparative study. *2021 International Conference on Information Technology (ICIT)*, 440–445.

[3] Arroyo, J. F. (2014). *The impact of waiting time management on customer satisfaction in the hotel industry*. มหาวิทยาลัยศิลปากร.

[4] Carvalho, A., & Belo, O. (2016). Predicting waiting time in customer queuing systems. *2016 IEEE International Conference on Knowledge Engineering and Applications (ICKEA)*, 155–159.

[5] Dumka, A., Ashok, A., Verma, P., & Verma, P. (2020). *Advanced Digital Image Processing and Its Applications in Big Data*. CRC Press.

[6] Erdelić, T., Carić, T., & Ravlić, M. (2017). Predicting waiting times at intersections. *2017 International Symposium ELMAR*, 31–34.

[7] Han, H., Guo, X., & Yu, H. (2016). Variable selection using mean decrease accuracy and mean decrease gini based on random forest. *2016 7th Ieee International Conference on Software Engineering and Service Science (Icsess)*, 219–224.

[8] Hensley, R. L., & Sulek, J. (2007). Customer satisfaction with waits in multi-stage services. *Managing Service Quality: An International Journal*, *17*(2), 152–173.

[9] Mourõo, R., Carvalho, R., Carvalho, R., & Ramos, G. N. (2017). Predicting waiting time overflow on bank teller queues. *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, 842–847.

[10] Noyunsan, C., Katanyukul, T., & Saikaew, K. (2018). Performance evaluation of supervised learning algorithms with various training data sizes and missing attributes. *Engineering and Applied Science Research*, *45*(3), 221–229.

[11] Rarh, F., Pojee, D., Zulphekari, S., & Shah, V. (2017). Restaurant table reservation using time-series prediction. *2017 2nd International Conference on Communication and Electronics Systems (ICCES)*, 153–155.

[12] Safdar, S., Khan, S. A., & Shaukat, A. (2021). A Novel Data-Driven Adaptive Technique to Generate a Physician Visiting Schedule for Better Patient Experience. *IEEE Access*, *10*, 3935–3948.

[13] Sanit-in, Y., & Saikaew, K. R. (2019). Prediction of waiting time in one stop service. *International Journal of Machine Learning and Computing*, *9*(3), 322–327.

[14] Sun, L. (2018). *The Influence of Goal orientations and the other Motivational Variables on Dropouts. Case HAAGA-HELIA UAS, Bite programme.*

[15] Van Riel, A. C. R., Semeijn, J., Ribbink, D., & Bomert-Peters, Y. (2012). Waiting for service at the checkout: Negative emotional responses, store image and overall satisfaction. *Journal of Service Management*.

[16] Watcharenwong, N., & Saikaew, K. (2017). Spam detection for closed Facebook groups. *2017 14th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, 1–6.